Cost-effective Base Station Deployment Approach Based on Artificial Immune Systems

Djalma de Melo Carvalho Filho
Federal University of Campina Grande
Av. Aprígio Veloso, 882, CEP 58109-970
Campina Grande, Brazil
Tel: 558333101578
djalmacarvalho@uol.com.br

Marcelo Sampaio de Alencar
Federal University of Campina Grande
Av. Aprígio Veloso, 882, CEP 58109-970
Campina Grande, Brazil
Tel: 558333101578
malencar@iecom.org.br

ABSTRACT

This work presents a cost-effective base station deployment model based on artificial immune systems. It uses a multi-objective algorithm based on artificial immune systems (MO-AIS) as an optimiser. MO-AIS algorithms are a new class of evolutionary algorithms. The Binary-coded Multi-objective Optimisation Algorithm (BRMOA) is inspired by the clonal selection theory and the immune network theory. In this innovative approach, the network is optimised for high service coverage and low cost. The cost function takes into account user-defined geographical costs and environmental legislation. The optimisation strategy is applied to two realistic scenarios and results are compared.

Keywords

Base station deployment; optimisation; artificial immune systems.

1. INTRODUCTION

The base station deployment problem is a multi-objective problem (MOP). It involves many conflicting objectives: allow handoff between cells and at the same time guarantee minimum interference, produce the best coverage at the lowest possible cost of deployment and maintenance, respect the local environmental legislation and obey the rules imposed by the local government or by service regulatory agencies. It involves both site selection and site configuration. A subset of candidate sites is chosen based on traffic hold requirements and propagation data for a given area. For each selected site, the number of installed antennae as well as their configurations (type of antenna, azimuth, tilt, gain, power, etc.) are determined.

Several models have been proposed [12]. The models show differences in terms of detail or complexity, in the simulation environment, in the type of network planning adopted, in the number of objectives and which objectives are considered, in the propagation model used for the path loss calculation and in the optimisation algorithm. Obtaining an accurate estimation of deployment costs is a growing concern [9].

Many optimisation algorithms have been used: simulated annealing [9]; local search algorithm [13]; evolutionary algorithm [1]; genetic algorithm [10], [12]; tabu search [14].

The multi-objective optimisation algorithms based on artificial immune systems (MO-AIS) are a new class of evolutionary algorithms. They are inspired by processes that take place in the human immune system, such as: affinity maturation, antigen recognition and receptor editing [4]. Many multi-objective algorithms based on immunological mechanisms have been proposed [2], [5]: Constrained Multi-objective Immune Algorithm (CMOIA); Multi-objective Immune System Algorithm (MISA) [6]; Vector Immune System (VIS) [7]; Multi-objective Clonal Selection Algorithm (MOCSA) [8]. In all MO-AIS algorithms, local and global searches are carried out simultaneously [11].

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2. MULTI-OBJECTIVE OPTIMISATION

The goal of a multi-objective optimisation problem (MOP) is to find a solution that balances the conflicting objectives and constraints. This solution is not unique and cannot be considered a global optimum. The multi-objective optimisation problem or multiple criteria optimisation problem is described as follows.

Find

$$\mathbf{x} = [x_1, x_2, .., x_n]^T, \mathbf{x} \in \Omega, \tag{1}$$

that minimises or maximises the objective function

$$f(\mathbf{x}) = [f_1(\mathbf{x}), f_2(\mathbf{x}), \ldots, f_k(\mathbf{x})]^T, \tag{2}$$

subject to

$$g_i(\mathbf{x}) \leq 0 \text{ para } i = 1, \ldots, m, \tag{3}$$

and

$$h_j(\mathbf{x}) = 0 \text{ para } j = 1, \ldots, p, \tag{4}$$

where $\mathbf{x}$ is the vector of decision variables, m is the number of inequality constraints, p is the number of equality constraints and Ω contains all possible $\mathbf{x}$ that can be used to evaluate $f(\mathbf{x})$ (decision space). Equations (3) e (4) describe the dependencies among decision variables and parameters in the problem. The set of plausible solutions (or candidate solutions) is called the Pareto optimal set and form the Pareto front. Once the Pareto front is known, a decision maker is able to choose the most suitable solution to a given problem. The formal definitions of Pareto optimal set and Pareto front are provided next.

