A Cost-Function-Based Dynamic Channel Allocation and Its Limits

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***Abstract*—Design of efficient dynamic channel allocation (DCA) algorithms has an important impact on performance optimization of wireless mobile networks. The previously proposed DCA algorithms are shown to have good performance but only for certain services and under certain load conditions. Within this paper, we propose a new cost-function-based DCA algorithm, which is fully adaptive to service and load conditions and includes some well-known DCA algorithms such as Random, Minimum Interference, and Autonomous Reuse Partitioning DCA as special cases. By using dynamic system-level simulations, we show that the algorithm provides the same or substantially better performance than these DCA algorithms, with low signalization and computation overhead. We also show the general limits of DCA algorithms in the presence of other interference reduction techniques such as power control and smart antennas.**

***Index Terms*—Autonomous reuse partitioning (ARP), cost function (CF), dynamic channel allocation (DCA), measurement-based radio resource management (RRM) algorithms, power control (PC), smart antenna (SA).**

I. Introduction

EFFICIENT management of scarce radio resources, expensive bandwidth, and transmission power (TXPWR) gains importance due to the increasing number of users and demanding new services in modern wireless networks. Contemporary wireless networks are usually interference limited—The number of users who can be served with a sufficient signal quality is limited by the interference on the channel and not by the number of channels. The main source of the interference is intracell and co-channel or intercell interference. Intracell interference, i.e., interference among the users in the same cell can be kept low by allocating orthogonal or near-orthogonal resources to users, such as different frequencies in frequency-division multiple access, time slots in time-division multiple access, or codes in code-division multiple-access (CDMA)-based systems. We define co-channel interference as interference from the users in the other cells using the same channel. The intercell interference can be kept low by making the distance (reuse distance) between the cells using the same channel (co-channel cells) high. This is because signal power and, consequently, interference decays with distance d proportional to $d^{-\alpha}$, where α is an environment-specific parameter. Typically, α is between 2 and 5 [1]. The cellular systems make use of this idea [2] and reuse the same spectrum several times within a network. It is one of the main optimization criteria to keep the reuse distance small. In the past, the channels are usually allocated fixed to cells (fixed channel allocation) during the network planning process before system deployment. The distance between the cells using the same channels must be held high to be able to keep the co-channel interference low, even for the worst case user positions. The problem with the fixed channel allocation and large reuse distance is inflexibility and inefficient usage of the channels in the system. Only a subset of the total channels that are available in the system can be used in each cell. Furthermore, some cells need, in certain time periods, more channels than others due to traffic irregularities and changes in the environment. In order to provide better channel usage and adaptability to traffic changes, a class of dynamic channel allocation (DCA) algorithms has been investigated [3]–[12]. Distributed interference-based DCA algorithms enable flexible spectrum usage by dynamic channel selection according to actual load and interference situation. With decentralized DCA, signalization overhead is also reduced since each cell takes its own decisions about channel allocation using locally (in the cell) available information, e.g., interference on the channels.

However, the DCA, like those described in [3]–[12], use always basically the same algorithms for different loads and interference situations, although the performances of some algorithms vary considerably with load and interference. The existing DCA algorithms are also mainly designed and tested for speech service, wherein modern system packet data gain importance.

Furthermore, due to modern modulation and coding techniques (CDMA, turbo codes, etc.), requirements on minimum signal quality, i.e., carrier-to-interference ratio (CIR), are reduced; consequently, the distance among the cells using the same channels (reuse distance) is reduced. Whereas most DCA algorithms [3]–[12] are usually investigated for the cases when the cells can use only a subset of all available channels in the systems keeping reuse distance high, in our case, all cells can use all channels [reuse factor equals 1 (reuse 1)], and no channel planning is needed.

In this paper, we propose a distributed DCA based on cost function (CF), which flexibly combines the advantages of the different DCA algorithms by service, load, and interference-dependent parameter settings. The algorithm is designed to work for both speech and packet data in reuse-1 systems, achieving the same or better performance than any of the tested DCA algorithms.

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This paper is organized as follows: In Section II, we present our CF concept for a distributed measurement-based DCA algorithm. In Section III, a short description of our simulator and system model is given. Section IV describes the performance figures. Simulation results of our DCA algorithm for different loads (number of users) and services (speech and packet data), with and without power control (PC) and smart antennas (SAs) are discussed in Section V. Finally, the conclusions are given in Section VI.

II. CF-Based DCA

We start our discussion with the description and review of some basic distributed DCA algorithms, such as Random (RCA), Minimum Interference (Min I), and Autonomous Reuse Partitioning (ARP) channel allocation strategy. Since each of these algorithms performs optimal only under certain network conditions (load and interference), we use them as building blocks for our CF-based DCA, which is described in the second part of this section.

The basic idea of DCA algorithms is to avoid extensive interference by enforcing the cells that are close to each other to use different channels as often as possible. Distributed measurement-based DCA algorithms use interference information in each cell as the decision measure about channel usage in the neighborhood: High average interference is an indication that the channels are used relatively often in the neighbored cells, and vice versa. In this way, an explicit signalization between cells about channel usage is not needed in contrast to centralized algorithms.

Using the following well-known DCA algorithms (see [3]–[12]) as a building block, we developed our CF-based DCA.

A. RCA

This is the simplest DCA algorithm. The channel assignment to the user is done in random fashion, i.e., the channel is uniformly drawn out of the set of free channels at the time of assignment. Neither measurement results nor any other parameter is used. Due to its simplicity, no optimal channel allocation can be expected, but under certain conditions, the algorithm could provide sufficient performance with low signalization and computation overhead.

B. Priority-Based and Min I DCA

According to Priority-Based (Channel Segregation) DCA [5], [7], channel assignment is done according to the priorities of the channels. The channel priorities are also established according to interference on the respective channels. The set of free channels is sorted in descending order by priority. The first channel out of this new set of available channels is always selected first. If the interference on a channel is lower than a certain threshold, the priority of the channel is increased; otherwise, it is decreased. Fig. 1(a)–(c) represents how the Channel Segregation DCA emerges during the simulation.

