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Optimal evacuation planning under a partial traffic management regime

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ABSTRACT

Natural and man-created disasters, such as hurricanes, earthquakes, tsunamis, accidents and terrorist attacks, require fast evacuation. However, in extreme cases, such as earthquakes, road network infrastructures may adversely be affected, and may not supply their required capacities. Therefore, it is necessary to increase the network capacity, and to decrease the evacuation time. Network capacity can be increased, if the potential damage to critical roads segments can be identified in advance and retrofitted. Evacuation time can be further decreased if the evacuation process is managed, meaning that all evacuees are being evacuated along predefined routes. However, managing the whole network is practically impossible, as rescue teams must be present at each intersection or road segment. This paper focuses on the development of a model that addresses these two objectives, and minimizes the evacuation time, the retrofit costs and the number of managed road segments. The selection of the managed road segments is based on the evacuation time difference between the system optimum and user equilibrium assignments. Due to the complexity of the model, a bi-level heuristic was developed. A case study of a real-world network confirms the usefulness of the algorithm. The results show that managing 4 road segments out of over 1,000 road segments, can reduce the evacuation time from 404 vehicle hours traveled (VHT) to 378 VHT. This is a 44% reduction of the evacuation time when compared to the fully managed network (361 VHT).

Keywords: Evacuation; Multi-Objective Optimization; Heuristics; Traffic management;

1 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 road networks. However, in extreme cases, such as earthquakes, road 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 managed evacuation network which simultaneously optimizes the following objective functions: 1) minimize construction costs, 2) minimize evacuation time, 3) minimize the number of managed road segments, and 4) minimize the delay caused by selfish route selection (the vehicle hours traveled (VHT) difference between system optimum and user-equilibrium).

In other words, the model is aimed at selecting an optimal set of critical links for retrofit (increasing resilience) and an optimal set of links to be managed by the rescue teams (increasing flow).

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.

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 bi-level 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 *(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. 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 travelers' 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, however, 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, 14)*.

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) *(15, 16)*, given their stochasticity *(17, 18)*. Disaster operation management review by Galindo and Batta *(19)* 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 *(20)*, considering dead and injured people after building damages *(21)*.

3 EVACUATION PLANNING MODELS CONSIDERING THE AVAILABILITY OF MOBILE TRAFFIC MANAGEMENT RESOURCES

In this work, we consider two types of evacuation schemes. The first model assumes that the evacuation is fully managed, while the second model takes into account that not all road segments are controlled and traffic flow is only partially managed. Both models are multi objective, and integrates stochastic reduction of critical infrastructures' capacities.

3.1 Fully Managed Evacuation model (FME)

The evacuation model used is based on *(22)* and *(7)*, with the extension of multi-objectives and stochastic capacities. Let $G(N, A)$ be a graph, with N nodes and A arcs, with $O \subset N$ 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 represents a road segment, and is associated with K retrofit alternatives. A retrofit is a structural improvement that given a construction cost, will increase resilience of the arc in terms of the capacity. Alternative $k = 1$ is the current state of the arc, with no costs associated. Naturally, the capacity of alternative $k > 1$ is higher than the capacity of alternative $k = 1$. 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, $a \notin A_c$, $K = 1$, meaning no retrofit is needed.

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

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

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

Subject to

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

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

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

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

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

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

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

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

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

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

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

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.

A chance constraint (14) is used 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^*.

3.2 Partially Managed Evacuation model (PME)

As stated, the main disadvantage of managed evacuation is the need to dispatch rescue teams to all road segments 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. To overcome that, a revised optimization model is to be developed. The objective of the model is to identify a small set of road segments which if managed, can reduce the total evacuation time significantly.

The definition of a managed road segment is that only preselected groups of evacuees are permitted to use that road segment. All other evacuees are not allowed to enter that road segment. The identification of those groups is based on the system optimum assignment. Furthermore, it is assumed that all evacuees are informed before the evacuation with regards to their designated shelter and which road segments they must use or avoid.

