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A Multi-Objective Optimization Model for Relief Facility Location in Crisis Conditions

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ABSTRACT

This research was conducted to study the issue of relief facility location hierarchically by consideration of possible road closure during the crisis conditions, road safety, and arrival time of relief facilities under disaster circumstances. High costs are allocated for facilities deployment in a suitable location to meet the demands of injured people. Therefore, location-allocation of emergency facility should be considered in a way to use them for long-term periods. To this end, the extant research designed a multi-objective optimization model to minimize the pre-disaster costs including costs of facilities deployment and road use, and to minimize the post-disaster costs such as cost transportation in-network roads. Moreover, the innovative part of the studied model in this research examined the road safety and reduction in time taken to have critical facilities in affected areas. To investigate the functional accuracy of the mathematical model, a numerical example with small dimensions was solved using CPLEX Solver, and required sensitivity analysis was described. As the facility location-allocation is an NP-hard issue, two meta-heuristic algorithms were used to solve numerical representations in real dimensions to examine numerical analyses effectively. Results showed that the dragonfly algorithm had the highest efficiency compared to other developed algorithms. The obtained results can be considered as an efficient managerial tool in management organizations involved in the crisis.

Keywords: Hierarchical Facility Location, Crisis Management, Multi-Objective Optimization Model, Meta-Heuristic Algorithm

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1. INTRODUCTION

One of the most important determinants of the success of rescue and relief operations during a crisis is the level of preparedness of crisis management facilities before the incident (Kaveh and Mesgari, 2019; Kovács and Spens, 2020). In other words, these facilities must be established and prepared in advance to handle the crises with proper rapid response to problems (Ghaffari *et al.*, 2020; Ghasemi *et al.*, 2019). Many developed countries including Japan, the United States, and South Korea have managed to achieve a high level of disaster preparedness through the use of strategic management and decision support tools. These countries can manage natural disasters with minimal loss of life and property and take action to repair the damages (Alaswad and Salman, 2020). One way to improve the response speed and performance of rescue and relief operations is to carefully plan the location of relief facilities. This facility location problem involves placing different relief facilities with different service levels so that they can cover different levels of demand in the affected areas (Madani *et al.*, 2021; Maulid-dina, 2020). The placement of relief facilities on the transportation network is extremely important for how well they can respond to the demand that will emerge during a crisis. Indeed, proper location of these facilities can significantly reduce the human casualties of a disaster. It should be noted that it takes a large budget to construct these facilities and they cannot be easily moved to another place if it turns out that they are not suitably located (Ghezavati *et al.*, 2015). Therefore, it is important to do extensive studies before starting the process of facility location as a strategic level managerial decision (Barber *et al.*, 2020). Given the importance of this subject, this study seeks to answer the question that how can one determine the appropriate locations for establishing relief facilities in a hierarchical structure for crisis management.

The problem discussed in this paper is the hierarchical facility location with cost and time minimization and safety maximization objectives. While many of the previous models are based on the assumption that the network structure is given and the goal is to just determine the optimal location of facilities, in this study, the goal is to determine not only the hierarchical location of facilities but also the routes that need to be opened or activated depending on crisis conditions. To check the performance of the developed model, a small-scale numerical example is solved with the CPLEX solver and a sensitivity analysis is also conducted. Since the facility location problem is NP-hard, two metaheuristic algorithms are also developed for solving the problem in real-world dimensions. The performance of these algorithms is also evaluated through numerical analysis.

As mentioned, while many of the previous studies in this field have assumed that the network structure is already known, in reality, it may not be possible to make a definite statement about the network structure and condition during a crisis, and it is therefore necessary to add new assumptions to previous models. In this study, the hierarchical relief facility location problem is formulated with the assumption that it is necessary to choose the routes that need to be activated according to crisis conditions based on the fact that rescue time and route safety are among the main concerns of emergency response organizations (e.g. crisis management organization, red crescent society, etc.) when choosing routes and vehicles for rescue teams. For this purpose, experts with the knowledge of the transportation network should determine the routes that are least likely to get blocked during a crisis, ensuring that rescue teams will have access to affected areas.