At the beginning of the simulation [Fig. 1(a)], neighbor base stations use almost all channels equally likely. After a certain

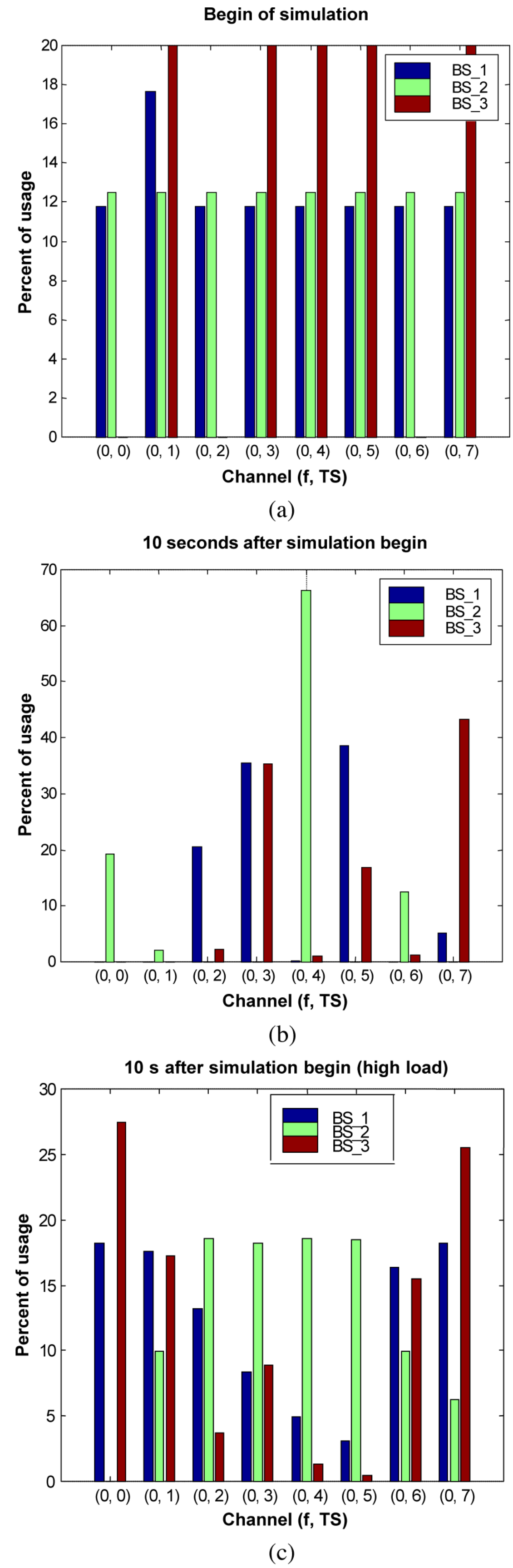

Fig. 1. (a) Channel usage after 500 frames (0.5 s). (b) Channel usage after 10 000 frames (10 s, low load). (c) Channel usage after 10 000 frames (10 s, high load) [x-axis: channels (f–TS pairs), y-axis: percentage of channel usage in neighbor cells (bars with different colors)].

simulation time (10 s), "channel segregation" is established [see Fig. 1(b)]: The channels that are often used by a cell are used relatively seldom by its neighbors, and vice versa. For example, the channel with frequency 0 and time slot 4 [channel (0, 4)] is used about 70% of the time in cell 2, only about 2% of the time in its neighbor cell 3, and not at all in an another neighbor cell 1. In the case of higher loads [Fig. 1(c)], almost all channels must be used in all cells, so that the channel segregation could not be accomplished.

The effect of channel segregation can be clearly seen for lower loads [compare Fig. 1(a) and (b)], where neighbor cells can use different channels most of the time. For higher loads [Fig. 1(c)], almost all channels must be used almost in all cells for almost all the time, and channel segregation is not possible.

Min I DCA [8], [9], [12] chooses channel k with the lowest interference from the set of free channels. Denoting with $I(k)$, i.e., the interference on channel k, we select the channel for allocation according to the following rule:

$$\text{channel}(k) = \arg\min_{k} I_k. \tag{1}$$

We obtain the same channel usage distribution as in the case of channel segregation [Fig. 1(a)–(c)] also in the case of Min I DCA. Since we apply reuse 1 (all channels can be used by all cells), a cell applying Min I DCA uses the channels with lower interference more often than those with higher interference. The same is true for channel segregation. According to channel segregation algorithms, the channels with lower interference also get higher priority because their interference is below a threshold more often. Consequently, the channels with lower interference are also used more often by channel segregation because they have higher priority. That is why we obtain basically the same distribution of channel usage in both cases: channel segregation and Min I DCA. It should be noted that we use reuse 1 and the interference threshold that is used by the channel segregation set appropriately. For reuse greater than 1 and some other threshold settings, channel distribution might not be the same.

An advantage of Min I DCA over Channel Segregation is that it does not need any interference threshold and achieves according to our simulations at least the same performance as Channel Segregation with optimal threshold settings (similar results are also shown in [8]). That is why we do not lose much if we investigate further only Min I DCA and not Channel Segregation.

For both algorithms, the system capacity cannot be improved further for high system loads. This is because nearly all channels are in use and the set for assigning the best channel reduces to only one selectable channel. That is why both DCA algorithms only gain performance for cellular networks that are operated at low load. The operator does not have the ability to increase network capacity for heavy-loaded systems, but both algorithms allow optimization for battery-power consumption in the mobile. This behavior makes these algorithms of limited importance for the operators. The question is "Which DCA algorithms maximize the system capacity for higher loads?" We try to give an answer on this question in the next section.

C. ARP

Min I DCA optimizes the channel allocation from the single-user point of view—A user gets the best channel (with lowest interference) when the user arrives in a system. The problem is that, from the point of view of the whole network, this allocation might not be optimal. Users arriving later might get worse channels (with higher interference), although these users might suffer under worse conditions [higher path loss (PL)]. In case we allocate the worse channels (but still good enough to serve for the required service) to the users with lower PL, enough "good" channels could be left free for the users with higher PL.

