Geospatial Analysis of Rural Emergency Medical Service (EMS) Stations in South Dakota

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Abstract

This research paper aims at evaluating rural Emergency Medical Service (EMS) stations from spatial perspective and performing location optimization under current transportation network to reach specific targets. This study used data collected in South Dakota, including EMS ambulance data, station data, and highway network information. Meanwhile, different statistical methods associated with GIS techniques were adopted in this study.

Keywords

Emergency Medical Service, transportation network, geospatial analysis, location optimization

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Introduction

Rural transportation network connects local residents to employment, health care, social activities, and business opportunities. Functional and reliable rural transportation system is critical to the rural economic growth, public health, traffic safety, and social welfare. Long travel distances in South Dakota, a prominent rural state, are not uncommon because of sparsely distributed population. Delivering people, goods, and services becomes more difficult as distances increase, especially for time-sensitive services such as EMS. Unintentional mortality rate attributed to diseases, fertility, and motor vehicle crashes is higher in rural settings than urban settings [1] According to the NHTSA, "Delay in delivering emergency medical services is one of the factors contributing to the disproportionately high fatality rate for rural crash victims" [2]. According to a survey of the rural experts, access to EMS has been considered as the top ranking rural health concern [3].

Longer distance has been considered as a critical factor for the higher en-route time (travel time to the incident scene) in rural areas [4], so the location of EMS stations can directly contribute to the service performance. Higher accessibility to the EMS station indicates a higher service performance. As a result, the objective of this study was to assess EMS station locations using GIS methods and provide possible optimal solution based on the current highway network.

Literature Review

To evaluate the EMS facility location, previous literatures were searched on geospatial analysis for similar problems. The spatial relationship of EMS stations and each 911 call can be considered as the co-location pattern, an ecological term indicating which kind of spatial features frequently locate together [5]. Thus, this co-location pattern served as an approach to identify if EMS stations cluster around 911 calls, providing a qualitative assessment of the local EMS performance: the accessibility to the EMS station location.

In terms of the optimization of the EMS station locations for a better service performance, maximizing the ambulance coverage and minimizing the en-route time or distance are considered as two basic measures. The former is treated as the maximal covering location problem (MCLP), where ambulances are located at existing stations on the network to maximize the demand that can be served in a specified time or distance [6]. Besides, another covering problem called location set covering problem (LSCP) aims to minimize the number of facilities when all demand points are covered [6]. The latter includes p-center problems and p- median problems, where *p*-median problem minimizes demand-weighted travel distance whereas the *p*-center problem minimizes the maximum distance between demand zones and their nearest ambulance station [6].

Although MCLP can maximize the service coverage, which can be considered as an evaluation objective, other aspects may need to be considered for rural areas. Unlike the urban areas which is more populous, disparities exist in the access to the EMS stations due to the sparsely distributed population. Besides the demand zones covered by the service, uncovered areas are also important because even if a zone cannot be responded to within the response time standard, patient survivability rates are directly related to response time [7]. So it's necessary to minimize the average distance from an uncovered zone to the closest station, which is a transformation of p-median problems considering only uncovered demand zones. Considering this additional objective which can be treated as the service equity problem, bi-objective problem was generated.

In all, MCLP model was selected to achieve the first objective to maximize the coverage rate; and bi-objective models considering additional equity objective would be proposed in the methodology part.

Metaheuristic was considered as the most effective solution to the proposed optimization problem. Some metaheuristic solutions including genetic algorithm, simulated annealing, ant colony optimization, tabu search suit for the location optimization problem, and genetic algorithm has been proven the most popular and effective one [8]. So genetic algorithm was selected to solve the proposed model.

