Emergency relief goods transportation strategies – a Monte Carlo simulation approach

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Abstract

A road transportation network and its strategic utilization has a crucial role in emergencies occurring after natural disasters. After most natural disasters, such as floods, hurricanes, tornadoes, earthquakes and tsunamis, one of the most important emergency responses is to provide or deliver relief goods, such as water, food or medicinal supplies, to the affected areas. The complication is that in determining the routes to take for deliveries to affected areas, one has to take into consideration, at the very least, the costs, duration of trips and the availability of the routes. Also the supply and demand situation of the relief goods has to be taken into consideration before choosing the most preferred routes for the deliveries.

In this paper, a Monte Carlo approach is applied for the emergency relief goods transportation strategy problem. Monte Carlo simulation has been used for varied applications in including project cost estimation, project schedule estimations, risk assessments, benefit cost analysis and selecting risk response strategies. The Monte Carlo model developed in this paper integrates costs, duration of routes and availability together with the supply and demands requirements to generate the most preferred routes. The results of the Monte Carlo simulations can be used by decision makers (emergency response team) to facilitate the decision making process while choosing the preferred and practical combinations of routes for various deliveries. The proposed approach is then applied to several simple situations to illustrate the simplicity, versatility and practicality of the approach.

1 Introduction

Throughout history, natural disasters have impacted various parts of the world causing terrible consequences for the inhabitants. According to the International Disaster Database (International Database of Disasters: EM-DAT, 2014), for the year 2018, there were 315 climate related and geophysical disaster events with 11804 deaths and over 68 million people affected across the world. Overall, floods affected more people than any other disasters, such as storms, droughts and extreme temperatures, earthquakes & tsunamis, volcanic activities and wildfires. In the Australasian region, it is usually floods, storms and wildfires that affect most communities. In terms of severity, Tonga topped the list of "*Top 10 Countries by the number of people affected per 100,000 inhabitants in 2018*", followed by Fiji Islands.

Disaster management is generally divided into four phases of mitigation, preparedness, response and recovery/reconstruction. This paper is focussed on the response stage of the disaster management. This stage occurs immediately after a natural disaster and includes taking injured people to the hospitals and taking vital supplies such as drinking water, food and medical supplies. In most disaster management plans similar to one adapted in Parwanto et al. (2015), there are certain considerations that will be incorporated in this research. For instance, firstly the supplies are sourced from nearby centres (towns) which have surpluses before being sourced from outside and secondly effective resource management principles are applied. Effective resource management ensures the best use of scarce resources and contributes to streamlined and efficient disaster management processes. Resources management include logistics, deployment of personnel and volunteers and assistance arrangements for money and goods. While performing resource management, for instance planning for efficient routes to carry resources to affected destinations, one often has to take into consideration the damage to infrastructure such as roads and bridges and hence the unavailability of certain routes including one which would have otherwise been the most preferred option.

This paper tackles the transportation strategy problem in disaster emergencies using a Monte Carlo simulation approach. The Monte Carlo model developed in this paper integrates costs, duration of routes and availability together with the supply and demand requirements to generate the most preferred routes. The results of the Monte Carlo simulations can be used by decision makers (emergency response team) to facilitate the decision making process while choosing the preferred and practical combinations of routes for various deliveries. When compared to other traditional exhaustive tree search algorithms, such as widely known depth first or breadth first search algorithms, Monte Carlo simulation approach uses sampling instead of exhaustive brute force approach. Hence Monte Carlo simulation approach can be used for instances when the traditional exhaustive tree search algorithms may fail due to a very high number of possible outcomes. This approach is simple to implement, likelihood of obtaining at least one solution is more and together with providing an optimal solution, other optimal solutions or near optimal solutions could be provided as well.

The simplicity, versatility and practicality of the Monte Carlo simulation approach is illustrated by applying to a simple situation.

2 Literature review

A large number of studies have been published regarding emergency logistics, however, according to Jiang and Yuan, (2019), "*research on emergency logistics is still in its infancy*". Emergency logistics problems can be broadly categorised as demand assessment, resource allocation, resource distribution and emergency evacuation. Demand assessment refers to the assessment of the damage from the disaster and the estimation of the possible resource allocation. Resource allocation refers to allocating limited resources to a disaster area using an agreed allocation approach. Resource distribution is solving the issue of how to deliver various needed resources to the affected area efficiently, and lastly emergency evacuation deals with evacuating people from dangerous areas.

The research in this paper can be classed in the category of resource distribution and the related work on this approach is as follows. In most studies, the emergency resource distribution problem is viewed as vehicle routing problem subject to various specific features such as infrastructure damage, delivery tools/vehicle availability and capacity. Haghani, Tian and Hu, (2004) developed a simulation model for evaluation of a medical service vehicle response that uses real-time travel time information to assist dispatchers and also to guide vehicles through efficient routes. Shen, Dessouky and Ordóñez, (2009) studied routing problems in response to large-scale bioterrorism emergencies. A chance constrained model for the planning stage and three different recourse strategies for the operational stage were proposed. (Lin *et al.*, 2011) proposes a logistics model for delivery of prioritized items in disaster relief operations using a multi-objective integer programming approach. Yuan and Wang, (2009) proposed two mathematical models of single-objective path selection model and a multi-objective path selection model using Dijkstra's algorithm and an ant colony optimisation approach, respectively. Tzeng et al. (2007), on the other hand, developed a relief-distribution model using the multi-objective programming method for designing relief delivery systems. Their method featured minimizing the total cost, minimizing the total travel time, and maximizing the minimal satisfaction during the planning period. Furthermore, models which account for uncertainty, multiple aid items and multiple time-periods were proposed by Yi and Özdamar, (2007) and Barbarosogu and Arda, (2004). Parwanto et al. (2015) formulated a transshipment network flow optimization problem under various types of uncertain situations. A comprehensive literature review relating to Emergency logistics is provided in Jiang and Yuan, (2019).

