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Network Design Model with Evacuation Constraints Under Uncertainty

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Abstract

Nepal earthquake, have shown the need for quick response evacuation and assistance routes. Evacuation routes are, mostly, based on the capacities of the roads network. However, in extreme cases, such as earthquakes, roads network infrastructure may adversely affected, and may not supply their required capacities. If for various situations, the potential damage for critical roads can be identify in advance, it is possible to develop an evacuation model, that can be used in various situations to plan the network structure in order to provide fast and safe evacuation.

This paper focuses on the development of a model for the design of an optimal evacuation network which simultaneously minimizes construction costs and evacuation time. The model takes into consideration infrastructures vulnerability (as a stochastic function which is dependent on the event location and magnitude), road network, transportation demand and evacuation areas.

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. The heuristic model is based on evolutionary algorithms, which also provides a mechanism for solving the problem as a stochastic and multi-objective problem.

Keywords: Evacuation; Multi-Objective Optimization; Heuristics; Evolutionary Algorithms;

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1. Introduction

On Friday, 11 March 2011, an undersea earthquake of magnitude 9.0 (Mw) occurred near the coast of Japan. This earthquake triggered a tsunami, that hit the Fukushima Daiichi Nuclear Power Plant, located about 250 north of Tokyo, causing equipment failures and eventually nuclear meltdowns following the release of radioactive material. The Fukushima Daiichi nuclear accident resulted in the immediate evacuation of all residents living within 3 kilometers from the plant during a period of approximately 16 hours, and subsequent evacuation of those living within a 20 kilometers radius over the next three days.

The Fukushima Daiichi nuclear accident and other recent years events, such as the 9/11 attacks, Hurricane Katrina, the 2014 Nepal snowstorm disaster and the 2015 Nepal earthquake, have shown then need for quick response 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.).

Moreover, evacuation is a stochastic process, however, most current evacuation models treat the problem in a deterministic way. In some cases, distribution laws are incorporated into the deterministic model to treat the randomness of human actions and decision inputs (Cuesta, Abreu et al. 2016). Obviously, stochastic modelling is more complex than deterministic modelling. It requires more data collection and processing, sophisticated computational models, which, in turn have a higher run times, output processing, etc.

In that context, 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 for various situations, the potential damage for critical roads can be identify 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.

This paper focuses on the development of a model for the design of an optimal evacuation network which simultaneously minimizes construction costs and evacuation time. The model takes into consideration infrastructures vulnerability (as a stochastic function which is dependent on the event location and magnitude), road network potential structure, transportation demand, and evacuation areas' capacities. 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 design usually refer to network design and traffic assignment problem. There are several different decisions that should be considered while developing an evacuation models (Cuesta, Abreu et al. 2016): (1) Selection of Evacuation Routes which should be performed in complex scenarios where various possible escape routes leading to the evacuation location exist. 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 and Roy 2015).

While the evacuation network model presented in this paper takes into consideration infrastructures vulnerability, according to Reggiani, Nijkamp et al. (2015), the vulnerability concept still lacks a consensus definition, and it depends on the application context (El-Rashidy and Grant-Muller 2014). The authors of this paper, in past works (Hadas, Rossi 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 (Jenelius and 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 et al. 2013, Zanini, Pellegrino et al. 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 and 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 (Zhou, Banerjee et al. 2010, Shinozuka, Zhou et al. 2015), or for links affected by building damages (Goretti and Sarli 2006).

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) (Yi and Özdamar 2007, Najafi, Eshghi et al. 2014), given their stochasticity (Giuliano and Golob 1998, Chang, Elnashai et al. 2012). Disaster Operation Management review by Galindo and Batta (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 et al. 2012), considering dead and injured people after building damages (Gao, Yang et al. 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), with the extension of multi-objectives and stochastic capacities. Let $G(N, A)$ be a graph, with N nodes and A arcs, when $\{O\} \in N$ is the origin candidate set (residential areas), and $\{D\} \in N$ is the destination candidate set (evacuation areas or shelters). Also let $\{(i,j)\} \in A$ arc candidate set, with $i, j \in [1, \ldots, N]$.

