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Evolutionary algorithms for solving the automatic cell planning problem: a survey

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Evolutionary algorithms for solving the automatic cell planning problem: a survey

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Automatic cell planning (ACP) is an optimization problem from the mobile telecommunications domain that addresses finding the location of the network antennae as well as their parameter settings in order to satisfy several cellular operator requirements. Due to its NP-hard complexity, evolutionary techniques have become popular for solving ACP instances. This article presents a survey of evolutionary algorithms (EAs) engineered for addressing ACP problems, analysing both the features of the considered ACP problem and the main aspects of the EAs used to solve them. The survey provides an up-to-date overview that is not limited to any particular kind of evolutionary approach, and comprises advanced algorithmic enhancements like hybridization and parallelization. The article ends by addressing some important issues and open questions that can be the subject of future research.

Keywords: evolutionary algorithms; automatic cell planning; survey

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1. Introduction

Planning and managing a cellular phone system means engineers have to face many challenging optimization problems (Resende and Pardalos 2006). Assuming that the business planning activities are already completed, *i.e.* choosing customer segments, network technology to be used, etc., one of the most significant technical optimization problems is radio network planning (Mishra 2004), also known as the *automatic cell planning* (ACP) problem, the *network dimensioning* problem, or the *capacity planning* problem. Indeed, the foundation of a well-performing cellular network is the basic radio platform since it is the part of the network which is closest to mobile users. Also, it has clear benefits for the operators since they reduce the infrastructure costs and, at the same time, increase revenue and user satisfaction.

In the initial deployment of a cellular network, the ACP problem addresses selecting the locations of base stations (BTSs) from a set of candidate sites, as well as their parameter settings, in such a way that a number of network requirements are satisfied. These requirements include maximizing the area covered and the traffic capacity, while minimizing the infrastructure cost. Configuring BTSs is not a simple task, since it implies setting up many configuration

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parameters, such as the antenna type, the emission power, and/or the tilt and azimuth angles. However, cellular networks need to be adapted to the highly competitive telecommunications industry: new services, new equipment technologies, increasing system capacity, etc. Even in relatively mature cellular markets, these issues force the deployment of additional sites, not only to enhance the system capacity but also to provide increased levels of in-building coverage as mobile users expect to be offered service in all geographical areas. The ACP problem therefore holds both for the second generation of cellular phone systems, the global system for mobile communication (GSM communication, see Mouly and Paulet 1992), and its enhanced releases GPRS (Granbohm and Wiklund 1999) and EDGE (Furuskar *et al*. 1999), as well as for current third-generation networks – universal mobile telecommunications systems (UMTSs, see Rapeli 1995).

The simplest version of the ACP problem, as an extension of the classical minimum cost set covering problem, has NP-hard complexity (Glasser *et al*. 2005). In more complex and realistic versions in which BTSs have to be dimensioned, the high number of configurations for each of these BTSs has to be taken into consideration. Even when the inherently continuous BTS parameters, such as emission power, tilt and azimuth, are discretized into a small subset of possible values, the search space becomes huge. However, an additional issue emerges in this optimization problem: changing the configuration setting of any BTS may affect other BTSs. For instance, if the maximum emission power of a BTS b is reduced to decrease the signal interference in a given area of the network, other BTSs should hold the traffic capacity that has been left unsupported by b. If these other BTSs are already operating at their full capacity, the network would simply start dropping calls of mobile users. This means that making small local changes would require most of the network predictions to be recomputed.

In general, two kinds of technique can be applied to solving hard optimization problems such as ACP – exact and approximate. Exact methods such as *brand and bound* or the A^* algorithm are effective for problems of small size; when problems become larger, usually because of their NP-hard complexity, approximate algorithms are mandatory. Among these approximate optimization techniques, *metaheuristics* (Glover and Kochenberger 2003) has become a highly active research area. Although there is not a commonly accepted definition of metaheuristics, they can be considered as high-level strategies that guide a set of simpler techniques in the search for an optimum (Blum and Roli 2003). Evolutionary algorithms (EAs, see Bäck *et al*. 1997) are one of these techniques and they are by far the most popular metaheuristics. They are based on maintaining a population of tentative solutions that are competitively manipulated by applying variation operators (selection, recombination, mutation). EAs have been widely used to address ACP problems. Indeed, they can provide this complex optimization problem with very accurate results, even when little knowledge is used in the exploration of the search space. As discussed before, achieving a satisfactory radio network design requires consideration of a number of issues which are contradictory to each other. For example, the cost of the entire network infrastructure can be reduced by using a small number of omnidirectional antennae operating at a maximum power. This would provide a wide coverage with small cell overlapping and, as a consequence, low interference. However, the network might not be able to satisfy the traffic demand of each cell. This issue can be tackled by adding more antennae, leading to a cost increment and potentially greater interference. As a consequence, it is mandatory to find trade-off solutions for these conflicting goals. The ACP problem is therefore *multiobjective* in nature. This fact has made EAs even more popular for solving the ACP problem. Indeed, when using a multiobjective formulation of a given optimization problem (*e.g.* ACP), the goal does not lie in finding one single solution, but a set of trade-off solutions. The point is that EAs are particularly well suited to solving multiobjective problems. Their main advantage is that they are able to find such a set of trade-off solutions in one single run (Deb 2001, Coello *et al*. 2007), whcih has promoted their utilization for addressing the ACP problem even more.

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This article is aimed at providing a survey of work related to EAs used to solve the ACP problem. To the best of our knowledge, it is the first attempt at covering this gap. The goal is that an interested researcher will be able to find references on relevant studies using EAs applied to different formulations of the ACP problem and define new strategies for improving the current state of the art. An up-to-date overview that is not limited to any particular kind of evolutionary approach is provided. More than 40 works have been revised and summarized in this overview, which analyses both the features of the ACP problem addressed and the main aspects of the EAs used for their resolution. Important aspects of the evolutionary search are considered, such as the encoding and genetic operators, as well as advanced algorithmic enhancements like hybridization and parallelization.

The rest of the article is organized as follows. In the next section, the basic concepts of EAs and the different models used for solving the ACP problem in the literature are described. The survey of related works is provided in Section 3. Finally, the main conclusions of this article are given in Section 4, which also addresses some important issues for future research.

