Models for Hospital Location and Capacity Allocation for an Area Prone to Natural Disasters

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Abstract

This paper develops and analyzes two basic models for hospital location and capacity allocation. The focus is on an area prone to natural disasters. The first model seeks to locate hospitals and allocate capacities so that the mean travel distance for patients to hospitals is minimized over a variety of disaster scenarios. The second model seeks to reallocate capacity among hospitals so as to maximize the system's effectivenss to the upcoming disaster event. Heuristic solution methods of the two models are investigated, so as to make the approach computationally viable and to gain insight into the location and capacity allocation strategies. A regional planner can use these models in various ways. For earthquake prone areas (where there is little forewarning) the first model's results can be compared to the current hospital locations and capacity allocations. A plan can then be developed to shift capacity between hospitals or in an extreme case to relocate hospitals so as to be better prepared for a disaster event. For hurricane prone areas (where there is considerable forewarning) the second model can be used to develop a plan for reallocation of capacities between hospitals in anticipation of the event. Furthermore the first model can be used to better locate hospitals and select capacities for an area that is being rebuilt after a large magnitude hurricane has largely destroyed the area (as Hurricane KATRINA did to New Orleans in 2005). The results are illustrated with the help of case studies–one based on earthquake scenario in Northridge, California, and another based on a hurricane scenario in New Orleans.

Keywords: Severity, Moment magnitude, Mainshock, Aftershock, Prioritized coverage, Landfall.

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1 Introduction

Hospitals or health care centers play a pivotal role in mitigating serious injuries that occur in a natural disaster. Examples of this include the events that followed KATRINA, TSUNAMI etc. KATRINA, a category 4 hurricane which struck New Orleans, on August 29, 2005, left around 710 dead and 10,000 or more injured as per news reports [1]. A 9.0 magnitude earthquake which struck the Indonesian coast on December 26th, 2004 left 11700 dead and hundreds of thousands of injured as per news reports [2].

Previous work in the planning of hospitals and/or health centers in a region has been done without considering the effects of damage to the hospitals and the transportation infrastructure in the event of a natural or manmade disaster. The focus of this extensive body of research is on optimizing a number of objectives, e.g. minimizing distance traveled by the patients and maximizing coverage of patients (percentage of patients who recevive care within a threshold time interval) [3]. A disaster can create hospital capacity reductions. The modeling of capacity reductions is itself a research endeavour and has recently received attention [4] in the context of natural disasters. Given the availability of capacity reduction data for a natural disaster prone region it is possible to improve the locations of hospitals and their capacities so as to minimize the impact of a disaster. This is the focus of our work.

Natural disasters are of two types, differentiated by the ability to predict the occurrence before it actually strikes a region. In case of a land earthquake, there is limited forewarning and hence little or no time available for capacity reallocation between hospitals. In case of a hurricane, reasonably accurate forecasting models are available and there is substantial time to plan for disaster mitigation. From the map displayed in Figure 1, the uncertainty with respect to Katrina's landfall can be seen. It can also be noted that after the initial tropical storm warning, three days time was available for capacity reallocation before it struck New Orleans.

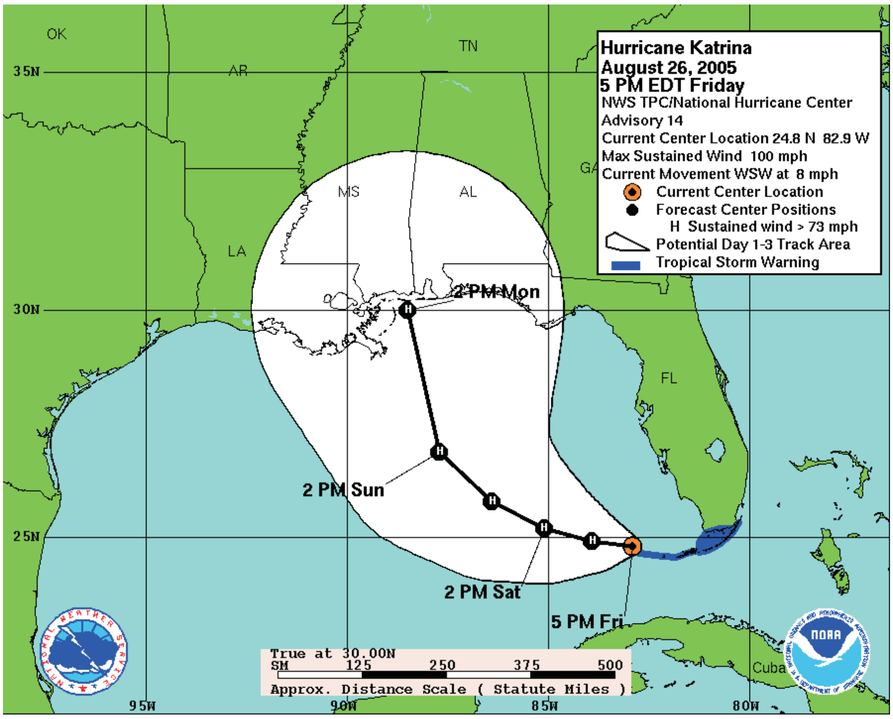


Figure 1: Katrina prediction uncertainty map, source: NHC archives

This work focusses on developing and analyzing two models for hospital location and capacity allocation for regions subject to natural disasters. A model for hospital location and capacity allocation is developed. A second model for capacity reallocation to an existing set of hospitals is also developed. Heuristics to solve realistic size problems are suggested. The use of these models towards strategic and tactical decision making in a natural disaster environment are illustrated through the aid of case studies.

The remainder of this paper is organized as follows. Section 2 contains a literature review. Section 3 presents Model I, its formulation, solution strategies and computational results. Section 4 presents Model II, its formulation and solution strategies. Section 5 demonstrates results of the models using case studies for an earthquake disaster. Section 5.1 focusses on a clean-slate design using scenario based modeling in Northridge, California and Section 5.2 uses results from section 5.1 for capacity reallocation by applying a variant of Model II. Section 6 focusses on a hurricane scenario in New Orleans. Section 6.1 focusses on capacity reallocation between existing hospitals. Section 6.2 demonstrates the use of Model I for clean-slate design toweards a rebuilt of the region. Section 7 presents our empirical observations in the case studies. Finally Section 8 contains our conclusions and suggests some directions for future work.

