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# A cost optimization model and solutions for shelter allocation and relief distribution in flood scenario

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ABSTRACT

Humanitarian operations and relief material supply are expensive tasks which have considerable impact on socio-economic conditions of a country. In this paper, we are concerned about the humanitarian logistics and relief distributions during flood, keeping in mind the cost and time aspects. The first priority is to attend the most affected regions for reducing casualties. Then the humanitarian operations need to be carried out efficiently and effectively. People of some regions also might require temporary shelters. Unlike other disasters, flood related disasters also give rise to water-borne and vector-borne diseases. To combat the spread of diseases and sufferings of people, relief materials must be quickly distributed along with the reallocation operation. Here, we have tried to address the issues of evacuation of people, their reallocation to comparatively safe places and distribution of relief materials by developing a cost optimization model. We have proposed two methodologies for the problem based on mixed-integer programming technique and genetic algorithm. The solutions have been illustrated using a case study and the results of the two methods have been subsequently compared. The result shows that, performances of both the techniques are good in the situation when there is sufficient evacuation time and number of blocks and shelters also are not outsized. But, as the number of blocks and shelters increases and the evacuation time decreases, the heuristic approach achieves much better result than its counterpart.

## 1. Introduction

Flood accounts for about one-third of all the geophysical hazards globally, affecting a large number of people compared to other natural calamities [57]. Remarkable flood disasters are the flooding in China in the years 1931 and 1938 in Yellow River, the 1974 flood of Bangladesh and flooding in Myanmar from cyclone Nargis in 2008 and so on. The International Flood Network indicates that from 1995 to 2004, natural disasters caused 471,000 fatalities worldwide and economic losses totalling approximately $49 billion USD, out of which approximately 20 percent of the fatalities and 33 percent of the economic damages were contributed by floods alone. Flooding claims more than 20,000 lives per year over the globe and adversely affects 140 million people on average each year according to [58,69,70]. Owing to the presence of large number of rivers, India and its subcontinent are mostly affected by flood and according to [65], about 83 percent of all the flood related disasters occurs in Asia. According to the International Disaster Database [20], since the year 1900, a total of 143 floods have occurred in India with more than 300 million people affected. More recent flood related disasters in India were the 2013 North-India flood which resulted in death of more than 5700 people and the 2015 Chennai flood where more than 500 people were killed and 1.8 million were displaced. Adhikari et al. [1] have made a compilation of flood related disasters which has occurred between 1998 and 2010 according to year of occurrence, duration, severity, causes and location.

The pre-disaster phase can be grouped into mitigation and preparedness phases. In order to effectively manage the disasters, the root cause needs to be looked into. Proper monitoring of river basin, drainage system, urbanization and vegetation cover are necessary requisites to lessen the flood related disasters. Smith [60] has done a review on monitoring of river inundation area, stage and discharge. The 2013 North-Indian floods were aggravated by the debris that blocked the rivers causing their over-flow and the 2015 Chennai Flood was the consequence of haphazard construction and poor urban planning that blocked natural flow of water. Extensive urbanization with the destruction of natural water bodies prevents seepage of rainwater during heavy downpour. Designing reliable flood warning system taking into account of relevant parameters is a necessary step in the mitigation phase. A warning system should be reliable enough to give accurate signals of oncoming crisis situations and should have a low probability of generating false alarms [16]. Though it is impossible to prevent disasters completely as it cannot be stopped to occur a natural

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phenomenon like flood, earthquake or tsunami but with the help of necessary preparedness, planning and apt response would mitigate the damages and sufferings. In case of any calamity, there is always a support required from an external agency, either for evacuation or resettlement to bring back things into normalcy. During a disaster upon a particular community, usually the affected people require external help. Total recuperation without any help seems very far-fetched or the consequences and losses of the event would be much higher. Shelter estimation and arrangement in pre-disaster phase are key parts of preparedness and planning, whereas reallocation of displaced people to a comparatively safer temporary shelter and relief material distribution are the most challenging parts in post-disaster situation. Lot of research papers are available on temporary shelter estimation along with discussions about different issues regarding reallocation policy [9,10,13,26,32,38,42]. Scientists also pay attention on different aspects of shelter arrangements [8,9,11,13,17,18,25,32,36,37,53]. Some researchers have developed risk assessment tools [27], and softwares (SYNER-G (2009–2012), HAZUS-MH (2006), ERGO-EQ (2014), the MCEER model (2008), InaSAFE (2014) and RiskScape (2014)) to estimate the number of displaced people as well as to assess the temporary shelter requirements [66,67].

In this study, we have focused on reallocation of displaced people to temporary shelters and relief distribution in post-disaster scenario with minimal cost. Shelter allocation and relief distribution during flood are complicated geographic optimization problems because of the involvement of multiple sites, strict constraints, and discrete feasible domain. Large solution space makes the problem computationally intractable. Exact optimal solutions can be gained from classical optimization techniques. However, it is not sophisticated enough to solve the complex optimization problem within reasonable time, especially in high-dimensional solution space. Heuristic techniques hold the promise of improving the effectiveness of location search. In the last few years, applications of evolutionary optimization methods like, ant colony optimization [73], particle swarm optimization [33], simulated annealing [2], GAs [19,21,30,40,46,49,56,63,68,71,74,76] etc. have become very popular in disaster management. In this study, we have applied two approaches - mixed integer programming (MIP) and genetic algorithm (GA) with matrix based chromosome to solve the problem mentioned here. These two algorithms have been validated using hypothetical data sets as well as a real-world data set and a comparative study has been done to prove their effectiveness.

The rest of the paper is organized as follows. Literature survey is presented in Section 2 which focuses on to solve complex and uncertain problems in pre-disaster as well as in post-disaster phases. Section 3 illustrates the model formulation, assumptions, parameters and decision variables. Section 4 discusses solution methodology; Section 5 describe the databases which are considered. Results and discussion on hypothetical data have been illustrated in Section 6. Section 7 describes a case study based on real-life data. Section 8 concludes this study with a scope of future research.

## 2. Past studies on flood disaster management

Humanitarian operations and relief logistic supply have been extensively studied in literature. Different situations arise depending on the location and type of disaster, number of affected people and unexpected shortages of resources and so on. All these aspects make the researchers to think about the problem from different angles. Researchers also focus on the uncertainties pervading in the occurrence of disasters. The objectives and planning of the problem also depend upon the phase of relief distribution under consideration. For example, the objective before the occurrence of disaster is the mitigation of vulnerability, accurate prediction of the probability of occurrence of the hazard and its tracking and taking steps to prevent or delay occurrence of a disaster, if possible. However, during and after the disaster, the objective is to minimize the loss of life and damages to property covering maximum affected area and to minimize the time for delivering the relief materials. In addition to that, according to Taniguchi et al. [62], some scenarios should be considered regarding the availability of roads for transportation of relief items and evacuation process after the disaster. We point out some of the relevant literature on relief planning in the pre-disaster and post-disaster phases.

### 2.1. Studies on relief planning in pre-disaster phase

Relief planning in the pre-disaster phase refers to the selection of warehouse locations, prepositioning of medical supplies and maintaining adequate inventory levels to have maximum effectiveness with a trade-off between inventory holding cost and the penalty for shortages. The key factors that are needed to consider while setting up a warehouse is identified by Roh et al. [54]. Using analytical hierarchy process, they have identified relative weights of the decision attributes and have found that co-operation is the most important factor followed by facility location in humanitarian relief, national stability, cost, logistics and location. Location of warehouses is a vital factor during crunch situations. Study regarding optimal warehouse location for non-consumable inventories for initial deployment of aid after a disaster has been investigated by [4]. Pre-positioning of inventories under cost-minimization approach considering the risk of damage of the pre-positioned items during a disaster has been studied by Campbell and Jones [12]. Facility location problem or quick on-set of disasters, with maximization of the covered area as the objective to determine the amount of inventory to be maintained, and maximizing the benefits is considered in Balcik and Beamon [7].

