Cell Size Determination in WCDMA Systems using an Evolutionary Programming Approach

José Antonio Portilla-Figueras [a], Sancho Salcedo-Sanz* [a], Alicia Oropesa-García [b] and Carlos Bousoño-Calzón [b]

[a] *Department of Signal Theory and Communications, Universidad de Alcalá*

[b] *Department of of Signal Theory and Communications, Universidad Carlos III de Madrid.*

Abstract

This paper deals with the problem of the cell size determination in WCDMA based mobile networks, in multiservice environments. The objective is to obtain the maximum cell size, given a set of services with their corresponding constraints, in terms of Quality of Service (QoS), binary rate, etc. To achieve this, we have to find the optimal services' load factors which maximizes the cell radius of the system under traffic criteria. We apply an evolutionary programming algorithm to solve the problem, which codifies and evolves the services' load factors. We have compared our approach with an existing algorithm in several multiservice scenarios, improving its solutions in terms of cell size.

Key words: Mobile networks, dimensioning, WCDMA systems, evolutionary programming.

* Corresponding author: Sancho Salcedo-Sanz. Dpto. Signal Theory and Communications, Universidad de Alcalá. Carretera Madrid-Barcelona Km 33, 28871 Alcalá de Henares. Madrid. Spain.
Tlf: +34 91 885 6731, Fax: +34 91 8854804.
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Email address: sancho.salcedo@uah.es (Sancho Salcedo-Sanz*).

1 Introduction

A classical problem in mobile network dimensioning is cell size determination [1]. It is a critical issue in mobile network strategic planning policies, since an underestimation of the cell size may result in a cost increment (more base stations are needed for covering a given area), whereas an overestimation of the cell radius may produce a lack of coverage, with the corresponding dissatisfaction of customers.

In most of second generation (2G) Mobile networks, like GSM, IS-54 or JDC, cell radius is mainly limited by the coverage, due to the *hard blocking* feature of these systems [2]. Furthermore, capacity planning in 2G mobile networks is performed considering mainly the voice service. However, due to new packet technology like General Packet Radio System (GPRS), multiservice traffic capacity studies in 2G mobile networks are getting larger relevance [3]. Anyway, in 2G mobile systems, capacity planning can be considered as independent from the coverage planning, and the capacity of the system can be increased by adding more equipment in the base station.

In 3G mobile networks, the situation is different. In these networks there is a tight relation between coverage and capacity planning (cell size determination), mainly in systems based on Code Division Multiple Access (CDMA) or Wideband Code Division Multiple Access (WCDMA) [1]. Moreover, 3G networks are designed as multiservice systems, which increases the planning complexity. Thus, the calculation of the cell size in 3G (WCDMA) mobile networks is a much more complex problem than in 2G.

Cell size calculation in WCDMA systems has been studied before [10], [11], [12]. Most of the models considered in these approaches only consider a single service, which may result in a non-accurate estimation of the cell radius in multiservice environments. In addition, the studies of multiservice environments are usually based on simulation [13]. Simulation-based methods have several disadvantages when are used in strategic mobile network dimensioning. First, they require a large number of data for a given area, that sometimes is not available. Secondly, they are focused in the study of a particular small area, whereas strategic mobile network planning need the study of large regions. Thus, it would be interesting to have an algorithm which can be applied to mobile network dimensioning. A nature-inspired or emerging algorithm can be a good option to solve this problem.

We propose an evolutionary approach to the cell size determination problem. Our approach uses an encoding of the capacity assignment for each service, which is evolved using the cell size as objective function to be maximize. The objective is therefore to obtain the optimal capacity assignment for each service, which provides the maximum cell size. The cell size determination problem includes a main constraint: the total capacity of the system (calculated as the sum of the capacity assignments for each service) must be less than a parameter $\eta < 1$. The parameter η is known as the *total load factor* of the system. This constraint makes that the classical evolutionary programming (EP) approach [9], [5] is not directly applicable to solve the problem. In this paper we propose several modifications to the EP in order to solve the cell size determination problem in WCDMA multiservices scenarios.

The rest of the paper is structured as follows: next section defines the cell size determination problem in WCDMA networks. In Section 3 we propose the evolutionary heuristic for solving the problem, and in Section 5 we show the performance of the proposed algorithm by solving some experiments in WCDMA multiservice scenarios. Section 6 concludes the paper giving some final remarks.