2 Literature Review

We consider various elements of the literature. We start by discussing on hospital location models, that consider objectives like distance minimization and priority queueing. The next part focusses on location models with a slant towards unreliable facilities. Due to absence of literature in hospital location in a disaster prone area we dedicate the third part of our literaure review on interdiction, i.e. when facilities are subject to manmade attack. The fourth part discusses methods for capacity allocation available in the literature. Since the disasters we model deal with inherently uncertain events we focus the final part of our literature review on decision making under uncertainty.

2.1 Objective based facility location models

Church [5] proposed that one way to measure the effectiveness of a facility location is determined by the average distance traveled by those who use it–the p-median problem does exactly this [6]. Another way to model the effect of distance is to assume that facilities become less reliable when the distance to a customer increases. Berman et al. [7] use this paradigm to locate service facilities.

Patients have different severity level injuries with their respective survivability times (time within which the patient should receive medical attention to have a viable chance of surviving). The assignment of patients to a hospital location should be prioritized based on the survivability times. Some work has been done in this regard by using principles of priority queueing [8, 9].

This basic work on facility location serves as a starting point for our models. Specifically, the objective function we use is akin to that of the p-median problem.

2.2 Locating unreliable facilities

Inherent in the vast majority of the location literature is the assumption that the facilities function normally and at full capacity when their services are needed. This assumption is reasonable for many applications, but not for a natural disaster setting. There has been some recent work in the area of unreliable facility location. The facility location problem with unreliable nodes or links has been studied extensively [10, 11]. Lee et al. [12]have developed heuristic solution methods for two location problems with unreliable facilities. Berman et al. [13] analyze a facility location problem in which some facilities might fail, causing customers to seek service from the remaining facilities and thereby increasing the cost of travel. Their major finding is that as the probability of failure or disruption grows the facilities tend to become more centralized and ultimately co-located.

The work on unreliable facilities is not directly used in our models but can be viewed as an alternative way of modeling facilities with reduced capacities (i.e., unreliable).

2.3 Models based on interdiction

A complementary way of modeling facility unreliability is to model the attack by an enemy on some of the facility sites. This is referred to in the literature by the term 'interdiction'. Whiteman [14] models both partial and complete interdiction at nodes of a network. Church et al. [15]have developed r-interdiction median covering problems to identify the set of r facilities whose loss would affect the service delivery the most. Hanley et al. [16]have developed a location-interdiction covering model that maximizes a combination of initial coverage level given p facilities and minimum coverage level after the loss of any subset of r facilities [16]. The work on interdiction is not directly used in our models, but can be viewed as a method to identify critical facilities (i.e., those whose capacity is most valuable).

2.4 Methods for capacity allocation

Choice of capacities of the service facilities are as important as are the choice of their locations. In maximal covering problems the capacities are allocated to sites based on the size of demand at the node [17, 18], which in case of a disaster is the number of casualties. Averbakh et al. [19] studied plant location with demand dependent capacity allocation. Previous work has dealt with capacity allocation based on demand, however in case of regional planning for hospitals, there exists constraints with respect to the available budget which influences the total capacity available to be allocated.

The term capacity in a hospital setting takes on several meanings, e.g., number of beds, number of operating rooms, and surgical efficiency. Thus categorization in addition to capacity allocation needs to be considered when dealing with hospitals. Categorization deals with the distribution of critical care service facilities among hospitals. Thomas et al. [20] have also studied categorization in hospital emergency planning. A higher capacity hospital has a greater chance of having more number of operating rooms and beds. This is because capacity has been postulated to be an empirical function of the number of beds, number of operating rooms, patient mix, and surgical efficiency [21, 22]. We use the empirically derived formulae in these papers to estimate capacity available at existing hospital sites in our case studies.

2.5 Decision making under uncertainty

Locating hospitals and allocating hospital capacity in a natural disaster prone area is a classic example of decision making under uncertainty. This is becuase the precise damage produced by a natural disaster is a function of many uncertain parameters (e.g., in a hurricane setting the parameters wind speed, width and shape of the cone, and mean height above sea level are relevant). One way to approach these types of problems is through the technique of robust optimization, wherein an effort is made to optimize the worst-case performance of the system [23]. The minimax regret approach is a good example of this technique. Similarly a risk based approach could be used to find a solution that works well over all the scenarios. Decision makers could apply regret approach in the following ways [24]:

1. Risk neutral decision-making: Decision is based on the expected value of the regret. Regret is defined as the additional cost incurred if an optimal solution for a particular scenario was used to solve the location allocation problem due to another scenario.

2. Risk averse decision-making: A very conservative strategy is that which yields minimum risk. In this case the maxmin of the expected payoffs is taken.

3. Risk prone decision-making: A risky strategy in which the solution with minimum regret is chosen. This is also called the optimistic approach in which the solution having the lowest cost is selected [25]. This is usually not a reasonable approach when human lives are at stake.

4. La Place Approach: This approach seeks a solution that yields the lowest average cost when all scenarios are equally likely to occur.

We use these four approaches in our case studies.

3 Model I: Hospital Location and Capacity Allocation

The output of this model is a set of hospital locations and capacity allocations. These are determined with the objective of providing services to the casualties in a manner that minimizes the average transport distance of a casualty to its closet hospital while meeting hospital capacity constraints. Since hospitals have a limited capacity it is possible that not all patients receive service. To accomodate these patients we create a fictitious site–which has a larger travel distance than the maximum travel distance that any serviced casualty may incur. We present the formulation for a specific damage scenario, i.e., when the capacity reductions due to disaster damage are assumed to be known.

Before we present the model we elaborate on the issue of hospital capacity. The least capacity that any real life hospital should have is equal to the Minimum base volume (smallest volume that the smallest sized hospital should be able to take) [21, 22]. At the same time there is an upper limit on the maximum capacity that any real life hospital could have, which is equal to Maximum critical volume (maximum volume that the biggest sized hospital would be able to take) [21, 22]. These minimum and maximum values are used when we decide hospital capacities in our model.