### 2.2. Studies on relief planning and distribution in post-disaster phase

A cost minimization formulation for distribution of single commodity relief materials, taking unexpected situations into account and transhipment of commodity between depots, has been studied by Rottkemper et al. [55]. They have considered a practical scenario and solution to the problem is done by rolling horizon method. In most of the cases, priority decisions regarding sheltering and relief distribution are made impromptu during rescue operations. A study regarding integrated facility location and vehicle routing problem for relief distribution is described in Yi and Özdamar [72]. Their paper proposes a two stage model where priority is given to supply critical commodities like medicine to wounded people. Stage 1 has illustrated a compact model of weighted sum of unsatisfied demand for overall commodities and weighted sum of wounded people with the goal of minimizing service delay. Stage 2 has generated vehicle routes and load/unload instructions from the solution of stage 1. Humanitarian supply management differs from commercial supply chain in its objective. This is realized in Nagurney et al. [47]. While commercial supply chain management aims to maximize profit, humanitarian supply chain minimizes cost. The model incorporates outsourcing and provides optimal capacity enhancements and volumes in each of the links connected between source and demand points, minimizing the total cost which includes cost of enhancement of capacity while subjected to demands being satisfied as nearly as possible. Sharawi [57] has approached the problem in two different ways, namely, with deterministic demand and probabilistic demand, thereby building two different models. The model has considered the set of all candidate shelter locations and decided which of the shelters should remain open to minimize the cost of handling relief materials and evacuation. A cost-optimization model to determine the facility location and the amount of inventory to maintain in each of the warehouses in flood disaster scenario is described in Manopiniwes et al. [45]. The model has solved though mixed-integer programming technique by considering capacity constraints and time restrictions. Tzeng et al. [64] has described a multi-objective optimization model for designing relief distribution systems. The objectives were to minimize the total cost and travel time while maximizing the minimum satisfaction level during the planning period. Solution for the model has done through fuzzy programming making use of the research described in [77].

Temporary shelter estimation and arrangement, aimed at displaced population in the aftermath of flood, is one of the key issues to emergency responder. But in this case, there are several complaints regarding the reallocation policy due to inadequate consideration of the socio-economic needs of the displaced families [9,10,26,32,38,42], inconsiderate deliberation about the vulnerability of makeshift shelters to potential aftermaths of the disaster [13], inability to lessen the adverse impacts of makeshift sheltering facilities on the surrounding [13,38]; and inefficiency to effectively control and minimize public expenses on temporary shelters [26,38]. However, developing and implementing robust makeshift sheltering plans become very difficult for the disaster management agencies. Researchers also have focused on these issues regarding multiple dimensions of post-disaster temporary shelter arrangements. These dimensions are the types of temporary sheltering and their definitions [11,37,53], loss of domestic shelters and problems faced during the recovery, after national and international urban disasters [17,18], practices about temporary sheltering after recent disasters [8,25], effects of provisional sheltering on the lodged families socially and culturally [9,32], planning for temporary sheltering before the disaster and issues regarding the choice of the impermanent sheltering type [36], and environmental factors prompting the selection of impermanent sheltering locations [13].

In spite of the significant contributions of these research studies, none of them have paid attention to optimize large-scale temporary shelter arrangements as well as the multi-objective nature of this critical optimization problem. El-Anwar et al. [5] had produced a multi-objective optimization model for temporary sheltering. The model was aimed to consider four objectives: minimizing socio-economic trouble for evacuated families, maximizing temporary shelter protection, minimizing disaster effects on host communities, and minimizing cost on temporary sheltering. El-Anwar et al. [6] have illustrated the computational simulation of the multi-objective optimization model developed in El-Anwar et al. [5]. The model had delivered few more objectives with the previously developed model: detecting and visualizing optimal temporary sheltering solutions and optimizing large-scale temporary sheltering problems in a reasonable computational time. Khazai et al. [39] have modeled the necessity for emergency shelter after earthquake damage which incorporates social vulnerability including intolerance of loss to household utilities, climate conditions and several socio-economic parameters which impacts of the building occupants to seek public shelters.

There are some available risk assessment tools [27], and software tools namely, SYNER-G [22,52], HAZUS-MH [23,24], ERGO-EQ [48], the MCEER shelter model (Chang et al. [15]), InaSAFE [34,35] and RiskScape [28,29] which specifically assesses the number of emigrant people who are most likely to seek public sheltering and will need temporary sheltering. SYNER-G have discovered robust connections between wide range of factors like, displaced person's age, type of housing, household tenure, perceived security, income, ethnicity, education, car ownership and combine them to determine the shelter needs index in post-disaster situation (European Commission). HAZUS-MH is a widely used geographic information system-based software developed by FEMA in the US to determine earthquake loss estimation and short-term shelter needs with the help of the weighted value of number of displaced households due to structural damage [51] and other socio-economic variables. Mid-America Earthquake Center have developed a seismic risk platform namely, ERGO-EQ for planning and responding to earthquake disasters. It used enhanced version of the HAZUS-MH shelter algorithm and takes into account the actual number of dwellings per residential structure and calculates household dislocation for each single family structure to evaluate and visualize expected physical, economic and social impact of seismic hazards at census block level. The MCEER shelter model, a modification of HAZUS-MH method with the combination of socio-economic variables mostly used in SYNER-G, takes a linear set of decisions [14]. However, it requires to be converted by the user in an operative tool using a calculus spreadsheet. InaSAFE was developed within the Australia-Indonesia Facility for Disaster Reduction project. It combines with the GFDRR and vulnerability functions to determine the disaster impact as displaced people and calculate requirement of shelters and relief items. RiskScape, a tool developed by New Zealand Government's Foundation for Research, Science and Technology, can model the impact and loss in a disaster. The tool provides several measures of loss, human displacement and shelter needs with respect to an input hazard that is pre-defined and corresponding to each analyzed asset. In case of last two models, only human displacement has been considered as a function of building damage.

The shelter allocation and relief distribution problem can be regarded as a complex geographic optimization problem involving strict constraints and a massive discrete feasible domain. In this context, classical optimization methods become unable to deliver optimal solution of the problem, as it offers an exact optimal solution after the enumeration of all possible combinations [41]. As state-of-the-art models, artificial intelligent algorithms come into play, because they can improve the performance of location search by providing a suitable trade-off between solution quality and computation. Tuson et al. [63] have constructed a solution for an emergency resource distribution planning problem using GA. The objective of the problem is to maximize the number of resource targets met and minimize the number of shipments. Kongsomsaksakul et al. [40] tried to solve shelter location problem for flood evacuation planning. The problem was formulated as a bi-level programming. The upper level is a location problem which models the authorities' decision and the lower level, a combined distribution and assignment model is proposed to model the evacuees. The bi-level programming problem is solved using GA. Real world data is used to test the model. The results show the importance of shelter location selection and the effects of capacity constraints in the evacuation plan. Na and Zhi [46] have developed a relief item distribution model which considered multiple transportation modes like, road, railways, air, and sea and so on. The objective of the model is to minimize the transhipment time. GA with its three operators, selection, crossover and mutation, have been used to solve this problem. Natural number encoding has been done to express each chromosome. Nolz et al. [49] proposed a disaster relief planning problem with two objectives - minimizing the tour length and maximizing the covering areas. To solve this problem, they had constructed a hybrid NSGA-II algorithm with variable neighbourhood search. The model was tested with real world data to show the effectiveness of the approach. Yang et al. [71] has described the freight transportation problem through railway under uncertainty of randomness and fuzziness. The goal of this problem is to satisfy demand and ensure the profit. They came up with three chance-constrained programming models and produced a hybrid methodology including GA, potential path searching and simulation for solving the models and to get optimal solution. Zheng and Ling [74] have illustrated a GA based co-operative optimization method to solve a multi-objective emergency transportation for disaster relief supply chain processes and its planning problem depending on the analysis of several natural disasters in China since 2007. Zidi et al. [76] have stated multi-agent based GA to solve the vehicle routing problem into two phases. The first phase deals with the planning to address the generated request for help in a major disaster and the second phase handles the uncertain events. Du and Yi [19] have considered a multi-objective emergency logistics vehicle routing problem and established a mathematical model of the problem. The aim of the study is to find out relatively best pathway taking minimum cost and time during emergency situations under certain constraints. To solve this problem, integer encoded elitist GAs have been used. Wang et al. [68] optimized the post-earthquake emergency logistics system using two-echelon multi-facilities. A model has been developed for fuzzy location-routing problem by considering fuzzy demand of relief materials, timeliness and limited resources. To

