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A Genetic Algorithm Approach to Solve Mobile Base Station Location Problem

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Abstract: Classical coverage models, adopted for second-generation cellular systems, are not suited for planning Universal Mobile Telecommunication System(UMTS) Base Station(BS) location because they are only based on signal predictions and do not consider the traffic distribution, the signal quality requirements and the Power Control(PC) mechanisms. In this study, we discuss mathematical programming models aimed at supporting the decisions in the process of planning where to locate new BS. These models consider the signal-to-interference as quality measure and capture at different levels of detail the signal quality requirements and the specific Power Control (PC) mechanism of the W-CDMA air interface. Given that these UMTS BS location models are Non-Polynomial (NP)-hard problem, we propose enumerative methods and Genetic Algorithm (GA) to find good approximate solutions for this model. A new method and tool for optimizing the base station locations, based on Genetic Algorithms, is presented along with simulation results. This text discusses the main issues in planning a third generation mobile network and presents an initial mathematical formulation for the problem. The results indicate that it is possible to arrive at higher quality solutions in reasonable time. The goals and the present status of our research are also discussed.

Key words: UMTS, Base Station (BS), Power Control (PC), W-CDMA, Genetic Algorithm (GA)

INTRODUCTION

Telecommunication companies are faced with an ever increasing pressure of competition and complexity of cellular radio network infrastructure. The need for adequate models for new radio network analysis, design, management and optimization framework is obvious and play a key factor for successful competition. Hence, they need a systematic design approach. With the rapid growth of network size and number of users, efficient quantitative methods to support decisions for Base Station (BS) location have become essential.

Mobile Phone base stations are low-power multi-channel two-way radios. With proper design, mobile phone base stations antennas can meet all safety guidelines by a wide margin. Therefore, Antenna selection and placement are important factors to consider achieving the best performance.

The Global System for Mobile Communications (GSM) is certainly the most successful second generation (2G) mobile communication system, serving more than 684 million subscribers distributed among 157 countries by April 2002[1]. The problem of planning 2G cellular systems adopting a Time-Division Multiple Access (TDMA)-based access has usually been simplified by subdividing it into a coverage planning problem and a frequency planning problem which are driven by coverage and respectively, a capacity criterion. However, it was designed primarily for mobile digital telephony and its current data rate (around 9.6 kbps) does not support the introduction of new services, such as multimedia.

To overcome this limitation, the Universal Mobile Telecommunication Systems (UMTS) is the Third generation mobile communication system standardized by the European Telecommunications Standards Institute (ETSI) and also considered by the International Telecommunications Union (ITU) among the standards for the IMT-2000 (International Mobile Telephone Standard 2000) family. UTMS will offer very higher data rates to the user, reaching to the users, reaching 144 kbps in macro cellular environments, 384 kbps in microcellular environments and 2 mbps in indoor or Pico cellular environments.

These enhanced data rates of 3G will allow the deployment of a myriad of new 'data-centric' services in contrast with the voice-centered services of 2G. The most important services might be the full access to the Internet. Finally, the location based services are expected to become a reality, since the UMTS network will be able to identify the location of the user with an error smaller than 100 meters.

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In this study, we discuss the mathematical programming model for locating Base Stations assuming a Power-Based (PC) mechanism and present a genetic algorithm approach to solve the optimum placement of Base Stations.

UMTS NETWORK DESIGN

The planning of a GSM Network (or, in a broader sense, the planning a second generation cellular system adopting a TDMA-based access scheme) is nowadays a well-understood task. From the planner's point of view, it can be divided into two main stages: base station location and frequency assignment. The former consists in choosing among a set of candidate sites those that will be used to install antennas, ensuring the coverage of the area under study. This step generally involves the use of propagation models to predict the signal level at each point of interest. The later deals with the allocation of a set of frequency channels to each cell, minimizing the adjacent and co-channel interference between them leads to maximizing the capacity of the whole network. In that phase, the traffic demand and the desired level of services, measured by the Signal-to-Interference Ratio (SIR) are considered[2].

The positioning of base station will also be of great importance in the deployment of an UMTS network. However, the frequency assignment phase is not required for third generation networks. Users in these networks do not receive a separate frequency channel, but instead occupy the entire allocated frequency and time domain. Since the air interface of UMTS is based on W-CDMA (Wideband Code Division Multiple Access), different users are distinguished through the use of unique codes[3].

Additionally, the capacity of each cell is not specified by the number of the user connections, but depends heavily on the traffic distribution. Indeed, the resource allocated to each user's channel is energy rather than time or frequency.