2. Basics on EAs and ACP

This section provides the reader with a brief overview of the two main topics of this work, namely evolutionary algorithms (EAs) and automatic cell planning (ACP) problems.

2.1. *Evolutionary algorithms*

EAs are stochastic search methods inspired by nature's capability to evolve individuals well adapted to their environment. Well-accepted subclasses of EAs are genetic algorithms (GAs), evolution strategies (ESs), and evolutionary programming (EP) (Bäck 1996). The basic outline of a standard EA is shown in Figure 1. At each generation (iteration) t, an EA operates on a population of individuals $P(t)$, each one encoding a tentative solution, thus searching in many regions of the problem space at the same time. Each individual is a string of symbols encoding a solution for the problem (*genotype*) and has an associated fitness value (*phenotype*) which is computed by the objective function. This fitness function is aimed at ranking the quality of the evaluated individual with respect to the rest of the population. The application of stochastic variation operators, such as mixing parts of two strings (*crossover*) or randomly changing their contents (*mutation*), leads this population towards the fittest regions in an iterative manner. The algorithm finishes when a

```
t := 0 ;
initialize & evaluate[P(t)] ;
while not stop_condition do ;
    P'(t) := variation [P(t)] ;
    evaluate [P'(t)] ;
    P(t + 1) := select [P'(t) ∪ P(t) ] ;
    t := t + 1 ;
end while
```

Figure 1. Pseudocode describing a standard EA.

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stopping condition is met (*e.g.* an optimum is found or a number of function evaluations has been carried out).

2.2. *Models for the ACP problem*

A number of different models have been defined in the literature to solve ACP problems (see Raisanen 2006), ranging from pure abstract models (*e.g.* based on graph theory) to rather detailed ones (models considering specific areas with known traffic and topologies). The intermediate models proposed move in two different directions. They either add real information to abstract models or they try to reduce the complexity of detailed models to reduce their computational demands. The three main models found in the literature – demand node, disc, and cell and test point – are described in the following sections.

2.2.1. *Demand node model*

The concept of demand nodes was introduced first by Gerlich *et al*. (1996), and it has since been used in different works (*e.g.* Tutschku 1998, Galota *et al*. 2000, Amaldi *et al*. 2001, Weicker *et al*. 2003). The basic idea is that the demand node represents the centre of an area where the traffic is being generated by the users. The main advantage of this model is that by combining the traffic of a small region in a single point, the computational requirements are drastically reduced; the drawback is that the realism of the problem is also simplified. The demand nodes comprise a number of test points, hence the need for fewer nodes; however, merging test points into a single demand node has the same effect as applying a lossy compression mechanism: the resolution is reduced.

Most of the research work using this model also allows total freedom as regards the positioning of candidate sites. This allows the uniform distribution of the sites over the full area to be covered, which usually is not possible in practice as a site cannot simply be placed anywhere, *e.g.* in the middle of a motorway.

2.2.2. *Disc model*

The first use of disc (circle) graphs in the design of cellular networks was in Hale (1980), where it was applied to solve the frequency assignment problem. Later extensions to this model consider intersections among discs and non-uniform traffic distributions (Huang *et al*. 2000a,b,c). The main advantage of the approach presented in Huang *et al*. (2000a) is that it is possible to take into account different goals related to the design of the network; thus, the problems of cell planning and frequency assignment can be addressed simultaneously. Furthermore, the computational costs are not high.

The main inconvenience of the disc model has to do with the fact that it assumes an ideal propagation model, so all the cells have the same shape. Even though the size of the cells can vary depending on a non-uniform traffic distribution (Huang *et al*. 2000b), the shape is always a circle. Another issue is that sites may be located anywhere, so the same problems as in the demand node model arise.

2.2.3. *Cell and test point model*

Although this model is known thanks to the works of Reininger and Caminada (1998a,b, 2001), it appeared first in Hao *et al.* (1997). In it, the working area is discretized into a set of test points which are spread over the whole area. These test points are used to measure the amount of signal

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strength in the region where the network operator intends to service the traffic demand of a set of customers.

Three subsets of test points are defined: reception test points (RTPs), where the signal quality is tested; service test points (STPs), where the signal quality must exceed a minimum threshold to be usable by customers; and traffic test points (TTPs), where a certain amount of traffic is associated with each customer (measured in Erlangs).

In this model, the set of candidate site locations does not have to be uniformly distributed in the terrain, so it is a better representation of the scenarios presented by the operators. Its main advantage is that it allows measuring all the network objectives (such as coverage and capacity). Notwithstanding, there is a clear inconvenience: the computational cost increases because a high number of points is usually used to face the problem (*e.g.* test points every 200 meters) in order to increase the realism. This realism is the main reason that this model is widely adopted in the literature (*e.g.* Vasquez and Hao 2001, Hurley 2002, Raisanen and Whitaker 2003, Zimmermann *et al*. 2003b, Raisanen *et al*. 2004, Raisanen and Whitaker 2005, Talbi and Meunier 2006, Talbi *et al*. 2007).

3. The survey

EAs, and more concretely GAs, have been widely used to tackle most of the ACP models proposed. This section includes detailed analysis of more than 40 works that show the different EA approaches developed to address this complex optimization problem. It starts by giving an overview of the literature, focusing on the main features of the particular ACP problem solved in each research work. Next, a more in depth review based on algorithmic details (encoding schemes, genetic operators, hybridization and parallelization) is provided.

3.1. *ACP problems addressed by EAs*

Table 1 summarizes the main characteristics of the ACP problems addressed by EAs in the literature. For each row, they show the following information.

- Ref.: Bibliographic reference. The publication year of the first work of the series is used to rank the entries.
- Alg.: Particular EA used for solving the problem (see Bäck 1996 for the details). Here, it distinguishes between the following.
  (1) GA: simple GA. This keyword is used when not enough information is given in the article for further specifications.
  (2) genGA: generational GA.
  (3) ssGA: steady-state GA.
  (4) dGA: distributed GA. This kind of GA may appear combined with the two previous algorithms. That is, dssGA refers to a distributed GA in which each subpopulation evolves by using the steady-state scheme.
  (5) ES: evolution strategy.
  (6) Concrete algorithms such as CHC, DE, NSGA-II, SPEA2, and others whose description can be found in the references provided.
- Multi: this column points out whether the problem is addressed by using multiobjective techniques based on Pareto optimality.
- ACP: ACP model used (see Section 2.2. Available values are Demand node, Disc and Test points).