ARP DCA algorithms [4], [6], [9] make use of this idea and allocate the channels with higher interference to the users with higher signal gain (lower PL) in order to leave channels with low interference free for the users with lower signal gain (higher PL). In this way, the number of users in the cell with sufficient CIR (satisfied users) should be maximized.

To simplify the implementation, we propose the following heuristic version of the ARP. When the user arrives in a certain cell, i.e., either through a birth process or a handover (HO), the channel k fulfilling

$$\text{channel}(k) = \arg\min_{k} |\text{PL} + I_k - C| \tag{2}$$

is chosen. The minimization criterion sums up the measured PL including shadow fading, the measured interference that is seen at the receiver, and a given parameter C. k denotes the communication channel between the user with resource request and the base station. This approach enables relatively simple implementation, i.e., as a user arrives at a cell, a channel may be allocated to a user by just evaluating (2) for all free channels in a cell, without taking into account other users and other cells. This approach provides linear algorithm complexity (proportional to the number of channels in a cell), no allocation delay, and no signalization overhead for communication between cells.

Parameter C can be set to a network-specific value, so that the user chooses the channel that is just sufficient, and not much better, for its minimum channel quality needs. In other words, C can be set in the way that the user chooses the channel where the outage-probability of the required CIR can be kept below a certain bound, e.g., $P(\text{CIR} < \text{CIR}_{\text{thr}}) \leq b$ for the duration of the active session in the cell. In that case, we say that the user will be satisfied. Assuming Gaussian CIR distribution, C can be set as follows:

$$C = P_{\max} - m\sigma_{\text{CIR}} - \text{CIR}_{\text{thr}}. \tag{3}$$

σ_{CIR} represents the standard deviation of the received CIR, CIR_{thr} is the desired CIR threshold for the user and service, and finally $P_{\max}$ is the maximum allowable transmitting power. σ_{CIR} is obtained from the statistical evaluation of the measurements that are already available in the network. To adapt the parameter to the current situation, a dynamic adjustment can be done, e.g., by a sliding window. Parameter m is set according to the desired outage probability. For example, assuming a Gaussian probability distribution for CIR for an outage

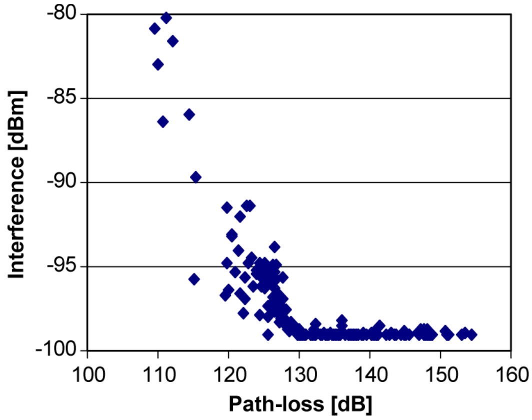

Fig. 2. With ARP DCA, users with lower PL get a channel with higher interference, and vice versa.

probability of 2% yields $m \approx 2$. ARP can then select channels according to (2); C is set according to (3), and m is set according to the required outage probability. In this way, the users choose the channels that just fulfill their minimum required signal quality, leaving channels with lower interference free for users with higher PL. Consequently, terminals with lower PL get the channel with higher interference, and vice versa (see Fig. 2).

We expect that the capacity of the system is higher with ARP compared to Min I or RCA because the number of users having sufficient CIR is increased.

D. Interference Estimation

In order to employ interference-based DCA algorithms such as Min I or ARP DCA, cells collect interference statistics on each channel that is available in the cell. In general, an estimate about the interference distribution on each channel is needed. However, for most applications, only the mean value m_I and standard deviation σ_I of the interference on each channel are sufficient (Gaussian interference distribution [13]). As a measure of relative changes of interference on a channel, ratio d_I between the standard deviation and mean value of the interference on the channel can be used, i.e.,

$$d_I = \frac{\sigma_I}{m_I}. \tag{4}$$

High-valued d_I indicate relatively high changes in the interference on the channel and impossibility to estimate the interference properly. d_I is usually high in the case of lower load since arrival and/or departure of each user and/or a data packet in a cell could cause significant interference changes in neighbored cells. In that case, interference-based DCA algorithms might not achieve optimal channel allocation due to unreliable interference estimation. If d_I is relatively low, better interference estimation is possible, and interference-based DCA algorithms may be successfully applied.

E. CF-Based DCA

As we have seen in previous paragraphs, every algorithm has its advantages and drawbacks. It is desirable to combine the

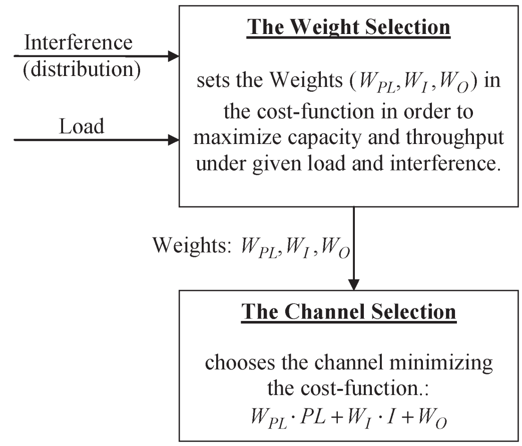

Fig. 3. CF-based DCA concept consists of weight selection according to the actual condition in a cell (load and interference) and channel selection by CF minimization.

advantages of different DCA algorithms such as RCA, Min I, or ARP. Our goal is to design a DCA algorithm with the following characteristics:

1) to be general enough to obtain the algorithms described previously, as special cases;
2) to achieve even higher capacity gain than the algorithms described previously, at least for certain loads and services;
3) to be adaptive to changes in, for example, load, interference, service type of the users, etc.;
4) to have relatively low implementation complexity and signalization overhead.