The necessary energy varies with the mobile users positioning, due to a power control mechanism. As a result, the number of users that can be served is large if they are close to the base station (and thus can use low transmit power), but small if they are far away (and demand higher power). The area actually covered by a cell then varies with the load, an effect known as cell breathing. So, to maximize the capacity of the system, it is vital to minimize transmit powers[4].

The explanation in the previous paragraphs show that the planning of an UMTS network possessed several new challenges. The base station location problem must take into account not only signal strength but also traffic distributions, the power control mechanism, the power limits and the quality constraints[5]. The goal of our research is to address the UMTS network design through the formulation and solution of an optimization problem considering these constraints.

RELATED WORK

Classical coverage optimization models do not consider SIR constraints but only constraints on the power level in the service area. In the traffic distribution is described by means of demand nodes which represent the center of an area characterized by a given traffic demand (usually expressed in Erlang). A common objective of the optimization process is that of finding the smallest set of BSs covering all demand nodes.

The quality of the signal, measured by the SIR, depends on the received power of the signal under study and of the interfering ones. Thus Power Control (PC) is necessary to minimize interference and assure quality. Two PC mechanisms are usually considered. In power-based PC, the transmitted power is adjusted so that the power received in each channel is equal to a given target value P_{target}. Similarly, in SIR-based PC the power is set to maintain the SIR equal to a target value SIR_{target}. The latter is more complex since the power emitted by each mobile station depends on the power transmitted by all the others, but it is also more efficient since achieve lower powers[6].

The modeling of an UMTS network design problem was analyzed detailed in[7], based on a useful survey on the topic. The studies closest to one we propose here are the ones by Amaldi *et al.*[8]. The users are modeled by the use of Test Points. Each Test Points is covered by only one base station. The propagation information is assumed to be known and is represented by a gain matrix.

PROBLEM FORMULATION

In this section, the mathematical formulation proposed and solved in[8] is presented as an example of a model addressing the planning of a third generation cellular network. We intend to use this formulation as a start point to our research, where we expect to include extensions or generalizations.

The model assumes that the planning phase of cellular networks usually takes as input the following kind of information about the service area are known: i) a set of candidate sites where base stations can be installed, ii) the traffic distribution estimated by using empirical prediction models and iii) the propagation description based on approximate radio channel models or ray tracing techniques. The main purpose of planning is then to select the sites where to install the Bss taking into account different aspects such as costs, signal quality and service coverage. Hence, the outputs are the selected sites where to install base stations and their configuration.

BASIC MODEL

The basic model assumes a power-based PC mechanism. Let us first introduce some general notation, Consider a territory to be covered by UMTS services. Assumes that a set of candidate sites J= {1,2....m} where a BS can be installed, is given and that an installation cost f_j is associated with each candidate sites j, $j \in J$. A set of test points (TPs) I = {1,2.....n} is also given. Each TP $i \in I$ can be considered as a centroid where a given amount of traffic d_i The required number of simultaneously active connections for TP i, denoted by a_i, The actual definition of the function ϕ is a degree of freedom of the planning process. It can simply correspond to the average number of active connections or to the number of simultaneous connections not exceeded with a given probability p.

The propagation information is also supposed to be known. In particular, let g_{ij}, $0 < g_{ij} \le 1$ be the propagation factor of the radio link between TP i, $1 \le i \le n$ and a candidate site j, $1 \le j \le m$. The propagation gain matrix G= $[g_{ij}]$ $1 \le i \le n$, $1 \le j \le m$ is estimated according to approximate propagation models such as those proposed by Hata or to more precise but computationally intensive ray tracing techniques.

I	set of test points that represent the area under study;
d_i	traffic demand in Erlang in the demand node i;
a_i	number of active connections in the demand node i, $a_i = \phi\_(d_i)$;
J	set of candidate sites where a base station can be installed;
g_{ij}	the propagation gain between demand node i and candidate sites j; G= $[g_{ij}]$ $i \in I$, $j \in J$
f_j	installation cost of a base station in candidate site j;
SIR_{min}	minimal Signal-to-Interference Ratio acceptable in the network;
P_{target}	target transmission power in a power-based PC mechanism;
P_{max}	maximum transmission power in a power-based PC mechanism.

In the general W-CDMA UMTS BS location problem, one wishes to select a subset of candidate sites within the set J where to install BSs and to assign the TPs to the available BSs taking into account the traffic demand, the signal quality requirements in terms of SIR and the installation costs.

Let us define the two following classes of decision variables:

$$x_{ij} = \begin{cases} 1 & \text{if demand node i is assigned to a base station located in j} \\ 0 & \text{otherwise} \end{cases}$$

for $I \in I$, $j \in J$ and

$$y_j = \begin{cases} 1 & \text{if a base station is installed in candidate site j} \\ 0 & \text{otherwise} \end{cases}$$

for $j \in J$.

