Particle Swarm Optimization for Base Station Placement

Marciel Barros Pereira
DETI-CT/UFC
Federal University of Ceara
Email: marcielbarros@gtel.ufc.br

Francisco Rodrigo Porto Cavalcanti
GTEL/UFC
Federal University of Ceara
Email: rodrigo@gtel.ufc.br

Tarcisio Ferreira Maciel
GTEL/UFC
Federal University of Ceara
Email: maciel@gtel.ufc.br

***Abstract*—This article shows the improvement of using Particle Swarm Optimization (PSO) for multiple Base Station (BS) placement in a metropolitan area. We evaluate the algorithm's performance using a combination of Shannon's capacity formula and Jain's index of fairness for two sets of traffic demand points, corresponding to an estimation of average and peak traffic, respectively. We show results performed by using 8, 32, 128 and 256 particles to place sets of new BSs versus number of iterations. We also exhibit potential optimal points for placement found by PSO. The optimization improved the average capacity by 17% with an increase on the number of BSs smaller than 10%.**

***Index Terms*—Particle Swarm Optimization and Base Station Placement.**

I. Introduction

In wireless communications, the placement of infrastructure, such as positions for BSs, is one of the most important tasks in the design of mobile networks. For operators, it represents capital expenditure, so that ideally it must be done as to improve user's satisfaction proportionally. Traditionally, it is established that the radio planning has to start from the predictions of coverage to estimate the number of base stations to cover a given area [1], but the rapidly growing usage of mobile broadband made the data rates experienced by the users in the network become increasingly important [2], especially for infrastructure expansion planning.

BS placement is an optimization problem which has a set of variables, such as traffic density, channel condition, interference scenario, number of BSs, and other network planning parameters [3]. Because of the number of variables and their relation with each other, it is not possible to solve it as a linear optimization problem, thus requiring the use of alternative nonlinear optimization algorithms.

A general optimization algorithm is implemented to optimize BS placement in a very realistic scenario containing a large set of variables. However, this large number of attributes makes algorithms runtime very long. On the other hand, limiting the set of variables produces coarse results. Also, the optimization problem can be formulated with various objectives, for example: capacity enhancement, network lifetime maximization, power minimization and node number minimization [4]. Thus, there is a compromise relation between realism of simulation parameters and the runtime of algorithm.

PSO was introduced as a method for optimization of continuous nonlinear functions [5]. BS placement using PSO was perfomed in various works: in [6] the authors deployed BSs to maximize coverage and economy efficiency, the work of [7] aimed to capacity maximization and network balancing. These works considered network planning for first placement of BSs. PSO has also been tested on wireless network optimization, such as sensor network coverage [8] and antenna ports placement [9].

The main objective of this work is to exhibit PSO performance enhancement for placement of multiples BSs in a metropolitan area considering combination of capacity and network balancing as maximization criterion. For deploying new BS, we consider already placed infrastructure and two different traffic distributions. This article has the following organization: Section II describes PSO theory; Section III explains the BS placement problem; in Section IV, the system modeling is addressed; Section V presents numerical simulation results and, finally, conclusions are shown in Section VI.

II. Particle Swarm Optimization

Particle Swarm is a population-based stochastic algorithm for optimization from social-psychological princi-

Marciel Barros Pereira is sponsored by *Funcap*. The authors would like to thank *Wireless Telecomunications Research Group - GTEL* for laboratory infrastructure granted.

978-1-4799-3743-1/14/$31.00 ©2014 IEEE

ples [10]. Unlike evolutionary algorithms, particle swarm uses all population members from the beginning of a trial until its end and their iterations result in incremental improvement of the quality of problem solutions over time.

In PSO, a number of simple entities – the *particles* – are placed in the search space of some problem or function, and each evaluates the objective function – the *fitness* – at its current location. Each particle combines social and individual elements – *social influence* and *persistence* –, with some random perturbation, to determine its own movement over the search space. The movement of particles is given by a velocity vector V. The particle iterations with each other leads the process to the global solution.

Usually, a particle is composed of a N-dimensional point with same dimension as the search space. Therefore, for a particle P_i:

$$\begin{aligned} P_i &= \begin{bmatrix} x_1^i & x_2^i & \dots & x_N^i \end{bmatrix}, \\ V_i &= \begin{bmatrix} v_1^i & v_2^i & \dots & v_N^i \end{bmatrix}, \end{aligned}$$

where x^i represents position components for P_i and v^i, velocities components for current velocity V_i.

