



Centro de Estudos de
Economia Aplicada do Atlântico

WORKING PAPER SERIES

CEEApIA WP No. 12/2013

A Regret Model applied to the Maximum Capture Location Problem

**Pedro Nunes
Francisco Silva
Helena Ramalhinho Lourenço**

December 2013

A Regret Model applied to the Maximum Capture Location Problem

Pedro Nunes

Universidade dos Açores (DEG e CEEApIA)

Francisco Silva

Universidade dos Açores (DEG e CEEApIA)

Helena Ramalhinho Lourenço

UPF- Barcelona GSE

RESUMO/ABSTRACT

A Regret Model applied to the Maximum Capture Location Problem

This article addresses issues related to location and allocation problems. Herein, we intend to demonstrate the influence of congestion, through the random number generation, of such systems in final solutions. An algorithm is presented which, in addition to the GRASP, incorporates the Regret with the p-minmax method to evaluate the heuristic solution obtained with regard to its robustness for different scenarios. Taking as our point of departure the Maximum Capture Location Problem proposed by Church and Reville [1, 26], an alternative perspective is added in which the choice behavior of the server does not depend only on the elapsed time from the demand point looking to the center, but includes also the service waiting time.

Key-words: location, allocation, coverage, heuristic, regret, scenarios.

Pedro Nunes
Universidade dos Açores
Departamento de Economia e Gestão
Rua da Mãe de Deus, 58
9501-801 Ponta Delgada

Francisco Silva
Universidade dos Açores
Departamento de Economia e Gestão
Rua da Mãe de Deus, 58
9501-801 Ponta Delgada

Helena Ramalhinho Lourenço
Universitat Pompeu Fabra
Barcelona Graduate School of Economics
Ramon Trias Fargas, 25-27
08005 Barcelona
Catalonia-Spain

A Regret Model applied to the Maximum Capture Location Problem

Pedro Nunes

Economics, University of the Azores

Francisco Silva

Economics and Business, University of the Azores

Helena Ramalhinho Lourenco

UPF- Barcelona GSE

Abstract

This article addresses issues related to location and allocation problems. Herein, we intend to demonstrate the influence of congestion, through the random number generation, of such systems in final solutions. An algorithm is presented which, in addition to the GRASP, incorporates the Regret with the p -minmax method to evaluate the heuristic solution obtained with regard to its robustness for different scenarios. Taking as our point of departure the Maximum Capture Location Problem proposed by Church and Reville [1, 26], an alternative perspective is added in which the choice behavior of the server does not depend only on the elapsed time from the demand point looking to the center, but includes also the service waiting time.

Key-words: location, allocation, coverage, heuristic, regret, scenarios.

1. Introduction

Given the vital importance of providing services in contexts of ever increasing demand and the costs of setting up such allocation systems, location problems are of utmost importance both in our daily lives as well as in scientific circles. Typically, the performance of such services is evaluated by the number of customers and the waiting time ensuing from the arrival of a request at the center. Overall, what can be concluded is that these indicators are highly correlated with the number of centers providing services and their specific location. Examples of such services are medical systems, police operations, firefighters, roadside assistance services, amongst others.

The problem that researchers strive to resolve is related to the location of service centers and the respective allocation of demand to these centers. In attempting to characterize such systems and

approximate them to reality, the location models have become so complex that obtaining results by complete enumeration has become more difficult, in great part as a result of the exponential growth of computing time.

The various models heretofore developed have been affected by the problem of complexity that hampers the process of finding a solution. Formulations have been constrained by simplifying assumptions, yet planners are often faced with deviations from reality that occur both in the public and private sectors. Technological advances have allowed the gradual development of more realistic formulations, given the possibility of finding solutions to complex models within acceptable computing times.

Despite the different formulations that have been proposed over time for the various problems related to location and allocation, it is commonly assumed that regions are represented by networks, a continuous space or a set of discrete nodal points.

This paper presents an algorithm which, besides the known GRASP - Greedy Randomized Adaptive Search Procedure - incorporates the *p-minmax* Regret method to evaluate the heuristic solution obtained with regard to its robustness for different scenarios. The use of these processes is undertaken in accordance with previous seminal works, such as that of Daskin et al [2]. It aims to integrate these new findings in order to explore new methodologies that improve or are better adapted to the circumstances of the cases studied.

We found that by varying the limits imposed on waiting times, maximum distance, demand processing capacity and size of network, it is possible to ascertain significant changes in the final solutions. The problem under study is the well-known Maximum Capture Location Problem developed by Church and Reville [1, 26] that incorporates an alternative model in which the server choice behavior does not only depend on the elapsed time from the node to the center, but includes also the waiting time for the service.

Our model and its various examples were tested using the random number generation model. In most cases different results were obtained by making it possible to confirm that the proposed formulation produces significant differences in terms of results. In general, the "tighter" the systems are, i.e., when the related distance limit between demand and center values are lower, the number of service centers to locate or the related waiting time limit, location decisions are generally more sensitive to pre-defined parameters for the model.

The classification of the location problems that concern us may be undertaken in accordance with the grouping suggested by Current et al. [3]: maximum distance models, "p-dispersion" problems and average or overall distance models. We can characterize this model as a maximum distance model given that maximum distances are explicitly considered as a pertinent factor as well as considerations relating to the maximum distance within which a facility must be located to provide the relevant service as well as the time limit within which the service can be provided. This is usually the case of schools, hospitals or police station locations where people generally expect to have access to a facility within acceptable limits outside of the original demand area.

