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Multi-Objective Evacuation Network Design with Chance Constraints

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ABSTRACT

Natural and man-created disasters, such as hurricanes, earthquakes, tsunamis, accidents and terrorist attacks, have shown the need for quick evacuation. 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 the 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, which 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. A mathematic model is introduced for the presented problem. Furthermore, a chance constraint is used to provide the decision maker the means to assess the solution based on different risk levels. 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;

INTRODUCTION

Natural and man-created disasters, such as hurricanes, earthquakes, tsunamis, accidents and terrorist attacks, require evacuation and assistance routes. A recent example is the Nepal 2015 earthquake. On Saturday, 25 April 2015, an earthquake of magnitude 7.8 (Mw), followed by two powerful aftershocks hit Nepal, killing nearly 9000 people and injuring about 21000 people. Other examples, include the 2014 Nepal snowstorm disaster, the Fukushima Daiichi nuclear accident (Japan 2011 tsunami), the 9/11 attacks and Hurricane Katrina, are examples in which quick response evacuation and assistance routes are needed.

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 *(1)*. 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 the infrastructures vulnerability associated with the construction of a 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. 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.

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 *(1)*: (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 *(2)*.

While the evacuation network model presented in this paper takes into consideration infrastructures vulnerability, according to Reggiani, Nijkamp *(3)*, the vulnerability concept still lacks a consensus definition, and it depends on the application context *(4)*. However, according to Mattsson and Jenelius *(5)* the definition suggested by Berdica *(6)*, *"Vulnerability in the road transportation system is a susceptibility to incidents that can result in considerable reductions in road network serviceability"*, is often cited and representative of part of the literature. Mattsson and Jenelius *(5)* who reviewed recent studied in the field of vulnerability and resilience of transport systems concluded that there are two distinct traditions in vulnerability studies. In the first approach vulnerability studies of transport networks are based on their topological properties, which requires definitional network. It allows detailed analysis of different attack strategies. Comparisons with other very different kinds of networks can also be done. The second approach uses more or less sophisticated models, which require large computational efforts, of the transport system, in which demand and supply side of the transport system and travellers' responses to disturbances and disruptions are integrated. This approach requires extensive data about demand and supply aspects of the studied transport system, as well as the availability of models for simulating the consequences of disruptive events, whoever, it provides a more complete description of the problem and its consequences.

Hadas, Rossi *(7)* adopted a 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 *(8)*. 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 *(9, 10)*, 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., *(11)*). 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 *(12, 13)*, or for links affected by building damages *(11)*.

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) *(14, 15)*, given their stochasticity *(16, 17)*. Disaster Operation Management review by Galindo and Batta *(18)* 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 *(19)*, considering dead and injured people after building damages *(20)*.

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 *(21)*, 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 $i, j \in [1, \dots, N]$.

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

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

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

Subject to

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

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

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

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

$$b_i = 0 \quad \forall i \notin O \cup D \quad (8)$$

$$\sum_{i\in O} b_i + \sum_{i\in D} b_i = 0 \quad (9)$$

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

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

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

$$T(Un_1, \dots, Un_i) > 0 \quad (13)$$

$$P\left(\sum_{o\in O}\sum_{d\in D}\sum_{i:(o,i)\in A} f_{oi}^{od} \ge F^*\right) \ge \alpha \quad (14)$$

Objective (1) represents the construction costs, and since the problem is to be defined with stochastic attributes, objectives, (2) and (3), are the 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.

Since the flows along the various arcs are stochastic, it is possible that a given network may have various solutions, meaning that the construction cost and evacuation time remain the same, however, the flow may be different in each solution. Since the evacuation time is dependent on the flow, building the network based on one possible solution, may not guarantee that the evacuation time will remain as planned. For that reason, a chance constraint (14) is also added to the model. The chance constraint is added to ensure that for every solution found, the flow will be equal or higher than F^* in α percent, for example $\alpha = 0.85$ (85%), of the cases.

