Using Metaheuristic Algorithms to Determine Where to Build Mental Health Facilities for Underserved Population Areas in the United States: a Constrained Budget Location-Allocation Problem

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Abstract

The United States Department of Health & Human Services has a Division of Policy and Shortage Designation that collects data on geographic areas, populations, and facilities with too few primary care, dental and mental health providers and services. This paper uses a publicly available dataset published by the Health Resources & Services Administration about the population per state that is a Health Professional Shortage Area or a Medically Underserved Area/Population for mental health providers. Assuming the Division were awarded a budget to establish new mental health clinics in the United States and they could build a maximum of one facility per state, this paper employs the use of two metaheuristic algorithms, a genetic algorithm and a particle swarm optimization algorithm, to determine where to optimally locate the clinics to stay within the budget and ensure at least 80% of demand is covered. Both algorithms produced the same optimal solution, suggesting building five facilities, creating a total coverage of 82.6%.

1. Introduction

The Bureau of Health Workforce's (BHW) Health Resources and Services Administration (HRSA) has a Division of Policy and Shortage Designation (DPSD), which develops shortage designation criteria and uses them to decide whether a geographic area is a Health Professional Shortage Area (HPSA) or a Medically Underserved Area (MUA) [1]. HPSAs may have shortages of primary medical care, dental, or mental health providers, and approximately 20 percent of the United States population resides in primary medical care HPSAs [1]. The HRSA provides publically available datasets on the HPSAs for dental health, mental health, and primary care [1].

Suppose the BHW was awarded a grant to improve mental health by building new facilities in an area that has a health professional shortage. Given the budget awarded by the grant, it is up to the HRSA to determine exactly how many facilities to build, and where to build them. Assume that each state can only have one new facility, with each facility able to service a specified number of people (constant across the states). Each facility will cost a different amount to build, based on the state in which it is located. The objective is to maximize the estimated underserved population to be covered (minimum 80% coverage) while also minimizing the cost to build the mental health facilities.

This problem is a location-allocation problem, and in this paper, two metaheuristic methods, simulated annealing (SA) and particle swarm optimization (PSO), will be used to solve them problem and then compared. SA was selected as a methodology for this project because… PSO was chosen as a methodology for this project because is a simple and popular algorithm to solve transportation network design problems, and research shows that it outperforms the solution quality of the current best-known methods [2]s.

2. Literature Review

Location-allocation (LA) problems are a class of problems in which the goal is to locate a new set of hubs (e.g. buildings, facilities, warehouses) optimally so that the cost (generally the cost of transportation) going from the hubs to the nodes (e.g. customers, patients) is minimized, and an optimal number of hubs are located in order to satisfy the customer demand [3]. The LA problem was first proposed in the early 1960s [4], and many variations on the problem have been proposed over the years, including spread to a weighted network [5].This problem is found in a variety of practical settings, including but not limited to public sector facilities such as public schools, pharmacies, and primary health care centers [6]. In healthcare, location-allocation studies have been undertaken for a variety of different purposes, including for health service development planning in developing nations [7]. This section will review a number of published LA studies related to health care.

Health service development planning in developing nations is a popular application for LA studies because available health data for these nations often indicates high degrees of incidence of preventable disease and mortality rates, such as polio and infant mortality [7]. Furthermore, studies highlight evidence that suggests the development of health along with other social improvements are vital for economic development [7]. Examples of LA studies in developing nations include the location of rural health clinics in the Eastern Region of Upper Volta by Mehretu et al. [8], LA techniques for ambulance deployment in the Dominican Republic by Eaton et al. [9], and the choice of locations for public health centers in rural India by Patel [10].

