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Stochastic Multi-Objective Evacuation Model Under Managed and Unmanaged policies

Oren E. Nahum[a], Yuval Hadas[a*], Mariano Zanini[b], Carlo Pellegrino[b], Riccardo Rossi[b], Massimiliano Gastaldi[b]

[a]*Bar-Ilan University, Department of Management, Max ve-Anna Webb Street, Ramat Gan 5290002, Israel*
[b]*University of Padova, Department of Civil, Environmental and Architectural Engineering, Via Marzolo 9, Padova 35131, Italy*

Abstract

Natural and man-created disasters, such as hurricanes, earthquakes, tsunamis, accidents and terrorist attacks, require evacuation and assistance routes. Evacuation routes are mostly based on the capacities of the road network. However, in extreme cases, such as earthquakes, road network infrastructure may adversely be affected, and may not supply their required capacities. If for various situations, the potential damage for critical roads can be identified in advance, it is possible to develop an evacuation model, that can be used in various situations.
This paper focuses on the development of a model for the design of an optimal evacuation network which simultaneously minimizes retrofit costs of critical links (bridges, tunnels, etc.) and evacuation time. The model considers infrastructures' vulnerability (as a stochastic function which is dependent on the event location and magnitude), road network, transportation demand and evacuation areas. Furthermore, the model evaluates the benefits of managed evacuation (system optimum) when compared to unmanaged evacuation (user equilibrium).
The paper presents a mathematic model for the presented problem. However, since an optimal solution cannot be found within a reasonable timeframe, a heuristic model is presented as well. This heuristic model is based on evolutionary algorithms, which also provides a mechanism for solving the problem as a multi-objective stochastic problem.
Using a real-world data, the algorithm is evaluated and compared to the unmanaged evacuation conditions. The results clearly demonstrate the advantages of managed evacuation, as the average travel time can be reduced by 5% to 30%.

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* Yuval Hadas
E-mail address: yuval.hadas@biu.ac.il

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1. Introduction

Natural and man-created disasters, such as hurricanes, earthquakes, tsunamis, accidents and terrorist attacks, require evacuation and assistance routes. As of today, most research on emergency response operations focuses on evacuation problems from the perspective of transportation modelling such as network design and traffic assignment. In that context, transport networks are lifelines which support essential services, and need to be preserved in their functionality in case of disruptions caused by events which originate within (e.g. traffic accidents and technical failures) or outside the transport system (e.g. debris-flows, floods, earthquakes, storms, etc.).

Although evacuation is a stochastic process, most current evacuation models treat the problem in a deterministic way, while some of the models incorporate distribution laws to treat the randomness of human actions and decision inputs (Cuesta, Abreu, & Alvear, 2016). Evacuation routes are mostly based on the capacities of the roads network. However, in extreme cases, such as earthquakes, roads network infrastructure may have adversely affected, and may not supply their required capacities. If this can be identified in advance, it is possible to develop an evacuation model that can be used to recommend the construction of new road segments, retrofit and improve critical links, locate shelter locations, etc.

While disasters, such as earthquakes, cannot be predicted, it is possible to plan evacuation routes in advance, and provide the information to the population.

This paper focuses on the development of a model for the design of an optimal “in advance” evacuation network which simultaneously minimizes retrofitting critical links costs and evacuation time. The model takes into consideration the infrastructures vulnerability associated with the retrofitting road segment (as a stochastic function which is dependent on the event location and magnitude), road network potential structure, transportation demand, and evacuation areas' capacities. Also, in order to investigate evacuation when it is possible to control the flow (advanced notice evacuation and the availability of rescue teams or not (sudden onset disaster), the model evaluates the benefits of managed evacuation (system optimum) when compared to unmanaged evacuation (user equilibrium).

Furthermore, a chance constraint is used to provide the decision maker the means to assess the solution based on different risk levels. Due to the overall complexity of the model (multi-objective and stochastic), an optimal solution cannot be found within a reasonable timeframe and therefore a heuristic algorithm has to be developed and used.

