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Coordinating debris cleanup operations in post disaster road networks

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ABSTRACT

We propose a constructive heuristic that generates roadside debris cleanup plans for a limited number of equipment in the post-disaster road recovery planning problem. Travel times between cleanup tasks are not pre-fixed but depend on the blockage status of the entire road network at the time of travel. We develop a novel mathematical model that maximizes cumulative network accessibility throughout the cleanup operation and minimizes makespan. We propose several practical and robust task selection rules that favor one or both goals that are tested on realistic size road networks with deterministic and stochastic debris cleanup times.

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1. Introduction

Clearing disaster debris from road networks is a first step to both disaster recovery and disaster response. According to a [9] on disaster debris management, cleanup operations consist of two phases. During Phase 1, the goal is to clear debris from evacuation routes and other important paths to ensure traffic flow in affected areas. This operation should start immediately after the disaster strikes and complete within 72 h because road blockages impede rescuers, emergency services and lifeline support. In Phase 2, all other debris are collected, reduced, transported, temporarily stored, recycled and disposed. These operations could take months.

In this study, we are interested in Phase 1 where work plans are generated for a fleet of D dozers that perform the task of debris cleanup from Q blocked roads so as to open evacuation routes and enable access of rescuers and relief to an affected area. Without loss of generality, it is assumed that each road (link or edge) has one blockage and that a road can be cleaned up by one dozer at a time. Furthermore, a dozer can start clearing a road if it can enter the road from either end; inaccessible roads remain blocked until one end is cleared. In our computational experiments, we test the robustness of our solution approaches under both deterministic and probabilistic cleanup times. These tests are conducted to address the uncertainty issue in damage assessment.

We also explicitly consider dozer travel time from one assignment to the next whenever an assignment is completed. Dozer travel time is calculated dynamically during schedule construction and it is defined as the shortest unblocked path between two consecutive assignments. Obviously, as more roads are cleared, the edges on the shortest paths (between all pairs of nodes) change, and hence, their lengths become time-variant. Thereby, dozer travel times between consecutive cleanup tasks change dynamically during the cleanup operation.

We define two goals for our problem. The first goal is to maximize cumulative network accessibility during the cleanup operation. Our measure of network accessibility is acquired from Ref. [1] and it is based on the sum of the lengths of the shortest paths between all pairs of locations (nodes) in the network computed over the entire time horizon of recovery efforts. To maximize such a measure reduces post-disaster travel times between all pairs of locations as early as possible and enables faster access to relief from all locations in the network. We also specify a second classical goal that is to minimize the time it takes to complete the cleanup (the makespan) with the aim of speedy economic recovery in the region.

Due to the dynamic nature of dozer travel times between consecutive tasks, this problem turns out to be a *recursive Mixed Integer Program* (MIP). Drawing an analogy to the parallel machine scheduling problem with static sequence dependent setup times, the problem presented here is classified as NP-hard [12]. Since exact optimization methods are not viable solution options in this case, we propose a constructive heuristic with several embedded task selection rules with a light computational burden hoping that they will be adopted by disaster response practitioners.

In the next section, we provide a review of the related literature, followed by the description of network inaccessibility concept in Section 3. In Sections 4 and 5 we present the mathematical model for the problem at hand and propose four heuristics, respectively.

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Section 6 describes the experimental design used to compute the numerical results obtained in Section 7. Additional analysis on the robustness of the heuristics is provided in Section 8. We end the paper with concluding remarks.

2. Literature review

In the literature, many models and measures are proposed to measure network accessibility (e.g. Refs. [4,8]). Among these, increase in travel time and travel distance seem to be the most common measures. [1] define a measure in terms of the extension of post-disaster shortest paths between all pairs of locations in a road network. [27] enhances this measure by weighing locations according to their populations and traffic densities. [14] discuss measures of post-disaster network reliability such as connectivity, travel time, capacity and accessibility. [13] propose several metrics for measuring probabilistic network reliability/dependency and compare them using a case study of the Istanbul highway system.

Using network accessibility measures, [27] and [16] adopt a slow sequential approach that closes one road (link) at a time to observe its impact on the whole network's accessibility value. This approach does not take the combined impact of groups of blocked links into account, hence, restoration plans based on sequential link criticality index ordering might be suboptimal. [5] take a different approach by clustering damaged network components to assign restoration crews and equipment. [6,15,18] address the problem by measuring commodity flows to assess economic loss under link damage, however, this method considers only commodity destinations and not the whole network. [19] minimize repair time and economic loss during reconstruction process under limited repair budget.

