Service Location Optimization Model for Improving Rural Emergency Medical Services

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Abstract

Approximately 35,000 fatalities are attributed to accidents on U.S. highways each year and more than half of them occurred in rural areas. With such a high percentage of fatalities, rural areas are in critical need of timely and reliable Emergency Medical Services (EMS). EMS provide important prehospital care to victims before they are transferred to a hospital. After an accident occurs, the time it takes for victims to receive care from EMS is crucial to their survival. Compared with urban EMS, rural EMS face multiple challenges. One of them is how to properly site EMS stations to provide cost-effective services in rural areas. The goals of this paper include analyzing the spatial patterns of EMS station and incident locations, and optimizing rural EMS station locations. The data were collected from South Dakota, a rural state. This dataset was used to perform spatial analysis and to develop and evaluate an EMS location optimization model. The location optimization model aims to maximize the rural EMS coverage while taking service equity into consideration. The model was solved by a genetic algorithm toolbox in R. The proposed model provides an important and practical tool for rural EMS officials to select new EMS stations or relocate existing stations to improve service performance under budget and resource constraints.

In 2015 alone, more than 35,000 people lost their lives on U.S. highways. More than half of these fatalities occurred in rural areas. The fatality rate, defined as the rate of crash-related deaths per 100 million miles traveled, in rural areas is 2.6 times higher than in urban areas (*1*). Much of the difference in the fatality rate between urban and rural areas can be attributed to the increased travel time needed to reach a victim in rural areas (*1*). Because rural areas have a sparsely distributed population and road network, and a limited number of Emergency Medical Services (EMS) stations, long travel distances are often expected for most EMS service trips. Obviously, a major challenge here is how to provide timely service in these time-sensitive situations. It is important to develop methods to decrease the travel time needed for EMS to reach a victim as this time reduction may significantly increase the victim's chances of survival. The National Cooperative Highway Research Program (NCHRP) 500 report entitled *Volume 15: A Guide for Enhancing Rural Emergency Medical Services* puts special emphasis on reducing "the time from injury to appropriate definitive care" to improve rural EMS (*2*). In addition, this report identifies some challenges related to rural EMS, including geographic barriers, lack

of professionals/paraprofessionals, aging or inadequate equipment, the absence of specialized EMS care, and local medical facilities (*3*).

With the objective of improving rural EMS performance, this study focuses on the locations of EMS stations. The goals of this study are to analyze the spatial patterns of EMS station and incident locations, and to optimize rural EMS station locations. Based on the spatial pattern analysis using EMS data from South Dakota, recommendations are provided to optimally locate EMS sites to obtain improved service performance. In addition, an EMS location optimization model is proposed. A case study using this proposed model and the South Dakota data is presented.

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Literature Review

The National Highway Traffic Safety Administration (NHTSA) developed 35 performance measures for local EMS systems, including time-based variables (e.g., Mean Emergency Patient Response Interval) and outcome-based variables (e.g., EMS Cardiac Arrest Survival Rate to Emergency Department Discharge) (*2*). To evaluate EMS performance, other metrics were also proposed, such as time-related, distance-related, and outcome-based variables. Among these performance indicators, response time is considered as a major performance index and has been extensively used to evaluate EMS performance (*2*, *4*, *5*). Although a patient's treatment outcome depends on many factors such as the injury severity and pre-existing conditions, the time needed for an EMS unit to arrive at the scene (response time) plays a significant role in the survival rate (*4*). This conclusion is also supported by a study done by Yasmin et al. using the Fatality Analysis Reporting System (FARS) dataset (*6*). To date, a clear relationship has not been fully established between clinically significant improvements in patients' outcomes and reductions in EMS time to definitive care (*4*). However, the consensus is that shorter time to definitive care is associated with improved outcomes for those who need emergency care.

Other than identifying key EMS performance measures, quite a few researchers have made efforts to explore ways to model EMS performance. Do et al. conducted a quantile regression analysis to identify significant factors related to response time. In their analysis, potential impact factors were first divided into patient and system levels (*7*). Meng et al. introduced a mixed logistic regression model to predict the fatality risk in work zones. In their model, the uncertainty involved in accident notification and response times was considered (*8*).

Besides the above regression models, several studies have focused on developing models to identify optimal locations for EMS stations. Maximizing the ambulance coverage and minimizing the en-route time/distance are considered as two primary objectives for EMS station location optimization (*9*). The first objective is referred to as the maximal covering location problem (MCLP), which maximizes the demand that may be served (i.e., within a required time or distance) by properly choosing EMS locations (*9*). The second one is referred to as *p*-median or *p*-center problem (*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 the importance of service uncertainty, such as availability of an ambulance, Daskin et al. proposed a maximal expected covering location problem (MEXCLP)

model (*10*). By treating the probability of ambulance availability as a station-specific variable, Hogan and ReVelle modified the MCLP model and introduced a "backup-coverage" term in the objective function (*11*). "Backup-coverage" means that another ambulance may cover the unserved demand points left by the initially assigned ambulance. The modified model aims to maximize both the first and the second coverages to improve EMS robustness. Building on this "backup-coverage" concept, Liu et al. proposed a double standard model, which incorporates two service coverage standards (*12*). Additionally, an adjusted MEXCLP was proposed by Batta et al. to further take into consideration the unavailability probabilities associated with each facility location (*13*).

Several other studies investigated ambulance location problems from a multi-objective perspective (*14*, *15*). For example, Daskin et al. proposed a multi-objective model that can balance between the number of facilities and the extra coverage (*14*). Furthermore, Chanta et al. proposed a bi-objective facility location model for rural EMS stations, with service coverage and service equity as the two objectives (*15*). In their model, service equity represents the fairness of the locations of EMS 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 aforementioned EMS location studies mostly are focused on issues related to urban EMS, and few of them address the unique characteristics (e.g., low population and volunteer stations) and needs (e.g., long travel distance) of rural EMS.

Data Collection

For the purpose of this study, EMS incidents, EMS stations, and highway network data were collected. A subset of the National EMS Information System (NEMSIS) data bank consisting of South Dakota EMS incident records was obtained from the Eastern South Dakota EMS Data office. The obtained dataset covers the period between 1/1/2013 and 12/31/2013. Figure 1 shows an example of how the EMS incident records are organized in the NEMSIS dataset and how EMS calls are processed.

