A Comparison of GIS-based Location Allocation Heuristics: Minimise Impedance vs Grouping Genetic Algorithm p-median

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1. Introduction

Modelling supply and demand is an important feature of location-allocation models. Such models have a long history of usage in different applications in order to determine the optimal geographical distribution of facility locations against some objective function (for example Hakimi, 1964; Teitz and Bart, 1968).One of the key issues arising from the increasing use of location-allocation models and their ease of implementation is how to determine which model to use for any given supply and demand, or location-allocation problem as different models produce different results when applied to the same problem. Many GIS software's now includes a number of models such as the Minimise Impedance p-median, the Minimise Facility, the Maximal Covering as part of their toolsets.

This research compares the Minimise Impedance implementation of the p-median model, a long standing model, top a modified Grouping Genetic Algorithm (GGA) implementation recently suggested by Comber *et al.,* (2011). The p-median model (Teitz and Bart, 1968) takes a vertex substitution heuristic approach. Grouping Genetic Algorithms (GGAs) are an extension of the classic GA heuristic that evaluates groups of individual solutions rather than individuals. The objective of this work is to evaluate these two heuristic approaches to achieving the shortest demand weighted distances between demand and supply locations, thereby helping to reduce such things as emergency response times, and to identify the advantages and disadvantages of the two approaches.

2. Methods
2.1 The case study

This paper compares the results produced by two p-median models employing different heuristic search strategies – a minimise impedance strategy and a Grouping GA - to identify the optimal locations for 5, 10, 15, 20, 25, 30 and 35 facilities from a set of 1991 potential locations. A demand surface was constructed from total population data. The supply could be for any kind of facility, such as EMS, and retail opportunities, etc, but this paper provides examples of how best to locate the optimum ten locations for future EMS out of 1991 identified 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 the city of Buraydah was estimated to be 377,701 people. Buraydah city is divided into 70 neighbourhoods (see Figure 1a)
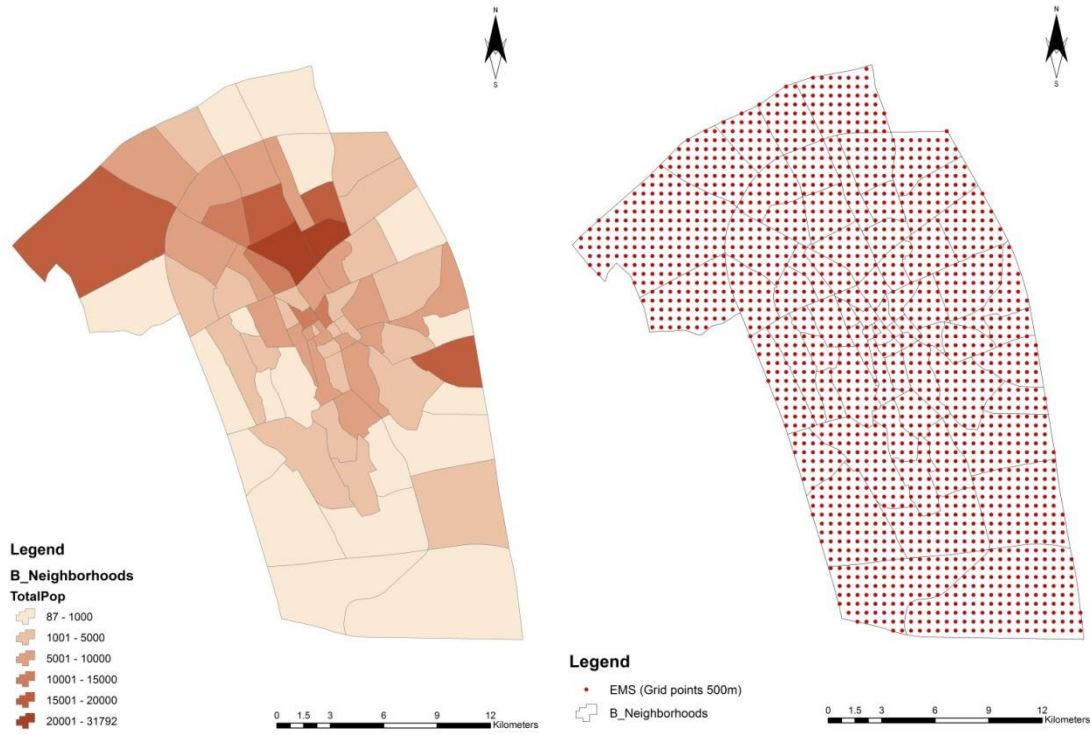
Figure 1. a) Population density in Buraydah city, b) potential locations from a 500 metres grid

2.2 Data and preprocessing

The road network dataset and neighbourhoods data was 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 EMS locations were created from grid cells in Buraydah measuring 500 metres across by using Hawth's tools extension in ArcGIS (see Figure 1b).

