

A Service Location Optimization for Improving Rural Emergency Medical Services

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ABSTRACT

Approximately 40,000 fatalities transpire on U.S. highways each year with more than half occurring in rural areas. With such a high percentage of total fatalities, efficient Emergency Medical Services (EMS) becomes even more crucial in these rural areas. After an accident occurs, the time necessary for victims to receive care from EMS is critical to their survival. EMS provides pre-hospital health care for patients from the time of the 911 call to the arrival of the ambulance where the care is then transferred to a hospital. When comparing urban EMS to rural EMS, there are obvious challenges the latter must navigate to provide efficient medical care. Consequently, it's necessary to identify approaches to improve the EMS performance in rural areas. The goal of this paper is to evaluate and optimize rural EMS stations from a spatial perspective, while evaluating the spatial pattern between EMS stations and incidents and recommending the optimal locations of EMS stations. The data that was analyzed to accomplish these goals was from South Dakota, a rural state. This data was used to perform the spatial analysis and to build the location optimization model. A location optimization model, using a genetic algorithm in R software, was developed for rural EMS to increase the coverage ratio and service equity. This method serves as a tool for rural EMS officials to develop new stations or even relocate existing stations to improve service performance, which is essential given their limited resources.

1 INTRODUCTION

2 In 2015 alone, more than 35,000 people lost their lives on U.S. highways with more than half of
 3 these fatalities occurring in rural areas (1). This issue appears even more serious in rural areas
 4 when analyzing fatality rate where rural areas had a 2.6 times higher rate than urban areas (1).
 5 Fatality rate is the rate of crash related deaths per 100 million miles traveled. Much of the
 6 difference in the fatality rate between urban and rural areas may be attributed to increased time
 7 needed to reach the victim in the latter area (2). Since rural areas have a sparsely distributed
 8 population, longer travel distances are often required for services such as EMS. Obviously, this
 9 creates a significant challenge to provide timely service for these time-sensitive situations.
 10 Logically, the best course of action is to develop methods to decrease the time needed for EMS
 11 to reach the victim as this time period is often critical to increase the chance of survival. Issues
 12 related to rural EMS have been identified by the National Cooperative Highway Research
 13 Program (NCHRP) 500 report "Volume 15: A Guide for Enhancing Rural Emergency Medical
 14 Services." They proposed an objective to be "to reduce the time from injury to appropriate
 15 definitive care" in order to improve rural EMS (3).

16 Besides the longer travel distance, challenges facing rural EMS include geographic
 17 barriers, lack of professionals/paraprofessionals, aging or inadequate equipment, the absence of
 18 specialized EMS care, and local medical facilities (3). Undoubtedly, it is necessary to make
 19 efforts to improve service performance in these rural areas.

20 With the intention of improving rural EMS performance, this study focuses on the spatial
 21 location of EMS stations. The goal of this paper is to evaluate and optimize rural EMS stations
 22 from a spatial perspective while evaluating the spatial pattern between EMS stations and
 23 incidents. Then a recommendation is given for the optimal locations of EMS stations to achieve
 24 better service performance. In order for this to happen, a location optimization model must be
 25 built to perform the spatial analysis. EMS data from South Dakota, a rural state, is used for this
 26 model.

28 LITERATURE REVIEW

29 The National Highway Traffic Safety Administration (NHTSA) developed 35 EMS performance
 30 measures for the local system, including time-based variables (e.g., Mean Emergency Patient
 31 Response Interval) and outcome-based variables (e.g., EMS Cardiac Arrest Survival Rate to
 32 Emergency Department Discharge) (4). In order to evaluate EMS performance, several metrics
 33 were proposed, such as time-related, distance-related, and outcome-based variables. To measure
 34 road safety performance associated with trauma management, researchers from Europe
 35 developed 14 indicators, which were categorized into five groups: a) availability of EMS
 36 stations; b) availability and composition of EMS medical staff; c) availability of and composition
 37 of EMS transportation units; d) characteristics of the EMS response time; and e) availability of
 38 trauma beds in permanent medical facilities (5). Among these performance measures, response
 39 time is considered as a major performance index, which has been extensively used to evaluate
 40 EMS performance (4-6). Although the patients' treatment outcome depends on many factors
 41 such as the injury severity and pre-existing conditions, the time required for an EMS unit to
 42 arrive at the scene (response time) plays a significant role in survival rate (6). To date, a clear
 43 relationship has not been fully established between clinically significant improvements in patient

outcome and reduction in EMS time to definitive care (6). However, the consensus is that shorter time to definitive care is associated with improved outcome of those that need emergency care.

Researchers have made numerous efforts to identify solutions to improve EMS performance. A couple of studies focused on approaches to improve service performance, varying from reducing response time by quantile regression to increasing survivability by logistic analysis (7; 8). Do et al. used quantile regression analysis to identify factors related to response time by dividing factors into patient and system levels (7). Meng et Al. introduced a mixed logistic regression model while considering the uncertainty for the accident notification and response times to predict the risk of death in work zones (8).

Besides the above regression models, numerous studies have focused on identifying the optimal locations of EMS stations by building optimization models. Maximizing the ambulance coverage while minimizing the en-route time or distance are considered as two primary objectives for location optimization of EMS stations (9). The former is referred to as the maximal covering location problem (MCLP), which is to maximize the demand that may be served within a required time or distance (9). The latter is referred to as the location set covering problem (LSCP), which aims to minimize the number of facilities when all demand points are covered. Demand points are based on which p-center and p-median problems are derived (9). The p-median problem tries to minimize demand-weighted total travel distance whereas the p-center problem aims to minimize the maximum distance between demand zones and their nearest ambulance station (9).