Each EMS incident record mainly includes time points (such as "Dispatch"), time intervals (such as "ERTime"), odometers, and incident location. "RespTime" in the NEMSIS dataset is referred to as chute time in many other EMS documents, and is the time period from the notification of the EMS dispatcher to the time the ambulance/responding unit starts moving. Thus, the sum of chute time (or RespTime) and en-route time in this study is equivalent to response time. As this study focuses on 911 calls (e.g., traffic crash, cardiac arrest, chest pain,
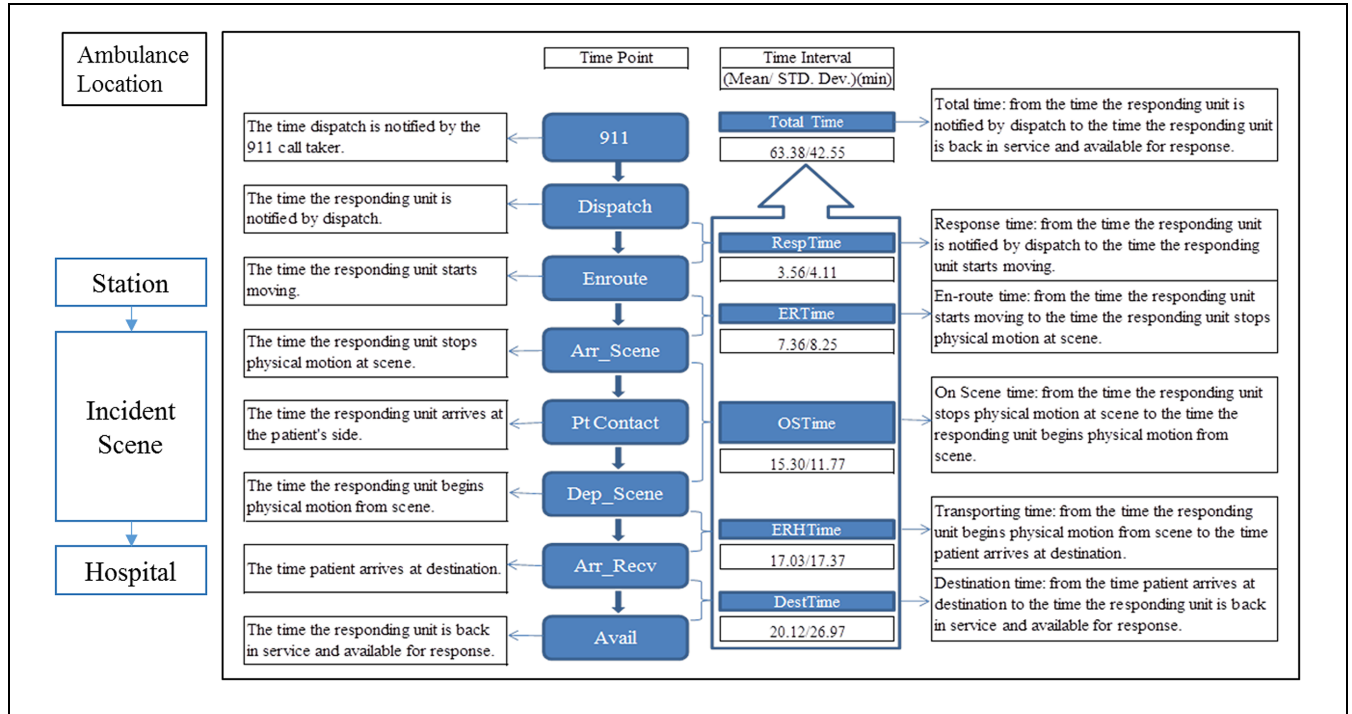
Figure 1. Timeline of EMS process.

animal bite, fall victim, ingestion/poisoning), the original dataset was processed and resulted in 36,198 qualified records in 2013. Google Map API was used to convert the addresses of these 911 incidents into coordinates.

The EMS ambulance station data were obtained from the South Dakota Emergency Medical Services website. This dataset contains information such as name, location, professional status, and vehicle counts for each EMS station. Figure 2 shows the locations for the 36,198 911 incidents and 109 EMS stations in 2013.

The Non-State Trunk Road Inventory (NSTRI) dataset provided by South Dakota Department of Transportation (DOT) was used to derive the highway data. NSTRI includes both interstate highways and local roads in South Dakota. The speed limit information in this dataset was used to perform the network-based analysis. A 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

As shown in Figure 2, it seems that 911 incidents cluster around EMS stations. A statistical technique called cross-K function was applied to analyze the 911 incident and EMS location data to confirm the visual assessment. The cross-K function is well suited to analyzing the co-location pattern between two kinds of points. For example, given two sets of locations A $(a_1, a_2, \ldots, a_i)$ and B $(b_1, b_2, \ldots, b_j)$, the cross-K can be used to answer whether the two sets of points are 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 locations in B (17). The cross-K function and the corresponding L function are formally defined as

$$K^{ba}(r) = \lambda_a^{-1} E$$

(number of points A within distance r of a point in B)

(1)

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

where

π is a mathematical constant

$\lambda_a =$ Density (number per unit area) of points in 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; and