Definition 1. *(Pareto Dominance) A vector* $\mathbf{u}$ *dominates a vector* $\mathbf{v}$ $(\mathbf{u} \preceq \mathbf{v})$ *if and only if* $\mathbf{u}$ *is partially less than* $\mathbf{v}$*, i.e.,* $\forall i \in \{1,\ldots,k\}\,,\, u_i \leq v_i \wedge \exists i \in \{1,\ldots,k\} : u_i < v_i$.

Definition 2. *(Pareto Optimality) A vector* $\mathbf{x}^* \in \Omega$ *is a Pareto optimal if and only if there isn't a vector* $\mathbf{x}' \in \Omega$ *for which* $\mathbf{v} = f(\mathbf{x}') = [f_1(\mathbf{x}'), f_2(\mathbf{x}'), \ldots, f_k(\mathbf{x}')]^T$ *dominates* $\mathbf{u} = f(\mathbf{x}^*) = [f_1(\mathbf{x}^*), f_2(\mathbf{x}^*), \ldots, f_k(\mathbf{x}^*)]^T$*. A non-dominant solution is Pareto optimal.*

Definition 3. *(Pareto Optimal Set) For a given multi-objective problem* $f(\mathbf{x}) = [f_1(\mathbf{x}), f_2(\mathbf{x}), \ldots, f_k(\mathbf{x})]^T$*, the Pareto optimal set* P^* *is defined as*

$$P^* := \left\{\mathbf{x} \in \Omega \mid \neg\exists\ \mathbf{x}' \in \Omega \quad f\left(\mathbf{x}'\right) \preceq f(\mathbf{x})\right\}. \tag{5}$$

When a vector $\mathbf{x}$ that is a Pareto optimal is evaluated by $f(\mathbf{x})$, the vector $\mathbf{u}$ é obtained. The components of the vector $\mathbf{u}$ are the optimal solutions for each of the optimising objectives. The performance of each component cannot be improved without affecting another.

Definition 4. *(Pareto Front) For a given multi-objective problem* $f(\mathbf{x}) = [f_1(\mathbf{x}), f_2(\mathbf{x}), \ldots, f_k(\mathbf{x})]^T$ *with the Pareto optimal set* P^**, the Pareto front* PF^* *is defined as*

$$PF^* := \{\mathbf{u} = f(\mathbf{x}) \mid \mathbf{x} \in P^*\}. \tag{6}$$

All vectors in the Pareto front are non-dominant. As it is sometimes difficult to obtain the Pareto front when real engineering problems are considered, approximations are used. It is necessary to make a distinction between the real Pareto front PF_r^* and the approximated Pareto front PF_a^*, obtained through the optimisation procedure.

2.1 Multi-objective Optimisation Based On Artificial Immune Systems

Most multi-objective optimisation algorithms based on artificial immune systems are inspired by the clonal selection theory [11], [6], [8]. The immune cells B go through a process called clonal expansion. The clonal expansion includes adaptation through mutation (somatic hypermutation) and a selection mechanism. This selection mechanism makes sure that the B cells, which produce antibodies with more affinity, survive and subsequently become memory cells. This combination of mutation and selection is called the affinity maturation of the immune system. Other concepts or theories usually applied to the development of artificial immune systems for multi-objective optimisation are [8]: the immune network theory, receptor editing through a DNA library and linfocines or chemical messages.

The MO-AIS algorithms include a memory population or offline population and is divided into the following phases: affinity evaluation, avidity evaluation, selection for cloning, proliferation and mutation (somatic hypermutation) and diversification [2]. The iterative process is repeated several times until a stopping criterium is met. The offline population is constantly updated in the process.

The memory population or offline population stores the best solutions, the Pareto front approximation. Dominance relations are used to compare the vectors obtained throughout the iterative process.