2. PROBLEM STATEMENT

In previous studies, researchers have developed hierarchical facility location models for multi-level health systems (e.g. a two-level system consisting of local clinics and hospitals). In this study, a similar approach is used to formulate a hierarchical relief facility location model with the following assumptions:

- The mathematical model is multi-objective.
- The hierarchy consists of two levels: elementary relief facilities (e.g. relief camps or field clinics) at level 1 and advanced relief facilities (e.g. better-equipped clinics or hospitals) at level 2, with demand points assigned to level 0.
- Level-2 facilities also offer the services provided in level-1 facilities.
- Demand has a multi-flow pattern, i.e. it starts from a point and runs to and between level-1 and level-2 facilities.
- The routes between demand points are known but there is a certain probability that they will be blocked after the disaster. Therefore, routing is done with reliability maximization and cost minimization goals.
- The number of facilities of each level is known.
- Demand points and potential facility locations are known.
- There is a minimum capacity and a maximum capacity for each facility.
- The routes between demand points, level-1 facilities, and level-2 facilities have a specific capacity.

Sets and Symbols

K = set of demand points

I = Set of candidate points for the deployment of level-2 facilities

J = Set of candidate points for the deployment of level-1 facilities

E = Number of routes from demand point to level-1 facilities
V = Number of routes from demand point to level-2 facilities
Z = Number of routes from level 1 facilities to level-2 facilities

Input parameters

$\tilde{t}_{kje}$: Transport time from demand point k to level-1 facility in route e
$\tilde{t}_{jiz}$: Transport time from level-1 facility to level-2 facility in route z
$\tilde{t}_{kiv}$: Transport time from demand point k to level-2 facility in route v
H_{kje} : Maximum allowed time for transport from demand point k to level-1 facility
H_{jiz} : Maximum allowed time for transport from level-1 facility to level-2 facility
H_{kiv} : Maximum allowed time for transport from demand point k to level-2 facility
α : Cost factor
F_j : Fixed cost of deploying a level-1 facility in location j
G_i : Fixed cost of deploying a level-2 facility in location i
C_{kje} : Cost of transport from demand point k to level-1 facility in route e
C_{jiz} : Cost of transport from level-1 facility to level-1 facility in route z
C_{kiv} : Cost of transport from demand point k to level-2 facility in route v
C_e : Cost of using route e
C_v : Cost of using route v
C_z : Cost of using route z
B : Number of potential level-1 facilities
D : Number of potential level-2 facilities
M_j : Maximum capacity of level-1 facility
M_i : Maximum capacity of level-2 facility
L_j : Minimum capacity of level-1 facility
L_i : Minimum capacity of level-2 facility
M_e : Maximum capacity of the route between demand point and level-1 facility
M_z : Maximum capacity of the route between level-1 facility and level-2 facility
M_v : Maximum capacity of the route between demand point and level-2 facility
q_v : Blockage probability of route v
q_e : Blockage probability of route e
q_z : Blockage probability of route z
$\tilde{\beta}_k$: Demand of point k

Continuous and binary variables

U_{kje} : Flow from demand point k to level-1 facility in route e
U_{jiz} : Flow from level-1 facility to level-2 facility in route z
U_{kiv} : Flow from demand point k to level-2 facility in route v
X_i : =1 if a level-2 facility is deployed in location i, =0 otherwise.
Y_i : =1 if a level-1 facility is deployed in location j, =0 otherwise
W_e : =1 if route e is used (assigned), =0 otherwise
T_v : =1 if route v is used (assigned), =0 otherwise
N_z : =1 if route z is used (assigned), =0 otherwise

Mathematical model

$$CJ = \sum_{j=1}^{J} F_j . Y_j \tag{1}$$

$$CI = \sum_{i=1}^{I} G_i . X_i \tag{2}$$

$$CE = \sum_{e=1}^{E} C_e . W_e \tag{3}$$

$$CV = \sum_{v=1}^{V} C_v . T_v \tag{4}$$

$$CZ = \sum_{z=1}^{Z} C_z . N_z \tag{5}$$

$$\begin{aligned} CT = \Bigg[& \sum_{V} \left[(1-q_V) \left(\sum_{k} \sum_{i} C_{kiV} . U_{kiV} \right) \right] \\ & + \sum_{E} \left[(1-q_E) \left(\sum_{k} \sum_{j} C_{kjE} . U_{kjE} \right) \right] \\ & + \sum_{Z} \left[(1-q_Z) \left(\sum_{j} \sum_{i} C_{jiZ} . U_{jiZ} \right) \right] \Bigg] \end{aligned} \tag{6}$$

