Diseño Inteligente de Redes Inalámbricas de Comunicación
Conserjería de Innovación, Ciencia y Empresa
P07-TIC-03044
http://diricom.lcc.uma.es

Málaga, 10 de Junio de 2009

Informe Ejecutivo

TÍTULO: RND-1.0

RESUMEN: En este informe se describe brevemente los resultados obtenidos en la resolución del problema de diseño de una red radio para ofrecer cobertura a la ciudad de Málaga. La instancia definida se ajusta a las características de la ciudad y es de gran complejidad.

OBJETIVOS:

1. Presentar el problema de diseño de red de radio.
2. Describir la instancia de Málaga, comentar sus características.
3. Presentar las técnicas empleadas para la resolución del problema.
4. Mostrar y comentar los resultados obtenidos.

CONCLUSIONES:

1. Los resultados obtenidos confirman que las técnicas metaheurísticas permiten la resolución de instancias de gran dimensión. Además, señalan a CHC como el algoritmo más adecuado para resolver el problema de diseño de la red radio.

Málaga, June 10th, 2009

Executive Summary

TITLE: RND-1.0

ABSTRACT: This report briefly describes the results obtained solving the radio network design problem in order to provide coverage to the city of Malaga. The instance defined corresponds to the features of the city and is of large complexity.

GOALS:

1. Present the radio network design problem.
2. Describe the instance for the city of Malaga, and its characteristics.
3. Present the techniques employed for the resolution of the problem.
4. Display and comment the results obtained.

CONCLUSIONS:

1. The results obtained confirmed our expectation that metaheuristics are capable of solving large size instances. Besides, CHC was found to be the most fit algorithm to solve the radio network design problem.

RND-1.0

DIRICOM

June 2009

1. Introduction

A generally accepted method for building a radio access network is to divide the terrain to be covered into small cells, each of which can be covered by a single transmitter conveniently located in a base station (BS); this solution is known as a radio network. The problem we solve is how to achieve maximum coverage of the terrain in order to obtain a valuable service for the customer (ideally the coverage should be complete) by placing the lowest number of transmitters, so that the cost of the service remains competitive. This is equivalent to selecting the optimal positions for placing the transmitters, and this problem is known as the Radio Network Design problem (it will often be referred to as the RND problem).

When the RND problem is solved for a given scenario, particularly for an urban one, a given set of constraints has to be met. A BS may not be freely placed, but only a restricted list of available location sites can be used. The RND problem amounts then to selecting the minimum number of locations from that list that provide the maximum coverage possible –or at least, a minimum required coverage. Let us consider the set L of all potentially covered locations and the set M of all potential transmitter locations. Let G be the graph, $(M \cup L, E)$, where E is a set of edges such that each transmitter location is linked to the locations it covers and let the vector $\vec{x}$ be a solution to the problem where $x_i \in \{0, 1\}$, and $i \in [1, |M|]$. The value x_i is 1 or 0 depending on whether a transmitter is being used or not in the corresponding site. As the geographical area needs to be discretized, the potentially covered locations are taken from a grid.

The rest of the deliverable is structured as follows. Section 2 describes the instance of Malaga. Section 3 presents the metaheuristic algorithms. Section 4 shows the results obtained, and finally Section 5 draws some conclusions.

2. The Instance for the city of Malaga

A real world-sized problem instance, defined upon the geographical layout of the city of Malaga (Spain), has been used to test the algorithm performances. This instance, named Malaga1000, represents an urban area of 27,2km^2 shown in Figure 1. The terrain has been modeled using a 450×300 grid, where each point represents a surface of approximately 15×15m. This fine grained discretization enables us to achieve highly accurate results

A dataset containing 1,000 candidate sites for the BSs, and their corresponding coordinates on the grid, is used. The dataset can be found at the website [3]. The cell model for BS coverage is a omni-directional isotropic model, with a radius of approximately one half kilometre (30 grid points). In this scenario, the maximum coverage that can be attained is 95,522 %. There are two major uncovered areas: the sea (at the bottom of the image), and the mountains (at the top). Figure 1 (left) illustrates the problem instance, and (right) displays the candidate locations to place a BS.

