Journal of the Eastern Asia Society for Transportation Studies, Vol. 6, pp. 4237 - 4252, 2005

SHELTER LOCATION-ALLOCATION MODEL FOR FLOOD EVACUATION PLANNING

Sirisak KONGSOMSAKSAKUL
Graduate Student
Department of Civil & Environmental Engineering
Utah State University
Logan, UT 84322-4110 USA
Fax: +1-435-797-1185
E-mail: sirisak@cc.usu.edu

Chao YANG
Associate Professor
Department of Traffic Engineering
School of Transportation Engineering
Tongji University
Shanghai, 200092 P.R. China
Fax: +86-21-6598-2274
E-mail: tongjiyc@mail.tongji.edu.cn

Anthony CHEN
Associate Professor
Department of Civil & Environmental Engineering
Utah State University
Logan, UT 84322-4110 USA
Fax: +1-435-797-1185
E-mail: achen@cc.usu.edu

Abstract: The optimal shelter locations for the flood evacuation planning are studied in this paper. We assume that the authority can control the traffic in certain part of the network while the evacuees choose which shelter to go and by which route. The shelter location problem is posed as a Stackelberg game, consisting of the leader (authority) determining the shelter locations to minimize the total evacuation time and the follower (evacuees) choosing the destination (shelter) and route to evacuate. The problem is formulated as a bi-level programming. The upper level problem is a location problem that models the authority's decision. A combined distribution and assignment (CDA) model is proposed to model the evacuees' decision as the lower level problem. In this study, the bi-level programming problem is solved using genetic algorithm. Numerical example with a real world network is given to demonstrate the application of the proposed model.

Key Words: location-allocation model, evacuation plan, bi-level programming, genetic algorithm, combined distribution and assignment model

1. INTRODUCTION

Disaster can be categorized into two types, i.e. man-made disaster and natural disaster. Man-made disaster such as terrorism attack is difficult to prevent due to the unpredictability of the event. Natural disaster, such as hurricane or flood, is inevitable even though there are advanced technologies on meteorology. It can be predicted under some degree of certainty but not precisely.

Earthquake, hurricane, wildfire, storm, volcanic eruption, and flood are the examples of natural disaster. They can cause disease, food scarcity, injury, accommodation loss, or even worse, loss of life. The severe effects of natural disaster to human beings are exemplified. NOAA World Data Center (1981) and Seach (2000) presented influence of earthquake and

volcanic eruption to human beings, respectively. This paper, however, concentrates on flood evacuation. In the United States, the largest flash flood caused by the South Fork dam failure, occurred on May 31, 1889, recognized as the Johnstown flood with over 2,200 people dead (Johnstown Pennsylvania Information Source Online, 2002). Another example is the Midwest flood (Illinois, Iowa, Kansas, Minnesota, Missouri, Nebraska, North Dakota, South Dakota, and Wisconsin) in 1993 that cause $18 billion loss, the highest financial damages from flood in the U.S., and 52 deaths (Zimmerman, 1994 and Changnon, 1996). From 1959 to 1991 in the U.S. and Puerto Rico, the total number of deaths due to floods was 3,984 with an annual average of 119 casualties per year (Dittamann, 1994). To protect life loss from disasters, disaster management should be prepared for the potential influenced area.

Disaster Management is defined as "the range of activities designed to maintain control over disaster and emergency situations and to provide a framework for helping at-risk persons to avoid or recover from the impact of the disaster" (Disaster Management Center, 1982). Disaster management copes with the situations before, during, and after disaster occurrences. The objectives of disaster management are to decrease losses (e.g., human, physical, and economical losses), to diminish personal suffering, and to recover as soon as possible. Planning is one of the tools used in disaster management to achieve these objectives.

The pre-disaster evacuation planning for flood is considered in this paper. In the content of pre-flood evacuation planning, some of the definitions need to be defined for clarification. Inundation area is denoted as an area that is flooded with water (National Oceanic and Atmospheric Administration, 2004). A buffer is located 500 feet outside the inundation area. An emergency planning zone (EPZ) is the area that includes the buffer and the inundation area. If flood occurs, people in the EPZ must evacuate to the shelters located outside the EPZ before the traffic is blocked by flooding. One of the critical tasks in developing a flood evacuation plan is to determine where evacuees should seek shelter in order to retreat from the EPZ. As indicated by Sherali, H. D. *et al*. (1991), the selection of shelter locations from among potential alternatives can critically influence the performance of an evacuation plan.

In this paper, a location-allocation model for flood evacuation plan is proposed to determine the location of shelters with capacity constraints. Different from the traditional location-allocation models in location theory, the proposed model is formulated as a bi-level programming problem. The problem is posed as a Stackelberg game. In this game, there are two players, i.e. a planning authority and a group of evacuees. The planning authority determines the number and locations of shelters with the objective of minimizing the total network evacuation time. The evacuees decide simultaneously which shelter to go and by which route given the location and capacity of the shelter.

The rest of the paper is organized as follows. After the introduction section, background and literature review will be presented. A bi-level location-allocation model for the flood evacuation planning with shelter capacity constraints is presented in Section 3. A genetic algorithm (GA) based method is presented in Section 4 to solve the bi-level programming problem. In Section 5, a real world network of in the City of Logan, Utah, is employed to demonstrate the application of the proposed model and solution procedure. Conclusions and further research are summarized in Section 6.

2. BACKGROUND

Several topics were conducted on evacuation planning research. For instance, Sherali, H. D. *et al*. (1991) studied the evacuation plan for hurricane/flood with explicit consideration of the impact of shelter locations on evacuation time. A location–allocation model was proposed to select a set of candidate shelters from among the potential shelters and to prescribe an evacuation plan which minimizes the total evacuation time. The problem is formulated as a nonlinear mixed integer programming problem.

ElDessouki (1998) studied both the pre and post disaster emergency management problems. The author linked the pre disaster evacuation plan with the combined trip distribution and assignment (CDA) problem. The evacuation problem is to evacuate the affected population to shelters (distribution) over a network (traffic assignment) so that the total evacuation time is minimized. The model considered shelter capacity constraints, but congestion is not considered (i.e., link travel time is flow independent). The post disaster emergency management was treated as a special case of the multi-period network design problem.