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

The expected value $\bar{L}(r) - r$ can be plotted with upper and lower 5% boundaries, which indicate a 90% confidence interval using the Monte Carlo simulation. If $L^{obs}(r) - r$ is greater than the upper boundary, the co-location pattern can be considered to be significantly
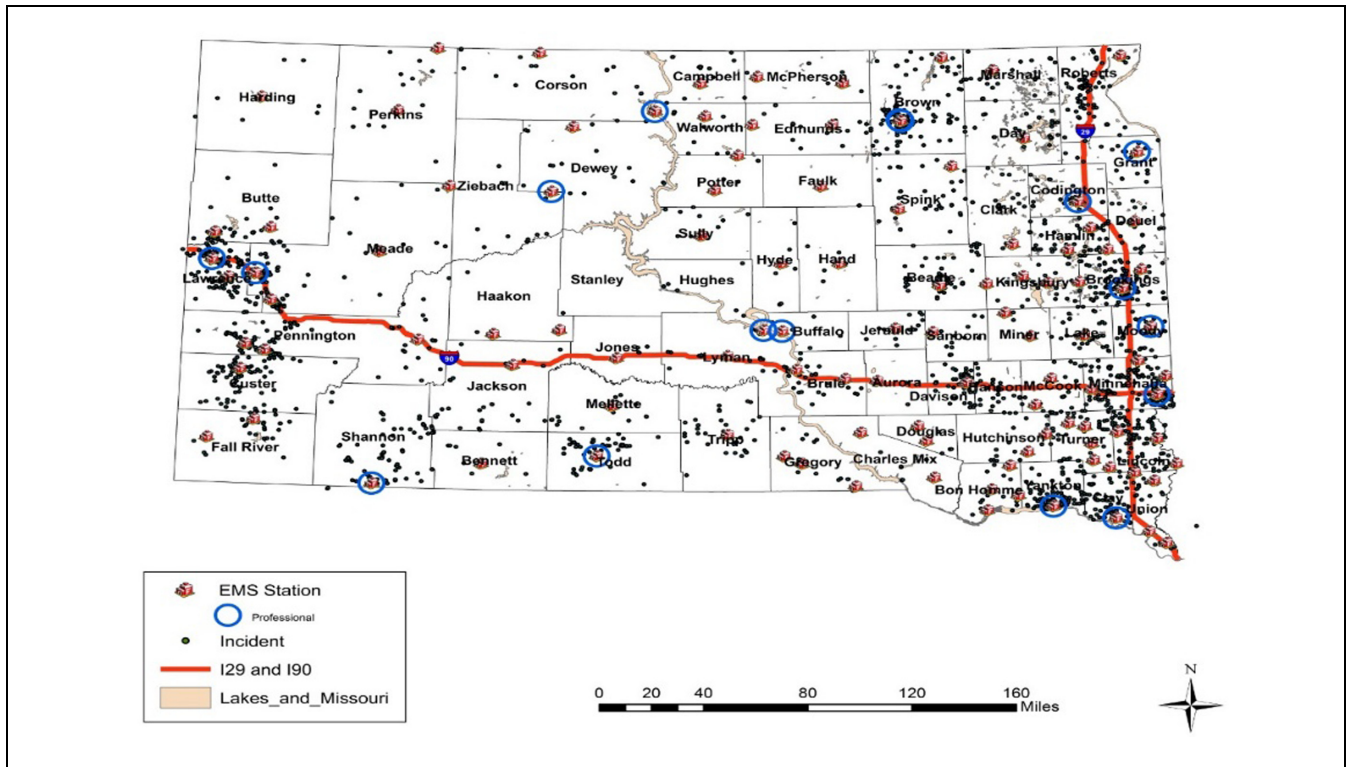
Figure 2. Incidents and EMS stations in South Dakota in 2013.

clustered. If $L^{\text{obs}}(r) - r$ is below the lower boundary, the pattern can be interpreted as significantly dispersed. If $L^{\text{obs}}(r) - r$ is between the upper and lower boundaries, the points in A and B can be considered to be randomly distributed.

The cross-K function was applied to examine the co-location pattern between 911 incidents (location A) and EMS stations (location B) by using the R software. The results are shown in Figure 3, where $L^{\text{obs}}(r) - r$ (represented by the solid black curve) is located above the 5% upper boundary when the distance r is shorter than 25 mi. This suggests that there is a strong co-location pattern (i.e., significant clustering) between EMS stations and 911 incidents if one considers a distance range of 25 mi or less. When the chosen distance is greater than 25 mi, the spatial association between EMS stations and 911 calls becomes statistically insignificant. As most 911 calls are with 25 miles of an EMS station as shown in Figure 2, the current EMS stations overall seem to be well positioned and are in line with where the 911 calls may occur.

Location Optimization of EMS Stations

Facts for Rural EMS

Before formulating the optimization model, the following important facts of rural EMS are analyzed.

Volunteer EMS. Lack of professional staff has long been a major issue affecting EMS service performance in rural areas. Studies indicate that approximately 75% of EMS providers in rural areas are volunteers whereas only 30% are in urban areas (*18*). In South Dakota, less than 20% of the EMS stations have professional personnel (*19*). Not surprisingly, the EMS data show that chute time ("RespTime") was significantly shorter for stations with professional staff than for those staffed by volunteers (2.76 min versus 4.53 min). This longer chute time for volunteers is mainly caused by their need for additional time to go to EMS stations for ambulances and necessary equipment. In the proposed optimization model, the extra time needed for volunteers to go to EMS stations was considered when calculating the chute time.