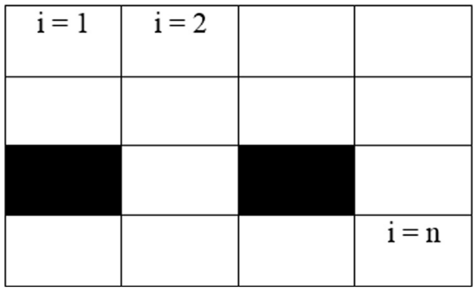


**Fig. 1.** Region of interest divided into several blocks. Yellow boxes represent regional depots. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

solve this problem, the authors propose an improved GA based on weighted coefficient transformation. Goerigk et al. [30] have proposed an elitist Non-dominated Sorting GA-II based solution to the problem of evacuating an urban area damaged due to disaster. The aim of the study is to maximize the evacuation and minimize the risk and evacuation time. Esmaeili and Barzinpour [21] have developed a multi-objective mathematical model for estimating the demand in an urban area which might be affected by neighbour wards. To solve this problem, GAs with binary encoded chromosomes were developed in order to reach a near optimal solution in a reasonable time. Finding out the location for earthquake relief centres and relief items distribution among them with minimal distance cover has been solved by Saeidian et al. [56] using GA and Bees algorithm.

## 3. Model formulation

The entire concerned area is divided into grids consisting of various blocks based upon a rule that the administration deems fit (Fig. 1). The relief distribution considered here is in the post-disaster phase along with the high priority areas identified. No attempt is made to identify the locations where the warehouses for relief materials can be pre-positioned as a preparation for an oncoming disaster. Relief aid distribution, considered here, is in the initial response which is a part of more elaborate and multi-period relief distribution model and adds penalty, if people, in need of shelter, do not get one and also demand of relief-kit in shelters is not met for already evacuated population. To identify the priority blocks, several parameters were taken into account like population, area, per capita income, property value and factors of drainage, urbanization and civic amenities. With the use of Eq. (1), the blocks were graded and priority blocks were identified. The function in the following form was considered to mesh all the attributes in their normal form and multiplying them by appropriate weights.

$$
\begin{aligned}
f_i = {} & a\left(\frac{population_i - \mu_{total}}{\mu_{total}}\right) + b\left(\frac{PCI_i - \mu_{PCI}}{\mu_{PCI}}\right) \\
& + c\left(\frac{property\_value_i - \mu_{property\_value}}{\mu_{property\_value}}\right) + d\left(\frac{area_i}{total\_area}\right) \\
& + e(drainage\_factor_i) + f(urbanization\_factor_i) \\
& + g(civic\_amenities\_factor_i)
\end{aligned} \tag{1}
$$

Constants '*a*' to '*g*' considered in the above equation are taken as per order of importance of the respective parameters. A separate problem can, of course, be considered for selection of optimum values of these multipliers. Here, the constants '*a*', '*b*', '*c*', '*d*', '*e*', '*f*' and '*g*' are weights given to the parameters: *population*, *per capita income*, *property value*, *area of the block*, *drainage factor*, *urbanization factor* and *civic amenities factor* respectively. Before multiplying with their allocated weights, all the parameters are normalized. In this case, we have taken the values of coefficients as, $a = 10$, $b = 8$, $c = 5$, $d = 10$ and $e, f, g$ each equal to 1 respectively. Since, we are finding the relative importance of the blocks

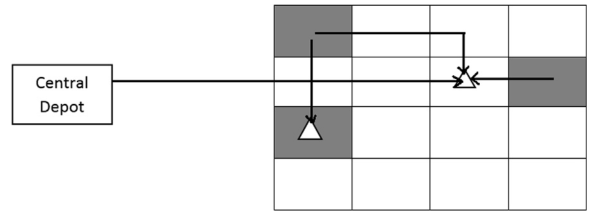


**Fig. 2.** Population and relief-kit flow as an initial response.

from which evacuation would be carried out, obviously, *population* would have one of the highest weights. Also, since larger area would involve more rigorous evacuation as the disaster-affected people are scattered everywhere in the wide landscape, it is also given higher weight. Accordingly, *per capita income* and *property value* are given weights 8 and 5, whereas weights of *drainage factor*, *urbanization factor* and *civic amenities factor* are taken as 1 respectively.

Fig. 2 is a pictorial representation of initial relief distribution. Population flows from the pre-identified priority blocks, marked in black, to the shelters, marked as triangles, and relief kit flows from central depot to the shelters. Flow of relief-kits to the shelters is according to the demand of the shelters. Following are the assumptions of initial response model.

### 3.1. Assumptions

We shall now discuss the assumptions which underline our model. Prior to the development of the proposed model for shelter allocation and relief distribution in post-disaster situations, we had gained sufficient insights about the different practical rescue operations and plans, after discussing with the Government officials of West Bengal, India, that were implemented in real time in the past. After critically analyzing the efficacy of each rescue operation, mainly in terms of time of evacuation and proper distribution of relief items with respect to the available data, we had identified some pitfalls as well as some beneficial aspects of these rescue plans. These have been reflected in the following assumptions in our study.

i) Possible location of shelters and their availability after the disaster is known.
ii) Fraction of the population that needs to be evacuated from each area (block) is known.
iii) Vehicles of different capacities are available in each block for transportation of people from blocks to shelters and the group of trucks is unique to the block-shelter combination.
iv) Partial loaded vehicles are not considered for transporting human population from blocks to the shelters except the last trip.
v) Vehicles of different capacities are available in the central depot for transportation of relief items from central depot to shelters based upon the number of occupants in the shelters.
vi) Depending upon the demand, numerous trips are made by the vehicles for transportation of people from the blocks to shelters and relief items from central depot to shelters.
vii) All the vehicles in a single trip plying between a block and shelter or between central depot and a shelter take the same amount of time to reach the destination.
viii) The total time taken to transport the required number of people or "relief-kit" is the sum total of time taken to make all the required number of trips.
ix) Cost of running each truck is dependent upon the distance it covers and its carrying capacity.

### 3.2. Model parameters

We shall now describe our model parameters and the notations used.

$I$ = Set of Priority blocks.
$J$ = Set of Shelter locations.
$K$ = Set of vehicles available capacity wise.
$i \in I$, $j \in J$ and $k \in K$,

$$x'_j = \begin{cases} 0 \text{ if } j^{\text{th}} \text{ shelter is not available.} \\ 1 \text{ if } j^{\text{th}} \text{ shelter is available.} \end{cases}$$

$A_j$ = Capacity of $j$th shelter.
$RF\ cost$ = Per unit cost of relief kit.
$z_{ij}^k$ = Number of $k$-type truck plying on $i$-$j$th route.
$z_j^k$ = Number of $k$-type truck plying from central depot to $j$th shelter.
$f^k$ = Cost per unit distance of running $k$-type truck.
$c^k$ = Capacity of $k$-type truck.
$y_i$ = Fraction of population that needs to be evacuated from the $i$th block.
$\mu_i$ = Population in $i$th block.
$d_{ij}$ = Distance of $i$th block from $j$th shelter.
$d_j$ = Distance of $j$th shelter from the central depot.
$s_{ij}$ = Average speed of the truck in $i$-$j$th route.
$\phi_1$ = Penalty factor associated while not meeting shelter demand.
$\phi_2$ = Penalty factor associated for failing to meet relief item demand.

### 3.3. Decision variables

We shall now list down the decision variables which have been used in this paper. The decision variables refer to the solution of the model. The output of the model is in the form of three matrices denoting three decision variables. The decision variables considered in the model are elaborated below.

$p_{ij}$ = Number of trips made by the vehicles between $i$th block and $j$th shelter.
$p_j$ = Number of trips made by the vehicles between central depot and $j$th shelter.
$x_j$ = Shelter that is to be used.