2 Cell size determination in WCDMA networks

Let us consider a 3G mobile access network based on WCDMA technology (Figure 1) where the mobile operator provides a set of S services (voice, data 16 kbs, data 64 kbs, etc.) each one defined by a set of parameters P (binary rate, user density, quality of service, etc.). The operator must be provided with a first estimation of the number of base stations (cells) required to provide coverage in the area under study. In order to obtain this, a good estimation of the cell size of each cell must be achieved.

In multi-service 3G systems, cell size calculation is usually derived from the individual *cell radius* for each service, resulting a vector $\underline{R}$ which components are the value of the cell radius for each service R_i. The final cell size is the minimum value over the components of the vector $\underline{R}$ (the most restrictive value R_i, since it guarantees the *quality of service* of the rest of services). It is important to note that cell size must be calculated independently in the uplink (link from mobile station to base stations)and in the downlink (link from base stations to mobile stations). This communication focuses on the calculation of the cell size for the downlink case, since this is the most restrictive direction from the capacity point of view.

The cell size for each individual service is calculated as a function of the number of sectors in the BTS, $N_{Sectors}$, the number of users of service i per sector M_i and the user density ρ_i as follows:

$$R_i = \sqrt{\frac{M_i \cdot N_{Sectors}}{\pi \cdot \rho_i}} \tag{1}$$

Note that the values of the user density (ρ_i) are not exactly known. To perform these calculations, 3G mobile operators makes a forecast using existing services in 2G.

The number of users in the cell M_i is obtained from the division of the total offered traffic for service i (A_i), over the individual traffic of a single user of this service (obtained from the connection rate α_i and the mean service time ts_i in the business hour):

$$M_i = \frac{A_i}{\alpha_i \cdot ts_i} \tag{2}$$

The total offered traffic demand A_i, is usually obtained through an algorithm for the calculation of the inversion of the *Erlang B* Loss formula [15]. It considers the maximum number of active connections in the cell ($\frac{L_{Total\_i}}{L_i}$) and the Quality of Service (QoS) of the service expressed by the blocking probability Pb_i:

$$Pb_i = ErlangB\left(\frac{A_i}{1+\overline{f}}\ ,\ \frac{L_{Total\_i}}{L_i} \cdot \left(1+\overline{f}\right)\right) \tag{3}$$

where $\overline{f}$ is the average inter-cell interference factor, which determines the influence of the interference of the neighbor cells in the own cell [16]. Note also that this equation depends on the total load factor allocated for the service i, L_{Total_i}, and on L_i (individual load factor of a single connection in a service i). L_i is defined as:

$$L_i = \frac{\left(\frac{Eb}{N_0}\right)_i \cdot \sigma_i}{\left(\frac{W}{Vb_i}\right)} \cdot \left[\left(1-\overline{\phi}\right)+\overline{f}\right] \tag{4}$$

where $\overline{\phi}$ is the downlink orthogonality factor (these values have been obtained from [17]), Vb_i is the binary rate, σ_i is the activity factor of the service i, $\overline{f}$ is the average inter-cell interference factor and W is the bandwidth of the WCDMA system.

The total load factor assigned to the service i (L_{Total_i}) can be obtained from L_i as follows:

$$L_{Total\_i} = K_i \cdot L_i \tag{5}$$

where K_i is the total number of connections of a service i [1]. If we consider S services, the sum of all factors L_{Total_i} must fulfill the following condition:

$$\eta = \sum_{i=1}^{S} L_{Total\_i} < 1 \tag{6}$$

where η is the total load factor allocated in the cell, that must be less than 1 [16]. Note that η can be interpreted as a measure of the total capacity of the system.

With the definitions given above, the cell size determination problem can be defined as follows:

Find $L_{Total\_i}, \quad i = 1, \cdots, S$, such that

$$\eta = \sum_{i=1}^{S} L_{Total\_i} < 1 \tag{7}$$

which maximizes

$$R = min(R_i) \tag{8}$$

3 Evolutionary Programming in cell size determination

Evolutionary programming is a population based heuristic, which was first proposed as an approach to artificial intelligence [4]. It has been successfully applied to a large number of numerical optimization problems [5], [8], including telecommunications problems [7]. Optimization through evolutionary programming can be divided into two essential parts. First, the mutation of the solutions in the current population, in order to obtain new individuals to be evaluated (offspring), and second, the selection of the next generation starting from the current one and the offspring. Specifically, the classical evolutionary programming algorithm proposed by Bäck and Schwefel [9] can be implemented as follows:

Let us suppose a global maximization problem, formulated as a pair (S, f), where $S \subseteq \mathbb{R}^n$ is a bounded set on $\mathbb{R}$ and $f : \mathbb{R}^n \to \mathbb{R}$ is a n-dimensional real-valued function. The problem consists of finding a point $x_0 \in S$ such that

[1] We have considered that all connections of a service have the same parameters, i.e. there is an average connection which represents all of them.

