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SOLVING FACILITY LOCATION PROBLEMS FOR DISASTER RESPONSE USING SIMHEURISTICS AND SURVIVAL ANALYSIS: A HYBRID MODELING APPROACH

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ABSTRACT

One of the important decisions for mitigating the risk from a sudden onset disaster is to determine the optimal location of relevant facilities (e.g., warehouses), because this affects the subsequent humanitarian operations. Researchers have proposed several methods to solve the facility location problem (FLP) in disaster management. This paper considers a stochastic FLP where the goal is to minimize the expected time required to provide service to all affected regions when travel times are stochastic due to uncertain road conditions. The number of facilities to open is constrained by a certain maximum budget. To solve this stochastic optimization problem, we propose a hybrid simulation optimization model that combines a simheuristic algorithm with a survival analysis method to evaluate the probability of meeting the demand of all affected areas within a time target. An experiment using a benchmark set shows our model outperforms deterministic solutions by about 8.9%.

1 INTRODUCTION

Climate change has increased the frequency of weather-related disasters in the past 50 years. In 2021, according to the Emergency Event Database, the world suffered from 432 natural disasters that affected 101.8 million people, resulted in 10,492 deaths and caused approximately US$ 252.1 billion of economic losses (CRED 2022). Therefore, research into disaster risk management has flourished as evidenced by the many literature review articles. A list of surveys on the topic can be found in Onggo et al. (2021). One of the important disaster management decisions is to determine the optimal location of facilities (such as warehouses, shelters, or medical centers). The facility location problem (FLP) is one of the classic optimization problems in Operations Research (OR). As a consequence, many OR models and methods have been applied to solve facility location problems in the disaster management context. Among these, one can find mixed integer linear and non-linear programming (An et al. 2015), two-stage stochastic programming (Oksuz and Satoglu 2020), and heuristic optimization (Salman and Yücel 2015). One technique that has not been used yet in this application area is simheuristics. A simheuristic algorithm is a hybrid approach that combines a metaheuristics component –to efficiently explore a vast solution space– and a simulation component –to take into account the uncertainty in the problem. Simheuristics have been applied to solve many stochastic optimization problems (Chica et al. 2020). Hence, it has the potential for solving the stochastic FLP in disaster management.

This paper considers an uncapacitated FLP with stochastic travel times (caused by damages to road infrastructure) and a budget constraint to open (for disaster response) or run (for disaster preparedness) facilities. The goal is to minimize the expected time required to service all the affected regions in a geographical area. The service is carried out by fleets of vehicles (e.g., unmanned aerial ones), each fleet being based in a different facility. Hence, we consider a set of locations (demand points) that can potentially be hit by a sudden onset natural disaster. Decision makers need to decide the location of facilities such that all demand points are covered while the maximum travel time between any demand point and its nearest facility (i.e. makespan) is minimized. In the context of disaster preparedness, this model helps decision makers to determine the optimal facility locations, so that they can preposition their emergency resources at the facilities. In the context of disaster response, the model helps decision makers to deploy temporary facilities at the right locations, while respecting the available budget. The remainder of this paper is organized as follows. In Section 2, we review the literature on FLPs for disaster management, and how other authors have addressed these problems. We highlight that simheuristics have not been applied yet in disaster management. Then, we review the simheuristics literature to show that it has the potential for solving stochastic FLPs in disaster management. Next, we describe the problem and provide the model formulation in Section 3. The details of the simheuristic approach are explained in Section 4. The experiment setting and its result are presented in Section 5. Finally, we draw our conclusions and identify future work in Section 6.

2 LITERATURE REVIEW

This section reviews previous work on FLPs applied in the context of disaster management and provides an overview of recent simheuristics applications in several fields.

