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Facility Location Problem Using Genetic Algorithm: A Review

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Abstract
A facility location problem is like a firm having some possible locations to locate facilities in. At each location the firm has a particular value of the objective function determined on the basis of various factors involving number of employees, setup cost etc.. Given a budget to build the facilities and fixed construction cost depending upon the size of customers to be served by the facility, the objective is to minimize the total traveling distance by the employees. In the facility location problem, each node i is associated with a facility cost fi, which reflects the cost of opening a facility at this node. The problem is to open a subset of facilities so as to minimize the sum of facility costs and the service cost. The service cost is defined to be the sum of distances from each node to its closest open facility. In this paper we use Genetic Algorithm (GA) to solve Facility Location Problem. GA is a set of meta heuristics that derives its inspiration from natural evolutionary process of the survival of the fittest and have been successfully applied to many large scale combinatorial optimization problems.
Keywords: Facility location problem, Genetic algorithm, Selection, Crossover, Mutation.

1. Introduction:

Location and allocation of facilities is an often-raised spatial decision problem in urban and regional planning. Generally, the number of facilities is finite, and these facilities should be optimally sited in space to minimize the total travel cost from each demand point to its nearest facility [1]. Therefore, in most cases, location and allocation of facilities can be formulated as a well-known p-median problem (PMP), i.e. the problem of locating p facilities (medians) in order to minimize the total travel cost for satisfying the demand of customers with the closest open facilities. However, for some kind of facilities, capacity constraints as well as travel cost are significant. For example, if we plan to locate p shelters to accommodate all evacuee of a certain area, it is required to consider both travel cost from residents to assigned shelters and the finite capacity of each shelter. If the capacity consideration is ignored and residents are using the nearest shelters, it could cause overcrowding that may lead to other problems as insufficient food and water supply. Such a capacitated location-allocation problem can be formulated as the capacitated p-median problem (CPMP), which, as a variation of the PMP, has not received as much attention as the classical PMP. Regardless of the capacity consideration, algorithms devised for the PMP can be amended to solve the CPMP also.

The PMP has proved to be a NP-hard problem[2], and during the past several decades, a number of optimization algorithms have been proposed by various researchers like Lagrangean relaxation[3], dual formulations[4], Branch-and-bound algorithms[5], simulated annealing[6], tabu search [7], genetic algorithms[8], etc. Some approaches to the CPMP have also been developed based on the above algorithms. The paper does not intend to provide a wide spectrum covering all these algorithms, but focuses on the application of genetic algorithms in the capacitated location allocation of facilities, because in comparison to other algorithms, genetic algorithms are easy to be implemented and adapted to large-size problems in geography. Facility-location problem has several applications in telecommunication, transportation, scheduling and distribution problems. One important way to measure the effectiveness of facility location is by evaluating the average (total) distance, accessibility and effectiveness of the facility. This relationship applies to both private and public facilities such as supermarkets, post office, as well as emergency service centres, for which proximity is desirable. The p-median problem focuses on this measure and minimizes the average (total) distance between the demands and the selected facilities. The total cost of the solution presented is the sum of the distance between demand points and selected location.

2. Problem Formulation:

Generally, the demand points are non-uniformly distributed in an area, e.g. the spatial distribution of residents who need to be evacuated to shelters. In order to handle this non-uniform nature, we partition the entire area into a number of spatial units with mutually exclusive spatial extents. Customers (e.g. residents) are grouped into various spatial units according to their spatial distribution. A spatial unit is usually as small as a city block, and thus we assume that spatial distribution of demand in each unit is even, and customers in this unit use the same facility to satisfy their demand. Notably, the smaller the unit is, the more reliable the assumption is. A unit (i.e. a group of spatially aggregate customers) is treated as a demand point in the proposed approaches. Each facility is also located in an individual unit. In this paper, it has been assumed that spatial units are identical sized squares

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covering entire area. The total demand in such a square can be calculated based on the customers located in this square. According to the above discussion, the targeted problem is formulated as the following CPMP.

