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GIS-Based impact of different search heuristics in relation to demand surface characteristics: comparing P-median with Grouping Genetic Algorithm approaches

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Abstract. This research describes the impact of different search heuristics in relation to demand surface characteristics. A Minimise Impedance (MI) P-median model and a Grouping Genetic Algorithm (GGA) were used to determine the optimal subset of locations, of different sizes, from a set of 1991 potential supply locations, evaluated over a demand surface. The demand surface was constructed from census area centroids and road network distances between demand locations and from this the potential supply locations were subsequently calculated. Potential solutions were evaluated in terms of their demand-weighted distance. The results revealed differences in the locations which were identified as being optimal between the two approaches which dealt differently with the heterogeneity of the demand surface. The differences in facility selection are discussed in relation to varying population densities. Examination of the total average distance between the demand and potential supply locations showed that there were only minor differences between the two approaches. However, it can be argued that heterogeneous demand surfaces (for example with clusters of demand) may produce bigger differences than the solutions suggested by each model.

Keywords: Supply and demand; Minimise Impedance P-median model; Location-Allocation models; Grouping Genetic Algorithm and heuristics.

1. Introduction

Modelling supply and demand is an important feature of location-allocation models. It has a long history of being used in a range of contexts to determine the optimal geographical distribution for facility locations, when measured against some objective function (see for example Hakimi, 1964; Teitz and Bart, 1968; Toregas *et al.,* 1971; Schilling *et al.,* 1993; Love and Lindquist, 1995; Parker and Campbell, 1998 and Cromley and McLafferty, 2002). These models have been extensively used to support the planning of health facilities' locations; see for example ReVelle and Swain (1970); Serra and Marianov (1999); Dessouky *et al.,* (2007); Sasaki *et al.,* (2010; 2011) and Comber *et al.,* (2011).

Many location-allocation approaches are now incorporated into standard GIS software. For instance, one of the most recent ESRI^{TM} products includes a Minimise Impedance *p*-median model as well as Minimise Facility and Maximal Covering models as part of their toolsets. Thus, one of the critical issues that arises from the widespread use of location-allocation models and their ease of implementation is how best to determine which model to use to resolve any given supply and demand problem. Different location-allocation models produce different results when applied to the same problem. In addition, different algorithms are better or less well suited to specific facility location optimisation and demand, depending on the spatial characteristics of the demand surface.

This research compares the *P*-median model, a longstanding model, with a modified Genetic Grouping Algorithm that has been recently suggested by Comber *et al.,* (2011). The *P*-median model (Teitz and Bart, 1968) employs a vertex substitution heuristic approach. Grouping Genetic Algorithms (GGAs) are an extension of the classic GA heuristic which can be used to evaluate groups (subsets) of individual solutions together rather than as individuals (Falkenauer, 1998). The objective of this research is to evaluate the impact of these two heuristic search approaches when seeking to achieve the shortest demand weighted distance between the demand and supply locations in Buraydah and to identify the advantages and disadvantages of the two approaches. Such analyses support a number of different objectives affecting medical resource planning contexts, including reducing emergency response times through improved ambulance locations.

The paper proceeds as follows: Section 2 reviews the background to the supply and demand models in GIS, and the use of heuristics and meta-heuristics. Section 3 outlines the data sources and models. Section 4 presents the results. Section 5 discusses the results in light of the models, and then some conclusions are drawn in Section 6.

2. Background

2.1 Spatial analysis of supply and demand

GIS in combination with spatial and network analyses has been widely used to analyse supply and demand and different methods for meeting both have been suggested (Church and Murray, 2009). Network distance has been used by many researchers to study accessibility in support of location planning in many different domains including health (e.g. Parker and Campbell, 1998); commerce (e.g. Naude *et al.,* 1999); green space (e.g. Comber *et al.,* 2008) and shopping centres (Liu and Zhu, 2004). Langford and Higgs (2010) used a network analysis approach to study the impact of post office closures on accessibility to services in Wales. Kotavaara *et al.,* (2011) used a network analysis to determine railway station access in relation to population changes in Finland and Kar and Hodgson (2008) evaluated and ranked emergency evacuation shelters based in Florida. Carlson *et al.* (2011) chose to apply this approach to the selection of sites suitable for public health centres to serve elderly people. There are many other examples of similar research that has used network distances with the aim of studying accessibility.

Other approaches which have been used to determine the spatial arrangement of supply in relation to demand have utilised buffer analyses and catchment based analyses. For example Ritsema van Eck and de Jong (1999) used market areas to support the planning of facilities locations. Farhan and Murray (2005) used area based approaches to model the location of facilities such as park-and-rides; whilst buffers were used by Crawford (2006) to describe accessibility to national forests in the US. Catchment area methods have also been used. Furthermore, Martin *et al.,* (1998) used them to calculate the travel distances to renal replacement therapy units in England; and Luo and Wang (2003) offered an assessment of the spatial differences between the accessing of primary care in a floating catchment area. A floating catchment area was also used as a model in another study to identify those areas which were experiencing a shortage of physicians (Luo, 2004).

Thus a range of different methods have been used in different applications to spatially analyse supply and demand problems. These have employed network analyses and other spatial tools.