2.3 The MI *p*-median model

The MI *p*-median model seeks to minimise the weighted distance, aggregated over supply and demand. The objective of this model is described by Teitz and Bart, (1968) and has been written in Cromley and McLafferty (2002) as follows:
The objective function of this model is to:

$$\text{Minimize } Z = \sum_{i \in I} \sum_{j \in J} a_i d_{ij} x_{ij} \tag{1}$$

It is faced with the following restraints:
A facility has to be allotted with a separate demand site: $\quad x_{ij} \leq x_{jj}$ for all (i, j)
An open facility must be allotted a demand:

$$\sum_{j \in J} x_{ij} = 1 \text{ for all } i \tag{2}$$

Only the *p* facilities are to be located:

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

(All the communities assigned to them equal the number of facilities to be located).
Total demand from a separate demand site: $x_{ij} = (0, 1)$ for all (i, j)
is allotted to only one facility.
When:
Z = objective function.
I = all the demand areas where the nodes on network along the subscript *i* are an index signifying a specific demand area.
J = the collection of candidate facility sites when frequently the nodes on network along with the subscript *j* are an index which signifies a particular facility site.
a_i = the amount of people who are present at demand site *i*.
d_{ij} = denotes the distance or time in terms of the travel cost and separates place *i* from candidate facility site *j*.
x_{ij} = equal to 1 when demand at place *i* is allotted to a facility opened at site *j*, or equal to 0 when the demand at place *i* is not allotted to that site.
p = the amount of facilities that need to be located.

2.4 The GGA approach

The GGA approach applied in this paper was derived from the 'genalg' package described by Willighagen (2005) for R statistical programming (http://cran.r-project.org/web/packages/genalg/genalg.pdf). Full details of this algorithm can be found in Comber *et al.,* (2011).
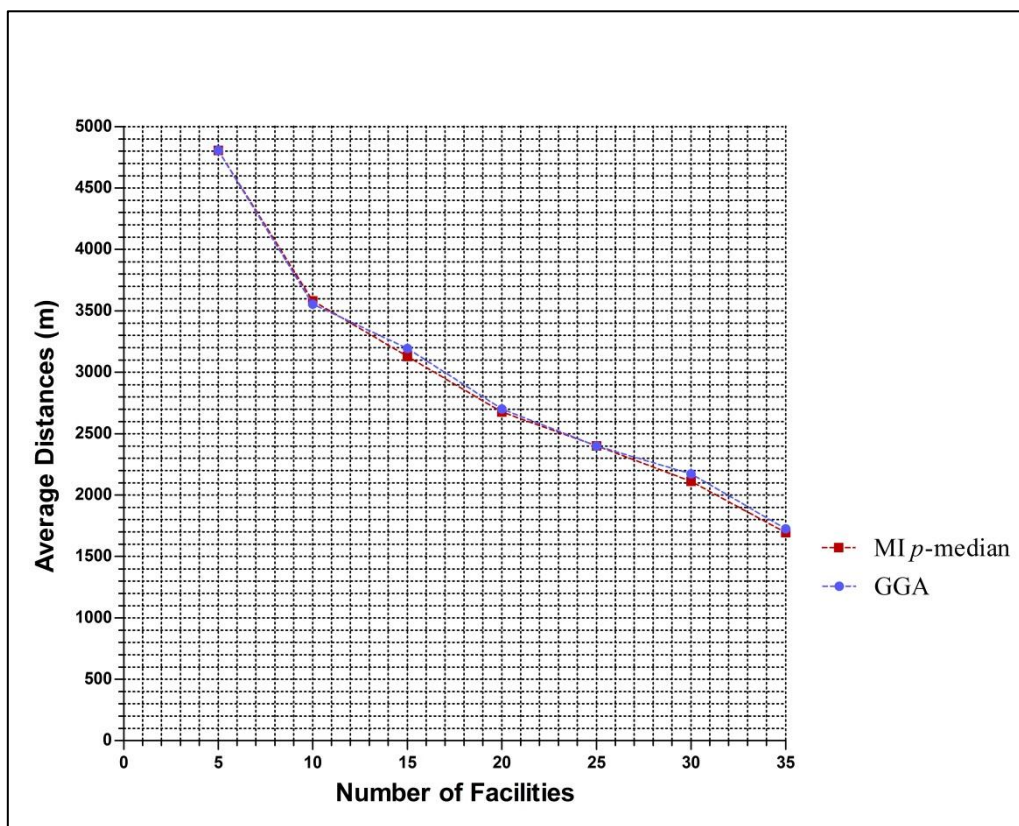
3. Results