To the best of authors' knowledge, there is no previously published work wholly applying Monte Carlo approaches to solve emergency relief goods transportation problem. The motivation to use this approach was derived from Jiang and Yuan, (2019), which after a comprehensive literature review recommended using the Monte Carlo approach for future research.

3 Monte Carlo simulation

Monte Carlo simulation is a computerized mathematical technique that approximates solutions to quantitative problems through statistical sampling. This technique is used by professionals in fields such as finance, project management, energy, manufacturing, engineering, research and development, insurance, oil & gas, transportation, and the environment, including project cost estimation, project schedule estimations, risk assessments, benefit cost analysis and selecting risk response strategies, see for example (Prakash and Jokhan, 2017; Prakash and Jokhan, 2016; Prakash, 2018; Prakash and Mitchell, 2015) to name a few.

This method is useful for obtaining numerical solutions to problems which are too complicated to solve analytically. Monte Carlo simulations can be done using add-ins, such as Crystal Ball from Oracle® and @RISK from Palisade, to commonly used spreadsheets software like Microsoft® Excel. Monte Carlo simulation furnishes the decision-maker with a range of possible outcomes and the probabilities of the possible outcomes. Also the reason for its wide usage is its applicability and also for the simplicity in which one can construct models as compared to certain optimisation models, which would require expert knowledge.

The technique was first used by scientists working on the atom bomb (Kochanski, 2005).

Monte Carlo simulation involves building models of possible results by substituting all the input values having inherent uncertainties, with probability distributions. It then calculates results repeatedly, each time using a different set of random values from the probability distributions. The results of Monte Carlo simulation are not single values but distributions of possible outcome values (Vose, 2008).

Generally, the following steps are involved in performing a Monte Carlo simulation:

- Step 1: Create one (or more) parametric Model(s), $y = f(x_1, x_2, \dots\dots, x_m)$
- Step 2: Represent the inputs $(x_1 x_2, \dots\dots, x_{m)}$using probability distributions
- Step 3: Generate a set of random inputs $(x_{k1}, x_{k2}, \dots\dots, x_{km})$ from the distributions for each iteration $k,\ k = 1\ to\ t$
- Step 4: Evaluate the model using the random inputs, $y_k = f(x_{k1}, x_{k2}, \dots\dots, x_{km})$for each iteration, k
- Step 5: Analyse the results of $y_k = f(x_{k1}, x_{k2}, \dots\dots, x_{km})$, obtained for all the iterations, $k = 1\ to\ t$.

4 Model formulation

The transportation strategy selection problem involves choosing a combination of various routes from a selected origin to a particular destination, taking into consideration, the effects of implementing these combinations of strategies, at the very least, travel costs, duration, availability of routes and the supply and demand requirements of the origin and destination respectively.

In graph theory, the widely known shortest path problem (Ahuja *et al.*, 1990) is the problem of finding a path between two vertices (or nodes) in a graph such that the sum of the weights of its constituent edges is minimized. The problem of finding the shortest path between two towns on a road network can be viewed as a special case of the shortest path problem whereby the vertices correspond to the towns and the edges correspond to the road segments and the weights are the lengths of the segment. For the purposes of this paper and considering the possibility that the shortest path may not be available (due to road unavailability because of disasters), we apply Monte Carlo simulation to generate an extended set of routes going from various origin to destination towns.

To formulate the Monte Carlo simulation model, given the origin, A_O and the destination, A_D towns, the task is to generate possible intermediate towns until the destination is obtained. That is:

Given $A_O,$randomly select the next town to be traversed from range of inputs $(A_i, \dots, A_j)$ represented using probability distribution. These input distributions can be derived from the adjacency matrix for the network. If the next input is the desired destination town, A_D then stop otherwise select the next town visited from respective range of inputs represented by appropriate probability distribution until desired destination town, A_D is reached.

Hence following the sequence of steps as provided in Section 3:

Step 1: Use parametric model: $y = f(A_1, A_i \dots\dots A_j, A_n)$, where A_1 and A_n are the origin and destination towns respectively and $(A_i, \dots, A_j)$ are the towns to be traversed to reach destination from the origin.

Step 2: Represent the inputs $(A_i, \dots, A_j)$ using probability distributions (possibly derived from adjacency matrix)

Step 3: Generate a set of random inputs from the distributions for each iteration k, $k = 1\ to\ t$

Step 4: Evaluate the model (cost, duration etc) using the random inputs, for each iteration, k

Step 5: Analyse the results of $y_k = f(A_1, A_i \dots\dots A_j, A_n)$, obtained for all the iterations, $k = 1\ to\ t$.