Low and Sparsely Distributed Service Demand. When optimizing the locations of EMS stations for urban areas, one important consideration is the availability of ambulances because of the high EMS demand. However, for rural EMS, ambulances are available for most of the time. Unit hour utilization (UHU) is defined as the percentage of time an ambulance unit is occupied. It indicates how busy an EMS station is. Based on the 2013 data, most stations in South Dakota had a UHU less than 2%, and the highest UHU was around 10%. This suggests that most EMS stations were not busy and many stations did
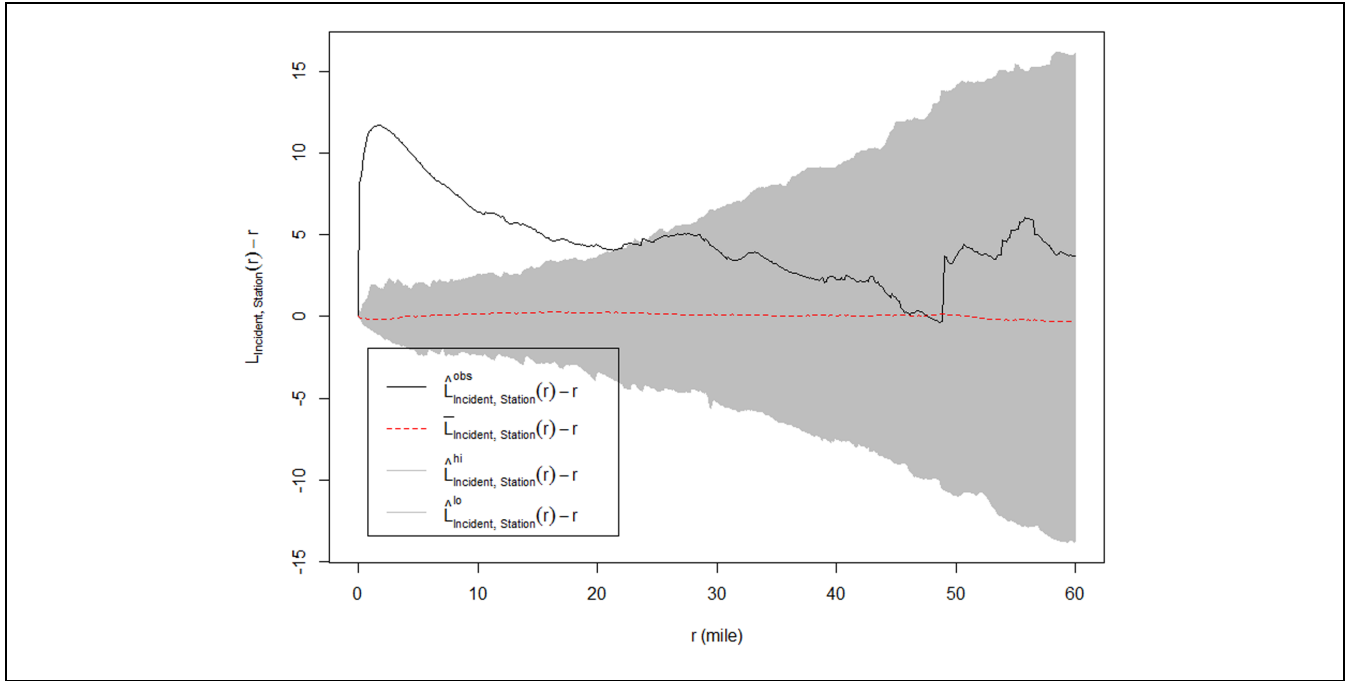
Figure 3. Cross-*K* function and *L* function for 911 incidents and EMS stations.

not have any dispatch request for several days. Even during the busiest days, the service demand was relatively low. Thus, the service/ambulance availability was not considered in the model development in this study.

Long Travel Distance. Besides volunteer EMS, and low and sparsely distributed EMS demand, long travel distance is another major challenge for rural EMS. Unlike populous urban areas, disparities exist in the access to rural 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 the patient survival rate is directly related to response time. To account for this factor in the optimization model, two objectives were considered. One is to maximize the size of the covered areas that can provide timely EMS service, and the other is to minimize the response time for remote incident scenes to improve service equity.

Formulation of Optimization Model

To account for both the EMS coverage (Objective 1) and the service equity (Objective 2), a bi-objective location model is shown in Equations 3 and 4, where Z_1 and Z_2 represent the two aforementioned objectives. Specifically, Z_1 maximizes the number of 911 calls that can be covered

within a prespecified response time and Z_2 minimizes the average response time for uncovered 911 calls that are outside the prespecified response time zone. x_j is a decision variable, which indicates whether a station should be built at candidate location j. Equations 5 and 6 define y_i, which equals 1 only if demand node i is covered by one or more available EMS facilities. p in Equation 7 denotes the total number of available facilities that can be built. Equations 8 and 9 restrict x_j and y_i to being binary variables. Based on the requirement for South Dakota EMS (20), a 15-min threshold value was used for response time to determine whether a demand point is covered or not.

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

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

subject to

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

$$y_i \ge x_j, \ i \in I, j \in N_i \quad (6)$$

$$\sum_{j \in J} x_j = p \quad (7)$$

$$x_j \in \{0, 1\}, j \in J \quad (8)$$

$$y_i \in \{0, 1\}, \ i \in I \tag{9}$$

where

i, I are the index and set of demand points,

j, J are the index and set of candidate facility locations,

D_i is the 911 demand at point i,

t_j is the estimated chute time for each candidate facility j,

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

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

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

$N_i\{j | t_{ij} \leq T\}$ is a set of points j that is within a time of T for point i,

p is the number of facilities to be built,

x_j is a binary variable that equals 1 when a facility is built at point j and 0 otherwise, and

y_i is a binary variable which equals 1 if the node i is covered by one or more facilities and 0 otherwise.

Solution to Optimization Model: Genetic Algorithm

Metaheuristics are one of the most effective methods for solving the proposed EMS location optimization problem. Among the popular metaheuristic solutions (e.g., genetic algorithm, simulated annealing, ant colony optimization, tabu search), the genetic algorithm has been proven to be very effective (*19*). Thus, the genetic algorithm was chosen for this study.

The genetic algorithm adopts natural evolution from Darwin's theory of evolution for the optimization algorithm and has been used in many optimization problems including facility location (*19*). Similar to natural evolution, the essence of this algorithm is to improve the offspring using reproduction mechanisms such as crossover and mutations, resulting in offspring with higher fitness functions (*19*).

The basic procedures for the genetic algorithm are shown in Figure 4 (*21*).

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

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

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

The fitness function will be calculated for each solution. This will generate a set of fitness function values.
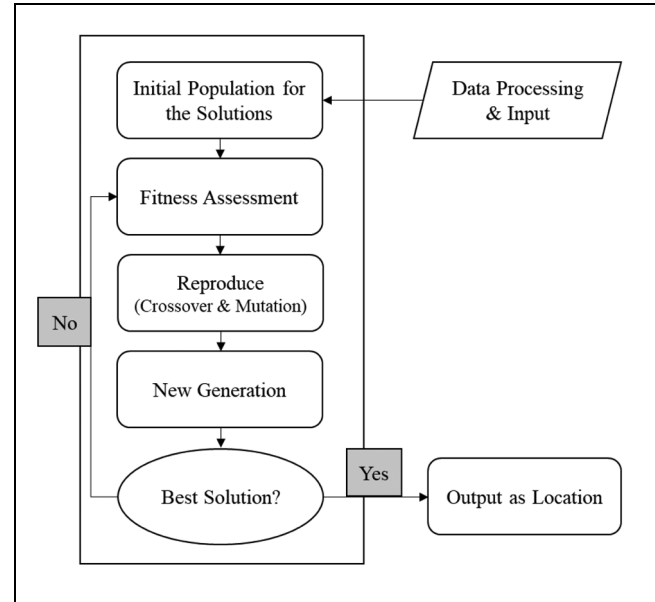

Figure 4. Flowchart for genetic algorithm.

