# Camp Location Selection in Humanitarian Logistics: A Multiobjective Simulation Optimization Approach

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**Abstract.** In the context of humanitarian support for forcibly displaced persons, camps play an important role in protecting people and ensuring their survival and health. A challenge in this regard is to find optimal locations for establishing a new asylum-seeker/unrecognized refugee or IDPs (internally displaced persons) camp. In this paper we formulate this problem as an instantiation of the well-known facility location problem (FLP) with three objectives to be optimized. In particular, we show that AI techniques and migration simulations can be used to provide decision support on camp placement.

**Keywords:** Facility location problem · Multiobjective optimization · Simulation · Evolutionary algorithms

## 1 Introduction

Forced displacement is a complex global phenomenon, which refers to the movement of people away from their home or origin countries due to many factors, such as conflict, violence, persecution, etc. In 2020, almost 26.4 million people had fled their countries according to the UNHCR (https://www.unhcr.org/uk/figures-at-a-glance.html). In this situation, relocating asylum-seekers/unrecognized refugees to camps becomes an urgent issue to humanitarian organizations or governments. Camps, as important infrastructures, provide protection and allocate available humanitarian resources to thousands of forcibly displaced people. As resources are commonly limited, it is critical to make optimal decisions in seeking the best location for establishing a new camp. Camp placement can be formulated as the well-known facility location problem (FLP) [6]. The FLP can be considered as a multiobjective optimization problem (MOP), which includes two or more objectives to be optimized simultaneously. The objectives of the FLP can include minimizing the total travel distance and maximizing the demand coverage, meanwhile satisfying some constraints [8].


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Several MOP-FLP approaches have been proposed, including traditional goal programming, $\epsilon$-constraint approaches and, more recently, metaheuristic optimization algorithms [13] such as particle swarm optimization (PSO) and evolutionary algorithm (EA). As a population-based metaheuristic optimization approach, EA may effectively handle MOPs as it can generate a set of trade-off solutions in a single run. It has specifically been applied to tackle the FLP in disaster emergency management [14], making it natural to employ EA in the context of camp placement. The main challenge here is to have exact number of forcibly displaced persons arriving in destination countries. Due to the ongoing conflicts in origin countries, the number of asylum-seekers/unrecognized refugees or IDPs continuously changes over time.

Here we aim to assist humanitarian organizations and governments in their decision-making on camp placement, and the paper has the following contributions: (1) we present an MOP for camp placement with three objectives regarding travel distance, demand coverage, and idle camp capacity; (2) we use an agent-based simulation to capture the demand uncertainty (i.e., the number of camp arrivals), which is crucial for camp placement but has not been considered in most existing literature; (3) we present a new multiobjective simulation optimization approach for our MOP, which consists of EA and an agent-based forced migration simulation; and (4) we successfully apply the proposed approach to a case study of the South Sudan conflict, and identify a group of optimal solutions for decision-makers.

### 1.1 Related Work

The camp location selection problem is a complex task for the humanitarian organizations to deploy aid. The research areas related to this problem can be generally divided into the modelling the movements of people [11], and the FLP in humanitarian logistics [1,4,7,9]. Here we attempt to address the optimization problem of how to find the optimal locations for establishing a new camp. This problem can be formulated as an MOP. Current approaches for multiobjective FLPs can be classified into two categories. The first is concerned with the traditional single-objective optimization approach, such as the goal programming approach [1], the weighted sum approach [9] and the $\epsilon$-constraint [4]. The second is the multiobjective optimization approach searching for the whole Pareto front, from which the decision makers choose their preferred solution. For example, the classic NSGA-II and a multiobjective variant of the PSO algorithm were applied in the earthquake evacuation planning problem [7]. The reason we consider the second category is that optimization approaches in the first may require prior knowledge, such as the relative importance of the objectives in the weighted sum approach. Such knowledge may not be easy to access, and even if it is available it has been shown that the search aiming for the whole Pareto front may be more promising since it can help the search escape the local optima [3]. Another strand of research is multiobjective optimization under uncertainty. Recently, some studies have proposed a number of robust or stochastic models for FLPs