PSO updates position and velocity for a particle P_i in every iteration k based on the fitness performance of the particle. PSO also stores the particle best positions P_i^* and global best particle P_g^*: P_i^* relates to the best positions so far for a single particle P_i and P_g^* represents the particle whose position resulted in the best solution. This process is repeated for a fixed number of iterations K.

The update of particles velocities considers current velocity, P_g^* and P_i^*, with some random perturbation ϕ_{gB} and ϕ_{pB} uniformly distribuited between 0 and 1. In a single iteration k:

$$\begin{aligned} V_i[k+1] &= V_i[k] \\ &+ \phi_{gB} \cdot \left(P_i^*[k] - P_i[k]\right) \\ &+ \phi_{pB} \cdot \left(P_g^*[k] - P_i[k]\right). \end{aligned}$$

A very common topology includes an *inertia weight* w to velocities and *acceleration constants* c_{gB} and c_{pB} to both social influence and persistence, respectively. Improvements for PSO have been found with inclusion of time-varying inertia weight [11], and with variation of c_{gB} and c_{pB} [12], which reduces cognitive component and increase social component with time. A linear time-varying function for weights of inertia, social influence and persistence (denoted as $w[k]$) is shown in (1):

$$w[k+1] = w_0 + \frac{(k-1)}{K} \cdot (w_K - w_0), \tag{1}$$

given initial (w_0) and final (w_K) desired values, as well as the number of iterations K.

These time varying components are used to control *exploitation*, when particles are lead to best results ever found, and *exploration*, when particles search towards new directions, but not ignoring completely best known positions. A general update function for PSO computes new velocities in (2) and updates particles positions using (3). For a single iteration k:

$$\begin{aligned} V_i[k+1] = w[k] \cdot V_i[k] + c_{gB}[k] \cdot \phi_{gB} \cdot \left(P_i^*[k] - P_i[k]\right) \\ + c_{pB}[k] \cdot \phi_{pB} \cdot \left(P_g^*[k] - P_i[k]\right), \end{aligned} \tag{2}$$

$$P_i[k+1] = P_i[k] + V_i[k+1]. \tag{3}$$

III. Base Station Placement Problem

A realistic model of a wireless communications scenario considers several issues, such as natural or artificial structures, topography, variation of attenuation law in some locations (dense urban, suburban etc.), non-uniform traffic distribution, infrastructure already placed in region, antenna patterns, etc. This large set of variables raises the level of complexity for a BS placement problem, impacting on runtime for algorithms.

Choosing the most significant variables is fundamental to limit scenario complexity without decreasing reliability. We consider a two dimensional search space to simplify the model for traffic density. A set of points inside the region relates to User Equipaments (UEs) where each one is associated with a propagation loss. Spatial capacity demand also changes in periods on a day. In order to simulate this variation for traffic distribution, we placed various sets of UEs.

Two suitable maximization metrics for the placement problem are the *Capacity* and *Fairness*, described as follows:

A. Capacity

Capacity C_i computes bit-rate for each traffic point i given the *Signal to Interference plus Noise Ratio* (SINR). From Shannon equation [13]:

$$C_i = \mathrm{BW} \cdot \log_2(1 + \mathrm{SINR}), \tag{4}$$

where BW denotes system bandwidth. For estimating SINR, we provide channel characteristics, such as path loss model and noise power. A general capacity expression assumes BW = 1, which returns capacity in bits per second per Hertz (bps/Hz). We obtain capacity

978-1-4799-3743-1/14/$31.00 ©2014 IEEE

estimations for all UEs connected to the set of BSs (already placed and new placed ones) to determine how much improvement is obtained from deploying new BSs. We compute the mean capacity for all UEs to estimate a network parameter, in bps/Hz/user. In order to avoid high values of capacity for users overly close to serving BS, we adopted a maximum value corresponding to the capacity measured for a user distant 35m from BS.

B. Fairness

The fairness measures the distribution of resources in a system. A quantitative concept of fairness measurement was proposed by Jain [14]. In this scenario, we calculate the fairness for all UEs considering capacity per user as the shared resource. The *Jain's Index* for n UEs is showed in (5):

$$J = \frac{\left(\sum_{i=1}^{n} C_i\right)^2}{n\left(\sum_{i=1}^{n} {C_i}^2\right)}, \tag{5}$$

where C_i is the capacity for UEs i. The Jain's index returns a value between 0 and 1: 0 means a completely unfair resource distribuition while 1 implies in balancing of network resources.

IV. System Modeling

We describe system modeling for testing PSO on BS placement.