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Table 1. EA approaches in the literature for the ACP problem (I).

Ref.	Alg.	Multi	ACP model	Search Space					Objective	Constraints
				Sites	Cell	Pw	Ti	Az		
Calégari *et al*. (1996, 1997, 2001)	dGA	•	Demand node	CSL	Propagation model	•	•	•	Cost, cover	–
Chamaret and Condevaux-Lanloy (1998)	dssGA	•	Demand node	CSL	Propagation model	•	•	•	Cost, cover	–
Lieska *et al*. (1998)	genGA	•	Demand node	CSL	Synthetic	•	•	•	Cover	4 BTSs
Molina *et al*. (1999)	genGA	•	Demand node	CSL	Propagation model	•	•	•	Cover, cost	–
Reininger *et al*. (1999)	genGA	•	Test points	CSL	Propagation model	✓	•	•	Cover, cost (dynamic)	–
Meunier *et al*. (2000), Cahon *et al*. (2006), Talbi and Meunier (2006), Talbi *et al*. (2007)	ssGA, hybrid	✓	Test points	CSL	Propagation model	✓	✓	✓	Cost, traffic, interference	Cover, handover
Huang *et al*. (2000b)	GA	•	Disc	Free	Omnidirectional	✓	•	✓	Cover, traffic, cost, interference	–
Zimmermann *et al*. (2000, 2003a,b)	ES	•	Test points	CSL	Propagation model	✓	✓	✓	Cost, interference, cell shape	Traffic, cover
Lee and Kang (2000)	dGA	•	Demand node	CSL	Propagation model	•	•	•	Expansion cost	Traffic, capacity, cover
Han *et al*. (2001)	ssGA	•	Disc	Free	Omnidirectional	•	•	•	Cost, cover	–
Laki *et al*.(2001)	genGA	•	Test points	Free	Ray tracing	•	•	•	Cover, delay	–
Altman *et al*.(2002a,b), Jamaa *et al*. (2006)	GA	•	Test points	CSL	Propagation model	✓	✓	✓	Cost, cover, capacity	Handover
Parl *et al*. (2002)	ssGA	•	Disc	Free	Propagation model	•	•	•	Cost, cover	–
Cerri *et al*.(2003, 2004) Cerri and Russo (2006)	Binary GA	•	Demand node	Free	Omnidirectional	✓	✓	•	Radiation, traffic, interference, efficiency, cover	–

Weieker *et al.* (2003)	SPEA2, NSGA-II, stEAPT	✓	Demand node	Free	Omnidirectional	✓	•	•	Cost, interference	Cover
Alba (2004), Alba and Chicano (2005)	ssGA, dssGA	•	Demand node	CSL	Square	•	•	•	Cost, cover	–
Brunetta *et al.* (2004), Chiara *et al.* (2005)	GA, hybrid GA-TS	•	Test points	Free	Propagation model	✓	•	•	Different cover conditions	Handover, capacity
Jamaa *et al.* (2004a,b) Picard *et al.* (2005)	NSGA-II	✓	Test points	CSL	Propagation model	✓	✓	✓	Cost, cover, capacity	Handover
Jeidi *et al.* (2004)	MOGA	✓	Test points	CSL	Propagation model	✓	✓	✓	Overlap, geometry	Cover
Lin *et al.* (2004)	Binary GA	•	Demand node	CSL	Propagation model	✓	•	•	Cost, cover, traffic, handover	–
Maple *et al.* (2004)	dGA	✓	Disc	CSL	Propagation model	✓	•	•	Capacity, cover, cost	–
Raisanen *et al.* (2004), Whitaker *et al.*(2004a,b), Raisanen and Whitaker (2005)	SEAMO, SPEA2, NSGA-II,PESA	✓	Test points	CSL	Propagation model	✓	•	•	Cost, cover	Handover
Zhang *et al.* (2004)	MOGA, EMOGA	✓	Disc	Free	Omnidirectional	•	•	•	Cost, cover	–
Créput *et al.* (2005)	Hybrid dES	•	Demand node	CSL	Hexagonal	•	•	•	Traffic, geometry, cost, overlap	–
Alba *et al.* (2007)	CHC, ssGA, genGA	•	Demand node	CSL	Square, Omnidirectional, Directive	•	•	✓	Cost, cover	–
Nebro *et al.* (2007)	MOCHC, NSGA-II	✓	Demand node	CSL	Square	•	•	•	Cost, cover	Maximum cost, minimum cover
Vega-Rodriguez *et al.* (2007a,b)	CHC, PBIL, DE	•	Demand node	CSL	Square	•	•	•	Cost, cover	–
de Melo Carvalho Filho and de Alencar (2008)	AIS	✓	Test points	CSL	Propagation model	•	•	•	Cover, cost, traffic	
Raisanen (2008)	NSGA-II	✓	Test points	CSL	Propagation model	•	•	•	Cost, cover	Traffic, handover

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- Sites: this shows whether the locations of the BTSs are chosen among a set of candidate sites (CSL – candidate site list – or they can be freely placed all over the geographic area).
- Cell: this column indicates how the cell or service area of BTSs is computed.
- Pw, Ti and Az: these three columns show, respectively, whether the power, tilt and azimuth of the BTSs are optimized. These are the most common settings adjusted when BTS dimensioning is addressed.
- Objectives: different aspects of the cellular network that are optimized.
- Constraints: aspects of the cellular network that are considered as constraints during the optimization process.