### 3.4. Model

$$\begin{aligned} &minimize\ \textstyle\sum_j \sum_i 2^* x_j x'_j p_{ij} d_{ij} (\sum_k z_{ij}^k f^k) + \sum_i \phi_1 \{\mu_i y_i - \sum_j x_j x'_j p_{ij} (\sum_k z_{ij}^k c^k)\} \\ &+ \textstyle\sum_j 2^* p_j d_j (\sum_k z_j^k f^k) + \sum_j \phi_2 \{\sum_i x_j x'_j p_{ij} (\sum_k z_{ij}^k c^k) - x_j x'_j p_j (\sum_k z_j^k c^k)\} \\ &+ \textstyle\sum_j RFcost^* p_j (\sum_k z_j^k c^k) + \sum_j x_j^* shelteropeningcost \end{aligned} \tag{2}$$

The total cost is the sum of the cost for transporting population and relief-kits and penalty cost associated with un-evacuated in-need population. The first term in the bracket is the travel cost of vehicles in $p_{ij}$ trips for transporting people from $i$th block to $j$th shelter. People are transported to available shelters with optimal cost while maintaining capacity and time constraints. This cost is dependent upon the capacity of the truck used for transportation and the total distance covered. Thus, the algorithm would try to find the shortest cost effective path. The second term is the penalty cost for not being able to provide shelter to in-need people of $i$th block. This term reduces the number of unattended people by introducing a penalty cost associated with such people. The third term is the transportation cost of relief-kit from the central depot to $j$th shelter. This is also dependent upon the capacity of truck and distance travelled. The fourth term is the penalty cost associated for not being able to provide relief-kit to already evacuated victims. The last two terms represent cost of relief items and the cost associated with the opening of a shelter.

### 3.5. Constraints

The binary variables $x'_j$ and $x_j$ denotes the status of the shelters. The dimension of $x'$ denotes the number of all possible shelters. Some of the shelters might be rendered unusable after the disaster and hence vector $x'_j$ denotes the availability of the shelters, which will be fed to the system. $x_j$ is the decision variable to decide which of the available shelters to be used to achieve optimum cost. Constraint (3) restricts the values of $x_j$, $x'_j$ strictly to two levels, 0 signifies closed and 1 signifies in-use.

$$x_j, x'_j \in \{0, 1\} \quad \forall \quad j \in J \tag{3}$$

Constraint (4) restricts the number of evacuees from various blocks in each of available in-use shelter to the shelter capacity.

$$\sum_i x_j x'_j p_{ij} \left( \sum_k z_{ij}^k c^k \right) \le A_j \quad \forall \ i \in I, \ j \in J \tag{4}$$

Constraints (5) and (6) model the time restrictions. The initial emergency relief distribution should be done as quickly as possible and hence a time constraint is considered. In a trip consisting of a group of vehicles, plying in a particular route, the time taken by each of them is assumed to be same. However, the total time taken to meet the demand is the sum of time taken by all the trips. The time taken to complete each trip is dependent upon the speed and distance. Since, the process occurs simultaneously in all the blocks, the maximum of them is set to meet the time constraint.

$$\sum_j 2x_j x'_j p_{ij} \frac{d_{ij}}{s_{ij}} \le T \quad \forall \ i \tag{5}$$

$$2x_j x'_j p_j \frac{d_j}{s_j} \le T \quad \forall \ j \tag{6}$$

$$\sum_i x_j x'_j p_{ij} \left( \sum_k z_{ij}^k c^k \right) - x_j x'_j p_j \left( \sum_k z_j^k c^k \right) \ge 0 \quad \forall \ j \tag{7}$$

$$\mu_i y_i - \sum_j x_j x'_j p_{ij} \left( \sum_k z_{ij}^k c^k \right) \ge 0 \quad \forall \ i \tag{8}$$

## 4. Methodology

In this study, we have used two methods – MIP and GA to solve our proposed relief distribution model. We validate our approaches using some hypothetical data. Further, comparison of both the results have been performed and also a case study is developed using real world data.

### 4.1. Classical method

IBM ILOG CPLEX Optimization Studio Version 12.6.3 is used to solve the model using the classical optimization technique. The model was run using hypothetical datasets. Indexing of the dataset is done in the format $T$ = time for evacuation (Total number of blocks, number of selected priority blocks, number of shelters). Three datasets were used: (6 blocks, 3 shelters); (20 blocks, 15 shelters); and (10 blocks, 6 shelters). Each of the datasets is run at evacuation time 12, 24, 36 and 48 h respectively.

As expected, the decision variable, i.e., the number of trips for human population was taken to be an integer but the number of trips for the relief-kit was taken as float without violating any other constraints. CPLEX uses branch and bound method for finding out the optimal solutions and cannot handle non-linear constraints. Hence, the constraints were linearized before solution could be obtained by CPLEX.

$b[s][p] <= tripSB[s][p];$
$b[s][p] <= 999*x[s];$
$b[s][p] >= tripSB[s][p] - (1 - x[s]);$
$b[s][p] >= 0;$

Where $s \in$ {Shelters}, $p \in$ {Priority Blocks}, $tripSB[s][p]$ is the integer decision variable for number of optimized trips need for evacuating human population from $p$th block to $s$th shelter and $x[s]$ is the binary decision variable whether to use the $s$th shelter.

Constraints (4), (5), (6), (7) and (8) can respectively then be re-written in the following ways.

$$\sum_i b[s][i]*people\_in\_one\_trip[p] \le shelter\_capacity[s] \quad \forall\ p,\ s \tag{9}$$

$$\sum_j 2*b[s][p]*\frac{prior distance[s][p]}{avg speed} \le T \quad \forall\ p \tag{10}$$

$$trip\_relief[s]*\frac{CDS\_distance[s]}{avg\_speed} \le T \quad \forall\ s \tag{11}$$

$$\sum_i b[s][p]*people\_in\_one\_trip[p] - trip\_relief[s] *relief\_kit\_in\_one\_trip[s] \ge 0 \quad \forall\ s \tag{12}$$

$$evacuate[p] - \sum_j b[s][p]*people\_in\_one\_trip[p] \ge 0 \quad \forall\ p \tag{13}$$

### 4.2. Genetic algorithm

GA [61] is one of the heuristic search techniques, drawing inspiration from natural adaptation and follows the "survival of the fittest" principle of natural selection, developed by John Holland in 1975 (For details one may refer to [31,75]. It is an iterative optimization technique and have a high probability of locating the global solution optimally in multi-modal search. In GA, the decision variables can be encoded as binary, integer, or real representation. This method offers optimal solution through randomly generating a series of chromosomes. The reproduction operator generates diversity in the gene pool. Evolution is initiated when the chromosomes of two parents recombine during reproduction. New combinations of genes are generated from previous ones; a new gene pool is created. Specifically, the exchange of information among chromosomes cause the continuous evolution of the gene pool and the generation of individuals that survive better in a competitive environment. Each individual in the population is evaluated to give some measure of its fitness. Most fit individuals are always retained in the next population. A key aspect of GA has been the issue of robustness, enabling the method to be employed a wide range of problems.

$$\mathbf{A} = \begin{pmatrix} A11 & A12 & A13 & A14 \\ A21 & A22 & A23 & A24 \\ A31 & A32 & A33 & A34 \\ A41 & A42 & A43 & A44 \\ A51 & A52 & A53 & A54 \end{pmatrix} \qquad \mathbf{B} = \begin{pmatrix} B11 & B12 & B13 & B14 \\ B21 & B22 & B23 & B24 \\ B31 & B32 & B33 & B34 \\ B41 & B42 & B43 & B44 \\ B51 & B52 & B53 & B54 \end{pmatrix}$$

The chromosome representation, fitness function and GA operators are explained below with respect to shelter allocation and relief distribution problem.

#### 4.2.1. Chromosome representation

Chromosome representation is one of the most important tasks in GA. Each chromosome represents a feasible solution of the problem. This block-shelter allocation problem is one type of general assignment-allocation problem. GA based solutions already exist for assignment and allocation problem. Some useful references on these topics include in [3,40,43,44]. However, it should be noted that the representation of chromosome in the above mentioned references cannot fit into our study. In our case, each chromosome is represented by a matrix of order (number of shelters X number of priority blocks). Hence, each of the element is represented by either 0 or any positive integer. Each row of this matrix should hold the capacity constraint of shelter and each column should hold the capacity constraint of block.