Notations:

N the number of units
P the number of facilities
M the number of candidate facilitate sites
C_i *the* maximum capacity of the facility on candidate site in unit *i*
A_i *the* actually-employed capacity of the facility on candidate site in unit *i*
D_j *the* total demand volume in unit *j*
X_{ij} = 1 if demand from unit *j* is satisfied by the facility in unit *i*, 0 otherwise.
S_i = 1 if unit *i* is selected to locate a facility, 0 otherwise.
T_{ij} *is* the total travel cost of satisfying demand from unit *j* by the facility in unit *I*
Fq = 1 if unit *q* has a candidate site, 0 otherwise.

Here, some equations have been given describing various objective functions. Equation 1 defines the objective, i.e. minimizing travel cost, which is also the objective of the PMP. Equation 2 represents a trivial constraint that guaranties that the number of facilities or candidate facility sites is no more than that of spatial units. Equation 3 indicates that each spatial unit must be assigned to one and only one facility. Equations 4 and 5 respectively define the numbers of needed facilities or candidate facility sites. Equation 6 describes the capacity constraints, i.e. the actually employed capacity of each facility must be no more than its maximum capacity

$$\text{Minimize } V = \sum_{i=1}^{N}\sum_{j=1}^{N} t_{ij}\, x_{ij} s_i \tag{1}$$

$$\text{Subject to: } \quad N \geq M > P \tag{2}$$

$$\sum_{i=1}^{N} x_{ij} = 1 \quad \text{for each j} \tag{3}$$

$$\sum_{i=1}^{N} s_i = P \tag{4}$$

$$\sum_{q=1}^{N} f_q = M \tag{5}$$

$$C_i \geq A_i, A_i = \sum_{j=1}^{N} D_j\, x_{ij} \text{ for each } i \text{ and } s_i = 1 \tag{6}$$

Fitness Function

A fitness function is used to compare different solutions encoded as chromosomes by their fitness values. Most existing approaches employ the objective function of the problem, i.e. equation 1, as the fitness function. For a given chromosome, it is noted that t_{ij} and s_i are known in equation 1, and x_{ij} unknown. For uncapacitated location-allocation problems, the calculation of x_{ij} is straightforward because each spatial unit is only assigned to the nearest facility. However, for capacitated location allocation problems, more computation efforts are needed because some spatial units can not use the nearest facilities with respect to capacity constraints. Furthermore, many facilities also require that spatial units sharing the same facility, i.e. the service area of a facility, must be spatially continuous. For example, if a shelter's service area is divided into several parts and interlocked with other shelters' service areas, then an immediate consequence could increase difficulty of efficiently transporting residents to shelters in a large-scale evacuation process: people are unwilling to move on, when they have reached a shelter though it is not assigned to them, and there might be heavily conflicting traffic flow towards different shelters from their interlocked service areas. All the above considerations make the calculation complicated and significantly slower the reproduction process. Therefore, here the following measure to efficiently calculate fitness values have been provided.

A fact is that the more the number of spatial units which can use the nearest facility, the more optimal the solution it will be. Therefore, we can employ this number as the fitness value of the solution. The number of spatial units using the nearest facilities can be calculated through the following steps:

[1] Assign each spatial unit to its nearest facility.
[2] For each facility, sort its assigned spatial units in ascending order by the travel cost from units to the facility, and save the sorted units in a list.
[3] Sequentially accumulate the demand volume of spatial units in each list until the accumulated demand volume reaches the maximum capacity of the facility.
[4] Let the spatial units whose demand volume has not been counted become unassigned spatial units.
[5] Return the total number of assigned spatial units as the fitness value of the solution.

Figure 1 illustrates the calculation of fitness values for two solutions. It is noticeable that the solution B is better than solution A. Although the proposed measure can't exactly figure out all x_{ij} in equation 1, mathematically increasing the number of assigned spatial units is not sufficient but a necessary condition to evaluate an optimal solution. This measure achieves the same objective of comparing solutions in a more efficient way.