$f(x_0)$ is a global maximum on S. The EP procedure solves this problem, using the following algorithm:

(1) Generate the initial population of μ individuals. Set $k = 1$. Each individual is taken as a pair of real-valued vectors $(\mathbf{x}_i, \boldsymbol{\sigma}_i), \forall i \in \{1, \cdots, \mu\}$, where $\mathbf{x}_i$'s are objective variables, and $\boldsymbol{\sigma}_i$'s are standard deviations for Gaussian mutations.

(2) Evaluate the fitness value f, for each individual $(\mathbf{x}_i,\boldsymbol{\sigma}_i)$.

(3) Each parent $(\mathbf{x}_i,\boldsymbol{\sigma}_i)$, $\{i = 1, \cdots, \mu\}$ creates then a single offspring $(\mathbf{x}'_i,\boldsymbol{\sigma}'_i)$ as follows:

$$\mathbf{x'_i} = \mathbf{x_i} + \boldsymbol{\sigma}_i \cdot \mathbf{N_1(0,1)} \tag{9}$$

$$\boldsymbol{\sigma}'_i = \boldsymbol{\sigma}_i \cdot exp(\tau' \cdot N(0,1) + \tau \cdot \mathbf{N(0,1)}) \tag{10}$$

where $N(0,1)$ denotes a normally distributed one-dimensional random number with mean zero and standard deviation one, and $\mathbf{N(0,1)}$ is a vector containing random numbers of mean zero and standard deviation one, generated anew for each value of i. The parameters τ y τ' are commonly set to $(\sqrt{2\sqrt{n}})^{-1}$ and $(\sqrt{2n})^{-1}$, respectively [5].

(4) If $x_{ij} > up\_limit$ then $x_{ij} = up\_limit$ and if $x_{ij} < low\_limit$ then $x_{ij} = low\_limit$. up_limit and low_limit stand for the upper limit and lower limit of each component x_{ij}.

(5) Calculate the fitness values associated with each offspring $(\mathbf{x}'_i,\boldsymbol{\sigma}'_i,\ \forall i \in \{1, \cdots, \mu\})$.

(6) Conduct pairwise comparison over the union of parents and offspring: For each individual, p opponents are chosen uniformly at random from all the parents and offspring. For each comparison, if the individual's fitness is better than the opponent's, it receives a "win".

(7) Select the μ individuals out of the union of parents and offspring that have the most wins to be parents of the next generation.

(8) Stop if the halting criterion is satisfied, if not, set $k = k + 1$ and go to Step 3.

The best value in the final population is taken as the solution x_0 to our optimization problem.

4 Adapting EP to cell size determination

The cell size determination problem can be tackled with EP. In order to do that, the EP encoding of the problem, the objective function and the problem's constraints must be defined.

4.1 Encoding of the problem

The most intuitive encoding for the cell size determination problem is to use the load factor of each service L_i as the components of the vector $\mathbf{x}_i$ in the EP. Since the load factor of each service must fulfil that

$$0 < L_{Total\_i} < \eta < 1 \tag{11}$$

the limits *up_limit* and *low_limit* must be fixed to be $up\_limit = 1$ and $low\_limit = 0$, respectively, for all the elements of vector $\mathbf{x}_i$.

4.2 Objective function and problem's constraints

The objective function for the cell size determination problem in WCDMA systems is given by the following expression:

$$f(x) = min\,(R_i) = min\left(\sqrt{\frac{M_i \cdot N_{Sectores}}{\pi \cdot \rho_i}}\right) \tag{12}$$

that is, we have to maximize the minimum value over the components of vector $\underline{R}$. Note that this value depends on load factors of each service η_i through Equation (5).

There is, however, one important constraint to the problem, given by Equation (6), i. e. the sum of the individual services load factors must be less than η. This constraint must be taken into account in order to use the EP to solve the cell size determination problem. The following heuristic is applied to deal with the problem's constraint:

(1) For each individual l, calculate $S = \sum_{i=1}^{S} x_{li}$.
(2) If $S > \eta$, re-calculate values of x_{li} as

$$x_{li} = x_{li} \cdot \frac{\eta}{S} \tag{13}$$

where $\eta < 1$ (values of η between 0.6 and 0.8 are frequently used).