However, one of the problems commonly encountered with only moderately complex supply and demand problems relates to the reality of a highly dimensional solution space. For example, Comber *et al.,* (2011) described a relatively modest site selection problem with over 10^{3347} sets of possible solutions for evaluation. In these situations, deterministic methods may not be appropriate for solving supply and demand problems and thereby indicate the need for the use of non-deterministic or heuristic methods. Heuristic searches have been used in many studies to analyse supply and demand problems (see for example Teitz and Bart, 1968; Goldberg, 1989; Church and Sorensen, 1994; Falkenauer, 1998; Li and Yeh, 2005; Sasaki *et al.,* 2010 and Comber *et al.,* 2011). The second part of this section reviews a number of heuristic approaches in order to provide scientific background for this research.

2.2 Heuristics

Heuristic approaches adopt different types of strategies to search through potential solutions (Church and Murray, 2009). Heuristic searches are included in many optimisation solutions, particularly for evaluating supply and demand problems. An example is the *P*-median model and Teitz and Bart (1968) used the first heuristic approach for this (Church and Sorensen, 1994). The *P*-median model was developed to minimise the total weighted distance aggregated over all supply and demand locations (Hakimi, 1964; Teitz and Bart, 1968; ReVelle and Swain, 1970 and Church and Sorensen, 1994). Genetic algorithms (GAs) are part of another family of heuristic search approaches, which were developed to solve the *P*-median model problem for very complex (highly dimensional) supply and demand problems (Hosage and Goodchild, 1986; Goldberg, 1989; Church and Sorensen, 1994; Sasaki *et al.*, 2010 and Comber *et al.*, 2011). Grouping GAs (GGAs) are an extension of the classic GA heuristic approaches, in which groups of solutions are evaluated rather than individuals. Other heuristic approaches such as the Greedy, Simulated Annealing, Tabu search, Hybrids and Ant Colony approaches (Church and Sorensen, 1994 and Church and Murray, 2009) have not been considered here. The aim in each case has been to minimise some evaluation function (e.g. the total distances between the supply and demand or population weighted distances) and accessibility and location-allocation research has been predicated on the assumption that optimal accessibility of locations could be achieved by minimising the total weighted distance between the supply and demand locations (for example Hakimi, 1964; Teitz and Bart, 1968; ReVelle and Swain, 1970; Hodgson, 1988 and Church, 1990).

Teitz and Bart (1968) developed a *P*-median problem which incorporated interchange heuristics as an alternative search approach. The process of the *P*-median heuristic approach depends on the interchange or substitution of locations in order to select the candidate locations that would minimise the weighted distance between supply and demand locations (Church and Sorensen, 1994). Rosing *et al.*, (1979) compared optimal solutions derived by the linear searches with the heuristic *P*-median model presented by Teitz and Bart (1968) and the Teitz and Bart model was better in terms of performance when the size of the problem is greater than the capacity of other methods. Church and Sorensen (1994) tested two heuristic approaches, the Global-Regional Interchange Approach and the Teitz and Bart (1968) *P*-median model. The study found that the performance of the Global-Regional Interchange Approach was as robust as the *P*-median formulated by Teitz and Bart. However, there are situations in which the use of the *P*-median model may be less appropriate. It has been found to be ill-suited to solutions which may have a hierarchical nature (Hodgson, 1988) such as those services which have a hierarchy in the form of classes. According to Rahman and Smith (2000: 440) “it has frequently been observed that the use of service facilities may decline rapidly when the travel time exceeds some critical value.” In this case the *P*-median model may lead to solutions that are unacceptable from the standpoint of service.

Genetic algorithms also provide heuristic solutions to problems that are complex and highly dimensional (Goldberg, 1989). The heuristic solutions proposed by GAs to solve the *P*-median problem are frequently used to minimise weighted distance or time, aggregated over supply and demand. For example, Hanta (2002) presented a model that contributed to the reduction of the cost of transportation in the Czech Republic. This was achieved through the allocation of warehouses, using a supply and demand algorithm considering transport distance on the road network between customers and distribution centres. Alp *et al.* (2003) proposed a new GA, based on the *P*-median supply and demand problem, to minimise the total travel distance between the demand point and the location of the facilities. Other authors have addressed the use of GAs to solve problems in terms of land use planning. For example, Stewart *et al.,* (2004) presented a GA approach to support the decision-makers involved in land use planning in the Netherlands. Li and Yeh (2005) applied the GA method in combination with neighbourhood search methods using GIS and simulated annealing in order to choose the optimal locations for hospitals in Hong Kong, according to the population density and road network data. They found that using the GA method led to very effective solutions. Liu *et al.,* (2006) suggested an approach to the distribution of new fire stations whereby an ant colony optimisation algorithm was used to identify fire station locations. Iannoni *et al.,* (2008) used the GA/hypercube algorithm to study the optimal locations for emergency medical services (EMS) on Brazilian highways.

Grouping genetic algorithms address specific problems by encoding objects within groups (Pitaksringkarn and Taylor, 2005). GGAs develop heuristic procedures that restore original group membership at the crossover phase to account for any displacement of other similar members (Comber *et al.,* 2011). Falkenauer (1998) proposed the GGAs to solve three obstacles associated with applying classical GAs to grouping problems: Firstly, standard GAs are not relevant to the group setting; secondly, when performing a recombination, new population members may emerge containing none of their parents' qualities and thirdly, an operator may produce individuals that disrupt the activities of successful population members. According to Nicholson (1999: 1137) "the aim of a grouping problem is to group the members of a set of objects into one or more groups, where each object is in exactly one group". Comber *et al.* (2011) described the development and application of a modified GGA and Sasaki *et al.* (2010) used this to optimise current and future ambulance locations based on projected future population growth. Brown and Sumichrast (2003) demonstrated that the use of the replacement heuristic could significantly improve the GGA. Pitaksringkarn and Taylor (2005) used GGAs to study the accessibility of jasmine rice for the markets in Thailand and to suggest solutions to the problem of transport costs; and provided a good discussion of the differences and similarities between GGAs and GAs. Wroblewski and Brown (2006) developed GGAs to achieve the minimum impact when planning mobile networks. Comber *et al.,* (2009) proposed using GGAs together with the output of GIS-based network analysis, when evaluating the provision of post office services in Leicestershire. Comber *et al.* (2011) also selected optimal locations for ambulances using GGAs. The GGA approach, combined with the *P*-median model (that will be used in this paper) is similar to the GGA approach as used by Comber *et al.* in 2011. More details about the GGAs used in this study are presented in the methods section.