Given service uncertainty, such as availability of an ambulance, additions were made to the previous EMS location optimization models. When considering the probability for the unavailability of an ambulance, Daskin et al. proposed a Maximal Expected Covering Location Problem (MECLP) model (10). By treating the probability of ambulance availability as a station-specific variable, Hogan and ReVelle modified the MCLP model by introducing the “backup-coverage” objective (11). “Backup-coverage” means that another ambulance may cover the demand points left by the initially assigned ambulance with the goal being to maximize both the first and the second coverages. Building on this concept, Liu et al. proposed a double standard model, which incorporates two service coverage standards, making the model more complicated than the “backup-coverage” model (12). An adjusted MEXCLP was suggested by Batta to add the unavailability probabilities associated with each facility location (13). Unfortunately, all of the aforementioned studies focused on urban EMS, and none of them were built based on the unique characteristics for rural EMS.

Ambulance location problems were analyzed by several papers where multiple objectives were developed (14; 15). For example, Daskin et al. associated various covering models with different objectives into a multi-objective model, allowing it to balance number of facilities and the extra coverage (14). Furthermore, Chanta et al. proposed a bi-objective covering location model for rural EMS, with service coverage and service equity as the two objectives (15). Service equity represents the fairness of the locations of stations relative to patients. McLay and Mayorga concluded from their research that “*longer response travel time results in more equitable patterns of survival: patient lives were saved in rural areas at the expense of losing patient lives in the urban areas*” (16).

The current study aims at evaluating and improving rural EMS from a spatial perspective. An overall spatial assessment of all EMS stations was made by analyzing the spatial co-pattern

between 911 demand points and station locations. After examining the system as a whole, the study shifted its focus to the most efficient allocation of individual EMS stations in order to provide timely service. This timely service known as response time, starts at the dispatch of the ambulance to the arrival at the incident scene. Consequently, response time was selected as the service performance metric. In turn, location optimization of EMS stations, considering characteristics of rural EMS, was performed to improve EMS efficiency.

DATA COLLECTION

EMS incident, EMS ambulance station, and highway network data were collected in this study. A subset of the National EMS Information System (NEMSIS) data bank consisting of South Dakota EMS incident records covering the period between 1/1/2013 and 12/31/2013 was obtained from the Eastern South Dakota EMS Data office. Figure 1 shows the timeline of the EMS process with the information from the NEMSIS dataset.

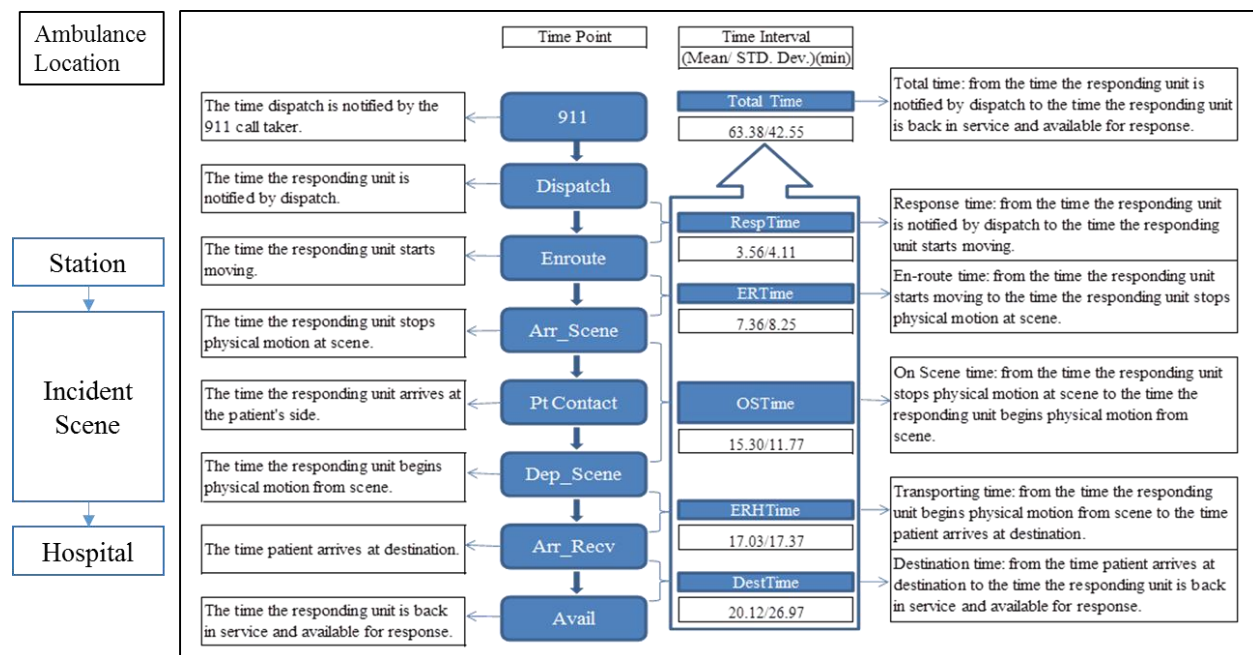


FIGURE 1 Timeline of EMS process.

The EMS incident data mainly includes time points (such as “Dispatch”), time intervals (such as “ERTime”), odometer, and incident location. This study focuses on 911 calls, which has 36,198 records in 2013. “Google Map API” was used to convert the addresses of incident locations to coordinates. “RespTime” in the dataset is called chute time in most EMS documents, which starts from the notification of dispatch to the moving of the ambulance. Thus, the sum of chute time and en-route time is equivalent to response time for this study.

EMS ambulance station data was found from the home page of South Dakota Emergency Medical Services. This data contains information such as name, location, and professional status and vehicle counts for each EMS station. Figure 2 shows the spatial location for the 36,198 911 incidents and 109 EMS stations in 2013.

