Online optimization of first-responder routes in disaster response logistics

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After a disaster, first responders should reach critical locations in the disaster-affected region in the shortest time. However, road network edges can be damaged or blocked by debris. Since response time is crucial, relief operations may start before knowing which edges are blocked. A blocked edge is revealed online when it is visited at one of its end-nodes. Multiple first-responder teams, who can communicate the blockage information, gather initially at an origin node and are assigned to target destinations (nodes) in the disaster-affected area. We consider multiple teams assigned to one destination. The objective is to find an online travel plan such that at least one of the teams finds a route from the origin to the destination in minimum time. This problem is known as the online multi-agent Canadian traveler problem. We develop an effective online heuristic policy and test it on real city road networks as well as randomly generated networks leading to instances with multiple blockages. We compare the performance of the online strategy with the offline optimum and obtain an average competitive ratio of 1.164 over 70,100 instances with varying parameter values.

Introduction

As natural and man-made disasters have been increasing in number within the past decades, the importance of response operations has been acknowledged in recent literature in addition to practice [1]. In this article, among the post-disaster response operations, we focus on collecting information on road network accessibility and routing of first responders for search-and-rescue (SAR) operations at the same time. Due to the urgency of the first-response operations, when providing a solution strategy for the problem of finding a route to reach a destination from an origin location in shortest time, very low running time is required for real-time decision support.

The condition of the roads and time to traverse them is, unfortunately, uncertain right after a disaster. Damage on road segments, and collapsed bridges and viaducts, together with resulting blockage of the roads is a commonly experienced complication in disaster response [2]. **Figure 1** shows an example of road damage after an earthquake in Myanmar in 2001. As another vivid example, we note that in the Japan triple disaster in 2011, a majority of the roadways, motorways, and the main artery running from north to south were blocked in the immediate response phase [3].

Gathering road damage information by satellites is expensive, and the images may only be partially useful since clouds may block the sight of the camera in the affected area. Using drones and helicopters is restrictive since typically these vehicles are limited in number and cannot cover a large area completely. Crowdsourcing does not provide reliable data. Data veracity is a serious issue. Hence, we propose to gather information by sending teams (agents) to the disaster-affected area, which may also consist of motorcycled explorers, while they try to reach critical points within the disaster zone with SAR personnel, police, and firefighter forces, together with necessary machinery and equipment.

In our article, we propose online optimization for the effectiveness of the aforementioned response operations. An online strategy should be fast enough computationally in order to be able to collect information and take actions in real time. Due to its efficiency, our proposed online strategy can be run in real time. Also, we show its performance on real-life road networks in various disaster risk-prone areas, as well as realistic random networks, in terms of yielding

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Figure 1

Damage of bridge approach road due to Myanmar (Burma) earthquake in 2001 [4].

solutions very close to the optimal solutions that are found under perfect information.

Problem description

We study a post-disaster situation in which emergency response operations, such as SAR and core relief item delivery, are required at a *critical* location, e.g., a temporary shelter location, a residential complex, a shopping center, etc. We represent the road network of the disaster-affected region by an undirected graph where some road segments become damaged or blocked and are rendered nontraversable. We consider the situation in which multiple first-responder teams, who can communicate the blockage information, gather initially at an origin node, e.g., a rescue center, a fire station, etc. The blockages are not known to the first-responder teams at the beginning. Since response time is of utmost importance, operations may start before blockage information is available. A blocked edge is revealed online when at least one of the first-responder teams visits one of its end-nodes. A mission is launched such that at least one of the first-responder teams reaches the critical location in the shortest time. Developing a routing strategy in such a case falls into the realm of online problems. In online problems, information is revealed incrementally, while taking actions, and decisions must be made before all information is available. In such problems, the objective is to devise a strategy that performs well over all possible problem instances, compared to the optimal solution found assuming that all of the information is available beforehand.