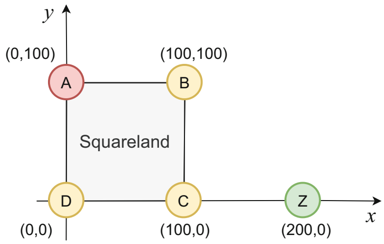


**Fig. 1.** An illustration of the route network for a basic camp placement, where 1) a source country is represented by a square region with one conflict zone (i.e., point A), three towns (i.e., points B, C, and D) and all possible links among these points, and 2) one camp (i.e., point Z) is connected to the nearest location in the source country.

under uncertainty [2]. However, there is a lack of studies on FLPs under uncertainty that take the preferences of people into account. As popular simulation approaches, different agent-based modelling frameworks have been developed to model the movements of displaced persons (or the preferences of those people).

## 2 A Multiobjective Camp Location Selection Model

Our multiobjective model aims to determine the optimal location of a new camp and is constructed according to four main steps. First, we create a source country with conflict zones and towns, and interconnecting links. Second, we add a camp at given coordinates in a destination country. Third, we create a link between the camp and its nearest location in the source country, and lastly we run the Flee simulation [11] and calculate the objectives. Figure 1 illustrates the route network for a basic camp placement problem with one conflict zone, three towns and one camp, and interconnecting roads (lines). The coordinates $(x, y)$ associated with each conflict zone, town or camp are used to indicate their positions.

We have the following model assumptions: the locations of conflict zones and towns, the number of asylum-seekers/unrecognized refugees or IDPs (i.e., agents in Flee simulation), and the conflict period are given, agents are spawned in conflict zones, destination countries are represented by a continuous region, camps have limited capacities, agents move during each time step based on predefined rules in [11], and agents stop moving once they reach the camp. With the notation in Table 1, the MOP can be formulated as follows:

$$\text{minimize}: f_1(j) = \frac{\sum_i^{n_{sim,t,j}} d_{sim,t,i,j}}{n_{sim,t,j}}, \quad t = T \tag{1}$$

$$\text{maximize}: f_2(j) = n_{sim,t,j}, \quad t = T \tag{2}$$

$$\text{minimize}: f_3(j) = \frac{\sum_t |c - n_{sim,t,j}|}{T}, \quad t = 1, 2, \ldots, T \tag{3}$$

**Table 1.** Notations for the MOP.

| Notations | Type | Explanation of notations |
|---|---|---|
| $J$ | Set | The set of candidates sites indexed by $j$ |
| $a$ | Parameter | The total number of agents in all conflict zones |
| $n$ | Parameter | The number of potential camp sites |
| $c$ | Parameter | Camp capacity (unit: agent) |
| $k$ | Parameter | The total number of new camps that will be placed and open |
| $T$ | Parameter | The simulation period or the conflict period (unit: day) |
| $j$ | Decision variable | The index of a candidate site |
| $d_{sim,t,i,j}$ | Dependent variable | The distance travelled by an agent $i \in I_{sim,t,j}$ in the new camp at candidate site $j$ at time $t$ based on the simulation predictions |
| $n_{sim,t,j}$ | Dependent variable | The number of agents served by the new camp at candidate site $j$ at time $t$ based on simulation predictions, indexed by $i$ |