Feng and Wen (2003) studied different traffic control strategies for the earthquake-raided area in post earthquake periods. Different models were proposed to maximize the traffic volume entering the controlled area and to minimize the rescue time in disaster area. Recently, Tuydes and Ziliaskopoulos (2004) presented a model to reallocate the available capacity by reversing the direction on certain road segments in case of a disaster to better utilize the network capacity under an unusual demand pattern. The model is an extension of the dynamic traffic assignment problem using the cell transmission model to capture the traffic dynamics in the network. The proposed model can optimize the capacity reversibility and assignment simultaneously.

Murray and Mahmassani (2003) considered household behavior into the evacuation modeling. The household behavior here refers to the meeting point where the household members meet each other and evacuate as a single unit. A series of two linear integer programming problem were proposed to model the household behavior, i.e. meeting location choice and pick-up route and sequence choice.

The evacuation planning and management have been studied from different aspects, i.e. shelter location, shelter and route choice, traffic control strategies, evacuee behaviors. Only Sherali, H. D. *et al*. (1991) and ElDessouki (1998) considered the impact of shelter locations and the capacity constraint on shelters on the performance of an evacuation plan. However, in both studies, the authority is assumed to have total control on the evacuees' shelter and route choice.

In this paper, we study the optimal shelter location-allocation for flood evacuation planning. We relax the assumption that evacuees determine which shelter to evacuate to and by which route, which is considered to be more realistic compared to the models given in Sherali, H. D. *et al*. (1991) and ElDessouki (1998). The evacuees' decision is formulated as a CDA and the authority's decision is formulated as a location problem. The problem is a bi-level programming problem given in the next section.

3. BI-LEVEL PROGRAMMING FORMULATION

In this section, we present a bi-level programming formulation for modeling the flood evacuation planning problem with shelter capacity constraints. The model determines the number and shelter locations among a given set of potential locations and allocates the evacuees to the selected shelters according to the CDA model. The bi-level location-allocation model can be interpreted as a Stackelberg game with two players, i.e. a leader (the planning authority) and a follower (the evacuees). In this game, the planning authority determines the number and shelter locations, while the evacuees choose the shelter and route to evacuate. This is different from the studies by Sherali, H. D. *et al*. (1991) and ElDessouki (1998) that assume the authority has total control on the shelter and route choices for the evacuees. In our bi-level location-allocation model, the leader cannot control the behavior of the follower, but can influence the behavior of the follower by choosing the number and location of shelters. Fisk (1984) highlighted the relation between the Stackelberg game and network design problems and presented a bi-level programming formulation as follows.

$$\underset{u}{Min}\ F(u, v(u))$$

$$\text{s.t.} \quad \mathrm{G}(u,v(u)) \le 0,$$

$$\underset{v}{Min}\ f(u, v)$$

$$\text{s.t.} \quad \mathrm{g}(u,v) \le 0,$$

where F is the problem objective function of the upper level; u is the decision vector of the upper level problem; G is the constraint set of the upper level problem; f is the problem objective function of the lower level; v is the decision vector of the lower level problem; g is the constraint set of the lower level problem. The upper level problem models the decision of the leader in the game, while the lower level problem models the decision of the follower.

The location-allocation problem has the same structure as the Stackelberg game and is formulated as a bi-level programming problem here. Before presenting the model, notation and assumptions are given first.

3.1 Notation and Assumptions

The notation used throughout this paper is listed as follows.

a index of links, $a \in A$

i index of origins, $i \in I$

j index of potential shelters, $j \in J$

$\bar{j}$ index of selected shelters, $\bar{j} \in \bar{J}, \bar{J} \subseteq J$

r index of routes, $r \in R_{i\bar{j}}$

β impedance parameter in the CDA model

$\delta_{ar}^{i\bar{j}}$ link/path incidence matrix, equal to 1 if link a is on route r between origin i and shelter $\bar{j}$, and 0 otherwise

$f_r^{i\bar{j}}$ traffic flow on route r between origin i to shelter $\bar{j}$

p_a maximum acceptable degree of saturation for link a

q_{ij} demand between origin i and shelter j

$q_{i\bar{j}}$ demand between origin *i* and shelter $\bar{j}$

v_a traffic flow on link *a*

$t_a(v_a)$ travel time on link *a*, which is a function of v_a

C_a capacity of link *a*

K_j capacity of shelter *j*

O_i trip production from zone *i*

$R_{i\bar{j}}$ route set for origin *i* and shelter $\bar{j}$

X_j 1 if shelter *j* is selected, and 0 otherwise

Assumptions are given as follows:
1. All potential shelter locations and their shelter capacities are given;
2. The number of trips to be evacuated from each origin is given;
3. There is only one type of vehicles (passenger car) in the network;
4. The traffic network (the topology, link capacity, link cost function, etc.) is given.

3.2 The Mathematical Formulations

3.2.1 Upper Level

$$\underset{X}{Min} \sum_a v_a(X)\, t_a(v_a(X)) \tag{1}$$

s.t.

$$X_j = \begin{cases} 1 & \text{if shelter } j \text{ is selected} \\ 0 & \text{otherwise} \end{cases}, \quad \forall\, j \in J, \tag{2}$$

$$\sum_{i \in I} q_{ij} \le K_j X_j, \quad \forall\, j \in J, \tag{3}$$

$$v_a(X) \le p_a C_a, \quad \forall\, a \in A, \tag{4}$$

Upper level formulation represents the decision of the authority. For this problem, evacuation planner wishes to minimize the total evacuation time (TET) (i.e., total travel time for all evacuees to safe shelters) in the network by choosing the number and location of shelters as given in equation (1). Equation (2) ensures the shelter location variables are binary, 1 if shelter *j* is selected and 0 otherwise. Constraint (3) is the shelter capacity constraint. The total demand from all origins *i* to candidate shelter *j* should not exceed the shelter capacity. Constraint (4) is the link capacity constraint. The link flow should not exceed the maximum acceptable degree of saturation of a link. v_a and q_{ij} are determined by the lower level problem for a given set of location decision variables, *X*. Define $\bar{J} = \{ j \mid X_j = 1 \}$ as the set of shelters selected by the upper level; for the shelters that are not selected (i.e., $j \notin \bar{J}$), $q_{ij} = 0$ (i.e., shelter *j* should not have any demand).