This procedure reduces the capacity η_i of all services in the system. In addition, this procedure guarantees that the reduction in capacity is more accused in the services with more capacity assigned. Note also that, after applying the capacity reduction, the new value of $S = \sum_{i=1}^{S} x_{li}$ is $\eta < 1$.

4.3 Proposed Algorithm

The EP algorithm modified for tackling the cell size determination problem can be summarized as follows:

(1) Generate the initial population of μ individuals.
(2) Evaluate the fitness value (the cell size) R for each individual ($\mathbf{x}_i$,$\boldsymbol{\sigma}_i$).

(3) Each parent creates then a single offspring ($\mathbf{x}'_i$,$\boldsymbol{\sigma}'_i$) as follows:

$$\mathbf{x'_i} = \mathbf{x_i} + \boldsymbol{\sigma}_i \cdot \mathbf{N_1(0,1)} \tag{14}$$

$$\boldsymbol{\sigma}'_i = \boldsymbol{\sigma}_i \cdot exp(\tau' \cdot N(0,1) + \tau \cdot \mathbf{N(0,1)}) \tag{15}$$

(4) If $x_{ij} > up\_limit$ then $x_{ij} = up\_limit$ and if $x_{ij} < low\_limit$ then $x_{ij} = low\_limit$. up_limit and low_limit stand for the upper limit and lower limit of each component x_{ij}.

(5) For each individual of the population l, calculate $S = \sum_{i=1}^{S} x_{li}$. If $S > \eta$, then re-calculate values of x_{li} as

$$x_{li} = x_{li} \cdot \frac{\eta}{S}. \tag{16}$$

(6) Calculate the cellular radius values using equation associated with each offspring (by means of Equation (1), and use them as fitness values.

(7) Select the μ individuals out of the union of parents and offspring by means of a tournament selection.

(8) Stop if the halting criterion is satisfied, if not, set $k = k + 1$ and go to Step 3.

5 Computational Experiments

5.1 Algorithm for comparison purposes

The majority of the existing approaches to the cell size determination problem considers a single service, or are based on simulation, so it has been difficult to find in the literature a good algorithmic approach to the multiservice case, for comparison purposes. We have implemented a version of an algorithm by Lindberger, first proposed and applied to ATM networks [19], which reduces the set of services to a unique artificial/equivalent service, and we have adapted it to the cell size determination problem. We will refer to this approach as the *reduced* algorithm hereafter. The main advantages of the reduced algorithm is that it provides a robust method for solving the cell size determination problem, which offers good quality solutions and it is easy to implement and adapt to the case of the WCDMA systems.

Briefly, the reduced algorithm starts considering an artificial cell radius, typically $R = 1000$. Then, it calculates the total traffic demand offered to the cell, A_i, for each service i, by means of the user density of each service, ρ_i, the individual call rate, α_i, and the mean call duration, ts_i. The artificial service is defined then in terms of equivalent parameters: binary rate, Vb_{eq}, call rate, α_{eq}, mean call duration, ts_{eq}, blocking probability, Pb_{eq}, activity factor, σ_{eq} and user density, ρ_{eq}. These parameters are defined by the following equations:

$$\begin{gathered}
Vb_{eq} = \frac{\sum_{i=1}^{S} A_i \cdot Vb_i^2}{\sum_{i=1}^{S} A_i \cdot Vb_i};\ Pb_{eq} = \frac{\sum_{i=1}^{S} Pb_i \cdot A_i \cdot Vb_i}{\sum_{i=1}^{S} A_i \cdot Vb_i};\ \alpha_{eq} = \frac{\sum_{i=1}^{S} \alpha_i \cdot A_i \cdot Vb_i}{\sum_{i=1}^{S} A_i \cdot Vb_i} \\
ts_{eq} = \frac{\sum_{i=1}^{S} ts_i \cdot A_i \cdot Vb_i}{\sum_{i=1}^{S} A_i \cdot Vb_i};\ \rho_{eq} = \frac{\sum_{i=1}^{S} \rho_i \cdot A_i \cdot Vb_i}{\sum_{i=1}^{S} A_i \cdot Vb_i};\ \sigma_{eq} = \frac{\sum_{i=1}^{S} \sigma_i \cdot A_i \cdot Vb_i}{\sum_{i=1}^{S} A_i \cdot Vb_i} \\
\left(\frac{Eb}{No}\right)_{eq} = \frac{\sum_{i=1}^{S} \left(\frac{Eb}{No}\right)_i \cdot A_i \cdot Vb_i}{\sum_{i=1}^{S} A_i \cdot Vb_i}
\end{gathered} \tag{17}$$

Considering this new artificial service, the reduced algorithm calculates a corresponding value of the cell size, $R_{Reduced}$, assigning the whole load factor, η, to the artificial service. From the obtained $R_{Reduced}$, the load factors for each individual service, $L_{Reduced_i}$, can be calculated inverting the process shown in Section 2, [16].