Modeling wise, there is a need to integrate a traffic assignment model within the optimization, with additional objective functions aimed at (1) minimizing the number of managed road segments, and (2) minimizing the vehicle hours traveled (VHT) difference between system optimum and user-equilibrium.

The proposed model aims at simulating traffic conditions of a road network in case of evacuation (considering the car as the main transportation mode), to better understand the effects of traffic management and control strategies. In the traffic assignment model, road network features, specifically link capacity, vary to consider the effects of the hazard (e.g. links becoming not accessible due to an earthquake) and traffic control strategies.

In order to assess the advantages of a completely managed evacuation, we first performed a system optimum assignment to simulate effects of mandatory instructions on prescribed evacuation routes aimed at minimizing the total travel time *(23-26)*. At that point evacuees' compliance with prescribed routes has to be considered.

Based on social sciences view and several studies on evacuation travel behavior, mostly related to hurricanes, we can assume that, in real-world situations, when the evacuation network is not managed, evacuees' routes selection relies more on past experience and familiarity with the road network than on current traffic conditions. Hence the evacuees often selecting familiar routes, due to the perception of both high reliability of known roads and high uncertainty on performance of alternative routes *(27-31)*.

Starting from that consideration, a deterministic user-equilibrium (UE) based on BPR delay functions, calibrated for each road segment, was performed to identify actual routes selection by the evacuees (users choose route trying to minimize their own personal travel cost rely on past experiences/familiarity, selfish behavior). Stochastic and deterministic user equilibrium assignment approaches were applied based on several previous evacuation studies *(13, 32-35)*, assuming that evacuees perform pre-trip route selection before departure without the possibility to deviation during the trip.

In order to address the selection of managed road segments, the FME model presented is revised with the inclusion of a decision variable y_{ij}, which represent whether or not a road segment (i,j) is managed, and the following objective functions.

$$Minimize \sum_{(i,j)\in A} y_{ij} \tag{15}$$

$$Minimize \sum_{(i,j)\in A} (1-y_{ij}) \max\{0, VHT_{ij}^{UE} - VHT_{ij}^{SO}\} \tag{16}$$

Where VHT_{ij}^{SO} and VHT_{ij}^{UE} are the vehicle hours traveled along arc $(i,j) \in A$, induced by constraints (4)-(14), for system optimum (SO) and user-equilibrium (UE) respectively.

Objective (15) is to minimize the number of managed road segments, where y_{ij} is a decision variable equals to 1 when arc $(i,j) \in A$ is managed, and is equal to 0 otherwise. Objective (16) is to minimize the total VHT difference between system optimum and user-equilibrium for all unmanaged arcs. These objectives simultaneously responsible for the construction of an optimal solution set. Each solution provides, for a given number of managed road segments, their optimal locations, which minimize the delay caused by deviating from the system optimum assignment.

The constraints of the new evacuation model remain the same with the addition of constraint (17) which refer to decision variable, y_{ij}. This constraint states that y_{ij} can be equal to 1 or 0.

$$y_{ij} \in \{0,1\} \quad \forall (i,j) \in A \tag{17}$$

3.3 Bi-level Heuristic Framework (PMEH)

Due to the complexity of PME model, which is multi-objective, stochastic, and integrates traffic assignment models, it cannot be optimally solved in reasonable time. Therefore, this paper introduces a bi-level heuristic framework.

The framework consists of three stages. 1) the execution of FME, 2) the selection of candidate solutions for partial management, and 3) the identification (for each solution) of the road segments to be managed.

