Efficient Pre-Disaster Planning and Optimization for A Multi-Echelon Relief Distribution Network: A Case Study in Bangladesh Perspective

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Abstract

Natural disasters are serious challenges for the underdeveloped regions of the world, who usually works with very limited resources. In this research an efficient multi-objective, multi-echelon, multi-commodity pre-disaster planning model has been developed, which can be used by aid management agencies in underdeveloped countries with limited resources. The proposed model minimizes the travelling distances among different key nodes in the logistics network by choosing appropriate locations for setting up regional warehouses with the necessary capacity, while complying with the budgetary constraints, and selects appropriate suppliers from a pool of available suppliers, while ensuring service equity. A scenario-based approach has been used here to ensure that the proposed facilities can accommodate moderate fluctuations in demand in the future. The applicability of the model has been tested via a real-world case study on the recurrent flash flood problem of the Sylhet district in Bangladesh. A Branch-and-Cut algorithm has been used via CPLEX platform to solve the developed linear integer programming model. Results have been demonstrated both numerically and graphically to aid the decision maker to properly visualize the solutions, which has offered several important managerial implications and insights on the disaster management. This way the proposed research intends help the decision makers to plan an efficient and effective humanitarian logistics network and thereby to minimize human suffering, wastage of relief goods, and associated operational costs.

Keywords

Humanitarian Logistics, Constrained Resources, Multi-Objective Optimization, Pre-Disaster Planning, Integer Programming

1 Introduction

In most cases, underdeveloped countries of the world do not possess highly sophisticated facilities or adequate computational capabilities that can help them to manage relief operations in the most efficient ways. Consequently, they cannot run complex optimization or simulation models like big agencies in the United States or European countries do. For them, a simpler mathematical optimization model, which is good enough to plan an effective operation for relief activities, can save lives. For example, different regions of a small, underdeveloped country like Bangladesh suffers from different disaster issues. When the southern region of the country has to deal with coastal cyclone issue, the eastern region often has to deal with flash flood problem during monsoon. The affected area is not too big, since Bangladesh itself is a small country. However, it happens to be one of the world's most densely populated countries. Which means lack of proper aid management can lead significant loss of human lives. Hence to plan humanitarian logistics system in a country like Bangladesh, the agencies involved require mathematical model which can run without using overly sophisticated computational facilities and can give results in a shorter time frame. This research was developed aiming such necessities, since not many researchers have focused on this issue.

There are several key challenges when it comes to pre-disaster planning. At the beginning of the planning period, decision makers have to determine locations for setting up regional relief distribution warehouses or distribution centers (DCs), to select appropriate suppliers, and to determine how to manage relief inventory. Both the location and the capacity of the warehouses are important. Long distances between the warehouse locations and a tentative supplier or a tentative affected area increases the overall transportation cost. Consequently, these locations have to be chosen wisely. Again, decision makers usually work under a fixed budgetary limit while setting up these warehouses. Hence, a small warehouse may not always satisfy the storage requirement, while a large warehouse may exceed the budgetary limit.

Unpredictable nature of the disasters is also an issue. Purely deterministic models at the pre-disaster planning period can often be naive because of the uncertainty associated with the scale of these disasters. Another complaint about relief operations often arises when it comes to prioritizing some specific affected areas or making sure whether each affected area has received similar levels of service. Keeping these in mind, this research has used a scenario-based approach to develop a logistics model that can prioritize or maintain equity among affected areas, when needed, giving the decision makers more flexibility.

Supplier selection is a very important issue as well since it plays an important role in optimizing logistics operations. In this regard, decision makers often have to consider multiple criteria for selecting appropriate suppliers. Different suppliers may perform differently under different evaluation criteria. Decision makers should pick the proper ones that are best suited for their purpose considering all the evaluation criteria. The location of each supplier should be considered as well, since long distances between suppliers and warehouses increase the overall transportation cost. In this research, the developed model selects appropriate suppliers by considering both the overall supplier ranking and the location of the supplier.

Another important part of pre-disaster inventory management is ‘prepositioning’ some portion of the non-perishable relief goods to the distribution center (DC) locations in the pre-disaster period to reduce the logistical load on the transportation network, and thus improve the disaster response in the post-disaster period (Duran et al., 2011, Duran et al., 2013). However, if the decision makers preposition too much and too early, a good portion of those relief items will either get wasted or expired. If they preposition too little, it may overburden the post-disaster transportation network later. These situations must be kept in mind when modelling an efficient relief network. Prepositioning of relief goods during the pre-disaster period.

This research has considered the flash flood problem of Sylhet District, Bangladesh, as a case study for the developed model. These “flash” floods occur abruptly and stay for a short period of time but cause large economical damage and human suffering to the surrounding areas of the major rivers. Crops in the inundated agricultural area are washed away, causing many people in that area to starve to death if the relief agencies do not respond promptly to their needs for relief. These flash floods in this area of Bangladesh are often recurrent in nature as well. Hence, a good working pre-disaster planning model can assist the local relief agencies to better prepare for post-disaster relief activities.

To solve the developed multi-objective integer programming model, a Branch-and-Cut algorithm has been utilized via CPLEX platform. Obtained results have been demonstrated both numerically and graphically in the results section of this paper for an enhanced visual understanding. In short, in this research work, a multi-echelon multi-objective humanitarian logistics model has been developed, which intends to achieve the following objectives:

- To address most of the pre-disaster logistics issues in a single one step model, which can be easily utilized by the underdeveloped countries with limited computational capabilities
- To find the optimal locations and capacities for the regional relief distribution centers to minimize the total facility setup cost, while ensuring that the total setup cost stays within the budgetary limit
- To determine the optimum quantity of goods that needs to be transported from different supplier locations to different DC locations and from different DC locations to different affected areas or demand nodes
- To make sure that the unsatisfied demands at the affected areas are minimized
- To make sure service equity is ensured, i.e., no certain affected area gets priority over other affected areas

- To address the issue of uncertainty in both demand and supply. This has been addressed in this research by using a stochastic scenario-based approach
- To solve the model to optimality by using an exact method (Branch and Cut algorithm has been used in this research) and generate the pareto optimum solution sets, from which the decision-makers can chose the solution set that is best suited for them
- To show the obtained results both numerically and graphically for the ease of visualization and understanding by the decision-makers

The rest of the paper has been organized as following: Section 2 of this paper contains a brief literature review, along with research contributions. Section 3 demonstrates the developed the model and discusses the case study. Section 4 discusses the solution methodology used to solve the problem, and Section 5 discusses the obtained results and insights obtained from the results. Section 6 discusses the research implications of this study. Finally, Section 7 discusses the conclusions and recommends some directions for the future research.

