# A Framework for Shelter Location Decisions by Ant Colony Optimization

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### ABSTRACT

Earthquakes frequently destroy the homes and livelihoods of thousands. One of the most important concerns after an earthquake is to find a safe shelter for the affected people. Because of large numbers of potential locations, the multitude of constraints (e.g. access to infrastructures; security); and the uncertainty prevailing (e.g., number of places required) the identification of optimal shelter locations is a complex problem. Nevertheless, rapidly locating shelters and transferring the affected people to the nearest shelters are high priority in crisis situations. In this paper, we develop a framework based on Ant Colony Optimization (ACO) to support decisions-makers in the response phase. Using the same framework, we also derive recommendations for urban planning in the preparedness phase. We demonstrate our method with a case focusing on the city of Kerman, in Iran.

### Keywords

Crisis Management, Shelter Planning, Location Decision, Ant Colony Optimization.

### INTRODUCTION

A quick look at recent earthquakes over the last decade depicts that most of them have occurred in Asian countries leaving massive casualties (Hamada, 2014). According to (UNHABITAT)[1], shelter is one of the priority needs in humanitarian crises worldwide. Locations of shelters or camps will determine the logistics processes, and can have a major influence on the longer term economic and social stability (Rashed & Weeks, 2003). Locating these safe places before the crisis can play a significant role in improving the crisis management programs as well as reducing injuries (Givechi, Attar, Rashidi, & Nasbi, 2013). However, because of the uncertainty in predicting earthquakes and their consequences, such as the behavior of the population, finding an optimal combination of shelters before the disaster is a complex problem (Anping, 2010).

### BACKGROUND

The well-known crisis management cycle includes four stages: prevention, preparedness, response, and recovery. Because of the time pressure and limited capacity in the aftermath of a disaster, we propose to identify potential shelter locations in the Preparedness stage. During the response, information about the locations needs to be updated (e.g., safety, accessibility), and the evacuation to the operational shelters needs to be executed.

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1 http://mirror.unhabitat.org/content.asp?typeid=19&catid=286&cid=868

The shelter location problem involves three steps: (i) selecting shelter locations, (ii) routing (optimal paths to shelter location), and (iii) allocating of affected population to selected shelters (Saadatseresht, Mansourian, & Taleai, 2009). Previous research mostly includes only one or two of the aforementioned steps. For instance, (Arnaout, 2013) focused on locating and allocating (i and iii) an unknown number of service points by calculating Euclidean (not road) distances and minimizing transportation costs. (Kilci, Yetiş Kara, & Bozkaya, 2013) used mixed integer linear programming to solve a model with ten criteria for locating (i) shelters in Turkey. Few researchers have proposed solutions to address the complete shelter problem: a multi-objective evolutionary algorithm, NSGA-II, was used by (Saadatseresht et al., 2009) for the optimization of temporary settlement. Another study (Chen & Peña-Mora, 2010) applied Particle Swarm Optimization and Bee Colony Algorithm for the same purpose.

We propose a method on the basis of the Ant Colony Algorithm (ACO), a swarm intelligence and meta-heuristic method which has been frequently used to solve optimization problems (OPs) (Dorigo & Stützle, 2003). The first successful application of this method in solving the travel salesman problem proved its efficiency in combined and complicated OPs (Dorigo & Birattari, 2010). ACO has been used for disaster relief logistics, mostly in the response phase e.g., to locate distribution centers and finding optimized transportation routes (Yi & Kumar, 2007) or to determine pre-defined evacuation routes (Avilés, Takimoto, & Kambayashi, 2014; Forcael et al., 2014). To our best knowledge this algorithm has not been used for the shelter location problem throughout all three steps.

In this study, the number of safe locations required is considered to be unknown. In addition to application of network analysis to determine optimal routes for transportation, the novelty of this paper consists in simultaneously solving all three steps of the shelter location problem.

In the next section, the research methodology will be described. Then, the proposed model is examined in the city of Kerman as a case study. Subsequently, results will be discussed and the conclusion comes on the last section.

## RESEARCH METHODOLOGY

Determining the “best” places for shelter requires that different interests and uses of a location are considered. Hence, the problem can best be expressed as a multi-criteria problem (Zhou, Huang, & Zhang, 2011). Here, we consider quality of shelter locations in terms of compatibility/incompatibility criteria and measure the overall completion of shelter need by supply/demand criteria.