More recently, Harper et al. [11] developed a three-phase discrete-event simulation to determine the provision of dental services across London and the provision of coronary artery bypass graft services within Eastern England, illustrating the location-allocation problem at local district level planning as well as regional level planning. Bruni et al. [6] used the *p*-median model to determine the optimal allocation of transplantable organs across regions with the objective of attaining regional equity in health care. Cocking and Reinelt [12] used simple greedy heuristics, a local search heuristic, simulated annealing, variable neighborhood search, and several other approaches to solve the static budget constrained facility location-network design (FLND) problem, achieving noteworthy improvements in accessibility to health facilities for the people in the Nouna health district of Burkina Faso. Ghaderi and Jabalameli [13] used a greedy heuristic and fix-and-optimize (hybrid simulated annealing) heuristic to improve accessibility to the health facilities for the rural population centers in the Illam Province of Iran.

3. My Model

Mental health data for underserved populations for 48 states plus the District of Columbia (no data for New Jersey or Vermont) were collected from the U.S. Department of Health & Human Services HRSA website [1]. Some states had data at the city- or county-level, and some did not; as a result, the estimated underserved population was aggregated by state. The average underserved population per state is 1,239,914. The five states with the highest underserved populations are Florida, California, Arizona, Texas, and Tennessee (see Figure 1). The underserved population of each state was used as the demand, and the state will be considered the node. Latitude and longitude of each state was calculated by taking the average latitude and longitude of all of the zip codes within each state [14]s. This data was used as the coordinates for the demand notes. Latitude and longitude of each state capital was also recorded [15]s. This data was used as the coordinates for the facilities to be built. Assume every facility can serve ten million people.

As a proxy for cost of building a facility in each state, we will use the 2011 fiscal year average Medicare billing cost to a provider for diagnoses of psychoses by state. The source of this data is the Centers for Medicare and Medicaid (CMS) Medicare Provider Analysis and Review (MEDPAR) inpatient data [16]. Data was available for 47 states, excluding Wyoming, North Dakota, and the District of Columbia. The five states with the highest average Medicare billing cost for diagnoses of psychoses were Alabama, Nevada, Minnesota, California, and Rhode Island (see Figure 2).

For each solution generated by the algorithm, a matrix is created which calculates and stores the distances from each node to each open facility. Then, for each node, if a facility is open and the facility has the capacity to satisfy the node, the node is assigned to that facility. If a facility cannot fulfill the entire demand of a node, the node will not be assigned to that facility (i.e., no partial demand fulfillment). Each node will only be assigned to maximally one facility, so once a node is assigned to a particular facility and its demand fulfilled, it will not be assigned to any other facilities. For each solution, the percentage of demand covered is calculated. The minimum demand coverage allowed is 80%, so if a solution covers less than 80% of the nation's demand, the solution is infeasible. The cost of each solution includes three weighted aspects: 1) the distance to the nearest open facility with capacity to fulfill it; 2) the cost of building the open facilities; and 3) the penalty for not covering demand.