In order for the search techniques to be used, a fitness function was defined that associated each candidate solution $\vec{x}$ with a quality parameter, the value of which has to be maximized. We used the function f shown in Equation 1.

$$f(\vec{x}) = \frac{CoverRate(\vec{x})^2}{Number\ of\ transmitters\ selected(\vec{x})}. \tag{1}$$

During our executions, the maximum value found for the fitness value was 164,701.

3. Algorithms

In this section we briefly describe our techniques proposed to solve RND problem instances: Simulated Annealing (SA), and Cross generational elitist selection, Heterogeneous recombination, and Cataclysmic mutation (CHC).

3.1. Simulated Annealing

Simulated annealing is a trajectory based optimization technique [1]. It was first proposed by Kirkpatrick et al. in [4]. The pseudocode for this algorithm is shown in Algorithm 1.

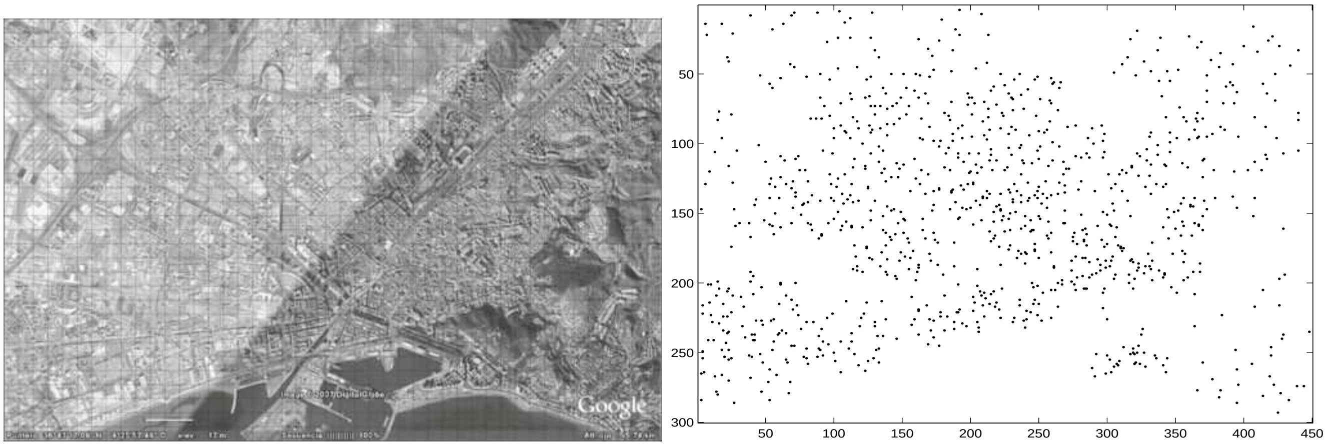

Figura 1: Map of the city of Malaga (left), candidate sites (right)

Algorithm 1 SA

$t \leftarrow 0$;
Initialize(T,S_a)
while not EndCondition(t,S_a) **do**
  while not CoolingCondition(t) **do**
    $S_n \leftarrow$ ChooseNeighbor(S_a)
    Evaluate(S_a,S_n)
    if Accept(S_a,S_n,T) **then**
      $S_a \leftarrow S_n$
    end if
    $t \leftarrow t+1$
  end while
  Cooldown(T)
end while

The algorithm works iteratively keeping a single tentative solution S_a at any time. In every iteration, a new solution S_n is generated from the previous one, S_a, and either replaces it or not depending on an acceptance criterion. The acceptance criterion works as follows: both the old (S_a) and the new (S_n) solutions have an associated quality value, determined with an objective function (also called *fitness* function). If the new solution is better than the old one, then it will replace it. If it is worse then it replaces it with probability P. This probability depends on the difference between their quality values and a control parameter T named *temperature*. This acceptance criterion provides a way of escaping local optima. The mathematical expression for the probability P is:

$$P = \frac{2}{1 + e^{\frac{fitness(S_a) - fitness(S_n)}{T}}} \tag{2}$$

As iterations go on, the value of the temperature parameter is reduced following a cooling schedule, thus biasing SA towards accepting only better solutions. In this work we employ the geometric rule $T(n+1) = \alpha \cdot T(n)$, where $0 < \alpha < 1$ every k interations (k is the *Markov chain length*).