Assume, $A_{mxn}$ is a chromosome. Then, $A_{i,j}$ $(1\le\ i\ \le\ m,\ 1\le\ j\ \le\ n)$ represents number people allocate from $j$th priority block to $i$th shelter. Therefore,

$0\le \sum_{1\le i\le n} A(i, j)\le$ Shelter capacity of $i$th shelter.

$0\le \sum_{1\le i\le m} A(i, j)\le$ Total number of people need to evacuate from $j$th priority block.

$0\le \sum_{1\le j\le n} travel\_time(A(i, j))\ \le$ Maximum time ($T$).

#### 4.2.2. Fitness function

In GA, each chromosome is evaluated to give some measurements of fitness. The fitness value not only represents how good the solution is, but it also indicates how close the chromosome is to the optimal one. To evaluate the fitness, the chromosome has to be decoded and the cost function is to be determined. Cost function can be divided into four parts; i.e., (a) cost for people evacuation from priority blocks, (b) penalty cost for people, if not fully evacuated, (c) cost for relief kit supplied from central depot to each shelter, and (d) penalty cost for relief kit, if not fully distributed. After determining the cost of a chromosome, fitness value is generated. Here, fitness value $= \frac{1}{cost}$ which means that chromosome with less cost is more fit.

#### 4.2.3. Selection operator

The population is divided into two groups depending on the average fitness value. There must be a set of chromosome, whose fitness value is greater than or equal to the average fitness value and another set of chromosomes, whose value is less than the average fitness value. Two chromosomes must be selected randomly, one from the later set and another from the former set.

#### 4.2.4. Crossover operator

Crossover is a crucial operator in GAs. After selection of two chromosomes through selection, the first step is to select a shelter and a priority block randomly from the set of shelters and blocks. During the crossover, the randomly selected row and column of two matrices are interchanged and two new matrices are generated.

After crossover, the newly created chromosomes are:

$$\mathbf{A'} = \begin{pmatrix} A11 & B12 & A13 & A14 \\ A21 & B22 & A23 & A24 \\ A31 & B32 & A33 & A34 \\ B41 & B42 & B43 & B44 \\ A51 & B52 & A53 & A54 \end{pmatrix} \quad \mathbf{B'} = \begin{pmatrix} B11 & A12 & B13 & B14 \\ B21 & A22 & B23 & B24 \\ B31 & A32 & B33 & B34 \\ A41 & A42 & A43 & A44 \\ B51 & A52 & B53 & B54 \end{pmatrix}$$

If the newly created matrix is not satisfied for at least one of these three constraints (shelter capacity constraint, block evacuate constraint and time constraint), the algorithm adjusts the elements of the matrix to satisfy those constraints depending on the weighted distance $\mathrm{dist}_w[i, j]$.

$$\mathrm{dist}_w[i, j] = \mathrm{dist}[i, j]*\frac{\mathrm{vck}}{\mathrm{vck} + \mathrm{nv}(j)*\mathrm{vch}(j)} + \mathrm{dist}[i, j]*\frac{\mathrm{nv}(j)*\mathrm{vch}(j)}{\mathrm{vck} + \mathrm{nv}(j)*\mathrm{vch}(j)} \tag{14}$$

vck = No. of kits carried by a vehicle from central depot.
nv($j$) = No. of vehicles at $j$th block.
vch($j$) = No. of people carried by a vehicle from $j$th block.
dist[$i$,$j$] = Distance between $j$th priority block and $i$th shelter.

After completion of crossover, two individuals from the population with lower fitness values are replaced with the new offspring if the newly created chromosome has the higher fitness value. This algorithm follows elitism. The population always contain the fit chromosomes.

#### 4.2.5. Solution algorithms

GAs for priority block-shelter allocation problem

Step 1: *Generation* = 0.
Step 2: Generate initial population P(0) of size $r$.
Step 3: Find the cost of each and every individual and determine their fitness value.
Step 4: *Generation* = *Generation* + 1.
Step 5: If $p_c \le p_{\mathrm{crossover}}$, go to Step 6, else go to Step 15. // $p_c$ is randomly generated real // number between 0 and 1.
Step 6: Randomly select two individuals from the pool of P(0) using selection operator.
Step 7: Select a row and a column randomly, and interchange the row and column of those two selected matrices and create two new matrices.
Step 8: Examine these two newly created matrices, whether they satisfy the three constraints mentioned above or not.
Step 9: If they satisfy those three constraints, then, go to Step 11.
Step 10: If they do not satisfy those three constraints, adjust the element of each matrices, so that they can satisfy those three constraints.
Step 11: Determine the cost, as well as fitness value of these two new matrices.
Step 12: Find the minimum fit two individuals $I_1$, $I_2$from the population, and compare them with the newly created matrices.
Step 13: If the newly created matrix is fit, then replace $I_1$, $I_2$with these new matrices.
Step 14: Determine the fitness value of each and every individuals of P(*Generation*).
Step 15: If *Generation* < Maximum Generation and does not meet the converge condition, go to Step 4, otherwise, go to Step 16.
Step 16: Stop.

**Initial population algorithm**

Step 1: For each priority blocks, do Step 2, Step 3 and Step 4, till those three constraints holds.
Step 2: Randomly select shelter from the set of shelters
Step 3: Populate the shelter in such a way that it never violates the shelter capacity constraints, priority block evacuation constraint and time constraint.
Step 4: If total number of people evacuated from a priority block < people needed to be evacuated from that block, total shelter capacity > 0, and time needed to evacuate people from a particular block < $T$, go to Step 2, else go to Step 5.
Step 5: Stop

Time complexity of this algorithm is $O(mn)$, where, $m$ = number of shelters and $n$ = number of priority blocks.

### 4.3. Summary of two methods

To solve the cost effective shelter allocation and relief distribution problem, a classical optimization technique (MIP) and a heuristic technique (GA) have been used and both the techniques can solve optimization problems. MIP is a special transformation of branch and bound technique. It is applicable when some variables in the model are real-valued and some of the variables are integer-valued and all of the constraints are in linear form. On the other hand, GA, a stochastic search method, is rooted in the mechanism of evolution and natural genetics. In each iteration, a new population of the same size is generated from the current population using GA operators and the new population, obtained after the reproduction, is again used to generate another set of population and this process continues till it finds the optimal or near-optimal solution. It has a high probability to locating the global optimal solution in a multi-modal search.

MIP and GA both can solve optimization problems. However, if the solution search space grows exponentially with the input instances, GA performs more efficiently than classical optimization technique as the former explores the solution search space from several points simultaneously rather than a single point and it finds an optimal or near optimal solution in polynomial time. But, classical technique can never reach to an optimal or near optimal solution in polynomial time because it searches exhaustively the entire solution search space. So, to solve a complex real life optimization problem where solution search space is large, heuristic search techniques are more preferable to classical techniques to find an optimal solution.

## 5. Database description

The above two methodologies are applied to two sets of data. The first set of data is synthetically created after detailed discussions with the relevant experts. The second set of data, which is evaluated as a part of case study, is obtained for Barrackpore Block-II from relevant government officials after prior requisitioning. The input data set consists of two parts, namely the socio-economic parameters for the sub-regions and the distance matrix between the sub-region and shelters. The socio-economic parameters that are considered here are the following:

**Population**: Denotes the population of the sub-region. Higher the population, more number of people are subjected to vulnerability if that region is vulnerable.
**Per Capita Income (PCI)**: Denotes the annual income of per person in the sub-region in Indian rupees. Urban areas are expected to have higher PCI than rural, thus less susceptible to vulnerability.
**Area**: Denotes the area of the sub-region in per unit square. Large area means more distance needs to be travelled to evacuate people, thus taking more time to evacuate, and thereby increasing the vulnerability.
**Drainage Factor**: Denotes the condition of drainage in the sub-regions. It is taken as an ordinal factor ranging between 1, 2 and 3; 1 being the best, 2 being average and 3, the worst. Regions having bad drainage conditions are expected to have more water-logging problems and hence more prone to flood related disasters.
**Urbanization Factor**: Denotes the level of urbanization in the sub-regions. It is also taken as an ordinal factor varying between 1, 2 and 3; 1 being high, 2 means moderate and 3 the lowest. Higher urbanization means less prone to flood.
**Civic Amenities Factor**: It denotes the quality of living in the sub-regions. It takes into account the presence of basic necessities like fresh water supply, electricity, access to healthcare etc. It is taken as an ordinal factor varying between 1, 2 and 3, 1 being the best and so on.