2.1 Facility Location Problem in Disaster Response

Facility location problems and their variants have been extensively studied in the literature. The usual goal of an FLP is to decide on the position of an undetermined number of facilities in order to minimize the fixed set-up cost for the facilities and the cost related to serving the demand. FLPs find applications in a variety of fields, including supply chain management (e.g., locating distribution and retail centers), telecommunication networks (e.g., locating cloud service centers in a network), and transportation networks (e.g., locating electric vehicle charging points). One particular area in which FLPs play a key role is humanitarian logistics or emergency logistics, which is defined in Sheu (2007) as “a process of planning, managing and controlling the efficient flows of relief, information, and services from the points of origin to the points of destination to meet the urgent needs of the affected people under emergency conditions.” Facility location under emergency conditions poses significant challenges compared to traditional facility location problems. Those challenges are identified in Balcik and Beamon (2008) as follows: *(i)* uncertainties related to demand (the size, location, and timing of demand are unknown, and even after a disaster hits, these information are often unreliable); *(ii)* communication complexities due to damaged roads, damaged communication lines, and involvement of third parties; *(iii)* the need for timely delivery (people who are affected by the disaster need timely delivery of tents, blankets, as well as consumable items such as food and water); and *(iv)* lack of adequate emergency resources such as supplies, people, and transportation capacity. Although facility location in disaster management is a relatively new area compared to traditional facility location, several survey papers have already emerged that summarize and categorize the work done with respect to several criteria, which include objective functions, constraints, solution methods, facility type, data modeling type, nature of disasters, and number of periods considered in the model (Boonmee et al. 2017).

In the literature, disaster management activities have been planned in two parts: pre-disaster and post disaster activities. Pre-disaster activities include facility location and inventory positioning, while post disaster activities include allocating demand nodes to facilities or routing decisions. We focus on the facility location decision in this paper. Facility location models in the context of emergency logistics during the pre-disaster phase usually combine facility location with other decisions such as inventory positioning. There is limited research on the facility location decision itself in disaster management literature (Caunhye et al. 2012). Some papers only consider facility location (Jia et al. 2007).

The earlier articles mostly study FLP in disaster management under a deterministic setting. However, the presence of uncertainty has recently been taken into account. Liberatore et al. (2013), Hoyos et al. (2015), and Dönmez et al. (2021) provide excellent reviews of the articles that consider facility location in disaster management under uncertainty. Three types of uncertainties have been studied: *(i)* demand uncertainty; *(ii)* supply uncertainty; and *(iii)* uncertainty related to transportation network connectivity. While demand and supply uncertainty have been studied extensively in the literature, the work on the uncertainty around transportation network, which may lead to roads being blocked or transportation taking more time due to the damages to the infrastructure, is rather limited. Recent studies that look at road disruption include those by Rath et al. (2016), Tofighi et al. (2016), Aslan and Çelik (2019), and Paul and Wang (2019). In our work, we aim to fill this gap by considering a stochastic increase in the travel time due to a potential damage to road infrastructure. Methods used to capture uncertainty in facility location problems in disaster management include stochastic programming, robust optimization, and chance-constrained programming. The solution methods that are employed range from exact methods to approximation methods and heuristics. Exact methods such as Benders decomposition (Bayram and Yaman 2018), Lagrangian relaxation, and branch-and-cut methods work efficiently for small to medium-sized instances. To overcome this particular drawback, several heuristic approaches have been proposed in the literature. Among those heuristics methods include tabu search (Noham and Tzur 2018), particle swarm optimization (Bozorgi-Amiri et al. 2012), simulated annealing (Lu 2013), genetic algorithms (Mostajabdaveh et al. 2019), variable neighborhood search (Ahmadi et al. 2015), etc. To the best of our knowledge, our paper is the first paper that proposes a simheuristic approach to solve an FLP in disaster management under uncertainty. We have proposed a simheuristic to solve this problem because they are a natural extension of both metaheuristics and simulation techniques, to address large-scale and NP-hard optimization problems under uncertainty –which is a frequent case in real-life applications, as the case of the problem tackled in this paper.

2.2 Recent Applications of Simheuristics

The approach of this paper is based on simheuristics, which is a hybrid methodology combining metaheuristics optimization and simulation (Rabe et al. 2020). The simulation component provides feedback into the metaheuristic component, which allows for filtering the solution space and promotes convergence towards stochastic solutions of increasing quality. One of the advantages of this methodology is its ability to integrate stochastic variables when formulating the problem mathematically, either in the objective function and/or in the constraints. Chica et al. (2020) provide a literature review on the applications of simheuristic algorithms in different industrial optimization problems. This review highlights the ability of simheuristics to solve real-life optimization problems under uncertain scenarios. Recent works employing simheuristics include applications in arc routing problems (Keenan et al. 2021), inventory routing problems (Onggo et al. 2019), scheduling problems (Hatami et al. 2018), or finance and insurance (Panadero et al. 2018). This wide range of successful applications of simheuristics in several application areas demonstrates its effectiveness in solving different logistics and manufacturing problems under uncertainty scenarios currently faced by decision-makers including in disaster management.