The total load factors of each service are obtained by simple reduction to the whole load factor, η:

$$L_{Total\_i} = \frac{L_{\mathrm{Reduced}\_i}}{\sum_{i=1}^{S} L_{\mathrm{Reduced}\_i}} \cdot \eta \tag{18}$$

these values of the load factors provide a new solution of the cell radius for each individual service, which is calculated following the process in Section 2, obtaining the solution vector $\underline{R}$. Its minimum value is the cellular size.

5.2 Results

In order to validate the EP algorithm presented in this paper, we have tested it on several experiments based on scenarios with different service combinations. Specifically, we have defined mixtures up to six services, each one having its own requirements in terms of binary rate, quality of service, user movement speed and user density in the coverage area. Furthermore we have considered services with balanced and unbalanced traffic. Balanced traffic means that the individual throughput of each service is similar to the throughput of the other services.

The parameters of the different services S_i are shown in Table 1, being Vb the binary rate, Us the user speed in Km/h (services in which users have different speeds can be considered as different services due to they have different values of $\frac{Eb}{N_0}$ and therefore different values of individual load factor L_i), $\left(\frac{Eb}{N_0}\right)$ the bit energy to noise ratio in the downlink, $\overline{\phi}$ the orthogonality factor and σ the activity factor. The quality of service is defined by the Blocking/Loss probability Pb. We have fixed the value of the total downlink load factor η to 0.75, and the value of the average inter-cell interference factor $\overline{f}$ to 0.88 obtained from [20] and [21] which studied the influence of $\overline{f}$ on the cell radius. As we have mentioned before the complete set of scenarios are divided into balanced and unbalanced traffic scenarios. Tables 2 and 3 provide the traffic figures for the different services in these two general categories.

Table 4 shows the combination of the services involved in each experiment. Note that the third column in the table shows if the experiment is based on balanced (B) or unbalanced traffic (U). The parameters of the EP algorithm used to solve the proposed instances are: population of 100 individuals, with $p = 50$ in the tournament selection and 400 generations (several experiments were performed with 500, 1000 and 2000 generations, with no improvement in the solutions obtained). We have run the algorithm 30 times keeping the best and average values of the cellular radius obtained.

Table 5 shows the results obtained by our EP algorithm in the Scenarios considered (best value of the cell radius obtained), compared with the results obtained by the reduced algorithm. These results are depicted in Figure 2. It is easy to see that the EP obtains cell sizes equal or better than the reduced approach.

Our algorithm obtains significantly better results than the reduced algorithm in scenarios Scn-5, Scn-6, Scn-10, Scn-11, Scn-12. The reason for this better performance of the evolutionary programming algorithm is that the reduced algorithm uses the problem's parameters of the different services for constructing an equivalent single service. This process works fair well in the case that the services are quite different (in terms of binary rate, call attempt rate, blocking probability and $\frac{E_b}{N_0}$). However, in the case of services with different user movement speed (S_1 and S_2) there are only significant differences in the parameter E_b/N_0, and the rest of parameters are quite similar in general, which affects the performance of the reduced algorithm. The EP algorithm does not have this drawback, since it does not use the services parameters for doing the search, only for calculating the fitness values.

Figures 3 and 4 show the evolution of the cellular radius obtained by the evolutionary programming approach (average of the 30 runs) for scenarios Scn-6 and Scn-12. Note that in both cases the value in the generation 200 is only about 1 percent lower than the final value at generation 400. This shows that the EP is able to get good quality solutions with a low number of iterations, about 200.

5.3 Discussion

The results obtained show a good performance of the evolutionary algorithm for the cell size determination problem. However, a detailed analysis of these results shows that the obtained cell radius for the scenarios considered are small, compared with common situations in real world cases. This is due to we have considered scenarios with heavy loaded cells (hot spots) and onmidirectional antennas, (a single cell per BTS). This way, we obtain the performance of the algorithms in a critical working zone, near to the system saturation.