We introduce the following notation:

$y_{mk} \rightarrow$ Proportion of casualties from cluster m allocated to site k

$$x_{kl} = \begin{cases} 1 \text{ if a hospital of capacity } l \text{ is built at site } k \\ 0 \text{ otherwise} \end{cases}$$

$d_{mk} \rightarrow$ Distance from cluster m to site k

$d_{ms} = \max\{d_{mk}\} + 1 \qquad \forall m \in M \qquad \forall k \in K$

$n \rightarrow$ Number of hospitals to be built

$Min\ B.V. \rightarrow$ Minimum Base Volume

$Max\ C.V. \rightarrow$ Maximum Critical Volume

$f_k \rightarrow$ Fraction of full capacity available at site k

$K\rightarrow$ Set of potential sites

$M\rightarrow$ Set of clusters(demand nodes)

$c_m\rightarrow$ Estimate of casualties at cluster m

$C\rightarrow$ Total capacity available to be allocated

Using this notation the model formulation is as follows:

(P1)

$$Minimize \sum_{m\in M}\sum_{k\in K\cup\{s\}} c_m y_{mk} d_{mk}$$

Subject to:

$$\sum_{m\in M} c_m y_{mk} \leq \sum_{l=MinB.V.}^{MaxC.V.} f_k l x_{kl}, \qquad \forall k \in K \tag{1}$$

$$\sum_{k\in K\cup\{s\}} y_{mk} = 1, \qquad \forall m \in M \tag{2}$$

$$\sum_{k\in K}\sum_{l=MinB.V.}^{MaxC.V.} x_{kl} = n, \tag{3}$$

$$\sum_{k\in K}\sum_{l=MinB.V.}^{MaxC.V.} l x_{kl} = C, \tag{4}$$

$$\sum_{l=MinB.V.}^{MaxC.V.} x_{kl} \leq 1, \qquad \forall k \in K, \tag{5}$$

$$x_{kl} \in \{0,1\}, \qquad \forall k \in K, \qquad \forall l = MinB.V., ..., MaxC.V. \tag{6}$$

$$0 \leq y_{mk} \leq 1, \qquad \forall m \in M, \qquad \forall k \in K \cup \{s\}. \tag{7}$$

An explanation of the formulation is as follows: constraint 1 ensures that the number of casualties allocated from a cluster m to any facility k are less than or equal to the capacities available at the facility k. To see this we note that the term lx_{kl} represents the capacity of the hospital prior to the disaster striking, and when this is multiplied by the damage factor f_k we get the hospital capacity after the disaster. Constraint 2 requires that casualties from all m clusters are allocated to some facility. Constraint 3 makes sure that a total of n facilities are located. Constraint 4 ensures that the total capacity allocated to the k facilities is equal to C, i.e. the total available capacity. Constraint 5 makes sure that a site has at most one facility/capacity combination.

3.1 Solution strategies

We have tried solving numerous problem instances for (P1) using the MIP solver in CPLEX. The solution times are reasonable for cases when the number of potential sites, $K = 100$. However for larger problem sizes wherein K consists of 300 or 500 sites, CPLEX is unable to deliver a feasible solution within an hour of computation time. To handle such instances we developed a heuristic procedure.

The heuristic procedure is based on a location allocation method [26]. The basic idea is to start off with an intelligent initial choice of facility locations for the hospitals and use this to dramatically reduce the size of the problem (P1). The reduced problem is readily solved using CPLEX, which yields the hospital capacities. Then we use Simulated Annealing (SA) to attempt an improvement in the facility location choices. The details are as follows:

Initial choice of facility locations:

The sites are ranked based on their scores using the function $\sum_{m \in M} f_k^2/d_{mk}$. The reason that the f_k term is squared is to give a greater weightage to facility damage. After the scores are computed for all the $|K|$ sites, the highest n ranked sites are chosen. This is used as the initial set of hospital locations for capacity allocation.

Reduced Problem:

This problem has a very small size compared to (P1) because here we deal with N set of sites with $|N| = n$ whereas in (P1) we had to deal with $|K|$ potential sites. Since the number of sites is equal to the number of hospitals, constraint 3 is not needed and constraint 5 is now on equality constraint. We arrive at the following reduced problem that is effciently solved via CPLEX.

(Q1)

$$Minimize \sum_{m\in M}\sum_{k\in N\cup\{s\}} c_m y_{mk} d_{mk}$$

Subject to:

$$\sum_{m\in M} c_m y_{mk} \leq \sum_{l=MinB.V.}^{MaxC.V.} f_k l x_{kl}, \qquad \forall k \in N \tag{8}$$

$$\sum_{k\in N\cup\{s\}} y_{mk} = 1, \qquad \forall m \in M \tag{9}$$

$$\sum_{k\in N}\sum_{l=MinB.V.}^{MaxC.V.} l x_{kl} = C, \tag{10}$$

$$\sum_{l=MinB.V.}^{MaxC.V.} x_{kl} = 1, \qquad \forall k \in N \tag{11}$$

$$x_{kl} \in \{0,1\}, \qquad \forall k \in N, \qquad \forall l = MinB.V., ..., MaxC.V. \tag{12}$$

$$0 \leq y_{mk} \leq 1, \qquad \forall m \in M, \qquad \forall k \in N \cup \{s\}. \tag{13}$$

An iteration of SA method:

An explanation of the SA procedure used in our work is as follows: For all our implementations, we start with a temperature of 5000K and cool it by a factor of 0.8 at the end of a fixed number of iterations. The algorithm proceeds until the temperature drops to 1K. Each of the n sites in the current solution is replaced by its neighbor and the problem is solved again. This new solution is accepted if it is better. If the solution is worse then it is accepted with a probability $p = \exp -\frac{\delta f}{t}$, where δf is the increase in objective function value and t is a temperature control parameter. The best solution is reported. The neighbors of a given site are selected first from the cluster to which the given site belongs; subsequently sites from the remaining clusters are chosen. An additional selection criteria is that the site should have a ranking less than or equal to the site under consideration. This is because all sites with better ranking would already be present in the set of N sites.

The clusters are developed using the K-Means clustering algorithm [27]. In this method the number of clusters is prespecified and the algorithm assigns the sites to the requisite number of clusters. We chose 10 clusters for our analysis as this gave approximately 10 sites per cluster.

3.2 Computational experiments

In this section, we present our computational results. We classify the problems into three categories- small, medium and large, based on their complexity. The choice of model parameters is based on the earthquake and hurricane case studies presented in Sections 5 and 6 respectively. For each category we solved one instance for all the different severity classes of earthquake and hurricane disasters. All problems were run on a Pentium IV, 1.4 GHz processor and 512 MB RAM. The numbers reported in the results table are the objective function values (total average weighted distance (miles) that the casualties have to travel to reach the hospital sites to get the required care) obtained after solving the instances of (P1) using CPLEX and the SA heuristic.