3. Methods

This research compares two heuristic approaches, the MI *P*-median model and the modified GGA as suggested by Comber *et al.,* (2011). The process involved in the *P*-median heuristic approach depends on the interchange or substitution between the locations to select the candidate locations able to minimise the weighted distance between the supply and demand locations (Church and Sorensen, 1994). The GGA approach used in this paper was designed to help select the optimal subsets of the locations based on single discrete sets of points of a fixed size (Comber *et al.,* 2011).

3.1 The case study

The study compared the results produced by the MI *P*-median model with those arising from a GGA when both were used to determine the best subsets of different number of evaluated over the demand surface derived from neighbourhood population data. The demand could be related to any kind of facility but this paper used the example of optimal locations for potential Emergency Medical Services (EMS) in Buraydah city, the largest city in Al Qassim province in the Kingdom of Saudi Arabia (KSA). According to the population census data of 2004, the total population of Buraydah city was estimated to be 377,701 people in seventy neighbourhoods (see Figure 1). This was due to the unavailable of neighbourhoods population census data in Buraydah in the census of 2010. EMS such as ambulances are one of the most important health services, and ambulance response times depend on their spatial distribution in relation to the road network and distribution of demand (Population). The methods used in this study aimed to optimise geographic coverage of the majority of the population within the city (see for example ReVelle and Swain, 1970; Serra and Marianov, 1999; Dessouky *et al.,* 2007; Sasaki *et al.,* 2010 and Comber *et al.,* 2011).

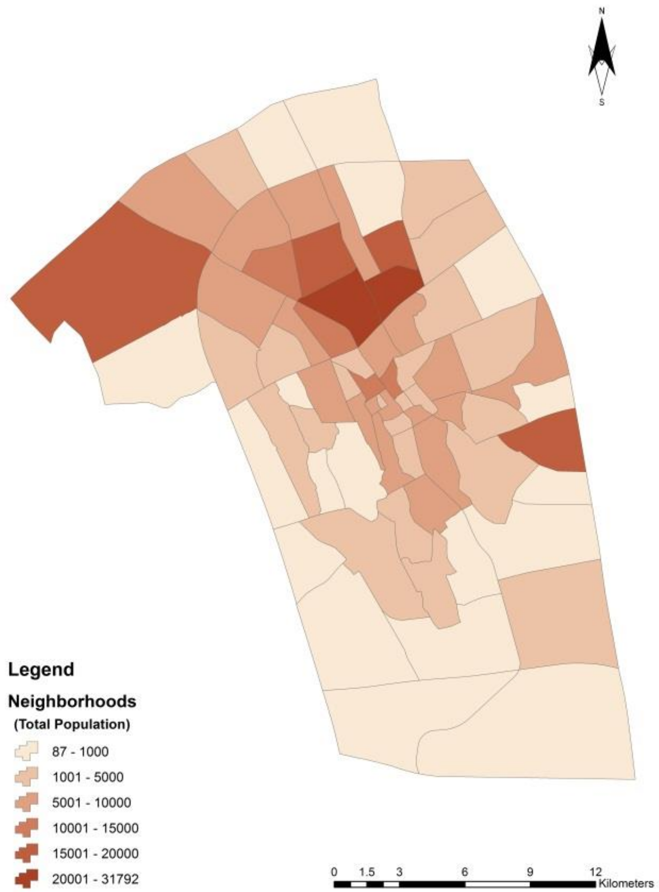

Figure (1). Population density in Buraydah city.

The road network dataset and the neighbourhood data were provided by the Ministry of Municipal and Rural Affairs in the Kingdom of Saudi Arabia (KSA). The population data was obtained from the Ministry of Economics and Planning in the KSA. The 1991 potential EMS locations (supply) were created from a regular 500m grid as an example (see Figure 2) and each centroid of each neighbourhood area was used to indicate demand locations. Thus each demand location was associated with a demand weight based on the population of that particular neighbourhood. Using the road network, the distances between each of the 1991 potential supply points and each of the seventy demand points were calculated using network analysis.