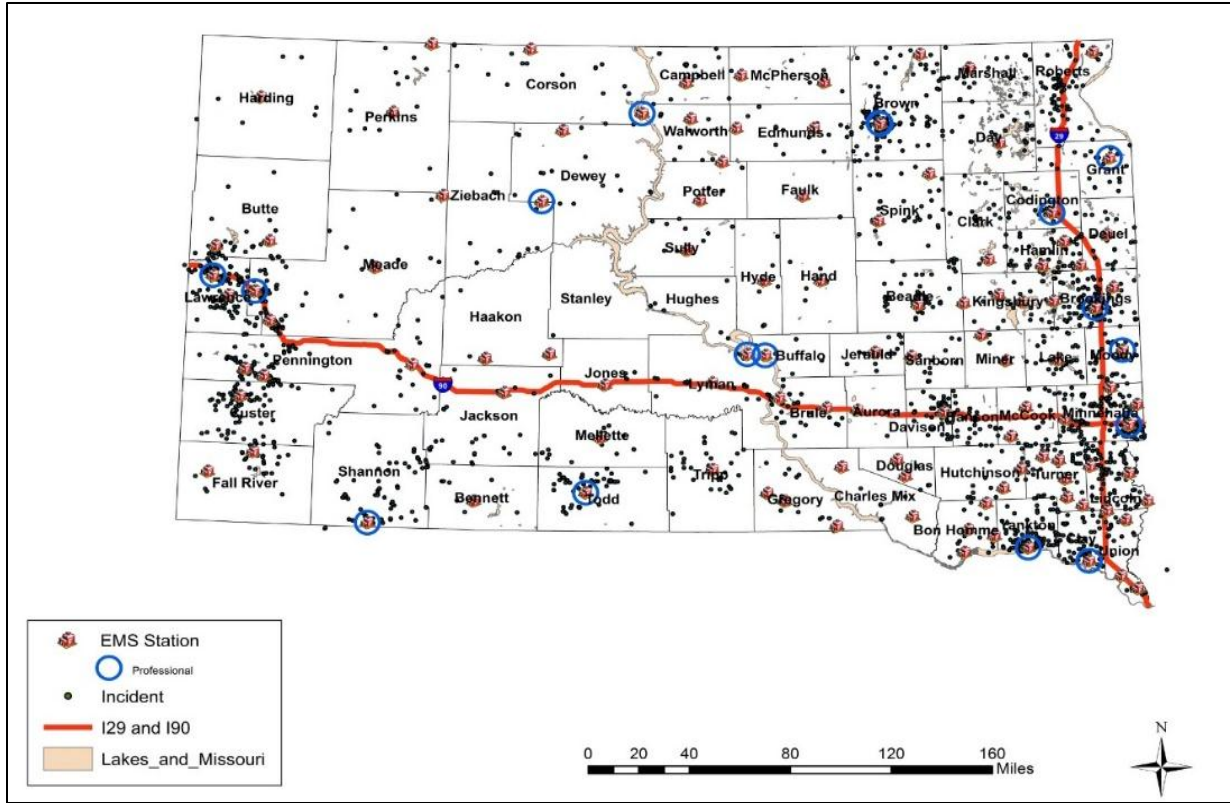


FIGURE 2 Incident and EMS stations in SD in 2013.

The Non-State Trunk Road Inventory (NSTRI) dataset was used as the highway data, which is provided by South Dakota Department of Transportation (DOT). It includes both interstate highways and local roads in South Dakota. Speed limit information in this dataset was used as travel speed to perform the network based analysis. The calculated average en-route speed of 35 mph was used as the travel speed for roads with missing speed limit information.

SPATIAL ASSESSMENT OF STATEWIDE EMS STATIONS

It may be observed that 911 incidents seem to cluster around EMS stations in Figure 2. A statistical technique called Cross-K function was applied to analyze the data to confirm the visual assessment. Cross-K function is well suited for analyzing the co-location pattern between two kinds of points, for example A ($a_1, a_2, \dots, a_i$) and B ($b_1, b_2, \dots, b_j$): whether the two kinds of points appear to be clustered, dispersed, or randomly distributed (17). The null hypothesis is that all the points in A are randomly distributed following a binomial point process regardless of the location of B (17). The cross K function, and corresponding L function is shown below:

$$K^{ba}(r) = \lambda_a^{-1} E(\text{number of points A within distance } r \text{ of a point in B}) \quad (1)$$

