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A STOCHASTIC PROGRAMMING APPROACH FOR SHELTER LOCATION AND EVACUATION PLANNING

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Abstract. Shelter location and traffic allocation decisions are critical for an efficient evacuation plan. In this study, we propose a scenario-based two-stage stochastic evacuation planning model that optimally locates shelter sites and that assigns evacuees to nearest shelters and to shortest paths within a tolerance degree to minimize the expected total evacuation time. Our model considers the uncertainty in the evacuation demand and the disruption in the road network and shelter sites. We present a case study for a potential earthquake in Istanbul. We compare the performance of the stochastic programming solutions to solutions based on single scenarios and mean values.

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1. Introduction

The 2004 Indian Ocean tsunami killed more than 225,000 people and dislocated millions of them in countries spread around the Ocean's rim from Kenya to Indonesia. In 1999 hurricane Floyd (CNN [31]), and in 2005 hurricanes Katrina and Rita (TRB [96]) required millions of people to evacuate creating largest traffic jams in the U.S. history. The 2010 Haiti earthquake measured 7.0 magnitude on the Richter scale. It caused a massive level of destruction and imposed tremendous operational challenges on the humanitarian agencies and governments. This resulted in a grim situation: three million affected people, 200,000 deaths, and more than one million wounded (Caunhye *et al.* [24]). The triple disaster that hit the Tohoku region of Japan on 11 March 2011 triggered a massive human displacement: more than 400,000 people evacuated their homes as a gigantic tsunami induced by a magnitude 9.0 earthquake engulfed the coastal areas, and the following nuclear accident in Fukushima released a large amount of radioactive materials into the atmosphere (Hasegawa [49]).

Natural or man-made disasters such as hurricanes, earthquakes, floods, terrorist attacks impose a serious risk on the humankind. Evacuation of the disaster region is the most predominantly used strategy to protect people threatened by a disaster (Hobeika [50]). Traffic management during an evacuation is critical (Yao *et al.* [100]) since people's lives are at stake and the unusual surge in traffic demand is generally far beyond the capacity of the road network.

Clearly, the shelter locations affect the time to evacuate a disaster region. Shelters are safe places that protect a population from possible damaging effects of a disaster. They also serve as facilities where evacuees

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are provided food, medical care and accommodation. FEMA [40], ARC [2], FEMA [41] and FEMA [43] provide the basis for the design and construction of shelters against different types of disasters. Whether it is built as a new shelter or as a retrofit construction, these preparations require time and need to be done before the disaster takes place. For that reason, the decision of which shelters to open are often made before a disaster occurs.

Disasters are uncertain events: it is not easy to anticipate when and where they will occur and with how much impact. As a result, evacuation planning must be done without exact or complete information. Related studies and real-life practices show a significant uncertainty regarding the evacuation demand due to the unpredictability of time, place and severeness of a disaster and human behavior as well as the changing roadway infrastructure as a result of disaster impacts. When preparing for a disaster, it is very difficult to predict the evacuation demand accurately. However, an accurate knowledge of threat and possible human responses to it is the first guideline that preparedness planning should be based upon (Perry and Lindell [82]). Key studies in the literature (Baker [4], Dash and Gladwin [36], Kim and Oh [57], Mawson [70], Murray−Tuite and Wolshon [74], Perry [81]) state that evacuee behavior is affected by many factors that causes uncertainty in the evacuation demand. We refer the reader to Bayram [7] for a detailed review of uncertainty in evacuation demand caused by human behavior. Although the number of evacuees during Hurricane Rita from the Galvestan and Harris Counties was predicted to be less than 700,000, the actual number turned out to be 1.8 million people (Lindell and Prater [65]). It is also highly probable that the traffic network will be affected and lose capacity in case of a hurricane because of flood. Road segments in the traffic network can be blocked by debris (Berktaş *et al.* [11], Çelik *et al.* [25], FEMA [42]) generated after a hurricane (Luther [67]) or by debris caused by collapsed buildings or landslides in an earthquake. They can also be damaged completely or partially in an earthquake, viaducts and bridges may collapse or become unusable. The 1985 Mexico City earthquake wiped out approximately 70 percent of the city's central transportation network (Ardekani and Hobeika [3]). Likewise, the predetermined shelter sites can be affected.

Our aim is to propose a scenario-based evacuation planning model that optimally locates shelter sites and assigns evacuees to the nearest shelter sites and to shortest paths (shortest geographical distance, shortest free flow travel time or shortest congested time) to those shelter sites within a given degree of tolerance to minimize the expected total evacuation time. We focus on this objective rather than minimizing maximum latency as we already impose constraints on the lengths of routes that can be used. We extend the study by Bayram *et al.* [8] where it is assumed that all parameters are known with certainty.

As we discuss in Section 2, there is a rich literature regarding evacuation planning and management studies. However, most of these studies employ deterministic approaches where only a single hazard scenario is considered, such as the most probabilistic one. On top of that, the number of studies that simultaneously and strategically consider shelter location decisions along with the assignment of evacuees to shelters and to routes is limited. None of these studies take into account the uncertainty in evacuation demand, the road network structure and the shelters simultaneously. Further, majority of the existing studies in the literature employ unrealistic traffic assignment approaches such as user equilibrium or system optimal. There are few studies that consider congestion on the road network and that try to combine the requirements from a system optimal approach of an evacuation management authority and the behaviors of the evacuees. Such studies are only able to manage that through use of bi-level models which can generally be solved through heuristics.

Unlike these studies in the literature, our model considers the uncertainty about future realizations of the evacuation demand, the disruption in the road network and degraded road capacities and disruption of the shelter sites simultaneously. It is a two-stage stochastic nonlinear mixed integer programming model that compromises the perspective of an evacuation planning/management authority and that of the evacuees. We solve practical size problems exactly and in reasonable times by representing the nonlinear objective function with second order cone programming.

Furthermore, we present a real world case study for evacuation planning of a potential major earthquake in Istanbul, Turkey. In our case study the population at risk is evacuated against the possible impact of aftershocks and the secondary disasters following the major earthquake.

Finally, we carry out extensive numerical testing on the case study to assess the effectiveness of the stochastic programming solutions comparing them with the results from wait and see solutions, where it is assumed that one has perfect information for every possible scenario and mean value solutions in terms of robustness and efficiency. We use criteria such as the expected total evacuation time, maximum regret, expected value of perfect information, value of stochastic solution, and performance measures such as the total evacuation time, maximum latency and percentage of evacuees reaching safety up to a specified time T, when both shelters are uncapacitated and capacitated. Maximum regret is the maximum difference between the total evacuation time of a given strategy in a scenario and minimum total evacuation time obtained in that scenario. Expected value of perfect information is the difference between the expected total evacuation time obtained by solving the deterministic problem for every scenario with perfect information and the optimal value obtained using the stochastic optimization solution. And maximum latency is the travel time of the vehicle that stays in the road network longest; it is also the time the evacuation network is cleared off vehicles as we assume that every vehicle enters the network at the same time. We observe that stochastic programming provides robust and effective solutions compared to models based on a single scenario and its superiority is emphasized when shelters are capacitated.

The rest of the paper is organized as follows. In Section 2 we present a literature review on evacuation planning focusing on stochastic location-allocation problems. In Section 3 we describe the problem and give a two-stage stochastic nonlinear mixed integer programming formulation. We present the results of our case study in Section 4 and conclude in Section 5.

2. Literature review

2.1. Traffic assignment models

We first review the traffic assignment models. These models differ mainly in their assumed driver behaviors. The common models are the (Stochastic) User Equilibrium ((S)UE, also known as User Optimal), the System Optimal (SO) and the Nearest Allocation (NA) models.

The SUE or UE approaches are not realistic to plan an evacuation during a disaster for the following reasons. The SUE approach assumes that the evacuees choose shortest travel time path depending on their perception of the travel time. The UE approach is a special case of the SUE approach when the variance of travel time perception by the evacuees is zero. For both SUE and UE, the goal of the evacuees is to minimize their individual travel times. The UE assumes that evacuees have full information on travel times on every possible route and that they are able to find the optimal routes (Sheffi [87]). Since evacuees act selfishly to minimize their individual travel times, the UE does not necessarily minimize the total evacuation time in the system. In addition, the assumptions may not be valid in case of a disaster (Galindo and Batta [45]), since the traffic demand is unusual and it is difficult for evacuees to choose the minimum latency routes using their past experiences (Pel *et al.* [79]).

Evacuation management authority on the other hand considers the benefit of evacuees as a whole and aims to evacuate everyone to safety as soon as possible by minimizing the total evacuation time. Such a traffic assignment plan is called SO. In an SO solution, some travelers may be allocated to routes that are much longer than the shortest ones they would take. Asking evacuees to accept such routes in a situation where they would like to leave the risk zone and reach safety at a shelter as soon as possible may not be reasonable.

In the NA model, each evacuee uses a shortest path based on length (geographical distance) or free flow travel time to reach the nearest shelter. This may be a reasonable approach since during an evacuation, the information on path lengths or free flow travel times is more accessible to evacuees compared to actual travel times. However, such a traffic assignment may lead to poor system performance.

Jahn *et al.* [55] define the notion of Constrained System Optimal (CSO), a traffic assignment model developed for a route guidance system. This model honors the individual needs by imposing additional constraints to ensure that drivers are assigned to "acceptable" paths only. They define the normal length of a path, as either its free flow travel time, its traversal time in UE, *i.e.*, the congested travel time or its geographic distance.

2.2. Deterministic evacuation planning models

Despite the fact that evacuation planning is typically characterized by great uncertainties, the studies in the literature (Alçada-Almeida *et al.* [1], Bayram *et al.* [8], Bish *et al.* [19], Bretschneider [20], Bretschneider and Kimms [21], Chiu *et al.* [30], Coutinho−Rodrigues *et al.* [33], Cova and Johnson [34], Hamacher and Tjandra [48], Kalafatas and Peeta [56], Kongsomsaksakul *et al.* [59], Sherali *et al.* [89], Sheu and Pan [90], Tüydeş [97], Yamada [99]), mostly rely on deterministic models.

Bayram *et al.* [8] propose a deterministic CSO (DCSO) model that optimally locates shelters and that assigns evacuees to the nearest shelters and to shortest paths (in terms of geographical distance, free flow travel time or congested travel time) to those shelters -shortest and nearest within a given degree of tolerance- to minimize the total evacuation time. The solution of their model evacuates the disaster region as quickly as possible, with an efficient but "fair" assignment of evacuees to shelters and to routes. They observe that the SO solution may have unacceptable levels of unfairness whereas the solution in which the evacuees travel to the nearest shelter using a shortest path may result in substantial deterioration in the system performance. Even a small level of tolerance on the side of the evacuees improves the system performance. Overall, they conclude that the location and the number of shelters opened drastically affect the evacuation plan and for a carefully selected number of shelters and tolerance level, an efficient yet fair evacuation plan can be achieved.

These models are deterministic models that adopt a hazard scenario such as worst-case or most probable scenario to plan for locations of shelters and/or evacuation of the endangered population. Our study extends the study by Bayram *et al.* [8] by incorporating uncertainty.

For a more detailed review of deterministic evacuation planning studies, we refer the reader to Bayram *et al.* [8] and Bayram [7].