We next define an online optimization problem for the situation described earlier. In this problem, first-responder teams receive an undirected network $G = (V, E)$ with a given source node $O \in V$ and a destination node $D \in V$ together with edge traveling times as input. Initially, all of the first-responder teams are located at O. Some of the edges are blocked in the network, but these edges are not known to the first-responder teams *a priori*. A blocked edge cannot be traversed and is revealed online when at least one of the first-responder teams visits one of its end-nodes. This information is immediately communicated to the other teams. Hence, the routes of the first-responder teams may change as blockage information is obtained. The objective is to provide an online strategy such that at least one of the first-responder teams finds a feasible path, i.e., one without blockages, from their initial location O to the given destination D in minimum total time. This problem is known as the online multi-agent Canadian traveler problem (CTP).

Competitive analysis

A solution strategy to an online problem is called an online strategy. Online strategies process their inputs piece by piece, without having the entire input available from the beginning. Online strategies are divided into two categories: *deterministic* and *randomized*. In a deterministic online strategy, actions of the decision maker do not depend on probabilistic outcomes. That is, given a particular input, a deterministic online strategy will always produce the same output. In a randomized strategy, actions of the decision maker are taken according to some probability distribution in the sense that, given a particular input, a randomized online strategy may produce different outputs.

The key concept in analyzing an online strategy is to compare a solution produced by the online strategy with the best possible solution under complete information, which is called the *offline optimum* solution. An offline strategy is to solve the same problem as an online strategy, except that all information about the problem inputs is revealed to an offline strategy from the beginning. An optimal offline strategy is the optimal strategy in presence of complete input information that produces the offline optimum solution.

This approach was first suggested in [5]. To evaluate the performance of online strategies, the notion of *competitive ratio* has been introduced by Sleator and Tarjan [5] and adopted by many researchers. For a deterministic online strategy, the competitive ratio is the maximum ratio of the cost of the online strategy to the cost of the offline strategy over all instances of the problem. For a randomized online strategy, the *expected competitive ratio* is the maximum ratio of the expected cost of the online strategy to the cost of the offline strategy over all instances of the problem.

Literature review

As we described, we investigate the online multi-agent CTP in the context of disaster response logistics. Hence, our primary focus will be on those studies in our literature review. First, we briefly discuss articles related to routing in disaster logistics. Next, we review the relevant literature on the online multi-agent CTP.

Routing in disaster logistics

Deterministic (e.g., [6]) and stochastic optimization models (e.g., [7–9]) have been proposed for routing relief aid after a disaster, either comprising stand alone decisions (e.g., [6] and [9]) or together with facility location decisions (e.g., [7] and [8]). In particular, Noyan et al. [7] proposed a stochastic programming model for designing last mile relief networks, which includes routing decisions, and the uncertainty is on road travel times and demand. Moreover, recently, Noyan and Kahvecioğlu [8] studied the last mile relief network design again with the same type of uncertainty, this time with resource reallocation and equity considerations. In another related study, Hu et al. [9] developed a multistage stochastic programming model for relief distribution. The uncertain state of the road network and multiple types of vehicles are considered. The uncertain and dynamic network capacity is characterized by means of a scenario tree. In these latter three studies, uncertainty is represented by discrete scenarios with given probabilities, whereas we assume no knowledge of probabilities in the chaotic immediate response stage.

The above-mentioned studies distribute aid to multiple destinations, while we target a single destination. However, our problem can be solved separately for all O-D pairs under consideration since the run times of our proposed strategy are extremely low even for large-scale networks. We illustrate this approach in our computational experiments.

Multi-agent CTP

We focus on studies that are conducted from an online optimization and competitive analysis perspective, since these are the most related works to our study. The CTP was defined first in [10]. Papadimitriou and Yannakakis [10] proved that devising an online strategy with a bounded competitive ratio is PSPACE-complete for the CTP. Bar-Noy and Schieber [11] also considered the CTP and its variants. They introduced the k-CTP, where an upper bound k on the number of blocked edges is given as input. They showed that for arbitrary k, the problem of designing an online strategy that guarantees the minimum travel cost is PSPACE-complete.