3.2.2 Lower Level

$$\underset{v,q}{Min} \sum_{a \in A} \int_0^{v_a} t_a(w)dw + \frac{1}{\beta} \sum_{i \in I} \sum_{\bar{j} \in \bar{J}} q_{i\bar{j}} (\ln q_{i\bar{j}} - 1) \tag{5}$$

s.t.

$$\sum_{r \in R_{i\bar{j}}} f_r^{i\bar{j}} = q_{i\bar{j}}, \quad \forall\, i \in I,\ \bar{j} \in \bar{J}, \tag{6}$$

$$\sum_{\bar{j} \in \bar{J}} q_{i\bar{j}} = O_i, \quad \forall\, i \in I, \tag{7}$$

$$f_r^{i\bar{j}} \geq 0, \quad \forall\, i \in I,\ \bar{j} \in \bar{J},\ r \in R_{i\bar{j}}, \tag{8}$$

$$q_{i\bar{j}} \geq 0, \quad \forall\, i \in I,\ \bar{j} \in \bar{J}, \tag{9}$$

$$v_a = \sum_{i \in I} \sum_{\bar{j} \in \bar{J}} \sum_{r \in R_{i\bar{j}}} f_r^{i\bar{j}} \delta_{ar}^{i\bar{j}}, \quad \forall\, a \in A \tag{10}$$

Traveler behavior for flood evacuation planning is modeled as a CDA program. Evacuees try to travel to safe shelter with the least travel time represented by the objective function in equation (5). Given the selected shelters determined by the upper level, the evacuees choose the route and destination (shelter) simultaneously. Equation (6) is the flow conservation constraint. The sum of all the path flows between origin *i* and shelter $\bar{j}$ must equal to its O-D demand. Equation (7) is the production constraint. The sum of the demand from all shelters $\bar{j}$ to origin *i* is equal to the trip production of origin *i*. Equations (8) and (9) are the non-negativity constraints on path flow and O-D demand, respectively. Equation (10) is the definitional constraint that defines the relationship between link and path flows. It can be proved that the route choice follows the Wardrop's first principle (Wardrop, 1952) and the destination choice follows the logit choice model (Sheffi, 1985). One important note should be declared is that proposed formulation is used for planning purpose not for operation purpose. Hence, it is practicable to assume traveler behavior as user equilibrium, static behavior.

4. SOLUTION ALGORITHM

Normally, bi-level programming problems are difficult to solve because the evaluation of the objective value in the upper level problem requires solving the lower level problem. Moreover, if the lower level problem is considered as nonlinear constraints, the bi-level programming problem can be considered as a non-convex problem and thus difficult to solve by standard optimization methods (Yang and Bell, 1998).

In the transportation field, many heuristic algorithms have been developed to solve the bi-level programming problem. Yang and Bell (1998) provided a summary of the algorithms for solving the continuous network design problem. Yin (2000) illustrated that, for continuous network design problem, the bi-level programming problem can be solved by using Genetic Algorithm (GA) approach. Chen, A. *et al*. (2003) developed a simulation-based GA procedure for solving the Build-Operate-Transfer network design problem with demand uncertainty. According to the reviews, GA has been successively applied to solve the bi-level programming problem in the transportation field.

In GA, the decision variables can be coded as binary, integer, or real representation (Rothlauf, 2002). For the problem here, the decision variables in the upper level problem are binary variables. It is straightforward to use the binary representation. In the GA evolution

process, three operators are included, i.e. reproduction, crossover, and mutation operators. The detail implementations of GA are described as follows.

Reproduction Operator

The population is divided into two groups, arranging in an ascending order of the fitness values, calculated by penalty method shown in later part. The top half will survive and be replicated into the next generation (GA is designed to minimize the objective value). The roulette wheel selection method is used to generate parent chromosomes for crossover and mutation. The crossover and mutation operators will generate the other half of chromosomes, which will go into the next generation.

Crossover Operator

The crossover operator here is a multi-point crossover operator. For each pair of chromosome, a binary mask is generated. If the value of the mask is 1, exchange the value of the allele of two chromosomes; otherwise, do not exchange. For each allele of the mask, a random number R in [0,1] is generated. If R is greater than the crossover rate, set the value as 0; otherwise, 1.

Mutation Operator

The chromosome in the algorithm is in a binary format. The mutation operator changes the value of an allele from '1' to '0' and vice versa at each mutation point. The mutation operator decides each allele of chromosomes whether perform mutation or not according to the mutation rate. For each allele, a random number R in [0, 1] is generated. If R is greater than the mutation rate, do not mutate; otherwise, mutate.

Penalty Method

To handle the constraints in GA, the penalty method is employed. For a chromosome *p*, the fitness function is defined as

$$h_p = \sum_{a\in A} v_a(X)\, t_a(v(X)) + \eta \sum_{j\in J} \max\left(\sum_{i\in I} q_{ij} - K_j X_j, 0 \right) + \lambda \sum_{a\in A} \max\left(v_a(X) - p_a c_a, 0 \right),$$

where η is the penalty parameter associated with constraint (3) and λ is the penalty parameter associated with constraint (4). Penalty parameter here is assumed as a big number.

4.1 Solution Procedure

Figure 1 presents a flow diagram of the GA based procedure. The procedure can be summarized as follows:

Step 1: Initialization. GA parameters such as mutation rate, crossover rate, population size (P), and maximum number of generations (N_m) are predefined. Initial population is generated. Randomly generate an initial population of solutions. Set n = 1 and p= 1.

Step 2: Evaluation. Solve the lower-level problem using the double-stage algorithm, and evaluate the fitness of solution p.

Step 3: Increment p = p + 1. Repeat Step 2 until p is reached the population size.

Step 4: GA evolution. Using GA operators to improve all solutions.

Step 5: Increment n = n +1. Repeat Steps 2, 3, and 4 until n is reached the maximum number of generations.

Step 6: Output. Solution set is summarized.