2.3. Uncertainty in facility location

The stochasticity regarding the demand, road capacities, facilities and other factors have been widely studied in classical facility location literature and the location literature for disaster management. Frank [44], Cooper [32], Louveaux [66], Laporte *et al.* [61], Chan *et al.* [26], Berman and Krass [13], Daskin *et al.* [37], Berman and Wang [17], Chang *et al.* [27], Berman *et al.* [12], study the uncertainty in demand in classical facility location problems and Belardo *et al.* [10], Psaraftis *et al.* [83], Wilhelm and Srinivasa [98], Barbarosoğlu and Arda [6], Chang *et al.* [27], Balçık and Beamon [5], Rawls and Turnquist [84], Mete and Zabinsky [71], Duran *et al.* [38] and Noyan [78] in disaster management.

Nel and Colbourn [75], Eiselt *et al.* [39] take into consideration the uncertainty regarding the disruption and/or degradation of edges. Barbarosoğlu and Arda [6], Rawls and Turnquist [84], Günneç and Salman [47] and Noyan [78] propose stochastic models employing similar uncertainty issues in humanitarian relief and disaster management problems.

Mirchandani and Odoni [72], Mirchandani and Oudjit [73], Berman and Odoni [16], Ingolfsson *et al.* [54] work on facility location networks using stochastic edge lengths or travel times. Mirchandani and Odoni [72] employ a nonlinear utility function for the random edge length. Mete and Zabinsky [71] take into account this same notion in their medical supply location and distribution model they develop for disaster management.

The effects of facility disruption has been studied to a large extent in the classical facility location literature (Bundschuh *et al.* [22], Snyder and Daskin [91], Snyder *et al.* [93], Berman *et al.* [14], Snyder and Daskin [92], Berman *et al.* [15], Cui *et al.* [35], Li and Ouyang [63], and Lim *et al.* [64], Huang *et al.* [51], Peng *et al.* [80]) and in disaster management (Rawls and Turnquist [84], Noyan [78]).

To the best of our knowledge, the only study in location literature that takes into consideration the congestion on the road segments is by Chang and Wang [28] for site selection of solid waste facilities.

2.4. Uncertainty in evacuation planning

As for the studies taking into account uncertainty in the evacuation literature, most focus on demand uncertainty (Rui *et al.* [85], Yao *et al.* [100], Huibregtse *et al.* [52], Ng and Waller [77], Yazıcı and Özbay

[101], Kulshrestha *et al.* [60]) and/or capacity (Shen *et al.* [88], Ng and Waller [77], Yazıcı and Özbay [101]). Shen *et al.* [88] develop scenario-based, stochastic, bilevel models that minimize the maximum UE travel time among all node shelter pairs by locating shelters at the upper level and assigning evacuees to shelters and routes in a UE manner at the lower level. Their model is an α-reliable mean-excess regret model in the context of the p-median problem Chen *et al.* [29] in which the distance between the demand nodes and the shelter sites as well as the demand are taken as uncertain parameters. To solve this first model they present a genetic algorithm based approach. The second model is proposed as a real time decision making tool for evacuations and a simulation based approach that uses successive shortest path algorithm is developed to solve it. Stepanov and Smith [94] suggest a multi-objective integer programming formulation for optimal route assignment that employs an $M/G/c/c$ state dependent queuing model to represent congestion and link travel times on links using random arrival rates. Yao *et al.* [100] consider the evacuation on a network under demand uncertainty. They model a deterministic LP model based on a modified CTM in which they introduce a measure called, coefficient of threat level, which is an estimate of susceptibility of an area to disaster at a particular time and by means of which they can capture the spatio-temporal priorities during evacuation. By focusing on this coefficient of threat level, they develop a robust optimization model. Huibregtse *et al.* [52] optimize evacuation measures to increase the efficiency of an evacuation plan by considering uncertainty in demand, the behavior of people and the hazard (location, time, and intensity). Ng and Waller [77] present an evacuation planning model that considers demand and capacity uncertainty. They provide a framework that determines the amount of demand inflation (evacuation demand exceeding the planned number) and supply deflation (degradations in road capacities) necessary to ensure a user-specified reliability level. Yazıcı and Özbay [101] propose a SO DTA formulation with probabilistic constraints that takes into account uncertainties in demand and roadway capacities. The model they propose is a CTM-based SO DTA formulation that uses chance constrained programming. They assume that demand and capacity distributions follow discrete probability distributions. They analyze the effects of probabilistic roadway capacities on clearance and average travel times, and the spatial shelter utilization is discussed in terms of shelter management. Their model does not endogenously select the number and location of shelter sites, rather they do sensitivity analysis. Kulshrestha *et al.* [60] develop a robust bi-level model that considers demand uncertainty and minimizes the total cost to establish and operate shelters at the upper level while assigning evacuees to shelters and routes in a UE manner at the lower level. They confine the uncertain demand to an uncertainty set and determine the optimal locations and capacities of shelters from the worst case scenario that can be realized from this set. Their model is formulated as a mathematical program with complementarity constraints and is solved by an approximation-based cutting plane algorithm, for a total of three (nominal, low and high) demand scenarios.

To the best of our knowledge, there is only a single study that consider the disruption in shelters in the evacuation literature. Li *et al.* [62] propose a scenario based location model for identifying a set of shelter locations that are robust for a range of hurricane events, by considering disruption in shelter sites. Their model is a DTA-based stochastic bi-level programming model in which at the two-stage stochastic upper level, the central authority selects the shelter sites for a particular scenario. The objective of the upper-level problem is to minimize the weighted sum of the expected unmet shelter demand and the expected total network travel time. In the lower level, evacuees choose their routes in a dynamic UE manner. They develop heuristic algorithms based on Lagrangian relaxation and present a case study for the state of North Carolina for 33 hurricane scenarios.

These studies propose bi-level models which are hard to solve. To solve these problems, heuristic methodologies are developed by Shen *et al.* [88] and Li *et al.* [62] and an approximation based methodology is employed by Kulshrestha *et al.* [60]. Shen *et al.* [88] take into account only the uncertainty in capacity, Kulshrestha *et al.* [60] only consider the uncertainty in demand, and Li *et al.* [62] only the uncertainty in shelter sites. They employ a UE traffic assignment.

Our model differs from these models and contributes to the literature in that it is a single level model that considers the uncertainty in demand, road network structure and the disruption in shelters simultaneously. It includes the fairness considerations for evacuees. Unlike the solution methodologies employed in the above mentioned studies, we employ an exact solution methodology to solve our problem.

2.5. Our contribution

In this study, we propose a two-stage stochastic scenario-based evacuation planning model. Against this background, the contributions of our study are the following: We introduce a novel model that decides simultaneously on the locations of shelters and the allocations of evacuees to shelters and routes under uncertainty. The model incorporates evacuees' preferences and fairness considerations by routing the evacuees on paths that are not much longer than the shortest paths to the nearest shelters. Unlike the studies in the literature, the model aims to achieve a compromise between evacuation planning authority and the evacuees.

Our study differs from the model by Bayram *et al.* [8] in that we use a stochastic programming approach, and hence instead of planning the evacuation based on a single hazard scenario, our model considers a range of hazard scenarios. To the best of our knowledge, our model is the first model in the evacuation literature that considers the uncertainty in the evacuation demand, the disruption in the road network, degradation in road capacities and disruption of the shelters simultaneously. This is important, since we are adopting a constrained system optimal approach for the evacuation of the population, the evacuation problem we are dealing with is NP-Hard and it gets harder as it is transformed from a solely assignment problem into a network design problem, *i.e.*, including shelter location decisions increases the complexity of an already NP-Hard problem. For that reason, most of the evacuation models that consider the optimal selection of shelter sites and that also take into account the congestion effect are bi-level models. On top of that, including uncertainty regarding the shelters render the problem even harder.

Further, we investigate a case study with real data about a pending earthquake in Istanbul, Turkey. We report the results of the case study and show that the solution of our stochastic model leads to a significant decrease in the total evacuation time compared to the deterministic and mean value solutions, and planning according to a single scenario can lead to very poor performance. We also analyze the impact of having capacitated shelters on performance measures.

3. Problem description and model formulation

We base our work on the DCSO model by Bayram *et al.* [8] and introduce a two-stage stochastic CSO model, that we refer to as SCSO. We develop our model as an "expected value model", which is the predominant approach in the stochastic programming literature (Sen [86]).

Our model decides on the number and locations of p shelters and the assignment of evacuees to shelters and routes so that the region is evacuated as quickly as possible. The problem is defined on a directed network $G = (N, A)$, where N is the set of nodes and A is the set of arcs (road segments) in the network.

We define the travel time spent on a given road segment as a positive and monotonically increasing function of traffic flow, since an increase in traffic volume will normally decrease the travel speed due to congestion and hence increase the travel time along the road segment.

Bureau of Public Roads (BPR) function is a convex, nondecreasing and differentiable function that expresses the relationship between travel time (or speed) and the volume of traffic on a road segment:

$$t(x) = t^0 \left(1 + \alpha \left(\frac{x}{c}\right)^\beta\right)$$

where $t(x)$ is the travel time at which assigned volume x can travel on the road segment, c is the practical capacity (maximum flow rate) and t^0 is the base travel time or free flow travel time at zero volume. The parameters $\alpha \geq 0$ and $\beta \geq 0$ are the tuning parameters defined in accordance with the road characteristics and they are taken as 0.15 and 4 by the U.S. Department of Commerce Bureau of Public Roads, respectively (TAM [95]). α is a parameter that specifies the ratio of free-flow travel time to the travel time at capacity. Parameter β determines the steepness of the function, *i.e.*, it specifies how rapidly travel time increases from the free-flow travel time. Among the evacuation planning literature, the studies that employ BPR function to represent the speed-flow relationship in a given road segment (Sherali *et al.* [89], Kongsomsaksakul *et al.* [59], Li *et al.* [62], Ng and Waller [77]) all use the same α and β parameters, *i.e.*, $\alpha = 0.15$, $\beta = 4$. For the reasons discussed above we also have employed the same values for these parameters.

Each arc a is associated with a convex travel time function (BPR function) t_a. O is defined as the set of origin (demand) nodes from where the evacuees at risk are to be evacuated and F as the set of destination nodes (potential shelter sites) where evacuees reach to safety, O and F being disjoint subsets of N. The number p is a predetermined parameter that restricts the number of shelter sites that can be opened due to budgetary and/or management issues.

When dealing with uncertainty it is important to consider what happens before (first-stage) and after (second-stage) the uncertainty is revealed (Birge and Louveaux [18]). Considering the evacuation problem in the framework of two-stage stochastic programming, the first stage is about where to locate the shelters before a disaster takes place, and given the location of shelters and realization of the evacuation demand and the disruption in the infrastructure, the second stage assigns evacuees to shelters and to routes.

We define Ω as the set of disaster scenarios and denote with $p(\omega)$ the probability that disaster scenario $\omega \in \Omega$ occurs. We define $F(\omega) \subseteq F$ as the set of potential shelter sites that are not disrupted in scenario $\omega \in \Omega$. Likewise, $A(\omega) \subseteq A$ is the set of arcs (road segments) that are not disrupted in scenario $\omega \in \Omega$. The binary variable y_s is 1 if a shelter site is opened at node $s \in F$, 0 otherwise. Let $P_{rs}(\omega)$ be the set of alternative paths for the origin-destination pair (r, s), in scenario $\omega \in \Omega$. The amount of demand at origin $r \in O$, $w_r(\omega)$, is the number of passenger vehicles that will be evacuated in scenario $\omega \in \Omega$.