subject to

$$1 \leq j \leq n \tag{4}$$

The objective function Eq. (1) minimizes the average distance travelled by each arriving agent in a destination camp at the end of the simulation. This objective focuses on the efficiency (i.e., distance) of allocating people to facilities. The objective function Eq. (2) maximizes the number of people in the camp at the end of the simulation. This objective function can be easily changed to a minimization problem by calculating the negative value of successful arrivals (i.e., $-n_{sim,t,j}, t = T$). The objective function Eq. (3) minimizes the average idle camp capacity over simulation days for the new camp. Note that the new camp can be overpopulated, and if the idle capacity is a negative value, we simply take the absolute value. Constraint (4) restricts the search space of the MOP (i.e., a set of $n$ possible sites), from which we select the optimal camp site. In our MOP, the decision variable $j$ is known as a solution to the problem. Different from the single-objective optimization problem, the MOP has a set of trade-off solutions, called Pareto front, rather than a single optimal solution. In this paper, only one camp will be established (i.e., $k = 1$) and we aim to find the Pareto front of the MOP. This MOP can be further extended to jointly solve the MOP for multiple camps by replacing the current single decision variable with a set of decision variables, expressed as a $k$-dimensional decision vector $\vec{j} = (j_1, j_2, \ldots, j_k)$, and considering all people who arrived at these new camps.

### 2.1 A Simulation-Optimization Approach

We develop a simulation-optimization approach, which combines a (Flee) simulation with a multiobjective optimization algorithm. For the optimization algorithm, we adopt a representative multiobjective evolutionary algorithm, called NSGA-II [5]. Our algorithm works as follows: for each generation of NSGA-II, a group of candidate solutions (each solution is a sequence of $k$ selected sites) are generated, followed by the Flee simulation taking the coordinates corresponding to each solution as input parameters, and assessing and outputting the objective values for the optimization stage. To implement NSGA-II, a candidate solution is represented as a chromosome using a grid-based spatial representation strategy. Each grid cell has longitude and latitude coordinates corresponding to its centroid. The chromosome is then sequentially encoded by the indexes of $k$ selected site(s), where $k$ is the number of camps that will be placed and opened. Note that in this paper we only consider one new camp (i.e., $k = 1$). To automate the simulation process, we utilize FabFlee [12], which is a plugin of FabSim3 (https://github.com/djgroen/FabSim3). Due to data complexity, simulation runs for a group of solutions (i.e., candidate camp locations) are computationally expensive. To reduce the runtime, we employ QCG-PilotJob (http://github.com/vecma-project/QCG-PilotJob) to schedule submitted ensemble runs for different camp locations.

## 3 Test Setup and Results

To demonstrate the application of our MOP, we conducted a case study for the South Sudan conflict in 2013. The geographic coordinates of examined region are $N0° - N16°$ and $E20° - E40°$, and the region was divided into 26842 $0.1° \times 0.1°$ (around 11 km $\times$11 km) grids. Our simulation instances (*ssudan_c1* and *ssudan_c2*) are constructed based on the South Sudan simulation instance presented in [12], which involves almost 2 million fleeing people in a simulation period of 604 days starting from the 15th December 2013, 25 conflict zones and 16 towns in South Sudan, as well as ten camps in neighboring countries Sudan, Uganda and Ethiopia. The *ssudan_c1* has no camp in place yet and aims to establish one new camp with a capacity of $80,000$ (i.e., $c = 80,000$), while the *ssudan_c2* involves all ten existing established camps and aims to add one new camp with a capacity of $12,000$ (i.e., $c = 12,000$). For both simulation instances, the distance between camp and its nearest location in South Sudan was estimated by using the route planning method in [10]. Furthermore, to shorten the execution time, we reduced the number of agents from all conflict zones by a factor 100 (i.e., $a = a/100$), and accordingly, the camp capacity for *ssudan_c2* and *ssudan_c2* are reduced to 800 and 120, respectively. Figure 2 plots the optimal camp locations for the two conflict instances. The objective values of optimal solutions obtained by NSGA-II are summarized in Table 2. For each conflict instance, NSGA-II can find a set of optimal solutions, which are incomparable based on the concept of Pareto optimality. In other words, each solution is a trade-off among average travel distance, the number of camp arrivals, and the average idle camp capacity.