Small-size problems

A set of 100 potential sites were considered for the facility location and capacity allocation for both earthquake and hurricane problems. 14 and 20 Clusters (demand nodes) were considered, respectively, for earthquake and hurricane disasters. We assumed that 30 sites were to be built. The capacity to be allocated was assumed to be 5000. The regions of study were Northridge, California and New Orleans. Earthquake and hurricanes belonging to five categories were simulated using [28]. CPLEX 9.0 was used as a benchmark. The heuristic was run for half an hour to obtain the best possible results. CPLEX successfully gave us the optimal solution for small size problems in a shorter period of time and hence is the preferred solution method for such instances. We note, however, that the heuristic solution for such problem sizes is of very good quality–this is important since it turns out that the heuristic is the only viable solution method for medium and large size problems (next sub-section).

Medium and Large size problems

A set of 300 (medium) and 500 (large) sites was chosen for these problems. The number of demand nodes, sites to be built, and capacity to be allocated was unchanged. As stated earlier, CPLEX was not able to generate a feasible solution for these problems within an hour of computation times. Thus we only report results of the heuristic after it ran for 30 minutes. We note here that, as expected, the total casualty travel distance increases dramatically as the earthquake and hurricane categories become more severe.

Table 1: Computational results: heuristic (earthquake)

Earthquake category	Small size problem (100 Sites)		Medium size problem (300 Sites)		Large size problem (500 Sites)	
	Heuristic	CPLEX	Heuristic	CPLEX	Heuristic	CPLEX
Small	282	273	363	Not solvable	334	Not solvable
Moderate	335	324	357	NS	348	NS
Strong	1083	1012	1143	NS	1128	NS
Major	2138	2012	2038	NS	2020	NS
Great	5398	5299	5355	NS	5343	NS

Table 2: Computational results: heuristic (hurricane)

Hurricane category	Small size problem (100 Sites)		Medium size problem (300 Sites)		Large size problem (500 Sites)	
	Heuristic	CPLEX	Heuristic	CPLEX	Heuristic	CPLEX
1	493	483	329	Not solvable	320	Not solvable
2	577	567	387	NS	375	NS
3	1837	1827	1242	NS	1184	NS
4	3643	3637	2456	NS	2341	NS
5	10576	7609	5967	NS	5563	NS

4 Model II: Capacity Reallocation

The objective of this model is to try to readjust hospital capacities so that the resultant capacity configuration minimizes a weighted sum of the average distance traveled by a casualty to its closest hospital (while meeting hospital capacity constraints) and the cost of the capacity readjustment itself. We note here that the capacities of the hospital are based on empirical formulae developed in the work [21]. Also, we note that casualties that are not served by the existing set of facilities are sent to a fictitious site, as in Model I.

We use the same notation as in the formulation of (P1) with the understanding that now K signifies the set of existing hospitals (as opposed to the set of potential sites), and with the following additions:

$Cap_k \rightarrow$ Current capacity of hospital k

$C = \sum_{k \in K} Cap_k$

$\theta \rightarrow$ Cost of moving one unit of capacity

The formulation is as follows:

(P2)

Minimize $\sum_{m \in M} \sum_{k \in K \cup \{s\}} c_m y_{mk} d_{mk} + \sum_{k \in K} \sum_{l=MinB.V.}^{MaxC.V.} \theta \left| Cap_k - l x_{kl} \right|$

Subject to: (1), (2), (4), (6), (7), and

$$\sum_{l=MinB.V.}^{MaxC.V.} x_{kl} = 1, \forall k \in K. \tag{14}$$

We note that constraint 14 ensures that exactly one capacity combination is used for each current hospital site.

Our numerical experience has shown that even large instances of $P2$ can be solved effectively using CPLEX, making the development of a heuristic unnecessary.

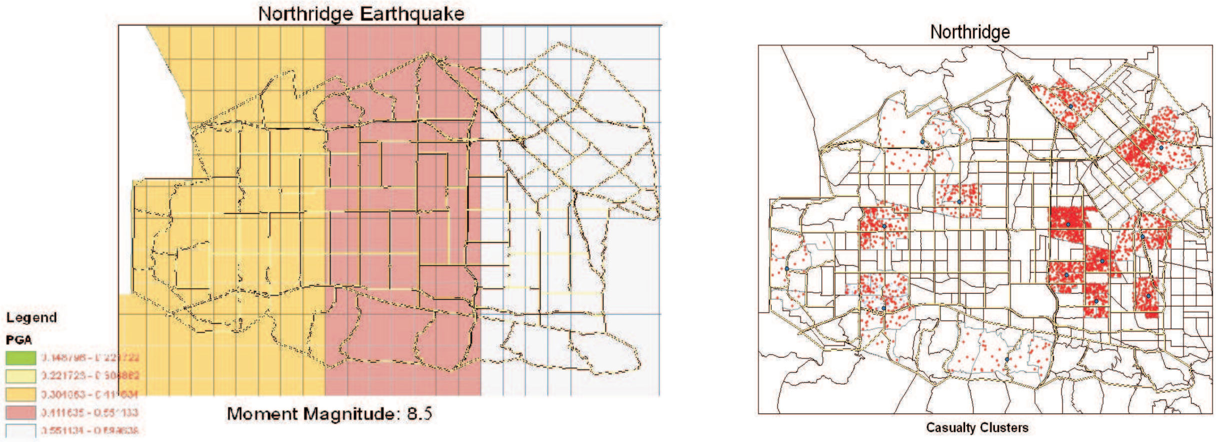
5 Earthquake Case Studies

A regional planner could make use of the two models in various ways. Model I could be used to perform a clean-slate design for an earthquake prone region. In such a design we assume that no hospitals have been built and the design tells us where to build hospitals and what capacity each hospital should be. However, a more likely situation is one in which hospitals already have been built in an earthquake prone region and a decision has to be made on capacity reallocation between these sites so as to best prepare for an earthquake. To do this we first close down hospitals that are likely to be severely damaged. Then we reallocate capacities among the remaining hospitals using a variant of Model II.

Since hospital location and capacity allocation for a region prone to earthquake is an example of decision making under uncertainty, a scenario based modeling is appropriate. The different size earthquakes would act as the scenarios to be considered. Magnitude is a measure of the size of the earthquake source and is the same number no matter where a person is or what the shaking feels like. The earthquakes are categorized as *great* for magnitudes greater than or equal to 8, *major* - between 7 and 7.9, *strong* - between 6 and 6.9, *moderate* - between 5 and 5.9, *light* - between 4 and 4.9, *minor* - between 3 and 3.9 and *micro* for those less than 3.