The optimal solution will have the highest fitness function value.

- *Phase 3: Repeat (generate offspring)*

Offspring will be generated in four steps, which are 1) selecting parents 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 individuals with small fitness function values. These steps will be repeated until termination criteria are satisfied.

The genetic algorithm toolbox in the R software was used to solve the proposed multi-objective optimization model. A multicriteria evaluation technique called the weighted sum method was adopted to convert the multi-objective problem into a single-objective one by assigning a weight to each objective (*22*). In practice, the weights can be determined by experts to reflect the relative importance of each objective. In this study, the same weight is used for both objectives, namely $w_1 = w_2 = 0.5$. Equations 10 and 11 show the fitness functions for objectives 1 and 2, respectively.

$$F_1 = Z_1 = \frac{\sum_{i \in I} D_i y_i}{\sum_{i \in I} D_i} \tag{10}$$

$$F_2 = \frac{1}{Z_2} = \frac{\sum_{i \in I} D_i(1 - y_i)}{\sum_{i \in I} D_i(1 - y_i)\min(t_{ij})} \tag{11}$$

These two functions are combined into a single function to normalize the different measurement scales. The combined fitness function is shown in Equation 12.

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.

$$F_3 = w_1 * \frac{F_1 - F_{1min}}{F_{1max} - F_{1min}} + w_2 * \frac{F_2 - F_{2min}}{F_{2max} - F_{2min}} \quad (12)$$

Case Study

Data Preparation

Minnehaha County in South Dakota was chosen to demonstrate how to optimize the locations of EMS stations. The data used in this demonstration were obtained 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-mi by 1-mi cells were chosen to represent the demand zones for 911 calls. The total number of 911 calls inside a cell was counted and assigned to that cell as its attribute (Figure 5).

2) Select Candidate Stations. According to the *National EMS Assessment*, about 40% 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 from 1) the existing stations (Station 1, Station 2, Station 3, and Station 4); 2) hospitals (Station 5, Station 6, and Station 7); 3) a police station (Station 8); and 4) randomly selected sites (Station 9 and Station 10). The

randomly selected locations were identified empirically based on the demand zone locations and the road network to increase EMS coverage. This random selection process could be improved by discussing the sites with county EMS officials. The identified candidate stations as well as the demand zones in Minnehaha County are shown in Figure 5. The existing stations are labeled as Station 1 to Station 4 with their volunteer status. Except for the existing stations, it is assumed that all others are volunteer stations.

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 needed 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 volunteers to get to a station and the preparation time at the station; for professional stations, on the other hand, chute time is equivalent to the preparation time.

To estimate the average time required for volunteers to get to a station, the authors assumed that the probability of a volunteer staying in one population block equals the percentage of that block's population. The block population data (shown in Figure 6) is obtained from the census website (https://www.census.gov/geo/maps-data/data/tiger-data.html). The estimated travel time for volunteers to get to each station equals the population-weighted average travel time from all population blocks to that station.
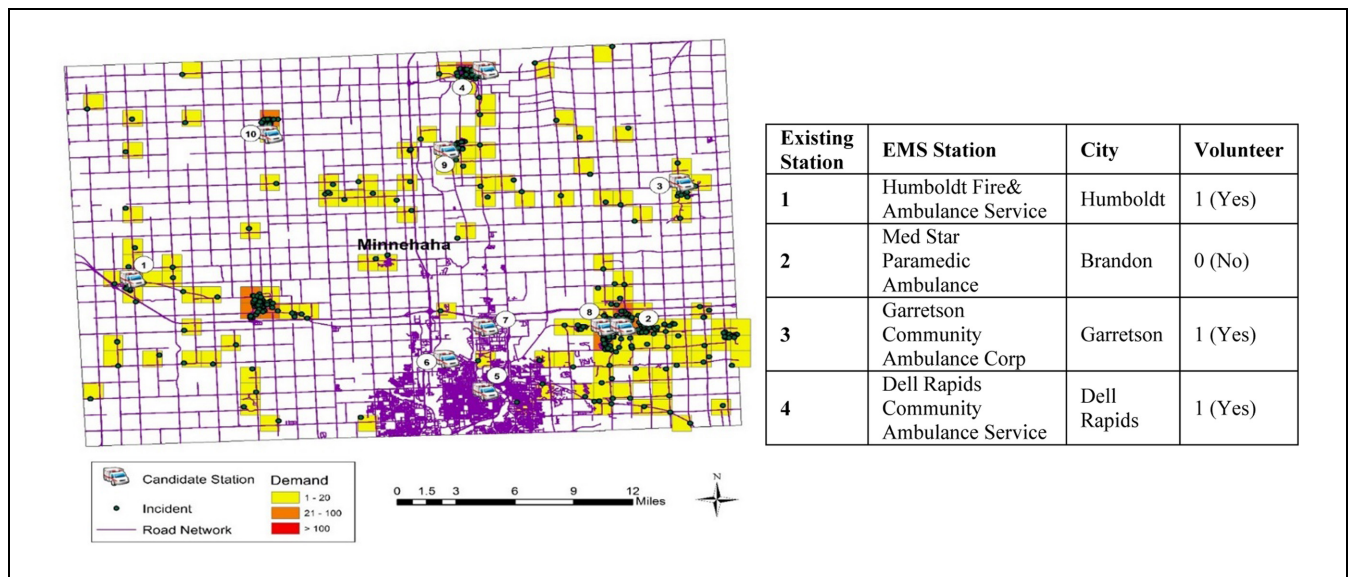

Existing Station	EMS Station	City	Volunteer
1	Humboldt Fire& Ambulance Service	Humboldt	1 (Yes)
2	Med Star Paramedic Ambulance	Brandon	0 (No)
3	Garretson Community Ambulance Corp	Garretson	1 (Yes)
4	Dell Rapids Community Ambulance Service	Dell Rapids	1 (Yes)