**Table 1**
Values of parameters which were served as input to the mathematical models.

| Average weight of a person | 60 kg. |
|---|---|
| Weight of relief kit | 2 kg. |
| Shelter Opening Cost | Rs. 500,000 |
| Penalty cost for not evacuating humans | Rs. 300,000 |
| Penalty cost for not supplying relief-kits | Rs. 100,000 |
| Capacity of vehicles carrying Humans | 2000 kg. |
| Capacity of vehicles carrying Relief Items | 500 kg. |
| Plying cost of vehicles carrying humans | Rs. 100/Km. |
| Plying cost of vehicles carrying relief-kits | Rs. 80/Km. |
| Average speed of vehicles | 40 km./h |

**Table 2**
Allocation matrix for 6 blocks, 3 shelters and 3 priority blocks for 12 h.

| **Priority block →** | | | | | |
|---|---|---|---|---|---|
| **Shelter ↓** | **4** | **5** | **2** | **Relief kit** | **Shelter capacity** |
| **1** | 0 | 0 | 0 | 0 | 1000 |
| **2** | 264 | 528 | 0 | 750 | 1000 |
| **3** | 0 | 0 | 396 | 396 | 1000 |
| **Need to evacuate** | 1500 | 1250 | 750 | | |

**Table 3**
Number of trips between blocks and shelters.

| **Trip matrix** | **4** | **5** | **2** |
|---|---|---|---|
| **1** | 0 | 0 | 0 |
| **2** | 8 | 16 | 0 |
| **3** | 0 | 0 | 12 |

## 6. Computational results and discussion on synthetic data

Comparison between MIP and GA has been done on three hypothetically created datasets and one real life dataset. The three synthetic datasets contains 6 blocks, 3 shelters; 10 blocks, 6 shelters; and 20 blocks, 15 shelters. All of these three datasets are executed for evacuation times 12, 24, 36 and 48 h respectively. Comparison between these two methodologies has been done on the basis of number of people evacuated and operational cost. The others required parameters are described in Table 1. The allocation matrix obtained from classical optimization for 6 blocks, 3 shelters and 3 priority blocks in shown in Table 2 as an example when the time required for evacuation is set at 12 h. Table 3 shows the number of trips made by the vehicles from the priority blocks. Output matrices of such kind were obtained for each of the blocks, number of priority block and time combination.

In Table 2, the rows represent the shelters which are identified by their numbers while the columns represent the priority blocks, which are also identified by their numbers. The priority blocks have been calculated from Eq. (1). Corresponding entries represent the number of people that needs to be evacuated from a particular block to a particular shelter. The column under 'Relief kit' represents the number of relief kits that was supplied within the given time frame. Table 3 represents the number of trips that needs to be undertaken from the block to the shelter to complete the task of evacuation. The program also produces the cost of executing the whole process.

Fig. 3, Fig. 4 and Fig. 5 describe the comparison of two methods on these three hypothetical data sets. Fig. 3 shows two graphs, where the graph on the left shows the number of people evacuated with respect to evacuation time and the graph on the right shows the cost incurred in evacuation time for both the classical optimization technique and GA for 6 blocks, 3 shelters and 3 priority blocks. It is clearly visible from the graph that performance of GA is better than the other when more number of people is to be evacuated in moderate evacuation time and also the solution using GA will be reasonable in terms of cost as the evacuation time increases.

Fig. 4 also demonstrates two graphs with the same parameters for comparison along the axes as in Fig. 3; but, here, the number of blocks is 10, no. of shelters is 5 and no. of priority blocks is 6. In this context, performance of GA is slightly better than the classical technique when greater number of people is to be evacuated in comparatively more evacuation time, incurring less cost for evacuation. When evacuation time is low compared to a large number of disease-stricken people, performance of both the techniques is almost same.

Fig. 5, also with the same parameters, compares two solution techniques considering 20 blocks, 10 shelters and 15 priority blocks. Unlike the other two scenarios described with the previous two graphs, GA shows good performance always in terms of number of people evacuated and evacuation cost, irrespective of how much time is there for evacuation.

Table 4 describes the comparison between classical technique and GA for measuring the percentage of people evacuated and percentage of relief materials distributed amongst the evacuated population. As the number of blocks, shelter and priority blocks increase, GA is able to evacuate more number of people in almost all cases as it is a multimodal search technique, it starts searching the solution space from multiple points rather a single point. In the table, it is clearly shown that when block is 20, shelter is 10 and priority block in 15, GA evacuate 835 people (4.34% of total people need to be evacuated) more in 12 h evacuation time and it evacuate 482 people (2.44% of total people need to be evacuated) more in 24 h than the classical optimization technique. So, GA should be more preferable though, in certain situations, the cost in GA is more than the classical optimization technique, as the number of relief kits supplied in GA is less than that of the classical optimization technique. However, since life is precious, focus should be on evacuation of more number of people.

## 7. Case study

A case study on Barrackpore Block II is conducted by implementing the above two methodologies. Barrackpore Block II is situated in the district of North 24 Parganas, West Bengal, India beside the Hooghly river (Fig. 6), one of the branch of the river Ganges and is one of the two blocks under Barrackpore block-division. It has a total area of 38.308 sq. km. and a population of 216,000. The block consists of 6 gram panchayats[1]: Bilkanda I, Bilkanda II, Bandipur, Patulia, Sewli and Mohanpur which are spread over spread over 28 mouzas.[2] Though natural disasters are not a common phenomenon in this block, but annual water-logging is an increasing nuisance.

Data for the block are collected from Block Development Office. *Population*, *PCI*, *area* of different mouzas are directly available from the block office records. Here, each of the mouzas is treated as areas from where population needs to be evacuated to the predefined shelters and provided relief materials. Data on *drainage factor*, *urbanization factor* and *civic amenities factor* in each of the mouza are collected by conducting a small survey involving the members of respective gram panchayat. A total of 27 shelters of varying capacities are identified by the authorities spread over the block, though not in a homogenous manner. The distance matrix is formed by using a scalable map that is provided by the Block Development Office. Owing to the version of CPLEX used, the size of the problem that could be solved using the traditional method was reduced and was solved considering 5 priority mouzas and 27 shelters for times 4, 6, 14, 16 and 18 h respectively. The

[1] A gram panchayat is the foundation of a local self-government organisation in India of the panchayati raj system at the village or small town level (https://en.wikipedia.org/wiki/Gram_panchayat).

[2] In India, mouza or mauza is a type of administrative district, corresponding to a specific land area within which there may be one or more settlements (https://en.wikipedia.org/wiki/Mouza).

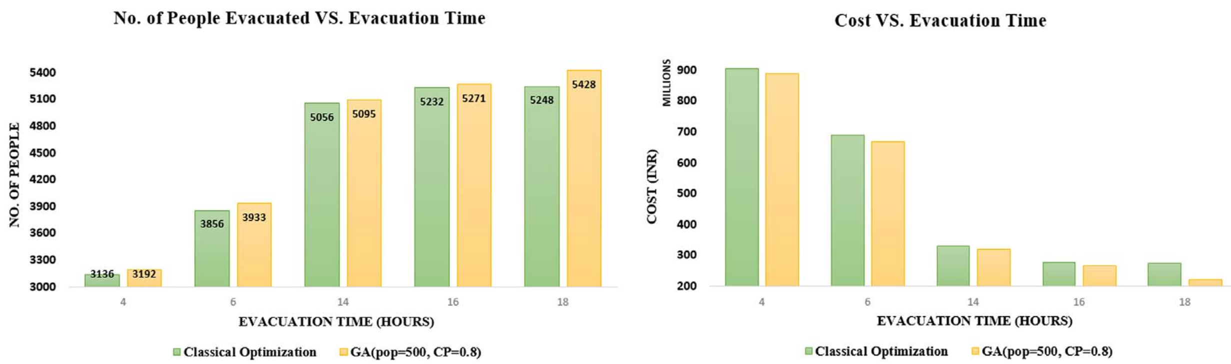


**Fig. 3.** No. of people evacuated vs. Evacuation Time (left) and Cost vs. Evacuation Time (right) for Classical optimization and GA for 6 blocks, 3 shelters and 3 priority blocks.