2 Literature Review

Rapid climate change over the last few decades has led to a larger number of natural calamities (Van Aalst, 2006). With the way climate change is progressing, it is possible that even more of these disasters will be seen in the future. The larger number of disasters entails that decision makers must be more efficient in pre- disaster planning to reduce human causalities and other damages caused by these disasters. This fact has prompted this research to explore the area of humanitarian logistics with broader perspectives to address important logistics issues, which has been either poorly addressed or not addressed at all in previous research.

Previously, many researchers have studied emergency management. Doerner et al. (2009) developed a multi-criteria optimization model for finding appropriate locations to set up public facilities close to a coastal area so that the impact of a tsunami is minimized. Nezhadroshan et al. (2020) developed a novel scenario-based stochastic programming model for disaster response. The objective of the proposed model was to improve resilience of the aid logistics network. Abazari et al. (2021) developed a preposition and distribution model for emergency situations. The model tried to minimize the total distance traveled , total set up cost, inventory cost and fixed cost associated to each vehicle type. Moreno et al. (2016) developed a bi-objective location selection and distribution model for relief operation. The objective of the model was to minimize the total logistics cost and minimize total unsatisfied demands at the demand locations. Ghorbani and Ramezanian (2020) developed a scenario-based two-stage stochastic programming model for efficient decision making for the relief operations to ensure proper integration in the carrier selection and the supplier selection process. However, none of the previous research addressed all the pre-disaster logistics issues in a single simpler model that can be easily utilized by the underdeveloped countries with limited computational resources. The local decision makers in those counties often make most of their logistics decision based on pure hunches or on previous experiences, instead of using mathematical models, which can result in a lot of mismanagement. A good, easy, and inexpensive relief logistics model can be of great help to them and can reduce their casualties to a great extent. This study intends to address this specific research gap.

For supplier selection process, Analytical Hierarchy Process (AHP) based methods are often considered to be very efficient pre-selection tool to eliminate underperforming suppliers at the early planning stage. Eliminating such suppliers can save a lot of money and time in the later stages of the planning process. Astanti et al. (2020) proposed a supplier selection model based on AHP technique for glove manufacturing industry. Rouyendegh and Erkan (2012) also proposed a supplier selection model for procurement of different items required for a commercial supply chain, which was based on an AHP technique as well. Their model considered various important selection criteria like cost, quality, flexibility, delivery, and variety to ensure efficient supplier selection. The model developed in this research selects the supplier in similar way as it has to consider multiple selection criteria to efficiently choose the appropriate suppliers.

To solve the humanitarian logistics models, different researchers chose to use different methods. For instance, a Branch-and-Bound algorithm was used by Dirk et al. (2020), who developed a MILP road clearance and distribution model for disaster response. Yi and Kumar (2007) used an ant colony optimization technique to solve their relief distribution problem. Both Hamedi et al. (2012) and Wang et al. (2020) used genetic algorithm based heuristic techniques to solve their humanitarian resource allocation models, while Abazari et al. (2021) solved their emergency preposition and distribution model using a Grasshopper optimization algorithm. Thereby, it is evident that, what solution methodology to be used, mainly appear to depend on the type of mathematical model that the respective researcher has formulated and the level of flexibility and accuracy that they desired in the output.

3 Problem Description and Test Case

The model developed in this research is a pre-disaster planning model that minimizes the travelling distance of the tentative warehouse sites from both the suppliers and the affected locations. In this model, positions of several potential locations were given as inputs where a DC warehouse of a certain capacity can be set up. The model selects a set of suppliers (as desired by the decision makers) from a pool of available suppliers, based on several evaluation criteria for multiple relief items, as well as other objectives, like their location distances and available capacities. Scenario based transported good data can be also obtained from the model output, which can be used later to determine an appropriate level of prepositioned inventories at the selected DC locations to reduce the transportation load on the logistics system in the post-disaster period. The scenario-based approach makes sure that the DC warehouse facilities are built in such a way so that they can accommodate moderate fluctuations in demand in the near future. Several assumptions have been made while developing this model. The details of those assumption can be found in the Appendix 1 of the supplementary materials file.

3.1 Model Formulation and Description

Table 3.1: Model sets, parameters, and variables

Model Sets	**Model Parameters**
The sets of the proposed model are as follows S Set of possible disaster scenarios (indexed by s) I Set of supplier nodes (indexed by i) J Set of potential Distribution Center (DC) nodes (indexed by j) K Set of Affected Area (AA) nodes (indexed by k) M Set of relief item types (indexed by m) H Set of capacity types of the DC warehouses (indexed by h) C Set of supplier selection criteria (indexed by c)	The parameters used in the proposed model can be divided into two categories – the deterministic parameters and the stochastic parameters, which are as following **Deterministic parameters** BL Budget limit for the fixed cost for setting up the regional DCs in USD. MRC Minimum required total supplier capacity in cubic meters. NS Maximum allowable number of suppliers. F_{hj} Set up cost for a DC of capacity h at node j in USD. LS_{ij} Distance of the shortest available path from supplier node i to DC node j in km. LS_{jk} Distance of the shortest available path from DC node j to AA node k in km.