In order to test the performance of our approach in a real world case, we can consider the case of the city of Espoo (Finland), comprising roughly 12×12 km^2. The parameters of this simulation are described in [16]. Table 6 shows the users distribution for this scenario. In this example, our EP algorithm obtains a cell radius of 1525 meters, very close to the result obtained by Holma et al. in [16] for this problem: 1555 meters. This shows that, in real cases situations, our algorithm is able to find feasible solutions, according with existing algorithms or simulations.

When the number of users increases, the cell radius should decrease. On the other hand, if the number of sectors per BTS increases, the cell radius should also increase (there are fewer users per sector). To observe these effects, we have performed several simulations with different number of users and sectors per BTS in scenario Scn-3 (Table 7). Note that in simulation 1, where the number of users is similar to the Espoo example, the cell radius is over 1000 meters if we consider 3 sectors (729 with a single sector). In the following simulations, the cell radius decreases until reaching the value obtained in scenario Scn-3 (Table 5) 322 meters. Note that this result is for the case of a single sector, whereas for 3 sectors the cell radius obtained is 557.

6 Conclusions

In this paper we have presented an evolutionary programming algorithm to solve the cell size determination problem. This algorithm is, to our knowledge, one of the first nature-inspired approaches applied to the design of the access part in third generation mobile networks. We have shown that our evolutionary programming approach is able to solve the cell size determination in multiservice scenarios, obtaining very good solutions in terms of the cell radius obtained.

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References

[1] T. Ojanperä and R. Prasad, *Wideband CDMA for third generation mobile communications*, Artech House, 1988.

[2] R. Verdone, J. Orriss, A. Zanella and S.K. Barton, "Evaluation of the blocking probability in a cellular environment with hard capacity: A statistichal approach", In *Proc. of the 13th IEEE Symposium on Personal Indoor and Mobile Radio Communications*, 2002.

[3] M. Mahdavi, R.M. Edwards, S. R. Cvetkovic, "Policy for enhancement of traffic in TDMA hybrid switched integrated voice/data cellular mobile communications systems," *IEEE Commun. Lett.*, vol. 5 , no. 6, pp. 242-244, 2001.

[4] L. J. Fogel, A. J. Owens and M. J. Walsh, *Artificial intelligence through simulated evolution*, Wiley, 1966.

[5] X. Yao, Y. Liu and G. Lin, "Evolutionary programming made faster," *IEEE Trans. Evol. Comput.*, vol. 3, no. 2, pp. 82-102, 1999.

[6] D. B. Fogel, *Evolutionary computation: toward a new philosophy of machine intelligence*, IEEE press, 2000.

[7] H. S. Lim, M. V. Rao, A. W. Tan and H. T. Chuah, "Multiuser detection for DS-CDMA systems using evolutionary programming," *IEEE Comm. Lett.*, vol. 7, no. 3, pp. 101-103, 2003.

[8] D. B. Fogel, "An introduction to simulated evolutionary optimization," *IEEE Trans. Neural Networks*, vol. 5, no. 1 pp. 3-14, 1994.

[9] T. Bäck and H. P. Schwefel, "An overview of evolutionary algorithms for parameter optimization," *Evol. Comput.*, vol. 1, no. 1, pp. 1-23, 1993.

[10] K. Gilhouse, I. Jacobs, R. Padovani, A. Viterbi and L. Weaver, "On the capacity of a cellular CDMA system," *IEEE Trans. Veh. Technol.*, vol. 40, no. 2, pp. 303-312, 1991.

[11] S. Burley, "Downlink capacity estimation in a WCDMA cellular network," In *Proc. of the 12th IEEE International Symposium on Personal, Indoor, and Mobile Radio Communications*, San Diego, pp. 26-30, 2001.

[12] B. Taha Ahmed, M. Calvo Ramon and L. de Haro Ariet, "Capacity and interference statistics of highways W-CDMA cigar-shaped microcells (uplink analysis)," *IEEE Commun. Lett.*, vol. 6, no. 5, pp. 172-174, 2002.

[13] A. Wacker, J. Laiho-Steffens, K. Sipila and M. Jasberg, "Static simulator for studying WCDMA radio network planning issues," In *Proc. of the IEEE Vehicular Tecnology Conference*, Houston, pp. 2436-2446, 1999.

[14] C. Dou and Y. Chang, "Class-based downlink capacity estimation of a WCDMA network in a multiservice context," *Computer Commun.*, vol. 28, no. 12, pp. 1443-1455, 2005.

[15] D.L. Jagerman, "Some Properties of the Erlang Loss Function," *Bell System J.*, vol. 53, no. 3, 1974.

[16] H. Holma and A. Toskala, *WCDMA for UMTS*, Wiley, 2001.