Figure 5. Minnehaha County with candidate stations and demand zones.
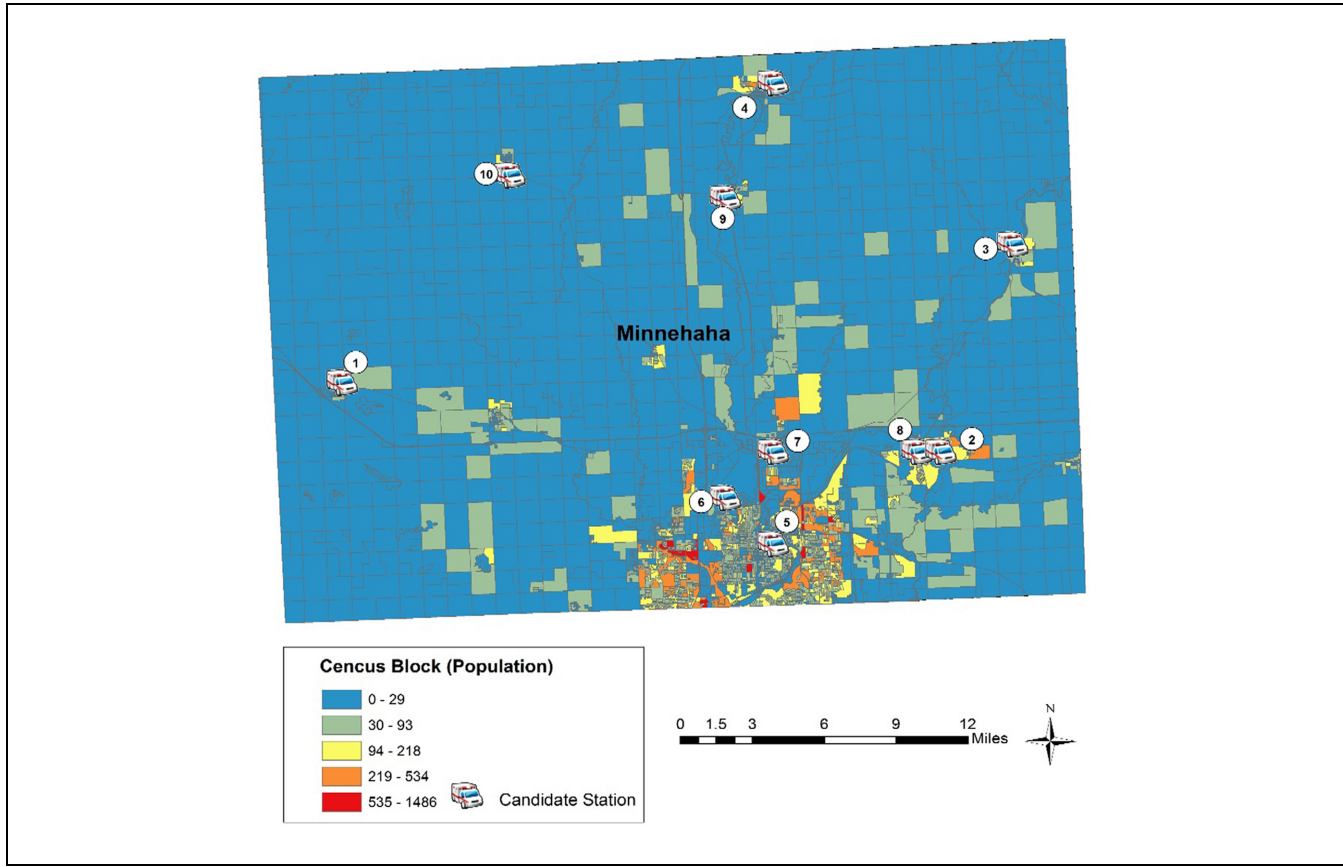
Figure 6. Census block map.

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	na	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	1.00	7.25	5.44	4.48	5.01	4.70	6.39	5.61	4.10

Note: na = not applicable.

Table 1 shows the estimated travel times for each candidate station. The United States National Fire Protection Association (NFPA) 1720 has a 1-min chute time requirement for professional EMS stations. Therefore, 1 min is used as the preparation time for all candidate sites as shown in Table 1 (*24*). The final response time matrix is prepared by adding the chute time to the en-route time.