3 PROBLEM DESCRIPTION

Figure 1 illustrates the FLP considered in this paper. A set of nodes (shown in circles) represents the locations where people live. These locations (or demand points) can potentially be hit by a natural disaster. In practice, the nodes can be districts or cities. Based on the budget constraint, decision makers can operate up to N_f facilities. Given N_f, decision makers have to determine their ‘optimal’ locations, i.e., those that minimize the *makespan* or the maximum travel time required to reach any location from its nearest facility. In Figure 1, the location of two facilities are shown in rectangles and the lines show their makespans.

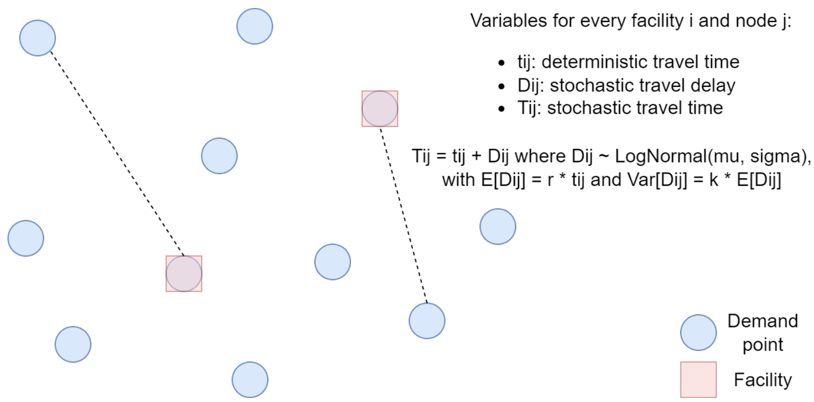

Figure 1: A schematic representation of the stochastic FLP considered.

Let us consider the following sets and indices: $i \in I$ is the index of demand points, while $j \in J$ is the index of facilities, and $J \subset I$. The decision variables in the model are the location of the facilities (x_j) and the allocation of demand points to their nearest facilities (y_{ij}). Here, $x_j = 1$ if a facility is located at candidate location j, and 0 otherwise. Similarly, $y_{ij} = 1$ if a demand point i is allocated to facility j, and 0 otherwise. The *makespan* of facility j (z_j) is shown in Equation (1), where T_{ij} is the travel time between demand point i and facility j. The travel time T_{ij} comprises two components: the deterministic travel time t_{ij} and the stochastic delay D_{ij}, i.e.: $T_{ij} = t_{ij} + D_{ij}$. The deterministic travel time represents the travel time required under perfect conditions and the stochastic delay represents the travel delay due to the damage to the transportation network:

$$z_j = \max_{i \in I} T_{ij} y_{ij} \tag{1}$$

The objective function is to find locations of N_f facilities that cover all demand points in such a way that the maximum (i.e., worst) makespan is minimized. Since our model is stochastic, the objective function will be to minimize the expected worst makespan. This is implemented using Equation (2) below:

$$\min \quad \mathbb{E}\left[\max_{j \in J} z_j\right] \tag{2}$$

subject to:

$$\sum_{j \in J} y_{ij} = 1 \quad \forall i \in I \tag{3}$$

$$\sum_{j \in J} x_j = N_f \tag{4}$$

$$y_{ij} \leq x_j \quad \forall i \in I, \forall j \in J \tag{5}$$

$$x_j,\, y_{ij} \in \{0,1\} \quad \forall i \in I, \forall j \in J \tag{6}$$

Constraint (3) ensures that each demand point is allocated to a facility. Constraint (4) ensures that we use exactly N_f facilities. Constraint (5) ensures demand points can only be allocated to open facilities. Constraint (6) states that the decision variables are binary.