In optimisation, affinity means the evaluation of the objective function $f(\mathbf{x})$ and the constraints (3) e (4). Avidity refers to the overall binding intensity between an antigen $f(\mathbf{x})$ and an antibody (the solution vector $\mathbf{x}$). Therefore, it measures the quality of the candidate solution. In MOCSA, the candidate solutions (antibodies) are classified into successive non-dominant fronts according to dominance relations.

The selection for cloning the best N_c might be performed deterministically or stochasticly. In order to promote selection proportional to the affinity between antibodies and antigens or selection according to avidity, any selection mechanism commonly used in evolutionary algorithms might be used, such as: roulette wheel selection, elitist selection, hierarchical selection, tournament selection and bi-classist selection.

The mutation rate inversely proportional to affinity and the number of clones proportional to affinity when combined result in a balance of local and global searches. Once the percentage of individuals to be cloned is chosen, the number of clones that each produces may be determined in different ways [4]. The greater the number of individuals proliferating, the longer is the processing time. In MOCSA, the number of clones is determined based on the Pareto front the antibodies belong [8]. The number of clones is given by

$$N_c = \mathrm{round}\left(\frac{\beta.N}{i}\right), \tag{7}$$

where β is a multiplying constant, N is the overall number of antibodies, round$(\cdot)$ is an operator that returns the closest integer value to its argument and i is the number of the Pareto front it belongs.

The diversification phase is related to the global searches. It is not present in all MO-AIS algorithms. By applying diversification, it is possible to add new solutions randomly. Based on the immune network theory, a common suppressing operator is usually applied [7]. When two antibodies are too close to each other, one of them might recognise the other and, therefore, one of them is eliminated. If the Euclidian distance between two antibodies in the objective space is greater than a given value ϵ_1, the antibody with the greatest affinity will be suppressed.

In MOCSA, suppression is applied both to the decision variable space and to the objective space [5]. In a more recent work, Campelo *et al.* only apply suppression to the objective space [8]. The objective space vectors are first normalized to the unitary hypercube to account for possible discrepancies between threshold values for each objective. Then the distances between the remaining antibodies N in the offline population are calculated. The distances of each individual to its k closest neighbours are obtained, where k is given by

$$k = \mathrm{round}\left(\sqrt{N}\right). \tag{8}$$

The individual with the smallest sum of the k distances is eliminated, as it is located in a dense region of the Pareto front. The procedure is repeated until the memory population reaches the maximum size specified by the user.

3. PROPOSED MODEL

The proposed model is a discrete test point model based on [12]. The working area or simulation area W is discretised into test points at Cartesian coordinates (x, y, z) at a given resolution and the following data is defined:

- The reception test points **RTP**, where signal reception quality is measured;
- The service test points **STP**, where the received signal must be above the service threshold S_q, to ensure the quality of service is met;
- The traffic test points **TTP**, with each carrying a traffic load in erlang;
- The candidate sites **CBS**, which may contain up to 3 antennae;
- The angle of incidence matrix **AIM**, that specifies the vertical angles from each **CBS** to each **RTP**;
- The path loss matrix **PLM**, with information regarding the signal loss from each **CBS** to each **RTP**.

The standard urban empirical propagation model proposed by Hata is used for path loss calculation. The model also considers random shadowing effects as proposed in [10]. These can either amplify or attenuate the strength of the signal at reception. They are obtained by the next pseudo-random Gaussian value (μ, σ), where μ is the path loss value and σ is 4dB.

The best server model is adopted, where each STP is served by the CBS providing the greatest received signal strength. A cell is defined by the set of STPs covered by one antenna, where $P_r \geq$-90dBm. Each site may contain up to 3 antennae.