- $VHTD\%_{min}$= VHT improvement potential threshold
- ML_{Max} = Maximum number of road segments to manage
- CL_{Max} = Maximum number of road segments to check

1. Perform the FME model and obtain a non-dominated solution

2. For each solution
   a. Perform SO and UE for the network G: $G(SO)$, $G(UE)$
   b. calculate $VHTD\% = \frac{\sum VHT_{ij}^{UE} - \sum VHT_{ij}^{SO}}{\sum VHT_{ij}^{SO}}$

3. For each solution with $VHTD\% > VHTD\%_{min}$
   a. $ML = \emptyset$ (the set of managed links)
   b. $CL = \emptyset$ (the set of candidate links)
   c. $m = 1$
   d. $n = 1$
   e. While $m < M_{Max}$ and $n < C_{Max}$
      i. Find link, $L = (i,j)$, with $max(VHT_{ij}^{UE} - VHT_{ij}^{SO}) > 0$, such that $L \notin CL$ and $L \notin ML$ and add L to CL
      ii. Identify OD pairs groups that pass via link L in G(SO) and set $t(L) = 0$, otherwise $t(L) = \infty$
      iii. $UE' = UE(ML \cup L)$
      iv. If $\sum VHT_{ij}^{UE'} < \sum VHT_{ij}^{UE}$
         1. $ML = ML \cup L$
         2. $m = m + 1$
         3. $UE = UE'$
         4. $SO = SO(ML)$
         5. $n = n + 1$

3.3.1 Stage 1- Stochastic Multi-Objective Heuristic

The following properties of the FME 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 *(36)*. 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 *(37)*. In this study, the NSGA-II genetic algorithm has been used. To simplify the algorithm's implementation, the algorithm was codes using MOEA framework *(38)*.

3.3.2 Stage 2 – Selecting Potential Solutions for Partial Management Evacuation

In order to identify whether a solution has the potential to be partially managed, the relative VHT increase from SO to UE is to be calculated. For that, both SO and UE assignments are performed and compared. Based on the relative increase in VHT (VHTD%), when compared to a predefined threshold, it is determined if a solution is to be further analyzed. For example, a VHTD%=5 represents that the difference in VHT between SO and UE is 5%, and practically it is ineffective to manage the evacuation as there is not a significant reduction in evacuation time when managing any subset of the road segments. On the other hand, a VHTD%=50 indicates that there is a substantial potential for evacuation time reduction when a sub set of the road segments are to be managed during evacuation.

3.3.3 Stage 3 – a Greedy Algorithm for the Allocation of Managed Road Segments

Based on the candidate set of non-dominated solutions obtained in the second stage, for each solution a greedy algorithm is used to determine which road segments have to be managed in order to achieve a reduction in evacuation time as close to SO as possible.

The greedy heuristic uses two sets of arcs: ML, the set of managed arcs that is empty at the start of the heuristic, and CL, the set of candidate arcs, equals to $A\backslash M$. In order to use the greedy heuristic, the decision maker has to decide on two variables: ML_{Max}, the maximum number of managed arcs, and CL_{Max}, the maximum numbers of arcs to be checked. In each iteration of the greedy heuristic, for every arc in each solution belongs to the candidate arcs list CL, $VHTD_{ij}$ is calculated. Next, the arc for with $max(VHT_{ij}^{UE} - VHT_{ij}^{SO}) > 0$ selected as a candidate arc for evacuation management. The managed network (based on ML and the candidate managed arc) is evaluated. If an improvement if found, the candidate arc is added to ML. Otherwise, the procedure is repeated with the arc with the second highest value of $VHTD_{ij}$ as a candidate arc, and so on, CL_{Max} times. If no improvement is found, and no arcs are added to ML, or the number of arcs in ML is equal to ML_{Max} the heuristics stops, otherwise, a new iteration of the heuristics is performed.

4 CASE STUDY

To assess and validate the advantages of the model and the PMEH framework, 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 *(7)*. FIGURE 1 presents the road network components, including critical links (bridges) and shelters locations (attraction sites).