Incompatible criteria involve the ones, which may invoke potential hazards, such as aftershocks, epidemics, or unrest. As shelters should be safe, the selected locations have to be as far as possible from them. Examples are high-risk infrastructures such as gas stations and pipelines. Contrarily, proximity to compatible installations or infrastructures renders a location more attractive. Among these resilience increasing infrastructures are hospitals, highways, police or fire stations. Furthermore, the capacity of each shelter is considered as compatibility criterion. Referring to (Xu, Okada, Hatayama, & Takeuchi, 2008), the capitation for determining the capacity defers from Japanese standard to American one which latter is more recommended.

For determining the demand data, population census and building infrastructures need to be surveyed. Residential locations are considered in the model as “demand points”: affected people need to be moved from them to shelters in a crisis situation. As potential shelter locations, we use schools, parks, sport complexes or government offices that comply with local regulations.

The limited capacity of each shelter and unknown number of safe locations put our problem in Capacitated Facility Location Problems (CFLPs) category (Hübner, 2007). We propose a combination of Geographical Information Systems (GIS), Multi Criteria Analysis and ACO algorithm to address this problem. In the following sections, we will outline all these steps through the framework.

### Selecting Shelter Locations

The starting point in our framework is to select potential locations from all possible locations in a city. We chose the Weighted Linear Combination (WLC) method, a common approach in Multi Criteria Analysis, to calculate and evaluate the appropriateness of locations. First, the distances for each criterion and each location must be determined (e.g., distance to gas pipeline; proximity to hospital).

To be as realistic as possible, we use road distances in meters.

The best places have the longest distance to incompatible criteria and shortest distance to the compatible ones. Equations (1) and (2) are used to normalize the distances per criterion in ascending and descending order for incompatibility (1) and compatibility (2), such that $D_{new}=1$ represents the optimal possible distance (i.e., minimal distance for compatible, maximum distance for incompatible).

$$D_{new} = \frac{d_{near} - \min(d)}{\max(d) - \min(d)} \quad \textbf{(1)}$$

$$D_{new} = \frac{\max(d) - d_{near}}{\max(d) - \min(d)} \quad \textbf{(2)}$$

The weight of each criterion reflects its importance compared with other criteria. To elicit weights, we used the Analytic Hierarchy Process (AHP), and performed pairwise comparisons of importance between all criteria and sub-criteria (Saaty, 1990). Here, we use a 9 point scale to capture the comparisons as (Xu et al., 2008) and assume that the experts' view for both compatible and incompatible criteria have the same effect in weighting process. After the calculation of final weights, the appropriateness of each location, Site Suitability (*SS*), can be determines as in Equation (3).

$$SS = \sum W_i \, . \, C_i + \sum W_j \, . \, I_j \quad \textbf{(3)}$$

$C_i$ and $I_j$ refer to the compatible and incompatible criteria. $W_i$ and $W_j$ are the weights of each criterion. The value *SS* is needed in the ACO calculations.

### *The ACO Algorithm*

The ACO makes use of *pheromones* to indicate whether or not a path has already been used. The more pheromones on a path, the more attractive it is. We start from equal pheromones for each potential shelter.

To distribute the pheromones, a colony of ants searches for shelters in each iteration of the ACO: each ant $k$ computes a set $A_k(r)$ of reachable locations in each iteration, and moves to one of these. The probability $p_{rs}^{k}$ of $k$ moving from location $r$ to $s$ is given by Equation 4, which depends on the combination of two values: the attractiveness $\eta_{rs}$ of the move, which is represented by the suitability SS, and the trail level $\tau_{rs}$ of the move, indicating how proficient it was in the past to make this particular move.

$$p_{rs}^{k} = \begin{cases} \dfrac{(\tau_{rs})^{\alpha}(\eta_{rs})^{\beta}}{\sum_{L \in N_r^k} (\tau_{rs})^{\alpha}(\eta_{rs})^{\beta}} & s \in N_r^k \\ 0 & \text{otherwise} \end{cases} \quad \textbf{(4)}$$

### Routing: Paths to Shelters

The objective in this step is to assign the demand points (residential areas) to the shelters through the shortest routes. To this end, we used ArcGIS with the Network Analyst extension, which allowed us to build a network dataset of a city, including population data and information on infrastructure capturing compatibility and incompatibility criteria. The network analysis for the defined dataset computes a network of shortest paths between each residential area and safe location.