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From the algorithmic point of view, classic GAs have been used in the literature for solving the ACP problem, both generational (genGA) and steady-state ones (ssGA). Indeed, they are applied in almost 50% of the works reviewed. Rather specific evolutionary techniques such as CHC (Eshelman 1991), differential evolution (DE, Storn and Price 1995), PBIL (Baluja 1994), or artificial immune systems (AIS, de Melo Carvalho Filho and de Alencar 2008) are also found. It can be seen that not only sequential approaches exist, but also parallel models deployed on standard parallel platforms such as clusters of computers (dGAs, Calégari *et al.* 2001, Alba and Chicano 2005) and even grid computing systems (Talbi *et al.* 2007). If multiobjective approaches are considered, NSGA-II (Deb *et al.* 2002) and SPEA2 (Zitzler *et al.* 2002), the two best known algorithms in the evolutionary multiobjective research community, have been applied in eight of the analysed works. Other specific multiobjective algorithms used are SEAMO (Raisanen and Whitaker 2005) and MOCHC (Nebro *et al.* 2007). From the point of view of the formulation, the first proposals have adopted a single objective approach in which the different network aspects to be optimized are weighted into a single (aggregative) function (Calégari *et al.* 1997, Chamaret and Condevaux-Lanloy 1998, Lieska *et al.* 1998, Reininger*et al.* 1999). However, recent advances in multiobjective EAs have meant that the number of works using this multiobjective formulation has increased in latter years (Cerri and Russo 2006, Nebro *et al.* 2007, Talbi *et al.* 2007, Raisanen 2008).

Figure 2 summarizes the number of reviewed contributions that fall into different categories: mono/multi, ACP model, site selection, cell shape computation, and BTS parameter optimization. Now, each group of columns of the figure is analysed. In the first group, from all the works in the literature reviewed, monoobjective formulations have been more widely used in spite of the fact that the ACP problem is naturally amenable to multiobjective ones. The additional complexity added by the Pareto optimality mechanisms makes ACP researchers reluctant to adopt this kind of technique. However, the multiobjective approach may be the most appropriate because it can provide the decision maker (network designer) with a set of different configurations for the BTSs, none of which is better than the others (non-dominated). These configurations could be used in particular scenarios that may appear during the operational lifetime of the network.

The second group of columns shows the ACP models used in the analysed contributions. It is clear that the demand node and test points are the most widely adopted models. Simplicity and low computational requirements in the former case, and realism in the latter, are the reasons that explain these facts. The Disc model has more to do with theoretical studies. Indeed, cellular networks composed exclusively of omnidirectional antennae are hardly found in the real world (vectorization allows the network capacity to be greatly increased). Looking at the third group of columns in Figure 2, it can be observed that using a candidate site list (CSL) instead of freely placing the BTSs in any location of the network is the most common option. This is because it is unlikely many network operators are granted such freedom (*e.g.* no BTS can be placed near schools or in the middle of a lake). The fourth group of columns also reflects the preferred choice for computing the cells (serving areas) of the BTSs: propagation models such as the *free space* model, the Okumura–Hata model or the Walfish–Ikegami model (COST231 1991). Selecting one

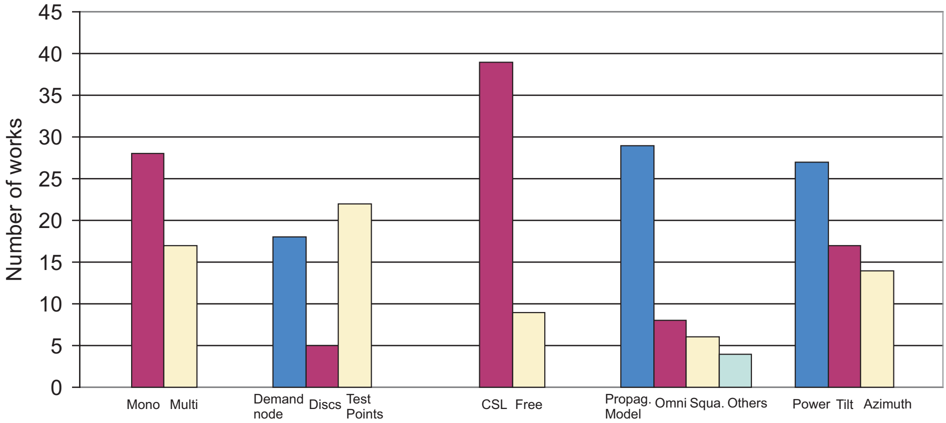

Figure 2. Summary of related work that addresses the ACP problem using EAs.

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or another depends mainly on the computational effort required (ITU 1997). Omnidirectional and square cells also appear in several contributions (eight and six works, respectively). Tables 1 and 2 include alternative methods for computing the cell associated to BTSs such as modern ray tracing techniques (Laki *et al.* 2001). Finally, the last group of columns summarizes the number of articles in which the power, tilt and azimuth are involved in the optimization process. That is, they are decision variables of the search space. Even though differences here are smaller, it can be seen that the power parameter is more often optimized than the other two. It applies to any kind of BTS (omnidirectional, directive, square, etc.) as the main setting to manage the cell size. The tilt and azimuth angles usually appear in very accurate ACP models. They normally lead to highly expensive computational tasks, which explains the lower incidence in the literature.

To conclude with this discussion about the analysed works, the objective functions and the constraints used in the different approaches are now analysed. On the objectives side, a clear trend exists in considering the network cost, measured in terms of number of installed sites, and the quality of services (QoS) provided by these sites. These two objective functions are clearly contradictory. The main difference between many contributions lies in the concept of QoS. Maximizing the network coverage is the most widely used option and it appears in 78% of the revised contributions. However, a more realistic approach is based on using such objectives as a constraint (*e.g.* at least 90% of the network must be covered) so as to discard useless configurations. Indeed, it does not make any sense to deploy an expensive, fully operational network infrastructure just to cover a small percentage of a given target area. Other ways of measuring the network QoS in the literature have taken into consideration the interference caused by cell overlapping or the traffic capacity of the network. As to the constraints, the *handover*, or the capability of the network to guarantee continuous communication while the mobile user is moving from one cell to another, is the one that most appears.

3.2. *Details on EAs for the ACP problem*

This section reviews the main features of the EAs found in the literature for solving the ACP problem. The potential advantages and drawbacks of each algorithm are analysed in light of their corresponding encoding schemes, genetic operators, local search and parallelization. Table 2 includes a summary of all these EA aspects.

Table 2. Details of EAs used for solving ACP problems.