A consumer is considered to be covered by a server – which is considered fixed and presents unlimited capacity concerning the possibility of processing the relevant service needs - if you have an installation within the pre-established distance limit. Where a service is provided by a facility located below this maximum, the service is considered appropriate or acceptable.

The formulation used in this work is based on previous studies, such as the works of Marianov and Serra [4] and those of Silva and Serra [5], particularly those relating to "Maximum Coverage Models" and the additional incorporation of results from the Queuing Theory.

The complexity associated with the model requires sophistication in our attempts to represent more elements or aspects of reality and the use of heuristic procedures in the search for

solutions. Thus, in addition to GRASP, the algorithm contains a Regret component, based on the work of Daskin [2] that has produced acceptable results, both in terms of computing speed and, perhaps more importantly, in terms of approximation to the optimal solution.

This work highlights the importance, corroborated by real-life events, of considering the various forms of system congestion as a vital factor in terms of location and allocation decision-making.

2. Related Literature

Location Models have been studied for decades and have produced implementation solutions for the public and private sectors. Classic examples of such problems are those that were explored and pioneered by Hakimi [6, 7]. He postulated a network without imposed direction on arcs, where consumers are located only at the nodes (or demand point). Each demand point presents a certain percentage of demand or need for care. The 1-median problem that is herein considered is based on the location of a facility on a network. Its goal is that helping consumers minimize the average travel distance between the facility and the demand node. Hakimi showed that, among all of the nodes, there was at least an optimal location for the server, in this manner reducing a continuous search by a finite one. A similar result is also applied to (p-median) multi-median problem, in which various facilities could be located so as to minimize the average distance from the nearest facility to the consumers.

The types of problems addressed by Discrete Location Models are generally formulated with integer linear programming and can be solved using the algorithm known as "branch and bound". However, when applying heuristic processes, even the most basic location problems are classified as "NP-Hard" and require unacceptable computation times to find patterns of employment associated with more realistic situations.

The maximum capture model proposed by Church and Revelle [1, 26] seeks to set a predetermined number of fixed serves, in order to maximize the population covered by its service, knowing before the location of a set of concurrent stores. The goal then becomes to locate a predetermined or budgeted number of facilities so that the requests directed to a certain server installation are maximized. This model does not require that all demand is covered.

However, problems of location have been studied for some time and the uncertainty that such allocation systems may exhibit lead researchers to explore alternative positions with regard to modeling demand, travel time or even costs associated with the chosen locations. Four basic approaches were formulated: approximations through a deterministic replacement, finding deterministic equivalents, probabilistic models with restraints, queuing systems spatially distributed and scenario planning.

Concerning this approach and its inclusion of allocation scenarios we highlight the seminal contribution of Sheppard [8] in 1974. His work demonstrated the importance of taking into account uncertain environments in location and allocation decision-making. These uncertain contexts are the object of this study inasmuch as they take into account randomness in the frequency of demand for certain services as a manifestation of uncertainty, the most important source of congestion of the systems in question.

Other researchers, such as Hogan and Revelle [9, 10] working within a deterministic paradigm are addressing system congestion with alternative formulations for models that address the location and coverage with redundant coverage. Daskin [11, 12] suggest that probabilistic extensions can be added to the "Maximal Covering" problem, assuming that servers are busy according to a given probability. In this case the goal is to maximize the demand covered by the other servers that are not busy.

In such studies, an attempt is made to incorporate interactions occurring in queues with location models. There have been some interesting advances in recent decades, particularly with regard to emergency services. The pioneering work in this field of research was Larson's [13] – "hypercube queuing" model. Its author proposes a system of stochastic service spatially distributed, with mobile servers scattered. Batta et al [14] used this model to demonstrate that the implicit assumption of independence of the server, as assumed by Daskin [11], [12], is often erroneous.

Fixed servers can "face" congestion. This is the case of health services and, in general, public services of any kind availing servers fixed. See it as an example Marianov and Serra [15].

Berman, Larson and Chiu [16] produced the first work that synthesized location theories and queuing theories. This work was expanded by Hakimi's [6] 1-median problem, incorporating it in the context of research on queuing. In order to decide where to locate service centers due consideration must be granted to service times, travel times and delays resulting from queuing. Larson's work [13] Hypercube Queuing Model has also served as a basis for such explorations.

In this context, the following objectives are proposed. Batta [17] considers the problem of locating a single service center in a network that operates as an M/G/1 queue where waiting calls are answered according to a class of queuing disciplines that rely solely on the information about the expected service time.

Brandeau and Chiu [18], also dedicated to congested systems, developed the model "Stochastic Queue Center Location" that aims to minimize the maximum response time to any consumer. For these authors the expected response time takes into account not only the waiting time until the server is on but also the travel time to the contact center.

In turn, the Revelle and Hogan [9] model previously mentioned, deals with congestion presenting a probabilistic version of the location problem. It is also in this line of reasoning that Marianov and ReVelle [19] presented the “Probabilistic Covering Problem with Queues”. With an identical formulation as the one adopted in the “Probabilistic Covering Problem”, a simple modification of Maximum Coverage Location Problem of Church and ReVelle [1], Marianov and Serra [4] introduce the “Maximum Coverage Location-Allocation Model with Queues” where the goal is to locate p service centers and affect these users so that the maximum population is covered.