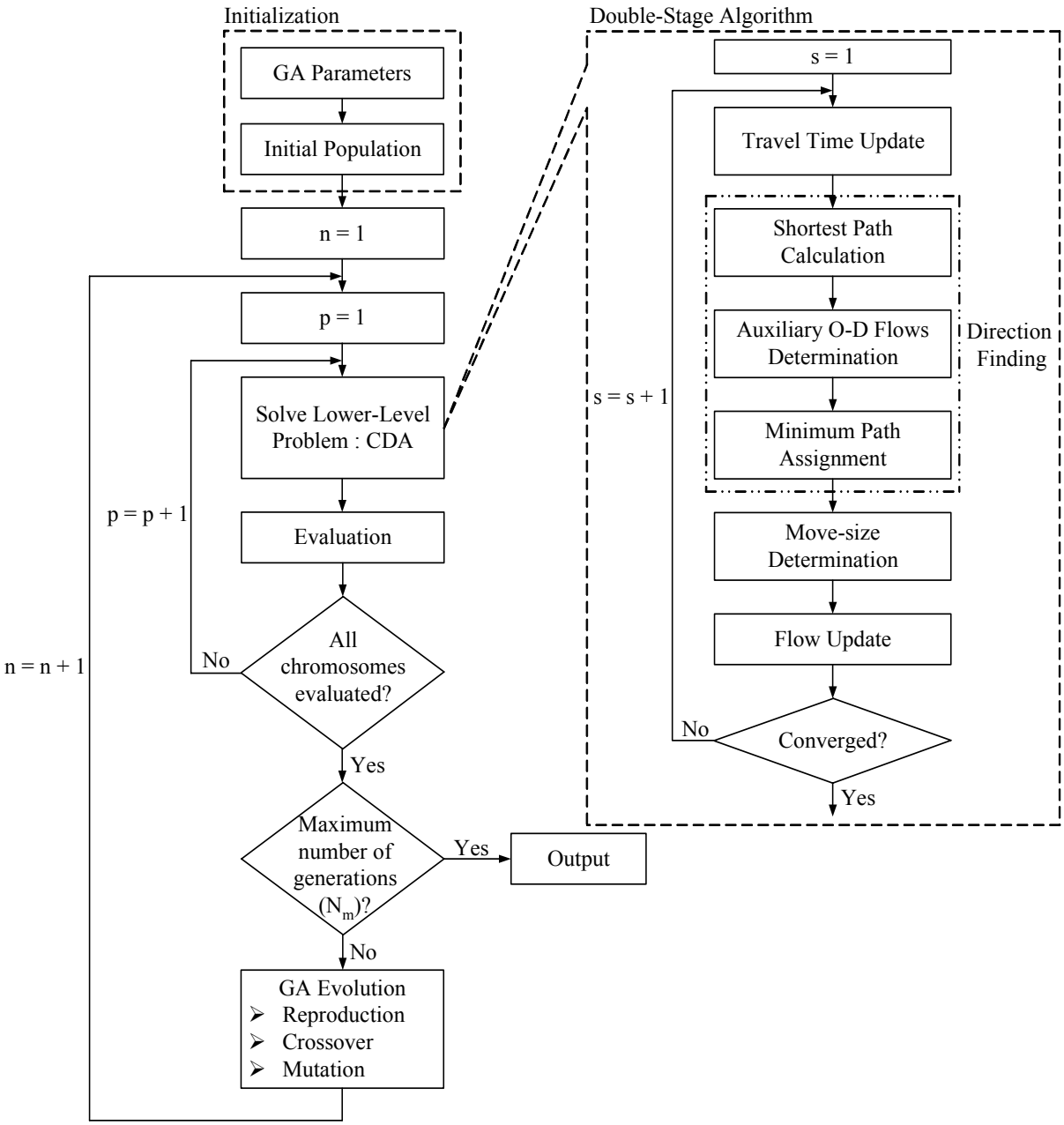

Figure 1 GA Based Solution Procedure

In the evaluation of the fitness value of each chromosome, the lower level problem (CDA) is solved to calculate the total travel time, O-D demand, and link flow. To solve CDA formulation, see Figure 1, the Double-Stage Algorithm is employed (Sheffi, 1985). At each iteration, shortest travel time path of each origin to all destinations is calculated. After that, auxiliary O-D flows are determined based on the logit distribution model. It is then assigned to the minimum travel time path between origins and destinations. The rest of the steps are similar to the convex combination method. Link flow is obtained from the previous step. Move-size is then determined. Link flows and O-D flows are updated according to move-size from the prior step. The final step is the convergence test. Algorithm will be terminated if convergent criteria are satisfied. Otherwise, next iteration is performed.

5. NUMERICAL EXPERIMENT

In this section, the Logan network in Utah as shown in Figure 2 is employed in the numerical experiments. The dam site and reservoir are located on the east side of the city. The inundation area is obtained using Mike21 software, two dimensional hydrodynamic model with finite difference engine to determine inundation area (Zhu, 2003). The EPZ is defined with a buffer distance of 500 feet of the inundation area. The population in the city of Logan is 42,670 (U.S. Bureau Census, 2000) with about 21% of the population are within the EPZ area. Figure 2 presents the Logan network, dam site and reservoir, inundation area, and EPZ.

