The Impact Of 3D Distance on Emergency Medical Service Location Planning.

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Summary

Various distance metrics have been used for health and emergency service facility location planning. These metrics have impact on location-allocation decisions. This paper introduces '3D travel time distance' a new distance metric to optimise location of Emergency Medical Services (EMS), a case study of EMS location planning in South Yorkshire, with an example of selecting 12 optimal sites from 3038 simulated candidate locations is presented. This problem was translated into a P-median model and was solved using Group Genetic Algorithm (GGA). Outcomes from this analysis showed that each distance type identified different sets of EMS optimal locations for night and day time population.

KEYWORDS: 3D travel time distance, Location-allocation, Night and Day time population, P-median and Optimisation.

1 Introduction

Location-allocation models are mathematical formulations used to optimise public facilities to ensure improved accessibility and efficient utilisation of services. Optimisation of public health or emergency services often involves minimisation or maximisation of distance metrics of some sort. Distance is an important component of location models, and it has considerable influence on the accuracy and solution quality of location problems (Krarup and Pruzan, 1980). The accuracy of the outcomes from locations models depend on how distance between facility location and demand is formulated. A review of the literature shows that previous works apply three types of distance metrics to address location problems. These include 2D distance metrics such as Network distance (with and without travel time) and Euclidean distance. Consider, for example Schuurman et al., (2006), used Network distance with travel time to model rural hospital catchments areas in British Columbia. In another study, Sinuany-Stern et al (1995) applied an Analytical Hierarchical Process and P-median model formulated using Euclidean distance norm to identify suitable location for Hospital in Negev, Israel. Some studies have also combined two metrics to produce hybrid location models. For example, Moller-Jansen and Kofie (1998) proposed a model combining network and Euclidean distance model to identify suitable areas for the location of health services in GA district of Ghana.

Traditional 2D metrics ignore the effect of elevation on distance, this could have an effect location decisions. As a result, this paper introduces a new distance metric "3D travel time distance" and explores its impact on EMS location planning using night and daytime population as case studies. 3D distance approach recognises the effect of road elevation and travel time on optimal site selection. By accounting for travel impedances due to elevation, 3D distance is a more robust approach to calibrate the length between demand and potential facility locations.

2 Modelling 3D Distance

In this study, 3D travel time was derived by extracting elevation (z values) of road nodes and arcs from a digital elevation model of the study area. Travel time values were estimated from speed limits of roads types and length of road arcs, weighted by z values from elevation data. For example, the 3D travel time distance between two points (x_1,y_1,z_1) and (x_2,y_2,z_2),connected by a straight-line can be estimated as:

$$\text{Distance} = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2 + (z_2 - z_1)^2} \qquad (1)$$

Where z_1 and z_2 represent the minimum and maximum height value for start and end nodes of the line. Elevation values for road nodes and edges were interpolated from a mosaicked raster image of the study area. The resultant network was used to analyse the shortest distance between set of potential EMS sites (supply points) and demand locations.

3 Data Processing

The study area is South Yorkshire. South Yorkshire has a plethora of hilly terrain. The landscape of the area provides a veritable surface, to demonstrate the effect of 3D travel time distance on the EMS location allocation. This study used night and day time population as proxy to EMS demand. Night time population is the net population of each Lower Super Output Area (LSOA) in the study area. Daytime population was derived from travel-to-work data (http://cider.census.ac.uk/cider/wicid) for each LSOA, with equation (2).

$$\text{Day Time Population} = \text{Total Population} - \text{Outcommuters} + \text{Incommuters} \qquad (2)$$

Night and day time population were based on 2001 census data. Demand points are from centroid of LSOAs and candidate locations for EMS were derived by simulating 3038 points from a 500m square grid of the study area.