$$L^{ba}(r) = \sqrt{K^{ba}(r)/\pi} \quad (2)$$

Where,

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

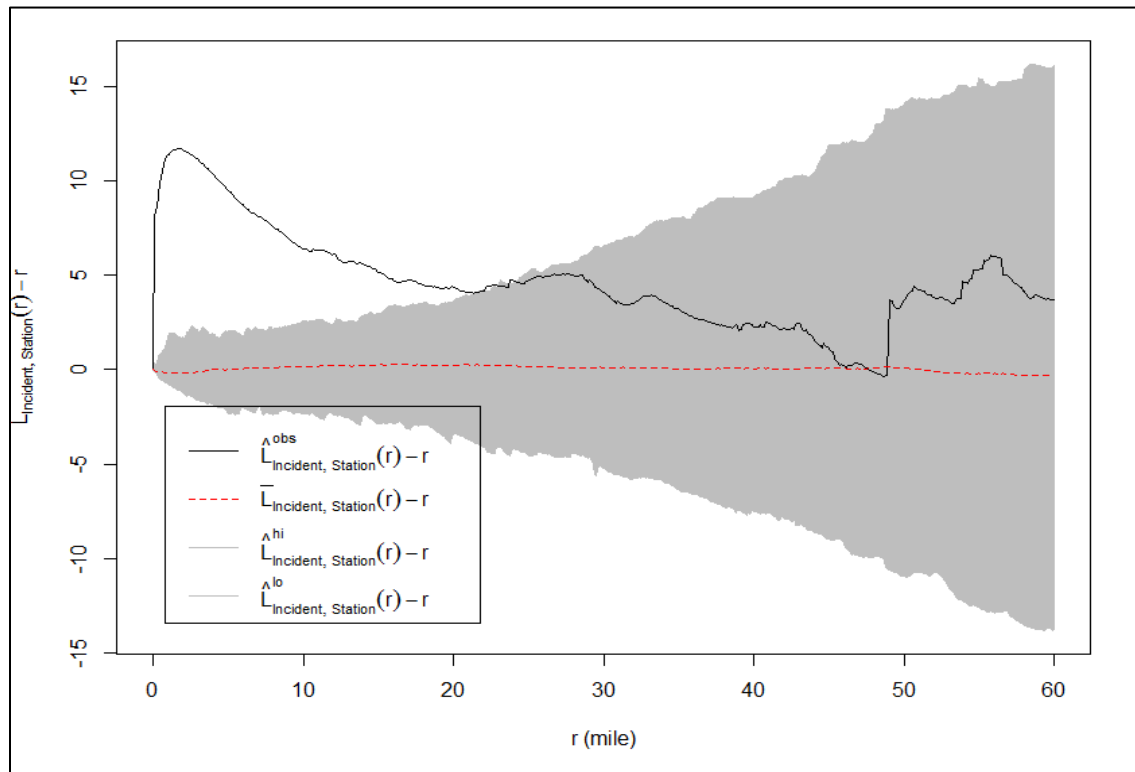
2 $E(\cdot)$ = expected value of A following binomial point process for each point in B;

3 $K^{ba}(r)$ = K function of A relative to B, for the binomial point process;

4 $L^{ba}(r)$ = L function of A relative to B, for the binomial point process;

5 The expected value can be plotted with upper and lower 5% boundaries, which indicate a
6 95% confidence interval using the Monte Carlo simulation. If the $L(r) - r$ is above the upper
7 boundary, the pattern can be considered to be significantly clustered. If the $L(r) - r$ is below the
8 lower boundary, the pattern can be interpreted as significantly dispersed. If the $L(r) - r$ is within
9 the boundaries, the points can be considered to be randomly distributed.

10 The Cross-K function was applied to examine the co-location pattern between 911
11 incidents and EMS stations by using R software. The results are shown in Figure 3: the observed
12 curve is located above the 5% upper boundary of the theoretical curve when the distance r is
13 shorter than 25 miles. This finding suggests there is a strong co-location pattern between stations
14 and their nearby incidents, which are located within 25 miles of the EMS station. When the
15 distance is greater than 25 miles, the spatial association between the EMS station and 911 calls is
16 weak. Since most concentrations of 911 calls are with 25 miles of the EMS station as shown in
17 Figure 2, the current EMS stations seem to be positioned in line with where the 911 calls may
18 occur.



19

20 **FIGURE 3 Cross K function and L function for locations of incidents and EMS stations.**

21

LOCATION OPTIMIZATION OF EMS STATIONS

Facts for Rural EMS

Before formulating the optimization models, some facts should be considered for rural EMS. Below show the major rural EMS facts, which are different from urban EMS.

1) Volunteer EMS

Lack of professional EMS staff has long been a major issue affecting service performance in rural areas. In fact, studies indicate that approximately 75% of providers in rural areas are volunteers while only 30% in urban areas (18). In South Dakota, less than 20% of the EMS stations have professional personnel (19). Not surprisingly, the EMS data shows that chute time ("RespTime") was significantly shorter for stations with professional staff than those staffed by volunteers (2.76 min vs. 4.53 min). This longer chute time for volunteers reflects the fact that volunteers need more time to reach EMS stations to pick up an ambulance. In the proposed optimization model, time spent for volunteers to get to the EMS station should be considered when calculating chute time.

2) Small Service Demand

When optimizing the locations of EMS stations for urban areas, one major consideration is the availability of an ambulance due to the large demand for service. However, for rural EMS, ambulances are available most of the time. Unit hour utilization (UHU), indicates the amount of time one ambulance unit is occupied over the total amount of time, which signifies whether a station is busy or not. Most stations in South Dakota had a UHU less than 2%, and the highest UHU was around 10%, which was also considered not busy. In other words, most stations may not have even one dispatch for several days. Even during the busiest days, the service demand remains low. Thus, the service availability is not considered in the models for the present study.

Besides the difficulties associated with a volunteer EMS, the longer travel distance is treated as one of the biggest challenges for rural EMS. Unlike populous urban areas, disparities exist in the accessibility to EMS stations. In addition, uncovered areas present another challenge as they increase the likelihood that a patient may not be served within the response time standard. This issue is of paramount importance because patient survivability rate is directly related to response time. In order to improve this issue in the optimization model, it is necessary to increase the covered areas of timely service while reducing the response time for remote incident scenes (service equity).

Formulation of Optimization Model

In order to account for both the coverage rate (Objective 1) and the service equity (Objective 2), a multi-objective covering location model is proposed. The model lets Z_1 and Z_2 represent the two aforementioned objectives, which are to maximize the number of calls covered by the timely service and to minimize the average response time for uncovered demand zones, respectively. x_j is the decision variable, which indicates whether a station should be built in the candidate location. Equation 5 defines y_i , which equals one only if the demand node i is covered by one or more available facilities. Equation 6 shows the total number of available facilities. Equation 7

and 8 defines x_j and y_i as binary variables. A 15-minute threshold was set for response time based on the requirement for South Dakota EMS (20).

$$\text{Objective:} \quad \text{Max } Z_1 = \frac{\sum_{i \in I} D_i y_i}{\sum_{i \in I} D_i} \quad (\text{Objective 1}) \quad (3)$$

$$\text{and Min } Z_2 = \frac{\sum_{i \in I} D_i (1 - y_i) \min(t_{ij})}{\sum_{i \in I} D_i (1 - y_i)} \quad (\text{Objective 2}) \quad (4)$$

Subject to:

$$y_i \leq \sum_{j \in N_i} x_j, \quad i \in I \quad (5)$$

$$\sum_{j \in J} x_j = p, \quad (6)$$

$$x_j \in \{0,1\}, \quad j \in J \quad (7)$$

$$y_i \in \{0,1\}, \quad i \in I \quad (8)$$

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_j The estimated chute time for each candidate facility j

t'_{ij} The shortest en-route time from demand point i to facility at point j

t_{ij} The response time required for demand i to facility j , $t_{ij} = t_j + t'_{ij}$

T The time standard within which coverage is expected ($T = 15$),

N_i $\{j | t_{ij} \leq T\}$ which is a set of points j that is within a time of T for 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 the node i is covered by one or more facilities and zero otherwise.