The model assumes that the 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 complete. 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.

GENETIC ALGORITHM

A survey on multi-objective optimization methods *(22)* classifies the various methods into four groups: (1) Methods with a priori articulation of preferences (such as the weighted sum *(23)* and lexicographic *(24)* methods), (2) Methods for a posteriori articulation of preference (such as the normal boundary intersection (NBI) *(25, 26)* and Normal constraint (NC) *(27)* methods), (3) Methods with no articulation of preferences (such as the min-max method *(28)*) 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 *(29)*).

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 *(30)*.

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 *(30)*.

In order to simplify the algorithm's implementation, MOEA framework *(31)* 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 (which is one of the most popular MOEAs *(32)*).

EXPERIMENTAL RESULTS

In order to test the algorithm, five networks were created. The characteristics of the networks are summarized in TABLE 1, 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 average flow is 16, and when the variance is large the average flow is 19.

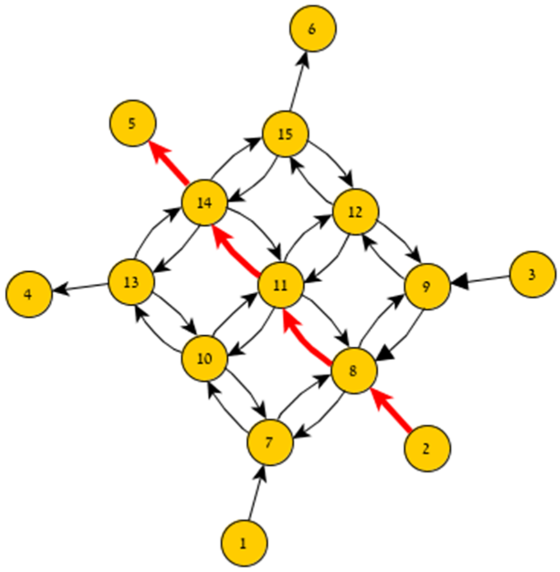


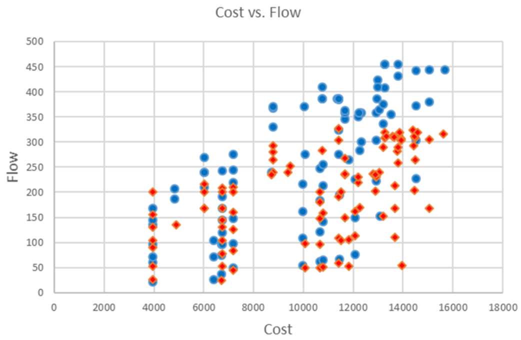
FIGURE 1 An example of possible evacuation network.

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. Nevertheless, similar relationships are found between the various objective functions for all test networks

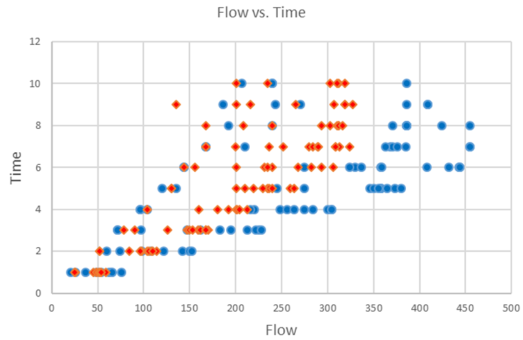
The relationships are demonstrated using the results of the algorithm for the first network. In this case the solution is a Pareto set with 96 non-dominated solutions. FIGURE 2 depicts the Pareto set for small variance (blue) and large variance (red). As can be seen from the results, and illustrated in C

FIGURE 2A, an increase in the cost allows the construction of a network with higher flow. FIGURE 2B shows that there is a positive correlation between evacuation time and flow. As the flow increases, the evacuation increases as well. However, for the cost and time objectives, no special relationships were found, both when there was small variance and large variance (FIGURE 2C).