Methodology

Cross K Function

Cross K function is to analyze the co-location pattern between two kind of points, for example A $(a_1, a_2, \dots, a_i)$ and B $(b_1, b_2, \dots, b_j)$: whether the two kind of points appear to be clustered, dispersed, or randomly distributed [9]. To test this effect, the null hypothesis is that all the points in A are randomly distributed following a binomial point process regardless of location of B. The cross K function and corresponding L function is shown below:

$$\mathrm{K}^{\mathrm{ba}}(\mathrm{r}) = \lambda_a^{-1}\mathrm{E}\begin{pmatrix} number\, of\ Points\ A\, within\, distance\, r \\ of\ a\ point\, b_i\ in\, B \end{pmatrix}$$

$$L^{ba}(r) = \sqrt{\mathrm{K}^{ba}(\mathrm{r})/\pi}$$

Where,

λ_a = Density (number per unit area) of points A;

E ( ) = expected value of A following binomial point process for each point in B;

K^{ba}(r) = K function of A relative to B, for the binomial point process;

L^{ba}(r) = L function of A relative to B, for the binomial point process;

Similar to the K function, the expected value can be plotted with upper and lower 5% bounds which indicated 95% confidence interval using the Monte Carlo simulation. If the L(r) –r is above the upper bounds, the pattern can be treated as significant clustered. If the L(r) –r is below the lower bounds, the pattern can be treated as significant dispersed. If the L(r) –r is within the bounds, the points can be treated as randomly distributed.

Genetic Algorithm

Genetic algorithm adopts the natural evolution from Darwin's theory of evolution to the optimization algorithm, and has been used in different problems including facility location[10]. Similar to natural evolution, the essence of the algorithm is to improve the offspring using reproduce mechanisms, including crossover and mutation, and the better ones with higher fitness functions are kept[10]. The algorithm is a kind of bottom up approach which starts with a set of solutions and results in one optimal solution[10].

Data Analysis

Data Collection and Processing

EMS dataset in 2013 and roadway dataset for South Dakota were used. The EMS dataset including incident address and EMS station address was requested from state EMS office and roadway dataset were obtained from SDDOT. Google API was used to convert the addresses to coordinates. 36,198 911 incidents with coordinates and 109 EMS stations in 2013 were used in the analysis, which is shown in Figure 1 Incident and EMS Stations in SD in 2013.