5.1 Clean-slate design

Earthquake scenarios for the Northridge region in California were generated using HAZUS MH software. The epicenter for the earthquakes was set as latitude 34.41000, longitude -118.40002. The casualties due to this earthquake were obtained from the results of scenarios simulated using the HAZUS software. Casualty clusters were formed based on the casualty distribution using the K Means clustering algorithm. The clusters were developed based on a 8.5 magnitude earthquake. We considered the situation with 14 clusters as this gave approximately 2 hospitals per cluster. The peak ground acceleration distribution of an earthquake with moment magnitude equal to 8.5 and the corresponding casualty distribution is shown in Figure 2(a) and 2(b) respectively. We have considered 100 potential sites for



(a) Peak ground acceleration (b) Casualty clusters

Figure 2: Peak ground acceleration and casualty clusters - Northridge, CA

hospitals, with an attempt of distributing them uniformly throughout the region and at the same time making them easily accessible to highways. These sites are shown in Figure 2(b). The number of hospitals to be built, is taken as 30. The total capacity available to be allocated has been considered as 5000. HAZUS was used to generate the following scenarios: magnitude 5, 5.5, 5.9, 6.0, 6.5, 6.9, 7, 7.5, 7.9, 8 and 8.5. CPLEX 9.0 was used to generate solutions for the scenarios using Model I. The risk neutral, risk averse, risk prone and La place approaches are used to judge solution quality and in making a recommendation. The results are shown in the Table 3 . It turns out that in this case the solution for scenario 8 is the suggested solution for the risk averse, risk neutral, risk prone and La place approaches. Hence this solution is recommended and is shown in Figure 3.

Table 3: Solution for clean-slate design(earthquake)

	Solution										
	5	5.5	5.9	6	6.5	6.9	7	7.5	7.9	8	8.5
Scenario											
5	optimal	0	0	0	0	0	13	0	0	28	163
5.5	0	optimal	0	0	0	2	32	0	0	39	347
5.9	0	0	optimal	0	0	3	41	0	0	58	604
6	29.85	27.6	27.6	optimal	0	3	47	0	0	166	1195.6
6.5	14.82	45.16	45	0	optimal	5	59	0	0	88	1113.6
6.9	1050	1297	1435	266	868	optimal	257	10	15	1394	9592
7	1243	1613	1816	382	1078	41.4	optimal	13.8	22.8	1911	11439
7.5	5390	5632	6146	5659	5032	3753	4492	optimal	0	9343	27122.1
7.9	9356	10691	11583	12026	14495	10134	12077	3804	optimal	15317	42941
8	57736.6	44846	53389	46017	67553.6	36992	58925	51324	85879	optimal	29382
8.5	97569	84951	92733	79148	104783	76922	98121	97167	130813	39221	optimal
Avg(Payoff)	42029	39912	41555	39402.72	43976	37979	42181	40201	46056	324996	37620
Min(E(Payoff))	12	12	12	12	12	4	25	12	12	40	175
Max regret	97569	84951	92733	79148	104783	76922	98121	97167	130813	39221	42941
Avg regret	17239.05	14910	16717	14350.01	19381	12785	17406	15231	216734	6756	12390
Stdev(regret)	31623	26748	29719	25494	34675	24015	31994	31256	44486	11871	14607
Minmax(regret)											39221
Min(Avg regret)											6756
Min(Stdev(regret))											11871
MaxMin(E(Payoff))											175
La Place											32499
Recommended solution											Scenario 8

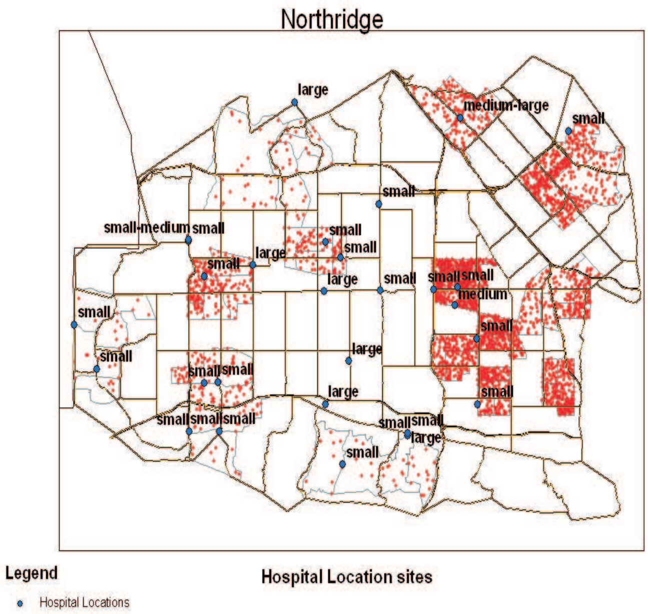


Figure 3: Solution for clean-slate design (earthquake)

5.2 Capacity reallocation

Some hospitals are so severely damaged due to an earthquake that they are not usable for any disaster mitigation purposes. Therefore when reallocating capacities we first need to close down these hospital sites and only consider the remaining sites. These hospital buildings are the ones which get red tagged by inspection teams evaluating the building status following the event of a severe earthquake. More precisely, the buildings damaged due to earthquake are given tags based on their damage state after the mainshock (the first earthquake). These are green, yellow and red in increasing order of damage. There typically are a series of earthquakes called aftershocks following the mainshock. Their effect needs to be considered to have reliable estimates of total damage possible over a period of time after the mainshock strikes. However, Paul et al. [4] have shown that there is no need for consideration of aftershock effects for green or yellow tagged buildings. This is because aftershocks resulting from an earhthquake causing damage equivalent to green or yellow tags are generally associated with a low magnitude mainshock. However red tagged buildings typically suffer additional damage due to aftershocks. Thus only red tagged buildings should be closed down and be not considered for any capacity reallocation.

Capacity reallocation among the existing set of hospitals is done using Model II with zero cost for moving one unit of capacity, i.e. $\theta = 0$. The existing set of hospitals, considered with their capacities, is shown in Table 5. We plan the capacity reallocation for Scenario 8. The set of hospitals with their existing and reallocated capacities is shown in Table 4.

