

RESEARCH PAPER

An Exact Branch and Fix Coordination (BFC) Approach to Solving a Relief Transportation Network for Disaster Management

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Received 11 April 2020; Revised 15 May 2020; Accepted 1 June 2020; Published online 30 June 2020
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ABSTRACT

The number of natural disasters and the people affected by them have been increasing in recent years. The field of optimization is a significant element of a relief operation and has been extensively studied so far, especially during the last two decades. The design of a relief logistic network as a strategic decision and that of relief distribution as an operational decision are the most important activities required for disaster operation management before and after a disaster occurs. In the proposed mathematical model, pre-disaster decisions are determined according to the postdisaster decisions in a multi-stage stochastic problem. Then, a well-known approach called branch and fixed coordination is applied to optimize the proposed model. The computational results confirm that the proposed approach has proper performance for disaster management in a multi-stage stochastic problem.

KEYWORDS: Multi-stage stochastic; Branch and fixed; Exact solution; Relief operation; Disaster management.

1. Introduction

Every year, natural disasters occur all over the world and according to the international disaster database, the number of natural disasters and, consequently, the losses arising from these events have been increasing significantly in the last decades. The trend of the number of natural disasters is illustrated in Figure 1.

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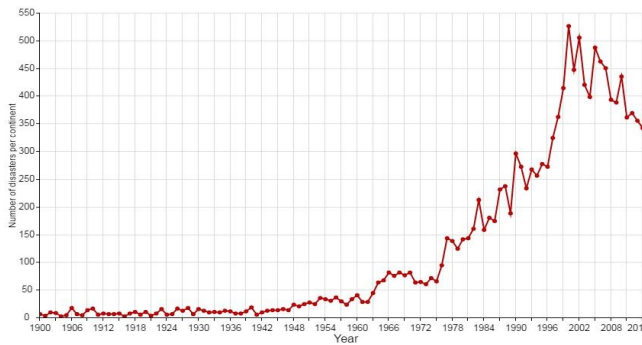


Fig. 1. Number of disasters and the people affected by disasters according to the international disaster database (emdat.be)

In 1985, McLoughlin (McLoughlin, 1985) defined a framework with four critical phases of disaster management as follows: 1) Mitigation phase (pre-disaster): activities for reducing potential risks; 2) Preparedness phase (pre-disaster): activities performed before the disaster to prepare proper responses such as the locations of relief centers; 3) Response phase (during the disaster): activities for relief distribution during a disaster such as planning the allocation of relief resources to the disaster area; 4) Recovery phase (post-disaster): long-term activities for restitution. A lot of research has shown the importance of the field of disaster management to deal with disaster events. According to a review on the related papers up to 2006 (Altay and Green, 2006), 44% of studies in the field of disaster operations management are related to the mitigation phase; however, another review paper on disaster management in 2013 (Galindo and Batta, 2013) showed that most of the recent studies in this

field focused on the response (33.5%) and preparedness (28.4%) phases, respectively. To the best of our knowledge, most of the previous studies have focused on the preparedness or response phases separately; however, a few of them considered the two phases together. Moreover, although the hub location model is one of the most effective models for reducing time and costs, few papers have attempted to consider the features of the model for disaster management. On the other hand, those papers with a focus on hub location networks have either considered certain data or ignored the relief distribution time after the disaster in the models presented. Accordingly, this study focuses on both the preparedness and the response phases of natural disaster management simultaneously to fulfill existing gaps in the literature. Thus, this study proposes a stochastic model for presenting a reliable relief network by considering the existing information about previous incidents.