Equations (1) and (2) compute the fixed cost of deploying a level-1 facility at location j and deploying a level-2 facility at location j, respectively. Equations (3), (4), and (5) determine the cost of using routes e, v, and z respectively. Equation (6) computes the cost of flow from demand point k to level-1 and level-2 facilities and between these facilities if the routes are not blocked.

$$SE = \sum_{k=1} \sum_{j=1} U_{kje} W_e q_e \tag{7}$$

$$SV = \sum_{k=1} \sum_{i=1} U_{kiv} T_v q_v \tag{8}$$

$$SZ = \sum_{k=1} \sum_{i=1} U_{jiz} N_z q_z \tag{9}$$

Equations (7), (8), and (9) determine the size of flow that will be disrupted in routes e, v, and z respectively. On this basis, the first and second objective functions are formulated as Equations (10) and (11):

$$\begin{aligned} &Min\, CI + CJ + CE + CV + CZ + CI \\ &+\alpha_1\left(\sum_{i\in I}\sum_{j\in J} U_{jiz} - 0.6\sum_{k\in K}\sum_{e\in E} U_{kje}\right) \\ &+\alpha_2\left(U_{kje} - M_e W_e\right) + \alpha_3\left(U_{kiv} - M_v T_v\right) \\ &+\alpha_4\left(U_{jiz} - M_z N_z\right) + \alpha_5\left(\tilde{t}_{kje} W_e - H_{kje}\right) \\ &+\alpha_6\left(\tilde{t}_{jiz} N_z - H_{jiz}\right) + \alpha_7\left(\tilde{t}_{kiv} T - H_{kiv}\right) \end{aligned} \tag{10}$$

$$Min\, SV + SE + SZ \tag{11}$$

$s.t.$

$$\sum_{j=1}^{J} Y_j = B \tag{12}$$

$$\sum_{i=1}^{I} X_i = D \tag{13}$$

$$L_j Y_i \le \sum_{k\in K}\sum_{e\in E} U_{kje} \le M_j Y_j \qquad \forall j \in J \tag{14}$$

$$L_i X_i \le \sum_{j\in J}\sum_{z\in Z} U_{jiz} + \sum_{k\in K}\sum_{v\in V} U_{kiv} \le M_i X_i \quad \forall i \in I \tag{15}$$

$$\sum_{j\in J}\sum_{e\in E} U_{kje} + \sum_{i\in I}\sum_{v\in V} U_{kiv} \le \tilde{\beta}_k \quad \forall k \in K \tag{16}$$

$$U_{kje}, U_{kiv}, U_{jiz} \ge 0 \quad \forall j \in J, i \in I, z \in Z, v \in V, e \in E \tag{17}$$

$$X_i, Y_j, T_v, N_z \in \{0,1\} \tag{18}$$

Constraints (12) and (13) state that the total number of level-1 facilities to be deployed must be equal to B and the total number of level-2 facilities to be deployed must be equal to D. Constraint (14) is the capacity constraint of level-1 facilities, which ensures that the sum of all flows to a deployed level-1 facility 1 remains below its capacity. Constraint (15) has a similar function for level-2 facilities, ensuring that the sum of all flows from demand points and level-1 facilities to a deployed level-2 facility remains below its capacity. Constraint (16) is the demand size constraint, which makes sure that the sum of all flows from a demand point to level-1 and level-2 facilities is less than or equal to the size of demand at that point. Constraint (17) specifies the domain of positive variables and Constraint (18) does the same for binary variables.