3. Maximum Capture Problem

This section seeks to present an employed notation (3.1) and a proposed formulation (3.2), the Maximum Capture Problem and the application and measurement of a heuristic model is applied in order to produce the desired outcome.

3.1. Notation.

The following notation is defined:

- i , index I and set of demand nodes;
- j , index J and set of possible locations;
- a_i , demand at node i ;
- d_{ij} , distance between node i to j ;
- b_i , server from firm B closer to demand node i ;
- d_{ibi} , distance from demand node i to the closest firm's B .

Sets and Decision Variables:

$$N_i(b_i) = \{j \in J, d_{ij} < d_{ib_i}\}$$
$$O_i(b_i) = \{j \in J, d_{ij} = d_{ib_i}\}$$

$$Y_i^A = \begin{cases} 1, & \text{caso a empresa A capture o nó de procura i} \\ 0, & \text{caso contrário} \end{cases}$$

$$Z_i = \begin{cases} 1, & \text{caso o nó de procura i seja dividido entre A e B} \\ 0, & \text{caso contrário} \end{cases}$$

$$X_j^A = \begin{cases} 1, & \text{caso a empresa A localize um servidor no nó j} \\ 0, & \text{caso contrário} \end{cases}$$

3.2. Formulation

The MAXCAP model assumes that, for a product with similar characteristics, the consumer's decision by choosing a particular store (or server) is based on the distance traveled. It is also assumed that the unitary costs of each of the stores to locate is identical. This model initially considers a firm A, which is going to compete with firm B, knowing the pre location of firm B's stores.

When solving this kind of problems, we seek to locate a fixed number of servers (stores) owned by a certain company in a market place where competing stores already exist and will cause the division of such clients. The entering firm's objective is to maximize its profits using, in this case, an approximation by the number of total sales.

A certain consumer reveals a specific attraction relating each of the competing stores, being this behavior described by the use of an “attraction function” (or utility function).

In this MAXCAP model the consumers will patronize on of the stores if the traveled time measured in terms of distance d_{ij} is lower when compared to the competing stores.

A possible formulation for the MAXCAP problem is:

$$\text{Max } Z^A = \sum_{i \in I} a_i Y_i^A + \sum_{i \in I} \frac{a_i}{2} Z_i \quad (3.2.1)$$

s. t.

$$Y_i^A \leq \sum_{j \in N_i(b_i)} X_j^A \quad \forall i \in I \quad (3.2.2)$$

$$Z_i \leq \sum_{j \in O_i(b_i)} X_j^A \quad \forall i \in I$$

$$Y_i^A + Z_i \leq 1 \quad \forall i \in I \quad (3.2.3)$$

$$\sum_{j \in J} X_j^A = p$$

$$Y_i^A, Z_i, X_j^A \in \{0,1\} \quad \forall i \in I, \forall j \in J$$

4. Heuristic Procedure

We proceed to formulate, with Reeves [22], a heuristic method that attempts to find good solutions (i.e. near-optimal) in reasonable computing time. Therefore it is assumed that the solutions found by these heuristics methods do not always ensure an optimal outcome and may not present possible solutions.

The implemented algorithm adopts, at some point, the "Greedy Randomized Adaptive Search Procedure" (GRASP) developed by Feo and Resende [23] which comes up as an unfolding of one of the heuristics used to solve the 1st location models designed by Teitz and Bart [24]. This is interpreted as an approach through "exchange" or "replacement", moving the servers from their current positions to other non-used positions whilst keeping this new position whenever

the objective value is improved. For additional information on the subject see Festa and Resende [25].

This methodology is also used in the proposed algorithm the heuristic *p-minmax* Regret that was developed by Daskin et al [2]. To understand the importance of this method and the issue it addresses in the attempt to deal with the unpredictability of demand, the problem is solved for different scenarios by random generation (where these represent different population levels) and different frequencies of demand for service.

The term Regret is associated with the notion of deviation or difference and it provides us with an "opportunity cost" when implementing the chosen location. Given the design of the service delivery system that we considered optimal for a given scenario, the Regret, based on population characteristics of the remaining scenarios and respective objective function value (covered population), returns the difference in case the locations were kept.

According to the author, there may be many objectives for this indicator. What is intended in the present work is to select the lowest from the largest differences and, by successive adaptations, minimize it. We can interpret this process as finding a location solution that, in the worst possible scenario (the one that presents the greatest Regret given the optimal solution) presents the lower deviation or "opportunity cost".

We now present the algorithm implemented in C++ in which we introduce the two heuristics discussed above - GRASP and *p-minmax* Regret. Beforehand, we indicate the notation used:

- j index of possible locations;
- i index of demand nodes;
- D_j list of potential location points for services ordered according to the total population;
- S solution

- \bar{S} complementary solution
- C candidate set of points
- p number of services to locate
- n number of demand nodes
- inc_j overall rate of calls to potential service location j

Thus, the allocation process starts by reading the distance file identifying and recognizing at this early stage the network of demand (nodal) points - all of which are potential locations – and the distances between them - our associated cost measured in terms of time units.

For each node representative of a population centre, the respective population is generated according to a Uniform distribution. Since this is a user-defined parameter, in order to subject the model to different conditions, the demand is then estimated based on a percentage of the population previously determined. These values – population and demand- are generated for each one of the (ns) scenarios and will be as many as the number of scenarios with which we intend to work.

When the network is characterized, i.e., the number of nodes, the distance between each node and the respective populations and demand, using the CPLEX optimization software, the model begins by solving the maximum coverage location problem for each scenario.