Tab. 1. Some of researches on the disaster management from 2006 to 2019

Authors	Year	Subject										Disaster phases			Data			Objective			Model structure				
		Relief network structure	Relief inventory	Relief distribution	Transportation system	Roadway repair	Mitigation	Preparedness	Response	Recovery	Certainty	Uncertainty	Time	Cost	Safety	Supply chain	Distribution Network	location routing problem	Covering	Hub location	Other				
(Beamon and Kotleba, 2006)	2006	*					*					*		*	*										
(Tzeng et al., 2007)	2007		*						*		*		*	*	*		*			*					
(Balcik and Beamon, 2008)	2008	*	*				*				*		*	*	*		*	*		*					
(Liu et al., 2009)	2009		*				*					*		*	*		*	*		*				*	

Continue Table 1. Some of researches on the disaster management from 2006 to 2019

International Journal of Industrial Engineering & Production Research, June 2020, Vol. 31, No. 2

(Burkart et al., 2017)	2017		*			*	*	*		*	
(Chowdhury et al., 2017)	2017	*	*			*	*	*	*		
(Al Theeb and Murray, 2017)	2017		**			*	*	*			*
(Li and Chung, 2018)	2018		*			*		**		*	
(Setiawan et al., 2018)	2018		*			*	*	**		*	*
(Yu et al., 2018)	2018		*			*	*	*	*		*
(Mostajabdaveh et al., 2018)	2018	*			*			*	*	*	*
(Ni et al., 2018)	2018	*			*	*		*	*	*	
(Moreno et al., 2018)	2018		*		*	*		*	*	*	
(Iqbal et al., 2018)	2018		*			*		**	*	*	
(Vahdani et al., 2018)	2018		*	*		*	*	*		*	
(Cao et al., 2018)	2018	*	*			*	*	*	*	*	
(Tavana et al., 2018)	2018	*			*	*	*	*	*	*	
(Ferrer et al., 2018)	2018		*			*	*	*	*	*	
(Hasani and Mokhtari, 2019)	2019	*				*	*	*	*	*	
This research	-	*	*	*	*	*	*	*	*	*	*

Generally, local and international aid organizations send emergency supplies from various areas to support disaster-stricken victims after a disaster, and injured victims must be transferred to hospitals and health centers as soon as possible; thus, the preparation of a safe and reliable transportation system based on bilateral routes instead of unilateral routes for transporting first-aid and injured victims can play a significant role in reducing

potential losses from a natural disaster. According to previous studies, researchers have made a distinction between preparedness and response phases in terms of managing transportation plans. However, this separation leads to a transportation network which is not appropriate in disaster situations. Therefore, this study proposes an integrated model to configure a relief transportation network based on the three steps defined in Figure 2.

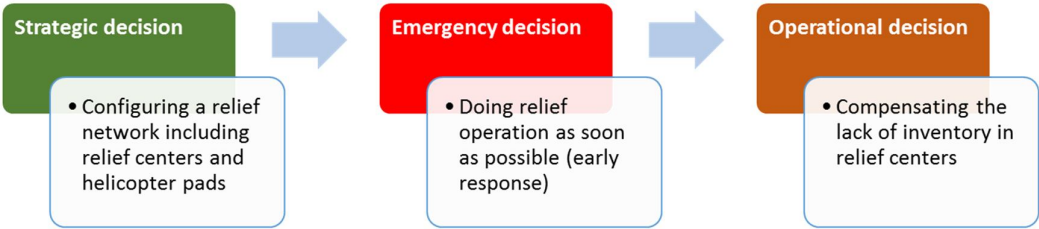


Fig. 2. An overview of different stages in the proposed model

It is clear that the proposed model is a type of stochastic programming. Therefore, an attempt is made to consider a scenario based a solution approach such as branch and fix coordination. Figure 3 shows three types of the main solution approaches based on disaster phases. Since the

relief operation time is the most important issue after a disaster, some meta-heuristic algorithms can be applied to finding the best solution (not definitely optimal). However, the exact solution to configuring a relief network as a strategic decision should be applied.