Table 4: Reallocation of capacity among non-red tagged hospitals in Northridge, CA

ID	Hospitals in LA	BED	OR	EFF	Existing Capacity	Capacity After Reallocation
1	VALUEMARK PINE GROVE HEALTH	80	3	400	64	510
2	ENCINO-TARZANA REG MEDICAL CTR	387	7	900	213	74
3	COLUMBIA WEST HILLS MED CTR	300	5	600	137	315
4	ENCINO-TARZANA REG MED CTR	286	11	1121	322	510
5	GRANADA HILLS COMM HOSPITAL	139	5	600	106	31
6	PROVIDENCE HOLY CROSS MED CTR	254	8	845	201	31
7	MISSION COMMUNITY HOSPITAL	158	3	540	91	66
8	SHERMAN OAKS HOSP HLTH CTR	153	3	420	80	31
9	PACIFICA HOSP OF THE VALLEY	217	5	285	77	31
10	KAISER FOUNDATION HOSPITAL	192	8	992	209	31
13	NORTHRIDGE HOSPITAL MED CTR	371	14	421	193	510
14	VALLEY PRESBYTERIAN HOSPITAL	290	7	566	151	31

The results from this reallocation can also be used to identify potential sites for any future expansion. From Table 4 we can see that Valuemark Pine Grove Health, Encino-Tarzana Regional Medical Center(Tarzana) and Northridge Hospital Medical Center are the hospital sites where future capacity expansion is recommended.

The results from Model I could also be used for hospital relocation and capacity allocation by setting the parameter C to be equal to the net capacity available from the existing set of hospitals. The solution obtained from the clean-slate design was significantly better than that obtained using the current hospital locations, which indicates that the initial planning of hospital locations was not good.

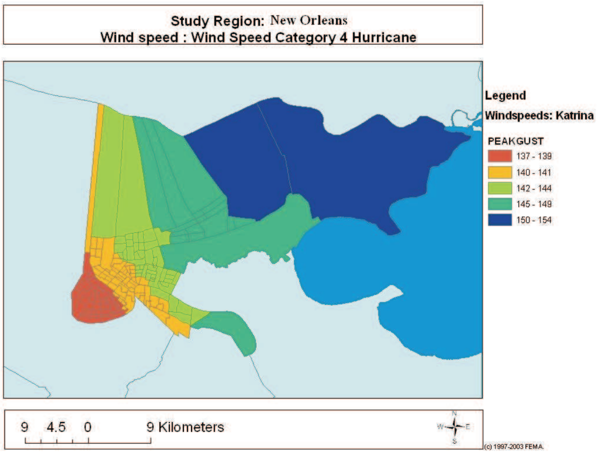
6 Hurricane Case Studies

For natural disasters like hurricanes, which have time available to plan, Model II could be used to reallocate capacities to an existing set of hospitals using scenario based modeling. Furthermore, Model I could be used for hospital location and capacity allocation for a rebuilt region devastated by a severe hurricane. Hurricanes are of different severities or categories. This categorization is based on the wind speeds. A wind speed is the most common measure of a hurricane's size. The Saffir/Simpson scale is often used to categorize hurricanes based on wind speed and damage potential. Wind speeds between 74 and 95, are classified as a hurricane of cateogry 1. Similarly wind speeds between 96 and 110, wind speeds between 111 and 130 , those between 131 and 155 and those greater than 155 miles per hour are classified as categories 2, 3, 4 and 5 respectively.

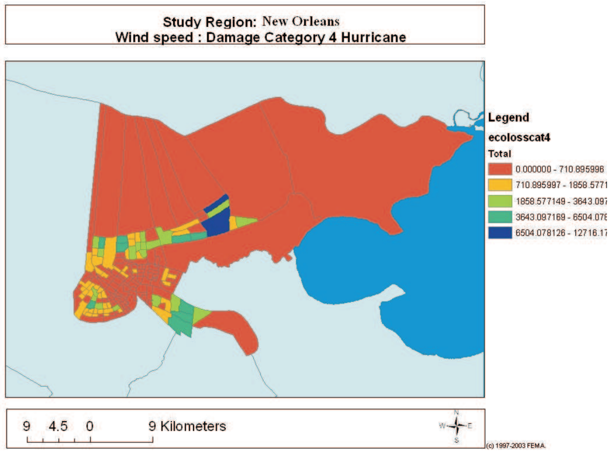
6.1 Capacity reallocation

HAZUS-MH was used to generate the following scenarios: category 1, 2, 3, 4 and 5 hurricanes. The region of study was chosen as New Orleans. The wind speed distribution and the damage caused by a category 4 hurricane are shown in Figures 4(a) and 4(b) respectively. A set of 20 casualty clusters were chosen to yield a one-to-one cluster to hospital ratio. They were developed using K Means clustering algorithm. The net capacity available at the existing set of hospitals was calculated using the empirical formulae developed in [21].

For the case of zero cost of moving capacity, the results after using Model II yield the numbers shown in Table 5. We note, by comparing the last two columns of Table 5, that a



(a) Wind speed-category 4



(b) Damage category 4

Figure 4: Wind speed and damage distribution for category 4

very significant reallocation occurs to prepare for the ensuing hurricane. If a cost is attached to capacity reallocation, this results in less capacity being reallocated and consequently in a larger total distance traveled by casualties. This increased travel distances (in percentage terms) is shown in Table 6. As expected, the distance increases as cost of reallocation increases, but the effect is concave and is more significant for hurricanes of higher category. It can also be noted that the travel distances increases with increase in severity of hurricane upto category 4 but it decreases for category 5. This is because number of casualties for hurricanes upto category 4 in this case study is less than the capacity available. However, for hurricane of category 5, the number of casualties is more than the capacity available.

6.2 Clean-slate design

The following factors need to be considered when chosing potential sites for facility location and capacity allocation for a region being rebuilt after being devastated by a severe hurricane (e.g., New Orleans after KATRINA):

Table 5: Capacity reallocation: hospitals in New Orleans

ID	Hospitals in New Orleans	BED	OR	EFF	Existing Capacity	Capacity After Reallocation
1	West Jefferson Medical Center	448	15	1200	507	31
2	Veterans Affairs Medical Center	203	5	600	119	510
3	Tulane University Hospital and Clinic	75	2	400	64	510
4	Touro Infirmary	175	5	900	140	510
5	St.Tammany Parish Hospital	203	5	1087	151	31
6	St.James Parish Hospital	566	9	1200	322	31
7	St.Charles Parish Hospital	476	15	895	425	31
8	Sidell Memorial Hospital and Medical Center	144	6	717	131	31
9	Ochsner Clinic Foundation	56	4	265	36	31
10	Medical Center of Louisiana at New Orleans	15	2	225	35	510
11	Meadowcrest Hospital	203	10	800	211	31
12	Lakeview Regional Medical Center	465	5	1200	166	120
13	Lakeside Hospital	341	9	1000	263	31
14	Kenner Regional Medical Center	144	5	1100	146	31
15	East Jefferson General Hospital	317	85	1000	234	510