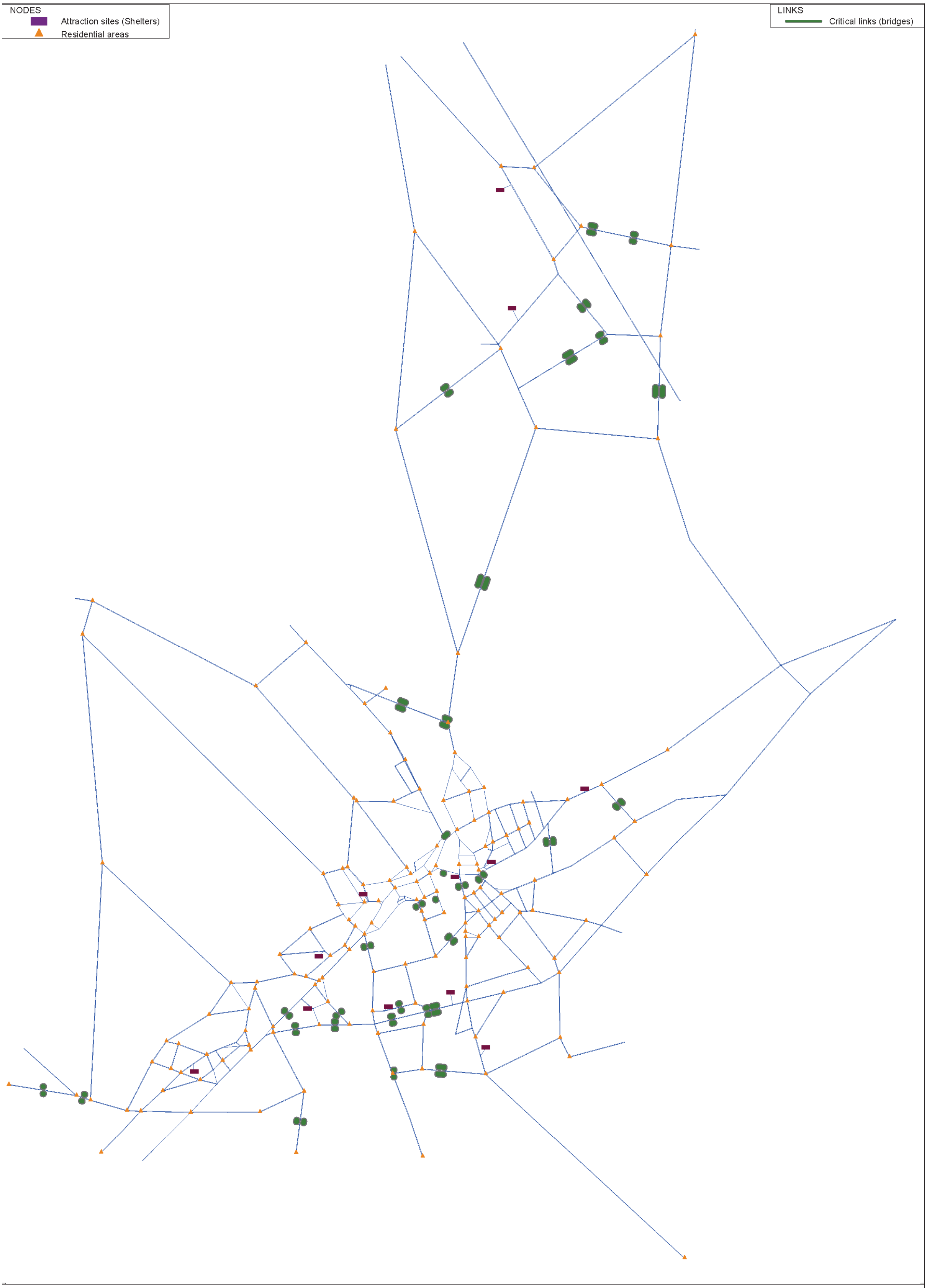

FIGURE 1 Conegliano road network *(7)*.