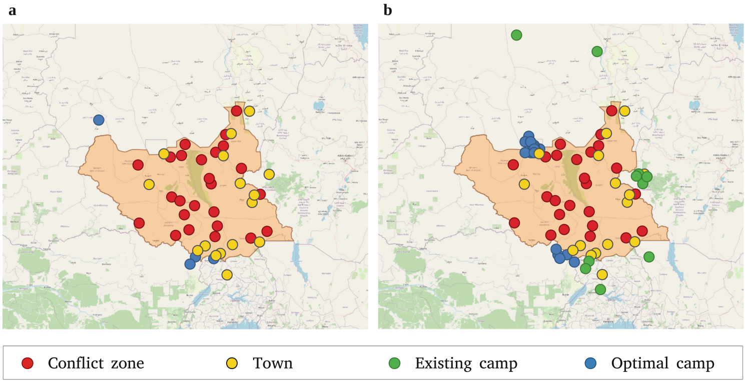


**Fig. 2.** Optimal camp locations (blue circles) obtained by NSGA-II on the (a) ssudan_c1 and (b) ssudan_c2 conflict instances, respectively. (Color figure online)

**Table 2.** The objective values of the optimal solutions obtained by the NSGA-II on the ssudan_c1 and ssudan_c2 conflict instances.

| Conflict instance | Camp location | | Objectives | | |
|---|---|---|---|---|---|
| | Longitude | Latitude | Travel distance | No. camp arrivals | Idle capacity |
| ssudan_c1 | 30.55 | 3.75 | 1380.2211 | 801 | 77.0182 |
| | 25.25 | 11.25 | 6785.469 | 809 | 173.0762 |
| | 31.55 | 3.65 | 1354.2624 | 803 | 82.1556 |
| | 30.25 | 3.35 | 1995.5878 | 804 | 91.2666 |
| ssudan_c2 | 30.35 | 3.85 | 558.905 | 166 | 49.7136 |
| | 29.85 | 3.85 | 651.9379 | 124 | 11.6589 |
| | 29.95 | 3.65 | 598.6553 | 120 | 7.6788 |
| | 28.25 | 10.35 | 440.0152 | 120 | 8.2483 |
| | 28.85 | 9.65 | 226.7078 | 143 | 29.096 |
| | 28.35 | 9.45 | 283.3134 | 150 | 35.351 |
| | 28.55 | 9.55 | 313.1518 | 160 | 44.2268 |
| | 28.45 | 9.55 | 281.1019 | 156 | 40.6904 |
| | 28.65 | 9.55 | 433.7734 | 147 | 32.5613 |
| | 28.05 | 10.05 | 507.1222 | 121 | 8.9636 |
| | 28.45 | 9.65 | 336.701 | 140 | 26.048 |
| | 28.55 | 9.85 | 262.416 | 132 | 19.0679 |
| | 30.75 | 3.45 | 580.9609 | 126 | 13.6225 |
| | 28.55 | 9.75 | 364.0978 | 129 | 16.0894 |
| | 28.45 | 9.45 | 397.1481 | 158 | 42.5331 |
| | 28.35 | 10.05 | 539.0705 | 131 | 18.0646 |
| | 29.75 | 4.15 | 634.4269 | 123 | 10.6474 |
| | 28.55 | 9.65 | 322.0341 | 138 | 24.2169 |
| | 28.05 | 9.45 | 371.0897 | 135 | 21.9901 |
| | 28.55 | 9.45 | 388.0439 | 144 | 29.7268 |

## 4 Conclusion

In this paper, a multiobjective model for the FLP in the context of humanitarian support for forcibly displaced people has been proposed, and the model has been solved by using a simulation-optimization approach. The proposed model has been employed in a case study of South Sudan conflict with a simulation period of 604 days from 15th December 2013. The results obtained by our simulation-optimization approach have demonstrated its ability to provide decision makers with diverse solutions, which strike a balance among the individual travel distance, the number of camp arrivals, and the average idle camp capacity. In the future, other algorithms in multiobjective optimization will be explored. In addition, it would be interesting to consider other factors in the context of forced migration, e.g., construction and transportation costs.

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