We model the tolerance of evacuees using parameter λ. An evacuee can be persuaded to take a path whose length is at most $(1 + \lambda)$ times the length of a shortest path to the closest shelter in a given scenario. The set of acceptable paths from origin r to destination s of tolerance level λ in a given scenario $\omega \in \Omega$ is defined as: $P^{\lambda}_{rs}(\omega) = \{\pi \in P_{rs}(\omega) : d^{\pi} \leq (1 + \lambda)d^{*}_{rs}(\omega)\}$, where d^{π} is the length of path π and $d^{*}_{rs}(\omega)$ is the length of a shortest path from r to s in scenario $\omega \in \Omega$. This set is computed using an algorithm developed by Byers and Waterman [23]. The algorithm by Byers and Waterman [23] combines the depth-first search with stacking techniques of theoretical computer science and principles from dynamic programming to list all near-optimal solutions.

In our model, we also use the following decision variables: $v_{\pi}(\omega)$ is the fraction of origin r's demand that uses path $\pi \in P^{\lambda}_{rs}(\omega)$ from origin $r \in O$ to destination $s \in F(\omega)$ in scenario $\omega \in \Omega$ and $x_a(\omega)$ is the amount of traffic, *i.e.*, the number of vehicles on arc $a \in A(\omega)$ in scenario $\omega \in \Omega$.

SCSO is formulated as follows:

$$\min \sum_{\omega \in \Omega} p(\omega) \sum_{a \in A(\omega)} t^0_a \left(1 + \alpha \left(\frac{x_a(\omega)}{c_a(\omega)}\right)^{\beta}\right) x_a(\omega) \tag{3.1}$$

$$\text{s.t. } \sum_{s \in F} y_s \leq p, \tag{3.2}$$

$$\sum_{s \in F(\omega)} \sum_{\pi \in P^{\lambda}_{rs}(\omega)} v_{\pi}(\omega) = 1 \qquad \forall r \in O, \omega \in \Omega, \tag{3.3}$$

$$\sum_{\pi \in P^{\lambda}_{rs}(\omega)} v_{\pi}(\omega) \leq y_s \qquad \forall r \in O, \omega \in \Omega, s \in F(\omega), \tag{3.4}$$

$$\sum_{s \in F(\omega)} \sum_{\pi \in P^{\lambda}_{rs}(\omega): d^{\pi} > (1+\lambda) d^{*}_{ri}(\omega)} v_{\pi}(\omega) + y_i \leq 1 \qquad \forall r \in O, \omega \in \Omega, i \in F(\omega), \tag{3.5}$$

$$x_a(\omega) = \sum_{r \in O} \sum_{s \in F(\omega)} \sum_{\pi \in P^{\lambda}_{rs}(\omega): a \in \pi} w_r(\omega) v_{\pi}(\omega) \qquad \forall \omega \in \Omega, a \in A(\omega), \tag{3.6}$$

$$v_{\pi}(\omega) \geq 0 \qquad \forall \omega \in \Omega, \pi \in \bigcup_{r \in O, s \in F(\omega)} P^{\lambda}_{rs}(\omega), \tag{3.7}$$

$$y_s \in \{0, 1\} \qquad \forall s \in F. \tag{3.8}$$

Objective function (3.1) is equal to the expected total evacuation time. Constraint (3.2) limits the number of shelter sites open to a pre-specified number p. Constraints (3.3) ensure that all demand is evacuated in each scenario. Constraints (3.4) forbid assigning demand to non-open shelter sites for each scenario. Constraints (3.5) ensure that if the shelter at site i is open and functioning in scenario ω, then the demand at origin node r cannot be routed on any path whose length is longer than $(1+\lambda)d^*_{ri}(\omega)$. Let i_r be the shelter that is open and that is closest to origin r. Due to constraints (3.5), the demand at node r cannot be routed on a path whose length is more than $(1+\lambda)d^*_{ri_r}(\omega)$. As i_r is the closest shelter to r and $d^*_{ri_r}(\omega)$ is the length of a shortest path from r to i_r in scenario ω, these constraints forbid the use of paths whose lengths are longer than $(1+\lambda)$ times the length of the shortest path. Constraints (3.5) for open shelters i other than i_r are dominated by constraints (3.5) for shelter i_r. As we do not know, which shelters are open, we need to include these constraints for all possible shelters. Finally, constraints (3.6) compute the traffic on every arc in each scenario and constraints (3.7) and (3.8) are variable restrictions.

DCSO is a special case of the SCSO model in which $|\Omega| = 1$ and Bayram *et al.* [8] show that DCSO is NP-hard even when $\alpha = 0$ and G is bipartite. We also note that our model generalizes the classical facility location model in that the arc costs of our model are nonlinear, we assign the customers (evacuees) to facilities (shelters) and to paths to those facilities. Our model also generalizes the SO and NA traffic assignment approaches. When $\lambda = 0$ we have the NA model. When $\lambda = \infty$, we obtain a model for the SO traffic assignment and hence generalize the model given in Sherali *et al.* [89].

The shelter location decisions y are first-stage (design) variables and are taken in the presence of uncertainty about future realizations. In the second stage, the uncertainty is revealed and recourse decisions v are taken. However, while making the first-stage shelter location decisions, their effect on the second stage assignment decisions and total evacuation time is taken into account. The future effects of shelter location decisions is measured by taking the expectation of the recourse function on possible scenarios. Because y is a binary variable, our model has a $0-1$ first stage problem. In addition, since the objective function of the second stage is nonlinear, the model has a nonlinear second stage problem.

We reformulate the SCSO as a second order conic mixed integer programming model as done in Bayram *et al.* [8]. Consider an inequality of the form,

$$r^{2^l} \leq s_1 s_2 \dots s_{2^l} \ for\ r,\ s_1,\ s_2,\ \dots,\ s_{2^l} \geq 0. \tag{3.9}$$

An equivalent representation of the inequality (3.9) can be achieved by using $O(2^l)$ variables and $O(2^l)$ hyperbolic inequalities of the form

$$u^2 \leq v_1 v_2,\ u,\ v_1,\ v_2 \geq 0, \tag{3.10}$$

as shown by Nemirovski and Tal [76]. Then each hyperbolic inequality can easily be transformed into a second-order cone inequality

$$\|2u, v_1 - v_2\| \leq v_1 + v_2. \tag{3.11}$$

We first define auxiliary variables $\mu_a(\omega)$ for each $a \in A(\omega), \omega \in \Omega$ and move the nonlinearity from the objective function to the constraints. The objective function of the SCSO model becomes:

$$\sum_{\omega \in \Omega} p(\omega) \sum_{a \in A(\omega)} \left(t_a^0 x_a(\omega) + \frac{t_a^0 \alpha}{c_a(\omega)^\beta} \mu_a(\omega) \right)$$

and we add the constraints $x_a(\omega)^{\beta+1} \leq \mu_a(\omega)$ for all $\omega \in \Omega, a \in A(\omega)$.

We take $\beta = 4$ and represent $x_a(\omega)^5 \leq \mu_a(\omega)$ with

$$x_a(\omega)^2 \leq \theta_a(\omega)h_a(\omega), \tag{3.12}$$
$$\theta_a(\omega)^2 \leq u_a(\omega)x_a(\omega), \tag{3.13}$$
$$u_a(\omega)^2 \leq \mu_a(\omega)x_a(\omega), \tag{3.14}$$
$$h_a(\omega) = 1, \theta_a(\omega), u_a(\omega), x_a(\omega), \mu_a(\omega) \geq 0. \tag{3.15}$$

These hyperbolic inequalities can be represented with second order conic inequalities presented below:

$$\|2x_a(\omega), \theta_a(\omega) - h_a\| \leq \theta_a(\omega) + h_a, \tag{3.16}$$
$$\|2\theta_a(\omega), u_a(\omega) - x_a(\omega)\| \leq u_a(\omega) + x_a(\omega), \tag{3.17}$$
$$\|2u_a(\omega), \mu_a(\omega) - x_a(\omega)\| \leq \mu_a(\omega) + x_a(\omega), \tag{3.18}$$
$$\theta_a(\omega) \geq 0, h_a = 1, u_a(\omega) \geq 0, x_a(\omega) \geq 0, \mu_a(\omega) \geq 0. \tag{3.19}$$

The resulting model is solved using an off-the-shelf solver.

4. An illustrative case study: evacuation of istanbul city after a potential Earthquake

4.1. Risk of aftershocks and secondary disasters

A study by Marano *et al.* [69] presents a quantitative and geospatial description of global losses due to earthquake-induced secondary disasters, including landslide, liquefaction, tsunami and fire, for events that took place through 1968-2008. Marano *et al.* [69] state in their study that 21.5% of fatal earthquakes have deaths due to secondary causes. In this study, Turkey is shown among the countries where tsunamis, landslides, and fires have been observed as secondary disasters following a major earthquake.

The 1999 Marmara (Turkey) earthquake that devastated the cities of Sakarya, Izmit and Yalova initiated the efforts for earthquake preparedness and response planning for a potential major earthquake in Istanbul. The Istanbul Metropolitan Municipality (IMM) started a disaster prevention and mitigation study that was conducted in collaboration with the Japan International Cooperation Agency (JICA) IMM-JICA [53]. Following the potential major earthquake in Istanbul, aftershocks as observed during the 1999 Marmara earthquake and different secondary disasters such as landslides, floods, fires and possibly tsunamis can impact different geographical areas of Istanbul city and can cause further fatalities. In the technical report by IMM and JICA it is stated that there does not exist an emergency evacuation system in Istanbul, Turkey and that it is imperative that a community evacuation system be established in order to mitigate and minimize human casualties due to second or third aftershocks and secondary disasters following the earthquake. For that reason, the case study we present here assumes an emergency evacuation in the sense that we are evacuating people to protect them from the impact of aftershocks and the secondary disasters.

4.2. Scenario and data preparation

In coordination with scientific institutions and researchers, IMM-JICA study determines four scenarios for the earthquake, scenarios A, B, C and D. Scenario A is referred to as the most probable scenario and scenario C as the worst case scenario. We consider 12 scenarios that correspond to different severeness of the disaster. In the IMM-JICA report, the evacuation demand specific to each origin node is only given for scenario A in detail, and the information for other scenarios is not disclosed. For that reason, our base (nominal) scenario is scenario A. By taking into account the length of the fault line that is predicted to be affected and the magnitude of the earthquake in scenarios B, C and D compared to those of Scenario A, we specify the values of arc and shelter disruption probabilities for risk zones and the evacuation demand at each origin node for these scenarios. We generate three different scenarios for each of the original scenarios A, B, C and D in the report, which adds up to 12 scenarios in total. Generally, scenarios 2, 6, and 10 represent more destructive earthquake scenarios.

No probability values regarding the scenarios are given in the report. Scenarios 0, 4 and 8 represent the original scenario A in our 12-scenario setting. We randomly assign probabilities to each of the 12 scenarios in such a way that the sum of the probabilities for scenarios 0, 4 and 8, which is the probability of scenario A, is highest and the probabilities related to 12 scenarios add up to 1.

The magnitude of the earthquake is expected to be 7.5, 7.4, 7.7, and 6.9 and the length of the fault line that is expected to be broken is 119, 108, 174, and 37 km.s long for scenarios scenarios A, B, C and D respectively. In the report by IMM-JICA [53], it is stated that 1.3 million citizens will require shelters in accordance with the most probable scenario. A similar number for evacuation demand is given by Kırıkçı [58]. The evacuation demand for other scenarios are not explicitly stated in the report by IMM-JICA. As the length of the fault line that is expected to be broken and the expected magnitute of an earthquake increase, the expected damages incurred and the expected evacuation demand will increase. By taking into account the length of the fault line that is predicted to be affected and the magnitude of the earthquake in scenarios B, C and D compared to those of scenario A, we specify the evacuation demand at each origin node for these scenarios.