A. Traffic distribution

We tested optimization for a region equivalent to a Brazilian city considering two different distributions of UEs (peak and average). We distributed these traffic as follows:

- *peak traffic*: we obtained Global Positioning System (GPS) coordinates centers and population from all neighborhoods of the modeled region [15]. We created Voronoi polygons from this set of coordinates, where we placed a number of traffic demand points proportional to the population of the corresponding neighborhood. We obtained a distribution shown in Figure 1.
- *average traffic*: we set the same number of points as peak traffic randomly inside city borders, as shown in Figure 2.

We assume GPS latitude and longitude coordinates as search space and a flat region. We gathered real BS positions from an operator obtained from a public database [16], from which we selected 100 points to simulate already placed BSs. Our link model considers that all BSs and UEs are equipped with single omnidirectional antennas.

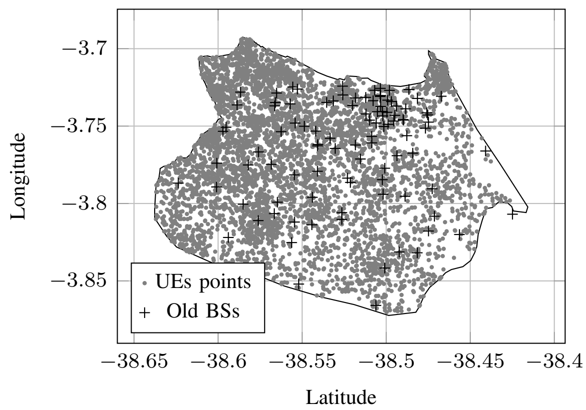


Figure 1: Peak traffic demand estimation and Old BSs positions.

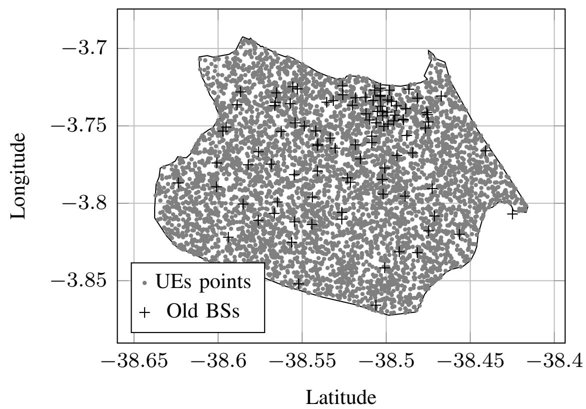


Figure 2: Average traffic demand estimation and Old BSs positions.

B. Fitness Function

We adopted a combination of capacity from (4) and fairness from (5) as global fitness function, shown in (6):

$$f = J \cdot C. \tag{6}$$

We used this combination to achieve substantial system capacity with the maximum possible network balancing for placement of BSs. We compute fitness for each traffic distribution described previously. Yet, we have to combine fitness from each traffic distribution in order to reach an improvement for both distribution simultaneously. We adopted a combination shown in (7):

$$f = c_{peak} \cdot f_{peak} + c_{avg} \cdot f_{avg}, \tag{7}$$

where c_{peak} and c_{avg} are arbitrary constants for peak and traffic influences for combination fitness.

C. PSO algorithm

The particles have information of positions for all new BS. Thus, the size of each particle is the *number of new BSs* $\times 2$ array of positions for the set of new BSs. We generated multiple scenarios by varying the number of BS for placement.

We adopted variation for social and individual constants according to (1), given initial and final values. In order to avoid particles to reach areas far outside the Region of Interest (ROI), we constrained velocities components for particles between $-V_{TH} \leq v_j^i \leq V_{TH}$, where V_{TH} is a velocity threshold for the ROI.

In each iteration, we obtain particle's fitness from calculus of capacity and fairness for the set of old BSs plus the set of new BSs provided by particle. From this result, the algorithm updates P_i^* and P_g^* of particles N_p. Update of velocities occurs using (2) and are used to modify new positions for particles from (3). This process is repeated until reaching the maximum number of iterations K.

At the end of algoritm, we obtain the fitness performance per iteration and the particle, whose set of optimized points amounts to the most probably new positions for BSs. We obtain fitness evolution and best points for 50 trials. We compute mean fitness, capacity and fairness for all trials. Table I summarizes simulation parameters, exhibiting major constant values for calculation of SINR, capacity and PSO parameters, such as number of iterations, social influence and persistence.