Westphal [12] considered the k-CTP from the competitive ratio perspective. He showed the lower bounds of $2k+1$ and $k+1$ on the competitive ratio of deterministic and randomized online strategies, respectively. He also presented an optimal deterministic online strategy for the k-CTP, which is called the *backtrack* strategy. Xu et al. [13] also considered the k-CTP and presented two online strategies, *greedy* and *comparison*, and proved competitive ratios of $2^{k+1}-1$ and $2k+1$, respectively, for these strategies. Bender and Westphal [14] presented a randomized online strategy for the k-CTP, which meets the lower bound of $k+1$ in special cases. Shiri and Salman [15] modified the strategy given in [14] and proposed an optimal randomized online strategy for the k-CTP on O-D edge-disjoint graphs.

The k-CTP with multiple agents was first considered by Zhang et al. [16]. They analyzed the problem in two scenarios, with limited and complete communication. They proposed lower bounds of $2\lfloor\frac{k-1}{L_1}\rfloor+1$ and $2\lfloor\frac{k}{L}\rfloor+1$ on the competitive ratio of the deterministic strategies for the cases with limited and complete communication, respectively. Note that in the proposed lower bounds, L denotes the total number of agents and L_1 denotes the number of agents who benefit from complete communication. They also proposed an optimal deterministic online strategy when there are two agents in the graph. Shiri and Salman [17] also investigated the multi-agent k-CTP. They provided an updated lower bound on the competitive ratio of deterministic online strategies for the case with limited communication. They also presented a deterministic online strategy, which is optimal in both cases with complete and limited communication on O-D edge-disjoint graphs. Randomized online strategies for the multi-agent k-CTP are investigated in [18], where lower bounds on the expected competitive ratio together with optimal randomized online strategies on O-D edge-disjoint graphs are proposed for the cases with limited and complete communication.

Xu and Zhang [19] studied a real-time rescue routing problem from a source node to an emergency spot in the presence of online blockages. They analyzed the problem with the objective to make all the rescuers arrive at the emergency spot with minimum total cost. They studied the problem in two scenarios: without communication and with complete communication. They investigated both of the scenarios on the grid networks and general networks, respectively. They showed that consideration of both the grid network and the rescuers' communication can significantly improve the rescue efficiency.

As discussed previously, most of the results for the CTP are presented to investigate the worst-case performance of online strategies. Also, these results are mostly optimal in special cases that do not resemble real-world instances. In this article, we propose a deterministic online strategy for the first-responder routing problem, which is designed to be applied on real-world instances. We conduct extensive computational experiments to measure the average-case performance of our online strategy. Our study is unique in terms of these aspects.

Description of the strategy

We next present a deterministic online strategy for the online problem under study. Our online strategy is based on the *iterative penalty method*, which is proposed in [20] for the generation of spatially dissimilar paths with a motivation of avoiding hazardous material accident risk.

Our online strategy first assigns dissimilar O-D paths to the first-responder teams by applying the iterative penalty method. Then, the first-responder teams move toward D through their assigned O-D paths. Whenever a blockage is found along the current path, this information is shared among all of the first-responder teams. For all of the first-responder teams who have the found blocked edge on their currently assigned paths, the shortest path, which links their current location (the first immediate node in front of them) to D is assigned using the updated graph. This procedure is repeated until at least one of the first-responder teams arrives at D. We formally describe our deterministic online strategy.

The online strategy is as follows.

- *Initialization.* Take an undirected graph $G = (V, E)$, a source node $O \in V$, a destination node $D \in V$, a number L that represents the number of first-responder teams, together with nonnegative edge travel times as input. Label the first-responder teams from T_1 to T_L arbitrarily. Let i be a counter variable and set $i = 1$ initially.
- *Step 1.* Compute the shortest O-D path P_i in G and assign it to T_i. Update G by doubling the travel times of the edges on P_i. Set $i = i + 1$. If $i \leq L$, go to the beginning of Step 1. Otherwise, reset the edge travel times in G to their original values given in the initialization step and go to Step 2.
- *Step 2.* Let the first-responder teams move toward D through their assigned paths. If at least one of the first-responder teams has arrived at D, stop. If one of the first-responder teams has encountered a blockage e, remove the blockage from the graph, i.e., set $G = (V, E - \{e\})$. Let $T^e \subset \{T_1, T_2, \ldots, T_L\}$ be the set of first-responder teams who have e on their currently assigned paths. For each first-responder team in T^e, assign the first-responder team to the shortest path from their current location, i.e., the first immediate node in front of them, to D in G. Go to the beginning of Step 2.