The report also includes a seismic microzonation that divides the city into smaller disaster regions with respect to a spatial risk analysis that takes into account their seismic characteristics and damage patterns in different scenarios. Peak Ground Acceleration (PGA) is a measure of how hard the earth shakes in a given geographic area. Five different risk zones are determined for scenarios A, B, C, and D in accordance with the PGA distributions. Damage probabilities specific to road segments, bridges and viaducts in each risk zone are determined and potential damage to the road network, infrastructure and buildings are calculated in accordance with the PGA distribution, as well. By taking into account the length of the fault line that is predicted to be affected and the magnitude of the earthquake in scenarios B, C and D compared to those of scenario A, we specify the values of arc and shelter disruption probabilities for risk zones in each of these scenarios. We assign the highest probability of disruption to risk zone 1, the risk zone closest to the fault line, and the lowest one to risk zone 5. We assign a higher probability of disruption to scenarios 2, 6 and 10 related to the original worst case scenario C.

We classify the arcs and potential shelter sites of the original network into sets in accordance with which risk zone they are located in. For a particular scenario, we randomly determine if an arc (road segment) is disrupted by considering the risk zone it is located in and the probability of disruption assigned to this zone. If the arc is disrupted, we again randomly specify how much of its original capacity is degraded in multiples of a single lane capacity. For instance, if a road segment with three lanes having a capacity of 6,000 vehicles per hour is disrupted, it may be degraded to a capacity of 4,000, 2,000 or 0 vehicles per hour.

The Disaster Coordination Center (DCC - AKOM in Turkish) specified 49 potential shelter sites in Istanbul to serve as safe facilities to provide the evacuees with food, accommodation and medical care Kırıkçı [58]. The main criteria used in determining potential shelter sites are accessibility by at least two alternative routes, proximity to major highways, and availability of land (Görmez *et al.* [46]). Likewise, in accordance with which risk zone a shelter site is located in and the probability assigned to that risk zone, a shelter site may get disrupted in which case it will no longer be able to serve the evacuees. We assign smaller disruption probabilities for shelters as they are fortified structures against earthquakes.

We generated our instances using the data from the IMM-JICA study and DCC. As the European and Anatolian sides of Istanbul are connected by three bridges, we assume that the population living on each side will be evacuated to shelters on their own side. We use the roads given in the IMM-JICA report together with some other smaller capacity roads. We assume that the free flow travel time in a degraded (not totally disrupted) road segment is the same as the one in the original network. Each vehicle is assumed to carry four passengers on the average. Figure 1 illustrates the road network structure, the potential shelter sites and the demand points that we use in our study (the district of Silivri with one demand point and one shelter site is out of the boundaries of Istanbul European Road Network Map).

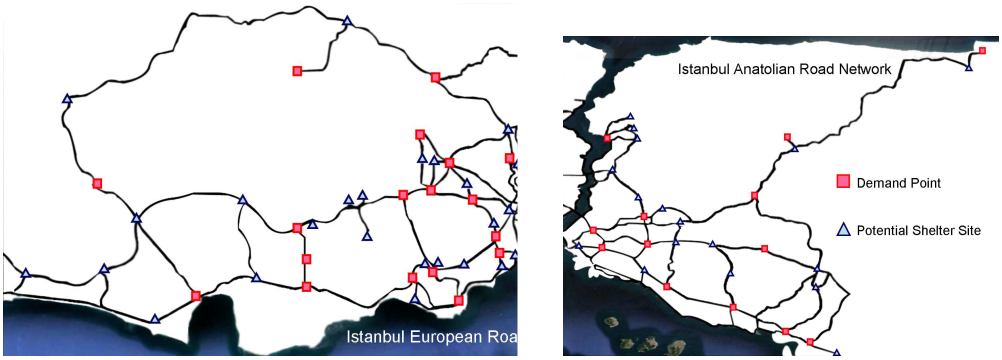

FIGURE 1. Istanbul European and Anatolian road networks, potential shelter sites and demand points.

TABLE 1. Istanbul European instances.

Scenario	$\mid N \mid$	$\mid A \mid$	Total Demand	$\mid F \mid$	Probability of Scenario	Total Road Network Capacity
ON	80	238	272,900	32		1,246,000
0	80	221	245,322	28	0.1461	1,098,000
1	80	228	219,960	30	0.0754	1,128,000
2	80	219	328,832	26	0.0436	1,074,000
3	80	213	133,161	28	0.0872	1,022,000
4	80	211	245,642	31	0.145	1,066,000
5	80	220	224,481	30	0.0439	1,072,000
6	80	223	325,988	29	0.0255	1,094,000
7	80	218	136,819	29	0.0834	1,068,000
8	80	221	245,622	30	0.1152	1,082,000
9	80	217	218,378	30	0.0897	1,080,000
10	80	223	327,002	25	0.0669	1,068,000
11	80	224	133,883	28	0.0782	1,094,000

We used the geographical distances as arc lengths in our analysis. Clearly, using geographical distances instead of real travel times as the normal length of a path in modeling evacuees' choices may result in a congested system. However, as pointed out earlier, assuming that the evacuees have full information on travel times on every possible route is not realistic. Instead, one may try to estimate the congested travel times. Our model permits the use of these estimates as normal lengths.

In Tables 1 and 2, we present the properties of our instances. ON is the original network when the road network and the shelters are not disrupted and the demand in ON is the demand of scenario A in IMM-JICA report. And rest of the instances in those tables are scenarios 0 through 11 with the remaining number of arcs, shelters and total road network capacity after the evacuation network is disrupted. We perform our computational tests on a personal computer with a 2.4 GHz Intel i7-3630QM CPU and 16 GB of RAM using Java ILOG CPLEX version 12.5.1.

4.3. Quality of stochastic programming solutions

If it were possible to wait until all the uncertainties are revealed and solve the evacuation problem with perfect information in hand for each scenario, this would be called a wait and see solution (WSS) Madansky [68]. On the other hand, one could solve the stochastic problem by replacing all the random parameters with their means,

Table 2. Istanbul Anatolian instances.

Scenario	$\mid N \mid$	$\mid A \mid$	Total Demand	$\mid F \mid$	Probability of Scenario	Total Road Network Capacity
ON	50	146	83,133	17		748,000
0	50	137	74,965	16	0.1461	666,000
1	50	135	63,263	17	0.0754	668,000
2	50	135	101,482	15	0.0436	676,000
3	50	133	41,920	15	0.0872	646,000
4	50	137	75,586	17	0.145	690,000
5	50	140	66,203	17	0.0439	676,000
6	50	136	103,708	17	0.0255	688,000
7	50	140	41,599	13	0.0834	700,000
8	50	136	75,299	16	0.1152	678,000
9	50	143	66,451	16	0.0897	724,000
10	50	136	97,111	13	0.0669	644,000
11	50	131	39,559	17	0.0782	642,000

this solution is called the mean value solution (MVS). Expected value of perfect information (EVPI) is the difference between the expected total evacuation times of wait and see solution and the stochastic programming solution and value of stochastic solution (VSS) is the difference between the expected total evacuation times of the stochastic programming and mean value solutions. Expected value of perfect information measures the value of knowing the future with certainty, while value of stochastic solution assesses the value of knowing and using distributions of future outcomes (Birge and Louveaux [18]).

To measure the expected value of perfect information and value of stochastic solution, we solve our evacuation problem first by considering a specific scenario, *i.e.*, employ the wait and see solution. We also solve the evacuation problem by taking the mean of the stochastic parameters in each scenario, which results in the mean value solution. Given the shelter locations from the wait and see solution and the mean value solution for a specific scenario, we solve our problem for each scenario and obtain the total evacuation times in these scenarios separately for both of these solution strategies. We adopt an approach that includes only the shelter location decisions from wait and see solution and mean value solution to solve the model for each scenario in order to compute expected value of perfect information and value of stochastic solution, and show the quality of our stochastic programming solution.

For the mean value solution, the demand for each origin is taken as the mean of the demand values at these origins in all possible scenarios. For the number of potential shelter sites, $|F|$, we take a shelter as disrupted if it is disrupted in two or more scenarios. As for the road segments, if a road segment is disrupted in three or more scenarios it is removed from the graph of mean value scenario, and if this is not the case we take the average of the arc capacities over all possible scenarios to find the capacity of the road segment as a multiple of lanes. This results in having 9 disrupted shelters and 23 disrupted road segments for Istanbul European network and 4 disrupted shelters and 7 disrupted road segments for Istanbul Anatolian network.

4.4. Uncapacitated Shelters

In our first experiment, we investigate the effect of the number of shelters p and the tolerance level λ on the total evacuation time and the difficulty of the problem when shelters are uncapacitated. We compute the set of feasible paths of tolerance degree λ by using the algorithm by [23]. In Table 3, we report the results of the SCSO model for the Istanbul European and Anatolian instances for different values of p and λ. For each instance, we report the number of shelters opened ($\#os$), the optimal expected total evacuation time and the solution time in seconds. All instances are solved to optimality and the longest computation time is a little more than one hour. As we increase the level of tolerance the number of feasible paths that the evacuees can be assigned

TABLE 3. Results for the Istanbul European and Anatolian instances

	Istanbul European				Istanbul Anatolian			
λ	p	$\#os$	Exp. Tot. Evac. Time	Solution Time	p	$\#os$	Exp. Tot. Evac. Time	Solution Time
0	10	10	25,448,247	300.60	5	5	78,850	72.46
	20	20	25,160,535	163.35	10	10	56,621	36.61
	25	20	25,135,322	199.10	13	12	56,592	29.11
	30	20	25,135,322	166.04	15	12	56,574	26.53
	32	20	25,135,322	215.57	17	12	56,574	27.86
0.1	10	10	10,293,567	2471.33	5	5	42,366	97.67
	20	20	10,167,674	880.59	10	10	32,306	47.48
	25	20	10,160,242	934.62	13	13	32,212	41.93
	30	20	10,160,242	1304.19	15	13	32,202	40.69
	32	20	10,160,242	755.29	17	13	32,202	39.01
0.15	10	10	6,432,920	3048.37	5	5	40,913	119.37
	20	20	6,390,771	2,344.98	10	10	32,318	54.62
	25	20	6,385,797	2682.86	13	13	32,218	47.10
	30	20	6,385,797	3634.32	15	13	32,193	46.41
	32	20	6,385,797	3522.80	17	13	32,193	42.54

increases. And due to this reason, we observe that the expected total evacuation time decreases drastically as the tolerance parameter λ increases for both networks. However, an increase in the number of feasible paths means an increase in the number of variables in the model. For that reason, the solution times deteriorates as the tolerance level increases. We observe that, in general, the solution times decrease with increasing p and increase with increasing λ.

We note here that at most 20 and 13 shelters are opened in Istanbul European and Anatolian instances, respectively, even when p is larger. As also noted in Bayram *et al.* [8], it is not necessarily beneficial to open more shelters as this may cause some road segments to be extremely congested.

For the case when shelters are uncapacitated, we compare the quality of 15 different solution strategies, named as 0, 1,...,11, ON, MVS, S. Among these, 0, 1,...,11 are the optimal solutions corresponding to the original scenarios, ON represents the solution obtained from using the original undisrupted network with the original demand from scenario A in IMM-JICA report, and MVS and S represents the mean value solution and stochastic programming solution, respectively. The regret of a solution in a given scenario is the difference between the total evacuation time for that solution in that scenario and the minimum total evacuation time for that scenario. The maximum regret for a solution is the maximum of its regrets over all scenarios.