A network subset $\mathbf{CBS'}$ refers to a set of sites **CBS** with at least one active antenna and satisfies the following objectives:

- Coverage - It is the sum of the covered STP_i in the working area divided by the total number of **STP** as a percentage. Thus,

$$\mathrm{COVER}_{CBS'} = \frac{\sum_{i=1}^{n_{STP}} STP_i}{n_{STP}} \times 100, \tag{9}$$

where

$$STP_i = \begin{cases} 1, \text{ if } STP_i \text{ is covered,} \\ 0, \text{ otherwise;} \end{cases} \tag{10}$$

- Traffic - It is the sum of the current overall traffic in the network divided by the total traffic load and expressed as a percentage. Thus,

$$\mathrm{TRAF}_{CBS'} = \frac{\sum_{i=1}^{n_{CBS'}} T_{CBS'_i}}{\sum_{i=1}^{n_{TTP}} TTP_i} \times 100; \tag{11}$$

- Cost - It is the overall deployment cost and is given by,

$$\mathrm{COST}_{CBS'} = \sum_{CBS_i \in CBS'} \left[C_f(CBS_i) + C_g(CBS_i) \right], \tag{12}$$

where $C_f(CBS_i)$ is the fixed cost of deploying a base station at a plain site and $C_g(CBS_i)$ is the geographical cost.

The fixed cost of deploying a base station at a plain site includes:

- Acquisition, shipping and installation of equipment;
- Software licenses;
- Site acquisition or rent in an area, where there are no restrictions on base station deployment, regarding environmental impact, radio emission or local environmental legislation;
- Site legalisation (bureaucratic fees, administrative fees for permission for radio emission, legal expenses, technical reports from experts in the field in order to approve the site location);
- Site preparation including construction.

The geographical cost depends on the site location. It may slightly increase overall costs or rather hinder site selection. The working area is divided into the following categories:

- Standard or plain area:

  It comprises urban and suburban areas where there are no restrictions on radio emission;

- Areas with surcharge:

  The surcharge refers to the high cost of property in the city centre or in any other high-priced residential areas and also to higher deployment costs in rural areas;

- Prohibited areas:

  Even though environmental legislation tends to limit base station deployment in certain areas, the companies may still need to choose a prohibited site so as to meet technical requirements or for business expansion purposes. Choosing a prohibited site means extra cost related to fines and other bureaucratic fees;

- Preferred areas:

  In order to reduce deployment costs, preferred areas are chosen. These include areas where site sharing is possible and buildings or areas belonging to the company or business partners. The local government might as well lease areas or buildings for deployment at reduced costs;

- Mandatory areas:

  These include areas where site deployment is mandatory for security reasons (inside tunnels and under overpasses) and areas where a large number of people are usually gathered (football stadiums, close to theatres, shopping malls, convention and trade centres, etc.);

- Non-regulated areas:

  These are not included in any of the previous categories and new procedures or fees may apply. In non-regulated areas, the geographical cost is a random value between the fixed cost of deploying a base station at a plain site and the geographical cost of deploying base stations in prohibited areas.

The optimisation strategy is divided into three phases: pre-processing, site initialization and iterative process. In the pre-processing phase, the configuration of the antennae that ensure that maximum traffic load in each cell is no greater than 5.4 erlang and the set of STPs covered by each site are determined. The key aspect of the approach is to perform cell dimensioning only once and optimise the network for high service coverage and low cost. If all STPs are covered, all TTPs are covered by definition, since $TTP \subseteq STP \subseteq RTP$.

Site initialization with binary representation speeds up the iterative process and reduces computational time [12]. Each individual in the population is identified by a binary string with length n_{CBS} (number of candidate sites). Whether a site is on or off is indicated, respectively, by 1 or 0. The initial population is randomly generated and the number of active sites is chosen according to the following criterium: For the first third of the population, the number of active sites is chosen between 1 and the minimum number of sites, which could satisfy 100% traffic hold; For the second third of the population, the total number of sites to be turned on is between the minimum and double the minimum.