Data generation and computational study

In this section, we present the results of our experiments to evaluate the performance of our proposed online strategy in comparison to the optimal offline strategy. We tested our strategy on the following four different network types:

1) a uniform two-dimensional (2-D) grid network;
2) multiple randomly generated Euclidean networks;
3) road network of the Gulf Coast area of the United States;
4) Istanbul city networks.

Remark 1. We simulated a total number of 701 scenarios to test our online strategy. We tested each scenario on 100 randomly generated instances, i.e., a total number of $701 \times 100 = 70{,}100$ instances are investigated. For each scenario, we report the values of the average and the maximum of the ratio of the cost of the online strategy to the cost of the offline optimum over 100 tested instances. Hereafter, we call these values the *average* and the *maximum* competitive ratio, respectively.

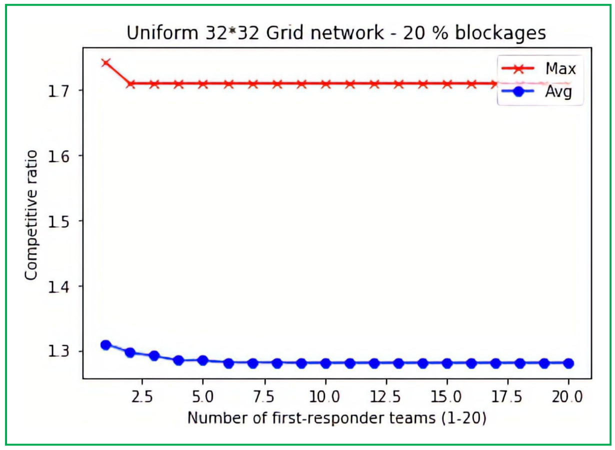

Figure 2

Results for the uniform 32×32 grid network with 20% of blockages.

Uniform grid network

Grid networks have been widely used to simulate real city road networks (see [19] and [21]). For a uniformly weighted 32×32 2-D grid network (with 1,024 nodes and 1,984 edges), various scenarios with respect to the percentage of blockages and the number of first-responder teams are simulated. We selected the blockages randomly while making sure that the source node (the node at the southwestern corner of the grid network) and the destination node (the node at the northeastern corner of the grid network) remain connected. We experimented with 10%–40% of blockages while the number of first-responder teams covers a range from 1 to 20. For each scenario, 100 random instances with different blockage patterns are generated. Hence, $4 \times 20 \times 100 = 8{,}000$ instances are investigated in total for the uniform grid network case. We report the maximum and the mean values for the competitive ratio of these 100 instances in each scenario. **Figures 2** and **3** show the results for 20% and 40% of blockages, respectively. Figures for 10% and 30% of blockages are provided in the website https://doi.org/10.6084/m9.figshare.8203358.v1.

We observe that as the percentage of blockages increases, the values of the maximum and the mean competitive ratio increase as well. As another observation, increasing the number of first-responder teams does not improve the solution significantly for the tested uniform grid network.

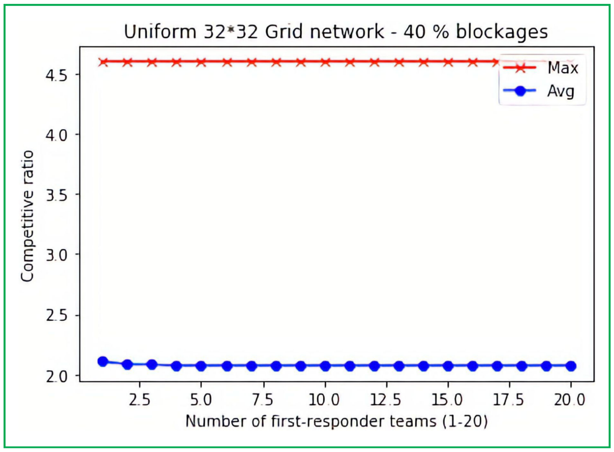

Figure 3

Results for the uniform 32×32 grid network with 40% of blockages.