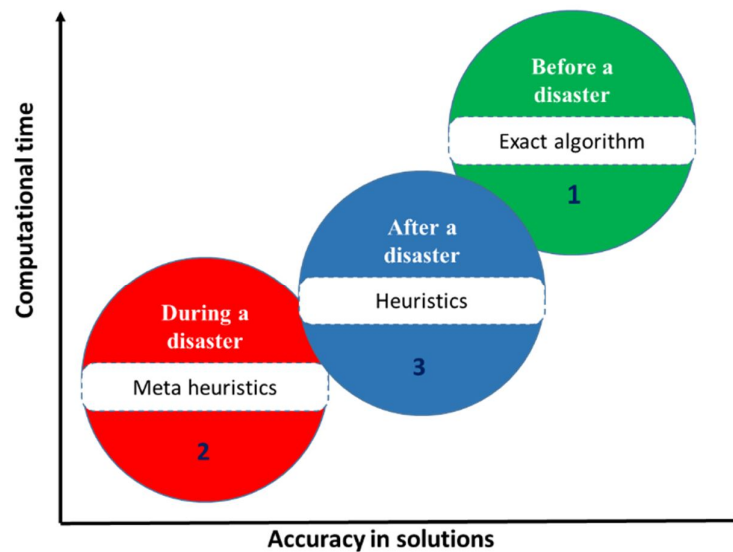


Fig. 3. Three main solution approaches based on disaster phases

The presented paper is organized as follows: In the next section, the proposed model based on a multi-stage stochastic programming is presented. Section 2 presents the solution approach according to a well-known exact method called branch and fixed coordination. Finally, the conclusion is presented in the last section.

2. Proposed Model (A Multi-Stage Stochastic Problem)

In this section, an integrated formulation based on a multi-stage stochastic programming is proposed. The effects of before and after disaster are integrated by defining several scenarios with possible features of real disasters. In other words, the proposed model is based on three types of decisions including a) strategic decision that should be made on predisaster such as the location of relief centers and their inventory, b) emergency decision that should be made on as soon as disaster occurs including relief operation early in the disaster (sometimes referred as golden 72 hours), and c) operational decision that can be made before disaster or after the golden 72 hours in order to complete relief operation. Considering all types

of decision simultaneously is one of the advantages of the proposed model. The objective values of relief operation in different scenarios are examined to configure the best relief network. The assumptions, parameters, variables, and mathematical model are explained as follows.

Assumptions

- Vehicles and helicopters are considered as relief transportation modes, where vehicles refer to roadways, helicopters to airways for accelerating the transfer time between hubs, and transportation vehicles to both roadways and airways.
- The disaster can occur at one of vulnerable points with a probability of occurrence.
- Types of arcs in the proposed network include relief center to higher-level center, higher-level center to high-level center, and relief or higher-level center to disaster point.
- The transfer of relief goods can begin from a relief center, at most, from two higher-level centers to the disaster point.

Tab. 2. Uncertainty information in each stage

First-stage	
1	Demand
2	Disaster point
3	Supply demand
4	Transportation Link
5	Health conditions of affected population
6	Travel time

7	Damages facilities/transportation link
Second-stage	
8	Health conditions of affected population
9	Exact demand
10	Shortage of inventory
Third-stage	

Parameters/sets & Variables

Let $N = \{1, 2, \dots, n\}$ be the set of vulnerable points, of which some should be selected as the location of relief or higher-level centers and the rest should be covered by centers. According to the third assumption, each vulnerable point is considered as a disaster point in different scenarios. Let $S = \{1, 2, \dots, s_d\}$ be the set of possible scenarios depending on three distinct components: the probability of occurrence (P^s), the disaster location (one of the vulnerable points), and the value of relief demands (D^s).

C_{ij} Collection cost per unit of flow between points i and j ;

C_{js} Collection cost per unit of flow between point j and the disaster point in scenario s ;

α Discount factor for transfer among higher-level centers;

F_k Cost of establishment of higher-level center at vulnerable point k ;

FF_k Cost of establishment of relief center at vulnerable point k ;

T_{ij} Transportation time of relief goods between vulnerable points i and j ;

T_{js} Transportation time of relief goods between vulnerable point j and the disaster point in scenario s ;

M A large number;

N_{i1} Number of vehicles available at relief center i ;

N_{k2} Number of helicopters available in hub k .