The optimal value of our objective function for each scenario is thus obtained, acting as a future reference when compared to the results obtained for other levels of population and when maintaining the optimum locations obtained. This solution includes: which nodes are located service centers, the allocation of demand points to the respective centers and the value for the objective function concerning the covered population.

Having simulated the scenarios, a matrix entitled Regret 1 (ns, ns) is activated. The diagonal of the matrices Regret 1 indicate the optimal values obtained in each of the simulated scenarios. Values outside this diagonal, i.e., adjacent to the optimal solution values, are obtained by calculating the objective function considering the characteristics of the other scenarios (populations and demands) but maintaining the location allocation patterns given to us by the CPLEX optimization software.

| | | | | | | | | | |
|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|
| 197182 | 201432 | 198357 | 196556 | 195265 | 194325 | 198562 | 196663 | 197701 | 194003 |
| 161050 | 190007 | 181250 | 182356 | 192123 | 179125 | 183459 | 168971 | 179157 | 189457 |
| 170892 | 167845 | 157853 | 164887 | 169741 | 190187 | 178112 | 156746 | 192454 | 189451 |
| 171313 | 175949 | 194848 | 164073 | 169787 | 199454 | 185464 | 177989 | 184188 | 188774 |
| 169787 | 191717 | 188772 | 169745 | 180869 | 183556 | 197010 | 191141 | 186311 | 188745 |
| 196787 | 192776 | 193741 | 183797 | 181579 | 171896 | 181235 | 182454 | 192478 | 179878 |
| 197121 | 195798 | 177131 | 193457 | 189743 | 172656 | 164681 | 165888 | 178432 | 182747 |
| 177336 | 181656 | 189743 | 187141 | 191778 | 194331 | 184556 | 175624 | 185655 | 189774 |
| 179487 | 173998 | 167131 | 189477 | 183454 | 199466 | 193473 | 195471 | 164635 | 167979 |
| 189741 | 185731 | 159887 | 169741 | 200874 | 190157 | 182486 | 189478 | 168635 | 182916 |

Figure 1. 10 scenarios Regret 1 matrix.

A note of caution since the calculation of the values adjacent to the "optimality diagonal" requires a possibility test so that, in the continuation of the algorithm, a necessarily workable initial solution is obtained. The possibility test of a value adjacent to the optimal solution should take into account:

- The distance limit (ldist) from demand node i allocated to service center in j is taken into account;
- The limit for the waiting time (wlim) in j is respected; and
- Whenever negative valued waiting times are associated to a solution, in the matrix Regret 1 a zero will be shown.

When the objective value calculated with the standard locations and allocations for the other scenarios is not possible, under the conditions of possibility described above, the value in the Regret 1 matrix will be zero. Thus the associated solution is omitted of the rest of the process as an initial starting solution for GRASP since this zero value will not be considered in the choice of maximum deviation that is performed in the *p-minmax* process.

After the possibility test, based on Regret 1 matrix, the Regret 2 and Regret 3 matrixes are build up, where each one being a transformation of the one preceding, as described below:

Regret 2: each value of this matrix will be obtained by the difference between the goal of a given scenario and its respective optimal (reciprocated by CPLEX and contained in the diagonal of the Regret 1 matrix). This way, imperatively the diagonal of matrix of Regret 2 will contain only zeros. This procedure allows us to obtain the values of an "Absolute Regret".

| | | | | | | | | | |
|--------|-------|--------|--------|-------|--------|-------|--------|--------|-------|
| 0 | 4250 | 1175 | -626 | -1917 | -2857 | 1380 | -519 | 519 | -3179 |
| -28957 | 0 | -8757 | -7651 | 2116 | -10882 | -6548 | -21036 | -10850 | -550 |
| 13039 | 9992 | 0 | 7034 | 11888 | 32334 | 20259 | -1107 | 34601 | 31598 |
| 7240 | 11876 | 30775 | 0 | 5714 | 35381 | 21391 | 13916 | 20115 | 24701 |
| -11082 | 10848 | 7903 | -11124 | 0 | 2687 | 16141 | 10272 | 5442 | 7876 |
| 24891 | 20880 | 21845 | 11901 | 9683 | 0 | 9339 | 10558 | 20582 | 7982 |
| 32440 | 31117 | 12450 | 28776 | 25062 | 7975 | 0 | 1207 | 13751 | 18066 |
| 1712 | 6032 | 14119 | 11517 | 16154 | 18707 | 8932 | 0 | 10031 | 14150 |
| 14852 | 9363 | 2496 | 24842 | 18819 | 34831 | 28838 | 30836 | 0 | 3344 |
| 6825 | 2815 | -23029 | -13175 | 17958 | 7241 | -430 | 6562 | -14281 | 0 |

Figure 2. 10 scenarios Regret 2 matrix

Regret 3: the difference obtained according to the calculations of the Regret 2 matrix are now divided by the optimal value of reference for the scenario in question. Hence, we ascertain the value of "Relative Regret" associated with each scenario.