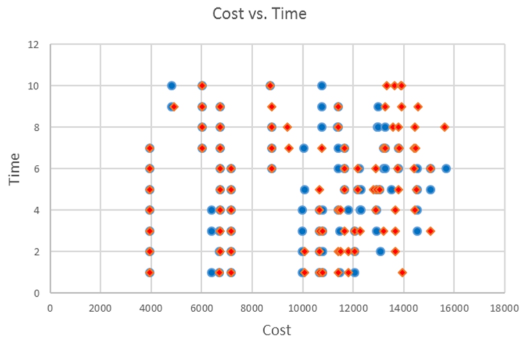
FIGURE 2 also portrays the advantages of a multi-objective model – the presentation of a full set of solution, from which the decision maker can choose a solution.



A



B



C

FIGURE 2 Cost vs. Flow (A), Cost vs. Time (B) and Flow vs. Time (C) for the first network, when 70% of the arcs have stochastic properties.

TABLE 2 summarizes the results obtained for all test networks, when 70% of the arcs have stochastic properties with small variance, with emphasis on the chance constraint. Each one of the solutions of the Pareto front was evaluated 100 times, therefore, for each solution it is possible to determine a flow F^*, that in α percent of the cases the obtained flow 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 flow, for $\alpha = 0.95$, $\alpha = 0.9$, $\alpha = 0.85$, including the average flow - $\alpha = 0.50$, and the evacuation time. 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.

As can be seen from the result, using a chance constraint results with a solution in which the flow is lower compared to the flow obtained for the same solution based on the average flow, as the higher the α, the more conservative the solution is (in terms of flow). This is due to the fact the obtained flow must satisfies the chance constraint. Furthermore, the higher the variance, the larger the change of the flow with respect to α.

TABLE 2 Algorithm Results for Various Possible Networks in which 70% of the Arcs are Stochastics with Small Variance

Problem #	Run Time (sec.)	Size of Pareto Front	Objective	Cost	Flow				Time
					$\alpha = 0.95$	$\alpha = 0.9$	$\alpha = 0.85$	$\alpha = 0.5$	
1	8.998	96	Cost	3956	126	126	147	168	7
				15674	420	425	426	444	6
			Flow	13255	433	437	441	455	8
				3956	18	18	18	21	1
			Time	3956	18	18	18	21	1
				10755	350	350	366	386	10
2	21.412	388	Cost	4924	160	160	160	180	10
				30693	650	658	674	696	7
			Flow	28902	658	672	679	706	7
				4924	16	16	16	18	1
			Time	4924	16	16	16	18	1
				23406	643	651	658	711	10
3	50.653	519	Cost	4257	148	148	148	149	6
				50439	1443	1474	1483	1530	10
			Flow	50439	1443	1474	1483	1530	10
				4257	14	14	14	18	1
			Time	4257	14	14	14	18	1
				50439	1443	1474	1483	1530	10
4	324.3	615	Cost	6548	120	120	120	168	8
				104283	1863	1881	1890	1944	9
			Flow	96385	2080	2100	2113	2162	10
				6651	17	17	17	18	1
			Time	6651	17	17	17	18	1
				100626	2068	2085	2096	2160	10
5	14627.943	413 / 356	Cost	37135	110	110	110	150	10
				530071	690	702	708	732	6
			Flow	436417	1070	1080	1090	1140	10
				40066	13	13	14	15	1
			Time	40066	13	13	14	15	1
				436417	1070	1080	1090	1140	10

TABLE 3 provides similar information for all test networks, when 70% of the arcs have stochastic properties with large variance.