4 SIMHEURISTICS METHOD

The proposed simheuristic method in this paper combines a multi-start (MS) metaheuristic framework with Monte Carlo simulation (MCS). We have used a MS approach since it offers a well-balanced combination of efficiency and relative simplicity. For this reason, multi-start algorithms are frequently employed to solve NP-hard optimization problems in vehicle routing and scheduling domains (Dominguez et al. 2014; Dominguez et al. 2016). Listing 1 shows the Python code for our simheuristic algorithm.

```
1 def createStochSolution(instance, detMakespan, rng):
2   # Create an initial solution using the savings-based heuristic
3   initSolution = createInitialSolution(instance, False, rng)
4   simulateSolution(initSolution, detMakespan, instance, nShort)
5   bestSolution = initSolution
6   # Create a pool of elite solutions
7   eliteSolutions = collections.deque(maxlen=3)
8   eliteSolutions.append(bestSolution)
9   # Start the multi-start process
10  elapsedTime = 0
11  startTime = time.process_time()
12  while elapsedTime < maxTime:
13    # Create a new solution using the savings-based heuristic
14    solution = createInitialSolution(instance, True, rng)
15    if solution.detMakespan < bestSolution.detMakespan:
16      simulateSolution(solution, detMakespan, instance, nShort)
17      if solution.stochMakespan < bestSolution.stochMakespan:
18        bestSolution = solution
19        eliteSolutions.append(bestSolution)
20    # Update the elapsed time before evaluating the stopping criterion
21    currentTime = time.process_time()
22    elapsedTime = currentTime - startTime
23  # Simulate and sort the pool of elite solutions
24  for solution in eliteSolutions:
25    simulateSolution(solution, detMakespan, instance, nLong)
26  eliteSolutions = sorted(eliteSolutions, key=lambda s:s.stochMakespan)
27  return eliteSolutions
```

Listing 1: Simheuristic procedure.

The algorithm receives the following input parameters: *(i)* the instance which comprises demand points, facilities and travel times; *(ii)* the makespan of the best deterministic solution; and *(iii)* a random number generator. The simheuristic algorithm works as follows: first, it generates an initial solution using a deterministic savings-based heuristic (line 3). We will explain the detailed savings-based heuristic later. Then, in line 4, we estimate the objective function (Equation 2) of the initial solution using the simulation model (we run `nShort` replications). The generated solution will be used by the MS framework as the best solution found so far (line 5). In line 6, we create a list to store the elite solutions. In this case, we will select the best three solutions. The initial solution (line 5) is considered to be the first elite solution and inserted into the list (line 6). Next, the multi-start process is executed until a maximum execution time is reached (lines 10-22). In each iteration, a new solution is generated using the biased-randomized version of the savings-based heuristic (line 14). The new solution is compared against the current best solution. If the former is better in the deterministic scenario (line 15), a few simulation replications (`nShort`) are performed on the new solution to obtain its performance in the stochastic scenario (line 16). If the new solution improves the performance of the best solution found so far in the stochastic scenario (line 17), then the current best solution is updated and the new solution is inserted in the pool of elite solutions. If the size of the elite solution list is greater than three then the worst performing solution will be removed from the list (lines 18-19). The elapsed time since the start of the multi-start process is updated in lines 21-22. Once the stopping condition is met, a much higher number of simulations replications (`nLong`) are performed over the pool of elite solutions (lines 24-25). This allows more accurate estimations of the different moments associated with the stochastic performance measure generated by each solution, e.g., mean, standard deviation, etc. Finally, the pool of elite solutions is sorted based on the expected performance measure (line 26) and returned to the caller of the procedure (line 27).