We will show that the CF concept that is described in the sequel is one of the algorithms, which fulfills all of the aforementioned requirements. CF is based on the idea that decisions in complex situations can be evaluated by using a function of relevant features (in our case, a linear function of PL and interference). The similar idea is proposed by Shannon for evaluating board positions in chess playing [14].

Our CF-based DCA algorithm consists of the following two phases: 1) channel selection and 2) weight selection (see Fig. 3).

Channel Selection: This part of the algorithm allocates channel k to user u for which the evaluation of the CF yields the minimum. CF is a generalization of (2) and is represented as a weighted sum of the PL (which is measured in decibels) between the user and the base station, the interference on channel k (I_k, which is measured in decibels below 1 mW), and a "free" (selectable) parameter W_O, i.e.,

$$\begin{aligned} \mathrm{CF}(u,k) &= W_{\mathrm{PL}}\mathrm{PL}(u) + W_I I_k + W_O(u,k) \\ \mathrm{channel}(k) &= \arg\min_k \left[\mathrm{CF}(u,k)\right]. \end{aligned} \tag{5}$$

The evaluation of the CF can be done in either the mobile terminal or the network. For network-controlled channel allocation, like in Global System for Mobile communications or Universal Mobile Telecommunications System (UMTS), the mobile needs to provide its measurements to the network for the downlink direction. In the case of mobile-controlled channel allocation, like in Digital Enhanced Cordless Telecommunications, the network needs to provide the weights to the mobile [parameters for (5)] and the measurements for the uplink direction.

Weight Selection: This part of the algorithm selects weights for the CF according to the load and the interference in a certain cell of the network. The weights are selected in a way that the channel selection part minimizing the CF allocates the channels to the users, so that the overall network capacity is maximized under given load and interference conditions. The weight selection can be done in a distributed manner for each cell individually and according to the (local) load and interference situation. Alternatively, the network operator has the possibility to set the weights, e.g., via operation and maintenance for each cell in the network according to the expected traffic occurrence and network planning issues.

The DCA algorithms described previously can then be obtained as a special case of our CF concept by appropriate setting of weights W_{PL}, W_I, and W_O in (5).

— By setting $W_{\mathrm{PL}} = W_I = 0$ and $W_O =$ random number, we obtain the RCA algorithm.
— By setting $W_{\mathrm{PL}} = 0$, $W_I = 1$, and $W_O \gg 1$, we obtain the Min I DCA algorithm.
— By setting $W_{\mathrm{PL}} = W_I = 1$, $W_O = -C$ if $\mathrm{PL} + I \leq C$, and $W_{\mathrm{PL}} = W_I = -1$, $W_O = C$ if $\mathrm{PL} + I > C$, we obtain $\mathrm{Cost}(u, k) = |\mathrm{PL} + I - C|$, i.e., ARP DCA [see (2)].

With CF, we can also obtain other DCA algorithms such as ARP, RCA, and Min I as special cases. Because CF is a linear function of the PL and the interference with real-valued parameters [see (5)], these algorithms represent only a small subset of possible parameter settings. For certain services and loads, some parameter values might yield better results than any of these DCA algorithms.

Like with ARP, with CF, we can also provide all users with "optimal" channels, i.e., channels that are just good enough to provide users with the required CIR most of the time but not better. Any other DCA algorithm, which provides users with better channels than what they need, would result in lower capacity: In the case of a high load, some users (with a high PL) would get worse channels since the "good" channels would be used by other users (with a low PL), who actually do not need so good channels. The problem with ideal CF is that we would need to make channel (re)allocation with each change in the network (changes in channel and interference) in order to provide each user with an optimal channel all the time. This would cause enormous signalization overhead and performance degradation due to setup times for PC. In order to reduce overhead, we evaluate channels only at call setup in the case of speech service and for each packet allocation in the case of nonreal-time (NRT) services. Due to lower duration of packet allocation, we expect better results of CF for the NRT service than for real-time (RT) services.

Each time the load and interference significantly changes, the weights in CF should also change. We can automatically adapt weights, taking into account actually encountered costs and moving in the negative gradient direction, i.e., according to least mean square algorithms that are widely used in signal processing, neural networks, and machine learning [15]. Thus,

$$W(n+1) = W(n) + \lambda \Delta \mathrm{Costs} \frac{\partial CF}{\partial W} \qquad (6)$$

where λ is a parameter $(0 \leq \lambda \leq 1)$, and ΔCosts is the difference between the actually encountered costs, i.e., experienced CIR (distribution) during channel hold time and predicted costs according to CF that is defined by (5).

Note that the algorithm complexity of a CF-based DCA is significantly reduced in comparison to a search for optimal channel allocation by enumeration. A search for a global optimal channel allocation over all possible combinations of users and channels would require exponential complexity. To see this, let us consider, for simplicity, only one cell having K channels that are available for allocation for N new users $(K \geq N)$. For this simple case, the DCA has the freedom to select out of $P = \binom{K}{N} N!$ combinations. Even in this simple case (with only one cell), it would require to evaluate $O(N!)$ possibilities, which is a prohibiting task in fast changing mobile environments. With the CF concept, the algorithm complexity is reduced to polynomial time. The search for the minimum of the CF (over the set of free channels in the cell) is performed for each user, independently of the other users in their own cells. The allocation is done sequentially, as users arrive to the cells, which reduces waiting time of the users.

If the channel selection is done by the mobiles themselves, only weight parameters need to be broadcast by the base stations to the mobiles. Otherwise (DCA done in the base stations), only measurements of PL and interference need to be signaled from the mobiles to the base stations. However, this signalization is required for radio link maintenance and for other radio resource management (RRM) algorithms such as fast PC, HO, etc. This means that we do not need to introduce additional signaling in the network for the purpose of CF-based DCA.

III. System Model

We have compared the performance of interference-based DCA algorithms by means of a dynamic event-driven system-level simulator. We modeled in the simulator user movement, antennas, propagation (geometric PL and shadow fading), and interference as well as the RRM algorithms such as HO and PC. In the simulator, speech and data services were simulated in rural (macro) environments. Channel models, user mobility, and traffic behavior was implemented according to [16]. We simulated UMTS time-division-duplex mode where channels are represented by frequency f, time slot TS, and code c triples. Since the intercell interference is the same for all codes of an f–TS pair, we use the term "channel" as the f–TS pair instead.