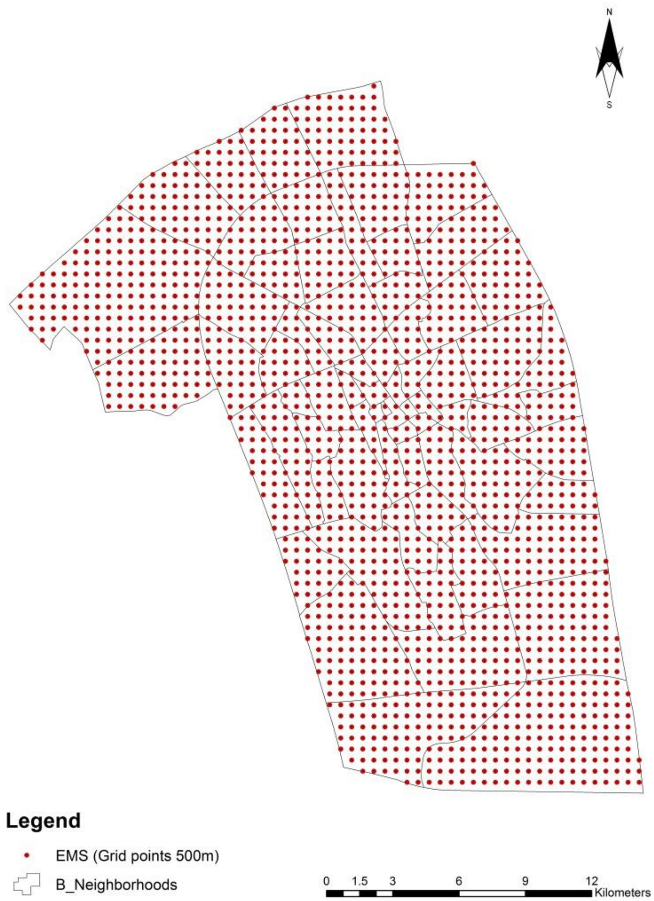

Figure (2). 1991 EMS locations created from grid cells measuring 500 metres in Buraydah.

3.3 The MI P-median model

The MI *P*-median model is a longstanding location-allocation model which seeks to minimise the total weighted distance aggregated over all of the supply and demand locations (Hakimi, 1964; Teitz and Bart, 1968). In terms of the operations, this model depends upon the interchange or substitution of the number of locations that are required to select the chosen and candidate locations capable of minimising the weighted distances between the supply and demand locations (Church and Sorensen, 1994). The objective function of this model, as has been described by Teitz and Bart (1968) and written in Cromley and McLafferty (2002) and it can be specified as:

The objective function of this model IS to:

$$\text{Minimise } Z = \sum_{i \in I} \sum_{j \in J} a_i d_{ij} x_{ij} \qquad Equation\ (1)$$

Given the following constraints:

1) A facility has to be allotted with a separate demand site: $x_{ij} \leq x_{jj}$ for all (i, j)

2) An open facility must be allotted a demand:

$$\sum_{j \in J} x_{ij} = 1 \text{ for all } i \qquad Equation\ (2)$$

3) Only the p facilities are to be located:

$$\sum_{j \in J} x_{jj} = p \text{ for all } j \qquad Equation\ (3)$$

4) The sum of the neighbourhoods assigned to them equals the number of facilities to be located.

The total demand from a separate demand site is given as:

$x_{ij} = (0, 1)$ for all (i, j) is allotted to only one facility, where:

Z = objective function;

I = all the demand areas where the nodes on the network along the subscript i are an index signifying a specific demand area;

J = the collection of candidate facility sites when the nodes on the network along with the subscript j are frequently an index which signifies a particular facility site;

a_i = the number of people who are present at the demand site i;

d_{ij} denotes the distance in terms of the travel cost and separates place i from candidate facility site j.

x_{ij} is equal to 1 when demand at place i is allotted to a facility opened at site j, or is equal to 0 when the demand at place i is not allotted to that site; and

p = the number of facilities that need to be located.

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3.4 The GGA approach

GGAs represent a modification to the classic GA approach. GAs use a ‘string’ (Huang *et al.*, 2004) or ‘chromosome’ of potential individual solution sites, where the sites are the ‘genes’ in a chromosome. The creation of new chromosomes (crossover) is repeated when the genes for successful individual sites (i.e. that meet some selection criteria) are passed on to new chromosomes, until either convergence criteria are realised or a pre-determined number of cycles are completed. There is a danger that were optimisation to continue it might stagnate and therefore GAs introduce some random new genes (mutation) in each cycle. On this basis, the optimal solutions in GA process ‘breeds’ use the approach that mimics natural selection, leading to increasingly fitter generations as a consequence of a combination of cross-selection and mutation (Comber *et al.,* 2011).

Comber *et al.,* (2011) argued that when using standard GA in a grouping context there was only low-level correlation with the *P*-median problem, because the GA referred to associations of individuals; whilst with the grouping GA categorised them into ‘used’ or ‘not used’. The GGA analysis applied in this study was related to work previously undertaken by Hosage and Goodchild (1986). To overcome the three major drawbacks of GAs as described by Falkenauer (1998), GGAs function to develop heuristic procedures that restore original group membership at the crossover phase to account for any displacement of other similar members (Comber *et al.,* 2011).

The GGA analysis in this paper was applied to select the *N* best potential locations (5, 10, 15, 20, 25, 30, 35, 40, 45, 50, 55, 60, 65 and 70) from a set of 1991 EMS locations, as shown in Figure 2, through evaluation over population-weighted distances. The algorithm was developed from the ‘genalg’ package described by Willighagen (2005) for R statistical programming (http://cran.r-project.org/web/packages/genalg/genalg.pdf) and modified to be more efficient, as described in Comber *et al.,* (2011).