The savings-based heuristic works as follows. First, the heuristic starts with an initial solution where all the facilities are open and each facility is assigned to serve the demand point where the facility is located. Then, we create a saving list where each element stores the makespan savings associated with closing a given facility. In particular, the makespan savings are computed as follows: the maximum travel time from the facility to all its demand points, minus the maximum travel time of its demand points when assigned to their alternative facilities. For each demand point, its alternative facility is the open facility closest to the demand point in case its current facility is closed. The list is then sorted in descending order according to the described makespan savings. Starting from the initial solution (where all facilities are open), the savings list is then traversed until the number of open facilities meets the budget constraint (see constraint 4). Unlike the greedy version of the heuristic, a biased-randomized heuristic considers each element in the list with a probability that follows a decreasing geometric distribution (i.e. the one with higher makespan saving has a higher probability to be selected). By employing a biased-randomized version of the greedy heuristic, we can generate multiple alternative solutions without losing the logic behind the original heuristic. Some of this solutions will naturally outperform the one provided by the greedy heuristic (Dominguez et al. 2014). At each iteration, the demand points assigned to the facility that is being closed will be reassigned to their second nearest facility, and the savings list will be updated according to the new configuration of open facilities.

```
1 def simulateSolution(solution, detMakespan, instance, nIter):
2   makespans = np.empty(nIter)
3   for i in range(nIter):
4     stochMakespan = 0
5     for facility in solution.openFacilities:
6       for node in facility.nodes:
7         stochDelay = 0
8         travelTime = facility.travelTimes[node.id]
9         if travelTime != 0 and travelTime < detMakespan:
10          # Travel delays follow a log normal distribution
11          mean = r * travelTime
12          variance = c * mean
13          mu = math.log(mean) - 0.5 * math.log(1 + variance / mean**2)
14          sigma = abs(math.sqrt(math.log(1 + variance / mean**2)))
15          stochDelay = np.random.lognormal(mu, sigma)
16        # Calculate the travel times stochastic makespan
17        stochTime = travelTime + stochDelay
18        stochMakespan = max(stochMakespan, stochTime)
19    makespans[i] = stochMakespan
20  solution.stochMakespan = np.mean(makespans)
21  solution.stochMakespans = makespans
```

Listing 2: Simulation procedure.

The simulation model is detailed in listing 2. The simulation model receives the following input parameters: (i) the solution to simulate; (ii) the makespan of the best deterministic solution; (iii) the instance that comprises the demand points, facilities and travel times; and (iv) the number of simulation replications. First, a list of stochastic makespans is created (line 2), which will be used to store the makespan estimated by each simulation replication. Then, the simulation is run multiple times based on the given parameter (line 3) to estimate the expected makespan of the solution. This is achieved by going through each open facility in the solution and to every demand point that is assigned to the facility (lines 5-6). In lines 7-17, we sample the travel time of each pair of facility and demand point (T_{ij}) to find the maximum makespan. The estimated travel time is a summation of the deterministic travel time (t_{ij}) and the estimated travel delay (D_{ij}). In disaster management, a long tail distribution is frequently used to sample the travel delay. In this paper, we choose lognormal distribution but any other long tail distribution can also be used. The sampling is only done for a pair in which the travel time is shorter than the makespan of the best deterministic solution (line 9). After the travel time is sampled, the current stochastic makespan is updated (line 18). After the travel times between all facilities and the node assigned to them are sampled, the stochastic makespan is calculated (line 18) and saved in the list of stochastic makespans (line 19). Finally, after all simulation replications are complete, the expected makespan of the solution is calculated and saved (line 20) and the list of stochastic makespan is also saved (lines 21).

5 EXPERIMENTAL RESULTS

The proposed algorithm has been implemented using Python 3.8 and tested on a workstation with a multi-core processor Intel Xeon E5-2650 v4 with 32GB of RAM. To the best of our knowledge, there are no benchmarks for the stochastic FLP. Therefore, we have adapted the benchmark proposed by Ahn et al. (1988), which was originally designed for the *p*-median problem, and later used in the context of FLP by Barahona and Chudak (2005). We have used the set of instances called MED, since they are the largest and most challenging ones. Each instance is composed of a set of points, which are randomly chosen in the unit square. A point represents both a demand point and a facility, and the corresponding Euclidean distance determines travel costs. The MED set consists of six different subsets, each with a different number n of facilities and demand points (500, 1000, 1500, 2000, 2500, and 3000). There are three different opening cost schemes for each subset: $\sqrt{n}/10$, $\sqrt{n}/100$, and $\sqrt{n}/1000$ corresponding to 10, 100, and 1000 instance suffixes, respectively. In our experiments, the number of facilities to open for each instance is computed as follows: 5%, 10%, or 20% of the total number of facilities are opened depending on the instance name suffix, respectively. For example, the number of open facilities for the instance $1500-10$ would be 75, and their opening cost would be proportional to $\sqrt{1500}/10$.