In Table 4, we present the total evacuation times for all 15 solutions and 12 scenarios, as well as the expectation of the total evacuation times. We take $\lambda = 0.1$ and $p = 32$ for the European network and $\lambda = 0.2$ and $p = 17$ for the Anatolian network. Table 5 gives the wait and see solution, expected value of perfect information and value of stochastic solution for both networks. Finally, in Table 6, we present the regrets of the solutions in all 12 scenarios and the maximum regrets.

It is clearly seen that, the stochastic programming solution provides a much better evacuation planning compared to ON solution. With the stochastic programming solutions, we obtain about 7 and 2 times better results with respect to expectation, compared to the ON solutions for Istanbul European and Istanbul Anatolian networks, respectively. With respect to maximum regret, the results are more striking. Stochastic Programming Solution has almost 70 and 7 times better maximum regret values for Istanbul European and Istanbul Anatolian networks, respectively.

For both Istanbul European and Anatolian networks, the stochastic programming solution performs best in terms of the expected total evacuation time and in terms of the maximum regret. When we use the stochastic

TABLE 4. Total evacuation times.

	Realized Scenario												
Sol.	0	1	2	3	4	5	6	7	8	9	10	11	Expectation
Eur													
0	401,261	13,105,568	3,542,209	100,045	618,028	186,761	3,043,580	53,916	872,288	309,581	2,175,269,495	237,142	147,062,200
1	5,182,927	599,421	9,582,876	271,566	5,747,337	245,165	26,199,557	925,467	6,489,759	6,290,393	2,178,326,729	86,659	149,882,018
2	1,584,639	644,151	1,221,336	836,989	620,289	1,110,192	8,592,209	321,992	7,071,255	2,403,956	5,036,314,169	116,299	338,759,711
3	1,236,185	977,131	7,069,495	77,090	1,774,549	3,215,344	7,919,391	319,085	21,916,560	2,016,525	5,036,376,277	234,567	340,853,840
4	501,085	12,970,605	3,557,423	357,217	192,609	703,203	3,038,228	62,706	1,080,314	495,758	998,767,044	82,879	68,371,867
5	1,241,925	743,241	9,584,396	233,115	1,826,228	166,686	25,151,462	924,985	912,536	1,411,165	2,175,245,104	230,655	147,439,960
6	761,586	13,097,345	3,450,679	102,303	866,572	3,481,574	1,012,426	54,291	1,032,087	303,566	2,175,257,308	511,325	147,277,842
7	402,008	13,106,206	3,545,843	347,278	657,467	3,289,101	3,046,602	51,658	1,404,953	302,015	2,175,245,104	508,196	147,306,123
8	5,182,927	732,691	9,582,876	271,566	19,922,789	245,165	25,134,765	925,467	516,151	4,414,396	2,178,326,729	508,477	151,096,905
9	429,509	13,095,126	3,245,833	100,839	617,673	312,604	3,029,981	52,094	832,955	288,826	2,175,198,104	231,126	147,046,022
10	156,825,960	8,217,426	171,431,615	431,443,643	9,570,567	1,977,081,898	608,062,355	4,314,125	141,098,313	48,409,756	113,229,230	27,449,743	202,993,673
11	4,178,835	18,565,606	24,761,353	490,517	1,471,541	3,397,331	35,097,250	668,328	21,992,283	635,031	998,729,233	82,676	73,857,901
ON	1,589,878	641,838	1,224,002	357,957	617,264	1,350,865	7,514,343	318,667	1,305,142	507,915	999,528,680	215,897	67,813,519
MVS	189,897,690	31,080,870	59,034,477	3,554,501	17,429,254	32,368,706	47,062,832	2,385,485	1,185,932,246	94,420,333	180,651,595	12,282,184	196,453,643
S	630,561	1,028,932	3,956,950	4,499,696	760,151	12,948,939	6,006,103	324,008	1,339,799	846,470	124,211,377	343,626	10,160,347
Ana													
0	7513	77,406	103,189	3726	14,438	6986	56,313	2926	95,121	8777	500,602	2527	61,271
1	8319	4540	44,636	3435	8780	5434	19,382	2705	112,868	5217	503,132	2729	53,378
2	12,479	53,731	36,576	3112	8984	8171	44,880	2789	10,389	7457	1,490,450	3240	112,609
3	12,091	53,746	59,917	2909	9413	7775	36,367	3128	10,420	6631	1,489,162	5117	113,400
4	8410	51,492	36,576	3164	8541	6184	22,232	2508	15,388	5217	500,265	2527	45,174
5	8319	4540	44,636	3435	8780	5434	19382	2705	112,868	5217	503,831	2729	53,425
6	8319	4540	44,636	3435	8780	5434	19,382	2705	112,868	5217	503,041	2729	53,372
7	10,442	52,791	59,703	9548	11,367	8359	43,511	2071	20,007	8281	291,919	2571	35,017
8	12,062	53,720	59,702	2909	9380	7462	35,792	3020	10,385	6540	1489,162	5104	113,329
9	8319	4540	44,636	3435	8780	5434	19,382	2705	112,868	5217	501,065	2729	53,240
10	18,646	85,480	3206,787	6772	30174	16,963	115,207	4310	28,776	20,501	193,259	3207	176,327
11	11,688	78,675	91,212	6908	17,511	9261	76,688	2625	99,511	11,821	499,907	2195	63,478
ON	8322	4542	44,661	3435	8780	5434	19,382	2707	113,000	5217	504,208	2728	53,467
MVS	12,091	53,746	59,917	2909	9413	7775	36,367	3128	10,420	6631	1489,162	5117	113,400
S	10,498	52,785	59,687	6237	11,359	8359	50,594	2105	19,999	8210	193,354	2401	28,303

TABLE 5. WSS, EVPI, VSS.

	Istanbul European	Istanbul Anatolian
WSS	7,896,033	20,197
EVPI	2,264,314	8106
VSS	186,293,296	85,097

programming solution, on the average, a vehicle spends about 10 hours more and 7 minutes more to reach its shelter, compared to what it would have spent if we had perfect information about the disaster for Istanbul European and Anatolian networks, respectively. If we look at a specific scenario, say, if we assume we have perfect information for scenario 10 in Istanbul Anatolian network and if we locate the shelters and make evacuation plans accordingly, and if indeed this scenario realizes, an evacuee will reach a safe shelter about at the same time he/she reaches safety in the stochastic programming solution. The value of stochastic solution is very high, especially for the Istanbul European network. Indeed, the ratio of the expected total evacuation time for the mean value solution to the one of the stochastic programming solution is 19.3 and 4.0 for Istanbul European and Anatolian networks, respectively. We also observe that planning according to a single scenario can lead to very poor performance. For Istanbul European network, if we plan according to scenario 10, the expected total evacuation time is about 20 times higher than the expected total evacuation time for the stochastic programming solution.

We also investigate the performance of the solutions for different values of tolerance levels. We report in Table 7 the total evacuation time *versus* λ for both networks when $p = 32$ and $p = 17$, respectively for scenario 10. We observe that the total evacuation time for the stochastic programming solution is almost as good as solution 10 for scenario 10. We notice that ON solution tends to give better solutions for small λ values compared to mean value solution. Neither ON nor MVS solution is able provide a better total evacuation time compared to stochastic programming solution. The solutions ON and MVS provide are about 3.1 and 33.2 times and 13.2 and 2.4 times worse than that of stochastic programming solution when $\lambda = 0$ and $\lambda = 0.15$, respectively. For Istanbul Anatolian network these numbers are about 8 and 2.5 when $\lambda = 0.1$ and 2.6 and 7.7 when $\lambda = 0.2$.

Finally, we use the performance measures "maximum latency (or maximum experienced travel time)", and "percentage of evacuees reaching safety up to a specified time T" to evaluate the performance of our solutions. Table 8 illustrates the maximum latency incurred by the evacuees for scenario 10 of Istanbul Anatolian network, for different tolerance levels, when $p = 17$. After solution 10, which is the optimal for the realized scenario, the stochastic programming solution has the least maximum latency, many times better than that of any other solution. For some λ values the maximum latency incurred in stochastic programming solution is the same as that of solution 10. In terms of maximum latency, stochastic programming solution provides 4.4 times and 14.6 times better solutions than those of the ON and mean value solutions, respectively. Figure 2 also depicts the percentage of evacuees reaching safety across time for different strategies, for scenario 10 of Istanbul Anatolian instance, when $p = 17$ and $\lambda = 0.2$ and for scenario 0 of Istanbul European instance, when $p = 32$ and $\lambda = 0.15$. Since realized scenario is 10, solution 10 evacuates 100% of the population in less than six hours. While the stochastic programming solution evacuates almost everyone to safety within the same time as solution 10, the original network solution ON and the mean value solution MVS, can only evacuate 85% and 69% of the population within the same time. Solution strategy 7 starts really poorly in the beginning but then evacuates everyone within almost the same times as solution strategy 10 and stochastic programming solution. With stochastic programming solution, almost 90% of evacuees reach safe shelters in less than 5 hours and it takes a little bit more than 5 hours to reach shelters only for less than 10% of the evacuees and everyone is evacuated to safe shelters in less than 6 hours. The situation is similar for the Istanbul European instance. Stochastic programming solution beats the ON and mean value solutions and most of the other solution strategies. With stochastic programming solution more than 70% of evacuees reach safety in less than 6.5 hours and only less

TABLE 6. Regrets.

Sol	0	1	2	3	4	5	6	7	8	9	10	11	Max Regret
Eur													
0	0	12,506,147	2,320,873	22,955	425,419	20,075	2,031,154	2,258	356,137	20,755	2,062,040,265	154,466	2,062,040,265
1	4,781,665	0	8,361,540	194,476	5,554,728	78,479	25,187,131	873,808	5,973,607	6,001,567	2,065,097,499	3,982	2,065,097,499
2	1,183,378	44,730	0	759,899	427,680	943,506	7,579,783	270,334	6,555,104	2,115,131	4,923,084,938	33,623	4,923,084,938
3	834,924	377,710	5,848,159	0	1,581,940	3,048,658	6,906,964	267,426	21,400,408	1,727,699	4,923,147,046	151,891	4,923,147,046
4	99,824	12,371,184	2,336,087	280,127	0	536,517	2,025,802	11,048	564,163	206,932	885,537,813	203	885,537,813
5	840,664	143,820	8,363,060	156,025	1,633,619	0	24,139,036	873,327	396,385	1,122,339	2,062,015,873	147,979	2,062,015,873
6	360,325	12,497,924	2,229,343	25,212	673,963	3,314,888	0	2,633	515,936	14,740	2,062,028,077	428,648	2,062,028,077
7	747	12,506,785	2,324,508	270,188	464,858	3,122,415	2,034,176	0	888,802	13,189	2,062,015,873	425,519	2,062,015,873
8	4,781,665	133,270	8,361,540	194,476	19,730,180	78,479	24,122,339	873,808	0	4,125,570	2,065,097,499	425,800	2,065,097,499
9	28,248	12,495,705	2,024,497	23,749	425,064	145,918	2,017,555	436	316,803	0	2,061,968,874	148,450	2,061,968,874
10	156,424,699	7,618,005	170,210,279	431,366,553	9,377,958	1,976,915,212	607,049,929	4,262,467	140,582,162	48,120,930	0	27,367,067	1,976,915,212
11	3,777,574	17,966,185	23,540,017	413,427	1,278,932	3,230,645	34,084,823	616,670	21,476,132	346,205	885,500,002	0	885,500,002
ON	1,188,616	42,417	2,666	280,866	424,655	1,184,179	6,501,917	267,008	788,990	219,089	886,299,449	133,221	886,299,449
MVS	189,496,429	30,481,449	57,813,141	3,477,411	17,236,645	32,202,020	46,050,406	2,333,826	1,185,416,095	94,131,507	67,422,364	12,199,508	1,185,416,095
S	229,299	429,511	2,735,614	4,422,606	567,542	12,782,253	4,993,677	272,350	823,648	557,644	10,982,147	260,950	12,782,253
Ana													
0	0	72,866	66,613	817	5897	1552	36,931	855	84,736	3560	307,343	332	307,343
1	806	0	8060	526	239	0	0	634	102,483	0	309,873	534	309,873
2	4966	49,191	0	203	443	2737	25,498	718	4	2240	1,297,191	1045	1,297,191
3	4577	49,206	23,341	0	872	2342	16,985	1058	35	1414	1,295,903	2922	1,295,903
4	896	46,952	0	255	0	750	2851	438	5003	0	307,006	332	307,006
5	806	0	8060	526	239	0	0	634	102,483	0	310,572	534	310,572
6	806	0	8060	526	239	0	0	634	102,483	0	309,782	534	309,782
7	2929	48,250	23,127	6639	2826	2925	24,129	0	9621	3064	98,660	376	98,660
8	4549	49,180	23,126	0	839	2028	16,410	949	0	1,324	1,295,903	2909	1,295,903
9	806	0	8060	526	239	0	0	634	102,483	0	307,806	534	307,806
10	11,133	80,940	3,170,211	3863	21,633	11,529	95,825	2240	18,391	15,284	0	1012	3,170,211
11	4174	74,134	54,636	3999	8970	3828	57,306	554	89,126	6604	306,648	0	306,648
ON	808	2	8085	526	239	0	0	637	102,615	0	310,950	533	310,950
MVS	4577	49,206	23,341	0	872	2342	16,985	1058	35	1414	1,295,903	2922	1,295,903
S	2984	48,245	23,110	3328	2817	2925	31,212	34	9614	2993	95	206	48,245