Solution to Optimization Model: Genetic Algorithm

Metaheuristic was considered as one of the most effective methods for the proposed optimization problem. Among the metaheuristic solutions (e.g, genetic algorithm, simulated annealing, ant colony optimization, tabu search) which are suitable for the location optimization problem, the genetic algorithm has been proven to be most popular and effective (19). Thus, the genetic algorithm was chosen for this study.

The 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 (19). Similar to natural evolution, the essence of the algorithm is to improve the offspring using reproduction mechanisms, including crossover and mutations, resulting in offspring with higher fitness functions (19).

The steps for the genetic algorithm are shown in Figure 4 (21).

- *Step 1: Create initial population for the solutions (G set of individuals)*

G set of initial solutions will be created to activate the process.

- *Step 2: Evaluate the fitness function of each in the population*

The fitness function for each solution will be calculated. In turn, the fitness function will generate different fitness values. The optimal solution will have the highest fitness value.

- *Step 3: Repeat (generate offspring)*

Offspring will be generated by four steps, which are 1) selection of parent from individuals in the population, 2) performing genetic operators (crossover and mutation) to produce new individuals, 3) adding new individuals into the population and 4) removing individual with small fitness function. This step will be repeated until termination criteria are satisfied.

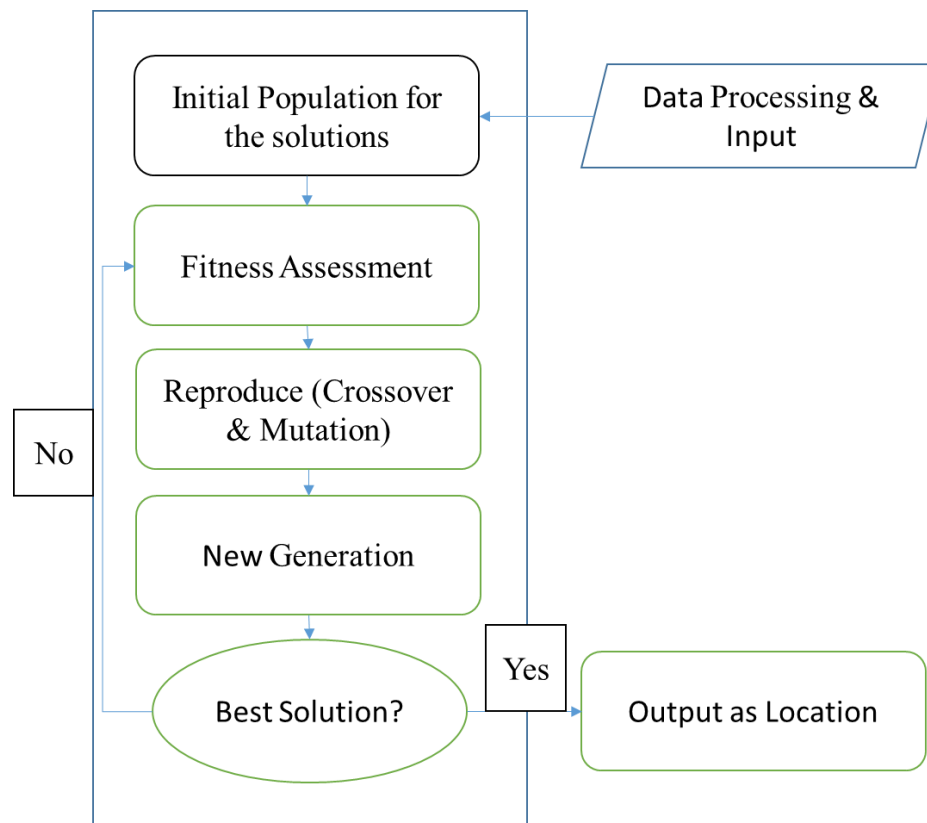


FIGURE 4 Flow chart for genetic algorithm.

The genetic algorithm in the R software was used to solve the multi-objective optimization model. A multicriteria evaluation technique called the weighted sum method was adapted, converting the multiple objectives (fitness functions) into a single objective (fitness function) by adding all of the weights for each objective (22). The weight should be determined by experts to represent the priority of each objective. Because there is no special preference in this study, equal weight is chosen for the fitness function, namely $w_1 = w_2 = 0.5$. As the genetic algorithm tries to maximize the fitness function, the corresponding fitness function of the second (minimization) objective should be the inverse. Equation 9 and 10 shows the fitness function for the two objectives.

$$F_1 = Z_1 = \frac{\sum_{i \in I} D_i y_i}{\sum_{i \in I} D_i} \quad (9)$$

$$F_2 = \frac{1}{Z_2} = \frac{\sum_{i \in I} D_i (1 - y_i)}{\sum_{i \in I} D_i (1 - y_i) \min(t_{ij})} \quad (10)$$

These two functions are combined into a single function in order to normalize the differing measurement scales. The combined fitness function is shown in Equation 11. F_{1max} , F_{1min} , F_{2max} , and F_{2min} can be obtained by using the genetic algorithm to maximize fitness functions F_1 , $\frac{1}{F_1}$, F_2 , and $\frac{1}{F_2}$, respectively.

$$F_3 = w_1 * \frac{F_1 - F_{1min}}{F_{1max} - F_{1min}} + w_2 * \frac{F_2 - F_{2min}}{F_{2max} - F_{2min}} \quad (11)$$

CASE STUDY

Data Preparation

Minnehaha County in South Dakota was chosen to optimize the locations of EMS stations. Data used for optimization in R software was prepared using ArcGIS by the following three steps.