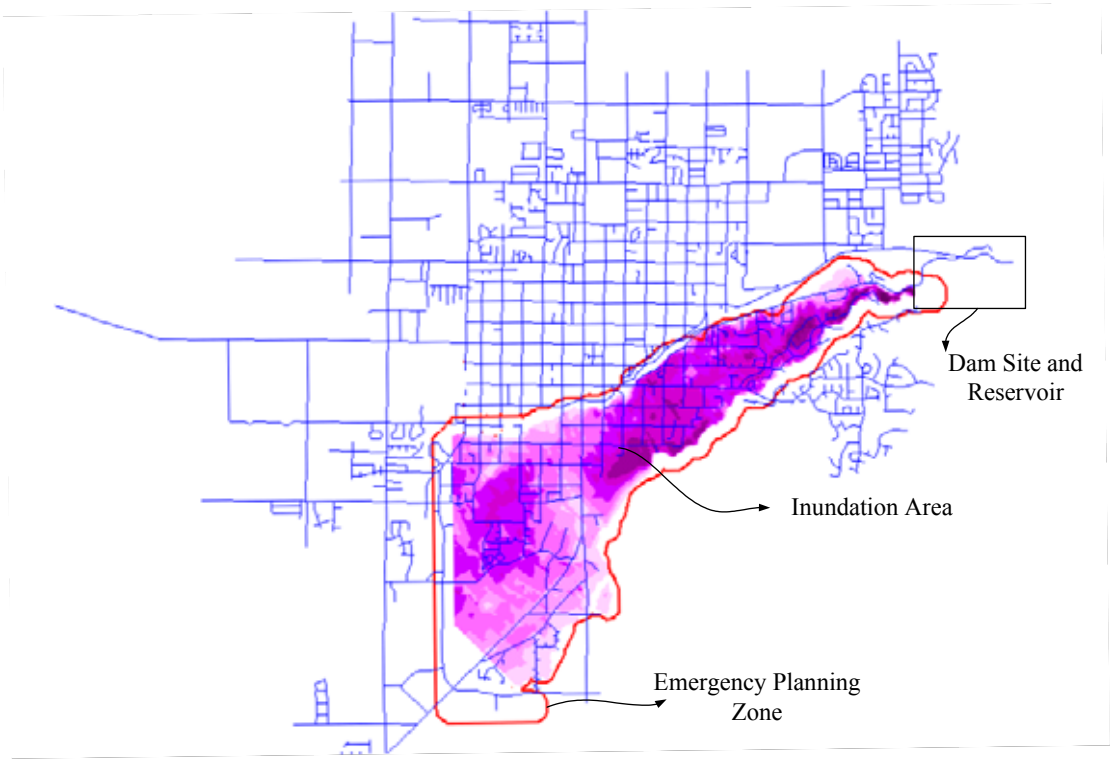

Figure 2 Logan Street Network and Dam Location

Using the GIS database, the Logan roadway network is coded for the numerical analysis. The study area is located in the southeast of the Logan city. The inundation area is approximately five square miles and aggregated into 15 origins according to the census data for planning purpose. The network is depicted in Figure 3, which consists of 15 origins, 10 potential shelters, 126 nodes, and 360 links. The standard Bureau of Public Road (BPR) function is adopted as the link travel time function in the CDA as follows:

$$t_a(v_a) = t_a^0\left[1.0 + 0.15\left(\frac{v_a}{C_a}\right)^4\right],$$

where t_a^0 is the free-flow travel time on link a, which is computed according to the link length and the speed limit of the link. The EPZ area is divided into 15 traffic analysis zones. It is assumed that vehicle occupancy (VOC) is 1.30 persons per vehicle. Number of people in each traffic analysis zone is divided by VOC rate to obtain traffic demand. Table 1 presents trip production of each traffic analysis zone with total demand 6900 vph.

Table 1 Trip Production of Each Traffic Zone (vph)

Zone	Production	Zone	Production	Zone	Production
1	400	6	600	11	500
2	400	7	600	12	100
3	500	8	600	13	300
4	700	9	650	14	400
5	500	10	450	15	200

Ten potential shelter locations are pre-defined, which consist of seven churches, two warehouses, and an educational institution. All are located outside the inundation area. The locations of origin and destination (potential shelter) nodes are also depicted in Figure 3.

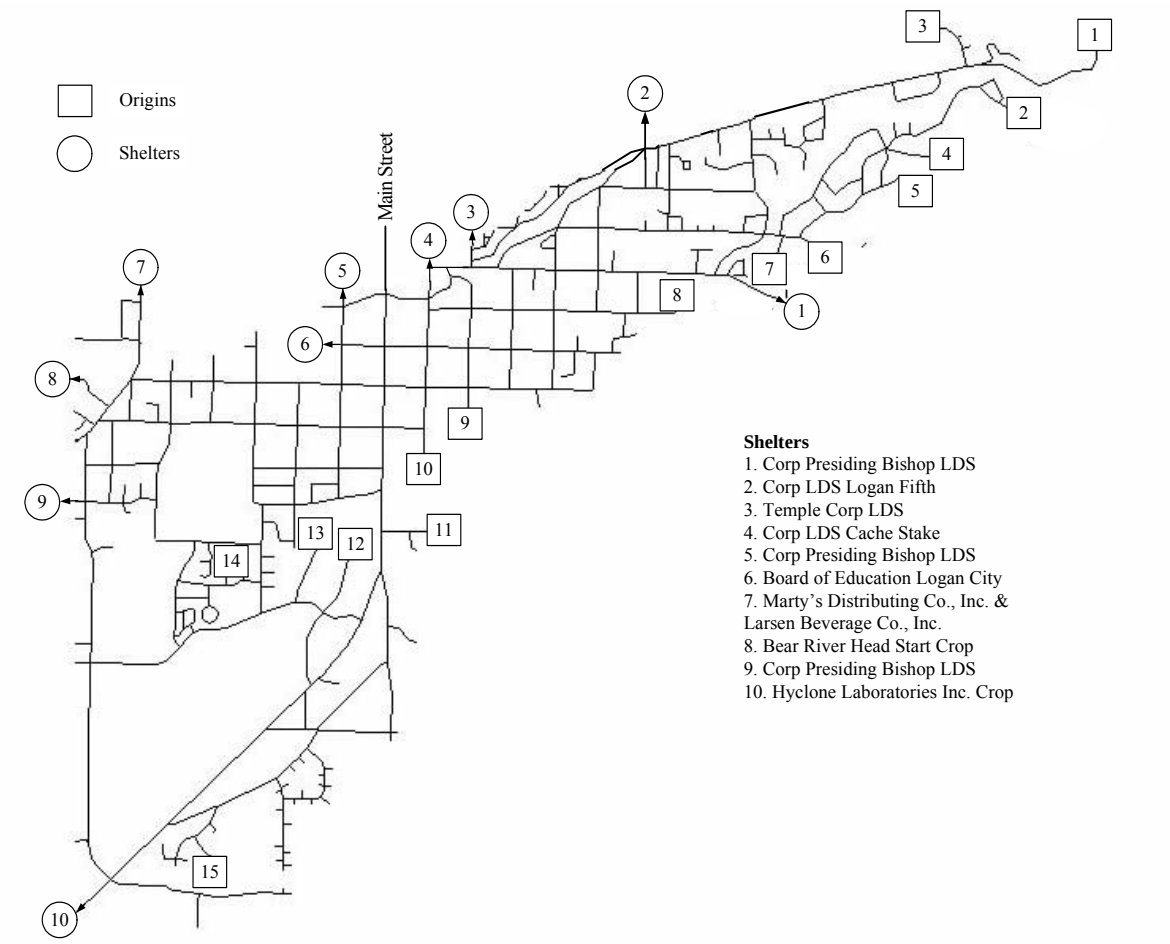

Figure 3 Study Area and the Locations of Origins and Shelters

The following assumptions are made for this case study:

- Most of the roads in the study area are local streets with a 25 mph speed limit. On Main Street, speed limit is between 35 mph and 45 mph when the road is located outside of the downtown area.
- All cars are passenger cars.
- Most of the local streets are one-lane per direction with a capacity of 1200 vph.
- Some street has two lanes per direction with a capacity of 3000 vph.

The evacuation plan proposed here is to evacuate people from the EPZ area to one of the shelters outside of the inundation area using the minimum total evacuation time. In this numerical experiment, the following parameters are used:

- Population size is 16 chromosomes.
- Maximum number of generations is 50.
- Probability of mutation is 0.20.
- Maximum acceptable degree of saturation on link *a*, p_a, is assumed to be 0.9 for all network links.
- Impedance parameter is 0.10.

Figure 4 presents the convergence curves of GA based approach for different capacities of the shelters. It can be observed that most of the results converged after the 20th generation.

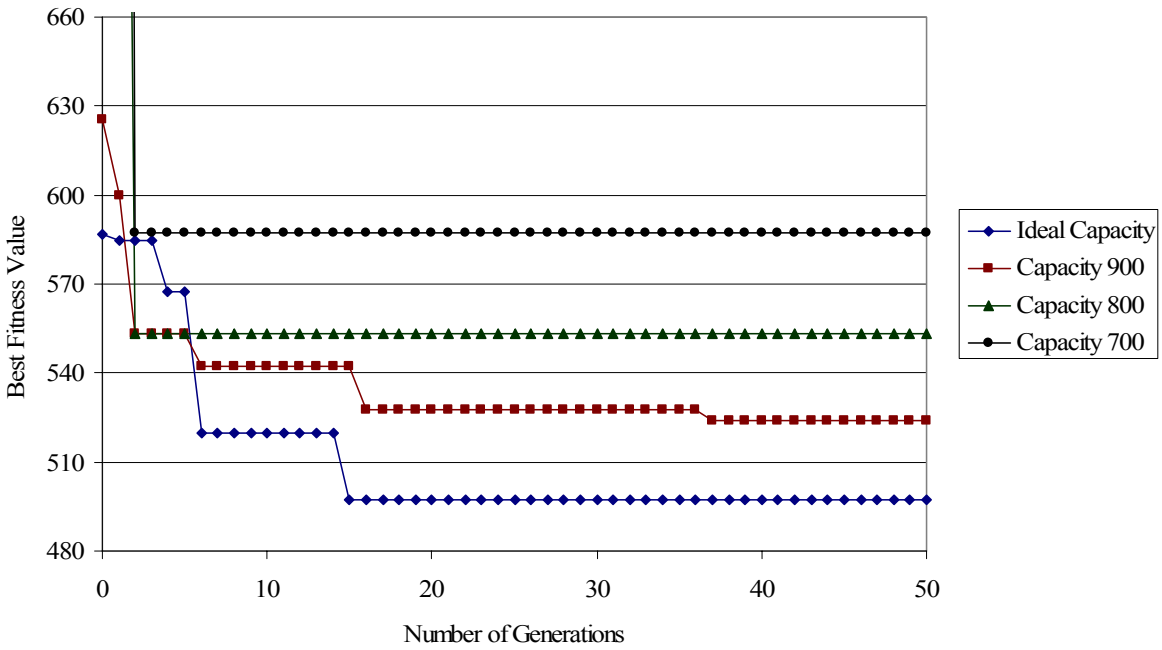

Figure 4 Convergence of GA Approach with Different Shelter Capacities

5.1 Effects of No Capacity Constraint

First consider the ideal case, capacity constraint is set to a relatively high value. The evacuees can choose any shelter without the need to consider the capacity constraint. In this case, seven shelters are selected with a total evacuation time of 492.42 veh-hr/hr. The maximal O-D travel time among all O-D pairs, which indicates the time required for all evacuees to arrive at the shelter, is 10.19 minutes. Minimal O-D travel time and average O-D travel time are 1.52 and 4.45 minutes, respectively. The selected shelters and the corresponding trips attracted to those shelters are listed in Table 2.

Table 2 Shelter Attraction for Different Capacities (vph)

Shelter	$K_j = \infty$	$K_j = 900$	$K_j = 800$	$K_j = 700$
1	987	864	768	692
2	987	864	768	692
3	987	864	768	692
4	987	864	768	692
5	985	863	767	691
6	985	863	767	691
7	*	*	764	688
8	*	859	765	688
9	982	859	765	688
10	*	*	*	686
No. of Shelters Selected	7	8	9	10
TET+ (veh-hr/hr)	492.42	524.13	553.21	587.04
Max O-D time (min.)	10.19	10.20	10.36	11.64
Min O-D time (min.)	1.52	1.51	1.51	1.50
Avg O-D time (min.)	4.45	4.68	4.89	5.13

*The shelter is not selected
+TET is the total evacuation time

To investigate the impact of shelter locations on the performance of an evacuation plan, we compare the ideal case with another set of eight shelters. Assumed that shelters 1 and 3 are not selected. The total evacuation time increases to 635.11 veh-hr/hr, and the maximal, minimal, and average O-D travel time increases to 11.80, 1.61, and 5.44 minutes, respectively. This result indicates the importance of shelter location selection in the evacuation plan.