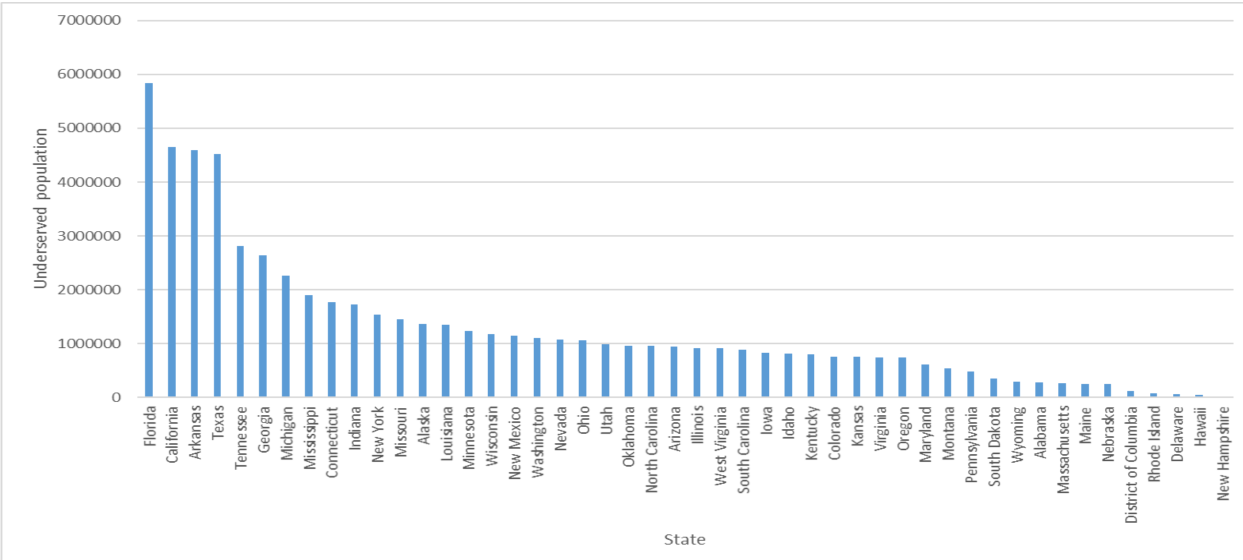

Figure 1 Estimated Underserved Population by State
(Source: Health Resources & Services Administration)

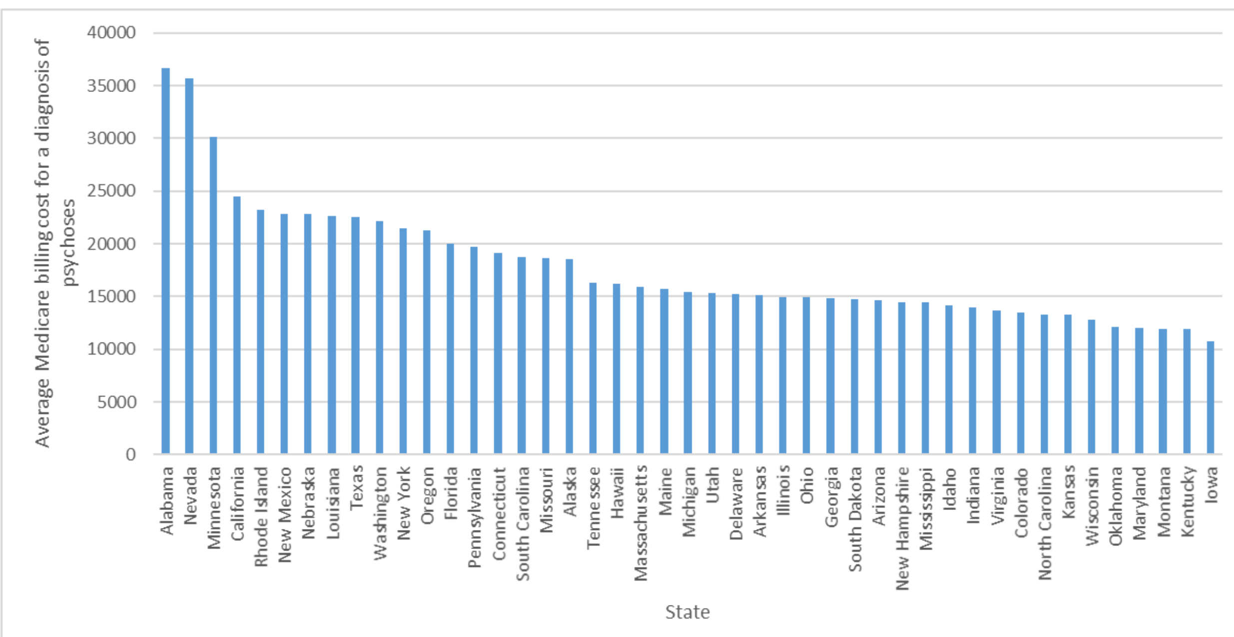

Figure 2 Average Medicare Billing Cost for Diagnoses of Psychoses by State
(Source: CMS Medicare Provider Analysis and Review (MEDPAR) inpatient data, 2011)