Two coverage radii are considered: one related to relief centers (R_{1i}) for covering vulnerable points and the other related to higher-level centers (R_{2i}) for covering relief centers. In order to avoid complexity in the proposed model, a_{ij} is applied as an auxiliary parameter equal to 1 or 0 depending on whether or not the vulnerable point j is covered by point i according to R_{1i} . The capacities of vehicles and helicopters are defined by V_1 and V_2 . Other parameters corresponding to the proposed model can be given as follows:

Since the main contribution of this study focuses on configuring a relief network of relief and higher-level centers, variables

corresponding to the locations of these centers can be considered as the main decision variables and are denoted as follows:

$$x_{ik} = \begin{cases} 1 & \text{if vulnerable point } i \text{ is allocated to higher-level center } k & i \neq k \\ 1 & \text{if higher-level center is established in vulnerable point } i & i = k \\ 0 & \text{otherwise} \end{cases}$$

$$y_i = \begin{cases} 1 & \text{if a relief center is established in vulnerable point } i \\ 0 & \text{otherwise} \end{cases}$$

Relief operation time, the number of vehicles, and flow are three other major variables of relief operation that should be considered under different scenarios. Total relief operation time under each scenario is denoted by t^s , $t_i^{1s}, t_{ij}^{2s}, t_i^{3s}$ denote the maximum time taken for transferring relief goods from relief centers to

higher-level center i , from higher-level center i to higher-level center j , and from relief/higher-level center i to the disaster point under scenario s , respectively. $\lambda_{ni}^{1s}, \lambda_{ij}^{2s}, \lambda_i^{3s}$ are integer variables that determine the number of transportation vehicles for transferring relief goods from relief center n to higher-level center

i , from higher-level center i to higher-level center j , and from relief/higher-level center i to the disaster point under scenario s , respectively. Finally, w_{ij}^s, w_i^s are denoted as the relief flow between vulnerable points i and j and that between vulnerable points i and the disaster point under scenario s , respectively. In addition, the route of relief operation has been considered by r_{ij}^s which is equal to 1 if $w_{ij}^s > 0$, otherwise 0. It is worth mentioning that a vulnerable point

which was considered as a disaster area in a scenario should be eliminated from set N in the proposed model. For example, suppose that there is a set of vulnerable points including $\{1,2,3,4,5,6\}$ and if Node 3 has been considered as the disaster point in a scenario, then the set of nodes should be considered equal to $\{1,2,4,5,6\}$ in the scenario. The mathematical formulation with predefined scenarios can be stated as follows.

$$\text{minimize } \sum_{s=1}^{s_d} P^s t^s \quad (1)$$

$$\text{minimize } \sum_{k=1}^n F_k x_{kk} + \sum_{i=1}^n FF_i y_i \quad (2)$$

$$\sum_{s=1}^{s_d} \sum_{k=1}^n \sum_{j=1}^n \sum_{i=1}^n P^s (w_{ij}^s C_{ij} x_{ij} + \alpha w_{jk}^s C_{jk} x_{jj} x_{kk} + \alpha w_k^s C_k x_{kk} + w_k^s C_k (1 - x_{kk})) \quad (3)$$

$$\sum_{j=1}^n w_{ij}^s \leq M(y_i + (1 - y_i)x_{ii}) \quad \forall i \in N, s \in S \quad (4)$$

$$\sum_{k=1}^n x_{ik} = y_i \quad \forall i \quad (5)$$

$$x_{ik} \leq x_{kk} \quad \forall i, k \quad (6)$$

$$\sum_{j=1}^n a_{ij} y_j \geq 1 \quad \forall i \quad (7)$$

$$T_{ik} x_{ik} \leq R_{2k} \quad \forall i, k \quad (8)$$

$$\sum_i w_i^s \geq D^s \quad \forall s \quad (9)$$

$$\sum_{k \neq i} w_{ij}^s x_{ii} x_{jj} - \sum_{k \neq i} w_{jk}^s x_{jj} x_{kk} + \sum_l w_{lj}^s x_{lj} = w_j^s \quad \forall j \in N, s \in S \quad (10)$$

$$Mx_{ij} \geq w_{ij}^s \quad \forall i, j \neq i, s \quad (11)$$

$$Mr_{ij} \geq w_{ij}^s \quad \forall i, j \neq i, s \quad r_{ij} \leq w_{ij}^s \quad \forall i, j \neq i, s \quad (12)$$