MIP models that decide on the sequence of roads to be cleared and assign work teams to repair tasks tend to be either link based or path based. Link based repair models represent roads as arcs in the network whereas path based models represent them as nodes. A path is then defined as an ordered set of nodes. Link based models are used more frequently, for instance, [3] propose a two-level link based model for sequencing road repair tasks over time, imposing a maximum completion time over all tasks. Travel times between tasks are explicitly considered but do not depend on the repair status of the network and there is no limit on the number of work groups. The goal is to minimize total traffic flow multiplied by travel times over all streets. The authors propose a Genetic Algorithm (GA) that represents a solution by a permutation of roads to be cleared. In another study, the authors use a multiobjective GA to solve the same problem on a network with 24 nodes [2]. [10] summarize the constraints in emergency road rehabilitation during the first 3 days after a disaster strikes: limitations on dozers, vehicles, manpower and a finite debris clearing capacity. The authors optimize three goals: maximize the total length of accessible roads, maximize the total number of cleared roads and minimize the risk of work teams. The constraints are: each road is visited only once on a route of a work team, all work should be completed in 3 days, and each road should be assigned to only one work team. The formulation describes a link based multi-tour traveling salesman problem that excludes cycle prevention constraints. Travel times between tasks are assumed to be fixed. The model is tested on a 50 node network with 10 damaged roads. In an effort to combine the road recovery problem with relief distribution, [29] propose a link based integrated road repair and relief distribution model with the goal of minimizing operation completion time. A network flow model with work team trips and relief material flows (over repaired roads) is proposed with an equity constraint on demand satisfaction. However, routes are not constructed for work teams and their travel times are not accounted for. A three-step heuristic is proposed. First, the heuristic prioritizes repair needs, next, it optimizes worker schedules and finally, it optimizes commodity flows. A 46 node network with 25 repair points is solved for a 3-day span where the time bucket is 15 min. Due to model size, this small network is solved in 900 CPU seconds. [20] also propose a link based network flow model for relief distribution over broken linkages where a budget constraint is imposed on fixing roads. Here, work schedules are undefined. Several goals are proposed, such as delivery time, satisfied demand and reliability of arcs used for distributing relief. [23] address a similar repair problem under budget constraints using a fixed cost network flow formulation for minimizing the cost of flows from each rural center to the nearest regional center. In a relief distribution model over a network with recovery needs, [25] define different measures to ensure the safe delivery of critical goods such as maximizing the number of alternative paths, minimizing unreachability of all alternative paths and maximizing the number of paths whose risk value is below a threshold. The authors propose a memetic algorithm that sequences repair tasks to develop a Pareto frontier for these objectives.

[21] take a path based approach that is also suitable for mitigation purposes. The idea is to protect most critical linkages in pre-disaster phase and recover them first in post-disaster phase. The authors identify vital node and arc blockages that would prevent the system flow the most. In their binary model, the authors maximize flows over broken source-sink paths given that p links are broken and identify the most critical p links. The contribution of the authors is the introduction of path aggregation constraints that dispose of the necessity to enumerate all source-sink paths. Results are illustrated on a network of 23 nodes and 34 arcs. [22] consider the tradeoff between the two objectives of system flow and system cost using a path based model. In an earlier study, [24] propose a similar model that identifies the most critical links that make a set of p facilities inaccessible. This model is tested on a fiber optic communications network. [28] propose a dynamic path based model that identifies the optimal repair order of blocked links during a three-day work shift given a limited number of equipment. Travel times of repair equipment between tasks are ignored to avoid the complexity of the TSP model and dozer routes are not defined. The goal is to open a specific set of predefined paths as early as possible.

All of the above models, assume deterministic road rehabilitation times and open-closed binary approach for roads. [11] emphasize the uncertainty in determining the restoration times of damaged roads and propose a GA that considers uncertainty.

In view of the above survey, we conclude that models for road network recovery planning mostly omit the routing issue of repair/cleanup teams. The few models that include this feature make the simplifying assumption of predefined travel times between tasks. Furthermore, to our knowledge, none of the models consider entire network accessibility as a goal. Finally, the size of the road recovery planning problems solved by meta-heuristics is modest.

The contributions of this paper to the literature are as follows. i) Considering cumulative network accessibility as a goal; ii) Accounting for dynamic travel times between clearing tasks based on incumbent road conditions; iii) Proposing a fast constructive heuristic with several embedded task selection rules that can generate routes for recovery vehicles in large scale disasters; iv) Considering the uncertainty related to debris cleanup times that is usually excluded in solution method evaluation.

3. The network inaccessibility measure

The idea behind the accessibility concept lies in making every location (node) i reachable from every other location j in the shortest possible time, so that firefighter vehicles, ambulances, rescue teams and special equipment can reach every road in a speedy manner. Network accessibility should be maximized throughout Phase 1 activities.

With this idea in mind, [1] has proposed the following dynamic accessibility measure ($A_i(t)$) over a continuous time horizon for a given location (node) i that lies in a network of N locations (Eq. (1)).

$$A_i(t) = \frac{\sum_{j=1}^{N} d'_{ij}(t)}{\sum_{j=1}^{N} d_{ij}} \tag{1}$$

In Eq. (1) d_{ij} is the pre-disaster shortest path length between locations i and j and $d'_{ij}(t)$ is the post-disaster shortest path length in period t of the debris cleanup process. $d'_{ij}(t)$ is calculated on a network where the augmented travel times of each road (edge) e, is the sum of the original travel time t_e and the remaining debris cleanup time $w_e(t)$ on the edge at time t. Both t_e and $w_e(t)$ are real numbers. Therefore, as more roads are cleared, the set of edges on the shortest path between locations i and j change over time, hence, $d'_{ij}(t)$ is dynamic. The overall network accessibility $A(t)$ becomes the average accessibility of all locations i in period t (Eq. (2)).

$$A(t) = \frac{1}{N}\sum_{i=1}^{N} A_i(t) \tag{2}$$

Here, we modify this measure to reflect network inaccessibility. In Eq. (3), we define the inaccessibility measure, $I(t)$, of a network. When all roads that take place on shortest paths are debris-free, $I(t)$ becomes zero.

$$I(t) = 1 - \frac{\sum_{i=1}^{N}\sum_{j=i+1}^{N} d_{ij}}{\sum_{i=1}^{N}\sum_{j=i+1}^{N} d'_{ij}(t)} \tag{3}$$

In Eq. (3), we calculate $d'_{ij}(t)$ as described above. First, t_e of each edge in the network is augmented by its $w_e(t)$. Then, the shortest path, $sp'_{ij}(t)$, between nodes i and j is identified and its length is calculated as $d'_{ij}(t)$.