4.1 Results of Fully Managed Evacuation

The first stage of the PMEH, the FME model was solved using the NSGA-II algorithm. TABLE 1 summarizes the results obtained for an earthquake scenario, with low and high impacts. Since the problem contains a chance constrain, 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 the earthquake scenario, the average running time was 526 seconds, and the Pareto front size was 11, with the cost of each solution, the number of non-evacuees, for $\alpha = 0.95$, $\alpha = 0.9$, $\alpha = 0.85$, the average number of non-evacuees - $\alpha = 0.50$, and the evacuation time as follows.

TABLE 1 Algorithm Results for the earthquake Scenario

Solution #	Cost	Number of Non-Evacuees				Evacuation Time
		$\alpha = 0.95$	$\alpha = 0.9$	$\alpha = 0.85$	$\alpha = 0.5$	
1	0	1215	1215	1215	1215	60
2	0	3	3	3	3	90
3	0	3555	3555	3555	3555	30
4	60498	3045	3045	3075	3135	30
5	60498	195	195	255	375	60
6	36498	375	435	435	555	60
7	36498	3135	3135	3165	3225	30
8	15800	3375	3375	3375	3375	30
9	20698	3315	3315	3315	3375	30
10	20698	735	735	735	855	60
11	15800	855	855	855	855	60

Based on the solution set, the decision maker can select the fittest evacuation plan, in terms of costs, evacuation time, and the number of non-evacuees. However, the FME model assumes that all road segments are managed.

4.2 Comparison of managed and unmanaged evacuation

For the second stage of the PMEH framework, the results obtained for two different earthquake scenarios were evaluated. Each scenario has two variations, in which critical arcs have stochastic properties with both small and large variance, to assess the advantages of managed evacuation versus a user-equilibrium traffic assignment. The results are summarized in TABLE 2. For each scenario, the VHT, the average travel time [minutes] (the average travel time per vehicle), and the VHTD% were calculated. The results showed that employing managed evacuation will result with faster evacuation, as the average travel time to the shelters is 5% to 30% shorter, and VHTD% in the range of 6%-49%. Furthermore, based on the VHTD% it is possible to identify which of the solutions is a candidate for partial managed evacuation. For example, solution 2, with VHTD%=6, is unfit, as the unmanaged evacuation is 6% longer than the fully managed evacuation, hence it is ineffective to assign rescue teams for that task. On the other hand, solution 3 and 4 are good candidate for partially managed evacuation, as the potential reduction in evacuation time is high (49% and 34% respectively).

TABLE 2 Evacuation performance comparison between system optimum and user equilibrium

Scenario				System Optimum		User Equilibrium		VHTD%
Level of impact on the road network	Critical links capacity variance	Evacuation time	Total Flow	VHT	Average Travel Time	VHT	Average Travel Time	
low	high	30	9279	779	5.04	911	5.89	17
low	low	30	9232	832	5.41	882	5.73	6
high	high	30	9873	1092	6.64	1629	9.90	49
high	low	30	9834	1169	7.13	1570	9.58	34

4.3 Optimal Selection of Managed Road Segments Under Partially Managed Evacuation

For the third stage of the PMEH framework, solution number 11 was selected for demonstration. The number of managed road segments was set to $ML = 4$, and the number of maximal number of road segments to check was set to $CL = 10$. Hence, based on the algorithm, four subsets of the solution were created, reflecting the addition of objectives (15) and (16). Given that, the decision maker can decide which of the four sub-solutions is to be selected as the chosen plan. TABLE 3 summarizes the results. For a fully managed evacuation (system optimum), VHT is equal to 361. On the other hand, totally unmanaged evacuation results with 404 VHT, an increase of 43 VHT. The effect of managing 1, 2, 3, and 4 road segments, leads to the decrease of 21, 23, 25, and 26 VHT respectively. The VHT reduction is equivalent to 44% reduction of the potential VHT reduction (404-361=43 VHT), which is achieved by managing only 4 road segments out of over 1000 road segments. FIGURE 2 presents the location of the four managed road segments.