Model Results and Analysis

Based on the time matrix and the call volume in each demand zone, a genetic algorithm tool in R is used to obtain the optimal solution for siting EMS facilities. To provide a comparison benchmark, a single-objective location model is included, which only considers the EMS coverage (Objective 1). The case study analyzes both single-objective and multi-objective models for a different number of station facilities, which equal 4, 5, 6, and 7, respectively. The results of the optimal locations are shown in Figure 7. As an example, when there are five stations and EMS is made available at candidate Stations 5, 6, 8, 9, and 10, the maximum coverage rate is achieved. When EMS is available at Stations 5, 6, 7, 9, and 10, both service coverage and equity are maximized. By comparing the existing stations (Stations 1, 2, 3, and 4) with the
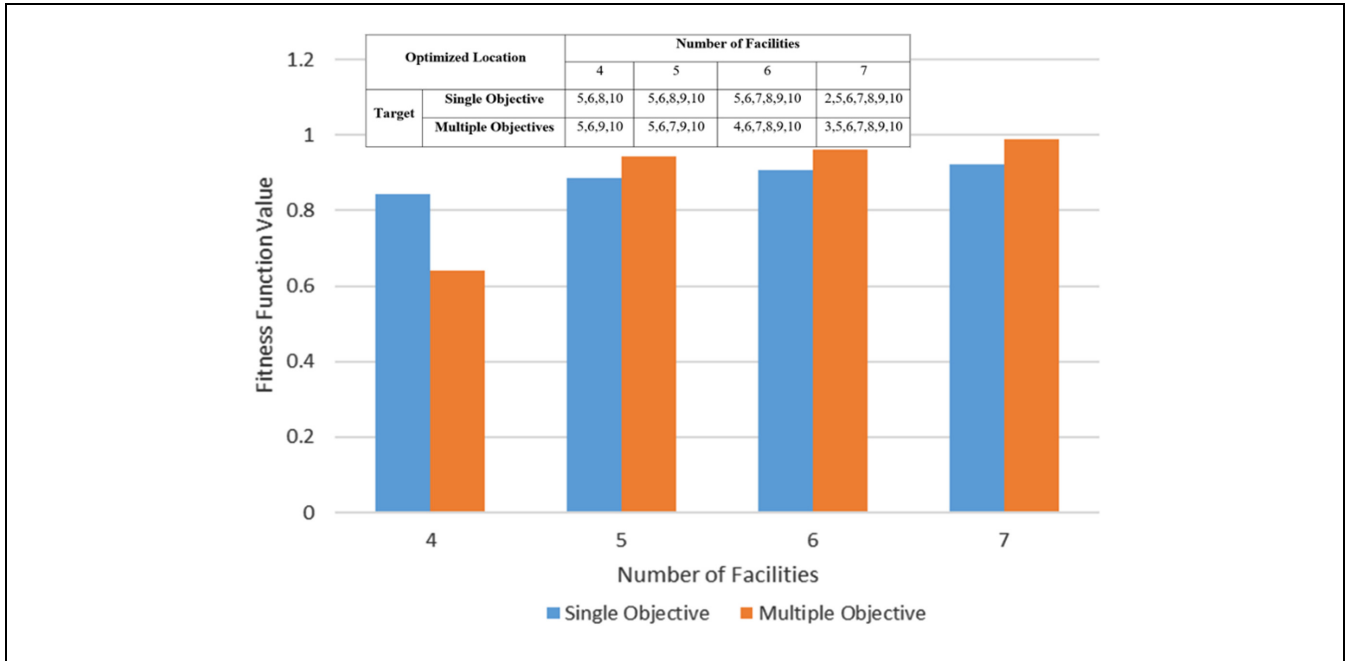
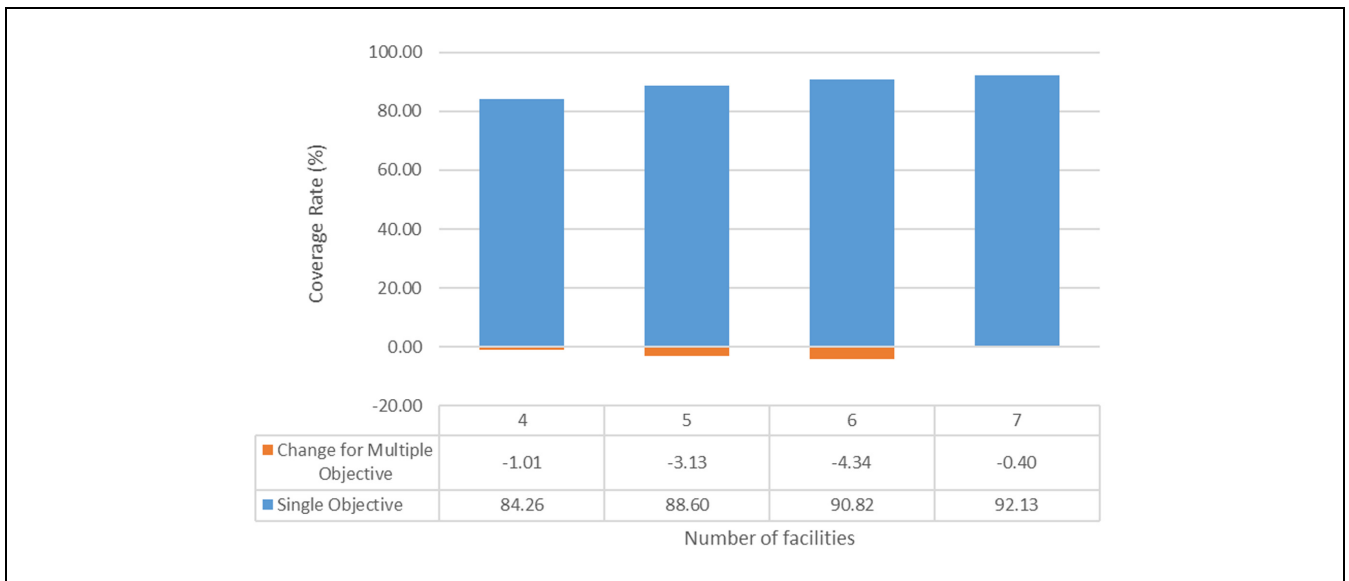**Figure 7.** Optimized location EMS stations and the fitness functions.

Figure 8. Coverage rate under optimized locations of EMS stations.

optimized stations, significant improvement is observed in both coverage rate and service equity, suggesting the current EMS stations are not optimally located. Figure 7 also displays the trend of the fitness function for different numbers of facilities. It suggests that the fitness functions for both single- and multi-objective models increase as the number of facilities increases. In the single-objective optimization model, service coverage is the EMS service performance measure, which is the fitness function as formulated in Equation 10. In Figure 7, the fitness function

value of 0.84 for the single-objective model indicates the coverage rate is 0.84 for the four optimized locations. In the multi-objective optimization model, service coverage and average response time for the uncovered areas are the two service performance measures. The fitness function is now a combination of the two objectives as formulated in Equation 12.

Figure 8 shows the effect of adding service equity as an objective on the service coverage rate for different numbers of facilities. The results from the single-objective

Table 2. Average Response Time (min) under Optimized Locations of EMS Stations

Optimized location		Number of facilities			
		4	5	6	7
Objective(s)	Single objective	14.07	13.55	13.23	12.89
	Multiple objectives	13.88	13.55	14.98	13.19

model are also included here for comparison. After adding the equity objective, an adverse effect on the coverage rate was observed. For the four EMS stations case, the added equity objective decreases the coverage rate by 1%. When the number of facilities increases from four to six, the negative effect becomes more significant with an increase from −1.00% to −4.34%. For the seven facilities case, the negative effect on service coverage, however, is minimal, which may be because there are already enough stations to cover the study area. This observation here suggests that the proposed model is particularly important and useful for rural areas, which usually have fewer EMS stations than urban areas. Before running the model, careful decisions should be made about the respective weights given to service coverage and equity. In this case, each objective was weighted equally. The results could be different if the weights were not the same.

Table 2 shows the average response times calculated based on the optimized location plans. When the number of facilities equals four, the average response time for the multi-objective model is lower than that of the single-objective model.

Conclusions and Future Work

This study sought to propose methods to increase EMS coverage ratio and service equity in rural areas. This was accomplished through the geospatial evaluation of 911 calls and EMS station locations and the optimization of EMS station locations. The spatial associations of 911 calls and EMS stations were confirmed visually as well as using the cross-*K* function. In the proposed EMS station location optimization model, essential characteristics of rural EMS, such as volunteer stations and long travel distances, were carefully considered. Finally, optimal EMS location solutions were obtained by solving the proposed optimization model using the genetic algorithm toolbox in the R software and the data from South Dakota. The results suggest that the optimization model provides a powerful and practical tool for EMS agencies to strategically plan new stations or relocate existing ones to improve EMS in rural areas.