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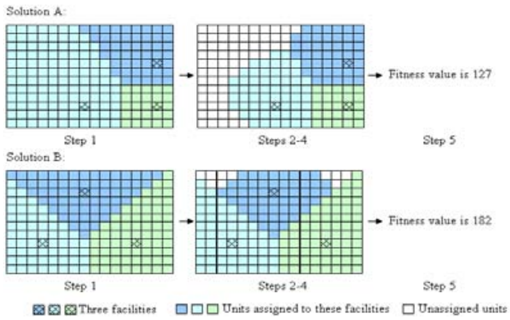

Selection

Genetic algorithm consists of three primary operators: 1) Reproduction, 2) Crossover and 3) Mutation. Reproduction is the process through which solution characteristics are passed from one generation to the next. The solution chosen for reproduction can be selected in a probabilistic manner. The selection operator selects chromosomes from the current generation to be parents for the next generation. The probability of each chromosomes selection is given by:

$$P_s(\mathrm{i}) = f(\mathrm{i}) / \sum_{J=1}^{N} f(\mathrm{j})$$

where $P_s(i)$ and $f(i)$ are the probability of selection and fitness value for the *i*th chromosome respectively. Parents are selected in pairs. Once one chromosome is selected, the probabilities are renormalized without the selected chromosome, so that the parent is selected from the remaining chromosomes. Thus each pair is composed of two different chromosomes. It is possible for a chromosome to be in more than one pair.

One way to think about this is in terms of a roulette wheel. Each solution in the set makes up a different section of the wheel. The best solution takes up a larger piece of the pie. The outcome is random when the ball is spun, but the better solutions are more likely to come as they have a larger probability.

Crossover

The crossover initially computes two exchange vectors, one for each parent as follows. For each gene of parent 1, operator checks whether the allele (facility index) of the gene is also present (in any position) at the genome of parent 2. If it is not present, that facility index is copied to exchange vector of parent 1. This means that facility index may be transferred to parent 2 as a result of crossover, since this transfer would not create any duplicate facility indices in parent 2's genotype. The procedure is performed for each facility index in the genotype of parent 2. Once the facility indices that can be exchanged are identified, the crossover operator can be applied. No fixed crossover probability is used and the crossover is performed only when two parents are not equal to each other, as reproduction of similar parents will result in reproduction of one of the parent unaltered while deleting the other parent to avoid that duplicate individual's insertion into the population.

Mutation

It is the process of gene being mutated having its current allele replaced by another randomly – generated allele (a facility index) subject to the restriction that the new facility index is not present in the current genotype of the individual.

Mutations are global searches. A probability of mutation is again predetermined before the algorithm is started which is applied to each individual bit of each offspring chromosome to determine if it is to be inverted. Mutation is used so that we do not get trapped in a local optimum. Due to the randomness of the process we will occasionally have chromosomes near a local optimum but none near the global optimum. Therefore the chromosomes near the local optimum will be chosen to crossover because they will have the better fitness and there will be very little chance of finding the global optimum. So mutation is a completely random way of getting to possible solutions that would otherwise not be found.

Elitism

The elitist operator insures the GA will not get worse as it progresses. The elitist operator copies the best chromosome to the next generation bypassing the crossover and mutation operators. This guarantees the best chromosome will never decrease in fitness. Computing the probabilities of crossover and mutation as a function of fitness allows the probabilities to reflect the current state of the GA.

Accepting and termination

In this work the offspring that produced by crossover and mutation is inserted into the population only if they have a better (smaller) fitness than the worst individual of the current population.

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The genetic algorithm iterates, and as the process proceeds, the generation includes chromosomes with higher fitness function values. Termination criterion is used to stop the iteration. A single criterion or a set of criteria can be used to halt the genetic algorithm. Three termination criteria are: test of population convergence, monitoring of improvement from generation to generation, and maximum number of generations.

3. Conclusions

We have presented an approach to CPMP, which is based on genetic algorithms. For a given solution, the fitness function calculates the number of the spatial units which can be assigned to their nearest facilities with respect to capacity constraints of facilities. A novel genetic operator, named unique-value operator, is proposed to fulfil the reproduction process. A series of experiments are conducted to validate the proposed approach in an application of locating shelters in Memphis, Tennessee. Studies have shown that the improved genetic algorithm for optimal selection problems can solve, and the algorithm is more applicable for solving the large scale location problems. The genetic algorithm reduces the difficulty of solving the location model, it also maintains that neighbourhood search technique avoids falling into local optimum; this process strengthens the fairness of the location method. The objective factors are also considered in the model, thus resulting into diminishing complexity of distribution and recycling centre location in the modem enterprise.

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