The objective of the first experiment is to evaluate the performance of our simheuristic approach when solving the stochastic FLP in disaster management. The evaluation is done by comparing the simheuristic solutions and the deterministic solutions. Due to space limitation, we only show the results of some instances in Table 1. The first column show the instances (combinations of number of demand points and opening cost scheme). The subsequent two columns show the best-found solution to the deterministic version of the problem (*OBD*) and the computational time to reach it, respectively. The next three columns show the solutions to the stochastic version of the problem. Please note that in the experiments, we set the lognormal mean and variance parameters to: $E[D_{ij}] = r \cdot T_{ij}$ with $r = 1$ and $Var[D_{ij}] = c \cdot E[D_{ij}]$ with $c = 20$. Column (*OBD-S*) shows the expected makespans when the best deterministic solution *OBD* is evaluated in a stochastic scenario using the simulation model. The last two columns report the expected makespan obtained by our simheuristic approach, *OBS*, and the computational time to reach it. Figure 2 depicts the box-plots of the results of all instances, where the vertical axis represents the gap between the stochastic solutions (*OBD-S* and *OBS*) and the deterministic solution (*OBD*). As the deterministic solution (*OBD*) does not include the stochastic delay, it provides a lower bound for the makespan. Therefore, the results from the stochastic solutions (*OBD-S* and *OBS*) demonstrate the significant effect of damages to road infrastructure on performance. The result also shows that for each instance, the simheuristic solution outperforms the deterministic solution when they are compared in a stochastic situation (i.e. comparing between *OBD-S* and *OBS*). On average, the solutions provided by our simheuristic approach (*OBS*) outperform the deterministic solutions by about 8.9%. In other words, an optimal solution for the deterministic problem might be sub-optimal in the stochastic version of the problem. This shows the utility of integrating a simulation model to a metaheuristic when solving stochastic optimization problems.

Table 1: Computational Results.

	Deterministic Scenario		Stochastic Scenario		
Instance	OBD	OBD Time (s)	OBD-S	OBS	OBS Time (s)
500-100	1386.0	34.7	2963.3	2829.9	112.5
500-1000	1185.0	68.9	2551.1	2386.4	186.1
1000-1000	996.0	92.7	2133.0	2034.8	126.5
1500-10	1110.0	9.4	2416.5	2366.6	180.5
2000-10	1004.0	31.3	2237.9	2148.3	297.1
2000-100	860.0	58.2	1912.5	1826.9	137.2
2500-10	930.0	68.8	2062.4	1979.0	223.0
2500-100	781.0	88.8	1755.1	1697.7	207.6
2500-1000	738.0	89.5	1590.6	1570.6	137.4
3000-100	764.0	32.8	1720.6	1617.6	200.8
Average:	975.4	57.5	2134.3	2045.8	180.8

The objective of the second experiment is to investigate the relationship between budget and expected makespan. This is important when dealing with disaster management because we can assess the impact of extra budget or budget reduction on the performance of humanitarian operations. Thus, an analysis of the budget required for the number of facilities that could be opened while still ensuring a reasonable makespan is important. In this experiment, we use the 2000-100 instance. We run the proposed simheuristic method and vary the number of open facilities from 1 to 20. As expected, Figure 3 shows that the makespan decreases as the number of open facilities is increased (i.e. more budget). However, the relationship is not smooth. Notice that there are two instances where the makespan does not decrease much when the number of facilities is increased (i.e. opening between 4 and 5 facilities and between 9 and 10 facilities). Therefore, given those choices, managers might be interested in deciding to open 4 or 9 facilities and use the remaining budget for other important resources.

Finally, the third experiment aims at showing how to complement the above analyses with risk assessment analysis. For the risk assessment analysis, we consider the probability that we can cover all demand points within a certain response time target. For example, given a certain configuration of facilities, what is the probability for the disaster management team to be able to cover all demand points in less than 24 hours? In other words, we are interested in analyzing the reliability or survival function associated with a given makespan, i.e., the probability that all the demand points can be covered within a given target time. To demonstrate this, we have carried out an experiment that applies survival analysis using the Kaplan-Meier estimator, which is a statistical measure used to estimate the percentage chance of survival of a population over a given length of time. In our case, the Kaplan-Meier estimator provides the probability that the humanitarian operation is still ongoing at any target time $t > 0$ –notice that subtracting this value from one gives us the probability that the operation has been completed on or before time t.