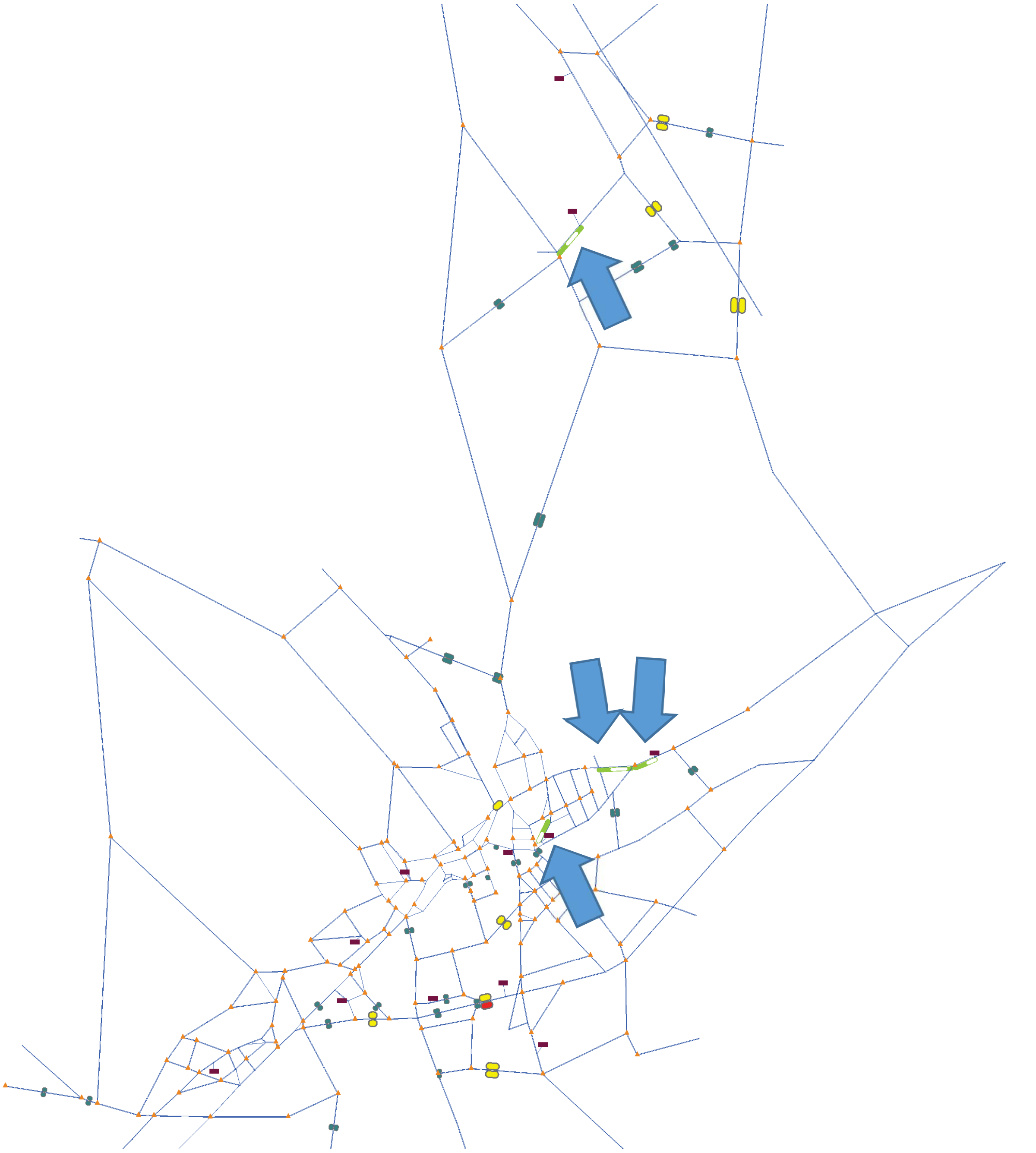

FIGURE 2 The locations of the selected managed road segments.