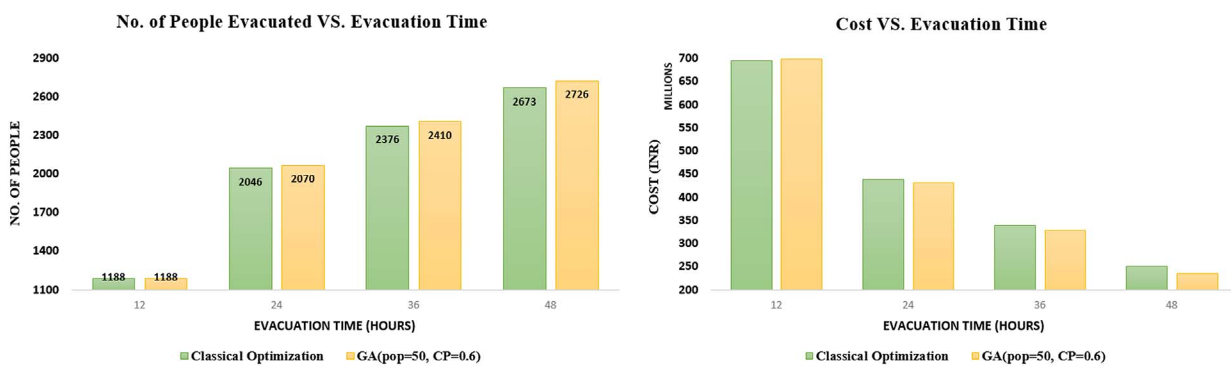


**Fig. 4.** No. of people evacuated vs. Evacuation Time (left) and Cost vs. Evacuation Time (right) for Classical optimization and GA for 10 blocks, 5 shelters and 6 priority blocks.

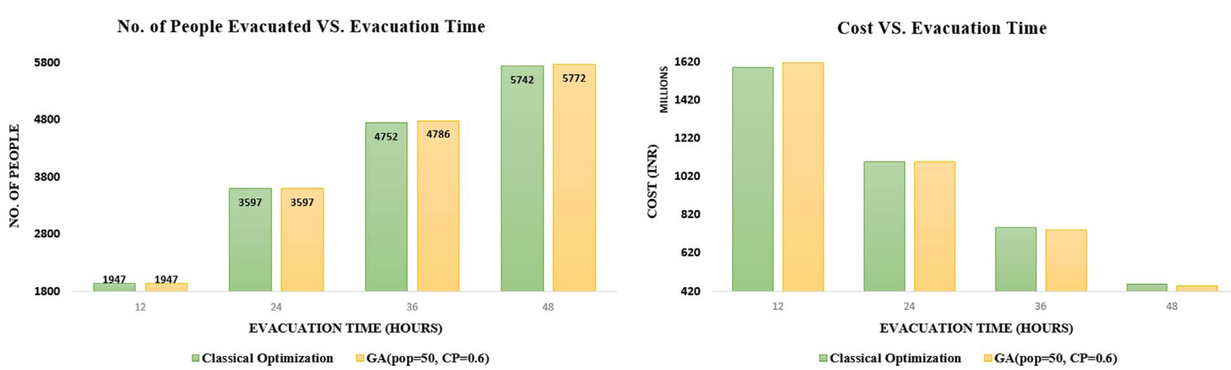


**Fig. 5.** No. of people evacuated vs. Evacuation Time (left) and Cost vs. Evacuation Time (right) for Classical optimization and GA for 20 blocks, 10 shelters and 15 priority blocks.

**Table 4**
Percentage of people evacuated in Classical Optimization (C.O) and GA.

| Block specifications | Time (Hours) | Percentage of people evacuated | | Percentage (%) of evacuated people supplied relief kits | |
|---|---|---|---|---|---|
| | | C.O | GA | C.O | GA |
| Block:6 | 12 | 33.94 | 33.94 | 100 | 96.46 |
| Shelter:3 | 24 | 58.46 | 59.14 | 100 | 100 |
| Priority Block:3 | 36 | 67.89 | 68.86 | 100 | 100 |
| | 48 | 76.37 | 77.88 | 100 | 100 |
| Block:10 | 12 | 26.86 | 26.86 | 100 | 87.67 |
| Shelter:5 | 24 | 49.61 | 49.61 | 100 | 100 |
| Priority Block:6 | 36 | 65.54 | 66.01 | 100 | 100 |
| | 48 | 79.2 | 79.53 | 100 | 100 |
| Block:20 | 12 | 19.88 | 24.27 | 100 | 89.59 |
| Shelter:10 | 24 | 38.59 | 41.03 | 100 | 100 |
| Priority Block:15 | 36 | 55.81 | 56.19 | 100 | 100 |
| | 48 | 70.34 | 70.34 | 100 | 100 |

total shelter capacity available is 5477 and keeping parity with that, it was assumed that 8% of the population needs to be evacuated from each of the priority mouzas.

Table 5 shows the parameter values taken to solve this problem and Table 6 describe the comparative result of total number of people evacuated, number of relief-kits provided and cost of operation though classical optimization technique as well as through GA. A graph is plotted (Fig. 7) using this data for pictorial visualization. It is seen that though the total shelter capacity was 5477, MIP is allocating at maximum 5248 people due to the hard constraints (9). This shortcoming is addressed through GA.

Fig. 7 shows two graphs, on the left, the number of people rescued with respect to evacuation time is illustrated and the graph on the right shows the cost incurred in evacuation time for both the classical optimization technique and GA. It is clearly visible from the graph that performance of GA is better than the other one as it is able to rescue more number of people with comparatively lower cost.

The total population of the Barrackpore Block II is approximately 216,000, whereas the available total shelter capacity is only 5477 i.e., 2.53% of the total population. Considering the density of the

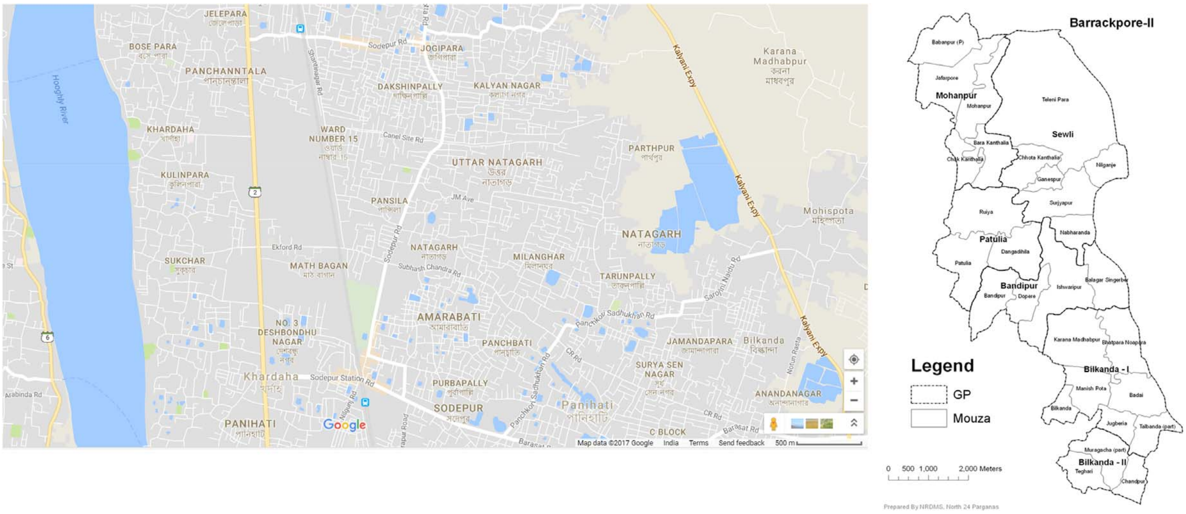


**Fig. 6.** Location identified from Google Maps (On the left side) and the actual map of the Barrackpore Block-II division (On the right side) collected from Govt. officials.