2. Literature Review

Evacuation model planning usually refer to network design and traffic assignment (Chilà, Musolino, Polimeni, Rindone, Russo, & Vitetta, 2016; Heydar, Yu, Liu, & Petering, 2016; Zimmerman, Brodesky & Karp, 2007).

There are several different decisions that should be considered while developing an evacuation models (Cuesta et al., 2016): (1) Selection of Evacuation Routes. Usually more than one escape route is required for the same group of people in order to manage the possible evacuation routes. (2) Introduction of delay times that act as a mechanism for avoiding possible congestion and bottleneck problems in overlapping routes, by delaying evacuation movement of a group of people. (3) By dividing the evacuation route into several parts, it is possible to control the speed of evacuation when the available safe egress time of each piece of a route is known.

The effectiveness of an evacuation operation is dependent on various factors, such as: (1) The availability of resources, such as transit vehicles, volunteers and medical staff that should be optimally allocated. (2) The risk of exposure to disaster impact, which is proportional to the waiting time at pickup locations, and therefore a common objective in this case is minimizing evacuation time. (3) The vulnerability of different locations within the evacuation zone and their proximity to disaster sites. Ignoring any of these characteristics can reduce the performance of the evacuation system (Dhingra & Roy, 2015).

While the evacuation network model presented in this paper takes into consideration infrastructures vulnerability, according to Reggiani, Nijkamp, and Lanzi (2015), the vulnerability concept still lacks a consensus definition, and it depends on the application context (El-Rashidy & Grant-Muller, 2014; Mattsson & Jenelius, 2015). The authors of this paper, in past works (Hadas et al., 2015), adopted the risk theory framework to represent degraded scenarios as a list of “triplets”, each consisting of a description of the scenario (characteristics of the event), the probability of that scenario occurring, and the impact of the scenario on the network, included the resistance of the infrastructure against the event (Erath, Birdsall, Axhausen, & Hajdin, 2010; Jenelius, Petersen, & Mattsson, 2006; Jenelius & Mattsson, 2015). Infrastructures vulnerability assessment can be performed with different approaches, depending on the type of events and the infrastructures considered in the analysis. For example in seismic events, fragility curves can assess the seismic vulnerability of bridges (Carturan, Pellegrino, Rossi, Gastaldi, & Modena, 2013; Zanini, Pellegrino, Morbin, & Modena, 2013), since they take into account the uncertainties of variables and apply probabilistic distributions to describe the properties of the materials composing the structures in question. Similarly, interactions between road networks and damaged buildings can be included, for short- and long-term conditions (e.g., (Goretti & Sarli, 2006)). In damaged road network link and node characteristics are updated according to the functionality variation produced by events. Capacity and speed reduction were commonly introduced for damaged links, such as bridges (Shinozuka, Zhou, Banerjee, & Murachi, 2015; Zhou, Banerjee, & Shinozuka, 2010), or for links affected by building damages (Goretti & Sarli, 2006; Zanini, Faleschini, Zampieri, Pellegrino, Gecchele, Gastaldi & Rossi, 2017).

As concern travel demand, post-event demand changes may be modelled with travel demand models which take in account specific analysis conditions and effects of supply changes. In evacuation conditions, travel demand modelling is fundamental for evacuation planning to mitigate the effects of events (such as earthquakes) (Najafi, Eshghi, & de Leeuw, 2014; Yi & Özdamar, 2007), given their stochasticity (Chang, Elnashai, & Spencer Jr, 2012; Giuliano & Golob, 1998). Disaster Operation Management review by Galindo and Batta (2013) and evacuation transportation modelling review by Murray-Tuite and Wolshon (2013) highlighted the variety of assumptions and methods adopted for evacuation models. For evacuation after earthquakes, travel demand variation was estimated according to the reduction of available surfaces of buildings (Ye, Wang, Huang, Xu, & Chen, 2012), considering dead and injured people after building damages (Gao, Yang, & Sun, 2012).