References	Algorithm	Encoding	Crossover	Mutation	LS	Parallel
Calégari *et al.* (1996, 1997, 2001)	dGA	Binary	SPX	Bit flip	•	✓
Chamaret and Condevaux-Lanloy (1998)	dssGA	Binary	SPX	Bit flip	•	✓
Lieska *et al.*(1998)	genGA	Binary	SPX	Bit flip	•	•
Molina *et al.*(1999)	genGA	Binary	SPX	Bit flip	•	•
Reininger *et al.*(1999)	genGA	Network	SPX	Random	•	•
Meunier *et al.*(2000), Cahon *et al.*(2006), Talbi and Meunier (2006), Talbi,*et al.*(2007)	ssGA, hybrid	Network	Geographical	Multilevel	✓	✓
Huang *et al.*(2000b)	GA	Binary	Fusion	Bit Flip	•	•
Zimmermann *et al.*(2000, 2003a,b)	ES	Network	•	Specialized	•	•
Lee and Kang (2000)	dGA	Group-based	Group- oriented	Group- oriented	•	✓
Han *et al.*(2001)	ssGA	Real	Distance- based	Random	•	•
Laki *et al.*(2001)	genGA	Binary	Uniform	Bit flip	•	•
Altman *et al.*(2002a,b), Jamaa *et al.* (2006)	GA	Network	Geographical	Multilevel	•	•
Park *et al.*(2002)	ssGA	Real	Distance- based	Random	•	•
Cerri *et al.*(2003, 2004), Cerri and Russo (2006)	GA	Binary	SPX	Bit flip	•	•
Weicker *et al.*(2003)	SPEA2, NSGA-II, stEAPT	ACP- targeted	Especialized	Several Especialized	•	•
Alba (2004), Alba and Chicano (2005)	ssGA, dssGA	Binary	DPX	Bit flip	•	✓
Brunetta *et al.*(2004), Chiara *et al.*(2005)	GA, hybrid	Binary	SPX	Bit flip	•	•
Jamaa *et al.*(2004a,b), Picard *et al.*(2005)	NSGA-II	Network	Geographical	Multilevel	•	•
Jedidi *et al.*(2004)	MOGA	Network	•	Multilevel	•	•
Lin *et al.*(2004)	GA	Binary	Uniform	Bit flip	•	•
Raisanen *et al.*(2004), Whitaker *et al.*(2004a,b), Raisanen and Whitaker (2005)	SEAMO, SPEA2, NSGA-II,PESA	Permutation	Cycle	Random Swap	✓	•
Zhang *et al.*(2004)	MOGA, EMOGA	Real	Multipoint	Random	•	•
Créput *et al.*(2005)	Hybrid dES	ACP- targeted	Several Especialized	Macro- mutation	✓	•
Alba *et al.*(2007)	CHC, ssGA, genGA	Binary	HUX	Bit flip	•	•
Nebro *et al.*(2007)	MOCHC, NSGA-II	Binary	HUX, SPX	Bit flip	•	•
Vega-Rodríguez *et al.*(2007a,b)	CHC, PBIL, DE	Binary	HUX	Bit flip	•	•
Raisanen (2008)	NSGA-II	Permutation	Cycle	Random Swap	✓	•

3.2.1. *Encoding schemes*

Several encoding schemes have been used, and some of them have been designed specially for solving ACP problems. In summary, they can be categorized into four types: binary, integer, real and ACP-targeted.

3.2.1.1. Binary encoding. The most widely adopted scheme is the classical binary encoding, *i.e.* the tentative solutions are bit strings. The information encoded by this bit string depends on the specific ACP problem addressed.

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The first usage of this encoding scheme appears when the optimization task is simply to position the BTSs of the network by selecting a subset of sites from a candidate site list (CSL). Then, EAs work on bit strings of length N, where N is the total number of candidate sites. Each position of the bit string corresponds to a site, *i.e.* the ith position represents the ith site. The value of the ith is 1 if the ith site is selected, and zero otherwise. This approach is specially used when solving ACP problems that follow the demand node model (see Section 2.2.1): Calégari *et al.* (1996), Calégari *et al.* (1997), Chamaret and Condevaux-Lanloy (1998), Lieska *et al.* (1998), Molina *et al.* (1999), Calégari *et al.* (2001), Alba (2004), Lin *et al.* (2004), Alba and Chicano (2005), Alba *et al.* (2007), Nebro *et al.* (2007), Vega-Rodríguez *et al.* (2007a,b).

Binary encoding has also been used when the BTSs can be freely placed anywhere on the geographical area of the network (no CSL exists). In this case, the bit string encodes the binary representation of a list of real numbers that represent the (x, y) coordinates of the sites. However, in all the material analysed the tentative solutions also include one or more values that allow dimensioning of the BTS (*i.e.* allow the BTS service area to be configured). Indeed, in Brunetta *et al.* (2004) and Chiara *et al.* (2005) the binary string has also considered the power level of emission. In the works of Cerri *et al.* (2003,2004) and Cerri and Russo (2006), the authors have not only included the encoding of the emission power, but also the tilt of the antennae. So, for each BTS, 24 bits are used: $9 + 9$ bits for the coordinates, 3 bits for the radiated power, and 3 bits for the tilt. Laki *et al.*(2001) have just added the height of the BTSs.

The main advantage of this binary encoding is that it allows the evolutionary search to be performed by means of classical EA operators. These operators have been originally developed to manipulate binary genotypes (Goldberg 1989), as will be further analysed in Section 3.2.2.

3.2.1.2. Integer encoding. Integer encoding has been used by Larry Raisanen, Roger Witaker and Steve Hurley at Cardiff University in several works: Raisanen *et al.* (2004), Whitaker *et al.* (2004a,b), Raisanen and Whitaker (2005), Raisanen (2008). Their approach is based on considering that each BTS is identified by an integer. Then, given n candidate BTSs, a permutation π of size n represents a solution to the ACP problem. That is, EAs manipulate integer permutations, so special care has to be taken with the genetic operators used. These BTS permutations are then translated into a cell plan by using a *decoder*. The decoder works by iteratively packing cells as densely as possible, subject to certain constraints not being violated. This cell plan is then used to compute the fitness function.

3.2.1.3. Real encoding. The real encoding is mainly used for solving ACP problems based on freely positioning the BTSs in the working area of the cellular network. Therefore, the tentative solutions are made up of real numbers that represent the BTS coordinates. This scheme is mainly used in works dealing with the disc model (see Section 2.2.2). Indeed, this is the approach used in Han *et al.* (2001) and Park *et al.* (2002). If K is the maximum number of BTSs to be placed, solutions are encoded as arrays $(c_1, \ldots, c_K)$, where $c_i = (x_i, y_i)$ are the coordinates of the ith BTS. When a BTS is not supposed to be deployed, a special 'NULL' value is used. This is the mechanism adopted in these three works to avoid using a variable-length representation and therefore special genetic operators have been developed.