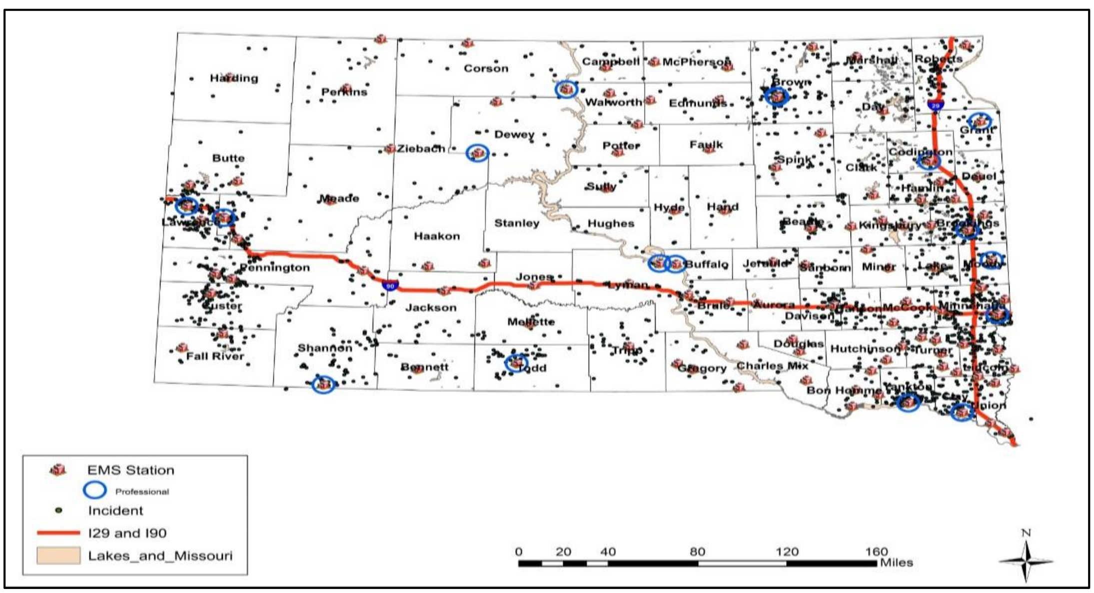

Figure 1 Incident and EMS Stations in SD in 2013

Geospatial Evaluation of EMS Stations

The Cross-K function was applied to examine the co-location pattern between incidents and EMS stations if there is any. Using R, the results are shown in Figure 2 where the observed curve is located above the 5% upper bound of the theoretical curve when the distance r is shorter than 25 miles. The finding concludes that there is strong colocation pattern between incidents located within 25 miles to an EMS station. When the distance is larger than 25 miles, the spatial association between the EMS station and 911 calls is weak. Since most concentrations of 911 calls are with 25 miles of the EMS station as shown in Figure 2, the current EMS stations seem to be positioned in line with where the 911 calls may occur, which means the accessibility to each EMS station from the incident spots is in an acceptable level.

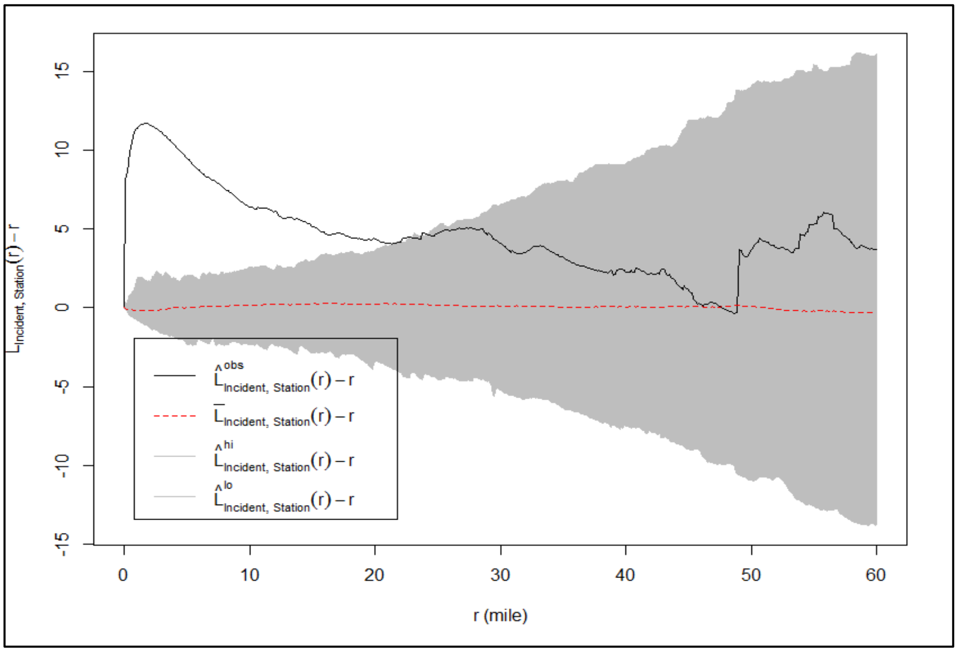

Figure 2 Cross K Function and L Function for Incident Location and EMS Station

Location Optimization of EMS Stations

According to NFPA 1710, “Advanced life support response time: Eight minutes (480 seconds) or less for the arrival of an advance life support unit at an emergency medical incident, where the service is provided by the fire department” [30]. In this report, response time refers to en-route time. Thus, 8-min service coverage was set as the benchmark.

The purpose of optimizing the EMS station locations is to increase the 8-minute coverage of the service area. In addition, it is necessary to consider service equity for demand areas that are under-covered or uncovered. Hence, the two objectives are listed as follows: 1) Objective 1 (Coverage Ratio): maximize the number of calls covered by the service Z1; and 2) Objective 2 (Service Equity): minimize average en-route time for uncovered demand zones Z2. To achieve both objectives, two targets for the optimization process were identified: the first target is just the first objective, and the second target is the combination of the two objectives, meaning to maximize the coverage rate as well as to minimize the average en-route time for uncovered demand points.

The optimization formulation is explained below. Let Z1 and Z2 represent the two objectives. Let the first constraint to be the definition of y_i, which is a binary outcome (i.e., y_i equals one if node i is covered by one or more available facilities and zero otherwise) and the second constraint to be the total number of available facilities.

