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SPATIAL OPTIMIZATION METHODS

Spatial optimization is concerned with maximizing or minimizing an objective related to a problem of geographic nature, such as route selection, location-allocation modeling, spatial sampling and land-use allocation among others. Location-allocation analysis is used to determine optimal locations for a single or more facilities with respect to the spatial distribution of demand; applications can range from locating a hazardous waste site or siting a landfill as far as possible from existing population, determining optimal bus stop locations to minimize walking distance from home, finding a location for a new cell tower to maximize population coverage, to determining a biological reserve for habitat recovery or the optimal location for a recreational site in a neighborhood.

Solving a geographic problem translates in the formulation of an objective function subject to some constraints. In the example of bus stops allocation where the objective is to maximize potential ridership, it may not be possible to locate bus stops everywhere since the geographic space is constrained. Additionally, if potential commuters live beyond a critical distance, they will be discouraged from walking to the closest bus stop. In the cell tower example potential locations for new towers may be rather limited; not only is it desirable to locate new base stations at higher elevation to minimize obstructions, but also not too close from residential areas (Not in My Backyard effect).

Single and Multiple Objectives

Different approaches exist in the literature to solve geographical problems. Depending on the nature of the problem, a single or multiple-objective approach can be taken. The optimal location of a recreational site may have a single accessibility objective in which the distance from residential units to the site is minimized. In locating an obnoxious facility such as a landfill, one objective may be to maximize the separating distance from population centers, but also to minimize transportation costs. Some objectives may be conflicting, and it is oftentimes desirable to reach a pareto solution.

Heuristics

Once a problem has been formulated with an objective function and constraints, a solver is generally used to find an optimal solution (e.g. Cplex, Lingo). Exact solution methods such as integer or linear programming, branch and bound as well as Lagrangian relaxation have often limited success, given that an increase in the number of variables will cause an exponential increase in the solution time. In some instances, the size of a spatial problem can create a combinatorial explosion, and heuristic search techniques are preferred. Heuristics are algorithms which are able to find a solution (optimal or not) for a given problem in a limited time frame. Some heuristics reach a suboptimal solution rapidly (e.g. myopic, naïve strategy), while others can lead to an optimal (simulated annealing, genetic algorithms, tabu search), at the cost of a longer running time. Limited research has been devoted to comparing the benefits and drawbacks of several heuristics and metaheuristics (combination of heuristics) in the context of spatial optimization.

Naive or random strategy

The naïve strategy randomly chooses a number of locations from a set of candidate locations. This approach does not account for the structure of the solution space and is therefore very inefficient. Nevertheless, the numerical results following the use of this algorithm provide a good lower bound to evaluate other heuristics.

Total enumeration

This method consists of evaluating which of all candidate locations optimizes the objective function the best. Total enumeration is sensitive to the size of the problem, but is optimal in the one-facility location problem as long the set of candidate solutions is finite (discrete). The method would however be inappropriate when the spatial problem calls for the allocation of more than one facility, because of combinatorial explosion.

Greedy algorithm

Greedy (or myopic) starts with a feasible solution. The current solution is then exchanged for another one only if the objective function improves. The process continues until no further improvements can be made. The algorithm is easy to implement and returns a good solution, which may be sub-optimal however. The algorithm can be effective when applied repeatedly as long the starting feasible solution is changed.

Simulated annealing

The greedy approach, as well as the total enumeration in the one-facility location usually get stuck in a local optimum while simulated annealing is able to reach optimality. The major advantage of Simulated Annealing is its ability to avoid becoming trapped at a local maximum. The algorithm employs a stochastic search that accepts changes improving the objective function, but also non-improving moves, which are accepted with a certain probability. The probability of acceptance decreases as the temperature (or system) cools down.

Tabu Search

Simulated annealing allows non-improving moves. Tabu search however deals with cycling problems of non-improving moves, in which the heuristic momentarily forbids swapping of solution that would return to a previously visited solution. The so called “tabu-list” records these forbidden moves.

Metaheuristics

The combination of two heuristic methods—also called a metaheuristic—allows one to improve upon a first solution. For instance, because the greedy heuristic may yield a suboptimal solution, an improvement may be desirable; simulated annealing can use the greedy solution at the start of its optimization procedure.

Genetic algorithm

A genetic algorithm is a metaheuristic that uses techniques from evolutionary biology to find better solutions at each iteration. The algorithm improves feasible or suboptimal solutions by operations which combine individuals of an improving population. The quality of each individual is evaluated, and several of them are randomly selected from the current solution, based on their solution quality. Solutions are then modified using mutation or crossover to form a new basic feasible solution.

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See also Spatial Multicriteria Evaluation, Spatial Decision Support Systems, Location-Allocation Modeling.

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