Hurricane Category	Percentage Increase in Distance					
	Unit Capacity Moving Cost					
	50	100	150	200	250	300
1	2.93	2.93	2.93	2.93	2.93	2.93
2	5.56	5.56	5.56	5.56	5.56	5.56
3	25.39	25.39	25.39	25.39	25.39	25.39
4	86.5	86.5	86.5	86.5	86.5	86.5
5	21.1	26.42	26.61	26.71	26.85	26.92

Table 6: Percentage increase in distance traveled by casualties

1. **Wind speeds:** Wind speeds severely affect the damage caused due to hurricanes. Category 1 causes minimal damage. The remaining categories cause moderate, extensive, extreme and catastrophic damage in increasing order of severity.

2. **Elevation:** Elevation of a region is very important. Flooding of a region when subjected to hurricanes is very significant concern if the height of the region is at or well below sea level. On August 30, 2005, one day after KATRINA made landfall, 80 percent of the city of New Orleans was flooded, with some parts of the city under 20 feet (6 m) of water. Many of the hospitals in New Orleans were well below the sea level, as shown in Table 7. The mean elevation of the fifteen hospitals is in fact 1.3 feet below sea level.

3. **Distance from nearest water source**: The heavy wind forces generated during severe hurricanes can push water from the surrounding lakes, seas and rivers into the city and cause lot of damage due to flooding. This situation is further aggravated if the height of the region under consideration is below sea level. For example, the severe damage due to KATRINA in New Orleans was largely because it is surrounded by the Mississippi river to the south, lake Pontchartrain to the north, and the Gulf of Mexico to the east.

Potential sites which were very near to these water sources were not considered as they incurred severe damage. Similarly we did not consider sites which have an elevation that was below a user specified limit. Risk neutral, risk prone, risk averse and La place approaches are used to judge the solution quality and make the final recommendation. CPLEX 9.0 was used to generate solutions for the scenarios. The results obtained are reported in Table 8. It turns out that in this case the solution for category 2 is the suggested solution for most of the approaches. Hence this solution (shown in Figure 5) is recommended.

Table 7: Elevation above sea level: hospitals in New Orleans

ID	Hospitals in LA	Height above sea level(feet)
1	West Jefferson Medical Center	-1.6
2	Veterans Affairs Medical Center	-3.1
3	Tulane University Hospital and Clinic	0.0
4	Touro Infirmary	0.0
5	St.Tammany Parish Hospital	0.0
6	St.James Parish Hospital	-6.3
7	St.Charles Parish Hospital	-1.3
8	Sidell Memorial Hospital and Medical Center	0.0
9	Ochsner Clinic Foundation	0.0
10	Medical Center of Louisiana at New Orleans	0.0
11	Meadowcrest Hospital	0.0
12	Lakeview Regional Medical Center	-0.2
13	Lakeside Hospital	-3.4
14	Kenner Regional Medical Center	-4.2
15	East Jefferson General Hospital	0.0

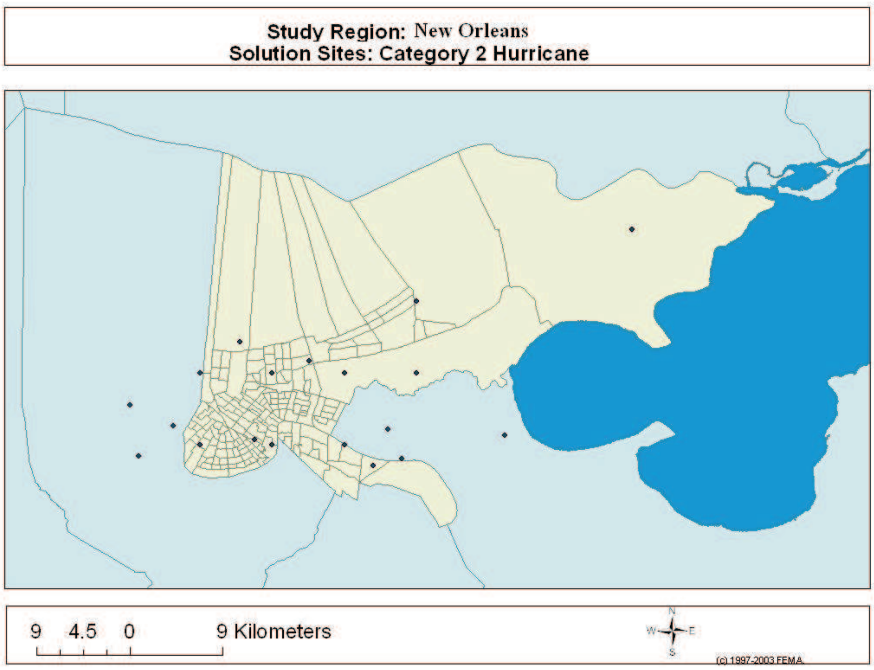


Figure 5: Solution - New Orleans

Table 8: Solution for Clean-slate design(hurricane)

	Solution				
	cat1	cat2	cat3	cat4	cat5
Scenario					
cat1	optimal	8.00	55.30	55.30	123.20
cat2	817.10	optimal	1.80	5.80	30.60
cat3	961.60	13.30	optimal	0.10	7.60
cat4	1803.80	12.40	10.00	optimal	4.20
cat5	2451.70	29.10	2.50	2.50	optimal
Max Regret	2451.70	29.10	55.30	55.30	123.20
Average Regret	1206.84	12.56	13.92	12.74	33.12
Stddev Regret	945.32	10.64	23.45	23.91	51.73
E(Payoff)	2398.00	2406.00	2453.30	2453.30	2521.20
Average(Payoff)	4822.1	3627.82	3629.18	3628	3648.38
MinMax					29.10
Minaverage					12.56
Minstddev					10.64
MaxMin(E(Payoff))					2521.20
La Place					3627.82
Recommended Solution					Sol-Scenario 2