With the results from step 5 in hand, analysis can be undertaken to choose the most practical and applicable combination of transport strategies to take. The analysis has to take into consideration factors such as available budget and other constraints such as availability of routes etc., though these can be incorporated into the Monte Carlo simulation as well. The advantage is that Monte Carlo simulations provide us with many choices and we don't necessarily have to adapt the cheapest one because the next best option could provide greater benefits for small additional cost.

5 Applied model

In this section, we present an example adapted from Parwanto et al. (2015) to demonstrate the use for Monte Carlo simulation approach for transport strategy selection for application to the Indonesian Sumatra earthquake case.

In 2009, two earthquakes of 7.6 and 6.2-moment magnitude struck off the coast of West Sumatra, Indonesia. These earthquakes caused widespread damages to housing and infrastructure in the communities in the 13 regions/cities (Parwanto, Morohosi and Oyama, 2015). The entire network of roads has been simplified by taking the main roads linking the capital cities of the affected cities as illustrated in Figure 1.

Common practise is that immediately after a natural disaster, relief is sent immediately from neighbouring 'Region with Excess Supply (RES)' regions to the 'Region with Excess Demand (RED)' regions. If this sent relief is not able to satisfy the demand requirements, then relief goods are transported from an established supply centre (SC).

Hence the logistical problem to be solved here is twofold:

1. To deliver relief good from RES to RED regions; and (1)
2. To deliver the remaining demand gap from the SC.

For the purposes of this paper, we will focus on the demand and supply of drinking water at affected areas. Table 1 shows the demand and supply for drinking water for one week at each of the main cities with SC established at [1] Padang city having 1058.76 m^3 of available drinking water for one week to be supplied where needed.

Figure 1: Simplified network of roads (adapted from Parwanto et al., (2015))

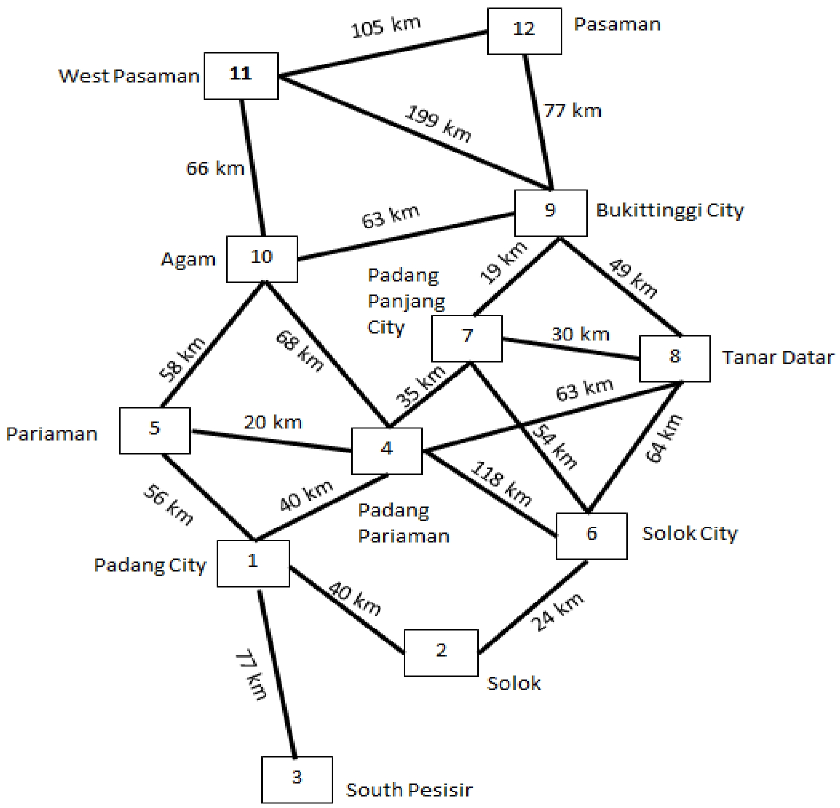


Table 1: Demand and supply for drinking water for one week

Ref #	Region/City	Supply (S) m^3	Demand (D) m^3	Gap (S-D) m^3
1	Padang city	843.4	984.0	-140.7
2	Solok regency	295.4	323.5	-28.1
3	South Pesisir regency	318.0	403.2	-85.3
4	Padang Pariaman regency	267.2	438.0	-170.8
5	Pariaman city	37.6	79.5	-41.9
6	Solok city	64.8	53.8	11.0
7	Padang Tanjang city	66.5	50.8	15.7
8	Tanah Datar regency	309.1	302.7	6.5
9	Bukttinggi city	134.9	96.9	37.9
10	Agam regency	318.7	387.7	-68.9
11	West Pasaman regency	21.9	304.4	-282.5
12	Pasaman regency	230.2	235.2	-5.0
	Total	2907.8	3659.7	-752.0

As shown in Table 1, there are two distinct groups of towns: one that can satisfy their demand and still have excess water (towns 6, 7, 8 & 9), denoted as RES regions, and the other group having demand shortage (towns 1-5, 10-12), denoted as RED regions.