TABLE 7. Total Evacuation Time for various levels of tolerance for scenario 10.

λ	Istanbul European							
	0	1	2	3	4	5	6	7
0	2,175,259,598	998,806,214	10,728,808,279	10,728,822,320	998,822,735	2,175,259,598	2,175,322,600	2,175,259,598
0.1	2,175,269,495	2,178,326,729	5,036,314,169	5,036,376,277	998,767,044	2,175,245,104	2,175,257,308	2,175,245,104
0.15	2,175,269,190	2,175,198,536	5,036,312,908	2,175,249,906	753,716,960	2,175,269,190	2,175,255,531	2,175,245,104
	8	9	10	11	ON	MVS	S	
0	2,175,265,854	753,696,271	323,291,760	998,743,086	1,002,780,099	10,728,776,770	323,365,972	
0.1	2,178,326,729	2,175,198,104	113,203,246	998,729,233	999,528,680	180,651,595	124,211,377	
0.15	2,175,198,890	753,632,213	74,770,390	753,679,132	999,527,218	181,278,134	75,875,383	
	Istanbul Anatolian							
	0	1	2	3	4	5	6	7
0	1,585,374	2,679,390	660,747	1,241,800	811,153	1,585,374	660,747	1,645,442
0.1	501,214	589,880	1,577,623	501,214	500,721	1,583,700	1,588,090	292,361
0.2	500,602	503,132	1,490,450	1,489,162	500,265	503,831	503,041	291,919
	8	9	10	11	ON	MVS	S	
0	1,585,370	2,420,442	547,125	817,167	661,202	1,577,324	547,212	
0.1	501,214	589,880	197,047	501,931	1,588,809	500,814	197,260	
0.2	1,489,162	501,065	193,259	499,907	504,208	1,489,162	193,354	

TABLE 8. Maximum Latency for various levels of tolerance for scenario 10, Istanbul Anatolian.

λ	0	1	2	3	4	5	6	7	8	9	10	11	ON	MVS	S
0	76.01	99.46	21.95	73.44	21.95	76.01	21.95	76.01	76.01	76.01	14.12	21.95	21.96	76.01	14.12
0.05	76.01	24.77	76.01	73.44	73.44	76.01	76.01	76.01	73.44	76.01	5.18	73.44	76.03	73.44	5.18
0.1	21.95	21.95	76.01	21.95	21.95	76.01	76.01	5.16	21.95	21.95	5.13	21.95	76.03	21.95	5.16
0.15	21.95	73.53	73.53	73.53	21.95	21.95	73.53	73.53	73.53	73.53	5.13	21.95	73.54	73.53	5.17
0.2	21.95	21.95	73.53	73.53	21.95	21.95	21.95	5.13	73.53	21.95	5.03	21.95	21.96	73.53	5.03

TABLE 9. Maximum Latency for various levels of tolerance across different scenarios for stochastic programming solution, Istanbul Anatolian.

Scen	0			1			2			3		
λ	Max	Min	Ave	Max	Min	Ave	Max	Min	Ave	Max	Min	Ave
0	0.513	0.019	0.194	4.093	0.019	0.871	1.919	0.022	0.590	1.111	0.023	0.225
0.1	0.513	0.018	0.194	4.093	0.018	0.870	1.919	0.022	0.588	0.631	0.023	0.149
0.2	0.513	0.018	0.140	4.093	0.018	0.834	1.919	0.022	0.588	0.631	0.023	0.149
Scen	4			5			6			7		
λ	Max	Min	Ave	Max	Min	Ave	Max	Min	Ave	Max	Min	Ave
0	0.454	0.019	0.152	0.360	0.018	0.157	4.968	0.021	1.445	0.093	0.018	0.057
0.1	0.454	0.018	0.150	0.360	0.018	0.156	4.968	0.018	1.444	0.093	0.018	0.057
0.2	0.454	0.018	0.150	0.360	0.018	0.126	1.851	0.018	0.488	0.088	0.018	0.051
Scen	8			9			10			11		
λ	Max	Min	Ave	Max	Min	Ave	Max	Min	Ave	Max	Min	Ave
0	0.639	0.019	0.266	0.423	0.018	0.186	14.123	0.024	5.635	0.615	0.018	0.228
0.1	0.639	0.018	0.266	0.423	0.018	0.156	5.162	0.024	2.031	0.146	0.018	0.078
0.2	0.639	0.018	0.266	0.423	0.018	0.124	5.028	0.024	1.991	0.140	0.018	0.061

than 7% of the population is evacuated to shelters in more than 15 hours. Everyone is evacuated to safety in less than 16 hours. In Table 9, we report the maximum, minimum and average latency values for various levels of tolerance across different scenarios for stochastic programming solution. For all of the instances, the ratio of the maximum latency to the average latency is less than 5, and for majority of the instances this ratio is between 2 and 3. This is due to our fairness considerations as we do not assign the evacuees to paths that are much longer that the shortest one they would take.

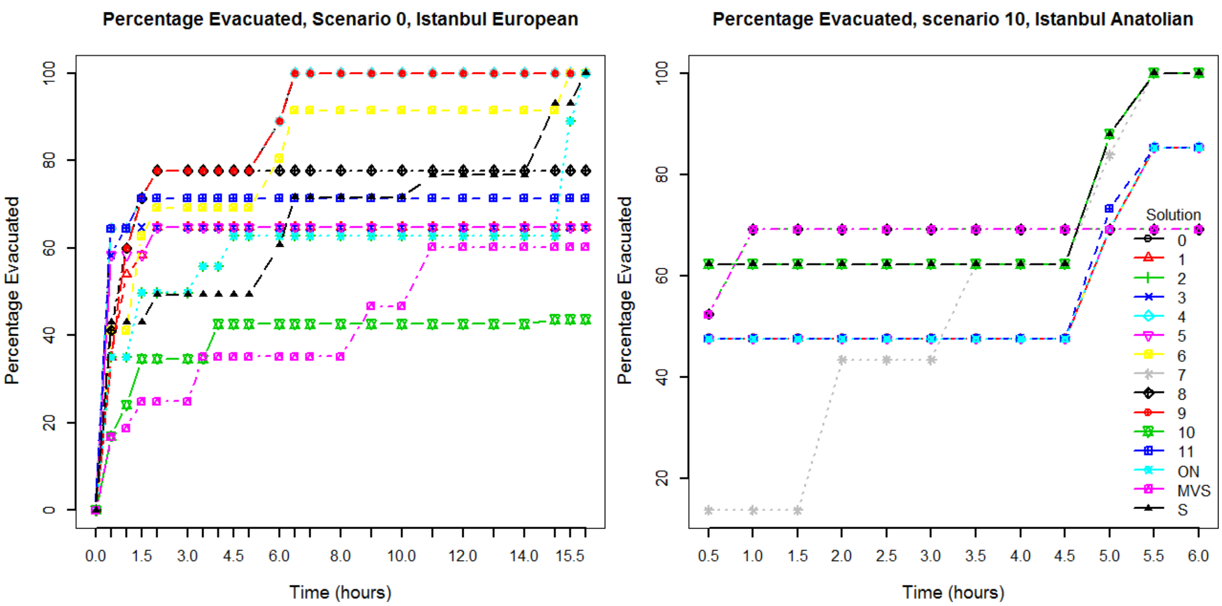

FIGURE 2. The percentage of evacuees reaching safety across time for different strategies.

TABLE 10. Shelter utilization, Istanbul Anatolian.

	Shelters																
Scenario	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
0	1785	0	0	4718	1630	15,621	14,983	D	0	12,334	0	8,517	10,316	543	278	0	4241
1	1496	0	0	4688	1495	11,965	12,032	2,647	0	10,380	0	7572	6458	342	276	0	3912
2	2386	0	D	9258	0	20,264	20,968	3997	0	17,382	0	20,706	D	1048	352	0	5122
3	825	0	0	D	3154	8306	8811	7811	0	D	0	0	9816	0	168	0	3031
4	1414	394	0	4744	1839	14,798	15,532	3084	0	11,936	0	3847	12,862	523	277	0	4337
5	1733	0	0	4738	738	13,568	12,956	2878	0	11,204	0	7434	6309	395	253	0	3997
6	2512	0	0	5459	3280	21,039	20,908	4037	0	17,221	0	11,970	10,260	1523	385	0	5115
7	905	0	D	2980	D	8919	7547	D	D	7126	0	5259	5930	0	159	0	2775
8	1755	0	0	4767	1898	14,597	15,110	2986	0	12645	0	0	16,710	321	269	0	4242
9	1533	0	0	5659	4484	D	21,921	2563	0	11,711	0	7587	6442	300	234	0	4017
10	D	2512	0	D	8286	28,213	D	8888	0	0	0	D	36,628	7095	342	0	5149
11	951	0	0	3926	0	7891	1895	5742	0	6194	0	3732	4432	2247	174	0	2376
Max	2512	2512	0	9258	8286	28,213	21,921	8888	0	17,382	0	20,706	36,628	7095	385	0	5149
Min	825	0	0	2980	0	7891	1895	2563	0	0	0	0	4432	0	159	0	2376
Ave	1572	242	0	5094	2437	15,016	13,878	4463	0	10,739	0	6966	11,469	1195	264	0	4026

In Table 10, we report the utilization numbers of the shelters for Istanbul Anatolian instance with $p = 17$ and $\lambda = 0.2$ for stochastic programming solution across different scenarios. We also report the maximum, minimum and the average utilization numbers. The utilization number reported in the table is the number of vehicles. Among the 17 potential shelters, *i.e.*, shelters numbered 14 through 30, only 13 are selected to be opened in the optimal solution. The four shelters that are not opened in the optimal solution, *i.e.*, the shelters 16, 22, 24, and 29 can be seen in table, as the utilization numbers in the column under them are all zero. D represents a shelter being disrupted in a specific scenario. As we do not restrict the number of evacuees a shelter can accommodate in the uncapacitated model, we assume that in an optimal solution the opened shelters should be able to hold a capacity of at least as much as the number of evacuees assigned to them. Hence, to be on the safe side with the uncapacitated model, one should prepare shelters with capacities as much as the maximum utilization numbers.