Decision variables	**Model Parameters (Continues…)**
Decision variables used in the proposed model can be divided in two categories–integer variables and binary variables, which are as follows.	WC_h Capacity of a DC of type *h* in cubic meters.
Integer variables	$T1$ Cost of pre-disaster transportation per km per pallet of relief commodities transported from supplier node *i* to DC node *j* in USD.
δ_{ijms} Amount (in number of pallets) of commodity of type *m* needed to be transported from supplier node *i* to DC node *j* in scenario *s*.	$T2$ Cost of pre-disaster transportation per km per pallet of relief commodities transported from DC node *j* AA node *k* in USD.
R_{jkms} Amount (in number of pallets) of commodity of type *m* needed to be transported from DC node *j* to AA node *k* in scenario *s*.	U_m Unit volume of one pallet of commodity of type *m* in cubic meters.
ψ_{kms} Amount of unserved demand (in number of pallets) of commodity type *m* at AA node *k* in scenario *s*.	SR_{cim} Rating of supplier *i* at selection criteria *c* for commodity *m*.
Binary variables	G_{cm} Weight of the rating for the supplier selection criteria *c* in case of commodity *m*.
μ_{hj} 1 if a DC of capacity *h* is established at node *j*; 0 otherwise.	θ_{km} Maximum allowable ratio of unsatisfied demands at AA node *k* for relief commodity *m* (usually a small fractional number defined by the decision maker)
Sup_i 1 if supplier at node *i* is selected; 0 otherwise.	**Stochastic parameters**
	ρ_s Probability of occurrence of scenario *s*.
	D_{kms} Demand of commodity type *m* at AA node *k* in scenario *s* in cubic meters.
	C_{ims} Capacity limit of supplier node *i* for commodity type *m* in scenario *s* in pallets.

Table 3.1 contains the list of sets, parameters, and the variables of the proposed model. The objective functions of the model are given as (1)—(4).

$$\text{Min } \sum_{h\in H}\sum_{j\in J} F_{hj}\,.\,\mu_{hj} \tag{1}$$
$$\text{Max } \sum_{m\in M}\sum_{i\in I}\sum_{c\in C} SR_{cim}.\,\mathrm{G}_{cm}\,.\,Sup_i \tag{2}$$
$$\text{Min } \sum_{s\in S} \rho_s\ \left(T_1\,.\sum_{i\in I}\sum_{j\in J}\sum_{m\in M} LS_{ij}\,.\,\delta_{ijms} + T_2\,.\sum_{j\in J}\sum_{k\in K}\sum_{m\in M} LS_{jk}\,.\,R_{jkms} \right) \tag{3}$$
$$\text{Min } \sum_{s\in S} \rho_s\ \left(\sum_{k\in K}\sum_{m\in M} \frac{\psi_{kms}}{D_{kms}} \right) \tag{4}$$

The constraints of the model are given below as (5)—(21).

Supplier and Facility location selection constraints:

$$\sum_{h\in H}\sum_{j\in J} F_{hj}\,.\,\mu_{hj} \ \le BL \tag{5}$$
$$\sum_{h\in H}\sum_{j\in J} WC_h.\,\mu_{hj} \ \ge MRC \tag{6}$$
$$\sum_{i\in I} Sup_i \ \le NS \tag{7}$$
$$\sum_{h\in H} \mu_{hj} \le 1 \qquad \forall\, j\in \mathrm{J} \tag{8}$$

Relief goods flow constraints:

$$\sum_{i\in I} \delta_{ijms} \ \ge \ \sum_{k\in K} R_{jkms} \qquad \forall\, j\in \mathrm{J}\,,\, m\in \mathrm{M}\,,\, s\in \mathrm{S} \tag{9}$$

Capacity constraints:

$$\sum_{j\in J} \delta_{ijms} \ \le C_{ims}\,.\,Sup_i \qquad \forall\, i\in \mathrm{I}\,,\, m\in \mathrm{M}\,,\, s\in \mathrm{S} \tag{10}$$
$$\sum_{i\in I}\sum_{m\in M} U_m\ .\,\delta_{ijms} \le \sum_{h\in H} WC_h\ .\,\mu_{hj} \qquad \forall\, j\in \mathrm{J}\,,\, s\in \mathrm{S} \tag{11}$$

Shortage/Unsatisfied demand constraints

$$\psi_{kms} = D_{kms} - \Sigma_{j\in J} R_{jkms} \qquad \forall k\in K, m\in M, s\in S \qquad (12)$$
$$\frac{\psi_{kms}}{D_{kms}} \leq \theta_{km} \qquad \forall k\in K, m\in M, s\in S \qquad (13)$$

Non-negativity, integer, and binary constraints

$$\delta_{ijms} \geq 0 \qquad \forall i \in I, j\in J, m\in M, s\in S \qquad (14)$$
$$R_{jkms} \geq 0 \qquad \forall j\in J, k\in K, m\in M, s\in S \qquad (15)$$
$$\psi_{kms} \geq 0 \qquad \forall k\in K, m\in M, s\in S \qquad (16)$$
$$\delta_{ijms} \in \mathbb{Z} \qquad \forall i \in I, j\in J, m\in M, s\in S \qquad (17)$$
$$R_{jkms} \in \mathbb{Z} \qquad \forall j\in J, k\in K, m\in M, s\in S \qquad (18)$$
$$\psi_{kms} \in \mathbb{Z} \qquad \forall k\in K, m\in M, s\in S \qquad (19)$$
$$\mu_{hj} \in \{0,1\} \qquad \forall j\in J, h\in H \qquad (20)$$
$$Sup_i \in \{0,1\} \qquad \forall i \in I \qquad (21)$$

The developed model has four objectives. Objective (1) minimizes the total DC warehouse setup cost, and objective (2) maximizes total supplier rating. Objective (3) minimizes the expected total transportation cost of different relief goods across different network nodes, while objective (4) minimizes the expected ratio of the total unsatisfied demand to the total demand, for all relief goods, in different affected area nodes. Here, although both objectives (1) and (3) are in USD, they managed by two different agencies, both of whom have separate and non-transferable budgets. Hence \$1 from the agency of objective (1) is not the same as \$1 from the agency of objective (3). Therefore, even though they are in same units (USD), these two objectives cannot be simply just added together.

There is a total of 3 constraints and 14 constraint sets in this model, including the non-negativity, integer, and binary constraints. The first four constraint sets are supplier and DC location selection constraints. Constraint (5) ensures that the total cost of setting up the DCs across the network does not exceed the available budget. Constraint (6) guarantees that the total storage capacity of the DCs is above the minimum required capacity. Constraint (7) ensures that the total number of suppliers selected by the model does not exceed the maximum allowable number of suppliers determined by the decision makers. Constraint set (8) guarantees that any prospective DC location does not get more than one facility of any capacity

Constraint set (9) is a relief goods flow constraint set, which ensures that the total amount of goods that are being transported from a particular DC location to different AA nodes is not more than the total amount of goods that the DC location receives from different suppliers. Constraint sets (10) and (11) are capacity constraint sets. Constraint set (10) ensures that the amount of goods or commodities transferred from different suppliers to the DC locations stays within the capacity limit of that supplier for that specific good. Constraint set (11) ensures that the total amount of goods that are being received in different DC locations does not exceed the capacity of that specific DC facility.