| | | | | | | | | | |
|---------|---------|---------|---------|---------|---------|---------|---------|---------|---------|
| 0,00000 | 0,02155 | 0,00596 | 0,00317 | 0,00972 | 0,01449 | 0,00700 | 0,00263 | 0,00263 | 0,01612 |
| 0,15240 | 0,00000 | 0,04609 | 0,04027 | 0,01114 | 0,05727 | 0,03446 | 0,11071 | 0,05710 | 0,00289 |
| 0,08260 | 0,06330 | 0,00000 | 0,04456 | 0,07531 | 0,20484 | 0,12834 | 0,00701 | 0,21920 | 0,20017 |
| 0,04413 | 0,07238 | 0,18757 | 0,00000 | 0,03483 | 0,21564 | 0,13037 | 0,08482 | 0,12260 | 0,15055 |
| 0,06127 | 0,05998 | 0,04369 | 0,06150 | 0,00000 | 0,01486 | 0,08924 | 0,05679 | 0,03009 | 0,04355 |
| 0,14480 | 0,12147 | 0,12708 | 0,06923 | 0,05633 | 0,00000 | 0,05433 | 0,06142 | 0,11974 | 0,04644 |
| 0,19699 | 0,18895 | 0,07560 | 0,17474 | 0,15219 | 0,04843 | 0,00000 | 0,00733 | 0,08350 | 0,10970 |
| 0,00975 | 0,03435 | 0,08039 | 0,06558 | 0,09198 | 0,10652 | 0,05086 | 0,00000 | 0,05712 | 0,08057 |
| 0,09021 | 0,05687 | 0,01516 | 0,15089 | 0,11431 | 0,21156 | 0,17516 | 0,18730 | 0,00000 | 0,02031 |
| 0,03731 | 0,01539 | 0,12590 | 0,07203 | 0,09818 | 0,03959 | 0,00235 | 0,03587 | 0,07807 | 0,00000 |

Figure 3. 10 scenarios Regret 3 matrix.

Basing our judgments on the Regret 3 matrix, we continue the application of our algorithm i.e., *p-minmax* heuristic as suggested by Daskin et al. [2]. Before the application of the latter matrix, the procedures are as follows:

- From the Regret 3 matrix, observing the values in line, we choose the one that presents the higher relative regret, in other words, the possible solution that departs furthest in percentage terms from the optimum control solution contained in Regret 1 diagonal obtained using the CPLEX;
- Subsequently, within all these maximum percentage deviations (relative Regrets) the minor is picked up with the intention of using it as an initial solution in the local search that follows on the GRASP heuristic.

The GRASP consists of two phases – construction phase and local search phase – and is an iterative process with reliable solution built independently at each iteration. Described below is a pseudo-code for the GRASP.

Procedure GRASP (Max_iterations, Seed)

For **k = 1** to **Max_iterations** do

$S \leftarrow \text{Greedy_Randomized_Construction}(\text{Seed}, \gamma);$

$S \leftarrow \text{Local_Search}(\text{Solution});$

$\text{Update_Solution}(\text{Solution}, \text{Best_Solution})$

enddo

end GRASP

Pseudo-Code 1: Pseudo-Code GRASP

From a general point of view, the process developed in this heuristic, after the selected initial solution as described above, follows like this:

- From the locations contained in the initial solution previously obtained, randomly one is chosen to be removed and replaced by another which, necessarily, must be on the RCL – *Restricted Candidate List*;
- The potential locations belonging to the RCL must meet the requirements of acceptability with regard, not only the distance limits imposed but presenting a priori a demand frequency greater than or equal to *gamma* percent of the search node with the highest demand frequency;
- If part of the RCL it is temporarily accepted to be considered in the iterative process and, when replacing the previous location, switches its position regarding its allocation to demand points;
- When the initial solution is improved, new location and allocation patterns are accepted;
- Otherwise, the initial solution persists.

These are again activated in the Regret 1, Regret 2 and Regret 3 matrixes based on the values obtained in the local search now held. In this process, the first matrix goes again through the possibility test already described. This process is repeated for a predefined number of iterations.

We now explain the use of pseudo-code for the two phases of that process, the GRASP heuristic. The construction phase, which will return an initial solution at each iteration, is invoked and is a function from the root in the random number generator and of the gamma parameter that defines what solutions will be included in RCL - *Restricted Candidate List*, the list containing the best solutions.

The development of the *Greedy_Randomized_Construction(Seed)* is now described:

```

procedure Greedy Randomized Construction (Seed,  $\gamma$ )
{sort candidate sites by decreasing order of population}
   $D_j \leftarrow \text{Sort\_Candidate\_Sites}( \text{population} );$ 
  {initialize solution set}
   $S := \{ \}$ ;
   $\bar{S} := C$ ;
  {while solution is not a complete solution}
  while  $|S| \neq p$  do
    {loop over all candidate sites not in the solution list}
    For  $j=1$  to  $|\bar{S}|$  do
      {initialize parameters}
      {restrict demand points list to the standard covering distance to site  $j$ }
       $D_{ij} \leftarrow \{i \in D, d_{ij} \leq d\}$ 
      {sort demand points by increasing distance to site  $j$ }
       $D_{ij} \leftarrow \text{Sort\_Demand\_Point } s( \text{distance} );$ 

      {loop over demand points in set  $D_{ij}$ }
      For  $i=1$  to  $|D_{ij}|$  do
        {sum frequencies at each demand point if waiting time limit is not reached}
        If  $(W_j < t \text{ and } \rho_j < 1)$  do
           $inc\_j := inc\_j + f_i$ ;
          actualize  $w_j$ ;
          actualize  $\rho_j$ ;
        Endif
      Enddo

      {construct the restricted candidate list}
       $c^{max} := \max\{inc\_j\}$ ;
       $RCL \leftarrow \{j \in \bar{S}, inc\_j \geq \gamma c^{max}\}$ ;
      {select randomly one site from the RCL}
       $j^* \leftarrow \text{Random\_Select}(RCL)$ ;
       $S := S \cup \{j^*\}$ ;
       $\bar{S} := \bar{S} \setminus \{j^*\}$ ;
      {take the demand points allocated to  $j^*$  out of the demand points list}
      For  $i=1$  to  $|D_{ij^*}|$  do
         $D := D \setminus \{i \in D_{ij^*}\}$ ;
      Enddo
    Enddo
  Enddo

```

end Greedy Randomized Construction

Pseudo-Code 2: Construction Phase Pseudo-Code

The proposed algorithm starts by choosing candidate nodes according to their respective demands/populations. We postulated in our example that all demand nodes are also potential service location points.