3. SOLUTION METHOD

Since the facility location problem belongs to the category of NP-hard problems (Maharjan and Hanaoka, 2020), the medium and large-scale numerical examples of this problem need to be solved with meta-heuristic methods. One of the most important issues in using meta-heuristic methods is the proper selection of the algorithm according to the nature and structure of the problem. Considering the good performance of population-based swarm intelligence meta-heuristic algorithms, they are a perfect choice for solving the modeled problem. Among these algorithms, the gray wolf optimizer, antlion optimizer, and dragonfly algorithm have shown excellent performance and found to be more or less superior over other algorithms in solving almost all problems. The multi-objective versions of these algorithms are also highly efficient and can swiftly shift from exploitation to exploration to produce high-quality solutions. In this study, the Multi-Objective Dragonfly Algorithm (MODA) is used to solve the problem. Given the generally good performance of genetic algorithms in solving all optimization problems, they can serve as good benchmarks for performance evaluation. The second version of the nondominated sorting genetic algorithm (NSGAII) is the most prominent multi-objective algorithm of this family in all areas of optimization. Therefore, in this study, the results of the proposed algorithms are compared with those of NSGAII.

3.1 Solution Structure

In this study, each solution consists of five parts, each with a vector of a certain size, which is related to one of the independent decision variables. The following figure shows the structure of a random solution of the proposed problem. The figure below each vector is the number of elements in that vector.

These matrices are generated with random bi-

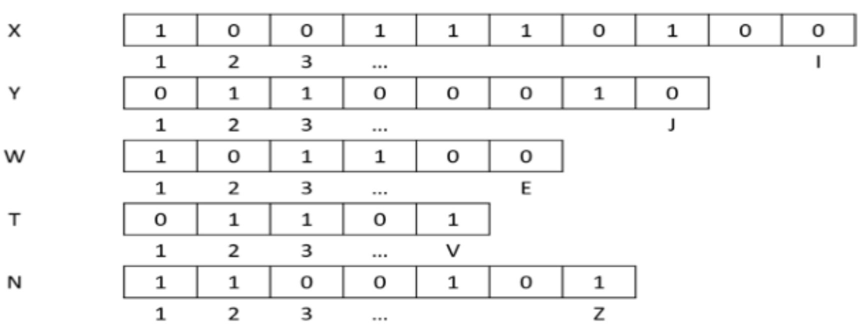

Figure 1. Structure of a random solution of the proposed problem.

nary numbers, which are then as a basis for determining the values of other decision variables. Also, the coding is done such not all elements of a matrix can be zero, i.e. there are at least one or more unity elements in each matrix so that the problem constraints are not violated.

4. NUMERICAL RESULTS

4.1 Parameter Setting

Since DA is an intelligent algorithm, it does not have any specific tunable parameter and all of its operators function based on equations with preset parameters. The only controllable parameters of this algorithm are the number of agents and the number of iterations. NSGAII however has four tunable parameters: population size, number of iterations, mutation rate, and crossover rate. To optimize the performance of these algorithms in solving different numerical examples, it is necessary to determine the optimal values of these parameters. In this study, the response surface method (RSM) is used for this purpose. Since the problem has two objective functions, it is impossible to use a single solution to quantify the response variable. Therefore, it was decided to use a response variable comprised of 5 criteria and with the formula given below for comparing multi-objective algorithms. However, since these criteria are not equally important for the decision, they were weighted according to the following table.

Weights of evaluation criteria in the calculation of response variables

Criteria	NPS	MID	Spacing	Diversity	CPU Time
weights	0.2	0.2	0.2	0.2	0.1

$$R_i = \frac{w_1\overline{RPD_1} + w_2\overline{RPD_2} \ldots + w_n\overline{RPD_n}}{w_1 + w_2 + \ldots + w_n}$$

As can be seen, the response variable R_i is calculated based on the Relative Percentage Deviation (RPD), which is given by the following formula:

$$RPD = \frac{Alg_{sol} - Min_{sol}}{Min_{sol}} \times 100$$

The three value levels considered for algorithm parameters are given in the table below.

After following the RSM procedure, the optimal levels of algorithm parameters were obtained as shown in the following table.