$$Minimize \sum_{(i,j)\in A} C_{a_{ij}} \cdot x_{a_{ij}} + \sum_{i\in N} C_{n_i} \cdot x_{n_i} \tag{1}$$

$$Maximize\ \mathbb{E}\left(\sum_{o\in O} \sum_{d\in D} \sum_{i:(o,i)\in A} f_{oi}^{od}\right) \tag{2}$$

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

Subject to

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

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

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

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

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

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

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

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

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

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

$$P(T(Un_1, \dots, Un_i) \le T^*) \ge \alpha \tag{14}$$

Since the problem approached in our study is stochastic, objectives (1), (2) and (3) represent the construction costs, expected flow and expected evacuation time respectively, when $C_{a_{ij}}$ is the construction cost of arc (i,j), C_{n_i} is the construction cost of node i, $x_{a_{ij}}$ and x_{n_i} are decision variables, f_{ij}^{od} is s a feasible flow from source $o \in O$ to the sink $d \in D$ along arc (i,j). 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 evacuation time will hold in α percent of the cases. Meaning, that for α percent of the case, for example $\alpha = 0.85$ (85%), the evacuation time will be less to equal to T.

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.

4. Genetic Algorithm

A survey on multi-objective optimization methods (Marler and Arora 2004) classifies the various methods into four groups: (1) Methods with a priori articulation of preferences (such as the weighted sum (Zadeh 1963) and lexicographic (Stadler 1988) methods), (2) Methods for a posteriori articulation of preference (such as the normal boundary intersection (NBI) (Das and Dennis 1998, Das and Dennis 1999) and Normal constraint (NC) (Messac, Ismail-Yahaya et al. 2003) methods), (3) Methods with no articulation of preferences (such as the min-max method (Yu 1973)) and (4) 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 et al. 2007)).

As can been from the above, genetic algorithms are suitable for solving multi-objective optimization problem, moreover, they can be used for stochastic optimization problems as well. Genetic Algorithms (GAs) usually assumes a stationary environment for solving an optimization problem. In the first stage, a typical GA usually generates a random set of n individuals, known as population, each associated with a solution. Next an iterative session starts. At each iteration, each individual from the current population is evaluated and assigned with a fitness value (using a fitness function), which states how "good" it is. Then, a new population of size n is created. The new solutions are created by randomly choosing two parent solutions from the current population, based on their goodness, on whom crossover and mutation operations are performed to create two new solutions. By using this method, we assume that the new solutions of the new population are better than those of the current population. The current population is replaced with the new population, and the process continues until a stop condition is met, which could be a number of iterations, specific run time or any other condition (Yoshitomi, Ikenoue et al. 2000).

For a stochastic optimization problem, the fitness function literally expresses the fitness of the individual, therefore the fitness function is fluctuated, according to the stochastic distribution-functions for the stochastic variables. In each generation, the fitness function is determined by random number generated according to the stochastic distribution-functions. Eventually, the frequencies of individuals associated with solutions are investigated through all generations. With roulette wheel selection strategy, for choosing parent solutions for creating new solutions, suitable individuals are selected in proportion to their fitness function value. Moreover, since roulette wheel selection allows sampling with replacement, the selection pressure is relatively high. Therefore, by using roulette wheel selection, it is expected that the higher the expected value is, the higher the individual frequency through all generations is (Yoshitomi, Ikenoue et al. 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.

5. Experimental Results

In order to test the algorithm, five networks, in which 20% of the arcs have stochastic properties, were created. The characteristics of the networks are summarized in

, and include the number of origin nodes, number to destination nodes, total number of nodes and number of arcs. Furthermore, the model representation was altered in a way that all origin and destination nodes were transformed to arcs. i.e. node i was transformed to an arc (i', i), with $C_{a_{i'i}} = C_{n_i}$, $U_{a_{i'i}} = U_{n_i}b$. This representation increases the computation efficiency, as the chromosome is composed of identical attributes.