3. Mathematical Model

There are several evacuation models in the literature, which can be extended. The proposed evacuation model is based on the one developed by Hadas and Laor (2013) and Hadas et al. (2015), with the extension of multi-objectives and stochastic capacities. Let $G(N, A)$ be a graph, with N nodes and A arcs, when $O \subset N$ is the origin set (residential areas), and $D \subset N$ is the destination candidate set (evacuation areas or shelters), such that $O \cap D = \emptyset$. Also let $\{(i,j)\} \in A$ arc candidate set, with $i, j \in [1, \dots, N]$. Each arc is associated with K alternatives, each is different in capacity and retrofit cost, such that the retrofit cost of alternative $k = 1$ is zero, and is higher than zero for all other alternatives, also, the capacity of alternative $k > 1$ is higher than the capacity of alternative $k = 1$. It should be noted that the capacities of the arcs are the capacities available for evacuation. Let $A_c \subset A$ be a subset of all critical arcs, for which $K > 1$. For all arcs $a \in A$, which are not critical, meaning $a \notin A_c$, $K = 1$.

$$Minimize \sum_{(i,j)\in A} \sum_{k\in K} C_{a_{ijk}} \cdot x_{a_{ijk}} + \sum_{i\in D} C_{n_i} \cdot x_{n_i} \tag{1}$$

$$Minimize\ \mathbb{E}\left(\max\left\{0, \sum_{i\in D} b_i \cdot x_{n_i} - \sum_{o\in O} \sum_{d\in D} \sum_{i:(o,i)\in A} \sum_{k\in K} f_{oik}^{od} \right\}\right) \tag{2}$$

$$Minimize\ \mathbb{E}\left(T\left(U_{n_1}, \dots, U_{n_i}\right)\right) \tag{3}$$

Subject to

$$x_{a_{ijk}} \in \{0,1\} \quad \forall (i,j) \in A, k \in K \tag{4}$$

$$x_{n_i} \in \{0,1\} \quad \forall i \in N \tag{5}$$

$$0 \leq b_i \leq U_{n_i} \cdot x_{n_i} \quad \forall i \in O \tag{6}$$

$$0 \leq -b_i \leq U_{n_i} \cdot x_{n_i} \quad \forall i \in D \tag{7}$$

$$b_i = 0 \quad \forall i \notin O \cup D \tag{8}$$

$$\sum_{i \in O} b_i + \sum_{i \in D} b_i = 0 \tag{9}$$

$$\sum_{o \in O} \sum_{d \in D} \sum_{k \in K} f_{ijk}^{od} \leq U_{a_{ijk}} \cdot x_{a_{ijk}} \cdot T \quad \forall (i,j) \in A \tag{10}$$

$$f_{ijk}^{od} \geq 0, f_{ijk}^{od} \in \mathbb{Z} \quad \forall (i,j) \in A, o \in O, d \in D, k \in k \tag{11}$$

$$\sum_{o \in O} \sum_{d \in D} \sum_{i:(i,j) \in A} \sum_{k \in K} f_{ijk}^{od} = \sum_{o \in O} \sum_{d \in D} \sum_{l:(j,l) \in A} \sum_{k \in K} f_{jlk}^{od} \quad \forall j \in O \cup D \tag{12}$$

$$T(Un_1, \dots, Un_i) > 0 \tag{13}$$

$$P\left(\max\left\{0, \sum_{i \in D} b_i \cdot x_{n_i} - \sum_{o \in O} \sum_{d \in D} \sum_{i:(o,i) \in A} \sum_{k \in K} f_{oik}^{od}\right\} \leq F^*\right) \geq \alpha \tag{14}$$

Since the problem approached in our study is stochastic, objectives (1), (2) and (3) represent the construction costs (retrofit costs, and shelters' construction costs), the expected number of non-evacuees in a given time and the expected evacuation time respectively, when $C_{a_{ijk}}$ is the retrofit cost of alternative k for arc (i,j), C_{n_i} is the construction cost of node i, $x_{a_{ijk}}$ and x_{n_i} are decision variables, f_{ijk}^{od} is s a feasible flow from source $o \in O$ to the sink $d \in D$ along arc (i,j) using alternative k. U_{n_i} is the capacity distribution function of node i, and T is the expected evacuation time.