4.2 Comparison of Algorithms

This section presents the results obtained by solving the numerical examples of the modeled problem with the meta-heuristic algorithms. The best solutions obtained from 10 independent runs of each algorithm for each numerical example are given in Tables 3, 4, and 5. It should be noted that the numerical examples were generated randomly based on the information of Example 2. Also, all algorithms were executed on a computer with a 3.2GH CPU and 16GB of RAM in the MATLAB R2016a soft-

Table 1. Levels considered for algorithm parameters

	Lower level (-1)	Middle level (0)	Upper level (+1)
Number of iterations	150	200	300
Population size (× chromosome length)	0.5	1.5	2.5
Mutation rate	0.5	0.7	0.8
Crossover rate	0.2	0.3	0.5

Table 2. Optimal levels of algorithm parameters

Problem size		Population size (× chromosome length)	Mutation rate	Crossover rate
small	NSGAII	1.5	0.8	0.5
	MODA	2.5	-	-
Medium	NSGAII	2.5	0.8	0.3
	MODA	2.5	-	-
Large	NSGAII	2.5	0.8	0.3
	MODA	2.5	-	-

ware environment. The table below compares the results of algorithms for small numerical examples.

As can be seen, MODA outperformed NSGAII in solving small numerical examples. The performance values of the algorithms are also compared in the following Figures 2 and 3.

Table 3. Comparison of the results of the algorithms for small-scale numerical examples of the problem

		CPU Time (sec)	NPS	MID	Diversity	Spacing
Prob1	MODA	22.83	5.09	3300.24	2382.29	1287.59
	NSGAII	23.50	2.98	7167.10	3460.36	2252.73
Prob2	MODA	36.70	10.97	13214.89	4425.70	2985.29
	NSGAII	25.11	16.03	1391.15	1123.69	2352.37
Prob3	MODA	0.41	19.38	9043.50	1925.42	519.79
	NSGAII	57.40	16.40	11536.16	7129.82	4088.29
Prob4	MODA	46.04	34.31	8995.06	4735.44	692.61
	NSGAII	105.64	26.05	12970.44	5408.34	5458.36

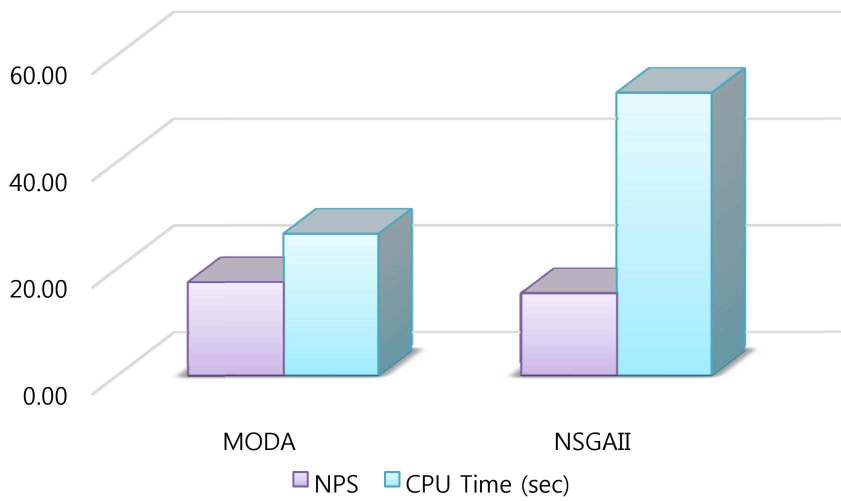

Figure 2. Comparison of average NPS and CPU TIME of the algorithms.