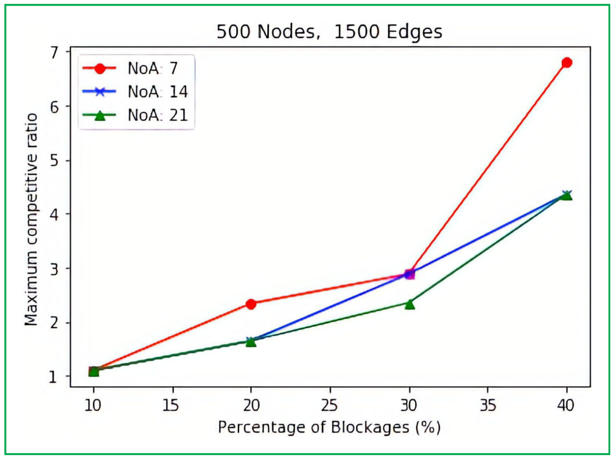

Figure 5

Maximum competitive ratio results for random networks with 500 nodes.

Random networks

The values of the average and the maximum competitive ratio of our strategy were also measured on random networks with different settings with regard to the network size, percentage of blockages, and the number of first-responder teams. We simulated different network sizes, namely 100, 200, 300, 400, and 500 nodes. For each network size, we experimented with 10%–40% of blockages. For each network size and each blockage percentage, we considered three different numbers of first-responder teams. For each scenario, 100 instances are tested. Hence, a total of $5 \times 4 \times 3 \times 100 = 6{,}000$ random scenarios are investigated.

Results for random networks with 500 nodes are demonstrated in **Figures 4** and **5**. The reported values for the maximum and the mean competitive ratio are calculated over 100 random instances for each scenario. In the website https://doi.org/10.6084/m9.figshare.8203358.v1, we also present the figures for networks of other sizes.

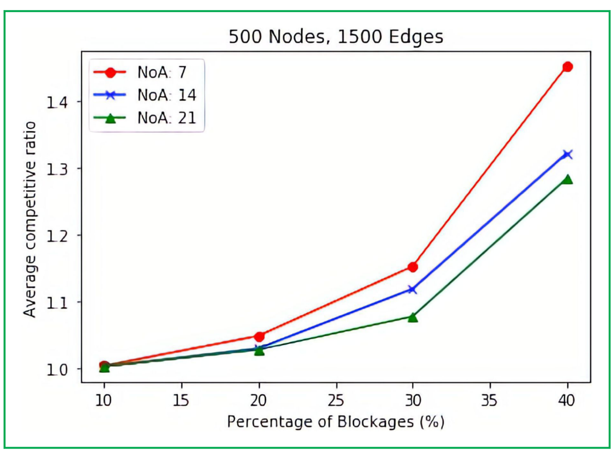

Figure 4

Average competitive ratio results for random networks with 500 nodes.

Figures 4 and 5 show that for a fixed percentage of blockages, as the number of first-responder teams increases, the values of the maximum and the average competitive ratio either decline or do not change. This means that with more first-responder teams, it is more likely to have a better solution. Another notable observation is that the average competitive ratio does not exceed 1.5 even with 40% of blockages.

Remark 2. Since the first-responder teams that are assigned to different paths may simultaneously encounter the same blockage in several occasions, we observe that increasing the number of first-responder teams does not improve the solution proportionally. This observation has been proven in [22] from the worst-case perspective.

Remark 3. The online strategy is devised such that the first-responder teams communicate with each other in the sense that they share the blockage information. Hence, the first-responder teams may change their routes whenever they learn about a blockage in the graph. This may lead to the following observation. In few cases (see https://doi.org/10.6084/m9.figshare.8203358.v1), for a fixed network and a fixed percentage of blockages, we observe that the solution of the online strategy with a fewer number of first-responder teams is better than the solution of the online strategy with a greater number of first-responder teams.