4. Results

The results are shown in Figures 3 and 4. These indicate that different locations were identified for each of the different subsets by the different approaches except for the subset of five locations. The similarities in the results for the subset of five locations are explained by the high population density of the neighbourhoods in the central, eastern and western parts of Buraydah. Thus, the five facilities that were selected by the two methods were the best locations to minimise the weighted distance between the supply and demand locations but were concentrated close to the demand points for neighbourhoods with high population density. On this basis, the demand in these areas can only be optimally satisfied in one way with five locations, for which little heuristic searching is needed. However, when the subset was larger than five facilities, clear differences in the facility selection was found to be evident. Despite the different locations that were selected, the differences in the average population weighted distances indicated that the impacts of these different locations were very small (Table 1). Distance has been identified as a key factor affecting accessibility to facilities locations with accessibility being negatively affected whenever there was an increase in the distance between demand and supply (Dessouky *et al.,* 2007). Thus, in order to test the two methods, the study compared the total average distances for the results of the best locations. The results indicated that there were minor differences between the average distances for the two approaches (see Table 1 and Figure 5).

The effectiveness of and the differences in the results between the two location allocations algorithms varied depending on the spatialities of the problem being tackled, indicating factors that affect the results of the location allocations algorithms. For example, the spatial nature of the demand surfaces in terms of the heterogeneity of demand distribution, the distance thresholds and the number of facility sites. On this basis, the study noted that the heterogeneous demand surface in Buraydah city resulted in differences between the results of the two approaches. These differences in the facilities selected are concentrated in neighbourhoods that have low population densities. In addition, with the open distance thresholds between the demand and the facilities there were also some differences in the facilities selection results and the average population weighted distances between the MI *P*-median model and GGA approach. It can be argued that whenever the distance thresholds between the demand and the facilities were decreased, the average population weighted distances would be less and the solutions would also be limited to the two approaches. The implications of these results are discussed below.

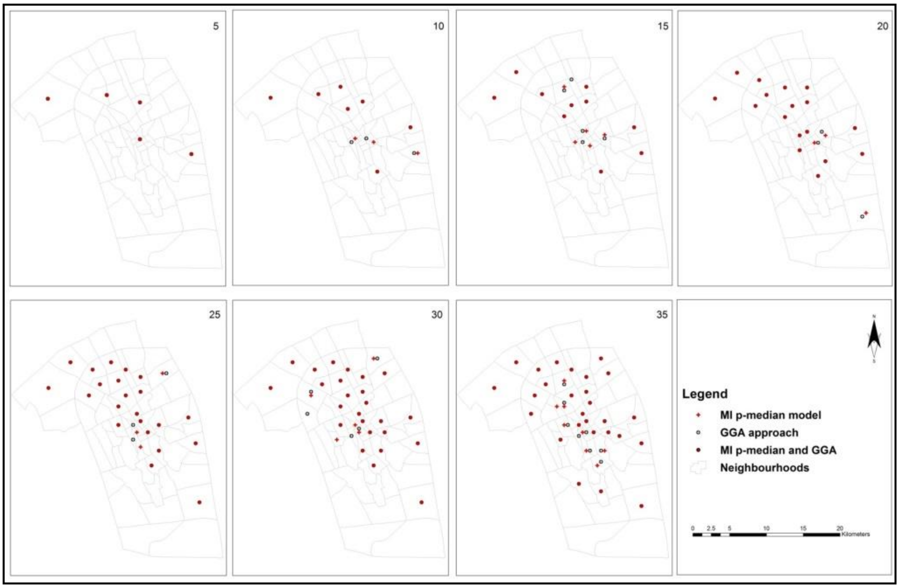

Figure (3). Results of applying the MI P-median model and the GGA approach to select the best 5, 10, 15, 20, 25, 30 and 35 potential locations from a set of 1991 potential locations.

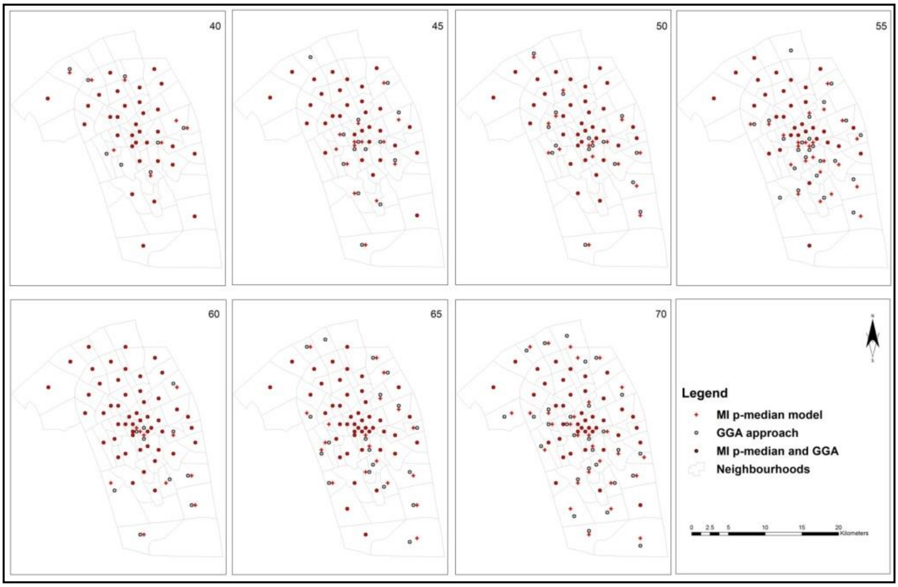

Figure (4). Results of applying the MI P-median model and the GGA approach to select the best 40, 45, 50, 55, 60, 65 and 70 potential locations from a set of 1991 potential locations.