TABLE 11. Results for the Istanbul European and Anatolian instances when shelters are capacitated.

Istanbul European					Istanbul Anatolian				
λ	p	#os	Exp. Tot. Evac. Time	Sol. Time	λ	p	#os	Exp. Tot. Evac. Time	Sol. Time
0.05					0.1	10	10	111,695	40.42
	20	20	22,033,781	111.84		13	10	111,686	44.64
	25	20	22,013,994	111.35		15	10	111,686	44.96
	32	20	22,013,994	107.43		17	10	111,686	42.55
0.1					0.15	10	10	99,754	59.06
	20	20	11,600,146	213.45		13	10	99,720	52.22
	25	20	11,579,937	224.95		15	10	99,720	52.23
	32	20	11,579,937	203.18		17	10	99,720	52.18
0.15					0.2	10	10	87,968	47.60
	20	20	8,948,507	825.94		13	13	45,490	41.80
	25	20	8,939,547	500.99		15	13	45,490	43.33
	32	20	8,939,547	652.65		17	13	45,490	43.91

4.5. Capacitated Shelters

In our SCSO model, we assume that the shelters have unlimited capacity and that their capacity can be planned according to the allocated demands. In this section, we analyze how fixed capacities affect the quality of stochastic solution.

We add the capacity constraints $\sum_{r\in O}\sum_{\pi\in P^{\lambda}_{rs}(\omega)} w_r(\omega)v_\pi(\omega) \le K_s y_s$, $\forall\omega\in\Omega, s\in F(\omega)$ where K_s is the capacity of shelter s. We refer to the resulting model as "stochastic constrained system optimal model with capacitated shelters" and abbreviate it with SCSO-CS. We take shelter capacities as used in Kırıkçı [58]. In Table 11, we present the results for the Istanbul European and Anatolian Instances when shelters are capacitated. With original capacities, the problem is infeasible for both Istanbul European and Istanbul Anatolian networks for all λ values up to 0.2. We increase the capacities of some of the shelters so that the problem becomes feasible for some λ values. With the updated capacities, the problem is feasible for Istanbul European network for $\lambda \ge 0.05$ and for Istanbul Anatolian network for $\lambda \ge 0.1$.

For the case when shelters are capacitated, we compare the quality of 14 different solutions, named as 0, 1,...11, MVS, S, with 0, 1,...11 being the optimal solutions corresponding to the original scenarios, MVS and S representing the mean value solution and stochastic programming solution, respectively.

In Table 12, we present the total evacuation times for all 14 solutions and 12 scenarios, as well as the expectation of the total evacuation times, when shelters are capacitated. We take $\lambda = 0.1$ and $p = 32$ for the Istanbul European network and $\lambda = 0.2$ and $p = 17$ for the Istanbul Anatolian network. Table 13 gives the wait and see solution, expected value of perfect information and value of stochastic solution for both networks. Finally, in Table 14, we present the regrets of the solutions in all 12 scenarios and the maximum regrets over all scenarios.

For both Istanbul European and Anatolian networks, there is no single solution other than the stochastic programming solution that is feasible over all possible scenarios, when shelters are capacitated. In Tables 12 and 14, "∞" basically means that the proposed solution is not feasible for that specific scenario. For that reason the stochastic programming solution is superior compared to all other solutions.

When we use the stochastic programming solution, on the average, a vehicle spends about 7 hours more and a little bit more than 11 minutes more to reach its shelter, compared to what it would have spent if we had perfect information about the disaster for Istanbul European and Anatolian networks, respectively. If we look at a specific scenario, say, if we assume we have perfect information about scenario 10, a possible worst case scenario, and if we locate the shelters and make evacuation plans accordingly, and if indeed this scenario realizes, an evacuee will reach a safe shelter at the same time he/she reaches safety in accordance with the stochastic programming solution, in Istanbul European network.

Table 12. Total evacuation times.

	Realized Scenario												
Sol.	0	1	2	3	4	5	6	7	8	9	10	11	Expectation
Eur													
0	619,554	∞	∞	4,496,552	∞	∞	∞	269,078	∞	∞	∞	∞	∞
1	∞	606,132	∞	∞	5,806,220	10,803,413	∞	2,687,014	6,615,177	19,334,866	∞	1,029,248	∞
2	∞	∞	1,623,788	∞	∞	∞	∞	∞	∞	2,285,037	∞	167,911	∞
3	∞	∞	∞	99,261	∞	∞	∞	∞	∞	∞	∞	∞	∞
4	∞	∞	∞	4,496,319	261,194	∞	∞	322,572	28,860,304	2,329,049	∞	1,029,384	∞
5	∞	∞	∞	∞	∞	6,693,301	∞	2,637,143	∞	∞	∞	487,205	∞
6	∞	∞	∞	4,496,716	∞	∞	3,024,328	331,004	28,868,756	2,379,558	∞	1,036,876	∞
7	∞	∞	∞	873,149	956,690	∞	∞	266,813	∞	∞	∞	153,834	∞
8	∞	∞	∞	∞	∞	∞	∞	2,728,662	1,012,485	7,677,118	∞	∞	∞
9	887,680	∞	∞	∞	∞	∞	∞	360,880	∞	918,019	∞	∞	∞
10	7,656,602	12,081,369	∞	9,572,308	∞	720,625,162	∞	4,079,307	∞	∞	135,952,177	392,754	∞
11	∞	∞	∞	∞	∞	∞	∞	∞	∞	∞	∞	82,540	∞
MVS	7,611,940	8,865,691	∞	2,018,039	∞	715,498,719	∞	3,481,212	∞	∞	∞	284,377	∞
S	637,163	611,072	3,921,490	4,500,243	264,425	12,952,928	4,763,189	324,303	7,214,394	2,357,504	135,952,177	126,355	11,605,694
Ana													
0	7676	77,569	∞	4007	∞	7105	∞	2928	∞	∞	∞	2588	∞
1	57,968	30,213	∞	8615	57,942	32,438	∞	12,237	91,637	25,506	∞	7664	∞
2	19,239	57,556	83,104	6511	19,725	10,616	59,691	3109	15,095	12,092	∞	3788	∞
3	∞	55,165	∞	2909	∞	∞	∞	∞	∞	∞	∞	9114	∞
4	10,405	52,885	∞	6224	11,341	8329	∞	2073	19,815	∞	∞	2194	∞
5	7676	77,569	∞	4007	∞	7105	∞	2928	∞	∞	∞	2588	∞
6	9265	79,816	∞	4615	26,605	7277	39,603	2928	23,030	14,824	345,159	3196	∞
7	∞	52,891	∞	∞	∞	8356	∞	2073	∞	∞	∞	2570	∞
8	∞	55,139	∞	2909	∞	∞	∞	∞	13,676	∞	∞	5188	∞
9	158,450	36,332	∞	7894	19,866	9625	48,515	3355	23,416	9541	∞	3031	∞
10	17,800	∞	∞	6774	∞	∞	∞	4279	∞	∞	342,800	3212	∞
11	11,682	78,716	∞	∞	∞	9259	∞	2627	∞	∞	∞	2194	∞
MVS	∞	55,067	∞	2936	∞	∞	∞	∞	13,657	∞	∞	5210	∞
S	22,509	59,101	83,104	6766	25,832	12,861	239,070	3223	20,818	13,438	344,465	2770	49,498

TABLE 13. WSS, EVPI, VSS for the capacitated shelters case.

	Istanbul European	Istanbul Anatolian
WSS	9,947,393	35,952
EVPI	1,658,300	13,546
VSS	∞	∞

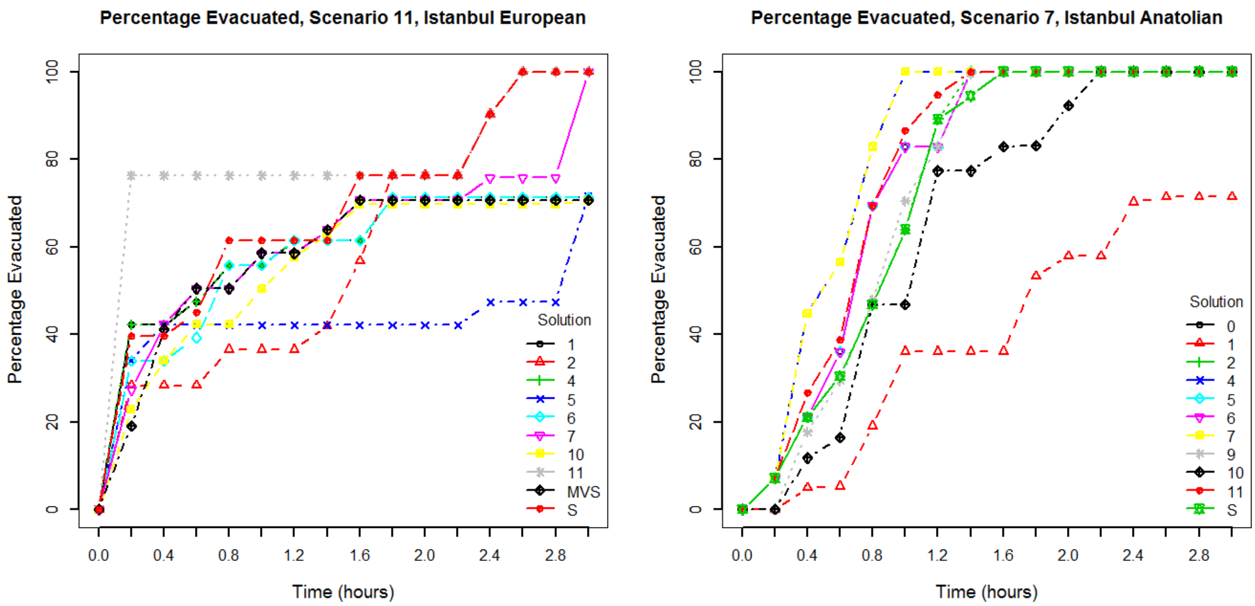

FIGURE 3. The percentage of evacuees reaching safety across time for different strategies when shelters are capacitated.

For both Istanbul European and Anatolian networks the value of stochastic solution is infinite. We also observe that planning according to a single scenario leads to much worse performance compared to the case when shelters are uncapacitated. Whichever scenario is chosen for evacuation planning purposes, the solution becomes infeasible for some scenarios in both Istanbul European and Anatolian networks. For that reason the maximum regret is infinite for all other solutions except that of the stochastic programming solution for both Istanbul European and Anatolian networks.

Figure 3 depicts the percentage of evacuees reaching safety across time for different strategies, for scenario 7 of Istanbul Anatolian instance, when $p = 17$ and $\lambda = 0.2$ and for scenario 11 of Istanbul European instance when $p = 32$ and $\lambda = 0.1$. For the Istanbul European instance, stochastic programming solution is the second best strategy after strategy 11 in scenario 11. Everyone is evacuated to safety in less than 3 hours with stochastic programming solution. Only a little bit more than 20 % of evacuees incur a latency of more than 2.8 hours. The mean value solution is not promising compared to the efficiency of the stochastic programming solution. The situation is similar for the Istanbul Anatolian instance. Stochastic programming solution turns out to be an efficient solution in this scenario, as well. With stochastic programming solution almost 90% of evacuees reach safety in less than 1.2 hours and only less than 5% of the population incurs a latency of more than 1.4 hours. Everyone is evacuated to safety in less than 1.6 hours. As the mean value solution is not feasible in this scenario, it is not in the graph. Table 15 illustrates the maximum latency incurred by the evacuees for different solution strategies across scenarios for Istanbul Anatolian network, when $p = 17$ and $\lambda = 0.2$. The stochastic programming solution has relatively a good maximum latency in most of the scenarios. For some scenarios the

Table 14. Regrets when shelters are capacitated.