The results show that there were different locations were identified for all each of the different facility numbers expect for when 5 facilities were identified (Figure 3). However, despite the large differences in the locations that were selected, the differences in average distances for the population, the differences indicate that these impacts of these different locations are very small. Distance has been identified as a key factor affecting accessibility to facilities locations with accessibility being negatively affected whenever there is an increase in the distance between demand and supply (Dessouky *et al.,* 2007). On this basis, in order to test the two methods, the study compared the total average distances for the results of best locations. The results indicated that there were minor differences between the average distances for the two approaches (see Table 1 and Figure 4). The implications of these results will be discussed.
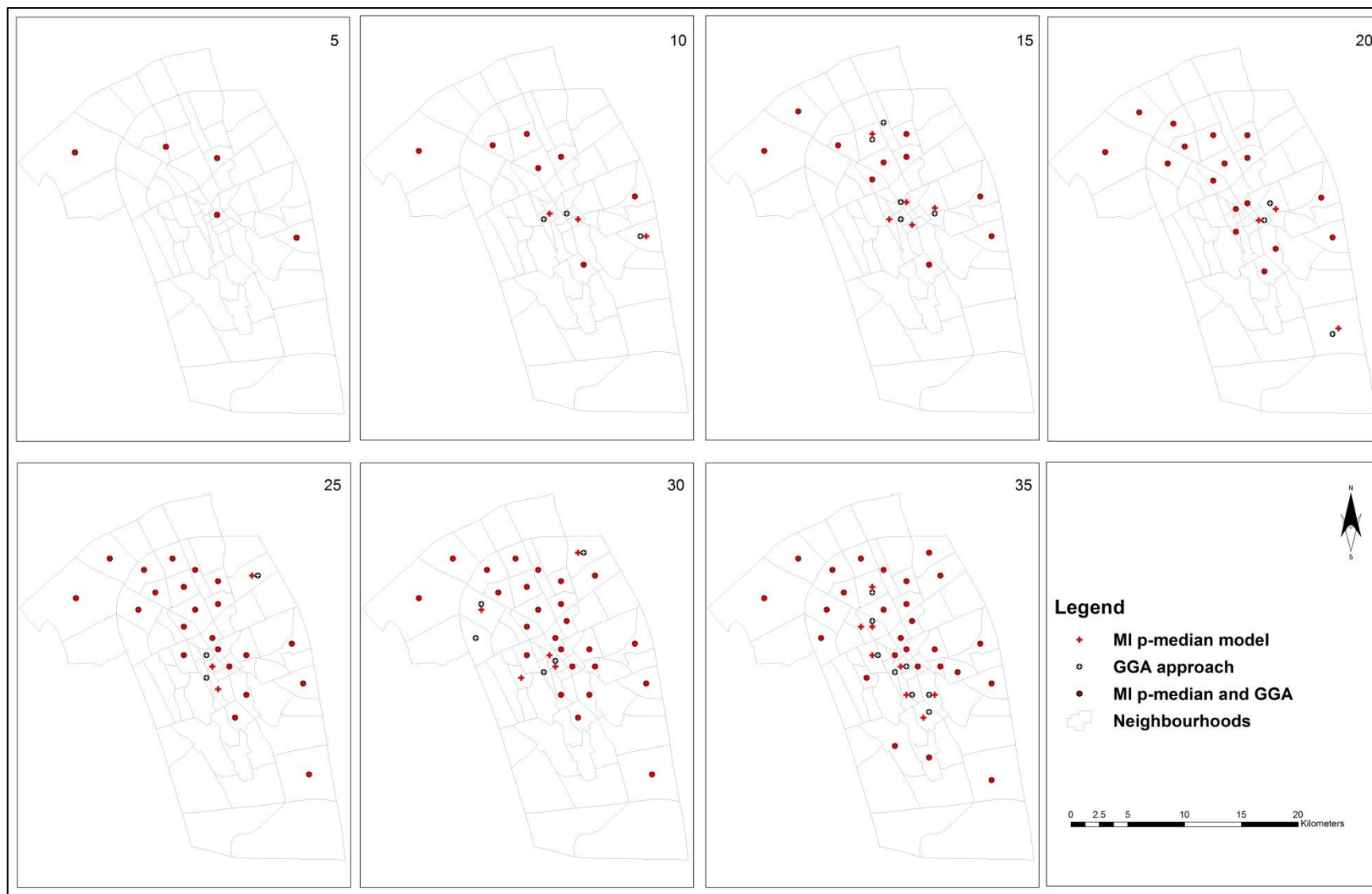
Figure 3. Results of applying MI *p*-median model and GGA approach to select the best 5, 10, 15, 20, 25, 30 and 35 potential locations from a set of 1991 potential locations

Table 1. Results of the average distances between the MI *p*-median model and GGA approach

Locations	Average distances (m)	
	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

Figure 4. Results of the average distances between the MI *p*-median model and GGA approach

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Biography

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