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A Modified Balcik Last Mile Distribution Model for Relief Operations Using Open Road Networks

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Abstract

The last mile in disaster relief distribution chain is the delivery of goods from a central warehouse to the evacuation centers assigned for a given area. Its effectiveness relies on the proper allocation of each kind of relief good amongst the demand areas on a given frequency. Because these operations involve a limited supply of relief goods, vehicles, and time, it is important to optimize these operations to satisfy as much demand as possible. The study aims to create a linear programming model which provides a set of recommendations on how the current disaster relief supply chain may be carried out, specifically on how distribution operations allocate supplies among demand nodes as well as the routes taken in a day. The areas visited per day would depend on the capacity of the vehicle fleet as well as on the routes that can be used. This linear programming model will use Balcik's last mile distribution model, while modifying it for the relief operations in the Philippines. The model minimizes routing costs as well as penalty costs for unsatisfied demands. Map data is used for determining routes and historical data from previous disasters are used to determine the supply and demand for relief goods while providing a benchmark for results. The model produces recommendations for (1) Demand node schedule, (2) Best route for schedule, (3) Relief good allocation, and (4) Operational costs. It also provides the computational backbone for relief distribution decisions in the Philippines, allowing for more optimal operations in the future.

Keywords: computational science; disaster management; last mile distribution; linear programming; operations research

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1. Introduction

Natural disasters have become much more common in the Philippines in the recent years. According to The Human Cost of Weather Related Disasters, a publication released by the Centre for Research on the Epidemiology of Disasters (CRED) and the United Nations Office for Disaster Risk Reduction (UNISDR), the Philippines has encountered 274 natural calamities over the past 20 years, making it the fourth-highest disaster-prone country in the world, next to the USA, China, and India. As such, Filipinos are among one of the top 10 most number of people in the world affected by natural calamities at 130 million [1].

Given this problem, it is logical to assume that disaster response management in the Philippines would have improved over the years. [2] reported on the large influx of relief goods from international organizations in the aftermath of Typhoon Haiyan. However, the relief goods were not reaching the intended recipients in far-flung areas. Relief workers have suggested to disregard prevailing relief distribution protocols to improve relief distribution performance [3].

In the case of Typhoon Haiyan, debris blockage on road networks from Tacloban Airport to pick-up points of relief goods was the main cause of the problem [3]. It was only days after, when the Department of Public Works and Highways cleared the road networks, that relief could be distributed using delivery trucks [4].

The challenges and difficulties experienced in Typhoon Haiyan show the importance of having well-planned logistics in handling relief operations and must be as critical as any other form of disaster preparation [5]. As such, the study and application of operations research in disaster response management is advantageous in providing human security before, during, and after calamities [6].

1.1. Objectives of the Study

The goal of this study is to create an optimized last mile distribution model for relief goods. This objective is broken down into four parts: (1) the model should create a route from the distribution centers of relief goods to the evacuation centers within its area of responsibility; (2) the model should allocate the limited resources among the relief centers in the area [7]; (3) the model must be able to take into consideration spatial/geographical distances [8], population density and demands [9], while trying to satisfy a given standard of demand per evacuation center [7]; and (4) the results of the model should provide actionable information on day-to-day relief distribution. The success of the said model will be based on minimizing operational costs, which covers both Travel Cost and Penalty Cost. Travel Cost is the total cost for all relief goods in the distribution center to be distributed to the evacuation centers while Penalty Cost is the total cost for unsatisfied demand [10].

1.2. Scope and Limitations

The study was conducted in Marikina City, Philippines. Marikina City is in a valley wherein lies one of the main rivers in Metro Manila. This makes Marikina City more flood-prone, which affects part of its 400,000 residents living in low-lying areas. This also makes it important for the local government unit to be prepared for disasters, and so disaster management data is readily available for the area. The study used the Balcik, Beamon, and Smilowitz Last Mile Distribution Model for supply allocation and determining routes for distributing relief goods in disaster areas [10]. The last mile distribution model only considers the movement from the distribution center of relief goods in LGUs to the evacuation centers within its area of responsibility. OpenStreetMap was used to create the road network. Road network changes and blockages in the aftermath of a disaster are not yet considered in this study. The SPHERE Handbook Standards for demand satisfaction was considered and adjusted based on the kind of supplies provided in actual relief operations [11].