The optimising algorithm is based on MOCSA. MOCSA adopts real-valued variables and is inspired by the clonal selection theory and the immune network theory. The Binary-coded Multi-objective Optimisation Algorithm BRMOA produced satisfactory results when compared to the NSGA-II algorithm [3]. BRMOA uses binary representation for the decision variables and replaces the Gaussian mutation, adopted by MOCSA, with a uniform mutation [4], with probability

$$p_m = \frac{1}{\sqrt{n_{CBS}}}. \qquad (13)$$

The proposed model is very flexible when it comes to candidate sites. It is possible to choose which sites to activate throughout the iterative process. The user may use his experience to interfere in the process and lead the search to previously selected sites.

4. SIMULATION RESULTS

The simulation environment used for analysis mimics a metropolis. Figure 1 shows the simulation Table 1 contains the simulation environment data. The candidate sites are divided into twelve categories according to different geographical costs as shown in Table 2. The standard or plain area accounts for 58.68% of the working area with randomly distributed candidate sites. Some preserved and high-priced residential areas are expected to handle high traffic load. Therefore, two prohibited sites are needed to meet traffic requirements. Preferred sites are randomly distributed in the working area. Both non-regulated and rural areas are far away from the city centre. Geographical costs are user-defined.

Two scenarios are considered for the analysis. In the first scenario, sites in mandatory areas are active during the whole iterative process. On the other hand, the sites in preserved areas are always disabled. The remaining sites are activated or disabled according to simulation results. In the second scenario, sites in mandatory areas as well as sites in preferred areas are always active. The analysis is carried out in order to find out if total coverage is obtained, which sites are selected and the criteria used to choose sites in both

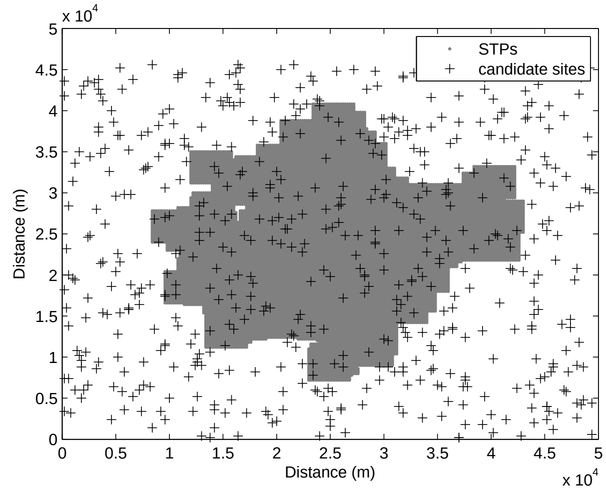

Figure 1: Simulation environment.

Table 1: Simulation environment data.

Working area	2,252.64 km^2
RTPs	56,792
STPs	17,393
Candidate sites	568
TTPs	6,602
Traffic load	3,221.84 erlang

Table 2: Number of candidate sites and geographical cost according to the different categories.

	Candidate sites	C_g (per site)
Standard areas		
Urban and suburban areas	339	0
Areas with surcharge		
City centre	7	1.00
High-priced residential areas	37	2.00
Rural areas	31	1.00
Optional areas		
Non-regulated areas	67	1.00-9.00
Prohibited areas		
Preserved areas	44	9.00
Preferred areas		
Site sharing	20	-0.50
Business partners	4	-0.50
Government	3	-0.25
Mandatory areas		
Indoor (shopping malls)	7	4.00
Indoor (tunnels and overpasses)	3	3.00
Crowded areas	6	1.00

scenarios.

Table 3 describes the two scenarios. Minimum cost and minimum number of selected sites refer to active sites before the optimisation strategy is applied.

Table 3: Description of both scenarios.