1) Create Demand Zone.

The “Create Fishnet” spatial tool in ArcGIS was used to create grid cells (demand zones). Here “1-mile by 1-mile” cell were chosen to reflect the location of each 911 call accurately. 911 calls were aggregated for each cell with the number of calls as its attribute (Figure 5). The central point represented each demand zone.

2) Select Candidate Stations

According to the “National EMS Assessment”, about forty percent of EMS agencies are Fire Departments (23). Alternatively, EMS may be stationed at a hospital, a police department, an independent government agency, or a nonprofit/profit corporation. In this study, 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 sites (Station9 and Station10). Herein the randomly selected locations were mainly based on the demand zone and road network to cover a greater area. This selection would

be better after discussing with the county EMS officials. Candidate stations with demand zones in Minnehaha County are shown in Figure 5. The existing stations were labeled from Station 1 to Station 4 with the volunteer status. Except for the existing stations; it's assumed that all others are volunteer stations.

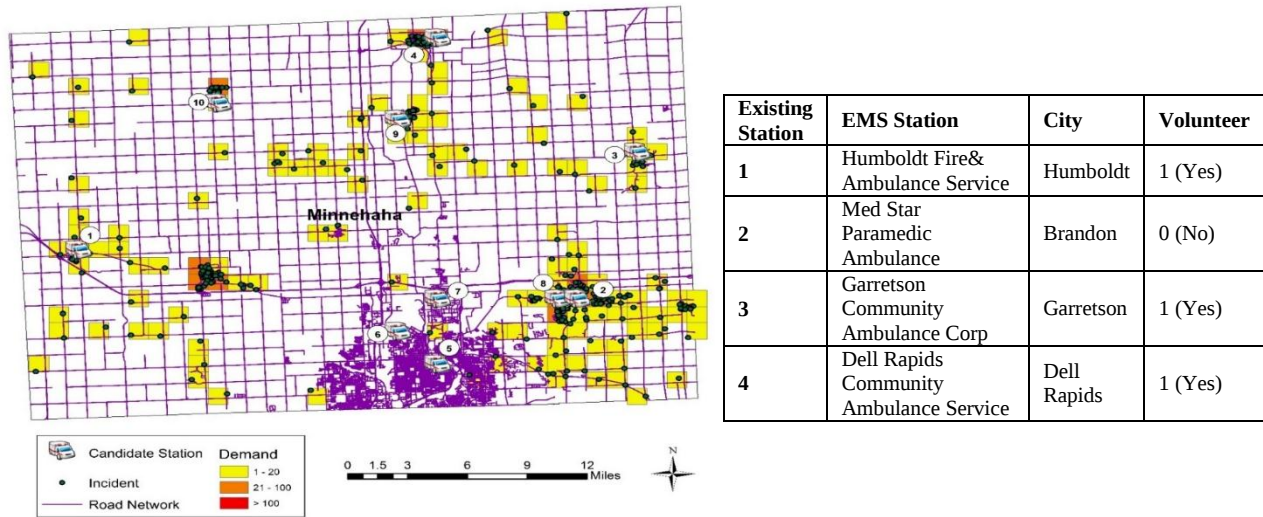


FIGURE 5 Minnehaha County with candidate stations and demand zones.

3) Create Time Matrix

Once the candidate stations were determined, the en-route time matrix, was calculated using the network analyst toolbox in ArcGIS. The en-route time matrix is the time necessary to travel from the candidate stations to the demand points. It should be noted that chute time differs between volunteer stations and professional stations. For volunteer stations, chute time includes the time required for the volunteer to get to the station and the preparation time in the station; while chute time is equivalent to the preparation time for professional stations.

To estimate the average time required for a volunteer to get to the station, the authors assume that the probability of a volunteer staying in one population block equals the percentage of that block's population. The census block data (shown in Figure 6) is obtained from the government website (<https://www.census.gov/geo/maps-data/data/tiger-data.html>). The estimated travel time to each station equals the population-weighted average travel time from all population blocks to each station. Table 1 shows this estimated travel time for each candidate station. National Fire Protection Association (NFPA) 1720 has a requirement of one-minute chute time, which may be used as the estimated preparation time in the station (24). All of the estimated chute times are shown in Table 1. The final response time matrix equals the chute time plus the en-route time.