Table (1). Results of the average distances between the MI P-median model and the GGA approach

	Average distances (m)	
Locations	MI *P*-median	GGA
5	4805	4805
10	3582	3553
15	3129	3193
20	2675	2700
25	2400	2398
30	2110	2171
35	1694	1726
40	1375	1356
45	1197	1192
50	975	1042
55	900	899
60	668	697
65	404	456
70	201	340

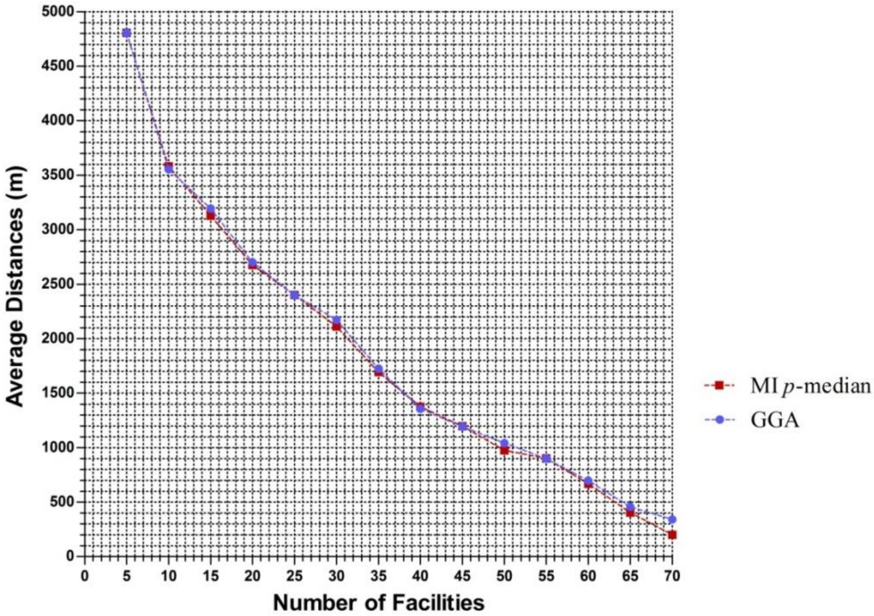

Figure (5). Results of the average distances between the MI P-median model and the GGA approach.

5. Discussion

The results of the two heuristic approaches aimed to provide the optimal subset of selections by minimising the weighted distance between the supply and demand locations. The results showed that with the exception of the subset of the best five locations there were differences in the facilities selection results for each subset number by the different approaches. The subset of the five locations was located in the high population density of the neighbourhoods in the central, eastern and western parts of Buraydah. In addition, there were minor differences between the average distances between the supply and the demand for the two approaches.

Location-allocation algorithms have inherent assumptions about the spatial nature of demand surfaces and how facilities are to be optimised over them, which make them differently suited to specific problems. The homogenous or heterogeneous population distribution (in terms of census areas), facilities locations, distance thresholds and the grid sizes are important problem factors and so should be taken into account when using the location allocation algorithms. Therefore, two different search heuristics were used in this paper to investigate the impact of the demand surfaces characteristics on these approaches.

Search operations for each of the two approaches are different in terms of facility location optimisation and demand. For example; the operations of the MI *P*-median employs a vertex substitution and meta heuristics in order to allow interchange or substitution between the locations, to select the candidate locations that are able to minimise the weighted distance between the supply and demand locations (Church and Sorensen, 1994). In contrast, the modified GGA approach is often used with criteria associated with specific problems by encoding the objects within groups (Pitaksringkarn and Taylor, 2005). The operations of the GGA approach, as described in Comber *et al.*, (2011) and used in this paper, were to restore original group membership at the crossover phase to account for any displacement of other similar members. The algorithm used by Comber *et al.,* (ibid) relied on benefitting from the requirement for only two groups, because the other set was implicit. The advantage of this was related to the fact that it was possible to choose the smaller of the groups in order to be stored as a chromosome (Comber *et al.,* 2011). However, when the study applied the two approaches on the heterogeneous demand surface there were some differences in the facilities selection results, as based on the subsets of the best locations in some of the neighbourhoods that had low population densities (see Figures 3 and 4). Therefore, the two approaches dealt differently with the heterogeneous demand surface which was distributed into seventy demand points and ranged between 31792 and 87 people (see Figure 1).

Different algorithms are more or less suited to specific facility location optimisation and demand depending on the spatial characteristics of the demand surface. The impact of the demand surface characteristics was clear with regards to the results of this study. However, a more heterogeneous demand surface may produce bigger differences, for example in terms of clusters of demand. Comparisons between methods such as the two heuristic approaches with different demand surfaces characteristics constitute a new research area. Future analysis will focus on the interaction of different supply and demand models with different demand surfaces, resulting from the use of areal interpolation techniques.

6. Conclusion

This research has provided a comparison between two heuristic approaches in order to investigate the impact of the demand surfaces characteristics on these approaches. Heuristic approaches provide solutions to problems that have complex, highly dimensional solution spaces. In seeking to minimise the weighted distances between supply and demand locations, different models were found to produce different results when applied to the same problem. However, the consequences of these differences were found to be small, with losses in one area being cancelled out by gains in another. Whilst the results of the heuristic approaches provide evidence for planning decisions and can support decision-makers in choosing the most appropriate locations for different services, this research has discovered that the differences between approaches are driven by the degree of heterogeneity or homogeneity in the demand surface.

The study also showed that the use of either the MI *P*-median model or the GGA approach varied depending on the spatialities of the problem being tackled in terms of the demand surface characteristics. The reduction of either response time or weighted distance between the facilities and demand locations are the main aims of planners and decision makers. The two heuristic approaches were different in terms of their operation but, in contrast, were similar in terms of their objective, which sought to minimise the weighted distances between supply and demand locations. Thus the problem type, in combination with the complexities of the demand surface, are crucial factors that must be considered by planners and policy makers before deciding which method is the most appropriate choice for use in each individual case.