3.2. CHC

The last algorithm we propose for solving the RND problem is Eshelman's CHC, a kind of Evolutionary Algorithm (EA) [2]. Like other EAs, CHC works with a set of solutions (*population*) at any time. The pseudocode for this algorithm is shown in Algorithm 2.

In every step, a new set of solutions is produced by selecting pairs of solutions from the parent population P_a and recombining them. An incest prevention criterion prevents individuals that are too similar to each other to mate, and recombination is made using a special procedure known as HUX. This procedure copies first the parents into the offspring, then randomly exchanges half of the diverging information between the offspring. This method has been designed to preserve the maximum amount of diversity in the population since no new diversity is introduced during the iteration (because there is no mutation operator). The next population is formed by selecting the best individuals among the parents and the offspring (elitism).

In a normal execution population convergence is achieved, so the normal behavior of the algorithm should be to stall on it. A special mechanism is used to introduce new diversity when this happens: the *restart* mechanism. Upon

Algorithm 2 CHC

$t \leftarrow 0$
Initialize(P_a,*convergence count*)
while not EndingCondition(t,P_a) **do**
  Parents $\leftarrow$ SelectionParents(P_a)
  Offspring $\leftarrow$ HUX(*Parents*)
  Evaluate(*Offspring*)
  $P_n \leftarrow$ ElitistSelection(*Offspring*,P_a)
  if not Modified(P_a,P_n) **then**
    convergence count $\leftarrow$ *convergence count-1*
    if *convergence count* $== 0$ **then**
      $P_n \leftarrow$ Restart(P_a)
      Initialize(*convergence count*)
    end if
  end if
  $t \leftarrow t+1$
  $P_a \leftarrow P_n$
end while

restarting, all the solutions except the very best ones (or only the best) are significantly modified through a high rate mutation.

4. Experiments

Our algorithms were compared to a large set of algorithms from other research groups collaborating to solve this problem instance. In total, 13 different algorithms were tried, among which we can mention Iterated Local Search (ILS), Population-Based Incremental Learning (PBIL), Genetic Algorithm (GA), a Chromosome Appearance Probability Matrix (CAPM), a Memetic Algorithm (MA) obtained from Local Search and Evolutionary Algorithms, Differential Evolution (DE), Greedy Randomized Adaptive Search Procedure (GRASP), several flavors of Variable Neighborhood Search (VNS), and some hybrid and multistart variation of other techniques. Since the instance is complex, the total number of allowed solution evaluations was set to $5,000,000$. The results are saved every $25,000$ evaluations in order to maintain the traceability of the executions. In every case, 30 independent runs were performed in order to obtain statistical confidence on the results.

Figure 2 displays the graphical representation of the highest fitness solution obtained by the CHC algorithm. This solution gets a coverage of 86 % by placing 47 BSs, resulting in a fitness value of 164,7. As expected, most of the urban area is covered, while the top and bottom areas (corresponding to the sea and the surrounding mountains) have some uncovered areas.