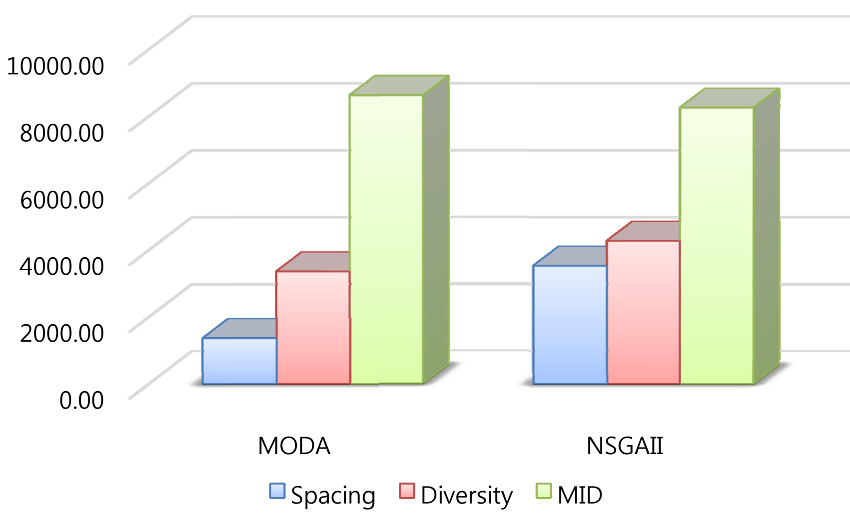

Figure 3. Comparison of average Spacing, Diversity, and MID of the algorithms.

Table 4. Comparison of the results of the algorithms for medium-scale numerical examples of the problem

		CPU Time (sec)	NPS	MID	Diversity	Spacing
Prob5	MODA	246.31	26.06	115691.96	39820.02	23067.77
	NSGAII	558.68	23.67	117718.36	36985.79	23984.03
Prob6	MODA	276.01	36.22	130090.22	47169.76	30610.23
	NSGAII	620.06	28.60	137847.94	41284.74	28825.06
Prob7	MODA	342.84	38.91	154451.98	58430.29	36515.03
	NSGAII	770.82	37.31	150603.67	46044.56	36632.37
Prob8	MODA	412.23	48.46	196837.09	69731.93	46570.76
	NSGAII	945.19	44.27	200488.39	57449.37	45292.43

Table 5. Comparison of the results of the algorithms for large-scale numerical examples of the problem

		CPU Time (sec)	NPS	MID	Diversity	Spacing
Prob9	MODA	1405.52	13.77	707705.24	235739.47	160186.70
	NSGAII	2858.08	17.04	607156.45	195482.77	165975.85
Prob10	MODA	1735.93	17.82	856327.17	301771.38	202481.48
	NSGAII	3608.39	21.27	704028.16	220780.60	193165.30
Prob11	MODA	1933.22	22.60	955041.27	365433.41	231842.29
	NSGAII	4196.17	25.55	791663.49	260839.78	230094.05
Prob12	MODA	2426.43	28.50	1149668.81	450648.41	259662.58
	NSGAII	5157.57	31.52	972134.07	292593.42	271911.08

It should be noted that for small problems, the differences between the algorithms were not significant and both of them showed a good performance. Therefore, they must be compared in terms of performance in solving larger problems. Table 4 presents the results obtained by solving the medium-scale numerical examples of the problem.

As Table 4 shows, MODA showed a great advantage in solving all medium-scale numerical examples, but it had slightly worse runtimes.

The numerical results of the algorithms for large-scale examples are compared in Table 5.

The results presented in the table above show the clear superiority of MODA in solving large-scale numerical examples of the problem. Overall, it can be concluded that MODA can generate far better solutions for the modeled problem than NSGAII. Therefore, this algorithm is more suitable for solving real-sized numerical instances of the problem.

5. CONCLUSIONS AND RECOMMENDATIONS

The subject of this research was related to two areas of crisis management, including relief facility location and reliability maximization. The problem model was formulated with the mathematical equations and assumptions described in the second section. This model has a linear structure and its objective is to determine the best locations for the deployment of relief facilities in order to form a supply network. Two meta-heuristic algorithms, namely Multi-Objective Dragonfly Algorithm (MODA) and Nondominated Sorting Genetic Algorithm II (NSGAII) NSGAII, were presented for solving this model. After evaluating the performance of these algorithms in solving numerical examples of the modeled problem, it was found that while both algorithms produce good solutions, MODA offers better performance for almost all problems and can therefore be recommended as the preferred solution method for large-scale instances of the problem. Future studies are recommended to try the following approaches for expanding this research in operational and theoretical dimensions.

- Considering decisions to be of the multi-period type to make the model more realistic
- Examining whether the problem can be solved better with other meta-heuristic methods, such as simulated annealing, tabu search, artificial neural network, etc.

Implementing the presented model in a case study to evaluate the utility of the model and the solution methods.

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