Thus, starting with the first node from the candidate list, the closest demand nodes are affected to it until the coverage limit is reached. Here the coverage limit can be determined through the utilization coefficient or the imposed limit for the waiting time.

Total demand affected to each of the potential sites j is called *incoming call rate*. The *incoming call rate* works as a “greedy” function of the algorithm and can be defined as a weighing of the demand nodes not yet covered but that will do if location j was chosen to have a server facility.

It is included on the RCL - Restricted Candidate List (sub-set of best solutions) the candidate nodes with a total *incoming call rate* greater to or equal to γ per cent of the *incoming call rate* indexed to the potential location with higher value.

In the GRASP, the γ parameter is established beforehand (for instance, if γ equals 0.8, we therefore mean that we include on the list containing the best solutions - *Restricted Candidate List* – all the potential locations with a total incoming call rate greater than 80% of the highest value between all incoming call rates).

Note that in the “greedy” heuristic, as suggested by Marianov and Serra [4], the choice would always be to locate a center at the node with the highest sum of incoming call rates, i.e., $\gamma=1$.

At each iteration, we choose randomly from among the candidate locations with the highest incoming call rate (i.e., the ones included on *Restricted Candidate List*) the p locations for servers.

```

procedure Local_Search (Solution, Best_Solution)
     $obj\_best := obj(S)$ ;
    {loop over sites in the solution}

    for all  $j_1 \in S$  do
         $S := S \setminus \{j_1\}$ ;
        {loop over sites not in the solution}
    for all  $j_2 \in \bar{S}$  do
        evaluate  $obj(S \cup \{j_2\})$ ;
        if  $obj\_best < obj(S \cup \{j_2\})$  do
             $S := S \cup \{j_2\}$ ;
             $obj\_best := obj(S \cup \{j_2\})$ ;
        else
             $S := S \cup \{j_1\}$ ;
        endif
    enddo
Enddo
end Local_Search

```

Pseudo-Code 3: Local Search Phase Pseudo-Code

At the local search phase, for each centre, we un-allocate its assigned demand and move it to all the potential locations not yet used, repeating at each time the steps 9 to 20 from the *Greedy Randomized Construction* procedure, aiming to evaluate the objective at hand. If any of the locations reciprocate a better objective value, we maintain the service centre at that node; otherwise, we keep it in the original location (see Pseudo-Code 3). We repeat the procedure until it is not possible to improve the initial solution or the limit of iterations is reached.

In a user-defined environment, the algorithm requires modification, both in its construction phase and in the local search in order to insure the closest possible allocation. The proposed algorithm penalizes the final objective whenever an unreliable solution is obtained. When a reliable solution is obtained, this set of locations are considered potential sites for the placement

of service centers. Otherwise, we consider this set of locations an initial solution and not a potential service location penalizing the objective with a large negative value M . This will match the following objective evaluation procedure:

procedure *evaluate_objective* (S)

Allocate each demand point to its closest center location;

Evaluate W_j and ρ_j ;

$obj(S) := 0$;

If ($W_j < \tau$ and $\rho_j < 1$) **do**

For $j=1$ to p **do**

For $i=1$ to n **do**

If (i is allocated to j) **do**

$obj(S) := obj(S) + f_i$;

endif;

enddo;

enddo;

Else

$obj(S) := M$;

end *evaluate_objective*;

Pseudo-Code 4: Objective Evaluation Pseudo-Code

During the Local Search phase, for each center at a time, we un-allocate assigned demands and move them to unused potential locations. We always affect a demand node to the nearest potential location and check the possible waiting time limit. If a solution is not possible, the objective is penalized with a very high negative value M . Whenever new allocations are found and a more efficient objective is identified we maintain that center in that location. Otherwise, the starting location is kept. This procedure is repeated until, when comparing with the previous, no better solution is found.

5. Computational Experience.

We now randomly generate different situations in order to compare the results obtained when using the heuristic solution with the ones initially obtained, the starting point for the local search phase of our heuristic.

For this purpose, networks of 25, 40, 50 nodes are generated and to each of those a demand frequency is associated. For each node it's generated, according to an Uniform Distribution [800;1800], a population number that will be used as data to compute the demand frequency. Given the population, 1% is considered the demand frequency or need of attendance.

Note that, in each of the generated scenario and specific network, the distance between nodes will be constant. Only the size of the network and demand associated to nodes is altered. The distance among the nodes is obtained according to a distance matrix common to all of the scenarios and studied networks. The same goes for the distance information concerning the competing firm, known before our location solution.