To solve the first of the two fold problem as stated in Equation (1), we demonstrate solving the logistical problem of delivering relief good from RES (towns 6, 7, 8 & 9) to RED (towns 1-5, 10-12) regions such that:

- The maximum demand gap is minimised; and
- The cost of transportation is minimised (we assume that the cost is directly proportional to the length of the routes chosen).

Given the possible origin, A_O (in this case (towns 6, 7, 8 & 9)) and the destination, A_D town (town 11 having the maximum demand gap of 282.5 as shown in Table 1), the task is to generate possible routes from towns 6, 7, 8 & 9 to town 11.

Given A_O, each Monte Carlo iteration randomly selects the next towns to be traversed from range of inputs until destination town is reached and evaluates the total cost of that journey which in this case is the distance travelled.

The adjacency list used for the generation of probability inputs is as shown in Table 2.

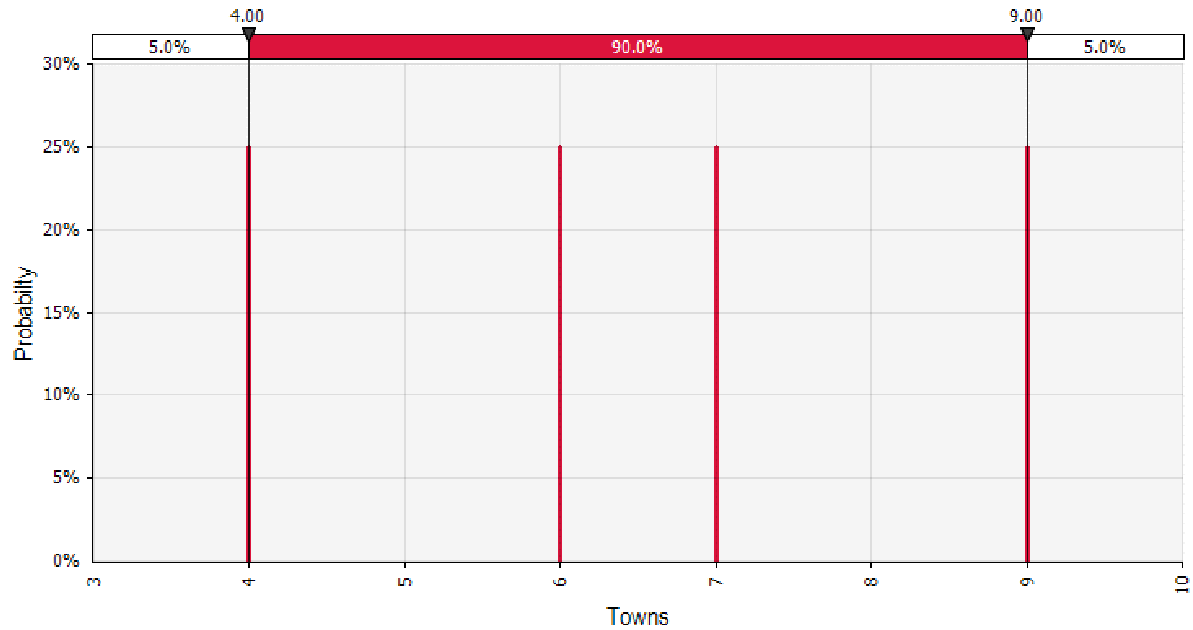
Table 2: Adjacency List for road network

Town ID						
1	2	3	4	5		
2	1	6				
3	1					
4	1	5	6	7	8	10
5	1	4	10			
6	2	4	7	8		
7	4	6	8	9		
8	4	6	7	9		
9	7	8	10	11	12	
10	4	5	9	11		
11	9	10	12			
12	9	11				

For instance, when $A_O =$ town 8, the input distribution for the possible next town is shown in Figure 2.

This implies that the next town can be any of towns 4, 6, 7 or 9, as per Table 2 and Figure 1, with equal chances of being chosen. This process is repeated until town 11 is reached. A subset of derived routes in ascending order of total distance is provided in Table 3.

Figure 2: Probability Distribution of possible next town traversed from Town 8



Suppose there are m number of towns in a road network denoted by $(A_1, A_2 \dots \dots A_m)$, from which a subset or combination has to be chosen to get from origin city to destination city, passing through various cities. Suppose there are n routes possible from a nominated origin and destination city. A selected route, with town a being the origin and town b being the destination, is represented by ${R^j}_{a-b} = (x_1, x_2, .., x_m)$ where $j = 1, 2, \dots n$ and x_i are integers and indicates the position of the respective in the sequence on the route. If a particular town does not fall in the selected route then it is 0. The town of origin, A_O is represented as 1 and the last non zero variable corresponds to the destination town, A_D.