Constraint set (12) includes equality constraints that define the unsatisfied demand variable for each affected area node. Constraint set (13) makes sure that each AA node has a limited amount of unmet demand. After constraint set (13), the rest of the constraint sets indicate that all the variables in this model are non-negative integers. The last two constraint sets, (20) and (21) require that the facility location and capacity selection variables and the supplier selection variables be binary. The model hence is an integer programming problem.

To reduce the transportation load on the post-disaster logistics networks, relief authorities often opt to preposition a portion of the relief goods that are expected to be used in the post-disaster period. After obtaining the values of the decision variables from the model above, they can calculate the expected amount of goods to be prepositioned at each DC location, using the following equation

$$IN_{jm} = \Omega \,.\, \frac{\Sigma_s \; \Sigma_k \;\; \rho_s \cdot R_{jkms}}{\Sigma_s \, \rho_s} \qquad \forall j, m \qquad (22)$$

Here, IN_{jm} is the amount of prepositioned commodity of type *m* at DC node *j*, and Ω is a user defined parameter for the percentage of prepositioned relief goods.

3.2 Sylhet test case

To test the efficacy of the model developed in this research, a test case based on the flash flood problem in the Sylhet region of Bangladesh has been used, which happens to be in an underdeveloped part of the world. All data required to develop this test case were gathered with the help of local authority, unless stated otherwise. The details of the test case are available in the Appendix 2 of the supplementary materials file.

4 Solution Methodology

The proposed model in this research is a multi-objective integer programming model. There are several popular ways to handle multi-objective optimization problems, like the scalarization (weighted sum) method, ε-constraints method, goal programming, etc. (Marler and Arora, 2004). Scalarization handles a multi-objective problem like a single objective one by multiplying each objective with a suitable and reasonable weight and then adding them together. Weights are usually defined by the user (usually decision makers) or SMEs. Users are free to manipulate weights in this method based on the relative importance of the objectives from their point of view.

In a multi-objective optimization problem, a solution may be optimal with respect to one objective but may be a poor candidate for another objective. Therefore, in multi-objective solution methods, it is possible to generate multiple optimal solutions, which are more commonly known as 'Pareto Optimal Solutions'. These Pareto optimal solutions can be generated by varying weights assigned to different objectives. In the case of multiple Pareto optimal solutions, it eventually comes down to the decision makers to select a solution that is best suited to serve their purposes.

One of the widely used integer programming problem solving methods is Branch and Cut, which is a combination of Branch and Bound and Cutting Plane methods. Popular commercially available solver platforms like CPLEX (CPLEX, 2009) or GUROBI often use a Branch and Cut algorithm to solve various real-life complex integer or mixed integer programming problems. In this research, since the developed model is an integer programming problem, the Branch and Cut algorithm has been used via CPLEX platform to solve it.

5 Results and Discussions

In this research, a multi-criteria multi-echelon pre-disaster planning model has been developed and then a numerical test case has been developed to show the effectiveness of the developed model. The model then has been solved by using Branch and Cut Algorithm in CPLEX solver v12.8 platform. The computer that has been used to run the solver had a 2.65 GHz processor and 4 GB of RAM. With the default settings, CPLEX requires only 2.09 minutes to solve the problem. In this section, the results obtained from CPLEX for the developed model and their significance have been discussed.

The weight assigned to each objective in each case here is quite important, as the weight value significantly influences the final optimized objective values and the optimal solution. The model has four objectives. In this instance, the authors have considered the weight values for the corresponding objectives as 10, 25, 25 and 190, respectively, as suggested by the SMEs. The results obtained from CPLEX for this model and the test case are shown in the tables below. Only the variables with non-zero output values have been displayed in the Tables 5.1 and 5.2.

Table 5.1: DC location and supplier selection results

Selected DC Location	Capacity type
Horipur	Medium
Sylhet Shadar	Large
West Barokut	Large

Selected Supplier location
Bodikuna
Phulbari

Table 5.2: Relief goods flow (in cubic meter) along different network arcs in the optimized network

Distribution of goods (in cubic meter)					
Supplier Node	DC Node	Goods Type	Scenario 1	Scenario 2	Scenario 3
Phulbari	Horipur	Food	16.5	21.5	27.5
Phulbari	Horipur	Water	9.5	14	17
Bodikuna	Sylhet Shadar	Food	52	63	88.5
Bodikuna	Sylhet Shadar	Water	23.5	33	39
Phulbari	West Barokut	Food	81.5	97.5	134
Phulbari	West Barokut	Water	45	60.5	75.5
DC Node	AA Node	Goods Type	Scenario 1	Scenario 2	Scenario 3
Sylhet Shadar	Bishwanath	Food	23	28.5	39
Sylhet Shadar	Bishwanath	Water	10.5	15.5	18
Sylhet Shadar	Gowainghat	Food	29	34.5	49.5
Sylhet Shadar	Gowainghat	Water	13	17.5	21
Horipur	Kanaighat	Food	16.5	21.5	27.5
Horipur	Kanaighat	Water	9.5	14	17
West Barokut	Kharavora	Food	24	29	41
West Barokut	Kharavora	Water	14.5	20	25.5
West Barokut	Beanibazar	Food	31	36	48.5
West Barokut	Beanibazar	Water	17	21.5	28
West Barokut	Fenchuganj	Food	26.5	32.5	44.5
West Barokut	Fenchuganj	Water	13.5	19	22

In the results, Table 5.1 shows us the selected DC locations and capacities and the selected appropriate suppliers. The results show that the model has chosen a medium capacity DC in Kanaighat and large DCs in Kharavora and Beanibazar, along with the suppliers located in Bodikuna and Phulbari. Table 5.2 shows us the amount of goods that need to be transported among the different nodes of the aid network, both from the suppliers to the DCs and then from the DCs to the affected areas.