Constraints (4) and (5) define binary decision variables. Constraints (6) and (7) restrict demand to facility capacity, when b_i is the quantity of demand allocated to node i (positive value – demand, negative value – supply), constraint (8) defines transshipment nodes and constraint (9) enforce that total demand is equals to the total supply.

Constraints (10) and (11) defines arcs' capacity over time, while constraint (12) defines conservation of flow. Constraint (13) enforces positive evacuation time.

Finally, a chance constraint (14) is also added to the model. The chance constraint is added to ensure that for every solution found, the number of non-evacuees will hold in α percent of the cases. Meaning, that for α percent of the cases, for example $\alpha = 0.85$ (85%), the number of non-evacuees will be less or equal to F^*.

The model assumes that flow is managed, meaning that the flow is controlled and directed, by the rescue teams. This is in contrast to unmanaged flow, in which route selection is based on user-equilibrium. Such an assumption can hold when evacuation is considered to be performed with sufficient time to evacuate. Hence the need to optimize decision variable T.

The following properties of the model, (1) multi-objective problem, (2) integer variables, and (3) integral flow, increase its complexity, such that an optimal solution cannot be found within a reasonable timeframe. Therefore, in order to decrease complexity, a stochastic multi-objective heuristic has to be developed and used.

There are several methods for solving multi-objective optimization problems, among them are genetic algorithms (such as the VEGA, MOGA, NPGA, and NSGA methods, which are non-elitism multi-objective genetic algorithms, in which the best solutions of the current population are not preserved when the next generation is created, and PAES, SPEA2, PDE, NSGA-II and MOPSO methods, which are example elitism multi-objective genetic algorithm, which preserve the best individuals from generation to generation. In this way, the system never loses the best individuals found during the optimization process (Coello, Lamont, & Van Veldhuizen, 2007)).

Genetic algorithms can also be used for solving stochastic optimization problems. For a stochastic optimization problem, the fitness function, used in each iteration for the selection process and creation of the new generation, literally expresses the fitness of the individual, and therefore is fluctuated, according to the stochastic distribution-functions for the stochastic variables. Eventually, the frequencies of individuals associated with solutions are investigated through all generations. Therefore, it is expected that the higher the expected value is, the higher the individual frequency through all generations is (Yoshitomi, Ikenoue, Takeba, & Tomita, 2000).

In order to simplify the algorithm's implementation, MOEA framework (Hadka, 2016) has been used. The MOEA Framework is a free, open source, Java library for developing and experimenting with multi-objective evolutionary algorithms and other general-purpose optimization algorithms. The MPEA framework provided several algorithms out-of-the-box, including VEGA, NSGA-II, NSGA-III, ϵ-MOEA, SPEA2 and others. The results presented next in this paper were obtained using the NSGA-II algorithm.

4. Experimental Results

In order to assess the model and validate its advantages, a real-world case study was conducted. The analysis is focused on an urban area, the Municipality of Conegliano, a town of 40,000 inhabitants located in the northern part of the province of Treviso, North-Eastern Italy; this area was chosen for its significant seismic hazard. In this test area there are 51 bridges of various typologies: single span, multi span, concrete, steel, and masonry bridges, straight or skewed (Hadas et al., 2015). Figure 1 presents the road network components, including critical links (bridges) and shelters locations (attraction sites).