3.2.1.4. ACP-targeted encoding. The encoding schemes shown in this section have been designed especially to deal with ACP problems, so they do not properly fall into any of the previously defined categories. The most widely used non-classical scheme in the EA literature encodes all the optimizable parameter settings of each BTS in the tentative solution. Let us call it *network encoding*. This encoding is usually aimed not only at positioning the BTSs but also at dimensioning them. Figure 3 displays an example in which the BTS type, the emission power, and the tilt and azimuth angles are to be optimized. It is worth mentioning here that, even though

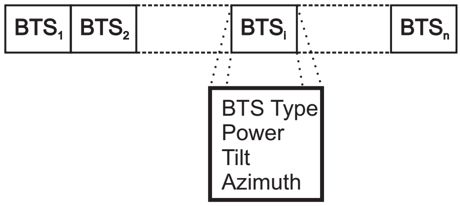

Figure 3. ACP-targeted encoding: all the parameter settings of the BTSs.

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power tilt and azimuth are actually real-valued parameters, they are usually discretized into a rather small set of values in order to reduce the complexity of the optimization problem. This is the approach used in Reininger *et al.* (1999), Meunier *et al.* (2000), Zimmermann *et al.* (2000), Altman *et al.* (2002a,b), Zimmermann *et al.* (2003a), Jamaa *et al.* (2004a,b), Jedidi *et al.* (2004), Picard *et al.* (2005), Cahon *et al.* (2006), Jamaa *et al.* (2006), Talbi and Meunier (2006) and Talbi *et al.* (2007). The main advantage of this encoding scheme is that EAs are put to work on real solutions so therefore problem-domain specific knowledge can be easily included in the search. Otherwise, no classical well-known operators can be used and newly specific ones have to be developed.

Other specific encodings are analysed next. With the goal of minimizing the number of BTSs required to cover a given area, Créput *et al.* (2005) have adaptively transformed the hexagonal cell shapes typically used in cellular networks. This adaptive meshing is performed according to a traffic density map and to geometrical constraints. Then, for each cell of the network, the encoding scheme includes six vertices (two real values) plus an attribute that indicates whether it is visible or not. This latter attribute is the particularity of this approach.

Lee and Kang (2000) have used group encoding (Falkenauer 1994) to maximize the coverage of traffic demand areas (TDAs) using as few BTSs as possible. In this group encoding, each tentative solution has two parts: the TDA part and the BTS part. In the TDA part a BTS is assigned to each TDA. The BTSs used in the TDA part are then represented in the BTS part. Specific group-oriented operators have been applied.

Maple *et al.* (2004) have proposed a matrix encoding with size $3 \times N$, where N is the maximum number of BTSs. All the BTSs are labelled so that the ith column corresponds to the ith BTS. In this encoding, the three values of the ith BTS indicate whether the BTS is present or not in the network (BTS selection), the BTS height and the BTS emission power. This encoding has many drawbacks but no further discussion is given since the authors only present their proposal in the article, with no experimentation at all. Consequently, this article will not be considered further in this survey.

The work of Weicker *et al.* (2003) presents an encoding that mixes real and integer values, as well as a set of frequencies. This specialized encoding is required because it addresses both the BTS positioning and the frequency assignment simultaneously. A candidate solution includes, for each BTS, two real values representing its coordinates, two integer values encoding the transmitting power and the number of available channels in the BTS, and the set of channels assigned to the BTS.

3.2.2. *Operators*

Several genetic operators have been investigated in the literature for solving ACP problems (Table 2). This section is only aimed at discussing the crossover and mutation operators since they are the ones which depend on the encoding schemes (selection and replacement operators are based on the fitness of the individuals).

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3.2.2.1. Crossover. The classical *single point crossover* (SPX) has been extensively used for solving ACP problems. Most of the existing work using binary encoding has adopted this approach (*e.g.* Calégari *et al.* 1996, Lieska *et al.* 1998, Molina *et al.* 1999). With this encoding, other well-known operators such as *two point crossover* (Alba 2004, Alba and Chicano 2005) and *uniform crossover* (Laki *et al.* 2001, Lin *et al.* 2004) have been applied. It is also worth mentioning that algorithm-specific crossover operators also appear when particular algorithms have been used. The works of Alba *et al.* (2007), Nebro *et al.* (2007), Vega-Rodrŕguez *et al.* (2007a) and Vega-Rodrŕguez *et al.* (2007b) use the *highly disruptive crossover* (HUX) designed for the CHC algorithm, whereas the *two-fusion crossover* (Hifi 1997) is applied in Huang *et al.* (2000a).

In the case of the integer encoding scheme, the *cycle crossover* has been used in the works of Raisanen *et al.* (2004), Whitaker *et al.* (2004b,a), Raisanen and Whitaker (2005) and Raisanen (2008). Since their algorithms work on integer permutations, this crossover operator is aimed at preserving the permutation, and as a result no repair mechanism is required. It is important to remark here that using the decoder procedure that translates the permutation of BTSs into a cell plan avoids the main concern of this representation: different permutations represent the same solution in the objective space.

Traditional recombination operators are not applied with the real encoding scheme since no pure real-valued strings have been used. Indeed, in the works of Han *et al.* (2001) and Park *et al.* (2002) this operator has to deal with the special NULL value used in any given position to indicate that the corresponding BTSs are not deployed. This way, given two parents p_1 and p_2, the operator returns one single child, c, in which the position of the ith BTS is computed as follows. If $p_1(i) = \text{NULL}$ and $p_2(i) = \text{NULL}$, then $c(i) = \text{NULL}$; if either $p_1(i) = \text{NULL}$ or $p_2(i) = \text{NULL}$, $c(i)$ receives the genetic material of the non-NULL parent; otherwise, the ith BTS is placed somewhere near the BTS positions of the parents (sampling a Gaussian distribution).

The main disadvantages of all these crossover operators is that they just manipulate genes, without taking into account the links with other genes (epistasis). Indeed, as explained in the introduction, either activating, deactivating or redimensioning one given BTS in a cellular network will surely affect the influence of other BTSs in the ACP problem at hand. It is therefore worth giving particular attention to the development of operators specially designed for ACP problems that use classical encoding schemes in their resolution.