In this paper, our goal is to minimize cumulative $I(t)$, denoted as $CI(t)$, during the time span between [0, $C_{\max}$] where $C_{\max}$ is the completion time of the road network cleanup operation, that is, the makespan. This goal is expressed in Eq. (4).

$$CI(t) = \text{minimize} \int_{0}^{C_{max}} I(t)\mathrm{d}t \tag{4}$$

We illustrate the shape of the function $I(t)$ with an example given in Fig. 1 where a small network is presented. Here, the edge travel times t_e are augmented by the debris cleanup times $w_e(t)$ on blocked links. We assume that there is one dozer to do the work. We provide the data for this network in Table 1. The travel time t_e for each edge defined by start and end nodes (i,j) and the initial debris cleanup time, $w_e(0)$, are indicated in Table 1 (in hours) as

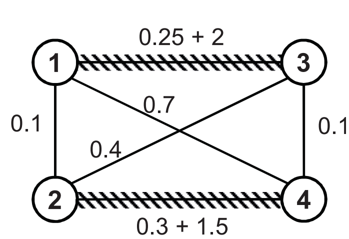

Fig. 1. The example network with two blocked edges.

well as the pre-disaster and the post-disaster shortest paths, sp_{ij} and $sp'_{ij}(0)$, between nodes i and j. The savings in the total travel times gained in the relevant post-disaster shortest paths by clearing the two blocked edges (i,j) are listed in the last column. For example, edge (1, 3) exists on the 2nd, 3rd and 4th pre-disaster paths, and the total savings in the corresponding post-disaster paths would be 0.55 h if edge (1, 3) is cleared in period zero.

While calculating $I(t)$, we assume that a blocked edge's augmented travel time does not change before it is debris-free because the road would not be traversable before it is completely cleared. In Fig. 2, we illustrate $I(t)$ over the time interval [0,$C_{\max}$], which is 3.6 h (sum of $w_e(0)$ for edges (1,3) and (2,4) and the dozer travel time between these two edges). Note that the sum of the lengths of d_{ij} is 1.45 h and that of $d'_{ij}(0)$ is 2.2 h. Therefore, $I(0)$ is 0.34. In Table 1, we observe that clearing edge (1,3) first results in higher savings in $d'_{ij}(0)$, therefore, we decide to clear edge (1,3) before edge (2,4).

In Fig. 2, $I(0)$ starts from the value of 0.34 and it remains at the same level until edge (1,3) is debris-free at the end of period 2. Then, the dozer spends 0.1 h to travel to node 2. In order to re-calculate $I(2)$, $sp'_{ij}(2)$ are calculated again assuming that $t_{13} = 0.25$ rather than 2.25 h ($w_{13}(2)$ is set to zero). The sum of $d'_{ij}(2)$ equals to $0.1 + 0.25 + 0.35 + 0.45 + 0.1 = 1.6$. Hence, $I(2) = 0.09375$ and stays at this level until $t = 3.6$ and drops to zero when after edge (2,4) becomes debris-free. As observed in Fig. 2, $I(t)$ is a step function. The value of $CI(t)$ is the sum of two rectangular boxes under $I(t)$, that is, $0.34 \times 2 + 0.09375 \times 1.6 = 0.83$. Accordingly, the integral in Eq. (4) can be expressed more simply in Eq. (5).

$$CI(t) = \sum_{q=1}^{Q}(t_q - t_{q-1})I(t_{q-1}) \tag{5}$$

where q is the index of the q^{th} task in the clearing sequence, Q is the number of blocked edges in the network and t_q is the debris cleanup time of q^{th} blocked edge in the clearing sequence.

If we had chosen to clean up edge (2,4) first, then $I(t)$ would have the shape illustrated in Fig. 3. The value of $CI(t)$ would then be 0.92.

Note that our objective in Eq. (4) is enhanced by sequencing blocked edges in descending order of their cumulative savings in $d'_{ij}(t)$ and in ascending order of their $w_e(0)$ values. In our heuristic, we develop some rules to prioritize blocked edges to be cleared. The last rule is based on this observation.

4. The mathematical model

We provide a mathematical model for the road network rehabilitation problem proposed here in Eqs. 6–17. The formulation is presented as follows.

Sets:

I: set of nodes in the network, indexed by $i,j \in \{1,2,\ldots,N\}$
E: set of edges in the network, indexed by $e,f \in E$ (edge 0 denotes the dummy edge that corresponds to the initial/final dummy clearance tasks)
M: set of dozers assigned to clear debris in the network, indexed by $m = 1,\ldots,D$, $m \in M$

Parameters:

w_e: clearance time required to clear the debris on edge e
d_{ij}: pre-disaster length of the shortest path between nodes i and j where the length of each edge $e \in E$ is the original travel time of edge e, i.e. t_e.
V: A sufficiently large positive number

Table 1
Data related to the example network in.Fig. 1.