A genetic algorithm (GA) [17] was one of two metaheuristics coded in MATLAB and used to solve this problem. Genetic algorithms are probabilistic search procedures meant for sizable search spaces with multiple states [17]. In the context of this paper, the facilities have two states: on or off, making this a binary problem. In the solution, a facility that is 'on' indicates that we should build the facility, and a facility that is 'off' means we should not build the facility. The genetic algorithm concepts of adaption and learning are based on the theory of Darwinian evolution and natural selection, namely that species develop over time as small, genetic variations increase the individual's ability to compete, survive, and reproduce. Over time, the individuals with the best advantage win out. The genetic algorithm begins with a random initial population of solutions and then reproduces (creates the next generation of the population) through crossover and mutation, treating the above-average parts of the population (the ones with competitive advantage) as building blocks for the next population [17].

The second metaheuristic coded in MATLAB and used to solve this problem was particle swarm optimization (PSO) [18]s. One way that PSO is similar to GA is that they both have a primary initialization of a population of random solutions. PSO is also based on a natural phenomenon: that of human interaction. In PSO, each potential solution (called a particle) is also assigned a randomized velocity, and the particles are then "flown" through hyperspace. As time goes on, the particles share their guesses with their topological neighbors. Therefore, each particle "teaches" others, as well as "learns" from others. Additionally, in the GA, interaction in the population detracts from progress toward the solution, but in PSO, this interaction enhances progress toward the solution [18]s. Another difference between GA and PSO is that the latter has a memory, while the former is memoryless [18]s. Each particle retains the coordinates that have generated the best solution it has found so far ("local best"), and the global version of the PSO keeps track of the overall best value and its location found by any particle in the population. With each iteration, the velocity is accelerated on each particle toward its local best and the entire population's global best.

4. Results and Analysis

See Table 1 for the parameters used to run the genetic algorithm model. The results of the genetic algorithm indicate that the lowest possible cost (including the distance to the nearest open facility with capacity to fulfill it; the cost of building the open facilities; and the penalty for not covering demand) is 52291839.23, which offers 82.6% coverage of demand. This solution created five facilities, located in Montgomery (Alabama), Phoenix (Arizona), Atlanta (Georgia), Jackson (Mississippi), and Columbia, (South Carolina) (see Figure 3). The average number of demand nodes assigned to a facility is 7.67, with Alabama having 5, Georgia having 6, South Carolina having 8, and Arizona and Mississippi having 9 each. This adds up to 37 of the 46 states having their demand met, leaving Alaska, Idaho, Michigan, Minnesota, New York, Oregon, Washington, and Wisconsin without coverage.

A sensitivity analysis was run on the population size of the GA (see Table 2). Results indicate that the optimal cost was first reached when the population size was 35. Interestingly, however, it was not until the population was 85 that the optimal cost was reached every time the model ran. The GA would sometimes get stuck in local optima until that point. For a population of 100, the optimal solution was first found at iteration 27, when the number of function evaluations (NFEs) was 2556.

See Table 3 for the parameters used to run the particle swarm optimization. The results of the PSO coincide with the results from the GA, indicating that the lowest possible cost is 52291839.75, offering 82.6% coverage of demand. This solution created the same five facilities as the GA solution (see Figure 4). The same states were also assigned to the same facilities as the solution in GA (see Table 4).

A sensitivity analysis was also run on the population size of the PSO (see Table 5). Same as the GA, the optimal solution was also reached at a population size of 35. However, in contrast to GA, the PSO was reaching the optimal solution almost every single time at larger populations. For a population of 100, the optimal solution was first found at iteration 103, when the number of function evaluations (NFEs) was 10502. See Figure 5 for the graph comparing Best Cost with NFEs for both the GA and PSO.