### Allocating Population to Shelters

The final step is to make sure that each population block is allocated to one of the selected shelters, while respecting its capacity. We assume that all the people living in an area will be routed to the same shelter. Because of limited capacities, we use a greedy approach that allocates larger areas first and then fills the remaining gaps by smaller areas. After the allocation process, the transportation costs $C_{trans}$ are calculated by Equation (5), where $N$ is the number of locations in the best combination, $Cost_{trans}$ represents the cost of transporting people *pop()* from area $D_i$ to shelter $j$ with the distance of $d_{Dij}$ (Equation (6)).

$$C_{trans} = \frac{\sum_{F=1}^{N} Cost_{trans} F}{N} \quad \textbf{(5)}$$

$$Cost_{trans_{Dij}} = pop(D_i) \times d_{Dij} \quad (6)$$

To find the best shelters among the candidate locations, the cost function is minimized considering three constraints; the average surplus/shortage per location, the maximum numbers of location selections by an agent, the minimum average of suitability of selected locations.

After several iterations of the ACO algorithm, the shelter locations converge. The pheromone approach allows recording the chosen combinations for the next stages and improves the solution per iteration.

Setting initial equal values for pheromones, the only difference between safe places in the initial phase is the shelter suitability SS. Since our framework is based on ACO algorithm, only the ant with the best objective function value can convey its pheromones across iterations. As a result of the ants searching for better locations in each iteration, pheromones accumulate in good locations. The total pheromone concentration is calculated by Equation (7), where $\Delta\tau$ is the amount of pheromone on $F_j$, which is the best safe place combination in the iteration. Ant $k$ will have a cost $FF_k$ , and $Q$ is a constant, 0.01.

$$\Delta\tau_{Fj}^{k} = \begin{cases} \frac{Q}{FF_k} & \text{if Fj} \in \text{BestAgent} \\ 0 & \text{otherwise} \end{cases} \quad \textbf{(7)}$$

Because different areas are allocated to the shelters in the different combinations, the transportation costs become distinct for each combination. To record the status of optimal combinations, we propose a "local pheromone" in this framework for the shelters in the combination that meet the constraints.

### Example Application: Earthquake Shelter Locations for the City of Kerman

To illustrate our approach we will apply it to the city of Kerman, Iran. Kerman has frequently been affected by earthquakes during the last century (Ghabili, Golzari, Salehpour, & Khalili, 2012). Geographical surveys and analyses revealed that Kerman is located in one of the most active earthquake areas and there are a lot of faults near this city (Amini Hosseini, Hosseinioon, & Pooyan, 2013)

There are currently about 800,000 people living in Kerman, and the population density is 6557 persons per km$^2$. According to local regulations, only places owned by to government authorities or wastelands can be considered as candidates for shelters, see **Table 1**. These places are highlighted in our possible locations map as well; see Figure 1.

**Table 1. Quantity of Possible Locations and Their Areas**

| Type | Quantity | Area (1000 km$^2$) |
|---|---|---|
| Parks | 59 | 9.35 |
| Schools | 181 | 8.85 |
| Wastelands | 81 | 23.7 |
| Total | 321 | 41.9 |

The constraints for our model are: the surplus/shortage mean should be smaller than 8 percent, maximum numbers of target selections by an agent should not exceed 120 units, and the mean of SS of selected places must be more than the total mean, 0.3391. Also for constraints in Equation (4), after proceeding to a suggested pre-defined two-step process, two parameters α and β are considered 0.5 and 1 respectively. The effect of different values for these parameters on the objective function is analyzed in two steps; first we consider α constant and calculate the objective value for different β, and second we do it vise versa. Two examples are shown in Figure 2 and Figure 3. The analysis revealed that our selection means not only the algorithm will not stick in optimization trap because of the high effect of pheromone, but also it can consist of variety of outcomes due to the β value.