When ACP-targeted encoding schemes are adopted, this crossover specialization is already addressed. Most of the works that use the network encoding (see previous section) apply the so-called geographical crossover defined in Meunier *et al.* (2000). This operator is based on exchanging the configuration of the sites located within a given random radius around a randomly chosen site. Figure 4 shows an example of the working principles of the geographical crossover. The main advantage of this operator is that it considers somehow the connection between the sites in a topological way: only nearby sites are modified. However, under this encoding, the classical SPX crossover has also been used by Reininger *et al.* (1999).

Other specialized crossover operators have been defined for dealing with ACP-targeted encodings. Créput *et al.* (2005) have proposed a mechanism that combines the vertices of the hexagonal cells used to cover the traffic demand in the cellular network. It works by selecting two individuals as follows. The first one, i_1, is chosen by fitness-proportional probability (*e.g.* roulette-wheel selection), whereas the second, i_2 is picked randomly. Since it is assumed that the former will have a better fitness than the latter, the crossover operator generates a child in which i_1 attracts i_2 by using a weighted average sum. Lee and Kang (2000), who have used the grouping GA, have adopted the grouping crossover operator defined by Falkenauer (1994). Finally, Weicker *et al.* (2003) have implemented a crossover operator based on the decomposition of the service area of the cellular network. Two halves along one of the dimensions are generated and then, for each half, the fitness of the parent individuals is evaluated. The offspring will inherit the configuration for each of the sub-areas from the fittest parent for that sub-area. The main drawback of

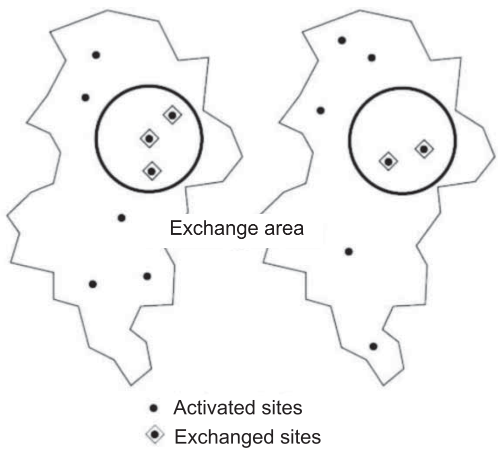

Figure 4. Geographic recombination: sites located within the radius are exchanged.

this approach is that the operator may generate unfeasible individuals, therefore requiring that the authors apply a repair function.

3.2.2.2. Mutation. The analysis of the mutation operators in the literature for solving ACP problems with EAs is similar to that performed for the crossover operators. It depends greatly on the encoding used. The classical *bit flip* mutation is the preferred operator for binary encoding schemes (see Section 3.2.1). In works using integer permutation encoding, a random swap that simply transposes two randomly chosen positions in the permutation is adopted (*e.g.* Raisanen and Whitaker 2005). Again, this operator is safe and no repair function is needed.

The two works categorized with *real* encoding, *i.e.* Han *et al.* (2001) and Park *et al.* (2002), have to manage the NULL value which is used to represent that a BTS is not deployed in the network. This way, for each BTS, the mutation operator either randomly updates the current position of the deployed BTSs or it is assigned with a NULL value; otherwise, if the BTS is not deployed yet, it can remain where it is or it can be placed in an arbitrary position in the network.

Using the network encoding (ACP-targeted encoding), the mutation operator usually works by first selecting a given site and then updating the configuration of this site. This is called *multilevel mutation* since it operates at different levels of the encoding. Depending on the parameters of each site, the mutation may affect the following.

- *Activation toggling*. If the site is activated, then it is just deactivated. On the other hand, if L_i is deactivated, then an entire random configuration for the site is generated.
- *BTS power tuning*. It requires the site to be activated. It randomly chooses a BTS of the site and then the power is randomly changed to one of its discretized values.
- *BTS tilt tuning*. The same as power tuning, but changing the tilt angle.
- *BTS azimuth tuning*. The same as power and tilt tuning, but modifying the azimuth angle.
- *BTS diagram tuning*. This mutation also requires the site to be activated. The goal of this operator is to change the BTS type, that is, from an omnidirectional BTS to several directive BTSs, or vice versa. The configuration for each newly generated BTS is randomly generated.

This is the approach used in Meunier *et al.* (2000), Altman *et al.* (2002a,b), Jamaa *et al.* (2004a,b), Jedidi *et al.* (2004), Picard *et al.* (2005), Cahon *et al.* (2006), Jamaa *et al.* (2006), Talbi and Meunier (2006) and Talbi *et al.* (2007).

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On the other hand, the works of Zimmermann *et al.* (2000, 2003a,b) have further detailed these mutations by defining more specialized search operators. The authors have distinguished between *repair operators* (RepairTraffic, RepairHole, DecreasePower, IncreasePower, ChangeAzimuth, ChangeTilt, DissipateTraffic) and *climb operators* (RemoveWeakAntenna, RemoveAntenna, RemoveWeakSite, RemoveSite, IncreaseCompactness, ReduceIrregularities and MinimizePower). They all are applied one at a time by randomly choosing one of them. Because unfeasible solutions may be generated, a repair phase is used.

Other mutation operators used with ACP-targeted encoding schemes are described next. Créput *et al.* (2005) have developed the *macromutation* operator. This is intended to perform simultaneous moves on the vertices of the cells that cover the cellular network, thus allowing these cells to exit or to reach traffic demand areas. Lee and Kang (2000) have adopted the grouping crossover operator defined by Falkenauer (1994) for the grouping GA. Finally, Finally, Weicker *et al.* (2003) have applied both *directed* and *random* mutations. The former ones (six different operators) include problem knowledge, and feasibility is always guaranteed since several preconditions have to be met prior to their application. However, directed mutations find it difficult to explore the entire search space, so this is why random mutations have been used. The goal is to promote exploration, but the drawback is that feasibility is no longer guaranteed and a repair function has to be applied.