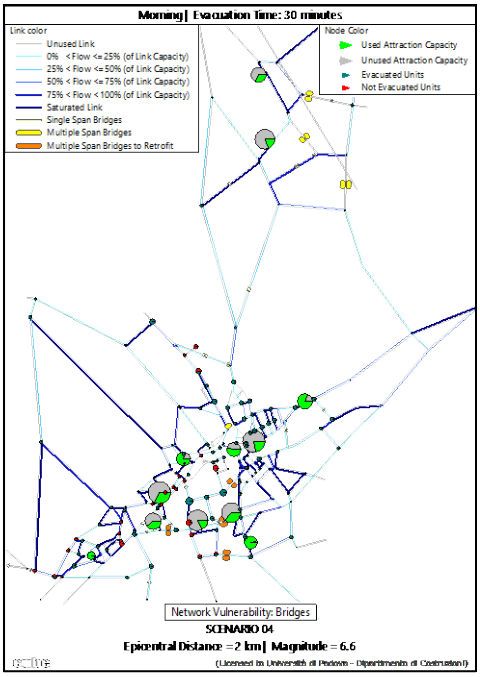

Figure 1 – Conegliano road network (Hadas et al., 2015)

Previous studies (Nahum & Hadas, 2017; Nahum, Hadas, Rossi, Gastaldi, & Gecchele, 2016) show that for networks with stochastic arcs, for each network there is a high difference in the results obtained as the variance in stochastics arc increases. This difference increases as the problem increases in size (larger networks with a higher number of stochastics arcs). The use of chance constraint, results with a solution in which the number of non-evacuees is higher compared to the number of non-evacuees obtained for the same solution based on the average flow, meaning that in order to construct a network having a given cost and an evacuation time, it is necessary to consider the number of non-evacuees F^*, such that in α percent of the cases the obtained number of non-evacuees will be equal or lower than F^*, which is higher than the average number of non-evacuees. This guaranties that in α percent of the cases the evacuation time will be held (and even may be shorter).

Table 1 summarizes the results obtained for two different earthquake scenarios, SCE04 and SCE12, with low and high impact, respectively. The former considered the effects of collapsed bridges on link functionality (capacity decrease) while in the latter the effects of built environment were also assessed (we take into account road obstructions caused by the collapse of jutting buildings). The higher the impact, the decreased capacity of the road segments. Furthermore, for each scenario, two variations were analysed, in which critical arcs have stochastic properties with both small and large variance (denoted as “large” and “small”). Each one of the solutions of the Pareto front was evaluated 100 times, therefore, for each solution it is possible to determine the number of non-evacuees, F^*, that in α percent of the cases the obtained number of non-evacuees will be equal or higher than F^* (the chance constraint). For each network, the average running time (in seconds) is given as well as the size of the Pareto front obtained, the cost of the solution, the number of non-evacuees, for $\alpha = 0.95$, $\alpha = 0.9$, $\alpha = 0.85$, including the average number of non-evacuees - $\alpha = 0.50$, and the evacuation time.

Table 1 – Algorithm Results for Various Possible Networks in which 70% of the Arcs are Stochastics with Large Variance

Problem #	Run Time (sec.)	Size of Pareto Front	Cost	Number of Non-Evacuees				Evacuation Time
				$\alpha = 0.95$	$\alpha = 0.9$	$\alpha = 0.85$	$\alpha = 0.5$	
SCE04-11_11 Morning large	744.279	4	0	17	17	17	17	60
			39178	2157	2127	2115	2115	30
			0	2445	2385	2355	2325	30
			20698	2159	2159	2159	2159	30
SCE04-11_11 Morning small	674.012	4	0	17	17	17	17	60
			0	2385	2355	2355	2355	30
			39178	2127	2115	2115	2115	30
			20698	2159	2159	2159	2159	30
SCE12-19_16 Morning large	694.112	4	0	187	187	187	187	60
			0	1685	1655	1655	1649	30
			42480	1647	1565	1545	1545	30
			24000	1677	1619	1619	1619	30
SCE12-19_16 Morning small	736.518	4	0	187	187	187	187	60
			42480	1647	1587	1557	1545	30
			0	1685	1655	1647	1625	30
			24000	1647	1617	1589	1589	30