	Scenario 1	Scenario 2
Preserved areas	2 active sites	2 active sites
Preferred areas	"on" or "off"	always "on"
Mandatory areas	always "on"	always "on"
Sites in other areas	"on" or "off"	"on" or "off"
Minimum sites	18	45
Minimum cost	77.00	91.25

The Pareto front approximations were obtained for an initial population of 30 individuals, when: $g_{\max} \leq 10$, $n_e = 12,000$, $P_m = 100$ e $d = 0.25$. As BRMOA is a stochastic optimiser, a statistical analysis was carried out based on ten runs of the software. Computing time was estimated based on the number of objective function evaluations. Schott's spacing metric was chosen as a quality indicator [5]. It does not require the researcher to know the real Pareto front. It measures the distance variance of neighbouring vectors in the Pareto front and is given by,

$$S_p = \sqrt{\frac{1}{N-1} \sum_{i=1}^{N} \left(\overline{d} - d_i\right)^2}, \tag{14}$$

$$d_i = \min_j \left| f_1^i\left(\overrightarrow{x}\right) - f_1^j\left(\overrightarrow{x}\right) \right| + \left| f_2^i\left(\overrightarrow{x}\right) - f_2^j\left(\overrightarrow{x}\right) \right|, \tag{15}$$

where N is the number of vectors in PF^*, $\overline{d}$ is the mean of all d_i and $f_k^i\left(\overrightarrow{x}\right)$ is each component of the objective function.

Figure 2 shows the best Pareto front approximations according to Schott's spacing metric for an initial population of 30 individuals for the first scenario. Figure 3 shows

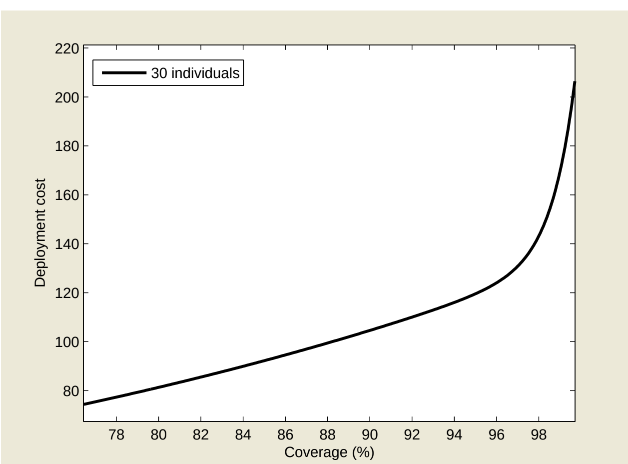

Figure 2: Pareto front approximation for scenario 1.

the Pareto front approximations for the second scenario. The minimum network configuration guarantees coverage at 76.44% in the first scenario and coverage at 96.24% in the second scenario. Total coverage is not obtained in any of the scenarios. In the first scenario, maximum coverage is 99.72%, which refers to deployment cost of 207.00. In the second scenario, maximum coverage is 99.97%, with deployment cost of 204.00. There is an increase of 0.26% at coverage and overall deployment cost is reduced by 1.45% when the second approach is adopted. The addition of preferred sites with low deployment cost guarantees satisfactory coverage even before the optimisation procedure is carried out. Overall deployment cost is higher for the first scenario, when the same coverage is attempted.

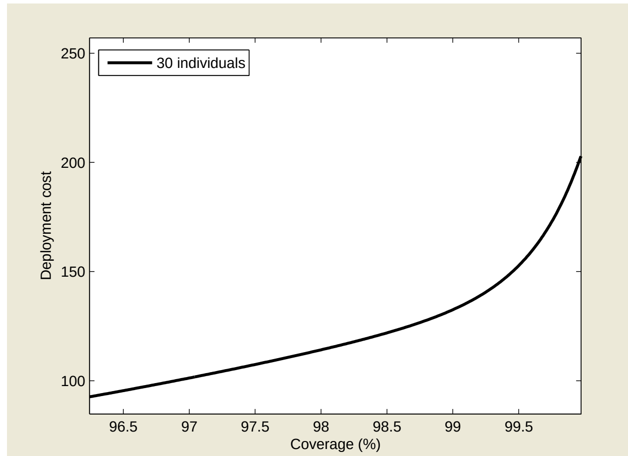

Figure 3: Pareto front approximation for scenario 2.