Target 1: Objective 1 Max $\mathbf{Z1} = \frac{\sum_{i \in I} D_i y_i}{\sum_{i \in I} D_i}$

Target 2: Objective 1 and 2 Max $\mathbf{Z1} = \frac{\sum_{i \in I} D_i y_i}{\sum_{i \in I} D_i}$

and Min $\mathbf{Z2} = \frac{\sum_{i \in I} D_i (1 - y_i) \min(t_{ij})}{\sum_{i \in I} D_i (1 - y_i)}$

Subject to:

$$y_i \le \sum_{j \in N_i} x_j \quad i \in I$$

$$\sum_{j \in J} x_j = p$$

$$x_j \in \{0,1\} \quad j \in J$$

$$y_i \in \{0,1\} \quad i \in I$$

Where:

i , I The index and set of demand points,

j , J The index and set of candidate facility locations,

D_i 911 demand at point i ,

t_{ij} The shortest en-route time from demand point i to facility at point j ,

T The time standard within which coverage is expected (T =8),

N_i $\{j \mid t_{ij} \le T\}$ the point j that are within a time of T to point i ,

p The number of facilities to be built,

x_j A binary variable that equals one when a facility is built at point j and zero otherwise, and

y_i A binary variable which equals one if node i is covered by one or more facilities and zero otherwise.

In this study, Minnehaha County in SD was used as a case study example. Figure 3 shows candidate stations and demand zones in Minnehaha County. According to the "National EMS Assessment", about forty percent of the EMS agencies are Fire Departments [11]. Besides, EMS can be stationed at a hospital, a police department, or an independent government agency and a non-profit or profit corporation. The existing stations were labeled from Station1 to Station4 which were all based on the fire station. The candidate station locations were selected as: 1) the existing stations (Station1, Station2, Station3 and Station4); 2) hospital locations (Station5, Station6, and Station7), a police station

(Station 8); 3) randomly selected locations (Station9 and Station10). Here, the randomly selected locations were just some intersections close to the obvious incident clusters and were chosen by the author. In the real planning, the randomly selected locations should be replaced by the suggested locations provided by the local agencies.

“Create Fishnet” tool was first used to create grid cells as demand zone. Here 1 mile by 1 mile cell was chosen to accurately reflect the location of each 911 call. After the grids were generated, 911 calls were aggregate by each grid cell and the number of calls in each cell was set as cell attribute. Then the central coordinates for each demand zone were identified, and the cost matrix, specifically the time matrix based on the highway network, from the candidate stations to the central points were calculated using the network analyst toolbox in ArcGIS. With the time matrix and the call volume in each demand zone, optimization process can be performed to obtain the solution for the selected number of facilities.