TABLE 3 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	Objective	Cost	Flow				Time
					$\alpha = 0.95$	$\alpha = 0.9$	$\alpha = 0.85$	$\alpha = 0.5$	
1	8.998	96	Cost	3956	170	182	187	200	7
				15624	234	247	267	316	8
			Flow	11413	235	248	258	327	9
				6696	17	17	20	25	1
			Time	3956	21	21	21	26	1
				13913	230	234	247	303	10
2	21.412	388	Cost	4924	130	130	130	160	10
				32661	488	488	488	571	9
			Flow	23296	488	488	488	539	9
				5629	5	5	10	14	1
			Time	4924	13	13	14	16	1
				27565	479	488	500	558	10
3	50.653	519	Cost	4257	124	124	124	134	6
				53718	1240	1273	1286	1402	10
			Flow	45395	1271	1306	1314	1378	10
				4749	20	22	22	23	1
			Time	4257	24	24	24	24	1
				53718	1240	1273	1286	1402	10
4	324.3	615	Cost	6548	32	32	32	40	4
				103379	1469	1494	1539	1611	9
			Flow	100898	1607	1663	1687	1760	10
				6548	10	10	10	18	1
			Time	6548	10	10	10	18	1
				100898	1607	1663	1687	1760	10
5	14627.943	413 / 356	Cost	37803	45	45	45	81	9
				540351	810	837	846	900	9
			Flow	540351	810	837	846	900	9
				40890	3	3	3	6	1
			Time	39709	4	4	4	5	1
				479612	600	630	650	750	10

To better understand the effect of the chance constraint, the same networks were redesigned, this time with 20% of the arcs have stochastic properties with small and large variances. Information regarding these network is provided in TABLE 4 and TABLE 5.

Again, as can be seen from the result, using a chance constraint results with a solution in which the flow is lower compared to the flow obtained for the same solution based on the average flow. Compared to the networks in which 70% of the arcs are stochastics with small variance, here there is a smaller change (sometimes there is no change at all) in F^* when choosing $\alpha = 0.95$, $\alpha = 0.9$ or $\alpha = 0.85$.

TABLE 4 Algorithm Results for Various Possible Networks in which 20% of the Arcs are Stochastics with Small Variance

Problem #	Run Time (sec.)	Size of Pareto Front	Objective	Cost	Flow				Time
					$\alpha = 0.95$	$\alpha = 0.9$	$\alpha = 0.85$	$\alpha = 0.5$	
1	9.659	88	Cost	3956	133	133	133	168	7
				15092	390	390	390	415	5
			Flow	13255	452	452	452	470	8
				3956	19	19	19	24	1
			Time	3956	19	19	19	24	1
				10755	440	440	450	450	10
2	23.418	389	Cost	4924	160	160	160	160	8
				31804	712	712	712	720	6
			Flow	23406	736	736	736	750	9
				4949	17	17	17	19	1
			Time	4924	20	20	20	20	1
				22031	636	636	636	681	10
3	59.529	597	Cost	4257	150	150	150	150	6
				53175	1572	1588	1598	1640	10
			Flow	45827	1610	1610	1640	1660	10
				4257	25	25	25	25	1
			Time	4257	25	25	25	25	1
				53175	1572	1588	1598	1640	10
4	334.368	649	Cost	6548	150	150	150	150	10
				108971	2136	2145	2145	2190	9
			Flow	96790	2250	2250	2250	2250	10
				6548	20	20	20	23	1
			Time	6548	20	20	20	23	1
				99052	2090	2130	2130	2200	10
5	69591.502	375	Cost	36912	24	24	24	34	2
				495462	928	944	960	1000	8
			Flow	479396	1250	1270	1270	1300	10
				41352	18	18	18	24	1
			Time	40060	18	18	18	20	1
				479396	1250	1270	1270	1300	10

TABLE 5 Algorithm Results for Various Possible Networks in which 20% of the Arcs are Stochastics with Large Variance