Sol	0	1	2	3	4	5	6	7	8	9	10	11	Max Regret
Eur													
0	0	∞	∞	4 397 291	∞	∞	∞	2265	∞	∞	∞	∞	∞
1	∞	0	∞	∞	5 545 026	4 110 112	∞	2 420 201	5 602 692	18 416 847	∞	946 708	∞
2	∞	∞	0	∞	∞	∞	∞	∞	∞	1 367 018	∞	85 371	∞
3	∞	∞	∞	0	∞	∞	∞	∞	∞	∞	∞	∞	∞
4	∞	∞	∞	4 397 058	0	∞	∞	55 760	27 847 819	1 411 030	∞	946 845	∞
5	∞	∞	∞	∞	∞	0	∞	2 370 330	∞	∞	∞	404 665	∞
6	∞	∞	∞	4 397 455	∞	∞	0	64 191	27 856 271	1 461 539	∞	954 336	∞
7	∞	∞	∞	773 888	695 496	∞	∞	0	∞	∞	∞	71 294	∞
8	∞	∞	∞	∞	∞	∞	∞	2 461 849	0	6 759 099	∞	∞	∞
9	268 126	∞	∞	∞	∞	∞	∞	94 068	∞	0	∞	∞	∞
10	7 037 048	11 475 238	∞	9 473 047	∞	713 931 861	∞	3 812 494	∞	∞	0	310 215	∞
11	∞	∞	∞	∞	∞	∞	∞	∞	∞	∞	∞	0	∞
MVS	6 992 386	8 259 559	∞	1 918 778	∞	708 805 418	∞	3 214 399	∞	∞	∞	201 837	∞
S	17 609	4 940	2 297 702	4 400 982	3 231	6 259 627	1 738 861	57 491	6 201 908	1 439 485	0	43 815	6 259 627
Ana													
0	0	47 355	∞	1098	∞	0	∞	856	∞	∞	∞	394	∞
1	50 292	0	∞	5706	46 601	25 333	∞	10 165	77 961	15 965	∞	5470	∞
2	11 563	27 342	0	3602	8384	3512	20 088	1036	1419	2551	∞	1594	∞
3	∞	24 951	∞	0	∞	∞	∞	∞	∞	∞	∞	6 920	∞
4	2729	22 672	∞	3315	0	1225	∞	0	6139	∞	∞	0	∞
5	0	47 355	∞	1098	∞	0	∞	856	∞	∞	∞	394	∞
6	1589	49 603	∞	1706	15 264	172	0	856	9354	5283	2359	1002	∞
7	∞	22 677	∞	∞	∞	1252	∞	0	∞	∞	∞	376	∞
8	∞	24 925	∞	0	∞	∞	∞	∞	0	∞	∞	2994	∞
9	150 774	6119	∞	4986	8524	2520	8912	1282	9739	0	∞	837	∞
10	10125	∞	∞	3866	∞	∞	∞	2206	∞	∞	0	1018	∞
11	4007	48503	∞	∞	∞	2155	∞	554	∞	∞	∞	0	∞
MVS	∞	24 854	∞	27	∞	∞	∞	∞	-19	∞	∞	3016	∞
S	14 834	28 887	0	3857	14 491	5757	199 466	1150	7141	3897	1665	576	199 466

TABLE 15. Maximum Latency when shelters are capacitated, Istanbul Anatolian, $\lambda = 0.2$ and $p = 17$.

Solution \ Scen	0	1	2	3	4	5	6	7	8	9	10	11
0	0.20	4.10	∞	0.21	∞	0.25	∞	0.14	∞	∞	∞	0.16
1	1.51	0.97	∞	0.34	1.40	1.08	∞	0.78	1.74	0.70	∞	0.46
2	0.68	4.10	2.22	0.63	0.73	0.36	2.04	0.15	0.56	0.42	∞	0.19
3	∞	4.10	∞	0.15	∞	∞	∞	∞	∞	∞	∞	0.71
4	0.51	4.10	∞	0.63	0.45	0.36	∞	0.09	0.64	∞	∞	0.11
5	0.20	4.10	∞	0.21	∞	0.25	∞	0.14	∞	∞	∞	0.16
6	0.24	4.10	∞	0.25	1.04	0.25	0.64	0.14	0.64	0.59	22.18	0.17
7	∞	4.10	∞	∞	∞	0.36	∞	0.09	∞	∞	∞	0.16
8	∞	4.10	∞	0.15	∞	∞	∞	∞	0.63	∞	∞	0.36
9	6.07	1.50	∞	0.63	0.73	0.36	1.85	0.15	0.64	0.42	∞	0.15
10	0.53	∞	∞	0.63	∞	∞	∞	0.20	∞	∞	22.18	0.14
11	0.51	4.10	∞	∞	∞	0.36	∞	0.12	∞	∞	∞	0.11
MVS	∞	4.09	∞	0.15	∞	∞	∞	∞	0.62	∞	∞	0.36
S	0.68	4.09	2.22	0.63	0.73	0.36	8.87	0.14	0.64	0.42	22.16	0.14

TABLE 16. Shelter Utilization when shelters are capacitated, Istanbul Anatolian.

	Shelters																
Scenario	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
0	1785	0	0	4712	1636	30,000	0	D	0	12,938	3013	0	15,820	0	278	0	4784
1	1496	0	0	4692	1491	19,990	0	6477	0	10,380	177	0	14,030	0	276	0	4254
2	2386	0	D	9673	6913	27,657	0	8769	0	17,925	21,639	0	D	0	352	0	6170
3	825	0	0	D	6687	9949	0	10,000	0	D	1447	0	9816	0	168	0	3031
4	1413	395	0	6462	4390	14,798	0	10,000	0	13,199	3084	0	16,709	0	277	0	4860
5	1732	0	0	7816	6549	17,633	0	1654	0	11,204	1224	0	13,743	0	253	0	4392
6	2512	0	0	11,514	9330	25,978	0	6473	0	17,221	1427	0	22,230	0	385	0	6638
7	905	0	D	4918	D	14,528	0	D	D	7126	1790	0	9399	0	159	0	2775
8	1755	0	0	4918	0	14,528	0	0	0	7126	1790	0	9399	0	159	0	2775
9	1533	0	0	10,920	8820	D	0	10,000	0	11,711	1028	0	14,029	0	234	3860	4317
10	D	463	2049	D	8286	28,867	D	10,001	0	0	15,684	D	25,000	0	342	0	6,421
11	951	0	0	4,698	1123	7891	0	7557	0	6624	2	0	8164	0	174	0	2376
Max	2512	463	2049	11,514	9,330	30,000	0	10,001	0	17,925	21,639	0	25,000	0	385	3860	6638
Min	825	0	0	4692	0	7891	0	0	0	0	2	0	8164	0	159	0	2376
Ave	1572	71	205	7032	5021	19,256	0	7093	0	10,496	4359	0	14,394	0	255	322	4399

maximum latency incurred in stochastic programming solution is the same as that of the solution strategy that considers the related scenario. Stochastic programming solution provides better results than those of the mean value solution, as the mean value solution is not feasible for many scenarios. The infeasibility of other solution strategies in many scenarios, shows the superiority of the stochastic programming solution.

In Table 16, we report the utilization numbers of the shelters for Istanbul Anatolian instance with $p = 17$ and $\lambda = 0.2$ for stochastic programming solution across different scenarios, when shelters are capacitated. We also report the maximum, minimum and the average utilization numbers. Among the 17 potential shelters, only 13 are selected to be opened in the optimal solution. The four shelters that are not opened in the optimal solution, are shelters 20, 22, 25, and 27. Because of the restrictions on the shelter capacities, the evacuees are distributed more evenly between shelters compared to the uncapacitated case, at the cost of an increase in total evacuation time.

5. CONCLUSION

Evacuation planning is done in the presence of uncertainty without exact or complete information. Due to the fact that the place, the time and the scale of a disaster can not be easily predicted, it is very difficult to estimate the evacuation demand accurately. Similarly, road capacities and shelter sites may be affected (degraded or disrupted), but the questions of "which ones" and "how much" are difficult to answer.

In this study, we first proposed a novel model that captures this stochasticity in evacuation planning by taking account of the uncertainty in demand, road capacities and availability of shelters. Following the methodology proposed by Bayram *et al.* [8], we showed that our problem can be solved exactly by using second order cone programming in small CPU times.

Then we presented a real world case study for a pending Istanbul earthquake where evacuation decisions are made to save people from the impact of aftershocks and/or secondary disasters. In our case study, we observed that planning in accordance with a single scenario such as the worst case scenario or most probable scenario, or solving the problem with mean value approach do not produce effective solutions and that using stochastic programming can lead to significant improvements. The improvement ranges from 2 to 33 and 4 to 15 fold in total evacuation time and maximum latency respectively, depending on the tolerance level used. We observed that stochastic programming solution results in significantly better maximum regret values ranging from 7 to 70 times compared to deterministic solutions, when shelters are uncapacitated. We showed that if the fairness considerations are applied using geographical distances rather than travel times, contrary to common managerial belief it is not necessarily more beneficial to open more shelters as this may cause congestion on the road network. We also showed as a managerial rule of thumb that for the case when shelters are uncapacitated, evacuation planning authority should take into account maximum utilization numbers of shelters to determine shelter capacities. The solutions provided by stochastic programming approach is robust across the range of scenarios in terms of the high percentages of the population evacuated within a certain time limit. Depending on the realized scenario, the tolerance level used and the decision on the number of shelters to open, stochastic programming solution is able evacuate around 90 % of the evacuees within 5 hours and everyone is evacuated to safety within 6 hours for the Istanbul Anatolian instances. The results for Istanbul European instances are as significant as those of Istanbul Anatolian instances.

We further observed that when shelters are capacitated, the superiority of stochastic programming solution is emphasized, as planning in accordance with a single scenario or mean value approach will possibly generate infeasible solutions for some scenarios, unlike in stochastic programming solution.

In this study, we were able to solve the stochastic programs in small CPU times as the number of scenarios was small. In a follow up study (Bayram and Yaman [9]), we work on decomposition approaches to solve the problem with large number of scenarios.

Specifying which routes are going play a major role during an evacuation is a question emergency evacuation planners are trying to answer. It is important that these routes are large enough to serve a demand surge during an evacuation and that they survive the destructive impact of a disaster. For that reason expanding and/or strengthening these routes subject to a budget would contribute to the effectiveness of an evacuation plan. As a continuation of our study we aim to incorporate capacity expansion and/or retrofit decisions in the first stage and analyse the trade off between the expansion/retrofit decisions and the total evacuation time.

In our model the uncertainty is caused by nature. Another interesting extension would be a game theoretic approach, where there is an attacker (a terrorist organization using a chemical/biological bomb) whose aim is to give the defender maximum possible harm by delaying the evacuation as much as possible by attacking critical road segments or bridges and shelter sites subject to a limited budget. Defender on the other hand, tries to minimize this effect by selecting the shelter locations and assigning the evacuees to these shelters and to routes that reach them in such a way that the total evacuation time is minimized.

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