The following table presents a close-up on the characteristics and parameters of the set of data studied.

| Cases | Number | | Number | |
|--------------|---------------|----------------|--------------------|------------------|
| | Nodes | Centers | Iterations | Scenarios |
| 1 | 50 | 5, 10 and 20 | 500, 1000 and 2000 | 10 |
| 2 | 40 | 5, 10 and 20 | 500, 1000 and 2000 | 10 |

| | | | | |
|---|----|-----------------|-----------------------|----|
| 3 | 25 | 5, 10 and 20 | 500, 1000 and 2000 | 10 |
|---|----|-----------------|-----------------------|----|

Table 1. Characteristics and parameters of the processed data

The analyzed algorithm was implemented on a computer with Dual 2.50 GHz Pentium Dual-Core processor with 1920 MB of memory and using the C++ Microsoft Visual Studio 2005 compiler where, for the resolution of the proposed problem, the optimization software CPLEX *Optimization Studio* 12.2 was integrated.

Our goal is to see to what extent the pattern of locations obtained by the heuristic is significantly different from the optimum obtained and used as the starting point of the heuristic.

5.1. Changing the Network size and the Number of Centers to Locate

We now present the data collected on the following table:

| | | 25 Nodes Network | | | 40 Nodes Network | | | 50 Nodes Network | | |
|-------------------------|-------------------------|-----------------------------|---------|---------|------------------|---------|---------|------------------|---------|---------|
| | | Number of Centers to Locate | | | | | | | | |
| | | 5 | 10 | 20 | 5 | 10 | 20 | 5 | 10 | 20 |
| 500 iteration ns | Average Processing Time | 4.955 | 20.73 | 84.01 | 12.11 | 51.1 | 208.35 | 19.06 | 81.84 | 345.62 |
| | % of Matching Locations | 100% | 95% | 81% | 100% | 99% | 99% | 100% | 100% | 100% |
| | Average Regret | 0.18213 | 0.16835 | 0.18075 | 0.14728 | 0.1164 | 0.13884 | 0.13837 | 0.13418 | 0.12164 |
| 1000 iteration ns | Average Processing Time | 10.14 | 41.35 | 183.17 | 24.08 | 101.9 | 432.69 | 37.25 | 159.29 | 670.45 |
| | % of Matching Locations | 95% | 99% | 73% | 100% | 99% | 99% | 71% | 100% | 80% |
| | Average Regret | 0.18373 | 0.15902 | 0.17961 | 0.12047 | 0.117 | 0.12721 | 0.11058 | 0.12614 | 0.11036 |
| 2000 iteration ns | Average Processing Time | 20.12 | 82.47 | 337.36 | 47.83 | 202.39 | 830.34 | 81.96 | 325.31 | 1291.7 |
| | % of Matching Locations | 100% | 87% | 81% | 100% | 100% | 98% | 95% | 100% | 55% |
| | Average Regret | 0.18284 | 0.18278 | 0.18304 | 0.16338 | 0.14242 | 0.11598 | 0.13074 | 0.14418 | 0.11701 |

Table 2. Simulation results for 100 examples and 10 scenarios; average processing time measured in seconds.

The average CPU processing time (in seconds), perhaps one of the more sensitive indicators here on this work, exponentially increases given the higher value of the network size, i.e., the number of demand nodes considered. This indicator presents the same behavior towards the number of iterations and the number of centers to locate. In any of these cases, before the network size growth, the number of centers to locate and the number iterations, the processing time shows the indicated pattern.

As for the percentage of final and initial matching locations, the values increase as the number of network nodes and number of centers to locate increase. On the other hand, considering the increasing number of iterations, we can generally conclude that the percentage of matching locations decreases. The highest values for this indicator are revealed for the smaller networks and with the smallest iterations number.

Despite the irregular behavior, it is possible to verify that with the increase of the network size proposed the value of the Minimum Relative Regret decreases.

5.3. Conclusions.

When solving the Maximum Capture problem with the developed heuristic procedure described before, it is possible to see that as the system on study becomes freer (less constrained) the method proposed allows us to improve the initial solution. We can state that for higher solution spaces, despite the processing time's increase, the heuristic procedure produces solutions that differ from the initial. In this generalization we include the increase of the number of centers to locate. Less strong is the relation mentioned if compared with the increase in the size of the network used.

6. General Conclusions.

When analyzing the literature that addresses location and allocation problems we found that when considering a certain demand for a service it appears that this demand is random and is one of the sources of system congestion.

This type of problem can arise both in the public or private sector, involving different types of formulations as maximum distance models and total/average distance models. The methodology associated with each specific problem should be carefully examined and the results that are obtained should be compared with others produced by other testing models.

In addition to the “*Greedy Randomized Adaptive Search Procedure*” (or GRASP), we also used the heuristic method developed the *p-minmax* Regret (Minimum Relative Regret) proposed by Daskin [2]. The use of these models processes is undertaken in accordance with previous research and aims at its integration into the current paradigm in order to explore new methodologies that enhance or better adapt to the circumstances of the cases studied. Thus, the developed models can be considered adequate to address the type of issue proposed in the current work. Varying limits, in terms of waiting times and maximum distance, limits of demand processing capabilities and network sizes, produces significant changes in the final solutions.

There are numerous real-life situations in which the waiting time is an important, oftentimes vital, factor when considering the duration of service rendered (time or distance traveled plus

the waiting time). In such cases, taking into account the determination of a location pattern, the waiting time is to be regarded as absolutely essential in the respective modeling of the system. It may also interfere with the processing time of the number of centers to locate at a certain network scale, as well as the capacity of facilities in providing the sought service.