The mathematical formulation is given by:

$$\text{Min} \sum_{j \in J} f_j \, y_j + \lambda \sum_{i \in I} \sum_{j \in J} a_i \, 1/g_{ij} \, x_{ij} \qquad (1)$$

subject to:

$$\sum_{j \in J} x_{ij} = 1, \quad \forall i \in I \qquad (2)$$

$$x_{ij} \le \min \{ 1, g_{ij} P_{max} / P_{target} \} \, y_j, \forall i \in I, \ \forall j \in J \qquad (3)$$

$$y_j (\sum_{m \in I} \sum_{n \in J} a_m \, g_{mj} / g_{mn} \, x_{mn} - 1) \le 1/SIR_{min}, \forall j \in J \qquad (4)$$

$$x_{ij} \in \{0, 1\}, \forall i \in I, \forall j \in J \qquad (5)$$

$$y_j \in \{0, 1\}, \forall j \in J \qquad (6)$$

The first term in the objective function corresponds to the total installation cost. The second one refers to the minimization of the total emission power, since $1/g_{ij}$ is proportional to the power emitted from test points i when assigned to base station j. $\lambda \ge 0$ is a trade-off parameter these two objectives. Constraints 2 make sure that each test point i is assigned to a single base station. Note that the model assumes total coverage of the service area. Constraints 3 impose that a test point can only be assigned to sites where a base station is installed. Further, they assure that a test point can only be assigned to a base station if the emission power to achieve the SIR level (P_{target}/g_{ij}) is below maximum acceptable power, P_{max}. Finally, Constraints 4 represent the SIR limitations when a power-based PC mechanism is used. To account for the power limit on the user terminals, if g_{ij} P_{max}/ $P_{target} < 1$, the TP i cannot be assigned to candidate site j due to power limits and therefore, the variable x_{ij} can be omitted from the model. So Constraints 3 is not included in our model.

PROPOSED GENETIC ALGORITHM

As computers become more and more powerful and omnipresent, they are expected to solve increasingly difficult problems. Since the BS location problems defined in the previous section as a special case, they turn out to be NP-hard. The development and use of optimization models is well established. Our research in this area is primarily concerned with using Genetic Algorithms to solve the BS locating problem. Genetic Algorithm (GA) is evolutionary optimization approaches which are an alternative to the traditional optimization methods. Genetic Algorithms are a fairly easy and effective method of computing a nondeterministic problem.

A Genetic Algorithm (GA) is an adaptive search technique based on the principles of natural evolution[9]. GAs iteratively applies genetic operators for selection, crossover, mutation and reproduction on a given population to improve its average fitness generation by generation. GAs has been successfully used to solve many combinatorial optimization problems such as Travelling Salesman Problem (TSP), the Assignment Problem and the Knapsack Problem.

In 1975 J.Holland introduced Genetic Algorithms which are a computational method of simulating nature's evolutionary methods in an attempt to solve some of our own optimization problems[10]. In order to introduce the concept of GAs, Fig. 1 provides an informal example of a simple GA.

To use a genetic algorithm, we must represent a solution to or problem as a genome (or chromosome). The GA then creates a population of solutions and applies genetic operators such as Crossover and Mutation to evolve the solutions in order to find the best one(s). A GAs can be used to find a solution in much less time. Although it probably will not find the best solution, it can find a near perfect solution in less than a minute. The three most important aspects of using GAs are i) definition of the objective function. ii) definition and implementation of the genetic representation iii) definition and implementation of the genetic operator. Once these three have been defined, the generic genetic algorithm should work fairly well. As GAs works on a population, or a collection of several alterative solutions to the given problem.

The GA consists of four main stages: evaluation, selection, crossover and mutation. The evaluation procedure (fitness function) measures the fitness of each individual solution in the population and assigns it a relative value based on the defining optimization (or search criteria). Typically in a non-linear programming scenario, this measure will reflect the objective value of the given model. It is user-defined and problem-specific. The selection procedure randomly selects individuals of the current population (pair of chromosomes) for the development of next generation. It ensures survival of fittest.

1. Randomly generate an initial population.
2. Calculate fitness for each individual in the population.
3. Probalistically selects surviving members of the current population based on their relative fitness's.
4. Generate the next generation by applying genetic operators (Crossover and Mutation) to the surviving individuals.
5. Repeat steps 2 through step 4 indefinitely or until a halting condition is met (for example the desired maximum number of generations is exceeded.

Fig. 1: A basic genetic algorithm in high level pseudo code

The crossover and mutation are two basic operators of GA that are commonly used to generate offspring in the next generation. Performance of operators depends on the encoding and also on the problem. There are many ways how to perform crossover and mutation. The crossover procedure takes two selected individuals and combines them about a crossover point thereby creating two new individuals. Simple (asexual) reproduction can also occur which replicates a single individual into the new population. It is used for reproduction.