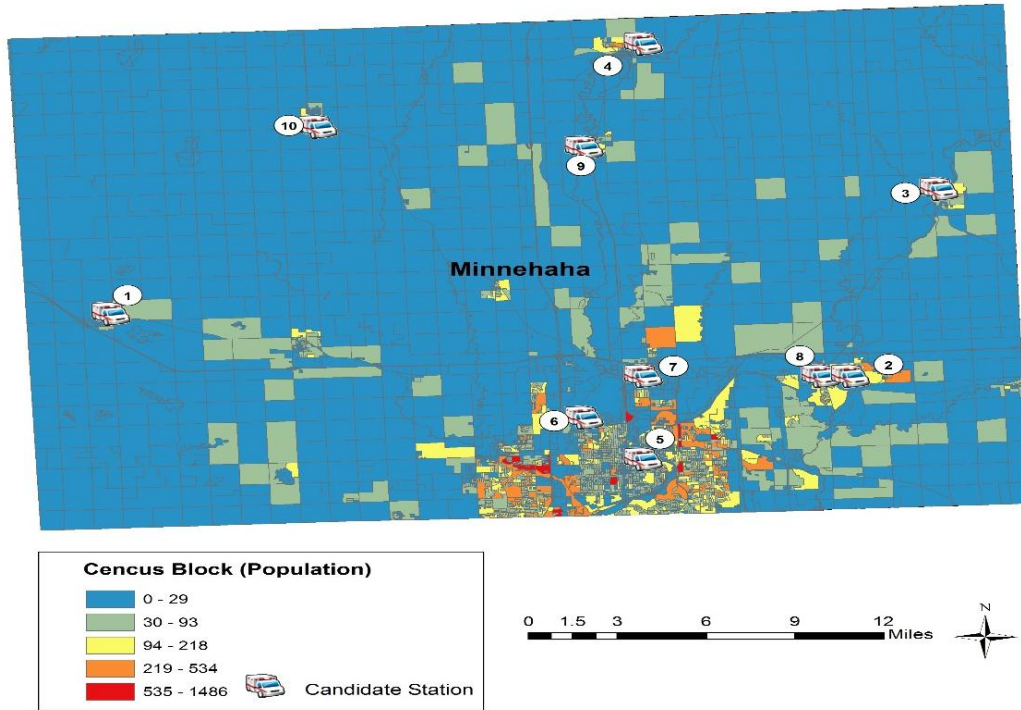


FIGURE 6 Census block map.

TABLE 1 Estimated Chute Time for Candidate Stations

Candidate Station	1	2	3	4	5	6	7	8	9	10
Volunteer or Not (1/0)	1	0	1	1	1	1	1	1	1	1
Estimated Time to Station (min)	4.17	-	6.25	4.44	3.48	4.01	3.70	5.39	4.61	3.10
Estimated Preparation Time in Station (min)	1	1	1	1	1	1	1	1	1	1
Estimated Chute Time (min)	5.17	1	7.25	5.44	4.48	5.01	4.7	6.39	5.61	4.1

Model Results & Analysis

By using the time matrix and the call volume in each demand zone, the optimization process is performed using R to obtain the optimal solution for the selected number of station facilities. As a means for comparison, a single-objective model was included as it only considers the coverage rate (Objective 1). The case study analyzes both single-objective and multi-objective models for a different number of station facilities, which equals 4,5,6,7, respectively. Results of the optimal locations are shown in Figure 7. As an example, when there are five stations and EMS is located in candidate Station 5,6,8,9,10, the maximum coverage rate is achieved. While when EMS is located in Station 5,6,7,9,10, both service coverage and equity are maximized. By comparing the existing stations (Station 1,2,3,4) and the optimized stations, significant improvement may be

observed for both coverage rate and service equity, suggesting the current EMS stations are not optimally located. FIGURE displays the trend of the fitness function for different numbers of facilities. It may be noted that both fitness functions increase as the number of facilities increases.

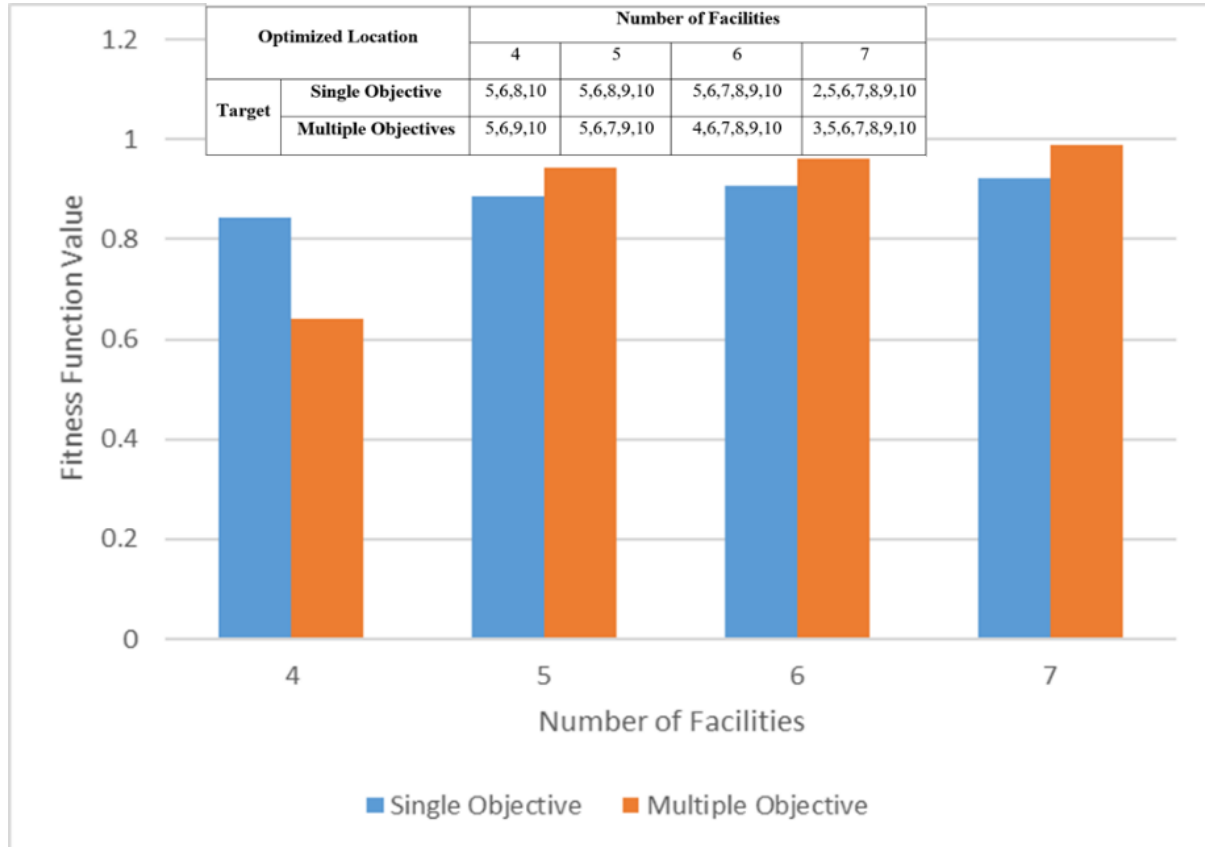


FIGURE 7 Optimized station locations and the fitness functions.