$$(13)$$

$$\lambda_{ni}^{1s} \geq \frac{(1 - x_{nn})(x_{ii})(w_{ni}^s)}{V_1} \quad (14)$$

$$t_i^{1s} = \max_n \begin{cases} \max\{(2k-1)T_{ni}, 0\} & \left(\frac{\lambda_{ni}^{1s}}{N_n^1}\right) = \left[\frac{\lambda_{ni}^{1s}}{N_n^1}\right] = k \\ (2k+1)T_{ni} & \left(\frac{\lambda_{ni}^{1s}}{N_n^1}\right) \neq \left[\frac{\lambda_{ni}^{1s}}{N_n^1}\right] = k \end{cases} \quad (15)$$

$$\lambda_{ij}^{2s} \geq \frac{x_{ii} x_{ij} w_{ij}^s}{V_2} \quad \forall i, j \quad (16)$$

$$t_{ij}^{r2s} = \begin{cases} \max \{ (2k-1) \alpha T_{ij}, 0 \} & \left(\frac{\lambda_{ij}^{2s}}{N_n^2} \right) = \left[\frac{\lambda_{ij}^{2s}}{N_n^2} \right] = k \\ (2k+1) \alpha T_{mi} & \left(\frac{\lambda_{ij}^{2s}}{N_n^2} \right) \neq \left[\frac{\lambda_{ij}^{2s}}{N_n^2} \right] = k \end{cases} \quad (17)$$

$$\lambda_i^{3s} \geq \frac{w_i^s}{V_2} \quad \forall i, s \quad (18)$$

$$t_i^{r3s} = \begin{cases} \max \{ (2k-1) T_i^s, 0 \} & \left(\frac{\lambda_i^{3s}}{N_i^2} \right) \neq \left[\frac{\lambda_i^{3s}}{N_i^2} \right] = k \\ (2k+1) T_i^s & \left(\frac{\lambda_i^{3s}}{N_i^2} \right) \neq \left[\frac{\lambda_i^{3s}}{N_i^2} \right] = k \end{cases} \quad (19)$$

$$t^s = \max_i \{ \max_i \{ \max_i \{ t_i^{r1s} + \sum_j t_{ij}^{r2s}, \sum_j r_{ij}^s t_j^{r1s} \} + \sum_k \sum_j r_{ij}^s t_{jk}^{r2s}, \sum_k \sum_j r_{ij}^s r_{jk}^s t_k^{r1s} \} + t_i^{r3s} + \sum_j r_{ij}^s t_j^{r3s} + \sum_k \sum_j r_{ij}^s r_{jk}^s t_k^{r3s} \} \} \} \quad \forall s \quad (20)$$

$$A^s = A^{s+1} \quad A \in \{\text{all variables in each scenario}\} \quad (21)$$

$$\lambda_{mi}^{1s}, \lambda_{ij}^{2s}, \lambda_i^{3s} \geq 0 \& \text{int} \quad (22)$$

$$t^s, t_i^{r1s}, t_{ij}^{r2s}, t_i^{r3s}, w_{ij}^s, w_i^s \geq 0 \quad (23)$$

$$x_{ik}, y_i \in \{0, 1\} \quad \forall i, k \quad (24)$$

The objective functions (1–3) seek to minimize the expected value of the relief operation time, total establishment costs, and expected transportation costs, respectively. The first and third objectives are related to operations after the disaster; therefore, they take into account the expected time and costs of relief operations, while the second objective is related to the pre-disaster strategic decisions. Constraint (4) ensures that relief services can be transferred from relief or higher-level centers. Constraint (5) ensures that each vulnerable point can be allocated to a higher-level center if it has been selected as a relief center. Constraint (6) ensures that the relief center i can be assigned to establish a higher-level center k . Constraint (7) ensures that each vulnerable point can be

covered by at least one relief center. Constraint (8) ensures that a relief center can be allocated to a higher-level center if it is inside the coverage radius. Constraint (9) guarantees that the relief services provided at the disaster point in each scenario should be more than the demand of the disaster point. Constraint (10) is the flow balance constraint between centers and the disaster point. Constraint (11) ensures that relief services can be provided to allocated centers. Constraints (12) and (13) determine the route of the relief operation according to flows of relief goods between centers under each scenario. Equations (14), (16), and (18) determine the number of relief vehicles required to transfer the relief goods from relief centers to higher-level centers, between two higher-level centers, and from centers to disaster area by