The proposed meta-heuristic reciprocates near optimal results demonstrating significant savings in computation time. Given the initial data, was with the use of simulation that in the present study the demand levels associated with each population data were obtained.

Regarding the application of Greedy heuristics to these formulations, these show acceptable behavior to the extent that the near-optimal solutions are sensitive to the worked examples and problematic situations proposed in each case.

On the other hand, the theory and the numerical examples obtained suggest that the solutions become less sensitive to the model parameters as the system becomes less busy. In the case that, for instance, the distance limit between the demand node and the service facility is smaller or when there are less service centers to locate, one can assume that henceforth there will be greater congestion associated with the model. These are cases where the heuristic has given results not identical to the initial solutions used as input in our algorithmic formulation.

Regarding the computational experiment conducted a few final remarks. The tested models and their various examples were obtained using random number generation. In many cases, different results were obtained, but there are others where the proposed formulation does not produce significant differences in the results. As already mentioned, generally speaking, the "tightest" systems are those wherein the distance limit is smaller and the number of service centers to be located is smaller. In such cases where there are inferior processing capabilities, location decisions are more sensitive to pre-defined parameters for the model.

Concluding, in this paper we simulated populations and their respective demand frequencies. Furthermore, we demonstrated the real-life paramount importance of system congestion in its various forms as a determining factor in location and allocation decisions.

References.

1. Church, R. and C.R. VELLE, *The maximal covering location problem*. Papers in Regional Science, 1974. **32**(1): p. 101-118.
2. Daskin, M.S., S.M. Hesse, and C.S. Revelle, *α -reliable p -minimax regret: A new model for strategic facility location modeling*. Location Science, 1997. **5**(4): p. 227-246.
3. Current, J., M. Daskin, and D. Schilling, *3 D iscrete N etw ork Location M odels*. 2002.
4. Marianov, V. and D. Serra, *Probabilistic, maximal covering location-allocation models for congested systems*. Journal of Regional Science, 1998. **38**(3): p. 401-424.
5. Silva, F. and D. Serra, *Locating emergency services with different priorities: the priority queuing covering location problem*. Journal of the Operational Research Society, 2008. **59**(9): p. 1229-1238.
6. Hakimi, S.L., *Optimum locations of switching centers and the absolute centers and medians of a graph*. Operations Research, 1964: p. 450-459.
7. Hakimi, S., *Optimum distribution of switching centers in a communication network and some related graph theoretic problems*. Operations Research, 1965. **13**(3): p. 462-475.
8. Sheppard, E., *A conceptual framework for dynamic location-allocation analysis*. Environment and Planning A, 1974. **6**(5): p. 547-564.
9. ReVelle, C. and K. Hogan, *The maximum availability location problem*. Transportation Science, 1989. **23**(3): p. 192-200.
10. Hogan, K. and C. Revelle, *Concepts and applications of backup coverage*. Management Science, 1986. **32**(11): p. 1434-1444.
11. Daskin, M.S., *APPLICATION OF AN EXPECTED COVERING MODEL TO EMERGENCY MEDICAL SERVICE SYSTEM DESIGN**. Decision Sciences, 1982. **13**(3): p. 416-439.
12. Daskin, M.S., *A Maximum Expected Covering Location Model - Formulation, Properties and Heuristic Solution*. Transportation Science, 1983. **17**(1): p. 48-70.
13. Larson, R.C., *A hypercube queuing model for facility location and redistricting in urban emergency services*. Computers & Operations Research, 1974. **1**(1): p. 67-95.
14. Batta, R., *A queueing-location model with expected service time dependent queueing disciplines*. European Journal of Operational Research, 1989. **39**(2): p. 192-205.

15. Marianov, V. and D. Serra, *4 Location Problems in the Public Sector*. 2002.
16. Chiu, S.S., O. Berman, and R.C. Larson, *Locating a mobile server queueing facility on a tree network*. Management Science, 1985: p. 764-772.
17. Batta, R. and O. Berman, *A Location Model for a Facility Operating as a M/G/K Queue*. Networks, 1989. **19**(6): p. 717-728.
18. Brandeau, M.L. and S.S. Chiu, *A center location problem with congestion*. Annals of Operations Research, 1992. **40**(1): p. 17-32.
19. Marianov, V. and C. Revelle, *The queueing probabilistic location set covering problem and some extensions*. Socio-Economic Planning Sciences, 1994. **28**(3): p. 167-178.
20. Kleinrock, L., *Queueing Systems. Volume 1: Theory*. 1975.
21. Berman, O. and D. Krass, *11 Facility Location Problems with Stochastic Demands and Congestion*. Facility location: Applications and theory, 2002: p. 329.
22. Rayward-Smith, V.J., et al., *Modern heuristic search methods* 1996: Wiley New York.
23. Feo, T.A. and M.G.C. Resende, *Greedy randomized adaptive search procedures*. Journal of global optimization, 1995. **6**(2): p. 109-133.
24. Teitz, M.B. and P. Bart, *Heuristic methods for estimating the generalized vertex median of a weighted graph*. Operations Research, 1968. **16**(5): p. 955-961.
25. Festa, P. and M.G.C. Resende, *An annotated bibliography of GRASP*. Operations Research Letters, 2004. **8**: p. 67-71.
26. ReVelle, C., *THE MAXIMUM CAPTURE OR "SPHERE OF INFLUENCE" LOCATION PROBLEM: HOTELLING REVISITED ON A NETWORK**. Journal of Regional Science, 1986. **26**(2): p. 343-358.