Edge defined by nodes (*i,j*)	t_e	$w_e(0)$	sp_{ij}	d_{ij}	$sp'_{ij}(0)$	$d'_{ij}(0)$	Total savings in $d'_{ij}(0)$ if edge defined by nodes (*i,j*) is Cleared
1,2	0.1	–	{1,2}	0.1	{1,2}	0.1	–
1,3	0.25	2	{1,3}	0.25	{1,2,3}	0.5	0.25 + 0.25 + 0.05 = 0.55
1,4	0.7	–	{1,3,4}	0.35	{1,2,3,4}	0.6	–
2,3	0.4	–	{2,1,3}	0.35	{2,3}	0.4	–
2,4	0.3	1.5	{2,4}	0.3	{2,3,4}	0.5	0.20
3,4	0.1	–	{3,4}	0.1	{3,4}	0.1	–

Variables:

C_e: completion time of task e
$C_{\max}$: makespan

$$x_{mef} = \begin{cases} 1 & \text{if dozer } m \text{ clears edge } e \text{ immediately before edge } f \\ 0 & \text{otherwise} \end{cases}$$

$d'_{ij}(\boldsymbol{x}, t)$: length of the shortest path between nodes i and j at time t according to dozer assignment $\boldsymbol{x}$. (Here, $\boldsymbol{x}$ denotes the dozer assignment defined by the variables x_{mef}, $\forall m \in M$, $\forall e, f \in E$. Shortest path is calculated based on the road network at time t where the travel time of each edge (t_e) is augmented by its remaining debris cleanup time, $w_e(\boldsymbol{x}, t)$ according to assignment $\boldsymbol{x}$.)
$l_{e,f}(\boldsymbol{x})$: length of the shortest path between edges e and f at the time edge e is cleared according to the dozer assignment $\boldsymbol{x}$ (calculated at time $t = C_e$ on the augmented road network as above)

$$\text{Min O1}: \int_{t=0}^{C_{\max}} 1 - \frac{\sum_{i=1}^{N-1}\sum_{j=i+1}^{N} d_{ij}}{\sum_{i=1}^{N-1}\sum_{j=i+1}^{N} d'_{ij}(\boldsymbol{x}, t)} \quad (6)$$

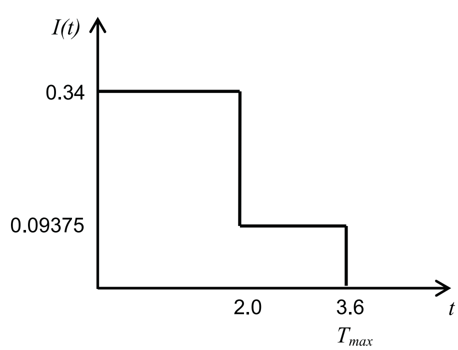

Fig. 2. Shape of $I(t)$ when edge (1,3) is cleared before edge (2,4).

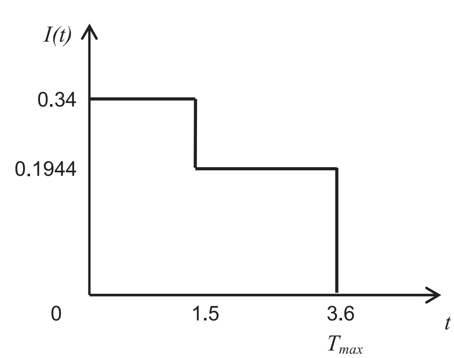

Fig. 3. Shape of $I(t)$ if clearing sequence of two edges is reversed.

$$\text{Min O2}: C_{\max} \quad (7)$$

s.t.

$$\sum_{m \in M} \sum_{e \in E, e \neq f} x_{mef} = 1 \;\; \forall f \in E \setminus \{0\} \quad (8)$$

$$\sum_{m \in M} \sum_{f \in E, e \neq f} x_{mef} = 1 \;\; \forall e \in E \setminus \{0\} \quad (9)$$

$$\sum_{f \in E} x_{m0f} \le 1 \quad \forall m \in M \quad (10)$$

$$\sum_{f \in E, f \neq e} x_{mef} - \sum_{h \in E, h \neq e} x_{mhe} = 0 \;\; \forall m \in M, \;\forall e \in E \quad (11)$$

$$C_f - C_e + V\left(1 - x_{mef}\right) \ge l_{ef}(\boldsymbol{x}) + w_e \;\; \forall m \in M, \forall e \in E, \;\; \forall f \in E \setminus \{0\} : f \neq e, \quad (12)$$

$$C_0 = 0 \quad (13)$$

$$C_e \le C_{max} \quad \forall e \in E \quad (14)$$

$$x_{mef} \in \{0, 1\} \quad \forall m \in M, \;\forall e, f \in E : e \neq f \quad (15)$$