considering the decision variables corresponding to the locations of centers and computing the flow path in each scenario. Equations (15), (17), and (19) determine the transportation time between any two nodes of the relief operation path in each scenario. It is worth mentioning that a discount factor has been used in Equation (17) because of the use of special transportation vehicles among higher-level centers such as relief helicopters. Equation (20) helps illustrate and calculate the relief operation time based on the locations of centers in each scenario, as explained by Hasanzadeh and Bashiri [6]. Moreover, the generalized form of the constraint was presented by these authors based on the utilization of more than two higher-level centers for transferring relief goods from relief centers to the disaster area. Constraints (21) corresponding to multi-stage stochastic and nonanticipativity. Constraints (22–24) show the types of decision variables in the proposed model.

3. Solution Approach and Computational Results

As shown in Figure 3, there are three main approaches to solving a mathematical model where an exact solution can be considered as the best solution approach to pre-disaster. Since this study proposed an integrated mathematical model to configure a relief network, an attempt was made to consider an exact solution called branch and fixed coordination. In this section, a summary of the solution approach is presented in the next subsection; then, the proposed model is solved according to the approach. The computational results show the performance of the proposed approach rather than other approaches.

3.1. Branch and fixed coordination (BFC)

$$\begin{aligned} \text{Min} \quad & \sum_s W^s (a^s x^s + c^s + y^s) \\ \text{s.t.} \quad & Ax^s + By^s = b^s \\ & x^s = x^{s+1} \\ & x^s \in \{0,1\}, y \geq 0 \end{aligned} \tag{25}$$

According to the proposed approach by (Alonso-Ayuso et al., 2003) (Escudero et al., 2009), the problem under study can be considered regardless of nonanticipativity constraint. Then, variables should be fixed in various scenarios. In other words, there are different trees based on the fixed variables and a

In the general information of a multi-stage problem, decisions on each stage have to be made stage by stage. For example, variables of the first stage should be selected based on some uncertain parameters. Then, the variable of the second stage can be considered based on the results of the pre-stage. Thus, some variables correspond to decisions that should be made in previous stages. In other words, there are two sets of variables: one representing the value it takes before one recognizes the realization of another random parameter and the other representing the value it takes after one realizes the value. In reality, the values of the two variables must be equal, since the value of the variable should be fixed before realizing it. This type of variables can be determined by nonanticipativity constraints. When a finite number of scenarios are considered, a general formulation of multi-stage stochastic becomes more complex with respect to nonanticipativity constraints. Generally, there are two main approaches to solving multi-stage stochastic programs: Benders decomposition decomposing the problem by scenario and Lagrangian decomposition decomposing the problem by time stage instead. By relaxing all of the nonanticipativity constraints in a Lagrangian fashion, a relaxation that decomposes into one independent subproblem per time stage is obtained. This gives a bound for the original problem. Then, standard techniques (such as the subgradient method) can be used to solve the Lagrangian dual, i.e., finding a collection of Lagrangian multipliers that can ensure the best bound. Uncertainty in the stochastic parameters is to be treated via a scenario analysis approach. To explain this concept, let us consider a simple mathematical formulation of a multi-stage stochastic programming as follows:

specific scenario. Figure 4 illustrates a scenario tree for the simple mathematical modeling (25). See Heitsch and Romisch (Heitsch and Römis, 2009) and Hoyland and Wallace (Høyland and Wallace, 2001) for more information about generating scenario trees. For example, there are 5 nodes in Stage 3 which

they can be considered based on 3 nodes in Stage 2. In other words, all nodes in Stage 3 can be categorized by pre-stage including {5,6}, {7}, and {8,9}. These nodes are called twin nodes. According to nonanticipativity, all members of twin nodes in any stage should be equal in variables corresponding to their pre-stage. One of the best strategies to solve a

scenario tree is integer strategy. The strategy is based on the branching of 0-1 variables for the first stage along with the scenario clustered trees and it simultaneously coordinates the satisfaction of nonanticipativity constraints for all of the twin nodes. For more information about this strategy and BFC, see the following:

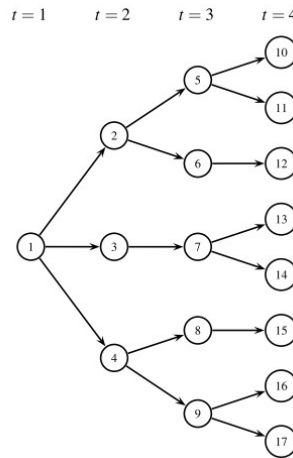


Fig. 4. An example of the scenario tree

3.2. Solving the proposed model based on BFC

In this subsection, first, the procedure of the proposed approach based on BFC is explained. Then, the computational results are reported. According to the proposed approach by Escudero et al., 2009, the proposed mathematical

model should be reformulated based on the scenario trees by considering some auxiliary variables to determine the variables of each stages. For example, $w x_{ij}^s$ can be converted to η_{ij}^s with additional constraints (26-28).

$$\eta_{ij}^s \leq M x_{ij} \quad \forall i, j \in N, s \in S \quad (26)$$

$$\eta_{ij}^s \geq w_{ij}^s + (1 - x_{ij})M \quad \forall i, j \in N, s \in S \quad (27)$$

$$\eta_{ij}^s \leq w_{ij}^s \quad \forall i, j \in N, s \in S \quad (28)$$

A new form of the proposed model is not mentioned since it is out of the research scope here. However, the first step of the procedure should be initiated at $Z = \infty$ as an upper bound (solving the problem regardless of nonanticipativity constraints). Then, each cluster scenario based on the scenario tree should be solved. If there is any variable that does not satisfy nonanticipativity constraints, it can be bounded. It is worth mentioning that since variables of each stage should be considered based on pre-stage, according to Figure 3, there are three groups of variables in this study. In this paper, instead of always branching the 0-1 variables according to inputs, there are other parameters such as

nonanticipativity constraints that determine the input. It is worth mentioning that all instances in this study were solved using IBM CPLEX 12.4 and MATLAB 9.0.0 on a PC with a 1.9-GHz AMD A8-4500M processor and 4 GB of RAM running Windows 7 (64 bit). To compare the performance of the proposed solution approach, this study attempted to apply a classical meta heuristic algorithm called Genetic Algorithm (GA). Generally, GA is a stochastic search technique that explores efficient solutions by different operators such as selection, mutation, and crossover (for more information about the GA, see (Koza, 1997)). Moreover, the computational results of the small-scale problem are compared to the the

step-by-step results, called real solution. It is clear that this type of solution cannot be extracted in case of large-scale problems. Table 3 provides information about the results of 30

instances in three approaches based on computational time, relief operation time (objective function 1), and total cost (objective function 2).

Tab. 3. Performance of the proposed model based on BFC approach

Instance	Number of scenarios	Number of variables	Genetic algorithm			BFC			Real solution		
			Computational time	the relief operation time	Total costs	Computational time	the relief operation time	Total costs	Computational time	the relief operation time	Total costs
P1	2	5	0.05	123	65260	4	123	65260	1260	123	65260
P2	3	8	0.05	148	74380	8	148	74380	4690	148	74380
P3	3	8	0.05	156	76536	7	156	76536	5600	156	76536
P4	3	8	0.05	149	69645	8	149	69645	5400	149	69645
P5	4	12	0.05	213	73564	13	213	73564	-	-	-
P6	4	12	0.05	218	82654	11	218	82654	-	-	-
P7	4	12	0.05	197	79657	12	197	79657	-	-	-
P8	5	16	0.05	196	81365	34	196	81365	-	-	-
P9	5	16	0.05	191	83456	41	187	80567	-	-	-
P10	5	16	0.05	204	88950	49	199	86793	-	-	-
P11	6	25	0.08	315	104354	115	298	98745	-	-	-
P12	6	25	0.08	323	118423	123	301	110380	-	-	-
P13	6	25	0.1	169	123402	154	169	123402	-	-	-
P14	6	25	0.12	199	114359	150	178	102314	-	-	-
P15	7	32	0.13	418	210345	254	362	182188	-	-	-
P16	7	32	0.12	429	211045	221	328	161381	-	-	-
P17	7	32	0.12	528	264761	219	301	150957	-	-	-
P18	8	41	0.12	635	543876	323	332	284380	-	-	-
P19	8	41	0.18	638	541761	301	387	328646	-	-	-
P20	8	41	0.18	592	503561	321	296	251804	-	-	-
P21	9	52	0.23	726	876301	402	310	374201	-	-	-
P22	9	52	0.25	701	812161	412	299	346437	-	-	-
P23	9	52	0.21	618	798123	437	198	255732	-	-	-
P24	10	64	0.35	623	997867	531	218	349196	-	-	-
P25	10	64	0.38	529	987675	564	219	408909	-	-	-
P26	11	73	0.31	779	1087634	1235	211	294620	-	-	-
P27	12	85	0.41	819	1265324	-	-	-	-	-	-
P28	13	91	0.39	888	1146534	-	-	-	-	-	-