Figure 4 shows the cumulative probability function of having finished all operations, at each target time $t > 0$, for the *OBD-S* solution and the three elite solutions returned by the simheuristic algorithm. Notice that the probability of covering all the demand points in less than 1900 time units is approximately 0.80 for the best stochastic solution ($Sol1$) of the elite solution pool, while for the rest of the solutions is about 0.60 or lower. Consistent with the result in the first experiment, the simheuristic solutions outperform the *OBD-S* solution. This analysis shows that managers can make a more informed decision by considering both the expected performance (i.e. makespan) of the best solution (i.e. the facility locations) and the risk of not meeting a target response time.

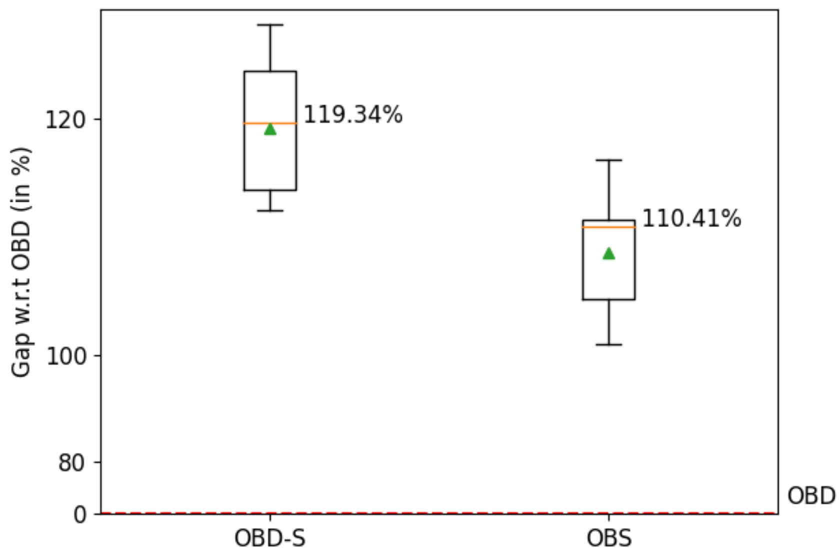

Figure 2: Gaps between *OBD-S* and *OBS* with respect to the *OBD*.

6 CONCLUSIONS AND FUTURE WORK

Motivated by the lack of simheuristics applications in disaster management, we have proposed a simheuristics algorithm to solve a facility location problem in disaster management. To evaluate the algorithm, we have adapted an FLP benchmark to reflect the realistic (but not real) disaster management case in this paper. The use of a known benchmark in the evaluation has built a confidence into the performance of our algorithm in in terms of the solution quality and computation speed before we apply it to a real-world application. The experiment shows that the combination of metaheuristic and simulation is able to find good solutions within a short computation time. Hence, this demonstrates the benefits of using hybrid modeling in solving a complex problem. Furthermore, we have demonstrated that using our approach, not only can we help decision makers by giving them a tool to find the optimal facility locations but also a tool to assess the risk of not meeting a certain target response time. In this early work, we have to make several simplifications to the model. In the future, we will relax some of these assumptions, notably, the infinite capacity of the facilities, the potential damage to the facility itself, and the supply and demand uncertainty. We will also test our model using real world cases such as the one presented in Onggo et al. (2021).