$$d'_{ij}(\boldsymbol{x}, t) \ge 0 \quad \forall i, j \in I \quad (16)$$

$$l_{e,f}(\boldsymbol{x}) \ge 0 \quad \forall e, f \in E : e \neq f \quad (17)$$

In the above formulation, the first objective function in (6) minimizes $CI(t)$, where the second objective function in (7) minimizes $\mathbf{C_{max}}$. Constraints (8) and (9) ensure that each debris clearance task is preceded and succeeded by only one clearance task, respectively. Constraints (10) state that at most one clearance task is assigned as the first task for each dozer. Constraint set (11) ensures that if a task is assigned for a dozer, then its predecessor and successor is also assigned for the same dozer, thus the route to be followed by each dozer to complete the cleanup tasks is defined by this constraint set. Constraint set (12) assigns the correct completion time for each task based on the precedence relationship between tasks; i.e., if task f is preceded by task e, then the completion time of f should be at least as large as the sum of the completion time of $\boldsymbol{e}$, the travel time from task e to task f and the debris clearance time of task f. Constraint (13) sets the completion time of the initial dummy task to zero, whereas constraint set (14) ensures that the makespan is at least at large as the completion time of all debris clearance tasks. Finally, constraints (15)–(17) denote the sign restrictions on the variables.

One can see that the variables $d'_{ij}(x,t)$ and $l_{ef}(x)$ in this formulation are functions of the dozer assignment x, which is another variable in the model. This recursive nature of the road network rehabilitation problem makes it intractable to solve using mathematical programming based approaches. Furthermore, meta-heuristics that typically represent solutions as permutations of tasks for D dozers would require additional computation to determine the completion times of repair tasks due to the dynamic travel times between consecutive tasks. Given the sequence of tasks to be performed by each dozer, travel times between consecutive tasks of the same dozer depend on the blockages on the entire road network at the time of travel and need to be re-computed. Therefore, each solution represented by the meta-heuristic would incur considerable computation time for objective function value assessment. Alternatively, we resort to rule-based heuristics which target the inaccessibility and makespan objectives given in Eqs. (6) and (7).

5. The heuristics

5.1. The basic algorithm

In this section, we explain the basic algorithm that identifies the sequence of blocked edges that each available dozer is to clear during Phase 1.

We assume that at the beginning of the planning horizon a limited number of D dozers wait at a fictitious dummy location that is linked to all temporary debris dump sites with zero travel times. To arrive at its first task, each dozer travels from this location to a point of entry to the region that is closest to its first assignment. A dozer that is assigned to a blocked edge e travels to e via the shortest unblocked path from its current location (note that the shortest path depends on the node from which edge e is entered). The dozer leaves the edge after w_e time periods (when edge e is cleared) and travels to its next assignment at edge f via the shortest unblocked path between e and f.

In Fig. 4, we illustrate the flowchart of a heuristic algorithm that creates an assignment schedule for every dozer. First, the list of blocked edges is checked. If the list is empty, then, the work and travel schedules for the dozers are reported. Else, the availability of dozers is checked. If all dozers are busy, then the time period t is updated to the earliest completion time, t', of tasks currently assigned to busy dozers. Then, the status of the relevant busy dozer(s) is set to idle, the debris cleanup times, w_e of completed tasks are set to zero, and $I(t)$ is re-calculated. For calculating $I(t)$, Dijkstra's algorithm is applied to identify the shortest paths between all pairs of nodes in the network with augmented edge lengths (t_e+w_e). The algorithm then selects an unprocessed blocked edge according to a given rule and the nearest idle dozer is assigned to it. The selected dozer can start work after traveling to the selected edge. The procedure is repeated until all blocked edges are cleared. Note that dozers are allowed to travel to blocked edges only over unblocked paths.

5.2. Rules for selecting a blocked edge

Four rules are developed for the blocked edge selection step in Fig. 4, where each one is implemented independently resulting in