Table 3: Subset of Monte Carlo simulation results of R_{8-11}

#	A_1	A_2	A_3	A_4	A_5	A_6	A_7	A_8	A_9	A_{10}	A_{11}	A_{12}	Distance (km)
R_{8-11}^{1}								1	2	3	4		178
R_{8-11}^{2}							2	1	3	4	5		178
R_{8-11}^{3}				2				1		3	4		197
R_{8-11}^{4}				3			2	1		4	5		199
R_{8-11}^{5}				2	3			1		5	6		207
R_{8-11}^{6}				3	4		2	1		5	6		209
R_{8-11}^{7}								1	2		4	3	231
R_{8-11}^{8}							2	1	3		5	4	231

Note: the zeros in the table have been omitted intentionally

Thus, $R_{8-11}^{1} = (0,0,0,0,0,0,0,1,2,3,4,0)$ represents a route where the origin is town A_8 and destination is town A_{11}, and passes through towns A_9 and then A_{10}, with a total distance of 178 km.

Interestingly, $R_{8-11}^{2} = (0,0,0,0,0,0,2,1,3,4,5,0)$ represents a route where the origin is town $A_8$and destination is town A_{11}, and passes through towns A_7, A_9 and then A_{10}, with a total distance of 178 km as well.

Pictorial representation of R_{8-11}^{1} and R_{8-11}^{2} are shown in Figures 3A and 3B respectively.

Figure 3A: Route R_{8-11}^{1}

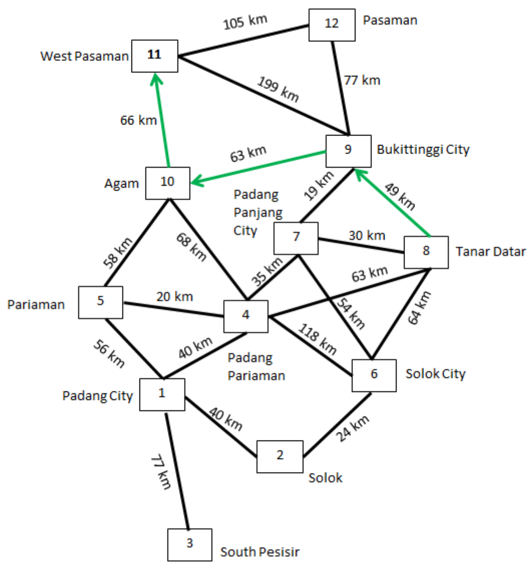
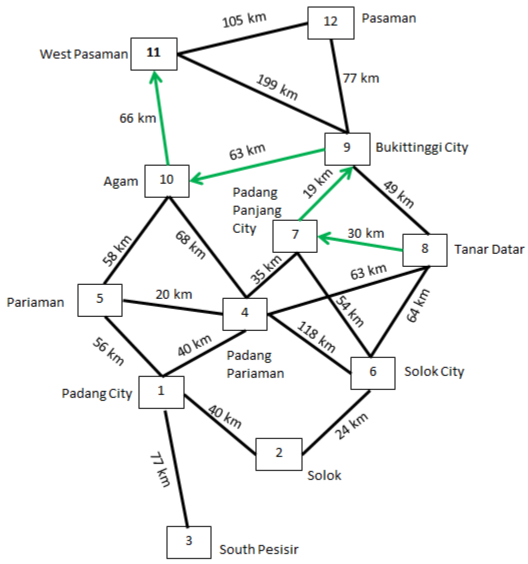


Figure 3B: Route R_{8-11}^{2}



Similarly using Monte Carlo simulations, the routes of all the RES regions to town 11 were derived. A subset of values sorted according to cheapest/shortest routes is presented in Table 4.

Table 4: Subset of Monte Carlo simulation results of R_{6-11}, R_{7-11} and R_{9-11}

#	A_1	A_2	A_3	A_4	A_5	A_6	A_7	A_8	A_9	A_{10}	A_{11}	A_{12}	Distance (km)
R_{6-11}^{1}						1	2		3	4	5		202
R_{6-11}^{2}				3		1	2			4	5		223
R_{6-11}^{3}				3	4	1	2			5	6		233
R_{6-11}^{4}	3	2		4		1				5	6		238
R_{6-11}^{5}						1	3	2	4	5	6		242
R_{7-11}^{1}							1		2	3	4		148
R_{7-11}^{2}				2			1			3	4		169
R_{7-11}^{3}				2	3		1			4	5		179
R_{7-11}^{4}							1		2		4	3	201
R_{7-11}^{5}							1	2	3	4	5		208

#	A_1	A_2	A_3	A_4	A_5	A_6	A_7	A_8	A_9	A_{10}	A_{11}	A_{12}	Distance
R^1_{9-11}									1	2	3		129
R^2_{9-11}									1		3	2	182
R^3_{9-11}				3			2		1	4	5		188
R^4_{9-11}				3	4		2		1	5	6		198
R^5_{9-11}									1		2		199