Gulf Coast area of the U.S. network

Our next experiments are based on a case study focused on hurricane threat in the Gulf Coast area of the United States (see [23] and [24]). A network with 30 nodes associated with 51 different distance matrix scenarios, which represents the U.S. Gulf Coast area under different post-disaster scenarios is under consideration. We investigated the competitive ratio of our online strategy for three different cases by selecting three

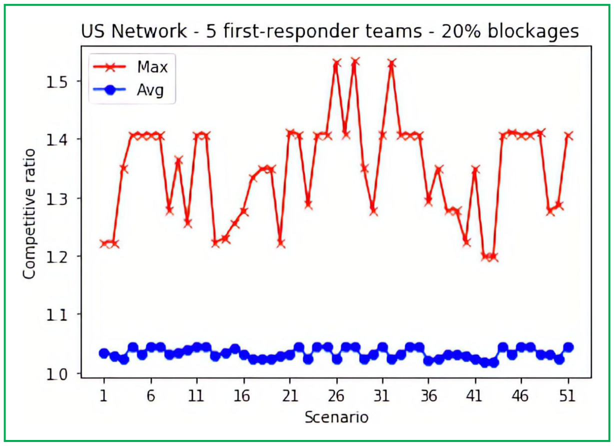

Figure 6

Results for scenarios with Dallas, TX, as the source node and Key West, FL, as the destination node.

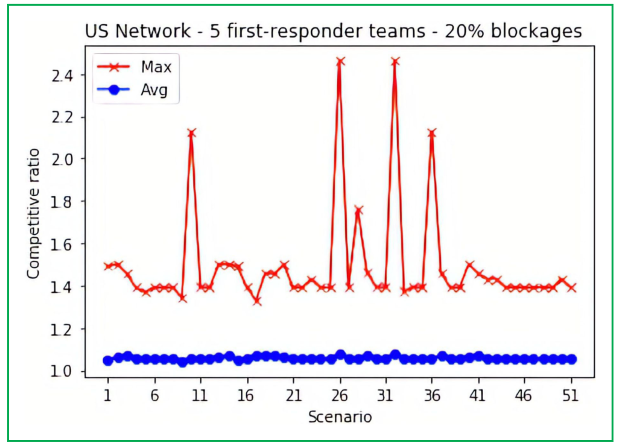

Figure 8

Results for scenarios with Atlanta, GA, as the source node and Brownsville, TX, as the destination node.

origin—destination pairs. Each origin node is one of the major cities in the area, and the corresponding destination node is the one farthest from the selected source node. We tested each case and scenario on 100 random instances with 20% of blockages with five first-responder teams. Thus, a total number of $51 \times 3 \times 100 = 15{,}300$ instances are analyzed.

We computed the values of the maximum and the mean competitive ratio for each distance matrix. **Figures 6–8** illustrate the results of our computations. It is remarkable that the average competitive ratio in all of the scenarios tested over 100 instances is very close to one, hence showing the near optimality of the strategy from the perspective of the competitive ratio.

Istanbul networks

We also used two real-life road networks of the city of Istanbul, which are taken from [25]. The first one is called *Istanbul detailed network* (349 nodes and 689 edges), and the other one is called *Istanbul southwest network* (250 nodes and 539 edges). For each network, we randomly generated instances with 10%–40% of blockages while the solution was tested with the number of first-responder teams ranging from 1 to 50. For each fixed number of first-responder teams and fixed percentage of blockages, we reported the values of the maximum and the mean competitive ratio derived from 100 random instances with different blockage distributions as well as different source and destination nodes. For each

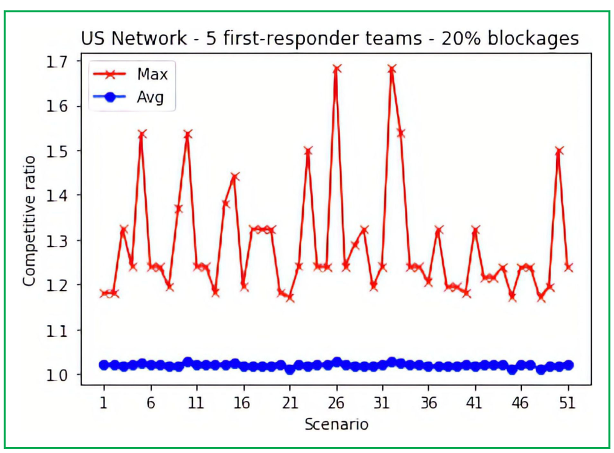

Figure 7

Results for scenarios with New Orleans, LA, as the source node and Wilmington, NC, as the destination node.