4.4 The Effect of Drivers' Compliance on the Evacuation Time

While the results are compelling, it is necessary to investigate the effect of the compliance level on the evacuation time. The above-mentioned results are based on the assumptions that all evacuees comply and avoid the restricted road segments. However, this might not be the case, as some of the evacuees will not obey, and will consider the managed road segments as free to use. In such cases those evacuees will be forced to detour, as the rescue team will enforce entry to the managed road segments. As a result, the non-compliant evacuees will experience a longer evacuation time, and might cause delays to other drivers as well.

However, pre-trip route choice cannot take into consideration partial traveler compliance behavior with evacuation route instructions *(39, 40)*. These models assume a full compliance that is certainly too restrictive (not all people automatically follow advice and orders from rescue teams, depending on evacuees' willingness to comply, level of enforcement, and information).

In order to relax that assumption, a mixed route choice model is proposed, that combines pre-trip and partial en-route switching decisions *(41)*. For that, two categories of evacuees were defined: 1) users with perfect knowledge of network travel times, i.e., they are informed of link restrictions before selecting their routes accordingly. 2) users with no initial information (or disregards the information) and behave following past experience and familiarity with the network. The second group of users are assumed to select initial routes before departure and travel along these routes towards their destination until some of them reach managed links and, based on new available information on link restrictions, are forced to take detours around inaccessible road segments. The route chosen by evacuees deviating to another route is identified by their knowledge on the best, minimum travel time, alternative (user equilibrium assignment).

This "dynamic" condition (unknown inaccessible road links) cannot be properly modeled only by pre-trip route choice models, but requires partial en-route detour simulation, once the evacuees become aware of road travel restrictions.

In summary, the proposed traffic assignment model allows to model and estimate the effects of evacuation plans (specifically route instructions), under various compliance levels (different percentage of compliant ratios).

TABLE 3 provides the results of a sensitivity analysis of various compliance ratios, with the comparison to the results of section 3.2 (100% compliance ratio). The compliance ratio is the ratio of the number of users from the first group out of total users. Indeed, the lower the compliance ratio, the longer the evacuation time. For example, for two managed road segments, and a compliance ratio less than 50%, there are no benefits of utilizing managed road segments, as the evacuation time will be similar (if not worse) to the unmanaged situation. As compliance is related to cultural and behavioral aspects, and can be estimated, such an analysis provides insightful information to the policy maker with regards to the applicability of evacuation management considering the compliance level of the population to be evacuated.

TABLE 3 Results of the effect of the number of managed road segments and compliance ratio on VHT

Number of managed links	Compliance ratio (%)				
	100	75	50	25	0
0 (UE)	404				
1	383	387	392	398	405
2	381	386	392	401	411
3	379	383	388	396	404
4	378	383	389	397	406
All (SO)	361				

5 CONCLUSIONS

This paper presents a multi-objective, stochastic model for the design of an optimal managed evacuation network which simultaneously optimizes the following objective functions: 1) minimize construction costs, 2) minimize evacuation time, 3) minimize the number of managed road segments, and 4) minimize the delay caused by selfish route selection (the vehicle hours traveled (VHT) difference between system optimum and user-equilibrium).

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 road segments in such a way that the evacuation time will be decreased. Indeed, based on the developed heuristic algorithm, a 44% reduction of the potential VHT is achieved by managing only 4 road segments out of over 1000 road segments.

Finally, a sensitivity analysis was performed in order to evaluate the effect of drivers' compliance on the evacuation time. Such an analysis provides the decision maker with insightful information if partially managed evacuation is effective, given the population's behavioral characteristics related to the evacuation plan.

Possible future works are the development of an efficient implementation of the PME model as well as considering the spatial properties of the managed road segments, for example, joining adjacent managed road segments.

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