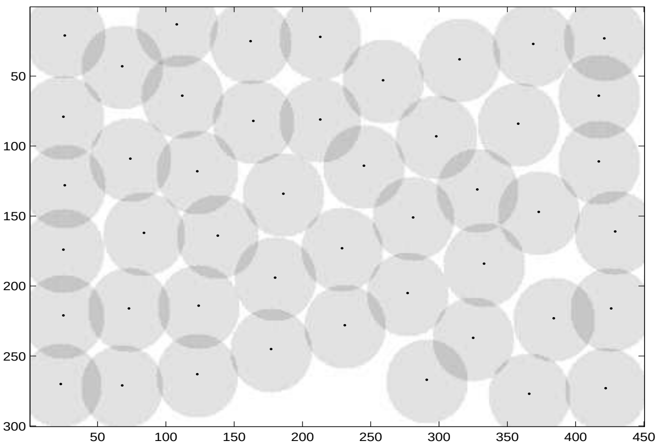

Figura 2: Optimal solution obtained with CHC

Figure 3 (left) shows the average execution trace for the best performing algorithms in the lot; Figure 3 (right) shows the trace for the algorithms with lower performances. We can notice that the results of CHC were among the top three of all the techniques, just behind MS_GEPVNS and ILS, and before PBIL. Differences among all four techniques were small. However, SA had noticeably poorer results and is located at the rear of the lot, outperforming only two other algorithms, GRASP and AGC.

The results suggest that CHC is a fair performing technique to solve complex instances of RND, like the one considered here. Besides, since it is not extremely instance-specific and its mechanism is less sophisticated than for

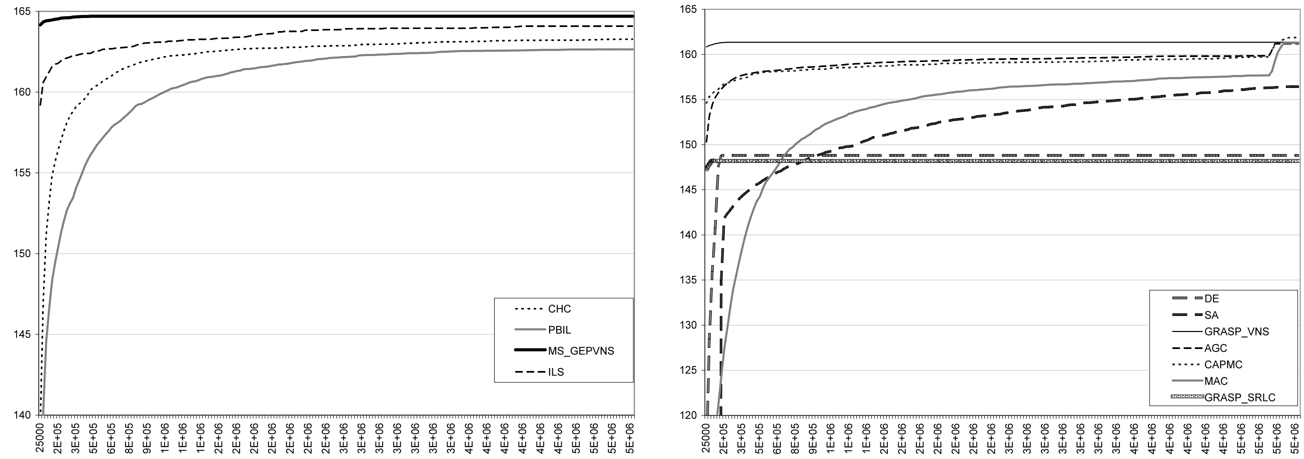

Figura 3: Execution traces of the best performing techniques (left), and the worst performing ones (right)

MS_GEPVNS, we expect it to have two advantages:

- Ease of use. CHC has little *tuning* required compared to other algorithms.
- Robustness. CHC can easily have its instance switched and still be competitive in terms of solution quality.

5. Conclusions

We have defined a complex real-world problem instance for the Radio Network Design problem, based on the city of Malaga. To solve this instance, two metaheuristic algorithms, SA and CHC have been proposed and used; their results have been compared against the results obtained by 11 other optimization techniques from 3 research groups working on this same problem instance. While not as sophisticated and problem specific as other techniques, CHC was the third best among the lot, only slightly outperformed by a multistart variant of Variable Neighborhood Search and an Iterated Local Search. Therefore, we suggest CHC as an easy-to-use and robust technique that achieves high quality results for high sized and real world instances of the RND problem.

Future work will study the use of multiobjective techniques to solve multiobjective variations of the problem, the extension of the problem to other cities, and the use of a more elaborate coverage model.

Referencias

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