Table 1 Genetic Algorithm Parameters

Parameter	Value
Number of iterations	500
Number of population	50
Crossover Percentage	0.7
Mutation Percentage	0.2
Mutation rate	0.02

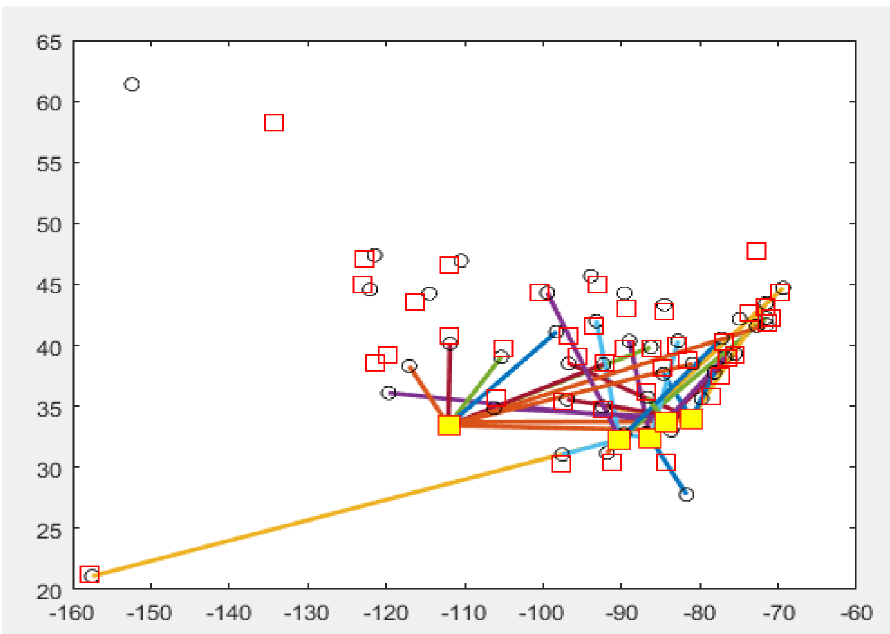

Figure 3 Genetic Algorithm Solution

Table 2 Best Costs for Different Population Sizes (GA)

Population Size	Best Cost
20	62703649.27
25	89685825.05
30	86999668.11
35	52291839.23
40	75917982.09
45	52291839.23
50	52291839.23
55	75917982.09
60	52291839.23
65	62703649.27
70	62703649.27
75	77331748.91
80	66089538.9
85	52291839.23
90	52291839.23
95	52291839.23
100	52291839.23

Table 3 Particle Swarm Optimization Parameters

Parameter	Value
Number of iterations	500
Number of population	50
Φ_1	2.1
Φ_2	2
Inertia weight	0.616
Damping ratio	0.99
Personal learning coefficient	1.5327
Global learning coefficient	1.4597