2. Related Literature

The last mile relief distribution is the final stage of a relief distribution chain. This is where goods are moved from the local distribution center or LGC (e.g., Regional Warehouse, Local Government Unit Warehouse) to the affected communities in evacuation centers [10]. Fig. 1 shows how last mile relief distribution operates in the relief distribution chain.

The last mile distribution problem refers to the need to optimize these operations to provide the most efficient and effective service to the affected communities. This becomes a difficult problem because of the unpredictability of a disaster, which affects road networks, supply availability, and relief demands in different areas [12]. As such, it is important to study some approaches used to address the problem.

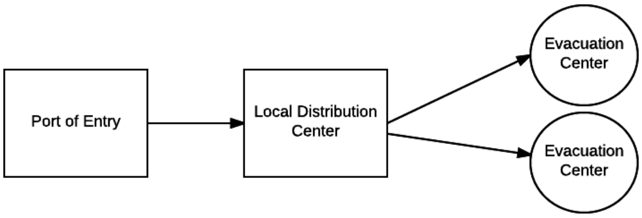

Fig. 1. Diagram for last mile distribution

The rolling horizon approach aims to minimize the total cost of operations, which is a combination of both the travel costs, and the cost for not being able to meet demands in an area. This is done by controlling both vehicle routes as well as relief good allocation for each demand node in its cluster. It is important to note that the study uses two types of relief goods, for consumable and non-consumable goods, with separate penalty costs of unsatisfied demand. The study also focuses solely on the distribution within a cluster of demand nodes and a single repository, both already given for the model. This approach involves two phases [10].

The first phase looks at all possible routes for each vehicle and uses a Traveling Salesman Problem to achieve the routes with the minimum travel time. The second phase then applies a linear programming model that minimizes the operational cost, and determines the order of nodes to visit, as well as the amount of each type of relief good to be allocated to each node. The linear model is seen in eqn (1) [10].

$$\min \sum_{r\in R}\sum_{t\in T}\sum_{k\in K} c_{rk} X_{rtk} + \sum_{t\in T}\sum_{e\in E} w_t^e \tag{1}$$

In the first part of the equation, R is defined as the set of routes, T is the set of planning intervals, K is the set of vehicles, c is the travel cost of a route for a vehicle, and X is a binary value to check if the route was visited at that time by a vehicle. This forms the routing cost for the relief operation. In the second part, E is the set of demand items and W is the penalty cost associated with each item at a time. This forms the penalty costs incurred in the relief operation.

The initial study used a computational example, wherein model behaviour is tested given differing number of nodes, and on differing scores for routes. This allows the approach to be tested based on more controlled conditions. That said, it was not tested on a real-world case and only on a general example, which had 2 vehicles and 4 demand nodes. Even on this general example, the model took around 4 hours to create a solution, which may be a problem when used in actual operations and with more data to handle [10].

The rolling horizon approach looks most ideal given the Philippine scenario where LGUs often have a set cluster for demand nodes and storage defined. It could be improved, however, for areas where clusters are very close to each other, opening the possibility for multiple storages catering to a single cluster [10].

3. Methodology

There are three stages in the creation of the Balcik et. al. based model: (1) Data Gathering Stage, where data needed to create the model was obtained; (2) Data Manipulation Stage, where the obtained data was preprocessed to fit the input format expected by the modeler; and (3) Model Formulation Stage, where the model produces the optimal route and supplies per stop given the needed data. Results were checked based on the multi-objective criteria of the study. It is important to note that these stages closely emulate the phases in the Last Mile Distribution Problem described in [10]. The stages can be seen in Fig 2. Data came from previous cases of disaster relief operations in Marikina City.