We assume that speech users arrive according to a Poisson process. The call duration is exponentially distributed with a mean duration of 120 s. The traffic model is a Markov on–off type, so that discontinuous transmission can be modeled. Packet data sessions also arrive according to a Poisson process. The number of packet data requests per session, the reading time between two consecutive packet call requests in a session, the number of packets in a packet call, and the time interval between two consecutive packets inside a packet call were modeled as geometrically distributed random variables, and the packet size was modeled as a truncated Pareto distributed random variable [16].

The channel allocation is done immediately when a user arrives in the cell in the case of speech users and after the scheduling (according to the first-in–first-out algorithm, assuming a shared channel) in the case of packet data users. The (hard) HO is channel-gain based and is performed in case a candidate cell has lower PL by a margin than the serving cell. The channel gain includes geometric PL and shadow fading, and the multipath effects coming from the channel model are averaged over time. The averaging is done in order to eliminate fading notches and rapidly changing effects, taking only slow-changing properties, i.e., PL and shadow fading, into account.

Simulations for speech users were done with and without fast closed-loop CIR-based PC [17]. This type of PC adjusts the TXPWR in the manner that a constant CIR (CIR target) at the receiver can be maintained. On average, the TXPWR is proportional to the user PL including shadow fading and interference on the channel. The CIR target was optimized for each load separately, in order to maximize the system capacity by maximizing the number of satisfied users. C-based PC was used for packet data, i.e., the power is set, so that a constant useful signal level (load dependent) is kept at the receiver [17].

The receiver performance is evaluated according to the actual value interface, as described in [18]. In the system-level simulator, CIR is calculated each frametick (10 ms). The signal-to-interference ratio (SIR) is obtained from the CIR after despreading and block-linear zero-forcing, taking into account the number of users in the time slot and the number of spreading codes in the time slot. Further SIR is mapped on the raw bit error rate (BER), eventually taking into account maximum ratio combining (MRC). Whenever MRC is done at the receiver with two diversity branches, the SIR in linear scale after MRC is modeled as the sum of the input SIR. From this signal-to-interference-and-noise ratio, the raw bit-error probability (raw BER) is obtained by mapping. The interleaving is modeled by averaging the raw BER. The link performance either as bit-error probability for the code-block or as packet error probability for data services (block error rate, BLER) finally is mapped from the averaged raw BER. The mappings from CIR to SIR, from SIR to raw BER, and from raw BER to user BER/BLER are defined by the polynomial regressions of the results from link-level simulations having all physical layer details implemented. The physical layer in the base station employs ideal joint detection of users belonging to the same cell. Link-level simulations of the physical channel, coder/decoder, modulator, and demodulator are done on a subchip duration scale, whereas the granularity of the system-level simulator is the time slot.

An overview of simulator parameters is provided in Table I.

TABLE I
PARAMETERS OF THE SYSTEM-LEVEL SIMULATOR

Parameter Name [unit]	Value
Number of base station sites	19
Number of sectors per site	3
Number of cells	57
Number of reference cells	3
Antenna height MS/BS [m]	1.5/30
Frame duration [ms]	10
Number of slots per frame	8 UL + 8 DL
Number of codes per slot	12
Carrier frequency [GHz]	2
Bandwidth [MHz]	5
Chip rate [Mchip/s]	4.096
Channel reuse	1
Shadow fading σ [dB]	10
Decorrelation length [m]	20
Speed mean [km/h]	120
HO-margin [dB]	5
Max MS/BS power level [dBm]	36/42
Noise Power MS/BS [dBm]	-99/-103
Service types	Speech and 384 kbps packet data
CIR threshold: speech/data [dB]	-11.8/-5.1
Power Control	CIR-based (speech) C-based (packet data)
HO type	Path-loss based
Scheduling	FIFO

IV. Performance Figure

An ultimate goal of all resource management algorithms is to maximize the network capacity in terms of efficiency and costs. For this purpose, we assess the system performance according to the number of users that can be supported by a system with required minimum quality. We used load normalization to ensure comparability between the results and figures. In the following, we define the criterion for which a user is said to be satisfied and, in addition, describe a performance metric about the power consumption.

A. Satisfied User Criteria

For users of real-time speech service, we say that a user is satisfied when three conditions are fulfilled [16].

1) The user was not blocked when arriving to a system.
2) The user had sufficiently low BER for more than a certain time (fraction) of the session, i.e., Probability $(\text{BER} > 10^{-3}) < 2\%$.
3) The user was not dropped. A call is dropped if BER $> 10^{-3}$ for more than 5 s.

For NRT packet data service, a user was regarded as satisfied if three constraints were fulfilled [16].

1) The user was not blocked when arriving to a system.
2) The active session throughput R of the session was equal to or greater than some minimal throughput $R_{\min}$ (10% of the nominal data rate, i.e., 38.4 kb/s for our 384-kb/s packet data service).
3) The user was not dropped. A user was dropped if the number of retransmissions of the same packet exceeded a predefined threshold (ten in our simulator).

B. Grade of Service (GOS)

In order to be able to compare the performance of different DCA algorithms for NRT packet data service, we use the GOS

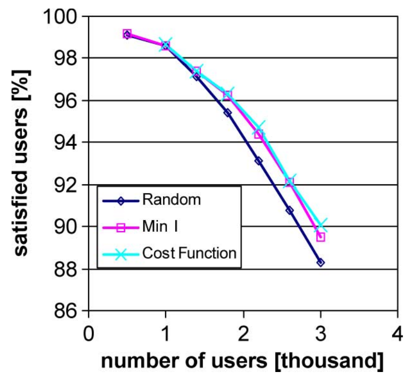

Fig. 4. Comparison of DCA algorithms for speech service [(y-axis) percentage of satisfied users depending on (x-axis) load].