Table 5.3: Relief good amounts (in cubic meter) to be prepositioned at different DC locations

DC locations	Prepositioned goods at different DCs (for Ω =16%) in cubic meter	
	Food	Water
Horipur	10	5
Sylhet Shadar	3.5	2
West Barokut	16	9

In Table 5.3, the amounts of relief goods (in cubic meter) that need to be prepositioned in different selected DC nodes during the pre-disaster planning period has been displayed. In the test case, the decision makers decided to store 16 percent (i.e. Ω =16%) of the expected amount of goods in each corresponding DC to satisfy some demands in the nearby affected areas. These values were in fact obtained as fractional values, according to equation set (22) given in section 3.1.5. However, since relief goods are to be stored as unit loads, those fractional values have been rounded to the nearest integer. These unit load amounts for relief goods to be prepositioned, have been shown in Table 5.3 in terms of cubic meters.

In this solution with objective weights 10, 25, 25 and 190, all of the demand is satisfied in every scenario. However, when different weights are assigned to the model objectives during the optimization, it is possible to obtain solutions with unsatisfied demands. Nonetheless, many decision makers often prefer solutions with no unsatisfied demand as it is an indicator of better performance by the logistics model in use.

Table 5.4: Pareto optimal solutions obtained from the pre-disaster model

Pareto optimal solution number	Weights used for four objectives respectively	Objective 1: Facility Setup Cost (USD)	Objective 2: Supplier Weighted Rating	Objective 3: Expected Transportation Cost (USD)	Objective 4: Expected Unsatisfied Demands (Cubic meter)
1	10, 25, 25, 190	3,820,000	342	166,585	0
2	15, 10, 35, 125	3,650,000	323	109,906	62
3	20, 15, 30, 160	3,480,000	335	124,876	28

Since this model is solved using the Branch and Cut method, it can be claimed that the obtained solutions are optimal for the given objective weights. However, since this is a multi-objective optimization problem, it is possible to obtain multiple Pareto optimal solutions from the model by using different objective weights. Some additional Pareto optimal solutions with different weights are shown in Table 5.4. First set of weights in the Table 5.4 were provided by the SMEs, where next two sets of weights were developed by the authors to show the variation in results with the variation in objective weights.

In case like this, when multiple solution sets are available, the decision makers should choose the solution that suits them best. For example, if the decision makers think that the minimization of the expected unsatisfied demands is more important, they should choose solution 1, or if they think that the minimization of the total transportation cost is more important, they should choose solution 2 and so on. Hence, the weights for each objective chosen by the decision makers are very important as it often determines the quality or the performance of the obtained output.

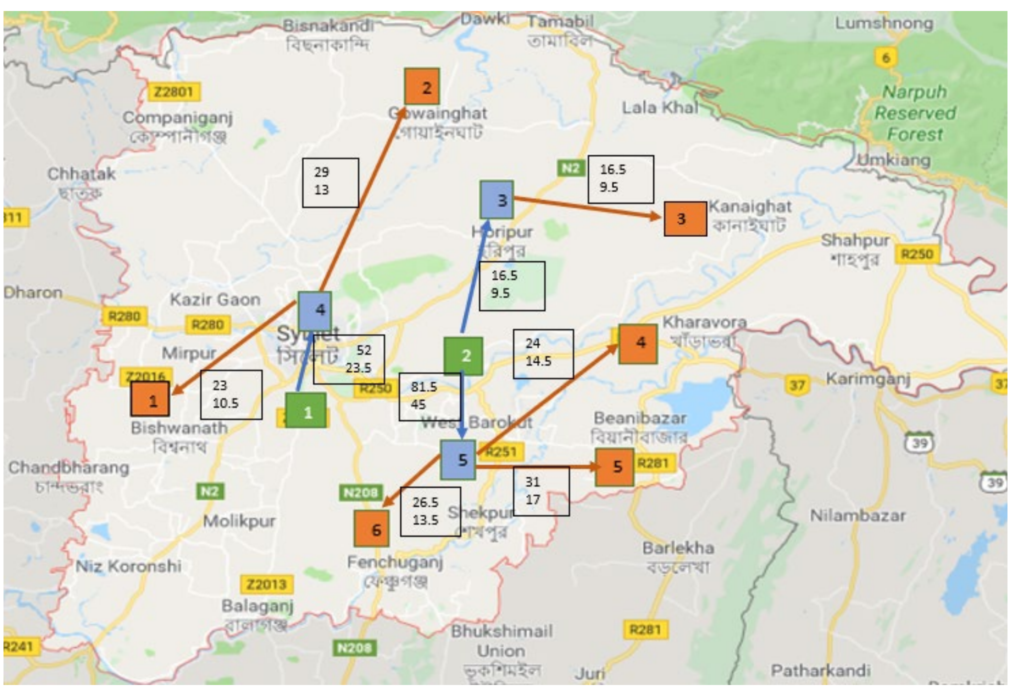

Figure 5.1: Optimized relief goods flow under scenario 1 (goods amounts are in cubic meter)

Figure 5.2: Optimized relief goods preposition (in cubic meter) at DC locations

Figure 5.1 shows the selected supplier and DC locations and the distribution of relief goods flow under scenario 1. In each box near the flow direction arrows, the number on the top row indicates the amount of food transported (in cubic meters), and the number on the bottom row is the amount of water transported (in cubic meters). Under the scenario 2 and 3 the design of the network does not change, but the amount of goods transported along the network arcs change. Figure 5.2 shows the amount of prepositioned food and water in cubic meters at each of the three DC locations under scenario 1. Visual representations can be derived for the scenario 2 and 3 as well in the similar way from the numerical results.

These information give the decision makers important insights on the prospective design of the post-disaster humanitarians logistics activity, such as positions of the prospective suppliers and regional distribution centers, potential transportation loads on each of the arcs of the network, amount of the goods that can be prepositioned at the DC locations to reduce load on the post-disaster transportation network, while ensuring service equity and minimum unsatisfied demand for relief goods at the affected areas. These insights will allow decision makers to be pro-active and thus will minimize casualties of the disaster.