Figure 8 shows the effect of the added equity objective on service coverage rate for different numbers of facilities compared to the single-objective model. An adverse effect on coverage rate for the added equity objective was observed. For four EMS stations, the added equity objective decreases the coverage rate by 1%. When the number of facilities increases from 4 to 6, the negative effect increases significantly (from -1.00% to -4.34%). For seven facilities, the negative effect on service coverage was minimized, which may be due to the fact that there are already enough stations to cover most of the county. This observation suggests the proposed model is particularly important and useful for rural areas, which have fewer EMS stations than urban areas. Before running the models, careful decisions should be made about the weights on service coverage and equity, respectively. In this case, each objective was weighted equally while the results would be changed if the weights were modified.

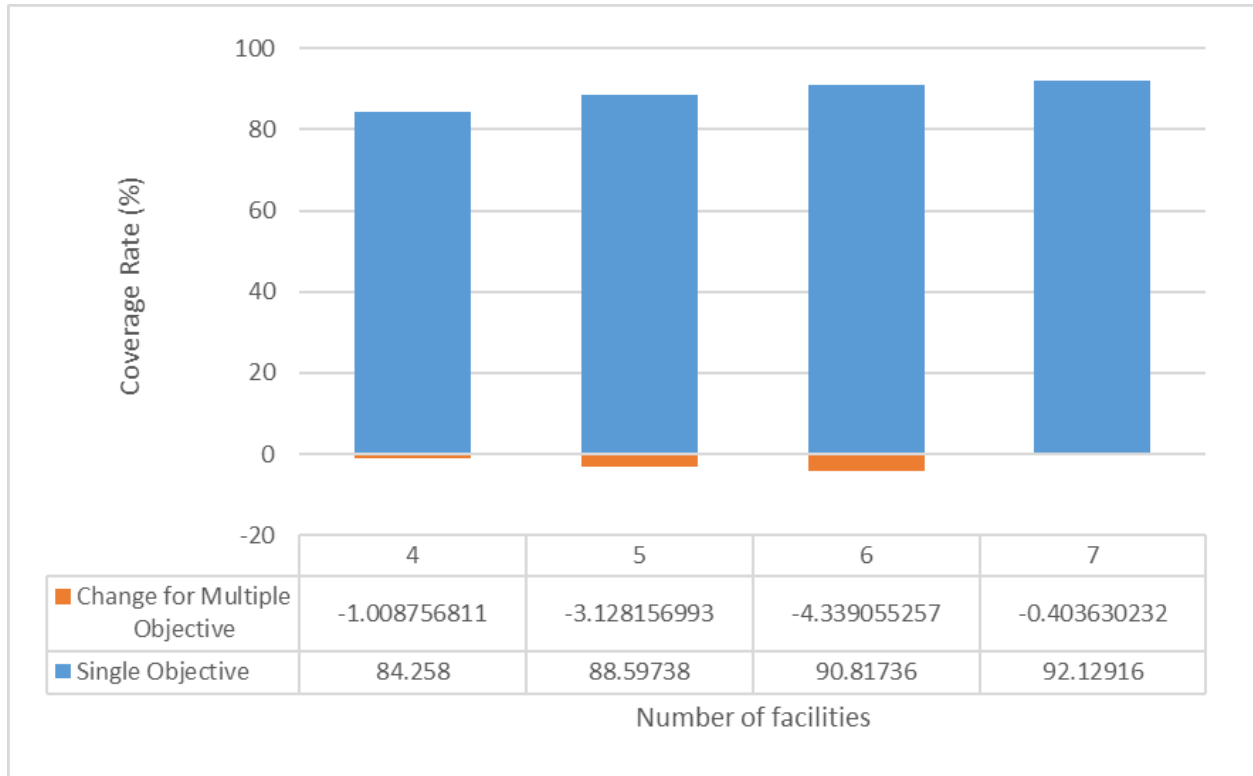


FIGURE 8 Coverage rate under optimized locations of EMS stations.

CONCLUSIONS & FUTURE WORK

This study sought to propose methods to increase coverage ratio and service equity. This was accomplished through the usage of geospatial evaluation and optimization of EMS station locations for rural areas. The spatial association of 911 calls and EMS stations were confirmed visually as well as using the Cross-K function. While major characteristics for rural EMS, such as volunteer stations, were considered in the location optimization model. Finally, optimal solutions were obtained by running the genetic algorithm in the R software. Assuming the information is accurate, the optimization tool helps the EMS agencies to strategically plan new or relocate existing stations to provide better services.

The findings of this study are logical because both 911 calls and EMS stations are more likely to be in populous areas. However, the co-location of the 911 calls and EMS stations do not always guarantee timely swift service. If the service provided by the current EMS stations is insufficient, the stations may be either relocated or supplemented by additional EMS stations to increase the service coverage and efficiency of service. It follows that all service stations should be strategically located to maximize their coverage.

Despite the realistic considerations introduced in the location optimization model, particular assumptions may not accurately reflect the actual situation. For example, this study used historical incident location data to represent the demand. Future work could include the

prediction of incident locations. Furthermore, the author made some assumptions to get an estimated chute time for the volunteer EMS. Thus, future research should analyze the chute time for volunteer EMS in a more in-depth manner. Simulation model is an option to analyze the dynamics of volunteer.

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