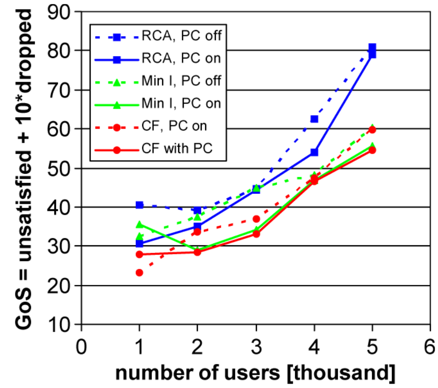

Fig. 5. Comparison of DCA algorithms for packet data service: GOS on the y-axis depending on (x-axis) load.

metric, which combines unsatisfied user rate (UR) and dropping rate (DR) through [19]

$$\mathrm{GOS} = \mathrm{UR} + 10 \cdot \mathrm{DR}\ [\mathrm{in}\%]. \tag{7}$$

Since call dropping is experienced by a user as a much more severe system failure than lower data rate (unsatisfied user), the relative weight of the dropping probability is much greater (ten times) than the weight of the unsatisfied user probability. The higher the GOS, the worse the performance of a DCA algorithm.

C. *Power Consumption*

We also used the average energy consumption for transmitting, without DSP and other energy consuming parts, as a performance metric of the DCA algorithms. In particular, for low-load scenarios, this metric shows advantages of some DCA algorithms, as discussed in Section II-E. However, note that this advantage remains only in the case of power-controlled radio links. Reduction of TXPWR is important for the mobile stations in order to increase battery lifetime.

V. Simulation Result

In Fig. 4, we present the results of RCA, Min I, and CF-based DCA algorithms for speech service in urban environment. RCA performs worse than any other investigated DCA algorithm. Min I is better than RCA and achieves for all loads almost the same performance as ARP or CF-based DCA. Although CF is better than RCA or Min I, the performance gain over Min I is not significant.

Although the CF-based DCA is the best for all loads, the gain is not significant in comparison to Min I DCA. This is because a channel is allocated to a user for the whole duration of the user's sojourn time in the cell. Since the user moves during the time, PL and interference change, and a channel that was optimal at the time of allocation might not be optimal during the whole time. That is why Min I performs well—It allocates the channel with the lowest expected interference during the whole user's sojourn time in the cell. One could introduce intracell handoff in order to switch to optimal channel more often, but this would cost additional signalization overhead and performance loss due to PC initialization.

However, in case of NRT services such as packet data, the CF brings significant gain over other DCA algorithms, particularly, for medium loads and no PC (see Fig. 5). CF is better, i.e., it has lower GOS than RCA or Min I DCA. The gain of CF is particularly high for low–medium loads and with PC off (all users send with maximal power). With PC (PC on), the difference between CF and Min I is relatively small. This is because, in the case of NRT packet data services, an optimal channel can be selected with the CF-based DCA for each packet, which lasts for a relatively short time compared with the user's sojourn time in a cell in case of speech service. For short-time channel allocation in the case of packet data, a significant advantage can be gained by allocating an optimal channel, which at this point in time is estimated according to CF with optimal parameter settings. We can also see in Fig. 5 a tradeoff between CF and PC: CF without PC achieves almost the same results as Min I DCA with PC.

The interference-based DCA algorithms such as Min I tend to nonoptimal decisions for lower loads due to unreliable interference estimation for packet data (high d_I, see Section II-D). In the case of medium-to-high load, Min I is better than RCA. This is because the interference-based DCA algorithms use more frequently the channels with lower interference and RCA uses all channels that are equally probable.

We investigate further how big the gain of the DCA is in the presence of other interference-reducing techniques such as PC and SAs (see Fig. 6).

According to Fig. 6, the most gain in system capacity (number of satisfied users) comes from SA, then from PC, and then DCA. Without SA, the gain of CF-based DCA is larger without PC (about 18%) than with PC (about 10%). If both SA and PC are used, the gain of CF-based DCA is negligible in comparison to the simple RCA. The gains from PC, SA, and DCA are not additive (see also [20] and [21]): PC and even more SA reduce overall interference so much that almost all channels (time slots) have sufficient quality, thus living little room for further improvements by the DCA.

This can also be seen in Table II. The highest reduction of interference comes from SA, followed by PC, and finally from DCA. The reduction of interference due to SA is almost

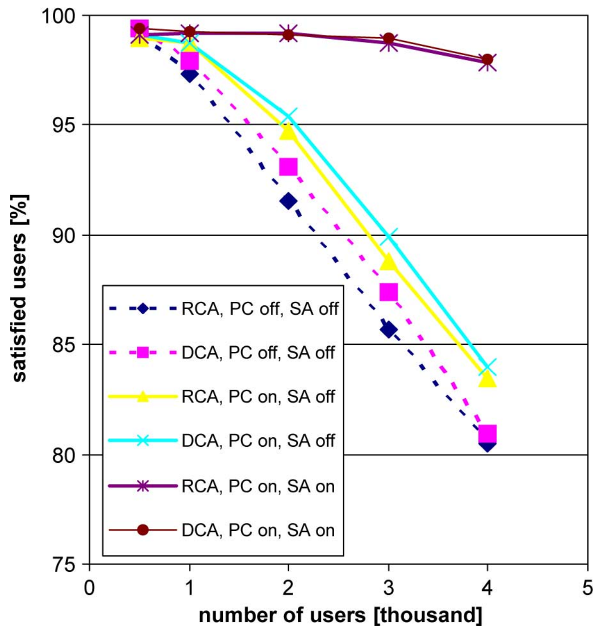

Fig. 6. Gain of CF-based DCA measured in the number of satisfied users with/without PC (PC on–off if PC off—All users send with maximal power) and with/without SA (SA on–off).