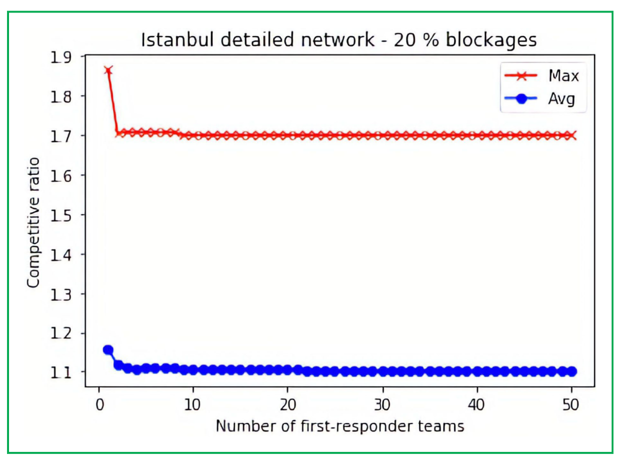

Figure 9

Sensitivity analysis of the online strategy on the number of first-responder teams for the Istanbul, Turkey, detailed network.

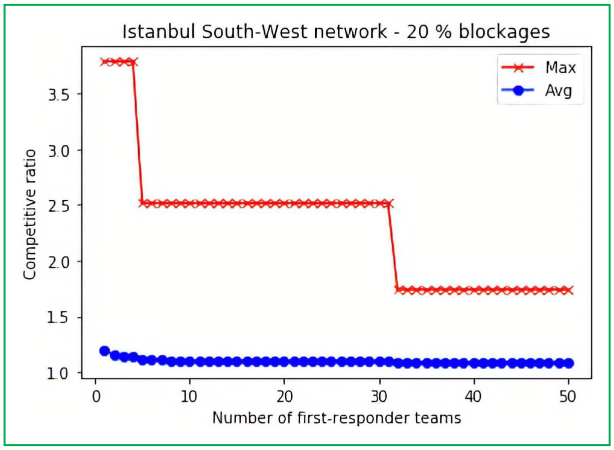

Figure 10

Sensitivity analysis of the online strategy on the number of first-responder teams for the Istanbul southwest network.

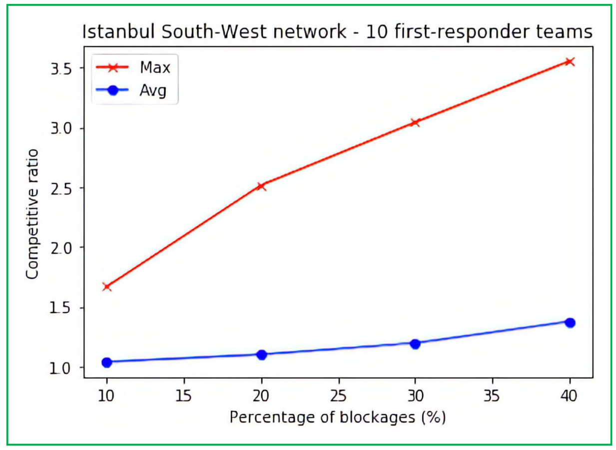

Figure 12

Sensitivity analysis of the online strategy on the percentage of blockages for the Istanbul southwest network.

instance, we made sure that the distribution of blocked edges does not cause disconnectedness of the source and the destination nodes. Hence, $2 \times 4 \times 50 \times 100 = 40{,}000$ instances are investigated.

Figures 9 and **10** present the competitive ratio results of our strategy on the Istanbul detailed network and the Istanbul southwest network, respectively, in presence of 20% of blockages. The values of the maximum and the mean competitive ratio mostly decrease as the number of first-responder teams increases in both Istanbul networks. It is also notable that the value of the average competitive ratio is less than 1.2 in both of the Istanbul networks with 20% of blockages. Figures for networks with various percentage of blockages are included in the website https://doi.org/10.6084/m9.figshare.8203358.v1.