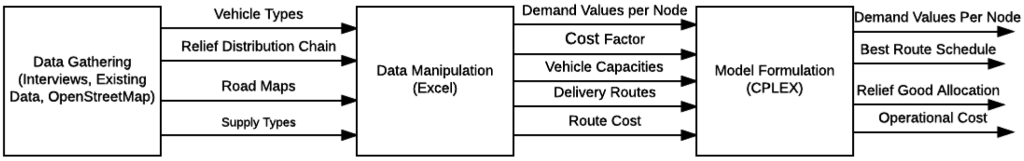

Fig. 2. Three-stage methodology for the study

3.1 Data Gathering

Data obtained and the process of obtaining them are described as follows:

- Locations of Local Distribution Centers (LDC) and Evacuation Centers (EC) – Names of LDCs and ECs were gathered from the LGU of Marikina City. Geospatial information about the LDCs and ECs were collected using OpenStreetMap. Refer to Table 1 for the sample data.

Table 1. Local Distribution Centers and Evacuation Centers.

Name of Area	Role	Geospatial Information
Marikina City Sports Center	Local Distribution Center	14.634055,121.099296
H Bautista Elementary School	Evacuation Center	14.657842,121.104312
Nangka Elementary School	Evacuation Center	14.672985,121.108485

- Vehicle types and capacities – This includes the several types of vehicles used, its respective load capacity, and its fuel economy. Table 2 presents sample data.

Table 2. Vehicle Types

Vehicle Model	Weight Capacity	Fuel Economy
JAC Coaster	4080kg	6.25 km/L
KM-250 Army Truck	5000kg	6.25km/L

- Road map of the region – Using OpenStreetMap, with the GraphHopper API, a matrix of durations and distances among evacuation centers and the LDC was generated. Tables 3 and 4 present the said matrix.

Table 3. Distance Matrix (in meters)

	LDC	1	2	3	4
LDC	0	3696	5522	2033	2630
1	3142	0	1942	1383	1822
2	4969	1942	0	3209	3648
3	2158	1769	3595	0	1624
4	2630	1822	3648	1238	0

- Supply types – Table 5 lists down the types of relief supplies distributed by Marikina City LGU in its previous operations. Supplies were categorized according to the standards set in the SPHERE Handbook [11]. The corresponding weight and cost of each supply type were also researched. Warehouse stock levels were also obtained per interval.

Table 4. Time Matrix (in seconds)

	LDC	1	2	3	4
LDC	0	209	313	160	171
1	190	0	119	90	128
2	294	119	0	194	233
3	154	130	234	0	142
4	171	128	233	103	0

Table 5. Supply Types

Supply Type	Description	Counted Per	Weight	Unit Cost
Food Kits	Canned goods, rice, and coffee for three days	Household	7.480kg	427.5 pesos
Food Packs	Meals in evacuation centers	Person	0.35kg	50 pesos/snacks; 100 pesos/full meal
Shelter	Beddings for evacuation centers	Household	0.30kg	35 pesos
Dignity Kits	Hygiene kits containing dental, sanitary, bathing items	Household	6.5kg	550 pesos

3.2 Data Manipulation

Data obtained from the first phase was pre-processed to fit the input format expected by the CPLEX modeler. The following matrices were generated based on the gathered data:

- Demand values per supply type – A matrix was generated for each supply type which shows demand values for each node for every delivery iteration. Table 6 presents a sample.

Table 6. Demand Values for Food Packs

Delivery Iteration	Food Pack Demand			
	Node 1	Node 2	Node 3	Node 4
1	17	0	0	0
2	357	617	0	0
3	3325	3861	0	3045

- Cost factor per supply type and node – Cost factors determine the penalty cost incurred in the relief operation for unsatisfied demand [10]. This is higher in places with high demand as well as for essentials such as food. Table 7 presents the cost factor associated with unsatisfied demand from Table 6.