P29	14	98	0.45	725	1221534	-	-	-	-	-	-
P30	15	104	0.39	714	1312612	-	-	-	-	-	-

According to Table 3, although the computational time based on BFC dramatically increased, the quality of the results was found better than that of GA. In order to illustrate this

concept, the comparison of relief operation time and total cost in two types of solution approach are depicted in Figure 5.

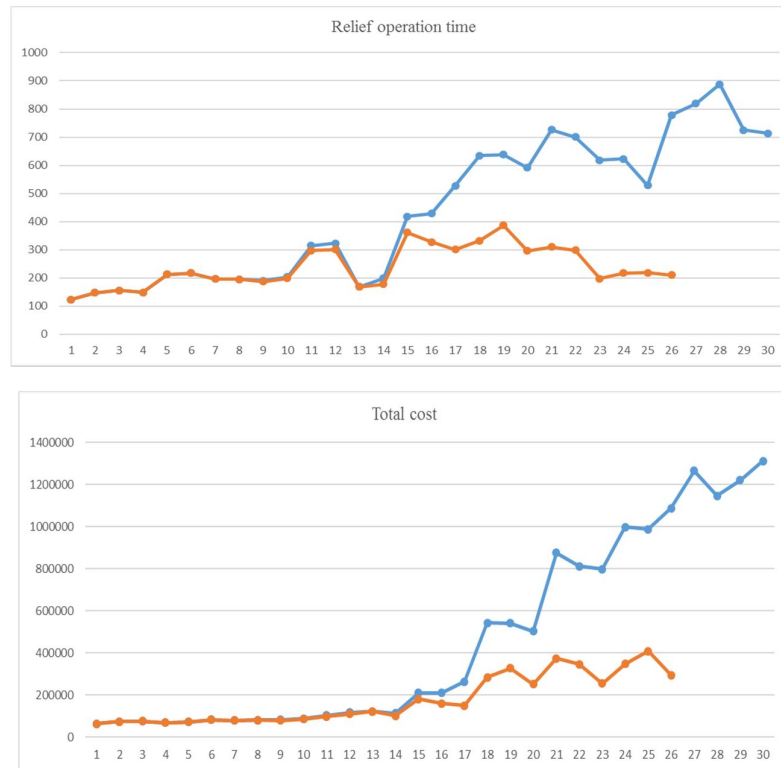


Fig. 5. Comparison of the results based on GA and BFC

4. Conclusion

This study reviewed some papers on disaster management in order to compare their subjects, disaster phases, data, objectives, and model structures. As a result, it was proved that most of the recent studies in this field have considered either response or preparedness only and few of them have researched the two phases together. Moreover, few papers have attempted to consider the features of the hub location problem for disaster management. In the proposed model, a mathematical model based on a multi-stage stochastic problem was presented. There were three main stages including configuring a relief network, supplying relief goods among affected people, and compensating the lack of inventory. Since configuring a relief network as a strategic decision should be determined precisely, a solution approach was proposed based on a well-known exact solution called BFC. As an

outcome of this study, this model not only optimized the cost of relief operations but also ensured minimal relief operational time in comparison to the existing models. However, this study implied that the last phase of disaster management should be considered in pre-disaster events in order to balance the relief operation and the location of relief centers. In addition, the application of the proposed model to a real case should be considered in future studies.

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