5.2 Effects of Capacity Constraint with Different Capacities

Now, given the available shelter capacity as 700 vph for all shelters. All ten shelters will be selected. The results are listed in Table 2. It is interesting to observe that with more shelters being selected, the total evacuation time increases.

In the ideal case, all the trips attracted to each shelter are less than 1000 vph. We choose two different capacities for all shelters (800 vph and 900 vph) for the sensitivity analysis. The results are listed in Table 2. In the case of 800-vph shelter capacity, for instance, 768 vehicles will go to shelter 1, 2, 3, and 4, 767 vehicles will go to shelter 5 and 6, 764 vehicles will go to shelter 7, 765 vehicles will go to shelter 8 and 9, and shelter 10 is not selected. For 900-vph shelter capacity, 864 vehicles will go to shelter 1, 2, 3, and 4, 863 vehicles will go to shelter 5 and 6, 859 vehicles will go to shelter 8 and 9, and shelter 7 and 10 are not selected.

It can be observed that the smaller shelter capacity provided, the higher number of shelters required. Graphical representation of the effects of capacity constraint with different capacities is depicted in Figure 5. It illustrates the trade-off between the shelter capacity and the number of shelters being selected. With a smaller shelter capacity, more shelters must be selected. This will increase the total evacuation time.

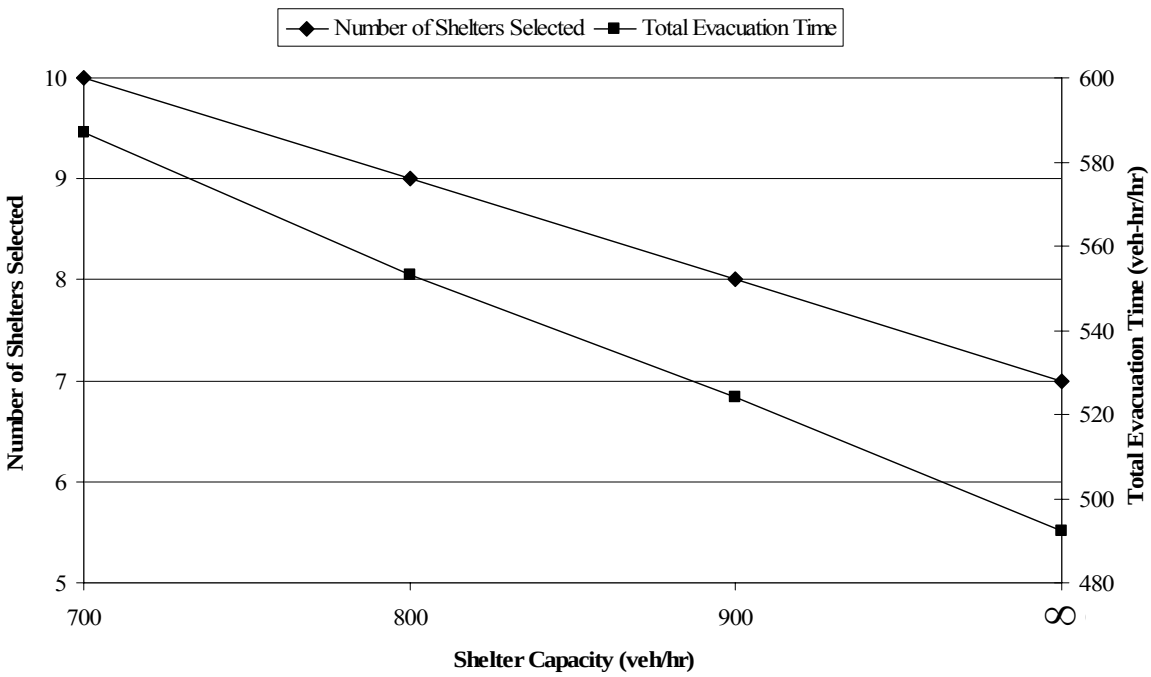

Figure 5 Number of Shelters Selected versus Shelter Capacity

5.3 Effects of Vehicle Occupancy

Vehicle occupancy rate, 2.00 persons per vehicle, is assumed at this moment to investigate effects to evacuation planning. Trip production and shelter attraction with vehicle occupancy 2.00 are illustrated in Tables 3 and 4, respectively. Apparently, the total number of shelters selected, TET^+, and maximal O-D travel time are less compared to the VOC 1.30 scenario due to higher occupancy per vehicle. TET^+ reduces about 45 percent on the average. Maximal, minimal, and average O-D travel time drops about 17, 83, and 53 percent on the average, respectively.

According to the results presented in Table 4, higher vehicle occupancy rate leads to less total evacuation time. It implies that evacuees would have more chance to arrive shelter safely. One way to have more efficient evacuation planning is, therefore, to promote high vehicle occupancy rate during evacuation period.

Table 3 Trip Production of Each Traffic Zone with Vehicle Occupancy 2.00 (vph)

Zone	Production	Zone	Production	Zone	Production
1	260	6	390	11	325
2	260	7	390	12	65
3	330	8	390	13	195
4	460	9	425	14	260
5	325	10	295	15	130

Table 4 Shelter Attraction for Different Capacities with Vehicle Occupancy 2.00 (vph)

Shelter	$K_j = \infty$	$K_j = 900$	$K_j = 800$	$K_j = 700$
1	900	900	750	644
2	900	900	750	644
3	900	900	750	643
4	900	900	750	643
5	*	*	750	643
6	900	900	750	643
7	*	*	*	*
8	*	*	*	*
9	*	*	*	640
10	*	*	*	*
No. of Shelters Selected	5	5	6	7
TET^+ (veh-hr/hr)	282.31	282.31	287.84	315.48
Max O-D time (min.)	8.44	8.44	8.42	10.04
Min O-D time (min.)	1.46	1.46	1.45	1.45
Avg O-D time (min.)	4.06	4.06	4.09	4.38

6. CONCLUSIONS AND FUTURE RESEARCH

In this study, we propose a bi-level location-allocation model for flood evacuation planning with shelter capacity constraints. In the model, the planning authority determines the number and locations of shelters and the evacuees choose which shelter to go to and by which route. The problem is formulated as a bi-level programming problem. The upper-level problem is to select the shelter with a minimum total evacuation time. The lower-level problem is a combined distribution and assignment (CDA) problem. The shelter capacity and link capacity are considered as constraints in the upper-level problem. The bi-level location-allocation model provides a more realistic approach by modeling the evacuees' route and destination choices, which is one of the contributions of this paper.