4 Problem Formulation and Algorithm

The Location model used in this study was the P-median model. P-median selects a subset of facilities known as ‘P facilities from a given set of candidate facilities that minimises the aggregate travel time or distance between demand and nearest facility locations (Fotheringham, et al., 1995). In this study, the classical P- median model first espoused by ReVelle and Swain (1970) was modified to account for 3D distance by adding a z dimension to demonstrate the effect of elevation as shown in equation(3).

$$\text{minimise} \sum_{i=1}^{n} \sum_{j=1}^{m} a_{i_{t_n}} * d_{ij(Z)} * x_{ij} \qquad (3)$$

P = Number of Optimal EMS site to locate (12 locations).
I...m = set of demand locations (845 centroids points weighted by night and day time population)
j...*n* = set of candidate EMS locations (3038 EMS potential locations)
a_{tn} = Demand weights (night and day time population)
d_{ijz}= This denotes the shortest distance between point *i* and *j* , based on various distance types (Euclidean, Network distance (with and without travel time), 3D distance (with Z values)).
X_{ij} = Decision variable with values [0, 1] to show which sites where selected.

In the context of this study, optimal sites are selected locations that minimises the weighted distance between demand (LSOAs) and supply points (EMS). Typically, location-allocation problem involves selecting optimum location choices from a pool of candidate location and allocating demands to these points. The pool of candidate location consists of 3038 simulated points in the study area, with a choice of selecting 12 optimal EMS locations to allocate to day and night time populations in 845 LSOAs. Finding solution for this type of problem is computationally difficult. For example, choosing a subset of 12 locations from a set of 3038 locations requires a solution search space of 3038! /12!*(3038-12)! Due to this intractability, The P-median problem was solved using a modified Group Genetic Algorithm (GGA). This was based on a stopping criterion of 10000 iterations. The GGA was developed by Comber et al. (2011) to handle subset location problems; GGA has been successfully tested on location-allocation problems (e.g., Sasaki et al., 2010 and Comber et al., 2009).

5 Discussions and Initial Results

Outcomes from application of P-median model (3) indicate that distance metrics have impact on optimal EMS location decisions. Table 1a and b shows optimal sites (p) and percentage of demand allocated to each site using various metrics of distance.

Table 1a. Optimal Locations and allocations for night time population using different metrics of distance.

3D Travel Time		*Network Distance (with travel time)*		*Network Distance (without travel time)*		*Euclidean Distance*	
P	*Allocation*	*P*	*Allocation*	*P*	*Allocation*	*P*	*Allocation*
21	225952(17.84%)	2007	183062(14.45%)	402	196884(15.54%)	366	224435(17.72%)
419	134754(10.64%)	402	166809(13.17%)	2007	148459(11.72%)	243	149874(11.83%)
2933	134067(10.58%)	225	149663(11.81%)	2428	137480(10.85%)	925	147676(11.66%)
1948	127315(10.05%)	2411	129800(10.24%)	773	137406(10.85%)	1834	125551(9.91%)
873	110932(8.75%)	1803	113853(8.99%)	208	131894(10.41%)	2472	122034(9.63%)
1525	105304(8.31%)	1024	108026(8.53%)	1729	113654(8.97%)	975	112878(8.91%)
2322	86625(6.84%)	756	88004(6.94%)	971	113581(8.96%)	1677	91026(7.18%)
756	84768(6.69%)	772	82476(6.51%)	1492	68633(5.41%)	653	72850(5.75%)
772	78073(6.16%)	1521	76356(6.02%)	903	63203(4.99%)	2331	67333(5.31%)
1521	64561(5.09%)	914	60864(4.80%)	2808	56550(4.46%)	1877	61674(4.87%)
387	61005(4.81%)	2615	54902(4.33%)	279	51217(4.04%)	2688	56130(4.43%)
2418	52992(4.18%)	278	52533(4.14%)	1576	47387(3.74%)	1608	34887(2.75%)

Table 1b. Optimal Locations and allocations for Day time population using different metrics of distance.