Table I: Simulation Parameters

SYSTEM PARAMETERS	
Path Loss	$128.1 + 37.6\log_{10}(R_{\text{Km}}{}^{1})$
Transmit Power	46 dBm
Frequency	2 GHz
Bandwidth	10 MHz
Noise Power	-124 dBm
PSO ALGORITHM	
Number of UEs	5 000
Number of Iterations K	100
Number of Trials	50
Number of Old BSs	100
Number of New BSs	4, 8, 16 and 32
Velocity Threshold V_{TH}	25% of city width
$w[0]$	1.2
$w[K]$	0.4
$c_{gB}[0]$ and $c_{lB}[0]$	2
$c_{gB}[K]$ and $c_{lB}[k]$	1.2
$c_{pB}[0]$	0.5
$c_{pB}[K]$	2
c_{peak}	0.66
c_{avg}	0.34
Number of Particles	8, 32, 128 and 256

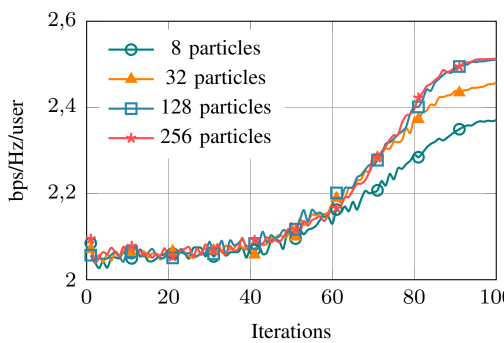


Figure 4: Capacity *versus* Iteration for deploying 8 new BS with different number of particles.

V. NUMERICAL RESULTS

We varied the number of new BS for positioning for 128 particles, considering the proposed system model. The results shown in Figure 3 exhibits improvement of all objective functions for each number of new BS. PSO enhanced system capacity by 17%, in Figure 3b, when increasing number of BSs by 8% (8 new BSs) . On the other hand, an increase of 32% of infrastructure resulted in an improvement of only 29.5% for capacity due to the higher interference in multiple BSs placement scenario. Also, PSO provided and increasing for the fitness function, shown in Figure 3a and fairness, in Figure 3c.

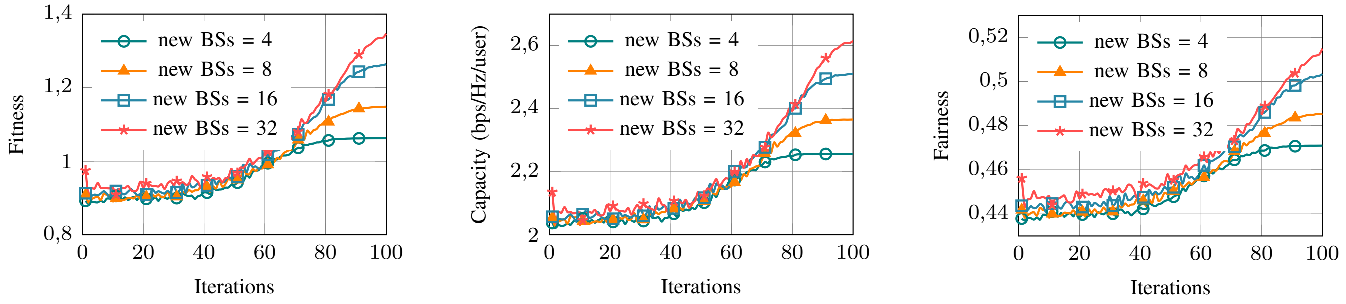
Figure 4 presents advances for a larger number of particles by means of capacity. Nevertheless, results for 256 particles improved capacity by only 0.62% as whose observed for 128 particles.

We acquired a distribution of the best points obtained in each trial for placing 8 new BSs, for 128 particles, in Figure 5, which corresponds to the most suitable regions for deployment of new BS. The overlapping of BS points, already placed infrastructure and peak traffic distribution of UEs implies the PSO reached regions with poor coverage and high traffic distribution, simultaneously.

VI. CONCLUSION

In this work, we exhibited PSO performance improvement of fitness, capacity and fairness for multiple BS placement in a metropolitan area, considering an already placed infrastructure. The algorithm identified

[1]distance of UEs and corresponding serving BS, in kilometers.



(a) Fitness *versus* Iteration (b) Capacity *versus* Iteration (c) Fairness *versus* Iteration

Figure 3: Performance of objective functions *versus* number of iterations for 128 particles.