TABLE II
MEAN INTERFERENCE IN DEPENDENCE OF LOAD AND INTERFERENCE REDUCTION TECHNIQUE

Algorithms	Load		
	LOW	MEDIUM	high
RCA, PC off, SA off	-85,47	-78,32	-74,92
DCA, PC off, SA off	-87,97	-79,70	-75,18
RCA, **PC on**, SA off	-91,77	-80,08	-75,70
DCA, PC on, SA off	-95,57	-81,10	-76,03
RCA, PC on, **SA on**	-96,50	-89,39	-83,86
DCA, PC on, SA on	-97,82	-91,12	-84,37

load independent because the SA capability to transmit in the direction of the desired users (using only a few space grades), instead of omnidirectional (using all 360 space grades), is almost load independent.

On the other side, the reduction of interference due to PC is not so much in the case of higher load because, in this case, interference is high and users must transmit with their maximum power to achieve the required CIR.

The DCA cannot reduce interference so much as the PC does and even less than the SA does because, in the case of higher loads, all cells use all channels almost all the time, and no interference reduction due to channel segregation can be achieved. The use of some kind of interference-based DCA is anyway more difficult in the presence of PC and SA since interference estimation is relatively bad due to high d_I ratio (see Table III).

From Table III, we can see that the usage of DCA, PC, and SA increases d_I because interference is not equally distributed over the channels (DCA), time (PC), or space (SA) as in the case of RCA, constant power transmission, and omnidirectional antenna.

This means that, for higher loads, interference might be reduced so much, due to the use of PC and, particularly, SA,

TABLE III
RELATIVE INTERFERENCE VARIABILITY IN DEPENDENCE OF LOAD AND INTERFERENCE REDUCTION TECHNIQUE

Algorithms	Load		
	LOW	MEDIUM	high
RCA, PC off, SA off	0,49	0,32	0,30
DCA, PC off, SA off	0,57	0,33	0,30
RCA, **PC on**, SA off	0,84	0,36	0,31
DCA, PC on, SA off	1,12	0,38	0,32
RCA, PC on, **SA on**	1,53	0,63	0,46
DCA, PC on, SA on	1,79	0,72	0,48

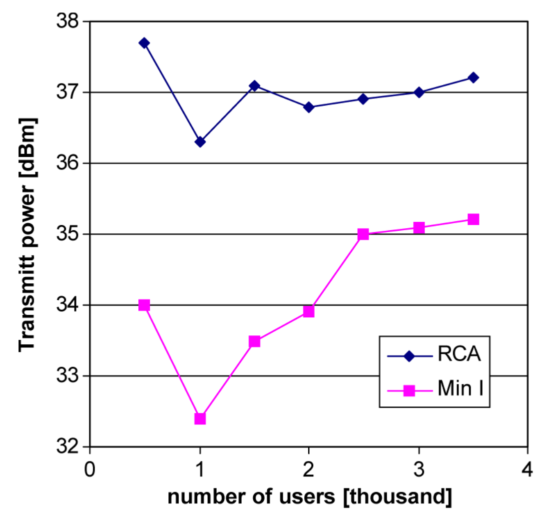

Fig. 7. TXPWR reduction due to Min I DCA in comparison to RCA.

that all channels are "good" enough and we do not need any sophisticated DCA but can apply simple RCA at least for this kind of service, i.e., speech. However, the advantage of the Min I DCA algorithms with PC and SA is the TXPWR reduction in comparison to RCA (see Fig. 7).

From Fig. 7, we can see that, taking channels with Min I always instead of RCA, TXPWR can be reduced for about 2–4 dB. For very low load, more power is needed than for low load (34 dBm for load 1 and 32.4 dBm for load 2 with DCA). This is because the CIR threshold for CIR-based PC should be set higher due to unreliable interference and consequently CIR estimation for higher loads (see Table III).

TXPWR reduction is of special importance for the mobile stations due to increase of battery life. Since, with SIR-based PC, TXPWR is equal on average to the product of the user PL and interference on the channel and, with the CF-based DCA, the time slots with lower interference are used on average more often than with RCA, less TXPWR is used on average with Min I DCA. The power reduction is particularly high in the case of lower loads since, with the Min I algorithm, neighbored cells can use different time slots most of the time and thus minimize interference on the most frequently used channels [see Fig. 1(b)]. In the case of higher loads, almost all time slots must be used in all cells, and the DCA algorithm must sometimes also allocate the time slots with higher interference [see Fig. 1(c)], so that the power reduction is not so high as in the case of lower loads.

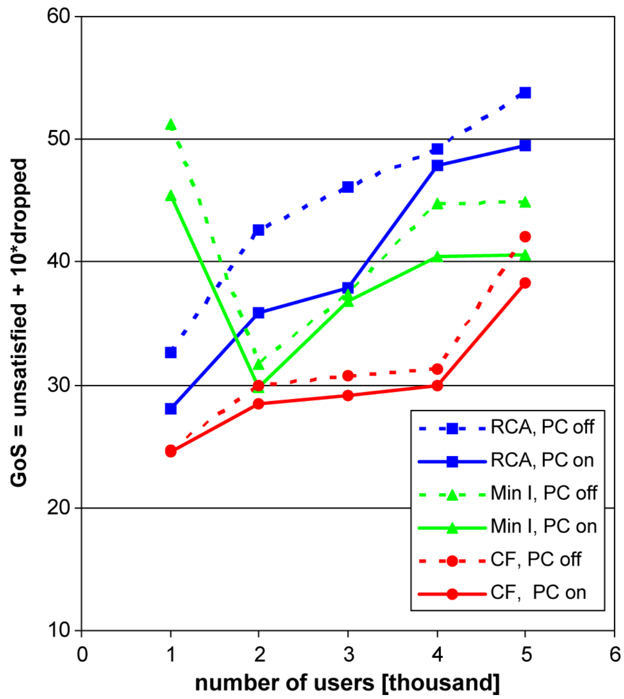

Fig. 8. Comparison of DCA algorithms for a packet data service with SA: GOS on y-axis depending on (x-axis) load.

However, even with SA in the case of NRT services such as packet data, DCA, particularly, CF-based DCA, can still bring significant performance advantages (see Fig. 8).