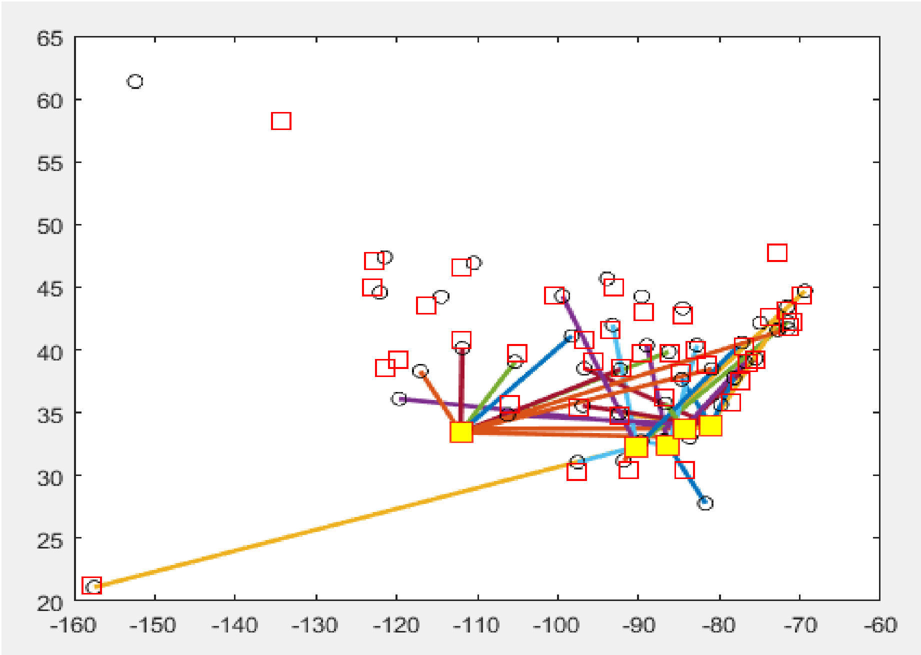

Figure 3 Particle Swarm Optimization Solution

Table 2 States assigned to each facility

Unassigned	Montgomery	Phoenix	Atlanta	Jackson	Columbia
Alaska	Alabama	Colorado	Arizona	Connecticut	Arkansas
Idaho	Florida	Georgia	California	Hawaii	Kansas
Michigan	Illinois	Indiana	Delaware	Iowa	Kentucky
Minnesota	Mississippi	Missouri	Maryland	Louisiana	New Hampshire
Montana	Ohio	Nebraska	South Carolina	Maine	New Mexico
New York		Nevada	Tennessee	Massachusetts	North Carolina
Oregon		Rhode Island		Pennsylvania	Oklahoma
Washington		Utah		South Dakota	Virginia
Wisconsin		West Virginia		Texas	

Table 3 Best Costs for Different Population Sizes (PSO)

Population Size	Best Cost
20	73267049.08
25	73225900.76
30	96862264.76
35	52291842.51
40	52291841.74
45	72668171.66

Population Size	Best Cost
50	52291841.33
55	52291840.88
60	66089540.28
65	52291840.27
70	52291839.99
75	52291840.39
80	52291840.92
85	52291840.81
90	52291840.25
95	52291839.75
100	52291839.75

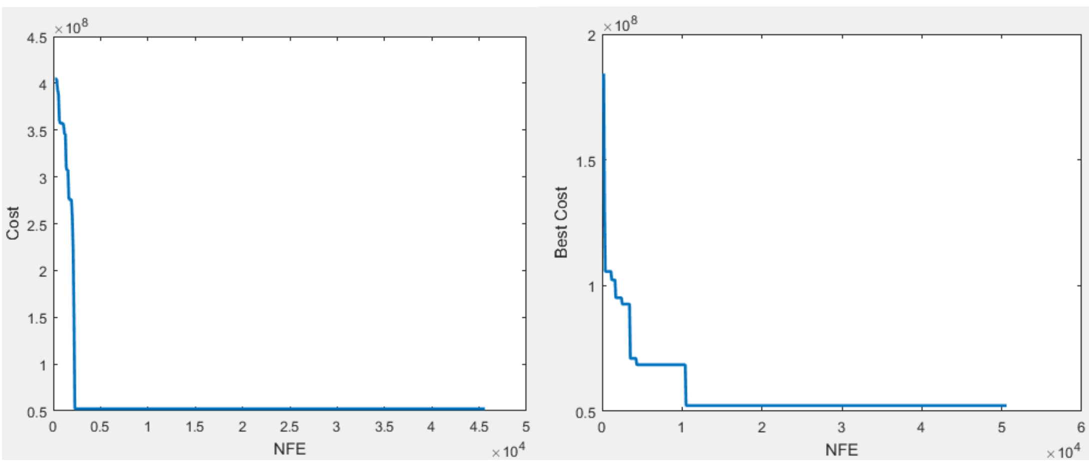

Figure 5 Best Cost against NFE (GA, left; PSO, right)

5. Future Work

One limitation to this work is that there is no maximum distance requirement; the model currently assumes that demand can be filled from states that are very far apart. For example, the solution assigns the demand from Hawaii to be filled in Jackson, Mississippi This is unrealistic, but a future model could incorporate that demand can only be filled from states that share a border, or are within a specified distance. Furthermore, while the algorithm decided to create a facility in Columbia, SC, it actually assigned South Carolina's demand to be filled by Atlanta, GA.

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