[17] N. Mehta, L. Greentein, T. Willis and Z. Kostic, "Analysis and results for the orthogonality factor in WCDMA downlinks", In *Proc. of the vehicular Technology Conference*, pp. 100-104, 2002.

[18] J. Laihoo, A. Wacker and T. Novosad, *Radio Network Planning and Optimisation for UMTS*, Wiley, 2002.

[19] K. Lindberger, "Dimensioning and design methods for integrated ATM networks," In *Proc. of the International Teletraffic Conference*, 14, 1994.

[20] C. K. d'Avila and M. D. Yacoub, "Reuse efficiency for non-uniform distributions in CDMA systems", *IEE Elect. Lett.*, vol. 34, no. 13, pp. 1293-1294, 1998.

[21] C. K. d'Avila and M. D. Yacoub, "The linear method to evaluate the frequency reuse efficiency of cellular CDMA systems", In *Proc. of the 11th International Symposium on Personal, Indoor and Mobile Radio Communications*, pp. 87-91, 2000.

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Table 1
Parameters of the services in the experiments carried out.

P	S_1	S_2	S_3	S_4	S_5	S_6
Parameter	Voice		Data			
Vb	12.2	12.2	64	64	144	384
Vm	0	3	0	3	0	0
$(\frac{Eb}{N_0})$	4.4	7.0	2.5	5.3	2.3	2.4
ϕ	0.5	0.5	0.5	0.5	0.5	0.5
Pb	0.01	0.01	0.05	0.05	0.05	0.05
σ	0.67	0.67	1	1	1	1

Table 2
Balanced traffic values.

P	S_1	S_2	S_3	S_4	S_5	S_6
α_k	1	1	1	1	1	1
ts_k	180	180	240	240	360	500
ρ_k	300	84	147	45	90	46

Table 3
Unbalanced traffic values.

	S_1	S_2	S_3	S_4	S_5	S_6
α_k	1	1	1	1	1	1
ts_k	162	162	23.4	23.4	7.92	7.92
ρ_k	1008	335	80	26	70	35

Table 4
Scenarios for the experiments considered.

Scenario	Services	Traffic
Scn-1	S_1, S_3	B
Scn-2	S_1, S_3	U
Scn-3	S_1, S_3, S_5	B
Scn-4	S_1, S_3, S_5	U
Scn-5	S_1, S_2, S_3, S_4	B
Scn-6	S_1, S_2, S_3, S_4	U
Scn-7	S_1, S_3, S_5, S_6	B
Scn-8	S_1, S_3, S_5, S_6	U
Scn-9	S_1, S_2, S_3, S_5, S_6	B
Scn-10	S_1, S_2, S_3, S_5, S_6	U
Scn-11	$S_1, S_2, S_3, S_4, S_5, S_6$	B
Scn-12	$S_1, S_2, S_3, S_4, S_5, S_6$	U

Table 5
Comparison of the cell radius (in meters) calculated through the EP (best values obtained) and the reduced algorithm.

Scenario	EP	Reduced
Scn-1	530	529
Scn-2	617	616
Scn-3	322	322
Scn-4	573	572
Scn-5	425	403
Scn-6	505	309
Scn-7	188	188
Scn-8	455	455
Scn-9	183	182
Scn-10	389	319
Scn-11	148	134
Scn-12	417	280

Table 6
Users distribution in the Espoo example.

Service	Users per Service	Users Density (ρ)
Voice	1735	12.04
Data 64 Kbps	250	1.736
Data 384 Kbps	15	0.104

Table 7
Cell radius (R) in meters for 1 and 3 BTS sectoring and for different users densities (ρ)

Simul	$\rho_{\ Voice}$	$\rho_{\ Data\ 64Kbps}$	$\rho_{\ Data\ 144Kbps}$	R(m) 1 Sector	R(m) 3 Sectors
1	60	38.4	18	729	1194
2	120	76.8	36	516	894
3	180	115.2	54	421	729
4	240	153.6	72	366	631
5	300	192	90	322	557

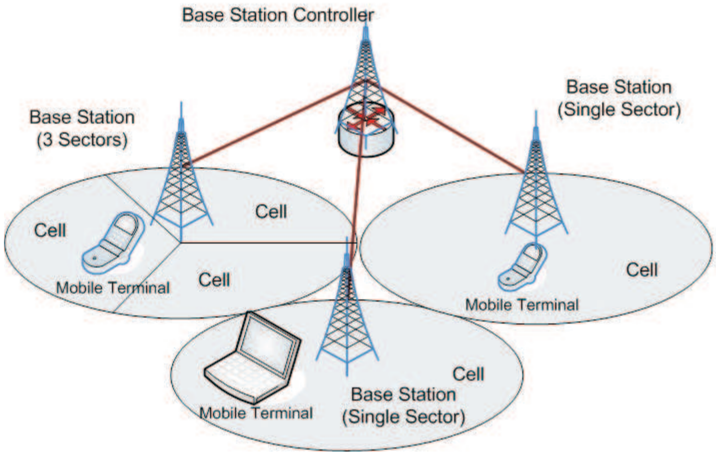

Fig. 1. Example of the architecture of the access network.