6 Research Implications

Most under-developed countries have limited computational capabilities, which prevents them from using multiple overly complex logistics models like developed countries do. If separate models are used to address different logistical issues, proper integration among those models' outputs can also become a difficult challenge. The model developed in this research addresses all the relevant logistical issues in a single model, which these counties can easily utilize.

Again, decision makers in underdeveloped countries mostly rely on their intuition or past experiences in designing aid logistics networks if a well-integrated decision support system, like the one presented in this research, is not in place. This might work well occasionally, but since various factors might change over time (like change in climate patterns or severity of disasters etc.), using any intuition-based system is unlikely to work well in the long run. Disaster planning is such a sensitive issue in which a very little mismanagement or miscalculation may cause serious loss of human life. However, in the case of a mathematical model-based decision support system, like the one developed in this research, changes in the factors and other information can be regularly updated, which results in greater performance in planning.

Moreover, in the case of a disaster management system, it is often difficult to exactly quantify its performance. An intuition-based system cannot always guarantee to satisfy demands in all the affected nodes. The developed model, however, if used with higher weightage on minimizing the unsatisfied demand, is capable of finding such desirable outcome, if such solution exists, which is an important contribution of this research.

Thereby, the implication of the proposed research is that it is able to address all of the above-mentioned issues in a single research model to ensure proper integration and reduce computational complexity, so that the proposed model can be easily utilized by underdeveloped countries, who often struggle to properly manage, and plan aid operations given their limited computational capacity.

7 Conclusions and Recommendations for Future Research

In underdeveloped parts of the world, where many disastrous events occur frequently, it is often noticeable that the local agencies responsible for carrying out aid operations often struggle to properly manage and plan. Issues like risk and uncertainty, selection of appropriate warehouse facility locations, supplier selection, inventory management, along with the prepositioning of relief goods are very crucial in the pre-disaster planning stage of humanitarian logistics management. Underdeveloped countries also typically have very limited computational capability. Developing a method to address these aid network issues in a single simpler research model is still a minimally explored topic. This research has thus contributed to address that research gap by developing an efficient aid logistics model for underdeveloped regions to effectively minimize operating expenses and human suffering by providing decision makers with powerful insights about the management of the overall aid logistics network.

Since the model in this research is a multi-objective integer programming model, a Branch and cut algorithm has been used via CPLEX platform to obtain multiple pareto optimal solutions, from which decision makers can choose the one that serves their purpose the best. Moreover, since the developed model is multi-objective in nature, a scalarization technique was used in order to handle multiple objectives of the model. The simplicity and ease of handing the weights of the associated objectives in scalarization method gives decision makers more freedom to generate the solution that they prefer for their unique situation.

The test case was developed with three realistic scenarios, based on the information collected from the local sources and the SMEs. Obtained results have been demonstrated both numerically and graphically to aid the visualization and understanding of the decision maker. From the results, it appears that the locations chosen for setting up the DCs and the affected area do not change based on the disaster scenarios. Consequently, the results also show that for all three scenarios the model chose the same travel arc for the distribution of relief goods, and only the amount of goods transported varied across different scenarios. However, it is possible, in extreme cases, for the model to choose different travel arcs for the distribution of relief if necessary.

There are several directions to which this research can be extended or modified in future. Although this model focuses mostly on pre-disaster planning, this research can be extended to form an integrated system of models that will cover both the pre- and post-disaster planning. More flexibility can be added to the model by using robust optimization methodologies. Modifying the model this way will make it more adaptive to changes at different stages of the planning process.

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Supplementary materials

Appendix 1 (Model Assumptions)

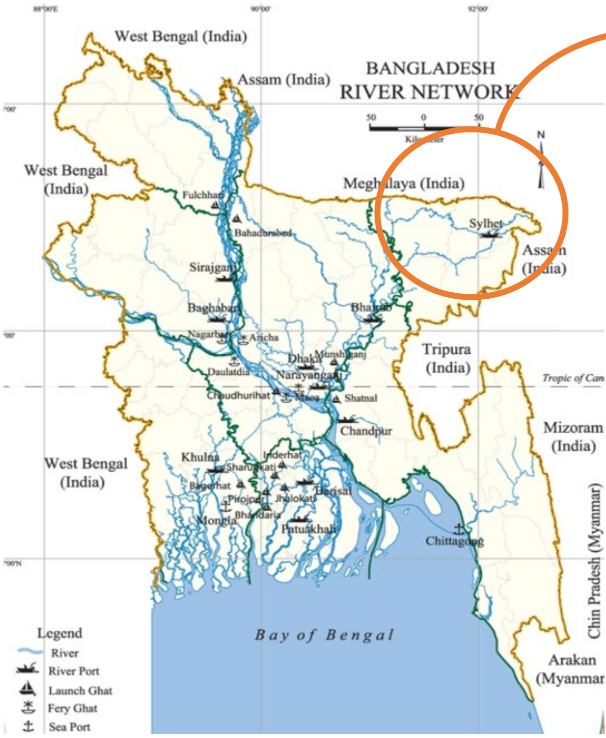
Some assumptions of the model developed in the proposed research are as follows:

- DC facility locations, and DC capacities are determined at the beginning of the planning process using this model. A budgetary constraint dictates how many DC warehouse facilities of different capacity can be constructed. DC warehouse setup cost is dependent not only on the capacity, but also on the location because land acquisition costs are different in different regions.
- For supplier selection, it is necessary to rate the suppliers on different criteria and for different commodities. There is no established best way to do these ratings. Opinions of SMEs have been used in this research for determining these ratings. In this case, SMEs are the representatives of the local administration who are familiar with the disaster situation. A similar assumption has been made for determining the importance ratings for each supplier selection criteria as well. If the priority of any of these selection criteria changes in a later period of the logistics planning, this model has to be modified accordingly and solved again to reflect those changes in the final output.
- The affected area locations (AA) are the demand points, which are to be determined based on historical record. These locations might change later, if necessary, in the post-disaster stage.
- At the beginning of the planning process in the pre-disaster period, decision makers do not know which route to follow in different scenarios. Hence, this model will be using the shortest distance of all available routes between the respective nodes.