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References

[1] Alp, O. Erkut, E. and Drezner, Z., 2003, An efficient genetic algorithm for the *p*-median problem, *Annals of Operations Research*, 122, 21-42.

[2] Brown, E. and Sumichrast, R., 2003, Impact of the replacement heuristic in a grouping genetic algorithm, *Computers and Operations Research,* 30, 1575-1593.

[3] Carlson, T. York, S. and Primomo, J., 2011, The utilization of geographic information systems to create a site selection strategy to disseminate an older adult fall prevention program, *The Social Science Journal,* 48, 159-174.

[4] Church, R and Murray, A., 2009, *Business site selection, location analysis and GIS,* New Jersey: John Wiley and Sons.

[5] Church, R. L., 1990, The regionally constrained *p*-median problem, *Geographic Analysis,* (22), 22-32.

[6] Church, R. and Sorensen, P., 1994, Integrating Normative Location Models into GIS: problems and prospects with the *p*-median model, *National Center for Geographic Information and Analysis,* Technical Report, 94-5.

[7] Comber, A. Brunsdon, C. and Green, E., 2008, Using a GIS-based network analysis to determine urban green space accessibility for different ethnic and religious groups, *Landscape and Urban Planning,* 86, 103-114.

[8] Comber, A. J., Brunsdon, C., Hardy, J. and Radburn, R., 2009, Using a GIS-based network analysis and optimisation routines to evaluate service provision: a case study of the UK Post Office, *Applied Spatial Analysis and Policy*, 2 (1), 47-64.

[9] Comber, A. J., Sasaki, S., Suzuki, H. and Brunsdon, C., 2011, A modified grouping genetic algorithm to select ambulance site locations, *International Journal of Geographical Information Science*. 25:5, 807-823.

[10] Crawford, T.W., 2006, Polygon-to-Polygon Spatial Accessibility Using Different Aggregation Approaches: A Case Study of National Forests in the US Mountain West Region. *Transactions in GIS,* 10 (1), 121-140.

[11] Cromley, E. and McLafferty, S., 2002, *GIS and Public Health*, New York: Guilford Press.

[12] Dessouky, M. Hongzhong, J. and Fernando, O., 2007, A modeling framework for facility location of medical services for large-scale emergencies, *IIE Transactions*, (39), 1-41.

[13] Falkenauer, E., 1998, *Genetic algorithms and grouping problems*, London: John Wiley and Sons.

[14] Farhan, B. and Murray, A., 2005, A GIS-Based Approach for Delineating Market Areas for Park and Ride Facilities, *Transactions in GIS*, 9 (2), 91-108.

[15] Goldberg, D.E., 1989, *Genetic algorithms in search, optimization, and machine learning*, Reading, MA: Addison-Wesley.

[16] Hakimi, S., 1964, Optimum Locations of Switching Centres and the Absolute Centres and Medians of a Graph, *Opns. Res*, (12), 450-459.

[17] Hanta, V., 2002, Planar multi facility location - the location-allocation problem, *Conference on Scientific Computing*, 260-267.

[18] Hodgson, M. J., 1988, An hierarchical location-allocation models for primary health care delivery in a developing area, *Social Science and Medicine*, 26, 153-161.

[19] Hosage, C. M. and Goodchild, M. F., 1986, Discrete space location-allocation solutions from genetic algorithms, *Annals of Operations Research*, 6, 35-46.

[20] Huang, B. Cheu, R. and Liew, Y., 2004, GIS and genetic algorithms for HAZMAT route planning with security considerations, *International Journal of Geographical Information Science*, 18, 769-787.

[21] Iannoni, A. P. Morabito, R. and Saydam, C., 2008, A hypercube queueing model embedded into a genetic algorithm for ambulance deployment on highways, *Annals of Operational Research*, 157, 207-224.

[22] Kar, B. and Hodgson, M., 2008, A GIS-Based Model to Determine Site Suitability of Emergency Evacuation Shelters, *Transactions in GIS*, 12 (2), 227-248.

[23] Kotavaara, O. Antikainen, H. and Rusanen, J., 2011, Population change and accessibility by road and rail networks: GIS and statistical approach to Finland 1970-2007, *Journal of Transport Geography*, 19, 926-935.

[24] Langford, M. and Higgs, G., 2010, Accessibility and public service provision: evaluating the impacts of the Post Office Network Change Programme in the UK, *Transactions of the Institute of British Geographers*, 35, 585-601.

[25] Li, X. and Yeh, A. G., 2005, Integration of genetic algorithms and GIS for optimal location search, *International Journal of Geographical Information Science*, 19, 581-601.

[26] Liu, N. Huang, B. and Chandramouli, M., 2006, Optimal siting of fire stations using GIS and ANT algorithms, *Journal of Computing in Civil Engineering*, (20), 5, 361-369.

[27] Liu, Suxia. and Zha, Xuan., 2004, An Integrated GIS Approach to Accessibility Analysis. *Transactions in GIS,* 8 (1), 45-62.

[28] Love, D. Lindquist, P., 1995, The geographical accessibility of hospitals to the aged: a geographic information systems analysis within Illinois, *Health Services Research*, 29, 629-651.