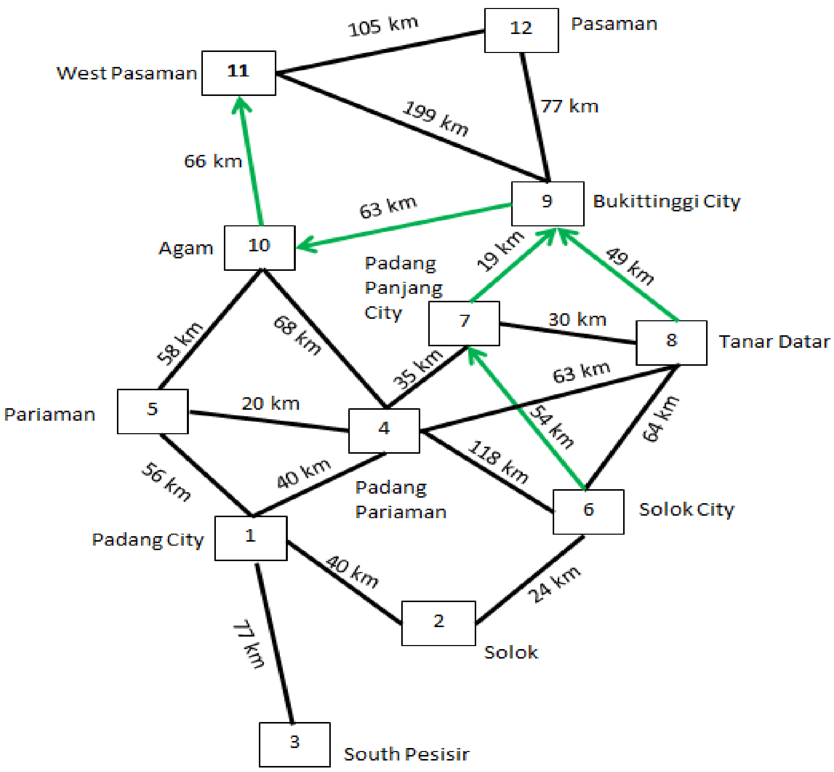
Hence looking at the values in Tables 3 and 4, to minimize the maximum demand gap (ie. to town 11 having a demand gap of 282.5m^3), the cheapest (shortest) route from any of the RES regions is from town 9, travelling via towns 10, having a distance of 129 km with a possible delivery of 37.9 m^3, ie. R^1_{9-11}.

Even when the demand of town 11 is decreased to 244.6 m^3 by this delivery from town 9, it is still the town of maximum demand gap. Hence the next delivery should be from town 7, via towns 9 and then 10, having a distance of 148 km with a delivery of 15.7 m^3, ie. R^1_{7-11}.

Similarly the next delivery would be using route R^1_{8-11} delivering 6.5 m^3 decreasing the demand gap for town 11 to 222.4 m^3, followed by R^1_{6-11} for delivering another 11.0 m^3, making the final demand gap for town 11 to 211.4 m^3.

Hence pictorially, the result is as shown in Figure 4.

Figure 4: Illustration for delivering drinking water from RES to RED (Option 1)

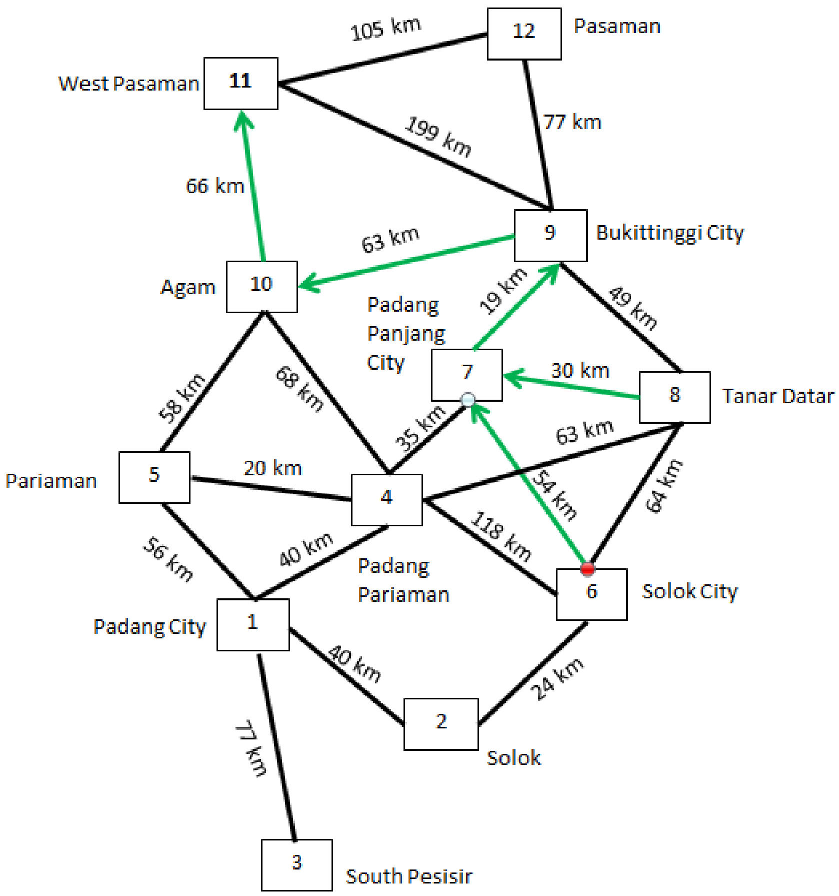


The result of Figure 4 is identical to the results provided in Parwanto et al. (2015).