Figure 4 shows the number of objective function evaluations after each generation for both scenarios. More objective function evaluations are observed in the first scenario, since more variables are considered. Figure 5 shows the number of vectors in the Pareto front after each generation for both scenarios. The number of solutions is sometimes reduced sharply in two successive generations. This is related to the suppression operator that eliminates similar or very close individuals from the memory population. The oscillations in the number of individuals in the memory population are more intense in the second scenario, although the number of individuals is the same after ten generations. It is important to point out that the number of solutions in the Pareto front is higher than 30 after the very first generation for both scenarios.

Table 4 and Table 5 show coverage, cost, number of sites and traffic for solutions at 97%, 98% and 99% coverage for both scenarios. The results were obtained in ten runs of the software and after only one generation. When the number of candidate sites is restricted, maximum coverage is attained faster as shown in Table 5.

Table 6 and Table 7 show the type of candidate sites selected for solutions at 97% coverage, 98% coverage , 99% coverage and maximum coverage. In the first scenario, low-cost preferred areas are only selected in order to reduce deployment costs. When higher coverage is attempted, standard sites are chosen. The optimisation strategy selects areas with surcharge based on technical requirements. Non-regulated areas are only selected when their geographical costs are low. In the second scenario, there is a sharp fall in the number of sites in standard areas. High-cost sites are only activated so as to meet traffic requirements. Figure 6 and Figure 7 show sample solutions at maximum coverage for both scenarios.

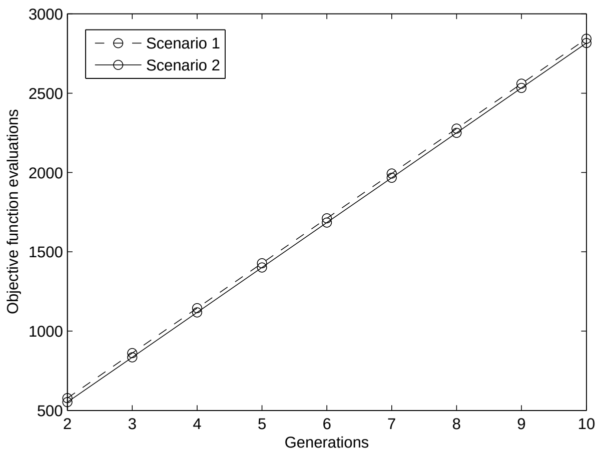

Figure 4: Number of objective function evaluations after each generation for both scenarios.

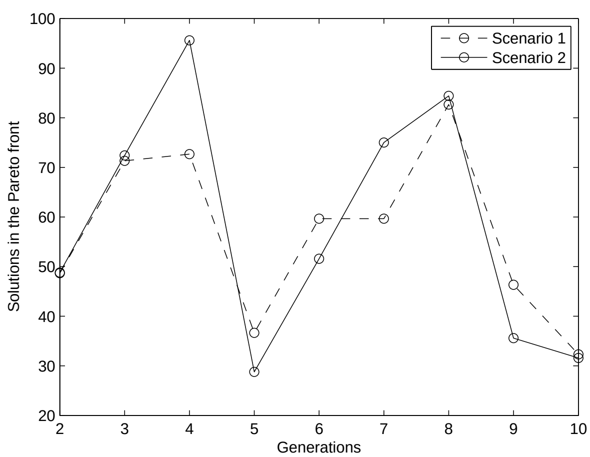

Figure 5: Number of solutions in the Pareto front after each generation for both scenarios.

Table 4: Coverage, cost, number of sites and traffic at 97%, 98% e 99% coverage for scenario 1.

Coverage	**Cost**	**Sites**	**Traffic**
mean	mean	mean	mean
Std. dev.	Std. dev.	Std. dev.	Std. dev.
97.026	141.167	60.667	96.717
0.204	6.449	1.528	0.639
97.984	152.583	67.667	98.101
0.098	8.064	3.055	0.324
98.948	181.167	74.000	99.064
0.168	20.642	10.001	0.295

Table 5: Coverage, cost, number of sites and traffic at 97%, 98% e 99% coverage for scenario 2.