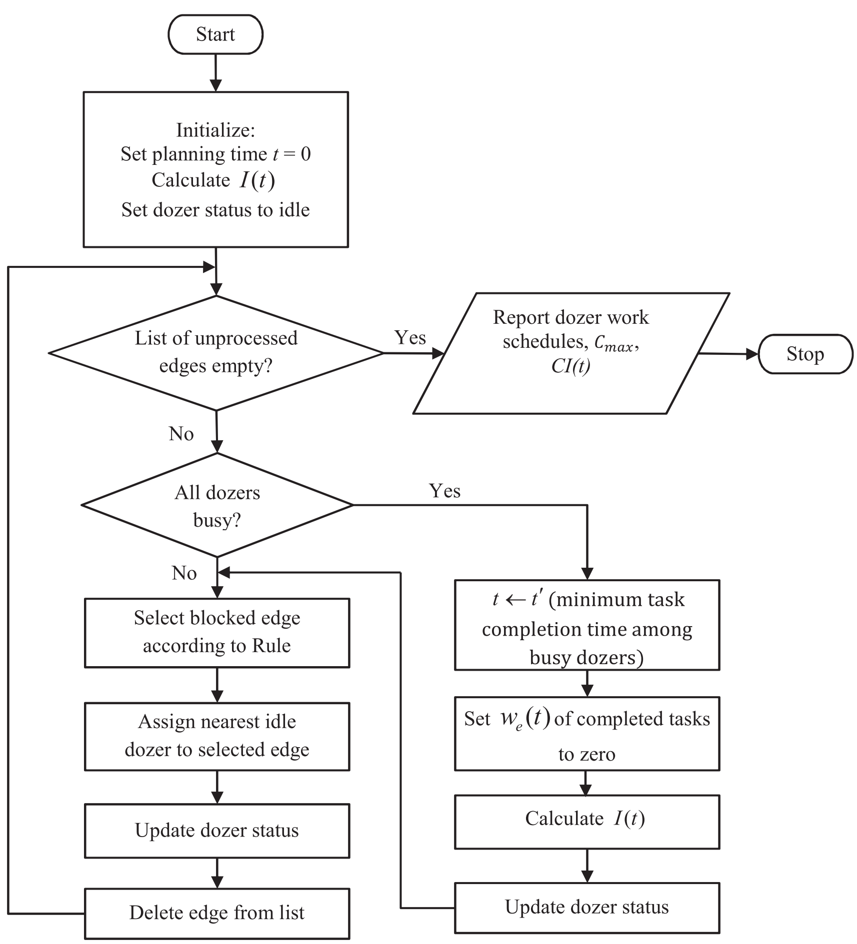

Fig. 4. Flowchart of the heuristic.

Fig. 5. a. Road map for Caddebostan district. b. Road map for Fatih district.

b

Fig. 5. (*continued*).

four different heuristics. These are listed below. In all rules, a selected edge is required to be accessible from either end, i.e., edges sandwiched between 2 or more blocked edges are not selected.

Rule 1. Select the accessible blocked edge that is directly linked to the maximum number of blocked edges.

Rule 1 guides the dozers towards clusters of blocked edges, so that once a dozer starts clearing the cluster, it does not have to travel far from one edge to the next. Minimizing travel times might enhance the $C_{\max}$ criterion. Furthermore, a cluster of blocked edges possibly lie on more shortest paths than singular blocked edges, hence, there might be gains in *CI(t)* as well.

Rule 2. Select the accessible blocked edge with the least work time, $w_e(0)$.

In Section 3, we illustrated that, along with the savings condition, *CI(t)* might diminish if edges are cleared according to ascending w_e. Rule 2 executes a work time based ordering of tasks without checking for the savings conditions in order to avoid the computational burden. Rule 2 completely ignores travel times. In fact, Rule 2 is often used as a standard benchmark dispatching heuristic (known as Shortest Processing Time) in machine scheduling literature [26].

Rule 3. Select the accessible blocked edge that is nearest to the first available busy dozer or if there are idle dozers, select the edge that has the minimum travel time to any idle dozer.

Rule 3's sole aim is to minimize the travel times of dozers in between two consecutive tasks. This rule is expected to favor the $C_{\max}$ criterion. Rule 3 is analogous to the Nearest Neighbor Algorithm developed for the Travelling Salesman Problem and this heuristic is also known to be an effective quick and dirty method [17] that minimizes tour length (or $C_{\max}$ in our problem).

Rule 4. Select the accessible blocked edge e whose cleanup results in the maximum ratio of its total savings (on the pre-disaster shortest paths it lies on) to its cleanup time:

$$\text{maximize} \sum_{(i,j):\, sp_{ij} \in S^e} \frac{\left(d'_{ij}(t) - d_{ij}\right)}{w_e} \tag{18}$$

where S^e is the set of pre-disaster paths that edge e lies on.

The savings represent the decrease in $CI(t)$. If the edge's w_e is small, then the network is more accessible sooner. This rule is inspired by the works of [27] and [16] who calculate the impact of an edge's closure on total network accessibility in the pre-disaster planning context. [16] show that this approach works well in deciding on edge criticality. In the post-disaster context, Rule 4 considers all edge closures simultaneously and decides on the savings of opening one edge at a time.

In all rules, ties are broken arbitrarily. While Rule 3 enhances the $C_{\max}$ criterion, Rules 4 and 2 target $CI(t)$, and Rule 1 balances both criteria. We expect Rule 4 to dominate Rule 2 but we consider both rules because Rule 4 is expected to be computationally challenging due to the calculation involved in Eq. (18).

6. Test scenarios

We perform tests of the approach using two road networks based on the maps of two districts in a post-earthquake scenario of Istanbul (Turkey). The names of the districts are Caddebostan and Fatih, and each of these networks contain different characteristics. The first district contains 212 roads, and the second 386 roads. Both district maps are given in Fig. 5a and b. It is noted that Caddebostan's network is more like a Manhattan block network (a modern residential area in the city), and Fatih is a downtown district that resides in the old city and hence, its network is fairly more complex. Both districts lie in the very high risk earthquake damage zone, have rather narrow roads (mostly with one or two lanes) and tall buildings on both sides of the roads.

Using the map of each district, we create several scenarios according to the following design based on blockage intensity and the number of dozers allocated.

i) Blockage intensity: 50%, 25% and 5% of roads are blocked
ii) Number of clearing equipment: 1, 3 and 6 dozers are allocated to each district.

Hence, we have 3^2 scenarios for each district. In each test, both $C_{\max}$ and $CI(t)$ expressed in Eq. (5) are recorded. With regard to the inaccessibility criterion, we expect clustered and intense blockages to be easier to solve than their counterparts because cleanup tasks get close to each other, and they are numerous, making the task ordering problem less tricky. On the other hand, a smaller number of allocated dozers results in longer sequences for each dozer and this might make the task ordering problem more difficult. In all experiments, travel times of dozers over roads t_e are calculated based on a dozer speed of 5 km/h.