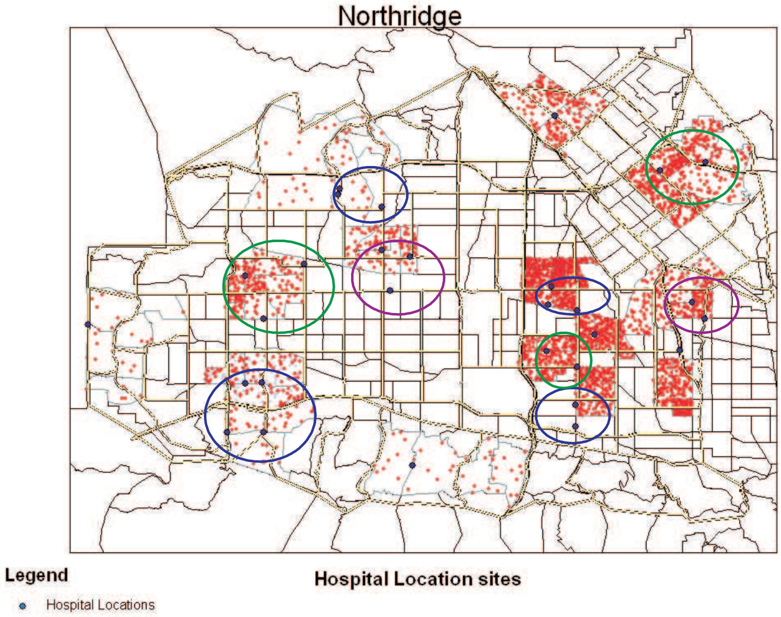


Figure 6: Observation 1

7 Empirical Observations

In this section we present a set of empirical observations based on our case study runs.

Observation 1: The set of facilities serving a cluster form a cluster themselves.

An example of this observation is seen in the solution presented in Table 5 for the case of a magnitude 8.5 earthquake, with n =30, C=5000 and K=100 has been shown in Figure 6.

Observation 2: The number of facilities that need to be located n varies with the magnitude of the disaster, with a minimum value of $n = (C/Max(CriticalVolume))$.

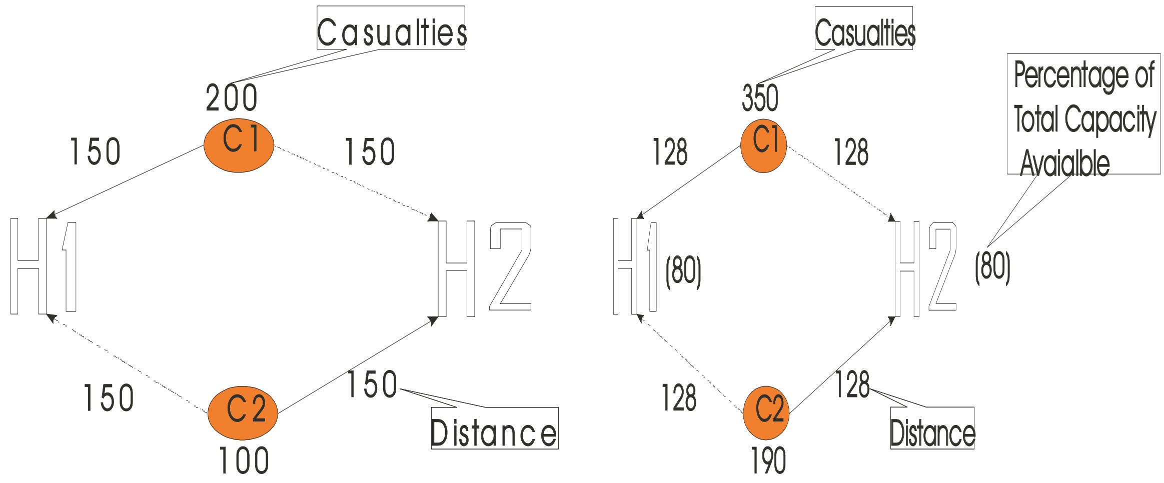
An example of this observation is that the objective function value when $n = 30$ is 2.62 x 10^5 while for $n = 10$, the objective function was 2.49 x 10^5. This example is based on an earthquake simulation for a 8.5 magnitude earthquake. For a $Max(CriticalVolume) = 600$ and $C = 5000$, we get a minimum value of $n = 9$.

Observation 3: The number of facilities which have reduced capacity is larger in a natural disaster than in a manmade disaster. This is because in a manmade disaster (e.g., a terrorist attack) the facilities will be targeted for maximum damage which may result in some facilities being totally damaged and others being unscathed, whereas in a natural disaster the damage to facilities is likely to be more widespread.

Observation 4: For the case when the total capacity is more than the number of casualties, reallocation of capacities is not desirable since the current solution is usually acceptable. For the dual case, i.e. when the total capacity is less than the number of casualties, reallocation is desirable and the extent of it depends on the cost of reallocating a unit of capacity.

Observation 5: There are two cases: In case 1 for low magnitude situations with two clusters ($m1$,$m2$) served totally by two hospital locations ($k1$,$k2$) respectively, an alternate solution can be obtained only if the two hospital locations are at approximately equal distance from the two clusters. In case 2 for higher magnitude disasters, the additional condition that needs to be satisfied is that the percentage capacity reduction should be approximately equal. See Figure 7.

Observation 6: For the case when the total capacity is greater than the number of casualties, the optimal number of facilities could be less than n, the prespecified number of hospitals to be built. However for the case when total capacity is less than or equal to the number of casualties, the optimal number of facilities could be greater than n, the prespecified number of hospitals to be built. This observation is of considerable significance to planners in deciding the number of hospitals to be built. This is because in low magnitude regions there could be some facilities which actually do not serve any casualties. The ca-



(a) Case 1 (b) Case 2

Figure 7: Observation 5 - cases 1 and 2

pacities of these hospitals could be reallocated to other facilities and the disaster mitigation can be made better. Similarly in a high magnitude disaster prone region, it is possible that disaster relief efforts would have been better if there were a larger number of hospitals.

8 Conclusions and Future Research

The hospital locations and capacity allocations obtained using Model I are much better than the original hospital sites in terms of disaster mitigation efforts. Also capacity reallocation to existing set of hospitals using Model II shows that there is significant amount of reallocation required to be done to maximize the benefit from the relief efforts. These models could be used to enhance hospital planning efforts for a natural disaster prone region.

In the current research, all the casualties are considered to have the same severity. However, the routing of the casualties needs to take into account this severity so as to maximize the number of lives saved. Capacity allocation too needs to take into account this factor. Similarly survivability time needs to be considered. This study has taken into account only natural disasters, however, similar models can also be developed for manmade disasters, e.g., terrorist attacks.

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