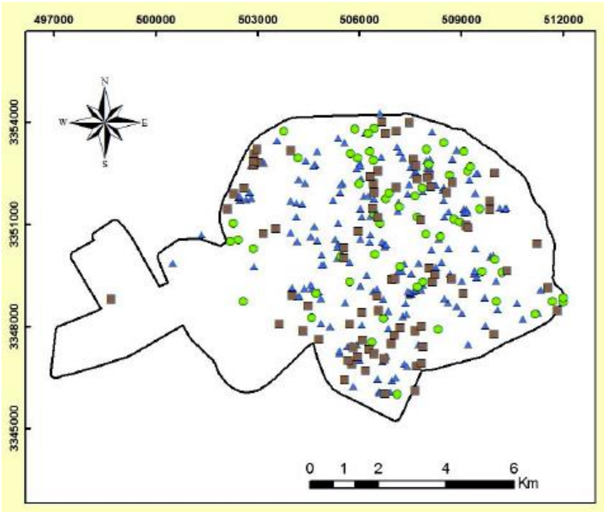


**Figure 1. Map of Possible Shelter Locations in Kerman**

Some further considerations should shape the interpretation of the results: first, since we order the residential areas by quantity, most populated areas will be allocated to shelters first. Second, we use network distance analysis for determining the nearest safe place to each population block. Third, the capacities of safe places are limited and this is the reason why some areas are not allocated to their nearest shelter. Using American standards, we considered 2 $m^2$ per each person in determining shelter capacities.

For determining the weights in SS calculation, we asked experts and researchers working at Iranian Crisis Management Organization (ICMO) to conduct the AHP comparisons. The resulting weights are summarized in Table 2.

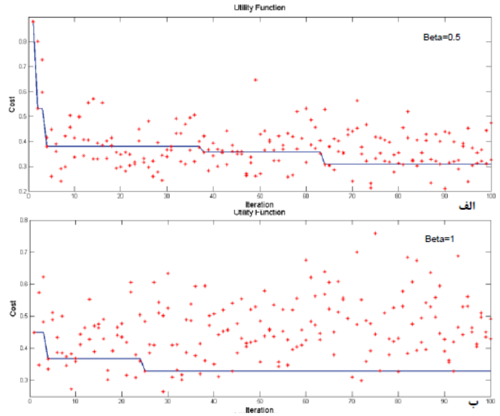


**Figure 2. The Effect of Different β (0.5 and 1) on Objective Function for α=0.5**

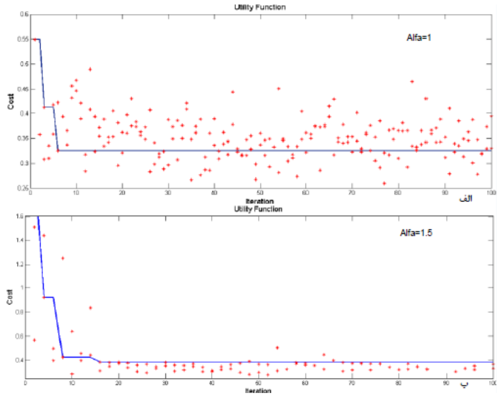


**Figure 3. The Effect of Different α (1 and 1.5) on Objective Function for β=0.5**

**Table 2. Final Weights of Criteria and Sub-criteria**

| Criteria | Weight | Sub-criteria | Weight |
|---|---|---|---|
| Compatibility | 0.5 | Capacity | 0.445 |
| | | Routes | 0.262 |
| | | Fire Fighting St. | 0.152 |
| | | Hospitals | 0.089 |
| | | Police St. | 0.052 |
| Incompatibility | 0.5 | Faults | 0.5 |
| | | Gas pipelines | 0.25 |
| | | Gas St. | 0.25 |

## RESULTS AND DISCUSSION

The suitability of potential shelter locations is shown in Table 3. More than 50 percent of the places are in moderate or higher levels of appropriateness. Yet, more than 100 shelter locations are in Low or Very Low suitability.

As it was mentioned before, one of the main criteria in evaluation of SS is the level of access to highways or main streets. Table 4, shows the suitability of locations with respect to this criterion only, highlighting that 50 percent of potential shelters have acceptable distances from a highway or main-road with the mean of 112 meters, which is acceptable according to experts.