The mutation procedure randomly modifies the genes of an individual subject to a small mutation factor, introducing further randomness into the population. Sometimes a mutation can lead to a better solution that a crossover would not have found.

This iterative process continues until one of the possible termination criteria is met: if a known optimal or acceptable solution level is attained; or if a maximum number of generations have been performed; or if a given number of generations without fitness improvement occur. Generally, the last of these criteria applies as convergence slows to the optimal solution.

RESULTS

The algorithms are implemented in C (Turbo Version 3.0). Detailed information about the development of the solution qualities in each of the experiments conducted is given. The performance of our implementation using GA has been studied and compared with the conventional approach (i.e.,) Enumerative Methods and the results have been tabulated. As can be seen, the complexity is increase exponentially with number of Test points and Candidate site while there is a nominal increase in the complexity of GA approach.

Comparison between Enumerative Method and Genetic Algorithm Approach is as follows

For enumerative instances,

Case 1: Assume the propagation gain matrix G, the installation costs f_j for each candidate sites are $f_1=3$, $f_2=5$ and $f_3=4$, y1,y2 and y3 are 1,1,1 respectively. We consider a number m of candidate sites m=3 in which to locate BS antennas and a number n of TPs, n=5.

Table 1: Enumerative method

n	m	No. of multiplication	No. of division	Time(seconds)	Optimal solution	Proposed candidate site
5	3	846	173	0.797216	81.120002	x_{13}, x_{23}, x_{33}, x_{41} & x_{52}
7	4	1396	280	1.483516	81.66	x_{12}, x_{22}, x_{33}, x_{44}, x_{51}, x_{61} & x_{73}

Table 2: Genetic algorithm

n	m	No.of multiplication	No. of division	Time(seconds)	Optimal solution.	Proposed candidate site	No. of generations
5	3	4	---	2.7527473	81.120003	x_{13}, x_{23}, x_{33}, x_{41} & x_{52}	50
5	3	4	----	0.824176	82.90	x_{13}, x_{23}, x_{33}, x_{41} & x_{51}	15
5	3	4	---	1.373626	95.839996	x_{11}, x_{23}, x_{32}, x_{43} & x_{51}	30
7	4	5	--	1.4538462	88.16	x_{12}, x_{22}, x_{31}, x_{41}, x_{52}, x_{61} & x_{74}	10

Case 2: Assume the propagation gain matrix G, the installation costs f_j for each candidate sites are f_1=2, f_2=3, f_3=3 and f_4=2, y1,y2 ,y3and y4 are1,1,1,1 respectively. We consider a number m of candidate sites m=4 in which to locate BS antennas and a number n of TPs, n=7.

The remaining parameters have been selected as follows SF= 128 and τ = 4 (so that SIR_{min} = 0.03125). For the case 1 and 2, Table I summarize the final results obtained by running Enumerative Methods. By applying Genetic Approach instances, for the case 1 and 2, Table II summarizes the final results obtained by running genetic algorithm Approach.

Note that if we increase the number of generations in GA it leads better solution, but converges very slowly with computational times.

RESEARCH STATUS

The research we propose is the formulation and solution of an optimization problem focusing the planning phase of an UMTS network. We expect to contribute to the research on the topic proposing a relevant mathematical model to the problem and solving it using Genetic Algorithm and compare the results with Enumerative method. In our research, we can locate maximum of 4180 candidate sites by using Genetic Approach.

In the Enumerative Method, the basis for enumerative techniques is simplicity itself. To find the optimum value in a problem space (which is finite), look at the function values at every point in the space. The problem here is obvious. This is horribly inefficient. For very large problem spaces, the computational task is massive, perhaps intractably so.

In the Genetic Algorithm, to evaluate the performance of a new method and tool for optimizing the base station locations, based on Genetic Algorithms, is presented along with simulation results. It is possible to arrive at higher quality solutions in reasonable time.

CONCLUSION

The research we propose is the formulation and solution of an optimization problem aiming to locate base stations at minimal cost, subject to maximum quality and coverage constraints. By using our GA Approach, Maximum of 4180 base station can be located at minimal cost, subject to quality and coverage constraints. It have been shown that the solutions obtained with the genetic algorithm approach have substantially effectively and less computing time than those from the Enumerative Methods when problem become complex. There are several issues for future research. First, it would be interesting to investigate the properties of promising alternatives for some of the components used in the algorithms. Second, the efficiency of the implementation must be increased to reduce the computation times. Further, new techniques are also under investigation.

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