Coverage	**Cost**	**Sites**	**Traffic**
mean	mean	mean	mean
Std. dev.	Std. dev.	Std. dev.	Std. dev.
96.901	101.583	51.333	96.424
0.304	1.528	2.517	0.443
98.244	119.25	64.000	98.101
0.295	3.606	2.000	0.581
99.047	138.917	69.667	99.185
0.009	5.033	1.528	0.131

Table 6: Selected sites in different solutions for scenario 1.

Types of candidate sites	Coverage			
	97%	98%	99%	Max.
Standard urban areas	31	41	41	43
City centre	2	1	1	2
High-priced urban areas	3	4	3	6
Rural areas	1	2	3	7
Non-regulated areas	2	2	6	4
Preserved areas	2	2	2	2
Preferred areas	2	3	2	4
Mandatory areas	16	16	16	16
Total	59	71	74	84

Table 7: Selected sites in different solutions for scenario 2.

Types of candidate sites	Coverage			
	97%	98%	99%	Max.
Standard urban areas	5	18	19	42
City centre	0	0	1	0
High-priced urban areas	0	1	1	9
Rural areas	0	0	3	3
Non-regulated areas	1	1	1	8
Preserved areas	2	2	2	2
Preferred areas	27	27	27	27
Mandatory areas	16	16	16	16
Total	51	66	70	107

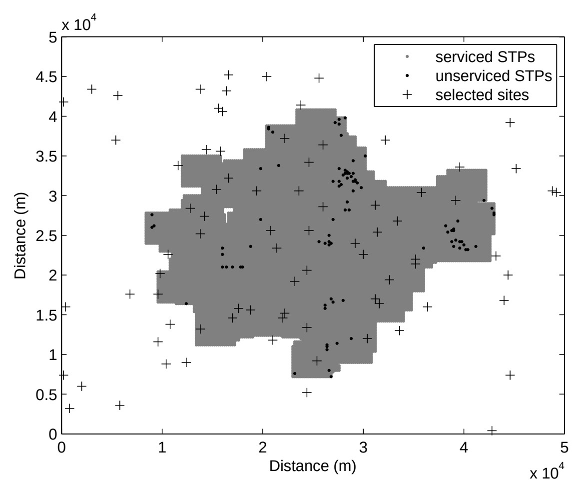

Figure 6: Maximum coverage for scenario 1.

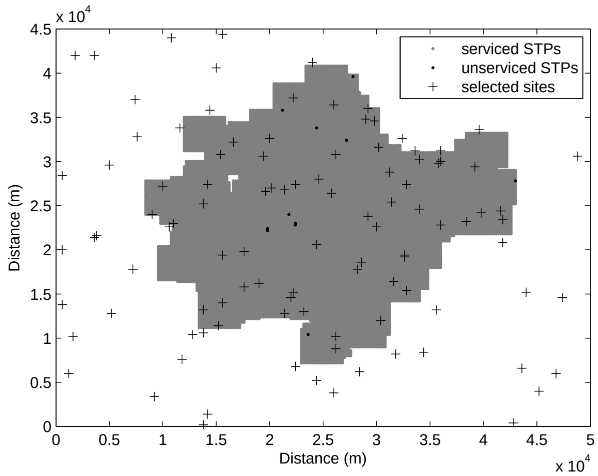

Figure 7: Maximum coverage for scenario 2.

5. CONCLUSIONS

This work has presented a cost-effective base station deployment model based on artificial immune systems. It uses a multi-objective algorithm based on artificial systems (MO-AIS) as an optimiser. The Binary-coded Multi-objective Optimisation Algorithm (BRMOA) is inspired by the clonal selection theory and the immune network theory.In this innovative approach, the network is optimised for high service coverage and low cost. The cost function takes into account user-defined geographical costs and candidate sites are classified as such. The optimisation strategy was applied to two realistic scenarios. An accurate estimate of deployment costs was obtained when candidate sites were grouped according to geographical costs and environmental legislation was considered. Even though prohibited areas limit full coverage goals, cost-effective solutions may still be obtained. By choosing low-cost preferred sites, it is possible to accelerate covergence and obtain high coverage solutions at low cost.

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