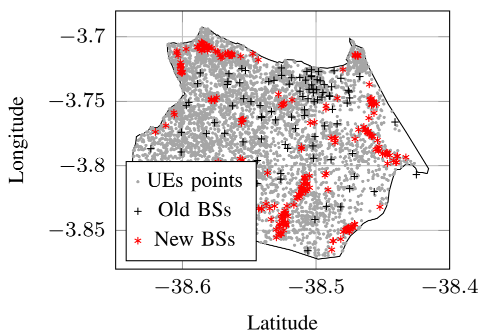


Figure 5: Optimum cloud points for deploying 8 new BSs – 128 particles.

a set of points corresponding to most suitable areas for BS deploying, after running 50 trials. Outcomes showed the increasing of fitness values comparing with initial deployment of PSO's particles. Further advances in system modeling will generate more realistic results and improve effectiveness and reliability of PSO as an appliance for the BS placement problem.

References

[1] C. Soto, D. Covarrubias, and S. Villarreal, "Base station placement optimization algorithm for heterogeneous distributions of mobile users with multi-service requirements," *Latin America Transactions, IEEE (Revista IEEE America Latina)*, vol. 10, no. 5, pp. 2032–2039, Sept 2012.

[2] S. Parkvall, A. Furuskar, and E. Dahlman, "Evolution of lte toward imt-advanced," *Communications Magazine, IEEE*, vol. 49, no. 2, pp. 84–91, February 2011.

[3] B.-S. Park, J.-G. Yook, and H.-K. Park, "The determination of base station placement and transmit power in an inhomogeneous traffic distribution for radio network planning," in *Vehicular Technology Conference, 2002. Proceedings. VTC 2002-Fall. 2002 IEEE 56th*, vol. 4, 2002, pp. 2051–2055 vol.4.

[4] Y. Lin, W. Yu, and Y. Lostanlen, "Optimization of wireless access point placement in realistic urban heterogeneous networks," in *Global Communications Conference (GLOBECOM), 2012 IEEE*, Dec 2012, pp. 4963–4968.

[5] J. Kennedy and R. Eberhart, "Particle swarm optimization," in *Neural Networks, 1995. Proceedings., IEEE International Conference on*, vol. 4, Nov 1995, pp. 1942–1948 vol.4.

[6] Z. Yangyang, J. Chunlin, Y. Ping, L. Manlin, W. Chaojin, and W. Guangxing, "Particle swarm optimization for base station placement in mobile communication," in *Networking, Sensing and Control, 2004 IEEE International Conference on*, vol. 1, March 2004, pp. 428–432 Vol.1.

[7] D. Tsilimantos, D. Kaklamani, and G. Tsoulos, "Particle swarm optimization for umts wcdma network planning," in *Wireless Pervasive Computing, 2008. ISWPC 2008. 3rd International Symposium on*, May 2008, pp. 283–287.

[8] N. Aziz, A. Mohemmed, and B. Sagar, "Particle swarm optimization and voronoi diagram for wireless sensor networks coverage optimization," in *Intelligent and Advanced Systems, 2007. ICIAS 2007. International Conference on*, Nov 2007, pp. 961–965.

[9] J. C. M. Feitosa, T. F. Maciel, E. M. G. Stancanelli, W. C. Freitas Jr., and F. R. P. Cavalcanti, "Particle swarm optimization for antenna port placement in coordinated multi-point systems," in *XXVII Simposio Brasileiro de Telecomunicacoes*, Sept 2009.

[10] J. Kennedy, *Encyclopedia of Machine Learning*. Springer Science+ Business Media LLC, 2011.

[11] Y. Shi and R. Eberhart, "A modified particle swarm optimizer," in *Evolutionary Computation Proceedings, 1998. IEEE World Congress on Computational Intelligence., The 1998 IEEE International Conference on*, May 1998, pp. 69–73.

[12] A. Ratnaweera, S. Halgamuge, and H. Watson, "Self-organizing hierarchical particle swarm optimizer with time-varying acceleration coefficients," *Evolutionary Computation, IEEE Transactions on*, vol. 8, no. 3, pp. 240–255, June 2004.

[13] T. Cover and J. Thomas, *Elements of Information Theory*. John Wyley & Sons Inc., 2006.

[14] R. Jain, D. Chiu, and W. Hawe, "A quantitative measure of fairness and discrimination for resource allocation in shared computer system," Eastern Research Laboratory, Digital Equipment Corp., Tech. Rep., 1984.

[15] "Prefeitura de fortaleza." [Online]. Available: http://www.fortaleza.ce.gov.br/regionais

[16] "Agencia nacional de telecomunicacoes." [Online]. Available: http://sistemas.anatel.gov.br/stel/consultas/ListaEstacoesLocalidade/tela.asp?pNumServico=010