Table 7. Cost Factor for Food Packs (in pesos)

Delivery Iteration	Food Pack Cost Factor			
	Node 1	Node 2	Node 3	Node 4
1	1700	0	0	0
2	17850	30850	0	0
3	332500	386100	0	304500

- Vehicle capacity – Vehicle capacity was expressed in terms of how many of a certain supply type it can carry. Table 8 presents sample data dependent on the carrying weight of the vehicle and unit weight of each supply.
- Route cost –The amount of gas consumed by each vehicle in a route was then obtained by comparing the fuel economy of the vehicle to the distance travelled in a usable route. This was then expressed in pesos by converting fuel consumed into the average peso value of gasoline. The route and duration matrices can be seen in Tables 9 and 10.

Table 8. Vehicle Capacities

Vehicle	Food Kits	Food Packs	Shelter	Dignity Kits
JAC Coaster	545	11657	13600	628
KM-250 Army Truck	668	14286	15000	769

Table 9. Duration Matrix (in fraction of a horizon)

	LDC	1	2	3	4
LDC	0	0.18	0.19	0.18	0.18
1	0.18	0	0.17	0.17	0.18
2	0.19	0.17	0	0.18	0.19
3	0.18	0.18	0.19	0	0.18
4	0.18	0.18	0.19	0.18	0

Table 10. Cost Matrix (in pesos)

	LDC	1	2	3	4
LDC	0	23.19	35.43	12.2	16.09
1	19.48	0	12.25	10.72	12.27
2	31.73	12.25	0	22.97	24.52
3	13.29	8.74	20.99	0	7.81
4	16.09	12.27	24.52	9.79	0

- Delivery routes – Each route will start from the LDC and end in the LDC, while visiting as many nodes as it can within the length of the planning horizon. The duration matrix obtained from OSM would be manipulated to represent the fraction of the planning horizon, and so each route must have a total fraction less than 1. Among all possible routes, those that visit the same nodes in the shortest time are used.

3.3 *Model Formulation*

The following equations show the constraints for the rolling horizon formula in eqn (1) that is adjusted based on the data gathered for the study:

$$W_t^e = p_{it}^e S_{it}^e ; \forall i \in N, t \in T, e \in E. \tag{2}$$

$$S_{it}^1 = \Big(\sum_{t1=1}^{t} d_{it1}^1 - \sum_{i \in N} \sum_{k} Y_{ik}^1\Big) / \sum_{t1=1}^{t} d_{it1}^1 ; \forall i \in N, t \in T. \tag{3}$$

$$\mathrm{S}_{it}^2 = \Big(d_i^2 - \sum_{i \in N} \sum_{k} Y_{ik}^2\Big) / d_i^2 ; \forall i \in N, t \in T. \tag{4}$$

$$S_{it}^3 = \Big(d_i^3 - \sum_{i \in N} \sum_{t1=1}^{t} \sum_{k} \in K Y_{it1k}^3\Big) / d_i^3 ; \forall i \in N, t \in T). \tag{5}$$

$$S_{it}^4 = \Big(\sum_{t1=1}^{t} d_{it1}^4 - \sum_{i \in N} \sum_{k} Y_{ik}^4\Big) / \sum_{t1=1}^{t} d_{it1}^4 ; \forall i \in N, t \in T. \tag{6}$$

$$\sum_{r \in R} \sum_{i \in N} \sum_{t1=1}^{t} \sum_{k \in K} Y_{irt1k}^e \le \sum_{t1=1}^{t} a_{t1}^e ; \forall t \in T, e \in E. \tag{7}$$

$$\sum_{i \in N} \sum_{e \in E} (Y_{irtk}^e / q_k) \le X_{rtk} ; \forall r \in R, t \in T, k \in K. \tag{8}$$

$$\sum_{r \in R} X_{rtk} \times T_{rk} \le 1 ; \forall t \in T, k \in K. \tag{9}$$

$$0 \le S_{it}^{e} \le 1; \forall i \in N, t \in T, e \in E. \tag{10}$$

$$Y_{irtk}^{e} \ge 0; \forall i \in N, r \in R, t \in T, k \in K, e \in E. \tag{11}$$

$$X_{rtk} \ge 0; \forall r \in R, t \in T, k \in K. \tag{12}$$

$$Y_{irtk}^{e} \le Y_{irtk}^{e} \times v_{ir}; \forall i \in N, r \in R, t \in T, k \in K, e \in E. \tag{13}$$