Table 1 – Characteristic of various test networks

Problem #	Num. of Nodes			Num. of Arc
	Total	Origin	Destination	
1	15	3	3	30
2	35	5	4	97
3	60	12	11	153
4	140	20	19	417
5	2700	100	99	10097

Figure 1 is an illustration of the first network. One possible solution for the first network, marked in red in Figure 1, is composed from one single path: 2-8-11-14-5. The results obtained for this possible solution were compared for three various scenarios: (1) all arcs along the path have deterministic capacities, (2) arcs along the path are stochastics, with small variance, and (3) all arcs along the path are stochastic with large variance. For the three scenarios, the construction cost of this path is 3956 and the evacuation time is 1, however, when all arcs have deterministic capacities, the flow along this path is 30, when all arcs are stochastic with small variance the flow is 16, and when the variance is large the flow is 19.

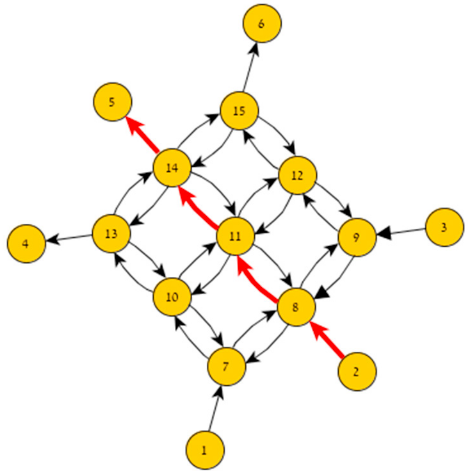

Figure 1- An example of possible evacuation network. Nodes 1,2 and 3 represent possible source node. Nodes 4, 5 and 6 represent destination nodes. All other nodes are transhipment nodes. Black arcs are possible evacuation arcs. Red arcs are the chosen evacuations arcs.

As the example, illustrated in Figure 1, shows, a path which has arcs with stochastic characteristics may have different flows and evacuation times for different situations. However, when looking at the results, for all test networks similar relationships are found between the various objective functions.

The relationships are demonstrated using the results of the algorithm for the first network, when 20% of the arcs have stochastic properties with small variance. In this case the solution is a Pareto set with 89 non-dominated solutions. As can be seen from the results, and illustrated in Figure 2, an increase in the cost allows the construction of a network with higher flow. For example, when the cost is about 4000, the highest value of flow obtained is about 200. However, if we increase the cost to 10000, then it is possible to construct an evacuation network in which the flow is about 400. If we keep increasing the cost, to about 15000, it is then possible to construct an evacuation network in which the flow is about 500. For comparison, Figure 3 illustrates the relationship between cost and flow for the first network, when 20% of the arcs have stochastic properties with large variance.

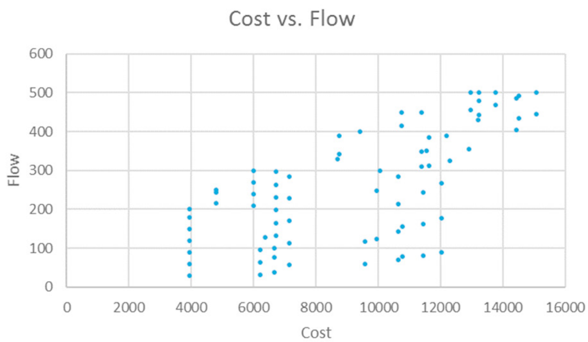

Figure 2 – Cost vs. Flow for the first network, when 20% of the arcs have stochastic properties with small variance

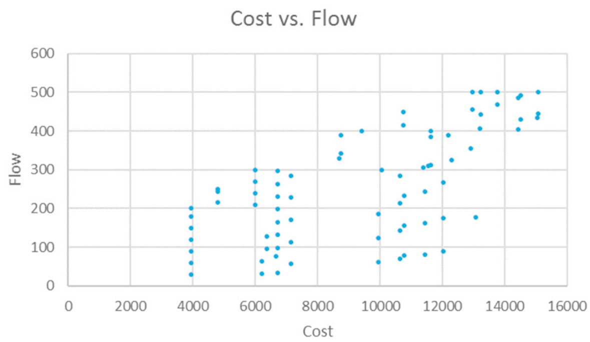

Figure 3 – Cost vs. Flow for the first network, when 20% of the arcs have stochastic properties with large variance

Figure 4 shows that there is a positive correlation between evacuation time and flow. As the flow increases, the evacuation increases as well. For example, when the flow is in the range of 0 to 100, the evacuation time is between one to three. On the other hand, when the flow is in the range of 400 to 500, the evacuation time is between 6 to 10. As before, for comparison, Figure 5 illustrates the relationship between flow and time for the first network, when 20% of the arcs have stochastic properties with large variance.