[29] Luo, W. and Wang, F., 2003, Measures of spatial accessibility to health care in a GIS environment: synthesis and a case study in the Chicago region, *Environment and Planning B: Planning and Design*, 30 (6), 865-884.

[30] Luo, Wei., 2004, Using a GIS-based floating catchment method to assess areas with shortage of physicians, *Health and Place*, 10, 1-11.

[31] Martin, D., Roderick, P., Diamond, I., Clements, S. and Stone, N., 1998, Geographical aspects of the uptake of renal replacement therapy in England. *International Journal Popular Geographer*, 4, 227-242.

[32] Naude, A. Jong, T. and Teeffelen, P., 1999, Measuring Accessibility with GIS-Tools: A Case Study of the Wild Coast of South Africa, *Transactions in GIS,* 3 (4), 381-395.

[33] Nicholson, M., 1998, Genetic Algorithms and grouping problems, *Software: Practice and Experience*, 28, 1137-1138,

[34] Parker, E. B. and Campbell, J L., 1998, Measuring access to primary medical care: some examples of the use of geographical information systems, *Health and Place,* (4), 183-193.

[35] Pitaksringkarn, L. and Taylor, M. A. P., 2005, Grouping genetic algorithm in GIS: a facility location modelling, *Journal of the Eastern Asia Society for Transportation Studies*, 6, 2908-2920.

[36] Rahman, S. and Smith, D., 2000, Use of location-allocation models in health service development planning in developing nations, *European Journal of Operational Research 123*: 437-452.

[37] ReVelle, C. S. and Swain, R. W., 1970, Central facilities location, *Geographic Analysis,* (2), 30-42.

[38] Ritsema van Eck, J.R. and de Jong, T., 1999, Accessibility analysis and spatial competition effects in the context of GIS-supported service location planning, *Computers, Environment and Urban Systems*, 23, 75-89.

[39] Rosing, K. Flillsman, E. and Rosing-Vogelaar, H., 1979, A note comparing optimal and heuristic solutions to the *p*-median problem, Geography Analysis 11: 86-89.

[40] Sasaki, S. Comber, A. J. Suzuki, H. and Brunsdon B., 2010, Using genetic algorithms to optimise current and future health planning - the example of ambulance locations. *International Journal of Health Geographics*, 9, 4.
[41] Sasaki, S. Igarashi, K. Fujino, Y. Comber, A. J. and Brunsdon, C. Muleya, C.M. and Suzuki, H., 2011, The impact of community-based outreach immunization services on immunization coverage with GIS network accessibility analysis in peri-urban areas, Zambia, *Journal of Epidemiology and Community Health*, 65, 1171-1178.
[42] Schilling, D. Jayaraman, V. and Barkhi, R., 1993, A review of covering problems in facility location, *Location Science*, (1), 25-55.
[43] Serra, D. and Marianov, V., 1999, The P-median problem in a changing network: the case of Barcelona. *Location Science*, 6 (1), 383-394.
[44] Stewart, T. Janssen, R. and van Herwijnen, M., 2004, A genetic algorithm approach to multi objective land use planning, *Computers and Operations Research*, 3, 2293-2313.
[45] Teitz, M. B. and P. Bart., 1968, Heuristic Methods for Estimating the Generalised Vertex Median of a Weighted Graph, *Journal of the Operational Research Society of America 16*, (5), 955-961.
[46] Toregas, C. Swain, R. ReVelle, C. and Bergman, L., 1971, The location of emergency service facilities, *Operations Research* (19), 1363-1373.
[47] Vroblefski, M. Brown, E., 2006, A grouping genetic algorithm for registration area planning, *Omega*, 34, 220-230.
[48] Willighagen, E., 2005, Genalg: R Based Genetic Algorithm [Online], R package version 0.1.1, Available from:
[49] http://cran.r-project.org/web/packages/genalg/genalg.pdf [Accessed 15 October 2011].

Biography

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وصف أثر استخدام أساليب البحث والاستدلال في بيئة نظم المعلومات الجغرافية وعلاقته بخصائص التوزيع الجغرافي لسطح الطلب: مقارنة بين أسلوبي المتوسط والخوارزمات الجينية

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ملخص البحث. يركز هذا البحث على وصف أثر استخدام أساليب البحث والاستدلال التي تندرج تحت:

(Location-Allocation Models)

في بيئة نظم المعلومات الجغرافية وعلاقته بخصائص التوزيع الجغرافي لنقاط الطلب (السكان) بهدف تحديد المواقع المثلى للخدمة من مجموعة مواقع محتملة.

ولقد تمت مقارنة نتائج نموذجين من تلك النماذج وهي:

P-median model and Grouping Genetic Algorithm

من أجل تحديد التوزيع الجغرافي الأمثل للخدمات من مجموعة مواقع محتملة تقدر بـ ١٩٩١ موقعاً وفقاً للتوزيع الجغرافي لأحياء مدينة بريدة. أساليب البحث والاستدلال في النموذجين واحدة من ناحية الهدف والوظيفة ولكنها تختلف في عملية التنفيذ، لذلك كان من المفترض أن تكون النتائج متشابهة، ولكن هذا البحث أثبت وجود بعض الاختلافات في نتائج أفضل توزيع جغرافي للخدمات بين النموذجين بسبب الخصائص الجغرافية الغير متجانسة للتوزيع الجغرافي لسطح الطلب (السكان) في مدينة بريدة. وعليه يمكن القول بأن أساليب البحث والاستدلال في نماذج تخصيص المواقع قد تتأثر بالأسطح الغير متجانسة سكانياً من حيث التوزيع الجغرافي.