Eqn (2) defines the penalty cost as the product of the cost factor and the unsatisfied demand. Eqns (3) (4) (5) and (6) define the unsatisfied demand to be a fraction of the total demand for each item type for the time interval. Eqn (7) limits the delivered amount to be less than the supply available at the central warehouse. Eqn (8) looks at vehicle capacity, where each supply type takes a fraction of the total vehicle capacity and the sum for all supply types should not exceed the number of times the vehicle takes a route. Eqn (9) deals with the time constraint for all routes. Eqn (10) ensures that unsatisfied demands will always be a fraction. Eqns (11) and (12) look at non-negative allocation and non-negative visiting of routes, respectively. Finally, eqn (13) makes sure that only nodes visited by a route are given an allocation.

The model produces the following results:

- Demand node schedule - This refers to the schedule of nodes a vehicle will visit in each planning schedule [10].
- Best route for schedule - This refers to the route that each vehicle will take when approaching demand nodes.
- Relief good allocation - For each demand node, an allocation of various relief good types will be given per visit.
- Operational costs - This is the sum of your normal routing cost and the penalty cost that comes with unsatisfied demand [10].

4. Results of the Study

Table 11 shows the Results for Food Packs and Kits while Table 12 shows the Results for Shelter and Dignity Kits.

Table 11. Results for Food Kits and Food Packs

Time	Nodes Visited	Food Kits				Food Packs			
		N1	N2	N3	N4	N1	N2	N3	N4
					JAC Coaster				
2	3,1,2	0	0	75	0	357	617	0	0
3	1,2,4	0	63	0	7	0	3861	0	3045
4	4,3,1,2	0	101	0	0	3085	2970	918	2092
5	3,1,2	67	164	83	0	2776	2078	0	0
	4	0	0	0	236	0	0	0	1420
6	1,2	117	111	23	20	2226	1680	0	1322
7	1,2	124	372	0	0	0	0	0	0
	1,4	342	0	0	203	0	0	0	0
					KM-250				
1	1,4	49	0	0	113	17	0	0	0
3	1	0	0	0	0	3325	0	0	0

Each row represents the number of items per supply type a vehicle will deliver to a given demand node for a particular route. The first column represents the time interval while the second column represents the route. The model allows the vehicle to take multiple routes in an interval if it goes back to the LDC on time. The total cost for operations was at 612.31 pesos, while satisfying all demand. It could also be noticed that both vehicles were operating and were using a variety of routes in the operations, utilizing the model's resources as much as possible.

Table 12. Results for Shelter and Dignity Kits

Time	Nodes Visited	Shelter				Dignity Kits			
		N1	N2	N3	N4	N1	N2	N3	N4
					JAC Coaster				
2	3,1,2	69	132	0	0	69	132	181	0
3	1,2,4	627	0	0	579	37	82	0	0
	2	0	679	0	0	0	597	0	0
4	4,3,1,2	0	0	181	0	0	0	0	0
					KM-250				
1	1,4	3	0	0	0	3	0	0	579
3	1	0	0	0	0	590	0	0	0

5. Conclusion and Recommendations

The last mile distribution model for relief goods proposed in the study could provide a computational backbone for optimizing relief operations in the Philippines. By creating a more defined routing procedure for operations, relief practitioners may avoid the need to make allocation decisions on-the-fly. With its nature as the final step in any disaster relief operation, it is still affected by all other decisions in the operation, namely facility location, transportation decisions, and inventory management decisions.

Improvements in the model for the Philippine setting would involve looking at more rural places for testing. Adding more nodes to the model would also help in seeing how the model would prioritize some areas over others while still providing relief to all areas. The model can also be made to consider changes to road network. Supplies could also be prepositioned in LDCs and inventories can also be maintained. Other optimization models, both linear and non-linear, can also be explored in finding other ways to improve disaster relief operations in the Philippines.

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