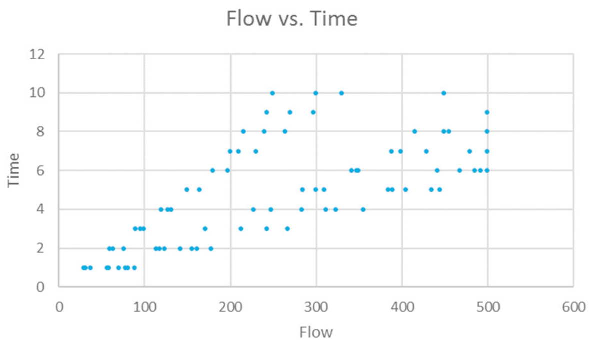

Figure 4 – Flow vs. Time for the first network, when 20% of the arcs have stochastic properties with small variance

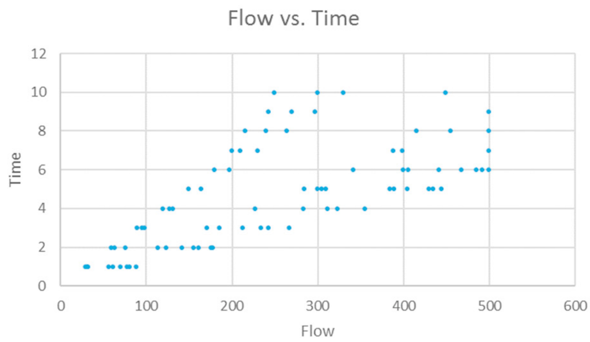

Figure 5 – Flow vs. Time for the first network, when 20% of the arcs have stochastic properties with large variance

However, for the cost and time objectives, no special relationships were found, both when there was small variance (Figure 6) and large variance (Figure 7) for the first network, when 20% of the arcs have stochastic properties.

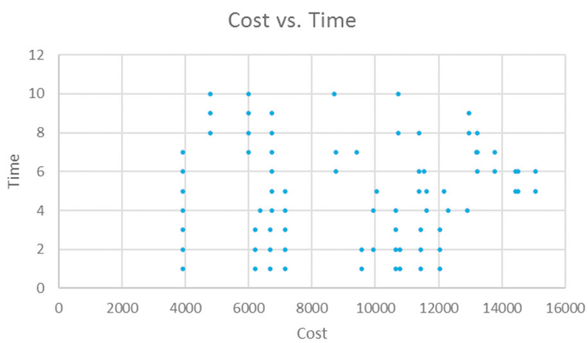

Figure 6 – Cost vs. Time for the first network, when 20% of the arcs have stochastic properties with small variance

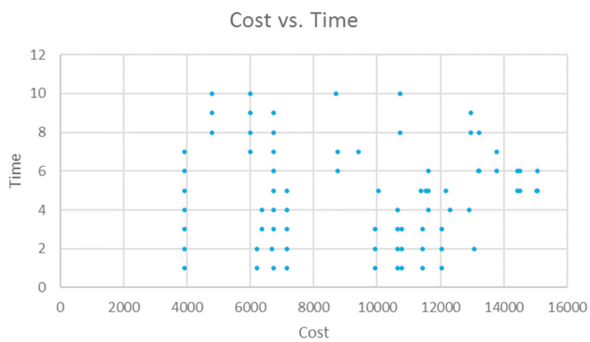

Figure 7 – Cost vs. Time for the first network, when 20% of the arcs have stochastic properties with large variance

Table 2 summarizes the results obtained for all test networks. For each network, the average running time (in seconds) is given as well as the size of the Pareto front obtained (the left number refers to the cases when small variance is used, and the right number refers to the cases when large variance is used). Since the size of the Pareto front, for each of the test networks, is large, six solutions from the Pareto front, are given as an example for each test network. The first solution is a solution with lowest cost, while the second solution is a solution with highest cost. Similarly, the third solution is a solution with highest flow, while the fourth solution is a solution with lowest flow. Finally, the fifth solution is a solution with lowest evacuation time, while the sixth solution is a solution with highest evacuation time.