3D Travel Time		*Network Distance (with travel time)*		*Network Distance (without travel time)*		*Euclidean Distance*	
P	*Allocation*	*P*	*Allocation*	*P*	*Allocation*	*P*	*Allocation*
21	198122(15.64%)	419	201865(15.94%)	402	225533(17.80%)	466	200147(15.80%)
419	177837(14.04%)	2007	191279(15.10%)	2007	175108(13.82%)	1970	165808(13.09%)
1948	137437(10.85%)	2322	146971(11.60%)	2411	139000(10.97%)	2411	159899(12.62%)
2933	123669(9.76%)	1003	122048(9.63%)	973	130318(10.29%)	893	131063(10.34%)
737	120067(9.48%)	225	113941(8.99%)	209	108689(8.58%)	1004	121769(9.61%)
971	103476(8.17%)	737	111272(8.78%)	1803	105775(8.35%)	259	106156(8.38%)
2322	88484(6.98%)	1733	86824(6.85%)	737	102970(8.13%)	1733	101407(8.00%)
754	77898(6.15%)	754	80266(6.33%)	754	78996(6.23%)	175	99142(7.82%)
1677	74492(5.88%)	1521	63012(4.97%)	705	64737(5.11%)	704	66330(5.23%)
1613	58140(4.59%)	914	56923(4.49%)	1492	56584(4.46%)	2662	52733(4.16%)
902	57689(4.55%)	2615	48814(3.85%)	2873	40195(3.17%)	2684	31857(2.51%)
2418	49037(3.87%)	279	43133(3.40%)	1576	38443(3.03%)	1608	30037(2.37%)

The implication of this outcome is that different demand with distance metric influences EMS location planning decisions. However, it is important to note that 3D travel time distance is a more realistic approach to quantify distance between potential facility locations and demand.

Figure 1a Distribution of optimal EMS locations for night time population using different metrics of distance

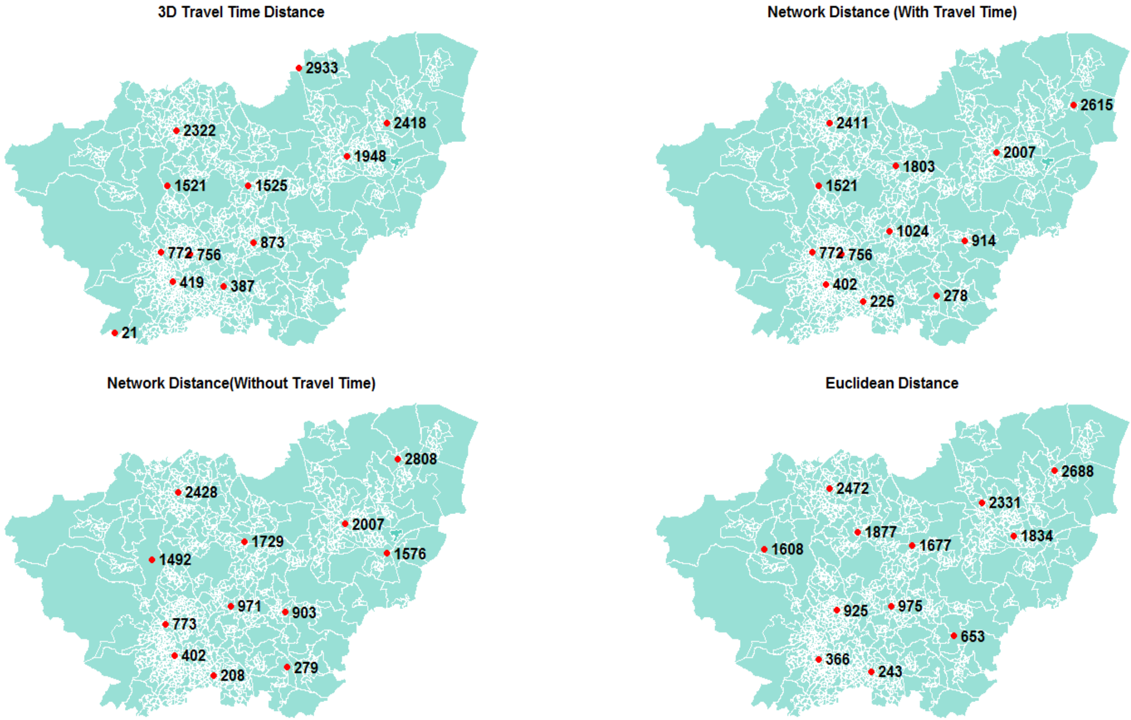

Figure 1b Distribution of optimal EMS locations for Day time population using different metrics of distance.