**Table 5**
Values of parameters which were served as input to the mathematical model.

| | |
|---|---|
| Average weight of a person | 60 kg. |
| Weight of relief kit | 2 kg. |
| Shelter Opening Cost | Rs. 50,000 |
| Penalty cost for not evacuating humans | Rs. 300,000 |
| Penalty cost for not supplying relief-kits | Rs. 100,000 |
| Capacity of vehicles carrying Humans | 2000 kg. |
| Capacity of vehicles carrying Relief Items | 500 kg. |
| Plying cost of vehicles carrying humans | Rs. 100/Km. |
| Plying cost of vehicles carrying relief-kits | Rs. 80/Km. |
| Average speed of vehicles | 20 km./h |

**Table 6**
Comparison between the classical optimization and GA (CP = 0.8) for the Case Study.

| | Classical Optimization | | | GA(pop = 500, CP = 0.8) | | |
|---|---|---|---|---|---|---|
| Time(Hours) | No. of people evacuated | No. of Relief-kits provided | Cost (in Rs.) | No. of people evacuated | No. of Relief-kits provided | Cost (in Rs.) |
| 4 | 3136 | 3136 | 906357100.9 | 3192 | 3192 | 889876740 |
| 6 | 3856 | 3856 | 690429381.1 | 3933 | 3933 | 667772640 |
| 14 | 5056 | 5056 | 330848694.8 | 5095 | 5095 | 319658662 |
| 16 | 5232 | 5232 | 278114678 | 5271 | 5271 | 266942132 |
| 18 | 5248 | 5248 | 273313752.7 | 5428 | 5428 | 219874852 |

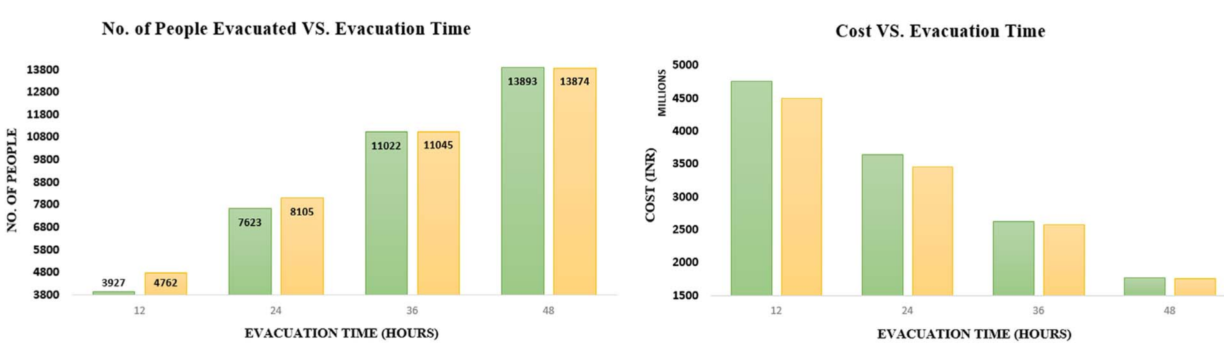


**Fig. 7.** No. of people evacuated vs. Evacuation Time (left) and Cost vs. Evacuation Time (right) for Classical optimization and GA for Case Study Data.

population, which is 5639 people/sq. km, the shelter capacity might be grossly inadequate in case of real disaster scenarios. It is seen from above that under ideal situations, it is possible to fill up 99% of the existing shelter capacity within 18 h. Thus, more number of shelters need to be built up and spread across the whole region (or closer to the priority regions) to achieve maximum effectiveness and coverage. Also, all shelters should consist of sufficient number of vehicles so that at the time of emergency, it would be possible to evacuate all the victims to the temporary shelters within a small time span.

The location and the capacity of the new shelters is under the purview of a separate optimization problem. The shelter locations should be strategic such that during a calamity, they should be accessible and less prone to damage. Intuitively, we can say that if the shelter building cost and shelter utilization are constraints to evacuate maximum number of people, then more number of shelters at strategic locations would be effective than a single large shelter. This would increase the reliability of the evacuation system. On the other hand, if the shelters are too much spread across, the shelter utilization would be less. The optimum solution would be achieved where the effects of the two constraints, as mentioned, break even with each other.

At the time of disaster, central depots are the sources of relief material for the displaced people. So, these must be placed at the optimal locations so that these can be utilized efficiently at the time of emergency. The positions of central depots should be planned in such a way that throughout rescue operation and relief distribution, they should be easily and quickly reachable and would be cost effective. Positions of central depots are under the scope of further research. This would certainly increase efficiency and effectiveness of the relief distribution.

## 8. Conclusions

This study is done in regard to the initial response just after the disaster. In reality, this needs to be followed by a detailed response action which may last for days/weeks/months until proper resilience. For this, a multi-period cost optimization model can be constructed. In addition to that, situations like shortages arising out of over-lapping disasters [55], transportation of multi-commodity items, transhipment between depots may also be needed to take into account to make the model closer to reality. Taking real time ground situation is also a very important factor while evaluating the models and thus needs to be effectively integrated in such models. In addition to all these, government echelons and proper communication also play vital roles. Needless to say that constructing, solving and implementing such types of models in practical scenario provides immense challenge. Though it is not always feasible to deploy the model in reality, it will surely give the directions and new insights to solve the problem in hand.

Disaster Management broadly consists of pre-disaster and post-disaster phases. Here, we have conducted a study for evacuation and relief distribution in case of a disaster. A mathematical model is developed and solved using MIP and GA. Both the algorithms are run on the hypothetically developed data as well as real life data and the results are compared. The results show that performances of both the methods are decent when sufficient evacuation time are available and number of blocks and shelters are also small. But, as the program instances increase and the evacuation time decreases, GA achieves much better result. This block-shelter allocation problem is one type of general assignment-allocation problems and it is also an NP-Complete problem [50]. So, solving this problem in polynomial time using classical optimization algorithm is not possible, as the input instances increase, solution search space grows exponentially. Though MIP has been used to solve this problem and it gives a consistent result when the input instances are small but its quality of solution degrades as the input instances are growing. Fig. 7 shows that the two graphs, in the left illustrated the number of people rescued with respect to evacuation time and the graph in the right shows the cost incurred in evacuation time for both the classical optimization technique and GA. It is clearly visible from the graph that performance of GA is better than the other one as it is able to rescue more number of people with comparatively low cost. In our case, we are not been able to compare both the techniques with larger data set as IBM ILOG CPLEX Optimization Studio Version 12.6.3 does not support larger data set.

The mathematical model has been built considering some of the real life variables. However, when one wants to implement this in reality, a lot other decisions needs to be taken. For example, it is assumed that in each of the mouzas, the vehicles were pre-positioned for evacuation purposes. This prepositioning of vehicles can be a potential assignment problem based upon the population that needs to be evacuated and the total number of vehicles that are available. The method followed to evaluate the priority of the sub-regions is based upon seven parameters. This method gives us a somewhat static calculation of the vulnerability and can be made more accurate and dynamic by considering real-time weather forecast with the movements of high-speed winds, rainfall etc. Also, availability of road network is an important factor during rescue and rehabilitation operations. In such a case, satellite imaging of the place just after the disaster or feedback from pre-positioned sensors on the road might also be an area of research.

Integrating the above study with the study of pre-disaster phase will result in a complete Disaster Management study. One of the aims is to deploy both the phases in an online dashboard system for predicting disasters and response after the disaster so that the administration and whole of the population can have access to the lifesaving information.

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