Since the problem is stochastic, and each network has different stochastic characteristics, when two parallel solution obtained have different values, the differences are colored in red.

Table 2 – Algorithm results for various possible networks with small and large variance

Problem #	Avrg. Run Time (sec.)	Size of Pareto Front	Objective	Small Variance			Large Variance		
				Cost	Flow	Time	Cost	Flow	Time
1	8.949	89 / 86	Cost	3956	200	7	3956	200	7
				15092	445	5	15633	500	6
			Flow	12973	500	9	12973	500	10
				3956	30	1	3956	30	1
			Time	3956	30	1	3956	30	1
				10755	450	10	12973	500	10
2	10.752	383 / 344	Cost	4924	200	10	4924	200	10
				31211	744	6	31361	708	6
			Flow	22030	750	10	22714	750	10
				4924	20	1	4924	20	1
			Time	4924	20	1	4924	20	1
				22030	750	10	22714	750	10
3	16.119	551 / 471	Cost	4257	150	6	4257	150	6
				52653	1760	10	52353	1690	10
			Flow	52653	1760	10	52353	1690	10
				4257	25	1	4257	25	1
			Time	4257	25	1	4257	25	1
				52653	1760	10	52353	1690	10
4	56.256	686 / 636	Cost	6548	150	8	6548	150	8
				111150	2229	9	114087	2470	10
			Flow	106397	2370	10	114087	2470	10
				6548	23	1	6548	22	1
			Time	6548	23	1	6548	22	1
				106397	2370	10	114087	2470	10
5	14627.943	413 / 356	Cost	37147	70	5	37095	54	6
				526507	1251	9	563523	1036	7
			Flow	525815	1450	10	508218	1116	9
				38891	20	1	39697	11	1
			Time	38891	20	1	39697	11	1
				525815	1450	10	489672	1080	10

As can be seen from the results, as the problem increases in size, and therefore the number of stochastics arcs increase as well, there is a higher difference in the results of the various test networks when comparing a network with a small variance in the stochastics arc against the same network but with a large variance in the stochastics arc.

6. Conclusions

Evacuation network design usually refer to network design and traffic assignment problem. There are several different decisions that should be considered while developing evacuation models: (1) Selection of Evacuation Routes, (2) Introduction of delay times and (3) controlling the speed of evacuation. The effectiveness of an evacuation operation is dependent on various factors, such as: (1) The availability of resources, (2) The risk of exposure to disaster impact and (3) The vulnerability of different locations within the evacuation zone.

This study focuses on the development of a model for the design of an optimal evacuation network (selection of evacuations routes), which simultaneously minimizes construction costs, flow, and evacuation time. The model takes into consideration infrastructures vulnerability of the different arcs (as a stochastic function which is dependent on the event location and magnitude), road network, transportation demand and evacuation areas.

The study presents a mathematic model for designing evacuation routes. however, since the problem presented is both multi-objective and stochastic, and an optimal solution cannot be found within a reasonable timeframe, a different solution approach is used. Since genetic algorithms are suitable for solving both multi-objective optimization problems and stochastic optimization problems, a heuristic model based on genetic algorithms, is used for solving the evacuation problem. In order to simplify the algorithm's implementation, MOEA framework (Hadka 2016) has been used.

In order to test the algorithm, several networks, in which 20% of the arcs have stochastic properties (with small and large variance), were created. The results of the algorithm are Pareto sets with non-dominated solutions. The results show a positive correlation between cost and flow - an increase in cost allows the construction of a network with higher flow. A positive correlation also exists between the flow and evacuation time, meaning that as the flow increases, the evacuation time increases as well.

The results also show that as the problem increases in size (a higher number of stochastics arcs), there is a higher difference in the results of the various test networks when comparing a network with a small variance in the stochastics arc against the same network but with a large variance in the stochastics arc. This difference has also been demonstrated using a single possible solution in three various scenarios: (1) all arcs have deterministic capacities, (2) all arcs are stochastics, with small variance, and (3) all arcs are stochastic with large variance.

A future work is the possibility of analyzing and predicting the impact of different evacuation scenarios and procedures in real-time, which can be incorporated into the model. This is one of the most important future applications for evacuation modelling, which is extremely relevant for the decision-making process during an actual emergency.

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