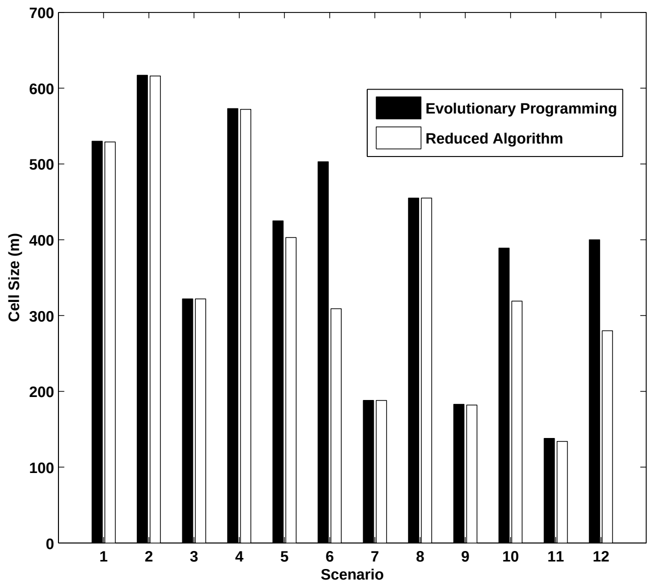

Fig. 2. Cell radius obtained by the EP algorithm compared with the results obtained by the reduced algorithm in the different scenarios considered.

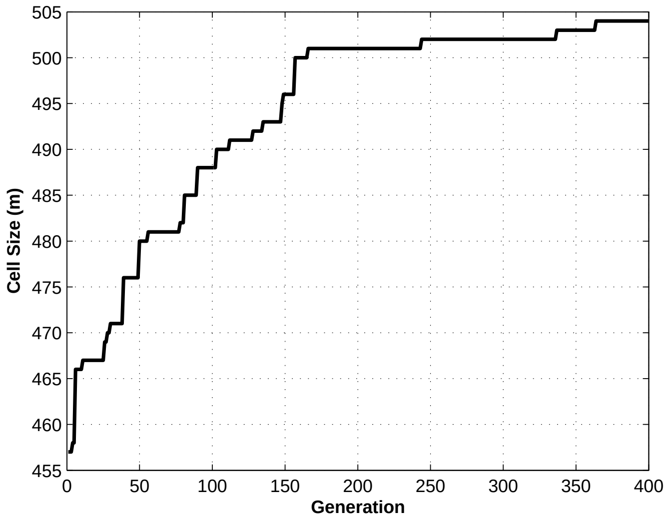

Fig. 3. Evolution of the cell radius for the scenario Scn-6 (average of 30 runs).

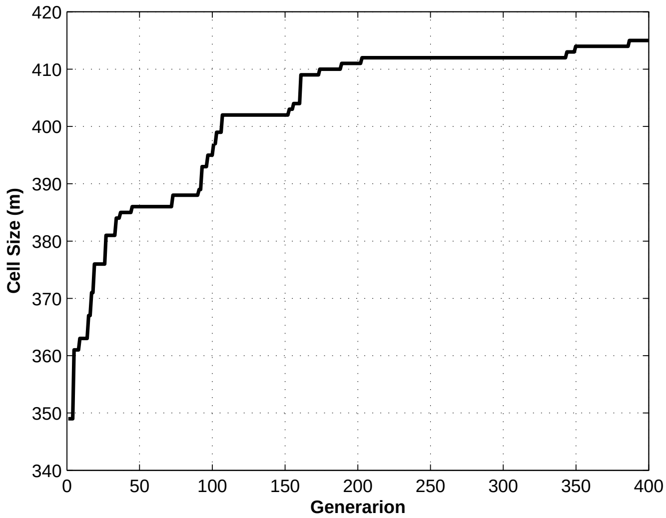

Fig. 4. Evolution of the cell radius for the scenario Scn-12 (average of 30 runs).