Although some practical factors related to rural EMS have been carefully modeled in the study, there are still assumptions made that may not accurately reflect real-world rural EMS operations. For example, this study used historical incident location data to represent the 911 demand. In practice, EMS demand may vary by time of day, although this variation is expected to be less significant in rural areas given the overall low traffic demand than in urban areas. To take into consideration the potential EMS demand variation, future work could include the prediction of incident locations and service availability. Furthermore, assumptions have been made to estimate the chute time for volunteer EMS agencies. Future research should thoroughly analyze the chute time for EMS volunteers and simulation models could be used to analyze their dynamics with respect to location, scheduling, and availability.

Author Contributions

The authors confirm contribution to the paper as follows: study conception and design: Qin, He; data collection: He; analysis and interpretation of results: He, Qin; draft manuscript preparation: He, Qin, Xie, Guo. All authors reviewed the results and approved the final version of the manuscript.

References

1. Qin, X., Z. He, and H. Samra. Needs Assessment of Rural Emergency Medical Services. *Transportation Research Record: Journal of the Transportation Research Board*, 2015. 2513: 30–39.
2. American Association of State Highway and Transportation Officials Strategic Highway Safety. *Volume 15: A Guide for Enhancing Rural Emergency Medical Services*, 2005.
3. National Highway Traffic Safety Administration. *Emergency Medical Services Performance Measures: Recommended Measures for System and Service Performance*. National Highway Traffic Safety Administration, Washington, D.C., 2009.
4. Centers for Disease Control and Prevention (CDC). *Motor Vehicle Safety*. *Injury and Violence Prevention*. http://www.cdc.gov/motorvehiclesafety/index.html. Accessed June 30, 2017.
5. Gitelman, V., K. Auerbach, and E. Doveh. Development of Road Safety Performance Indicators for Trauma Management in Europe. *Accident Analysis & Prevention*, Vol. 60, 2013, pp. 412–423.

6. Yasmin, S., N. Eluru, and A. R. Pinjari. Analyzing the Continuum of Fatal Crashes: A Generalized Ordered Approach. *Analytic Methods in Accident Research*, Vol. 7, 2015, pp. 1–15.

7. Do, Y. K., K. Foo, Y. Y. Ng, and M. E. H. Ong. A Quantile Regression Analysis of Ambulance Response Time. *Prehospital Emergency Care*, Vol. 17, No. 2, 2013, pp. 170–176.

8. Meng, Q., and J. Weng. Uncertainty Analysis of Accident Notification Time and Emergency Medical Service Response Time in Work Zone Traffic Accidents. *Traffic Injury Prevention*, Vol. 14, No. 2, 2013, pp. 150–158.

9. De Smith, M. J., M. F. Goodchild, and P. Longley. *Geospatial Analysis: A Comprehensive Guide to Principles, Techniques and Software Tools*. Troubador Publishing Ltd, 2007.

10. Daskin, M. S. A Maximum Expected Covering Location Model: Formulation, Properties and Heuristic Solution. *Transportation Science*, Vol. 17, No. 1, 1983, pp. 48–70.

11. ReVelle, C., and K. Hogan. A Reliability-Constrained Siting Model with Local Estimates of Busy Fractions. *Environment and Planning B: Planning and Design*, Vol. 15, No. 2, 1988, pp. 143–152.

12. Liu, Y., A. M. Roshandeh, Z. Li, K. Kepaptsoglou, H. Patel, and X. Lu. Heuristic Approach for Optimizing Emergency Medical Services in Road Safety within Large Urban Networks. *Journal of Transportation Engineering*, Vol. 140, No. 9, 2014, p. 04014043.

13. Batta, R., J. M. Dolan, and N. N. Krishnamurthy. The Maximal Expected Covering Location Problem: Revisited. *Transportation Science*, Vol. 23, No. 4, 1989, pp. 277–287

14. Daskin, M. S., K. Hogan, and C. ReVelle. Integration of Multiple, Excess, Backup, and Expected Covering Models. *Environment and Planning B: Planning and Design*, Vol. 15, No. 1, 1988, pp. 15–35.

15. Chanta, S., M. E. Mayorga, and L. A. McLay. Improving Emergency Service in Rural Areas: A Bi-Objective Covering Location Model for EMS Systems. *Annals of Operations Research*, Vol. 221, No. 1, 2014, pp. 133–159.

16. McLay, L. A., and M. E. Mayorga. Evaluating Emergency Medical Service Performance Measures. *Health Care Management Science*, Vol. 13, No. 2, 2010, pp. 124–136.

17. Ripley, B. D. *Spatial Statistics*. John Wiley & Sons, 2005.

18. March, J. A., and J. D. Ferguson. Volunteer EMS Systems. *Medical Oversight of EMS*, Vol. 2, Kendall/Hunt Publishing, 2009, pp. 239–244.

19. Sivanandam, S., and S. Deepa. *Introduction to Genetic Algorithms*. Springer Science & Business Media, 2007.

20. Safetech Solutions LLP. *An Introduction to Rural EMS Medical Direction in South Dakota*. The South Dakota Office of Rural Health, 2011.

21. Sivaraj, R., and T. Ravichandran. A Review of Selection Methods in Genetic Algorithm. *International Journal of Engineering Science and Technology*, Vol. 3, No. 5, 2011, pp. 3792–3797.

22. Grabaum, R., and B. C. Meyer. Multicriteria Optimization of Landscapes Using GIS-Based Functional Assessments. *Landscape and Urban Planning*, Vol. 43, No. 1, 1998, pp. 21–34.

23. Mears, G., B. Armstrong, A. Fernandez, N. Mann, K. McGinnis, C. Mears, N. Sanddal, T. Sanddal, and F. Shofer. *National EMS Assessment*. Report No. DOT HS 811 723. National Highway Traffic Safety Administration, Washington, D.C., 2011.

24. Hensler, B. NFPA 1710, 1720 and Response Times. *FireBureau.com*, 2008.