In order to assess the advantages of managed evacuation, a user-equilibrium traffic assignment was performed. The assignment was based on the system optimal Origin-Destination (OD) matrix, as it is assumed that each vehicle was pre-assigned to a shelter. Furthermore, BPR delay function was calibrated and used for each road segment. Both deterministic and stochastic user-equilibrium (UE) were performed. Two measures were used, a) Vehicles Hour Traveled (VHT) [hours] – the total flow multiplied by travel time based on the delay function, over all road segments. b) Average travel time [minutes] – the average travel time per vehicle, obtained by dividing the VHT by the total flow. The system optimum VHT was obtained based on the optimal flow per road segment and the corresponding delay function. Table 2 summarizes the results for the above-mentioned problems. It is evident that employing managed evacuation will result with faster evacuation, as the average travel time to the shelters is 5% to 30% shorter.

Table 2 – Evacuation performance comparison between system optimum and user equilibrium

			System Optimum		Deterministic UE		Stochastic UE	
Problem #	Evacuation time	Total Flow	VHT	Average Travel Time	VHT	Average Travel Time	VHT	Average Travel Time
SCE04-11_11 Morning large	30	9279	779	5.04	911	5.89	916	5.92
SCE04-11_11 Morning small	30	9232	832	5.41	882	5.73	890	5.78
SCE12-19_16 Morning large	30	9873	1092	6.64	1629	9.90	1629	9.90
SCE12-19_16 Morning small	30	9834	1169	7.13	1570	9.58	1577	9.62

The main disadvantage of managed evacuation is the need to dispatch rescue teams to all intersections in order to control the flow according to the optimal paths. Such a task is extremely difficult for medium to large networks, as it might not be practical to dispatch several hundreds of teams. For that it is possible to integrate the traffic assignment model within the optimization, with an additional objective functions aimed at 1) minimizing the number of rescue teams, and 2) minimizing the VHT difference between system optimum and user-equilibrium.

Nonetheless, based on the VHT comparison it is easy to identify the intersections with the highest total in- and out bound VHT difference (VHTD) between the system optimum and user-equilibrium, as can be formulate mathematically as follow:

$$VHTD_i = \sum_j \max\{0, VHT_{ij}^{UE} - VHT_{ij}^{SO}\} + \sum_j max\{0, VHT_{ji}^{UE} - VHT_{ji}^{SO}\} \tag{15}$$

Where $\boldsymbol{i}$ and $\boldsymbol{j}$ are nodes, $\boldsymbol{VHT_{ij}^{SO}}$ $\boldsymbol{VHT_{ij}^{UE}}$, the vehicle hour traveled between nodes $\boldsymbol{i}$ and $\boldsymbol{j}$, for system optimum (SO) or user-equilibrium (UE).

This procedure was used to valuate problem number 1, and out of 260 intersections, 10 contributes to 50% of the total VHTD, 20 to 65% and 30 for 75%. Meaning the it is possible to identify the critical intersections for which the in- and out-bound flows will be much higher than planned, and to assess which intersections should be managed. It should be noted, that in real world situations, when the evacuation network is not managed, the supply-demand system evolves through feasible states, that could not be internally equilibrated. Dynamic traffic assignment is able to simulate the changing of the system state over the time, but in this paper user equilibrium was chosen for comparisons reasons only.

5. Conclusions

This paper presents a multi-objective, stochastic model for planning managed evacuation with optimal allocation of retrofit budget for critical infrastructure, minimizing the evacuation time and the number of non-evacuees. The chance constrained modeling provides the decision maker to perform the analysis based on a predefined confidence level. Furthermore, it was shown that if the evacuation is managed, average travel time is reduced by 5% to 30% when compared to unmanaged evacuation. However, in real emergencies managing the entire evacuation network is difficult, if not impossible to achieve. Yet, it is possible to manage some of the nodes. In this case, it is possible that by choosing and managing certain nodes, the travel time will be decreased. A possible future work is developing an optimization algorithm that for a given evacuation network it simultaneously minimizes the number of managed and the average travel time.

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