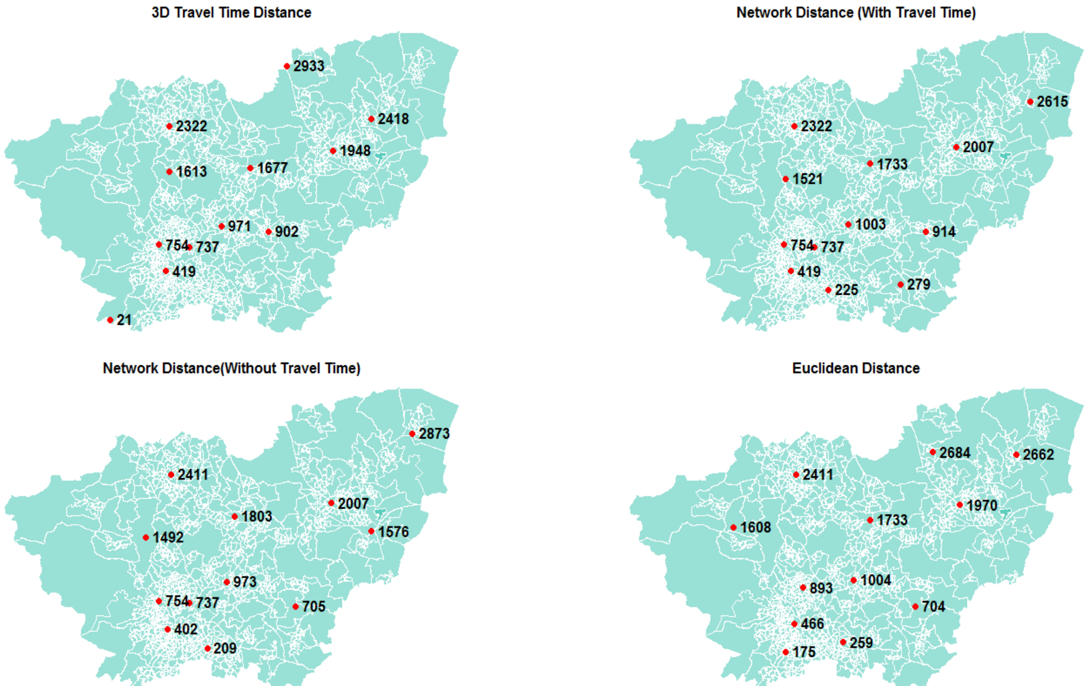

Figure 1a and b, shows the spatial distribution of selected optimal sites based on different metrics of distance. This shows a better spatial arrangement to site EMS facilities such as ambulance or paramedic units to reduce response time prior to an emergency. Optimal sites are represented as points; each optimal site has a proportion of demand allocated to it (see Table 1a and b). The distributions of selected locations also show that different set of locations were identified for night and daytime population. This suggests that location decisions are affected by distance metrics.

6 Conclusion

Evidence from an initial analysis shows that all distance types have varied effects on location decisions. This is because different sets of locations were selected using various metrics of distance. The implication of this outcome on system performance is that response time to emergency will be overestimated or under-estimated. This can lead to missed targets. 3D Network travel time offers a more realistic calibration of distance between facility and demand as compared to planar based or 2D metrics such as Euclidean and network distance formulations. The outcomes from this analysis show that location decision for EMS is sensitive to the metrics of distance used to analyse a location problem. Many studies on location-allocation to date have only applied 2D distance metrics to location problems. This study introduced a new distance metric for location models.

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8 Biographies

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