Appendix 2 (The Sylhet Test Case)

In a mostly agricultural country like Bangladesh, rivers are usually important assets. However, in a district like Sylhet, which contains the major rivers of the Surma-Meghna river system (see Fig 3.2 and 3.3), these rivers are boons and curses at the same time. In the dry season, rivers like Surma, Kushiara and Shari-Goyain supply most of the irrigation water required in the nearby mostly agricultural areas. The origins of all of these rivers are from nearby hilly region of India. During the monsoon season, if there is too much rain in the Indian up-stream hilly region, this large amount of water rushes through these rivers, mostly through Surma and Kushiara, in the down-steam regions of Sylhet. Being a lower area than the Indian up-stream and due to heavy sedimentation, these rivers cannot always hold this sudden deluge of water, so they inundate the surrounding agricultural areas. In such situations, people in that area starve to death if the relief agencies do not promptly respond to their needs for relief since most of their food sources get destroyed by the flood. This flash flood problem in this area of Bangladesh is also recurrent.

Previous relevant literatures (Akkihal, 2006, Balcik and Beamon, 2008) suggested using historical relief demand for disastrous incidents to develop aid logistics models. However, one of the problems in underdeveloped countries is that their data collection process and extent of data collection is neither very efficient nor very comprehensive. Sometimes, it is even difficult to collect data from the local government websites due to the lack of computerization and efficient and comprehensive bookkeeping. In this research, however, majority of the required data has been collected from the SMEs in the local administration and reasonable assumptions were made in the few cases where there was any missing information.



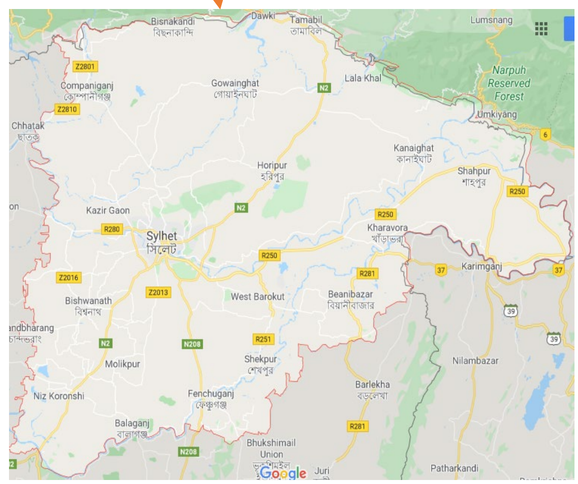


Figure 3.2: River networks in Bangladesh (2021)
(Source : Banglapedia.org)

Figure 3.3: Sylhet district, Bangladesh (2021)
(Source: Google map)

There are three prospective Distribution Center (DC) warehouse facility types (small, medium and large) that can be set up at candidate locations to store relief goods before dispatching them to the affected areas, as shown in Table 3.1;

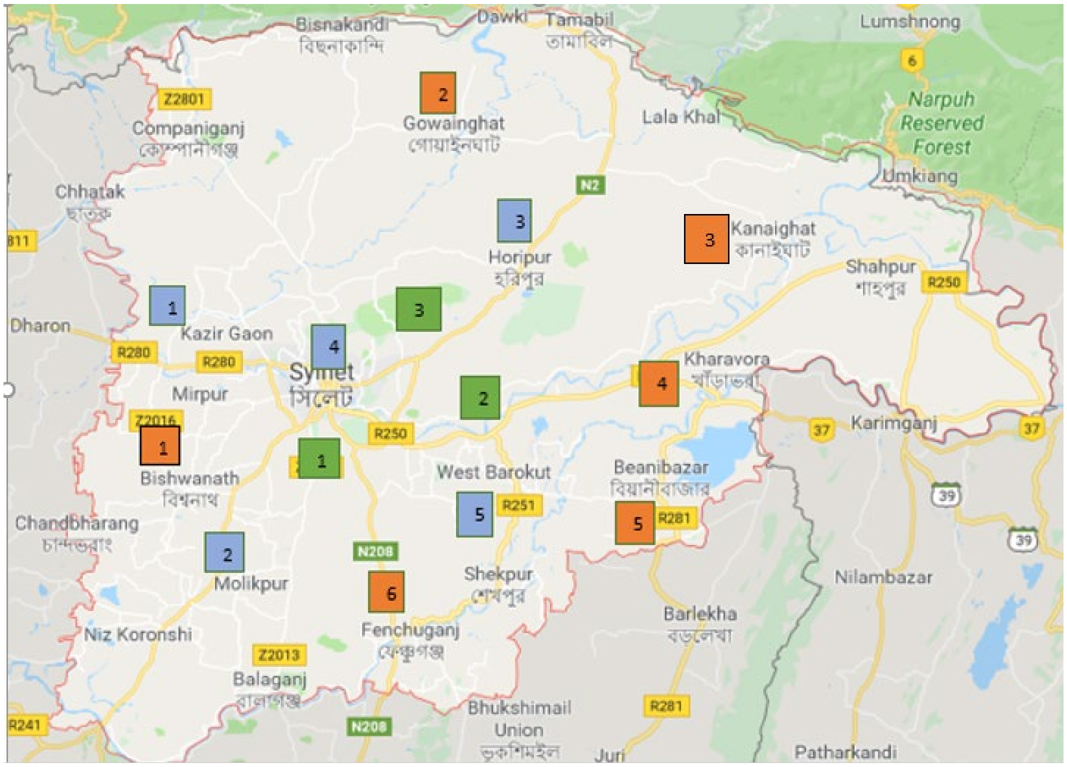
Table 3.1: DC warehouse capacity types

Capacity type	Capacity (in cubic meters)
Small	200
Medium	400
Large	600

There are three prospective supplier locations from which the model has to select at least two suppliers. Five prospective locations have been selected for constructing DC warehouse facilities. Six locations have been selected based on historical deserter strike records as prospective affected areas for distributing relief goods directly to the affected population. The tentative locations are shown in Table 3.2 and in Figure 3.4.