According to Fig. 8, the CF-based DCA brings significant performance advantages over RCA or Min I DCA, particularly, for low–medium loads. RCA and Min I achieve worse performance for almost all loads even with PC (PC on) than CF without PC (PC off—all users send with maximum power).

It is interesting that CF achieves, in the presence of SA, better results than Min I or RCA even without PC (in contrast to case without SA, see Fig. 5). This is because, with SA, interference variations are so high that PC cannot track interference accurately for a short duration of one packet. On the other hand, CF can use previous experience on the channel (interference) and allocate optimal channels to the users. Since improvement by PC is relatively small in the case of SA and packet data, it would be enough just to use CF and SA in order to achieve almost optimal performance for packet data.

VI. Conclusion

We summarize our main results here.

1) CF is general enough to obtain different DCA algorithms such as RCA, Min I, or ARP DCA as special cases. For some loads and services, CF-based DCA achieves significantly better results than any of these well-known DCA algorithms.
2) For RT speech services and without SA, Min I DCA is sufficiently good for almost all loads. In the case of SA, overall interference is significantly reduced, so that the capacity gain of any DCA algorithms is relatively low in comparison to RCA. However, even with SA and PC, power consumption is much lower with Min I DCA than with RCA.
3) In the case of NRT packet data services and without SA, a tradeoff can be made between PC and CF-based DCA—CF without PC achieves almost the same results as Min I DCA with PC. In the case of NRT packet data services and SA, CF-based DCA achieves significantly better results than Min I or RCA with or without PC.

Furthermore, our CF-based concept can also be applied in a similar manner to other RRM algorithms such as PC, handoff, or scheduling. This would be an interesting topic for further research.

References

[1] W. C. Jakes, *Microwave Mobile Communications*. New York: Wiley, 1974.
[2] V. H. Mac Donald, "Advanced mobile phone service: The cellular concept," *Bell Syst. Tech. J.*, vol. 58, no. 1, pp. 15–41, Jan. 1979.
[3] D. C. Cox and D. O. Reudink, "Increasing channel occupancy in large-scale mobile radio systems: Dynamic channel reassignment," *IEEE Trans. Veh. Technol.*, vol. VT-22, no. 4, pp. 218–222, Nov. 1973.
[4] S. W. Halpern, "Reuse partitioning in cellular systems," in *Proc. IEEE Trans. Veh. Technol. Conf.*, 1983, pp. 322–327.
[5] Y. Furuya and Y. Akaiwa, "Channel segregation, a distributed adaptive channel allocation scheme for mobile communication systems," *IEICE Trans.*, vol. E 74, no. 6, pp. 1531–1537, Jun. 1991.
[6] T. Kanai, "Autonomous reuse partitioning in cellular systems," in *Proc. IEEE VTC*, 1992, pp. 782–785.
[7] H. Furukawa and Y. Akaiwa, "Self organized reuse partitioning, a dynamic channel assignment method in cellular system," in *Proc. 43rd IEEE VTC*, 1993, pp. 524–527.
[8] M. M.-L. Chang and J. C.-I. Chuang, "Performance evaluation of distributed measurement-based dynamic channel assignment in local wireless communications," *IEEE J. Sel. Areas Commun.*, vol. 14, no. 4, pp. 698–710, May 1996.
[9] M. Nagshineh and I. Katzela, "Channel assignment schemes for cellular mobile telecommunication systems: A comprehensive survey," *IEEE Pers. Commun.*, vol. 3, no. 3, pp. 10–31, Jun. 1996.
[10] S. Jordan, "Resource allocation in wireless networks," *J. High Speed Netw.*, vol. 5, no. 1, pp. 23–34, 1996.
[11] Y. Argyropolous, S. Jordan, and S. P. R. Kumar, "Dynamic channel allocation in interference-limited cellular systems with uneven traffic distribution," *IEEE Trans. Veh. Technol.*, vol. 48, no. 1, pp. 224–232, Jan. 1999.
[12] S. M. Shin, C. H. Cho, and D. K. Sung, "Interference -based channel assignment for DS-CDMA cellular systems," *IEEE Trans. Veh. Technol.*, vol. 48, no. 1, pp. 233–239, Jan. 1999.
[13] J. A. A. Beaulieu, A. A. Abu-Daya, and P. J. MacLane, "Estimating the distribution of a sum of independent log-normal random variables," *IEEE Trans. Commun.*, vol. 43, no. 12, p. 2869, Dec. 1995.
[14] C. E. Shannon, "Programming a computer for playing chess," *Philos. Mag.*, vol. 41, no. 314, pp. 256–275, Mar. 1950. ser. 7.
[15] B. Widrow and B. Hopf, "Adaptive noise cancelling: Principles and applications," *Proc. IEEE*, vol. 63, no. 12, pp. 1692–1700, Dec. 1975.
[16] *Selection Procedures for the Choice of Radio Transmission Technologies of the UMTS*, Apr. 1998. UMTS 30.03 version 3.2.0, ETSI.
[17] ETSI, "Physical layer procedures (TDD)," *3GPP Technical Specification 25.224*, Mar. 2006.
[18] S. Haemaelaeinen, P. Slanina, M. Hartman, A. Lappetelaeinen, H. Holma, and O. Salonaho, "A novel interface between link and system level simulations," in *Proc. Acts Mobile Commun. Summit*, Aalborg, Denmark, Oct. 1997, pp. 599–604.
[19] J. Zander and S. L. Kim, *Radio Resource Management for Wireless Networks*. Norwood, MA: Artech House, 2001.
[20] M. Bublin, G. Diernhofer, C. F. Mecklenbräuker, T. Pacic, J. Plogsties, and P. Slanina, "Simulation of smart antennas in 3G mobile systems," in *Proc. 4th EPMCC*, Vienna, Austria, Feb. 2001. OVE.
[21] M. Bublin and G. Ostermayer, "Comparison of interference based dynamic channel allocation algorithms in mobile networks," in *Proc. IEEE SoftCOM*, Venice, Italy, Oct. 2003.

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