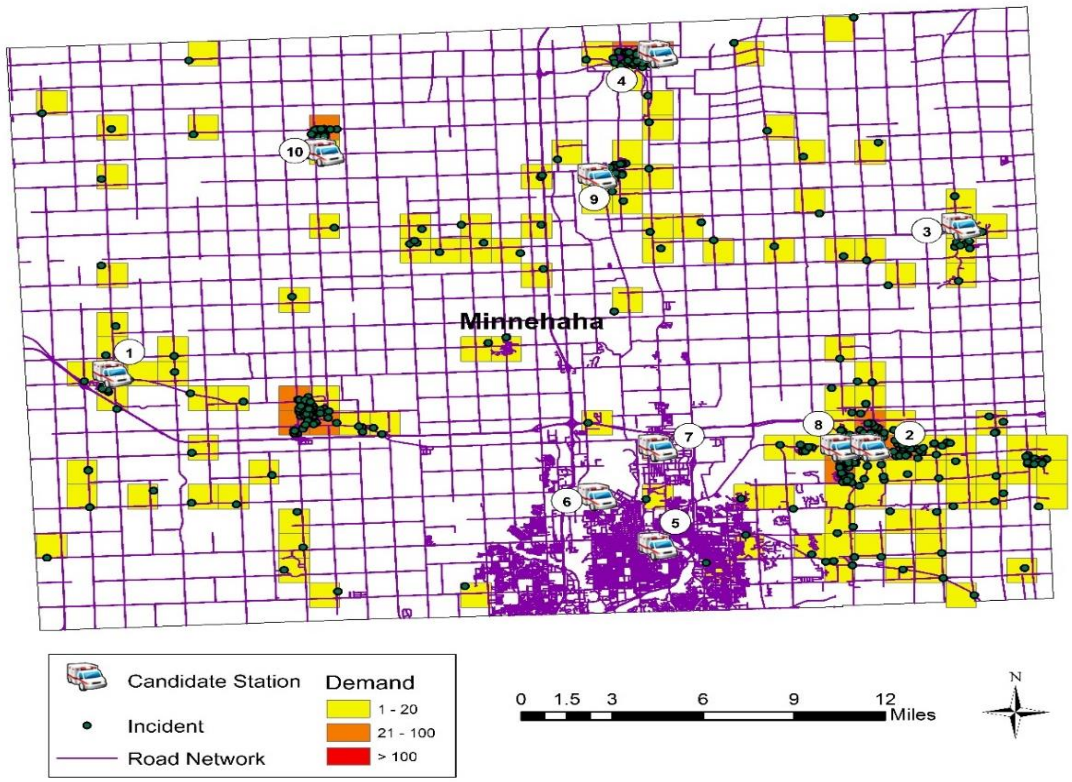

Figure 3 Minnehaha County with Candidate Stations and Demand Zones

Genetic algorithm in the R software was used to generate the optimal solutions for single objective and multiple objectives individually. Due to the limited source and moderate demand in Minnehaha County, the number of facilities to be located was set as 4, 5, 6 and 7 (p=4, 5, 6, 7) respectively. Table 1 shows the optimal solutions for both targets based on different number of facilities to be built.

Table 1 Optimal Solutions for Minnehaha County

Optimized Location		Number of Facilities			
		4	5	6	7
Target	**Single Objective**	4,6,8,10	3,5,6,8,10	2,4,6,8,9,10	1,2,5,6,8,9,10
	Multiple Objectives	5,6,7,8	1,5,6,7,8	1,2,5,6,8,10	1,2,3,5,6,8,10

Table 2 shows the coverage ratio and average en-route time for uncovered zones between the current station locations and optimized locations based on the current number of locations. Significant improvement has been observed on both coverage objective and equity objective, which suggests the current station locations are neither qualified nor located in the most effective places. The comparison between the single-objective and multi-objective solutions concludes that the added equity objective reduces the coverage rate from 75.18% to 64.28% in exchange of very slight decrease (i.e., 0.47 minutes) on average en-route time for uncovered zones.

Table 2 Current Station Location Vs Optimized Location

	Coverage Rate (%)	**Average ERTime for Uncovered Zones [12]**	**Facilities**
Existing	43.39	21.20	1,2,3,4
Single Objective	75.18	12.89	4,6,8,10
Multiple Objectives	64.28	12.42	5,6,7,8

In summary, optimal locations for EMS stations were identified based on the current road network targeting: single objective (coverage ratio) and multiple objectives (coverage ratio and service equity). Both coverage rate and service equity were significantly improved after the optimization process for the study county. When looking into the multiple objectives, the added equity objective has a negative effect on the coverage ratio but reduces the average travel time for the uncovered demand zones.

Conclusion

This study accomplished two tasks: geospatial evaluation and optimization of EMS station locations under the highway network. The spatial association of 911 calls and EMS stations were confirmed by the Cross-K function. It indicates an acceptable accessibility for the EMS stations in this state overall. However, the co-location of the 911 calls and EMS stations does not always guarantee a timely and swift service.

If the service provided by the current EMS stations is not sufficient, the stations can be either relocated or supplemented by more to increase the service coverage and quality when the resource is available. Travel time based on the current transportation network is considered as the key factor to the location of the EMS stations. All the stations should be strategically located to maximize their coverage. Two targets were set up for increasing coverage ratio and service equality. Optimal solutions were obtained by running the genetic algorithm in the R software. Assisted with accurate information, the optimization tool can help the EMS agencies to strategically plan new or relocate existing stations to provide better services with limited resource.

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