**Table 3. Safe Places Locations Distribution by Means of SS**

| Suitability SS | Very low | Low | Moderate | High | Very high |
|---|---|---|---|---|---|
| Quantity | 37 | 68 | 80 | 95 | 41 |
| Percent | 11.5 | 21.2 | 24.9 | 29.6 | 12.8 |

**Table 4. Safe Places Distribution by Their Access to Main Roads**

| Distance | Very close | Close | Moderate | Far | Too far |
|---|---|---|---|---|---|
| Quantity | 69 | 92 | 76 | 61 | 23 |
| Percent | 21.5 | 29.2 | 24 | 19 | 6 |

After 250 iterations, the best combination of safe places including 104 ones has become the final solution. The convergence diagram of the ACO iterations is shown in Figure 4. The descending trend of the diagram shows how the objective function in the optimization problem is minimized over the iterations. This is a good sign of process improvement toward selecting the best places, as from iteration No. 181 all new combination generates the same (lowest) cost.

The final goal of locating temporary settlements is to allocate residential areas to each selected shelter. Figure 5 shows an excerpt of the final allocation results. The final analysis depicts that more than 60 percent of population need to seek shelter that is less than 1500 meters away from their homes. However, most of the areas with less than 20 persons form the other 40 percent, which can be explained by our greedy allocating process: it allocates the areas with few members to distant places.

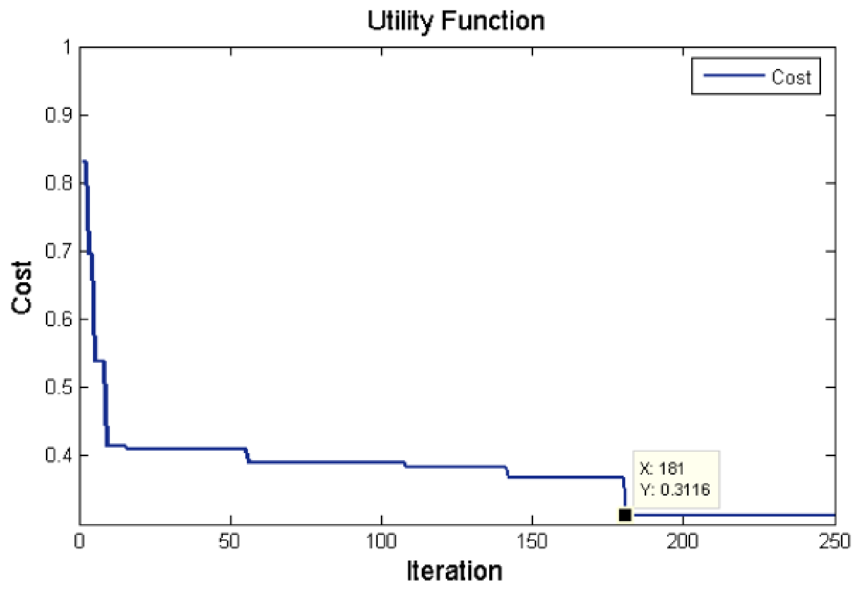


**Figure 4. The Final Convergence Diagram of Objective Function**


**Figure 5. Allocation of Population Blocks to Safe Places**

## CONCLUSION

In this paper, we developed a framework on the basis of ACO algorithm to locate shelters and allocate affected people to them. First, a number of agents (ants) make decisions in selecting locations as shelters. Then, the routes to the safe locations are chosen. Third, the population is allocated to the shelters selected by considering the distance and the capacity of each shelter. This process iterates until the objective function, capturing the transportation cost, is minimal while considering three constraints: the surplus/shortage mean, maximum numbers of safe places, the minimum mean of SS.

The results of allocating population undeniably rely on the distribution of safe places, their capacities and also the distribution of population blocks. The mean of transportation distance to the nearest safe place became 1200 meters. However, in spite of inappropriate distribution of available candidate locations and population blocks, about 40 percent of affected people have to pass more than 1500 meters to reach their nearest safe place. Therefore, identification and establishment of new safe places are mandatory to reduce this distance.

This study also revealed that ACO has many capabilities for combination with GIS in location decisions and solving related problems, where there are demands for dynamic simulation of changing safe places and capacities.

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