A GA-based solution procedure is developed to solve the bi-level programming problem. The Logan network in Utah is used to illustrate the proposal shelter location-allocation model with capacity constraints for a flood evacuation planning problem. The results verify the importance of shelter location selection and the effects of capacity constraints in the evacuation plan. There exists a trade-off between the available shelter capacity and the number of shelters selected. With a higher capacity, less number of shelters will be selected with a lower total evacuation time.

Nevertheless, by the evolution procedure, GA performs random search to explore solutions beyond the local optimum. It simultaneously performs stochastic search for solutions in the feasible region under predefined parameters. However, it is not an exact algorithm which can guarantee the exact solution. Another restriction on GA is the size of the problem which can significantly influence the total calculation time of the GA. The larger the network, the longer the calculation time. Hence, GA is suitable for solving small- to medium-size networks.

In this research, the evacuees' route choice is assumed to follow the Wardrop's first principle (Wardrop, 1952), i.e., user equilibrium. However, under disaster condition, evacuees may not have perfect information about the traffic condition. The route choice behavior of evacuees can be formulated as stochastic user equilibrium (Sheffi, 1985). An additional parameter affecting to evacuees' behavior under disaster condition is impedance parameter. With different β values, evacuees' behavior would be different. By a higher value of the impedance parameter, evacuees would be assigned to the nearest shelter first.

During the evacuation time, the flood will inundate certain area near the dam. As a result, the road will not be available for any traffic. The dynamic of flood-raided area and the dynamics of traffic in the road network can be captured using a dynamic traffic network modeling approach. One of the promising approaches is the Cell Transmission Model proposed by Daganzo (1995).

REFERENCES

a) Books and Books chapters

Changnon, S. (1996) **The Great Flood of 1993: Causes, Impacts, and Responses**. Westview Press, Inc., Boulder, Colorado.

Rothlauf, F. (2002) **Representations for Genetic and Evolutionary Algorithms: Studies in Fuzziness and Soft Computing**. Physica-Verlag, New York.

Sheffi, Y. (1985) **Urban Transportation Networks**. Prentice-Hall, Inc., Englewood Cliffs, New Jersey.

b) Journal papers

Chen, A., Subprasom, K. and Ji, Z. (2003) Mean-Variance Model for the Build-Operate-Transfer Scheme under Demand Uncertainty**. Transportation Research Record 1857,** 93-101.

Daganzo, C.F. (1995) The Cell Transmission Model, Part II: Network Traffic. **Transportation Research Part B, Vol. 29, No. 2**, 79-93.

Feng, C. M. and Wen, C. C. (2003) Traffic Control Management for Earthquake-Raided Area. **Journal of the Eastern Asia Society for Transportation Studies, Vol. 5**, 3261-3275.

Fisk, C. S. (1984) Game Theory and Transportation Systems Modelling. **Transportation Research Part B, Vol. 18, No. 4/5**, 301-313.

Sherali, H. D., Carter, T. B. and Hobeika, A. G. (1991) A Location-Allocation Model and Algorithm for Evacuation Planning under Hurricane/Flood Conditions. **Transportation Research Part B, Vol. 25, No. 6**, 439-452.

Yang, H. and Bell, M.G.H. (1998) Models and Algorithms for Road Network Design: A Review and Some New Developments. **Transport Reviews, Vol. 18, No. 3**, 257-278.

Yin, Y. (2000) Genetic-Algorithms-Based Approach for Bilevel Programming Models. **Journal of Transportation Engineering, Vol. 126, No. 2**, 115-120.

Zimmerman, R. (1994) After The Deluge. **The Sciences, Vol. 34, No. 4**, 18-23.

c) Papers presented to conferences

Murray, P. M. and Mahmassani, H. S. (2003) Model of Household Trip Chain Sequencing in an Emergency Evacuation. Presented at **82nd Annual Meeting of the Transportation Research Board**, Washington, D.C.
Tuydes, H. and Ziliaskopoulos, A. K. (2004) Network Re-design to Optimize Evacuation Contraflow. Presented at **83rd Annual Meeting of the Transportation Research Board**, Washington, D.C.

Wardrop, J. G. (1952) Some Theoretical Aspects of Road Traffic Research. **Proceedings of Institution of Civil Engineers, Part II, Vol. 1**, 325-378.

d) Other documents

Disaster Management Center (1982) Self Study Courses: Aim and Scope of Disaster Management. University of Wisconsin.

Dittamann, R. (1994) Annual Flood Death Statistics per State per Capita for The United States and Puerto Rico during the Period 1959-1991. Technical Memorandum NWS SR-153. Summitted to U.S. Department of Commerce, National Oceanic and Atmospheric Administration, National Weather Service, Fort Worth, Texas.

ElDessouki, W. M. (1998) Some Developments in Transportation Network Analysis and Design with Application to Emergency Management Problems. Ph.D. Dissertation, North Carolina State University.

Johnstown Pennsylvania Information Source Online. (2002) http://www.johnstownpa.com/history.html. Accessed July 15, 2004.

National Oceanic and Atmospheric Administration. (2004) http://www.pmel.noaa.gov. Accessed July 15, 2004.

NOAA World Data Center A. (1981) Catalog of significant earthquakes 2000 B.C.-1979, including Quantative Casualties and Damage.

Seach, J. Volcano Live. (2000) http://www.volcanolive.com/fatalities.html. Accessed July 15, 2004.

U.S. Bureau Census. 2000. Logan city, Utah. http://factfinder.census.gov/bf/_lang=en_vt_name=DEC_2000_PL_U_QTPL_geo_id=16000US4945860.html. Accessed July 09, 2004.

Zhu, Y. (2003) One-Dimensional Versus Two-Dimensional Hydrodynamic Analysis for Life Loss Estimation. Master Thesis, Utah State University.