As another type of sensitivity analysis, we fixed the number of first-responder teams to 10. We experimented with 10%–40% of blockages. For each scenario, we tested 100 instances, i.e., $2 \times 4 \times 100 = 800$ instances are tested. **Figures 11** and **12** display the values of the maximum and the average competitive ratio for ten first-responder teams. As the percentage of blockages increases, the values of the maximum and the mean competitive ratio increase. Also, the values of the mean competitive ratio for both Istanbul networks are less than 1.5 as another remarkable result.

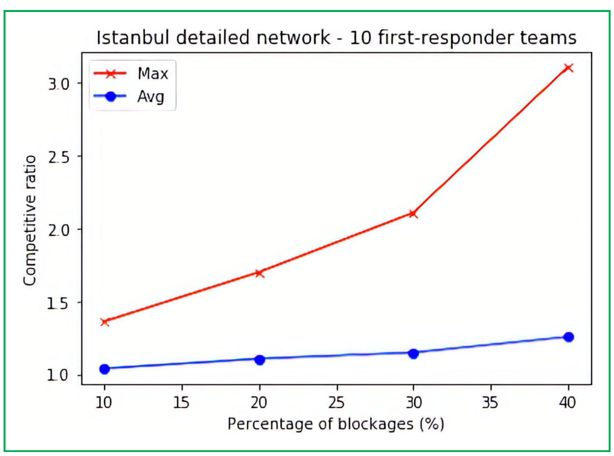

Figure 11

Sensitivity analysis of the online strategy on the percentage of blockages for the Istanbul detailed network.

Analysis of the running time of the online strategy

The computational experiments were implemented in Python 3.6 using NetworkX 2.3 on an Intel Core i5-4310 U CPU @ 2.00 GHz (4 processors) computer with 8-GB RAM, running under the Windows 7 operating system. **Table 1** summarizes the values of the average running time

Table 1 Average running times of the online strategy to solve an instance of the problem.

Network type	Average running time
Uniform 32×32 grid network	4.87 (seconds)
Random networks	0.18 (seconds)
Gulf Coast area of the United States network (30 nodes)	0.01 (seconds)
Istanbul detailed network (349 nodes)	0.59 (seconds)
Istanbul South-West network (250 nodes)	0.39 (seconds)

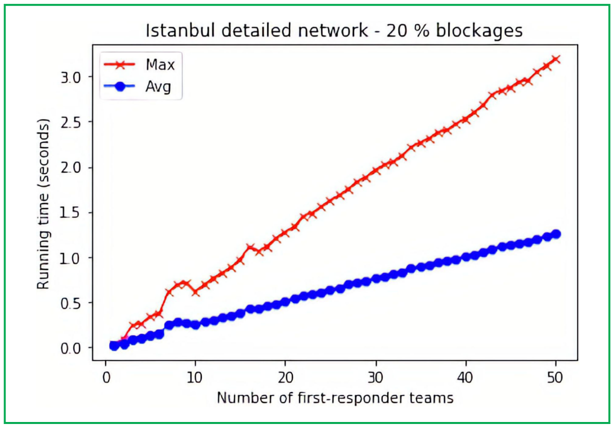

Figure 13

Sensitivity analysis of the running time of the online strategy on the number of first-responder teams for the Istanbul detailed network.

of the online strategy to solve an instance of the problem on each analyzed network type.

We also investigated the relationship between the number of first-responder teams and the running time of our online strategy for Istanbul city networks. **Figure 13** presents the average and the maximum running time of the online strategy as the number of first-responder teams varies from 1 to 50 for the Istanbul detailed network. Figures for the Istanbul southwest network are included in the website https://doi.org/10.6084/m9.figshare.8203358.v1.

Conclusion and future work

We studied an online optimization navigation problem in the context of disaster response logistics. In this problem, multiple first-responder teams who are initially at an origin node are assigned to paths such that at least one of them reaches a critical destination node in minimum time, where there are some online blockages in the graph and complete communication is feasible between the first-responder teams. We proposed a very fast online heuristic strategy for this problem. We tested our online strategy on an extensive number of real-world (urban and regional) and randomly generated instances and obtained an average competitive ratio of 1.164. This result implies that our online strategy has performed very close to the best possible offline strategy that has access to complete information.

As future work, one may investigate a more general version of the problem with multiple source and destination nodes.

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