The advantage of using Monte Carlo simulation and getting a few more results can contribute to the result provided in Figure 5 having the same cost/distance covered but using a different route. This is due to the result shown in Figure 3B. The supplies from town 8 can be delivered using R_{8-11}^{2} which has the same cost/distance covered as route R_{8-11}^{1}, hence providing us with yet another solution as shown in Figure 5. A situation could be that the route from town 8 to 9 is not available hence we don't have any option but to adopt the solution provided by Figure 5 without compromising on the cost/distance of the delivery.

If this situation was known beforehand, an alternative would be to use the adjacency list modified to reflect the change and hence the modified probability distribution. For instance in this case, town 8 won't have town 9 as its next town to traverse, i.e. probability of traversing town 9 after town 8 would be zero.

Figure 5: Illustration for delivering drinking water from RES to RED (Option 2)



Another advantage of having the various Monte Carlo simulation results available, such as ones shown in Table 4, is that if, for instance, town 9 is not available to be traversed for all deliveries from any of the towns (i.e.towns 6-8). Note that, delivery from town 9 is still possible. For this, Table 4 can be used but taking all the routes traversing town 9 as shown in Table 5. Once town 9 is removed out of consideration, the next available options are then listed. Hence from towns 6 and 7, the preferred route in terms of distance could be R^2_{6-11} and R^2_{7-11} having a travel distance of 223 km and 169 km respectively. Similarly from town 8, it would be R^3_{8-11} with a distance of 197 km. Route from town 9 will be unaffected with it still being R^1_{9-11}.

Table 5: Subset of Monte Carlo simulation results with town 9 unavailable for traversing.

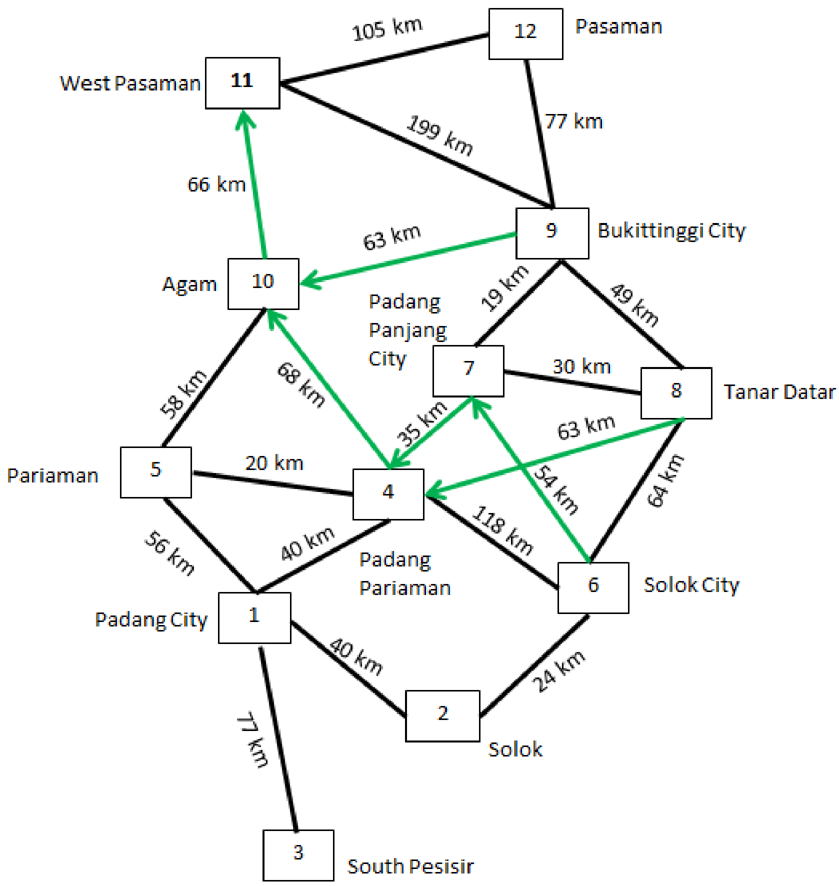
#	A_1	A_2	A_3	A_4	A_5	A_6	A_7	A_8	A_9	A_{10}	A_{11}	A_{12}	Distance (km)
R^1_{6-11}						1	2		3	4	5		202
R^2_{6-11}				3		1	2			4	5		223
R^3_{6-11}				3	4	1	2			5	6		233
R^4_{6-11}	3	2		4		1				5	6		238
R^5_{6-11}						1	3	2	4	5	6		242
R^1_{7-11}							1		2	3	4		148
R^2_{7-11}				2			1			3	4		169
R^3_{7-11}				2	3		1			4	5		179
R^4_{7-11}							1		2		4	3	201
R^5_{7-11}							1	2	3	4	5		208
R^1_{9-11}									1	2	3		129
R^2_{9-11}									1		3	2	182
R^3_{9-11}				3			2		1	4	5		188
R^4_{9-11}				3	4		2		1	5	6		198
R^5_{9-11}									1		2		199

A pictorial representation of delivery for delivering drinking water from RES to RED (Town 9 unavailable for traversing) is shown in Figure 6.