Table 3.2: Prospective Supplier locations, DC locations and Affected Area locations in Sylhet

Prospective supplier locations	Prospective DC locations	Prospective affected area locations
1) Bodikuna	1) Kazirgaon	1) Bishwanath
2) Phulbari	2) Molikpur	2) Gowainghat
3) Atgaon	3) Horipur	3) Kanaighat
	4) Sylhet Shadar	4) Kharavora
	5) West Barokut	5) Beanibazar
		6) Fenchuganj



Prospective supplier location nodes
Prospective distribution center (DC) location nodes
Prospective affected area (AA) location nodes

Figure 3.4: Sylhet District map with prospective key locations

There are two types of relief goods to be distributed– food and water. According to the SMEs, it is convenient to transport, load and unload the relief goods if the unit size is such that it can be handled without the help of mechanized material handling systems like forklifts, in the context of underdeveloped countries, to keep the associated handling costs low. Note that in underdeveloped countries, manual labor costs less than mechanized material handling. The unit description of each type of relief good is shown in Table 3.3.

Table 3.3: Volume and weight of a single unit of relief goods

Item type	Unit volume in cubic meter	Unit weight in kg
1. Food	0.5	190
2. Water	0.5	130

Here, one unit of load will occupy one pallet. However, for ease of understanding, visualization and explanation, the quantities of goods have been described in cubic meters instead of unit loads. For example, 22.5 cubic meters of relief goods is equivalent to 45 pallets of relief goods, since each unit load has a volume of 0.5 cubic meters.

Transportation costs from a supplier to a DC is usually higher than that from a DC to an AA because in the post-disaster period, transportation facilities and road conditions in the AA are usually worse due to the impact of the catastrophic incident. Considering the local labor rate, economy, transportation and fueling prices, the transportation cost from a supplier to a DC for all types of relief goods has been assumed to be 4$ per pallet/km. Similarly, the transportation cost from a DC to the affected area for all type of relief goods has been considered as 6.25$ per pallet/km. User defined parameters will vary depending on decision makers. In this test case, all θ_{km} values (the equity constraint limit) have been considered as 0.10 or 10%, and the proportion of the goods to be pre-positioned has been considered as Ω = 16%.

The value of the minimum required capacity is 1200 cubic meters, and the maximum allowable number of suppliers is 2. In this test case three disaster scenarios have been considered. The probabilities of occurrence for each scenario have been obtained using the available historical data. The calculated probability values for the 3 scenarios are 0.46, 0.31 and 0.23, respectively (DC Sylhet, personal communication, August 26, 2019). Under each scenario, the supplier capacity data (in cubic meters) for each type of relief goods are as given in Table 3.4.

Table 3.4: Supplier capacities for Scenario 1, 2 and 3 (in cubic meters)

Supplier No.	Scenario 1		Scenario 2		Scenario 3	
	Relief good type		Relief good type		Relief good type	
	Food	Water	Food	Water	Food	Water
Bodikuna	147.5	117	161	128	249	197.5
Phulbari	131.5	109.5	143	120	222.5	183.5
Atgaon	126.5	107	139	116.5	180.5	126.5

Under each scenario, the demand data for each type of relief good in each affected area (in cubic meters) are shown in Table 3.5.

Table 3.5: Demand data for Scenario 1, 2 and 3 (in cubic meter)

Affected Area No.	Scenario 1		Scenario 2		Scenario 3	
	Relief good type		Relief good type		Relief good type	
	Food	Water	Food	Water	Food	Water
Bishwanath	23	10.5	28.5	15.5	39	18
Gowainghat	29	13	34.5	17.5	49.5	21
Kanaighat	16.5	9.5	21.5	14	27.5	17
Kharavora	24	14.5	29	20	41	25.5
Beanibazar	31	17	36	21.5	48.5	28
Fenchuganj	26.5	13.5	32.5	19	44.5	22

In this problem, the initial budget for opening the required number DCs has been assumed to be \$4,000,000. Facility setup costs (in terms of \$1000) at different tentative DC locations for three different capacity types are shown in the Table 3.6 bellow.

Table 3.6: Facility setup costs (in terms of $1000)

DC location	Capacity type		
	Small	Medium	Large
Kazirgaon	710	1080	1270
Molikpur	670	1040	1250
Horipur	780	1120	1360
Sylhet Shadar	830	1240	1410
West Barokut	760	1150	1290

All the distances among different nodes of the network have been collected from Google Maps using the car-route option. If there are multiple routes to choose from between nodes, then the shortest path or route available has been used. Shortest available path distances between different supplier nodes and DC nodes are given in km in the Table 3.7 as shown below.

Table 3.7: Shortest available path distances between different supplier and DC nodes (in km)

DC location	Supplier no.		
	Bodikuna	Phulbari	Atgaon
Kazirgaon	17	28	72
Molikpur	27	46	47
Horipur	30	25	11
Sylhet Shadar	14	28	22
West Barokut	20	9	19

Shortest available path distances between different DC nodes and AA nodes in km are as shown in Table 3.8.

Table 3.8: Shortest available path distances between different DC and AA nodes (in km)

Affected Area nodes	DC locations				
	Kazirgaon	Molikpur	Horipur	Sylhet Shadar	West Barokut
Bishwanath	24	15	43	25	34
Gowainghat	40	71	32	37	51
Kanaighat	62	84	29	59	42
Kharavora	56	70	52	57	28
Beanibazar	52	66	49	53	18
Fenchuganj	48	62	51	49	42

Higher unserved demands indicate more unserved people, which means more human suffering, and reducing human suffering is very important. To consider unserved demands at affected areas in monetary terms, a penalty cost has been assigned with them. Penalty costs for each cubic meter of unserved demand for type 1 and type 2 relief goods (food and water) have been considered to be $160 and $130, respectively.

Evaluation criteria and corresponding rating information (G_{cm}, SR_{cim}) for supplier selection are in Table 3.9. These supplier rating values were acquired from the opinions of the SMEs.

Table 3.9: Supplier rating data for supplier selection

Evaluation criteria	Importance weight rating of the criteria for each commodities type (Food, Water), G_{cm}		Rating for each commodities type (Food, Water), SR_{cim}					
			Supplier 1		Supplier 2		Supplier 3	
	Food	Water	Food	Water	Food	Water	Food	Water
Item cost	4	3	9	8	8	7	7	8
Quality	4	4	9	7	9	8	8	7
Delivery lead time	2	3	8	9	10	8	9	8

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