Problem #	Run Time (sec.)	Size of Pareto Front	Objective	Cost	Flow				Time
					$\alpha = 0.95$	$\alpha = 0.9$	$\alpha = 0.85$	$\alpha = 0.5$	
1	9.048	86	Cost	3956	133	133	133	168	7
				15092	390	390	390	415	5
			Flow	13255	452	452	452	470	8
				3956	19	19	19	24	1
			Time	3956	6	6	6	11	1
				10755	274	291	310	381	10
2	22.233	339	Cost	4924	180	180	180	180	9
				29391	646	646	646	679	7
			Flow	20339	660	660	660	680	10
				5949	18	18	18	22	1
			Time	4924	20	20	20	20	1
				22714	605	605	605	662	10
3	47.047	451	Cost	4257	150	150	150	150	6
				49241	1330	1330	1330	1460	10
			Flow	46632	1390	1390	1390	1520	10
				4749	10	10	10	36	2
			Time	4257	25	25	25	25	1
				49241	1330	1330	1330	1460	10
4	338.398	603	Cost	6548	150	150	150	150	10
				105495	2054	2067	2085	2166	9
			Flow	102981	2210	2210	2210	2250	10
				6548	23	23	23	23	1
			Time	6548	23	23	23	23	1
				104121	2148	2158	2158	2190	10
5	14627.943	361	Cost	35949	65	65	65	90	5
				541670	840	856	880	952	8
			Flow	454292	1053	1071	1089	1143	9
				41378	6	6	6	12	1
			Time	41378	6	6	6	12	1
				460086	900	930	940	1040	10

To summarize the importance of the chance constraint, the average change of the flow (based on each Pareto set) was calculated for each problem, percentage of stochastic arcs, variance level and α. For each Pareto set, the median solution was obtained, and its flow was averaged across the set. Based on the average value, it is possible to calculate the percentage change when increasing α. This analysis is presented in TABLE 6. For example, there is a decrease of ~8% when increasing α from 0.50 to 0.85, for problem #1, 20% stochastic arcs, and small variance. From the results it is evident that: 1) the use of the average value (α=0.50) does not reflects the true nature of flow. 2) the higher the stochastic nature of the model, the more apparent are the changes in the flow when increasing α.

TABLE 6 Relative Difference Between Various Obtained Flows for the Various Test Networks

Problem #	Percentage of Stochastics Arcs	Small Variance			Large Variance		
		0.50 vs. 0.85	0.85 vs. 0.90	0.90 vs. 0.95	0.50 vs. 0.85	0.85 vs. 0.90	0.90 vs. 0.95
1	20	-7.96	-0.89	-0.11	-41.36	-6.13	-6.04
	70	-10.08	-2.07	-1.06	-22.29	-3.44	-4.69
2	20	-3.46	-0.35	-0.07	-8.04	-1.02	-0.42
	70	-6.01	-0.86	-1.17	-23.39	-5.05	-5.52
3	20	-2.29	-0.33	-0.16	-7.65	-0.93	-0.58
	70	-6.56	-1.05	-1.34	-10.70	-2.53	-2.49
4	20	-2.11	-0.29	-0.28	-2.94	-0.38	-0.25
	70	-5.24	-0.98	-1.02	-10.30	-1.91	-2.27
5	20	-5.83	-0.82	-0.75	-19.50	-2.74	-3.09
	70	-8.21	-1.43	-1.41	-31.91	-6.12	-5.70

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 *(31)* has been used.

In order to test the algorithm, several networks, in which 20%, and 70% 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.

Finally, using a chance constraint results with a solution in which the flow is lower compared to the flow 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 a flow F^*, which is lower than the average flow. The F^* should be chosen such that in α percent of the cases the obtained flow will be equal or higher than F^*. This guaranties that in α percent of the cases the evacuation time will be held (and even may be shorter). The results show that when 20% of the arcs are stochastics with small variance, there is a small change (and sometimes no change at all) in F^* when choosing $\alpha = 0.95$, $\alpha = 0.9$ or $\alpha = 0.85$. A larger change exists when the variance is large. To better understand the effect of the chance constraint, the same networks were redesigned, this time with 70% of the arcs have stochastic properties with small and large variances. Compared to the previous networks, here there is a larger change (although sometimes there is no change at all) in F^* when choosing $\alpha = 0.95$, $\alpha = 0.9$ or $\alpha = 0.85$. This change gets higher when the variance is large.

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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