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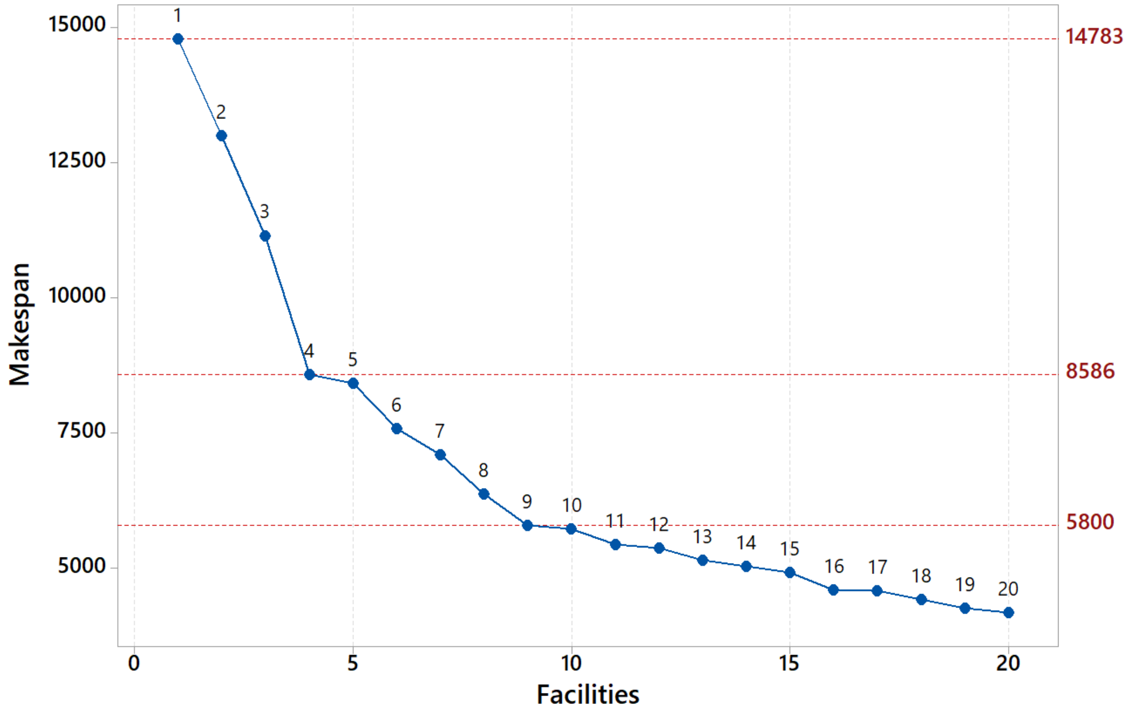

Figure 3: Makespan with respect to the total number of open facilities.

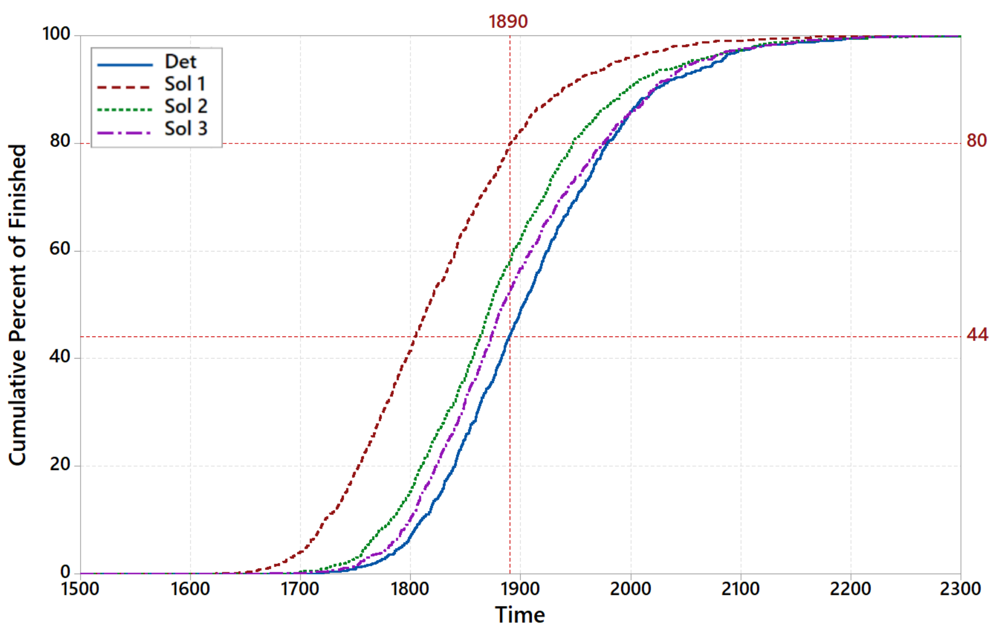

Figure 4: Survival functions for the 2000-100 instance.

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