Now that the demand gap is still unfulfilled, one has to solve the second part of the problem stated in Equation (1) which is to solve the logistical problem of delivering relief good from SC (town 1) to RED (towns 2-5, 10-12) regions such that:

- The cost of transportation is minimised (we assume that the cost is directly proportional to the length of the routes chosen);
- Available SC capacity is 1058.76 m^3;
- Transactional time for loading (T_c) is 2 hours;
- Maximum time horizon of delivery (T) is 24 hours;
- Number of tanker trucks is 39;
- Maximum capacity of tanker trucks is 6 m^3; (assuming all trucks deliver the maximum amount)
- Average velocity of tanker trucks is 30km/hr; and
- The demand gap at the destination towns is satisfied.

Figure 6: Illustration for delivering drinking water from RES to RED (Town 9 unavailable for traversing)



Given the origin, A_O (SC – town 1) and the destination, A_D towns (towns 2-5, 10-12), the task is to generate possible number of tankers traversing possible routes from town 1 to each of towns 2-5, 10-12, applying the conditions provided above to get the best possible outcome. Note that the Monte Carlo approach provides results by simulating:

- possible number of tankers delivering at each destination towns; and also
- possible routes those tankers can take.

Model Formulation:

Suppose there are m number of towns in a road network denoted by $(A_1, A_2 \ldots \ldots A_m)$ and also that there are $n = 39$, number of tanker trucks available for delivery and let TT_j denote the jth tanker truck where $1 \leq j \leq n$. Given $A_O \in (A_1, A_2 \ldots \ldots A_m)$ and $A_O =$ town 1, each kth Monte Carlo iteration randomly selects the destination town requiring delivery, $A_D \in (A_1, A_2 \ldots \ldots A_m)$, each truck, TT_j, $1 \leq j \leq n$, goes to deliver supplies. After A_D is randomly selected, it also randomly selects the next towns to be traversed from range of inputs until A_D is reached and evaluates the total cost of that journey R^k_{O-D}, which in this case is the distance travelled and also evaluates the over and under deliveries to towns. Note that the total deliveries to a town may involve a number of trips to and fro the SC as per time limitations

A subset of possible solutions is provided in Table 5. This subset of solutions can be chosen depending on the priorities to be considered. In our case, this could be the cost or the minimization of under/over deliveries.

Table 5: Subset of Monte Carlo simulation results for the possible number of trucks delivering to possible RED regions from SC (town 1)

	Number of trucks to each Red Town from SC (Town 1)										
Sample #	A_2	A_3	A_4	A_5	A_{10}	A_{11}	A_{12}	**Total no. of trucks**	**Total Distance (km)**	**Under-delivery (by no. of trucks)**	**Over-delivery (by no. of trucks)**
1	**1**	**5**	**6**	**2**	**5**	**21**	**1**	**41**	**22,734**	**0**	**5**
2	**1**	**5**	**6**	**2**	**4**	**20**	**1**	**39**	**21,557**	**3**	**3**
3	**1**	**4**	**6**	**2**	**5**	**20**	**1**	**39**	**21,602**	**3**	**3**
4	**1**	**5**	**6**	**2**	**5**	**19**	**1**	**39**	**21,506**	**3**	**4**

All the results presented have different advantages and hence the decision makers can decide what they need to prioritize.

Lets look at each of the samples presented in Table 5:

Sample # 1, all the RED towns get at least the required amount with a few towns getting a bit more. The over-delivery amounted to 5 truck loads. However the total number of trucks required to achieve this with a total distance travelled of 22,734km, is 41. Hence two extra trucks are required.

Sample # 2, 3 and 4 all use only the required amount of trucks, with sample # 2 and 3 under delivers by 3 trucks and over delivers by 3 truck-loads. The distances travelled for samples 2 and 3 are 21,557 and 21,602 km respectively. The only difference the towns in each sample which get under-delivered and towns which get over-delivered varies.

Sample 4 uses 39 trucks only but has the total distance travelled lesser than all the other samples but it over delivers by 4 truck-loads.

Hence in making a decision, if the priority is to make sure that all the RED towns get the required amount of supplies then the authorities need to see if they can secure two more trucks and of course the distance travelled would be a little bit more as well. If two extra trucks cannot be secured, then that leaves us with samples 2, 3 and 4. Samples 2 and 3 are almost the same but they both deliver similarly with 3 truckloads of over-delivery and 3 trucks equivalent of under-delivery. Hence the better choice out of these two would be sample 2 since it has lesser total distance travelled. If however the distance travelled is still important with some deliveries being done, then sample 4 is good since the distance travelled is the least amongst the provided sample however the over-delivery is 4 truck-loads, which is 1 more than the over-deliveries in samples 2 and 3.

6 Conclusion

In this paper, we have presented a Monte Carlo approach to solving emergency relief goods transportation problem. The results of the approach were presented and discussed in relation to the advantages that the Monte Carlo approach delivers. Apart from the obvious advantage of being provided with a few options (other optimal or near optimal solutions), which can be used by decision makers (emergency response team) to facilitate the decision making process as per their priorities and limitations, is to be able to use the results to deal with event of unexpected changes such as unavailability of certain roads as demonstrated in this paper. It is also important to note that the Monte Carlo approach can be used for instances when the traditional exhaustive tree search algorithms may fail due to a very high number of possible outcomes. This approach is simple to implement, likelihood of obtaining at least one solution is more and together with providing an optimal solution, other optimal solutions or near optimal solutions could be provided as well.

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