3.2.3. *Local search*

Adding ACP problem knowledge to the exploration performed by EAs can be further promoted with the usage of local search algorithms. That is, engineering hybrid algorithms (Talbi 2002). So far, this problem-specific knowledge has been added by using specific encoding schemes and genetic operators (as has been shown in the previous sections). However, there are several proposals in the literature in which EAs are endowed with highly tailored search methods, allowing the search to be intensified in promising regions of the search space.

When adaptively meshing the cell shapes of a cellular network, Créput *et al.* (2005) have used a local search algorithm based on a Lamarckian adaptive process. This process applies small mutations on isolated vertices of the hexagonal cells which makes an individual evolve to a local minimum. The mutation operator, called micromutation, performs a small move on some randomly chosen vertex.

Talbi *et al.* (2007) have designed a multiobjective local search to be used with the network encoding explained above. It is an iterative process that starts from a set of non-dominated solutions (or network configurations). Then, for each activated BTS of any network, it successively tests its removal, the updating of the power, azimuth and tilt with any of the available discretized values. By using the newly generated solutions, the set of non-dominated solutions is continuously updated. Finally, the local search algorithm restarts from any newly inserted solution, and so on.

Finally, the decoder approach of Raisanen *et al.* (2004), Whitaker *et al.* (2004a,b), Raisanen and Whitaker (2005) and Raisanen (2008) for translating the integer permutation of BTSs into a cell plan can also be mentioned here. As its authors have indicated, this decoder can be considered a local search algorithm.

3.2.4. *Parallelization*

As early as in the first works published on EAs for solving the ACP problem, *i.e.* Calégari *et al.* (1996) and Calégari *et al.* (1997), it was soon understood that this optimization problem involved tasks demanding high computational resources. With the aim of not only speeding up the computation but also improving the solution quality, most of the parallel EAs analysed have adopted the coarse-grained scheme, also known as the island model (Alba and Tomassini

2002). They have also used a unidirectional ring topology: Calégari *et al.* (1996, 1997), Chamaret and Condevaux-Lanloy (1998), Lee and Kang (2000), Calégari *et al.* (2001), Alba (2004) and Alba and Chicano (2005). The work of Créput *et al.* (2005) has also used the island model with a unidirectional ring topology but, instead of subpopulations, each island runs a hybrid evolution strategy.

Meunier *et al.* (2000) have used a master/slave approach for the parallel implementation of the function evaluation, *i.e.* each function evaluation is distributed to different processors. Talbi and Meunier (2006) have extended this work by using the master/slave scheme not only for the parallel evaluation of the function evaluation, but also for evaluating each tentative solution of the EA asynchronously in parallel. They have also used the island model in this work. Finally, the works of Cahon *et al.* (2006) and Talbi *et al.* (2007) have again proposed extensions of these previous publications by deploying a parallel hybrid EA on a computational grid (Berman *et al.* 2003). This EA is hybrid because a local search is used to improve the solutions generated within the evolutionary loop. The parallelism is applied at different levels: the main EA model is an island model. Then, on each island, individuals undergo local search in parallel. The third level of parallelism considers each single function evaluation in parallel by decomposing the fitness function.

4. Conclusions and future work

4.1. *Summary*

This articles presents a survey on evolutionary algorithms for solving ACP problems. It shows the profile of this area by focusing on both the particular ACP problems tackled and the evolutionary approaches engineered to address them. The key issues on the design of EAs have been discussed: usually adopted representations, evolutionary operators, and advanced features such as hybridization and parallelism. Concretely, the crossover and mutation operators described in the literature have been analysed, distinguishing between classical operators and ACP-targeted ones. Some hints on the advantages and disadvantages of several representation schemes have also been discussed.

In the next section which follows, some topics are outlined for the future research of engineers interested in EAs for ACP problems. In the authors' opinion, these topics deserve special attention in order that the current state of the art can be improved.

4.2. *Future trends*

There are several research lines that can be explored to address the ACP problem with EAs further. At a lower algorithmic level, the design of new encodings and genetic operators for the problem, as well as the analysis of current existing ones, are of great interest. Concretely, the more complex encoding, the network encoding presented in Section 3.2, has only been evaluated with a few genetic operators (multilevel mutation and geographical crossover, mainly). Additional operator developments may take advantage of this ACP-targeted encoding. Evaluating this encoding and operators with the search engine of well-known algorithms such as NSGA-II or SPEA2 is also a matter for research.

At a higher algorithmic level, a promising research line is targeted at hybridizing EAs (Talbi 2002), especially with other EAs. Up to now, EAs have been hybridized in the literature with local search algorithms (*e.g.* see Créput *et al.* 2005, Talbi *et al.* 2007) or Tabu Search (Chiara *et al.* 2005) to solve ACP problems, but hybrid algorithms involving two different EAs have not been found. The aim here would be to profit from the different search capabilities, for example, of

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a GA (diversification) and an evolution strategy (intensification). In the context of multiobjective EAs, hybridization is underexplored in the literature.

Checking whether other unused EAs can successfully address the ACP problem is a promising research topic as well. To the best of our knowledge, two main unused EAs have been left unexplored in the literature. On the one hand, no genetic programming approach has been found in the literature for ACP, even when this kind of EA performs well on other design problems (Koza 1992, Koza *et al.* 2004). On the other hand, the cellular model of structured EAs (Alba and Tomassini 2002) has not been used either. Cellular EAs have been shown to be very effective in other domains (Alba and Dorronsoro 2008), so evaluating their enhanced search engine may lead to an improvement in the current state-of-the-art algorithms.

There are several additional studies whose conclusions may result in relevant outcomes especially for telecommunications engineers who use EAs to solve their ACP problems. The analysis of both the scalability and the convergence speed of EAs on this problem also requires more investigation. The increasing size of cellular networks means EAs are faced with problem instances with thousand of decision variables. Therefore, evaluating the algorithms that perform better on very large instances is of great interest for cellular operators, since they can afford larger and more efficient network deployments. The study of how quickly EAs converge towards optimal solutions would also be of interest to the telecommunications industry. Indeed, execution time becomes a critical constraint for the operators and mainly for the software companies that are developing software for the operators. Within commercial applications, reaching ‘good’ solutions in a very short time is usually essential in order to provide operators with competitive software tools. These studies have to pay special attention to the statistical analysis of the results, which must be rigorously performed in order to draw useful conclusions. However, the works analysed in this articles for the most part lack such thorough analyses.

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