In each scenario, debris cleanup times w_e are calculated based on the debris amounts generated by an estimated number of collapsed buildings over given street maps. [7] provide the latest estimates on the number of medium, high and very high risk buildings resulting from a potential Istanbul earthquake. We adapt blockage intensity percentages for Caddebostan and Fatih districts according to this report. The collapsed buildings are distributed among streets of the road networks. Debris cleanup work on each street is calculated based on the number of collapsed buildings on that street. To replicate each test scenario, we create 10 randomly generated instances for each scenario in the following manner. We create normally distributed w_e values using a standard deviation of $0.2w_e$ around the deterministic w_e. Hence, for each district, we perform 180 runs (3 dozer settings X 3 blockage intensity levels X 2 networks X 10 replicates) for each rule. In this first set of experiments, we assume that there is no uncertainty in the set of w_e values. The results for such deterministic case is presented in Section 7. Then, in Section 8 we present a discussion based on a second set of experiments that considers uncertainty in w_e values. However, this set of experiments is conducted on all 10 instances of a single scenario where only deterministic w_e values are known in the pre-planning phase and their realized values differ while the plan is executed.

7. Computational results for the case of deterministic road cleanup times

Our discussion regarding our test scenarios is divided into two parts: i) analysis of the average performance of the four rules throughout all scenarios; ii) analysis of the average performance of each rule under each test scenario category defined by different levels of blockage intensity and vehicle availability.

The performances of all rules with respect to $C_{\max}$ and $CI(t)$ goals are indicated in Tables 2 and 3, respectively. In these tables, the average $C_{\max}$ value over the 10 problem instances are reported in columns 3-5 for the 9 scenarios defined by the blockage intensity and dozer settings indicated in the first two columns. The last 4 columns of Tables 2 and 3 display the number of instances where the minimum $C_{\max}$ or $CI(t)$ value is obtained for each rule. Table 4 displays the average CPU times required to solve each problem type using the four rules for each scenario setting.

As expected, Rule 4 provides the minimum $CI(t)$ for all but one instance throughout the debris clearing task, and Rule 3 almost always results in the minimum $C_{\max}$. While Rule 3 only aims at minimizing dozer travel times, Rule 1 performs better than Rule 3 in terms of $CI(t)$. The latter is also an expected result, because Rule 1 clears out interlinked blocked roads faster than Rule 3, thereby, improving $CI(t)$. With regard to both $C_{\max}$ and $CI(t)$, Rule 2 is dominated by Rule 4, however, its CPU times are incomparably small, hence we can say that it might be a useful rule in larger road networks. One can see that on the average, the best order of rules to use for $CI(t)$ is 4-2-1-3, whereas for the $C_{\max}$, the best order is 3-1-4-2.

In Table 3, we observe that the standard deviation of $CI(t)$ obtained by the heuristics is comparably higher with regard to the mean value for low blockage intensity scenarios. In low blockage intensity scenarios, there are more alternative routes for dozers, i.e. the solution space is larger. Therefore, there may be more variability in the performance of heuristics for such instances.

Table 2
Performance of the four rules with respect to C_{max}.

Blockage density	Dozer	Average C_{max}				Std. deviation C_{max}				No. of instances with best C_{max}			
		R1	R2	R3	R4	R1	R2	R3	R4	R1	R2	R3	R4
Caddebostan													
5%	1	64.87	71.65	65.24	70.24	3.50	4.12	3.50	3.73	10	0	0	0
	3	27.69	31.05	27.69	28.99	2.44	2.87	2.44	3.25	8	0	8	2
	6	19.43	19.64	19.43	19.58	2.54	2.96	2.54	3.09	7	2	7	3
25%	1	310.44	355.54	302.85	353.46	5.91	5.36	5.91	5.42	0	0	10	0
	3	108.20	124.59	104.43	122.57	2.53	3.33	2.40	1.44	0	0	10	0
	6	56.97	64.50	56.21	63.84	1.54	1.64	1.94	1.49	2	0	8	0
50%	1	606.11	683.49	590.39	685.13	16.98	15.33	16.98	19.76	0	0	10	0
	3	207.30	233.59	200.38	232.18	5.80	6.55	6.64	5.22	0	0	10	0
	6	108.03	120.40	103.23	116.93	3.91	4.16	2.91	4.14	0	0	10	0
Overall		167.67	189.38	163.31	188.10	5.02	5.15	5.03	5.28	27	2	73	5
Fatih													
5%	1	101.00	105.74	98.34	106.11	2.88	3.15	2.88	3.10	0	0	10	0
	3	34.94	40.04	35.43	37.61	1.47	2.03	1.62	0.88	6	0	4	0
	6	19.29	24.69	19.94	20.34	0.80	1.88	0.98	0.91	7	0	2	1
25%	1	448.38	488.12	439.00	485.29	8.01	8.11	8.01	8.91	0	0	10	0
	3	153.23	166.45	147.98	164.16	2.59	3.52	2.84	3.38	0	0	10	0
	6	79.82	85.81	75.90	83.59	1.84	1.88	1.49	2.04	0	0	10	0
50%	1	895.72	986.16	882.94	980.35	11.76	14.29	11.76	10.51	0	0	10	0
	3	301.91	334.69	297.24	327.31	4.21	8.24	4.24	6.44	0	0	10	0
	6	155.85	171.33	151.17	165.69	2.70	4.10	1.65	2.49	0	0	10	0
Overall		243.35	267.00	238.66	263.38	4.03	5.24	3.94	4.30	13	0	76	1

Table 3
Performance of the four rules with respect to *CI(t)*.

Blockage density	Dozer	Average *CI(t)*				Std. deviation *CI(t)*				No. of instances with best *CI(t)*			
		R1	R2	R3	R4	R1	R2	R3	R4	R1	R2	R3	R4
Caddebostan													
5%	1	3.00	3.64	2.45	1.17	0.37	1.57	0.30	0.24	0	0	0	10
	3	0.85	1.33	0.85	0.71	0.12	0.51	0.12	0.15	0	0	0	10
	6	0.65	0.75	0.65	0.56	0.11	0.30	0.11	0.10	0	1	0	10
25%	1	84.71	69.22	93.62	38.49	3.01	5.77	3.07	1.81	0	0	0	10
	3	30.02	24.35	32.04	14.08	0.96	1.94	1.47	0.89	0	0	0	10
	6	14.37	12.82	16.85	7.97	0.63	1.07	0.77	0.38	0	0	0	10
50%	1	341.87	287.46	366.30	249.78	12.89	14.04	11.12	10.28	0	0	0	10
	3	110.11	98.15	137.12	89.05	4.09	5.04	8.64	3.04	0	0	0	10
	6	59.90	51.93	70.69	46.62	3.01	2.12	2.16	2.17	0	0	0	10
Overall		71.72	61.07	80.06	49.82	2.80	3.59	3.08	2.12	0	1	0	90
Fatih													
5%	1	9.26	5.29	7.37	1.95	1.08	2.10	0.96	0.21	0	0	0	10
	3	3.02	1.91	2.69	0.91	0.39	0.75	0.33	0.11	0	0	0	10
	6	1.54	1.06	1.48	0.69	0.21	0.36	0.21	0.09	0	0	0	10
25%	1	128.72	108.42	140.46	59.47	5.09	18.81	3.15	3.72	0	0	0	10
	3	38.00	36.92	56.07	20.84	1.45	6.11	3.38	1.35	0	0	0	10
	6	19.94	18.96	23.98	11.10	1.03	3.11	1.04	0.79	0	0	0	10
50%	1	532.47	460.85	621.19	405.28	10.99	54.39	14.33	13.23	0	1	0	9
	3	176.21	156.87	208.29	132.03	6.52	18.83	6.09	4.86	0	0	0	10
	6	90.41	80.20	110.28	67.62	2.14	9.05	5.01	2.04	0	0	0	10
Overall		111.06	96.72	130.20	77.76	3.21	12.61	3.83	2.93	0	1	0	89

The differences in the C_{max} performance are not too significant, in fact, for Caddebostan district there are 26 h of difference between the worst and best C_{max} on the average (for 9 scenarios), and for Fatih district this value is 28 h. That is, the districts can be cleared 2 work shifts earlier if Rule 3 is utilized. However, with regard to *CI(t)*, the difference is larger. A graphical illustration of the variability in *I(t)* values achieved by the four rules on a particular Caddebostan district scenario is visually presented in Fig. 6 for the cleanup operation time span. Here, we observe that Rule 4 makes the network more than 90% accessible after about 40 h of clearing work, Rule 2 needs about 70 h, Rule 3 more than 100 h and Rule 1 about 90 h. In this instance, Rule 1's deviation from Rule 4's *CI(t)* is 78% while those of Rules 2 and 3 are 42% and 105%, respectively.

In order to evaluate the statistical significance of the results depicted in Tables 2 and 3, we have performed an ANOVA (Analysis of Variance) using a full factorial design with 10 replications. In this design, the rule type (4 levels), number of dozers (3 levels) and the problem type (6 levels for each network type and blockage density combination) are the independent variables and C_{max} or *CI(t)* is the response variable. ANOVA results on both C_{max} and *CI(t)* indicate that all independent variables and their two- and three-way interaction effects are statistically significant at a 95% confidence level (Please refer to Tables 1A and 1B in the Appendix). Therefore, we can conclude that the variability in the performance of the four rules we have discussed so far are statistically significant. The analysis also indicates that the performance of each rule varies significantly based on the scenario solved.

In order to analyze the difference in rule performance with regard to scenario properties, namely blockage intensity and the number of allocated dozers, Tables 5 and 6 display the average

Table 4
Average CPU times required by the four rules.

Blockage intensity	Dozer	Average CPU time (seconds)			
		Rule 1	Rule 2	Rule 3	Rule 4
Caddebostan					
5%	1	0.02	0.02	0.02	18.60
	3	0.02	0.02	0.02	18.60
	6	0.02	0.03	0.02	18.47
25%	1	0.44	0.42	0.42	89.56
	3	0.44	0.42	0.42	89.51
	6	0.45	0.42	0.42	89.51
50%	1	1.24	1.30	1.12	184.93
	3	1.21	1.19	0.93	184.75
	6	1.12	1.05	0.85	183.41
Average		**0.55**	**0.54**	**0.47**	**97.48**
Fatih					
5%	1	0.19	0.19	0.19	304.78
	3	0.19	0.19	0.19	304.74
	6	0.19	0.18	0.19	304.91
25%	1	4.06	4.02	4.04	1401.00
	3	4.08	4.03	4.03	1401.10
	6	4.07	4.03	4.01	1399.46
50%	1	11.75	12.60	9.44	2997.14
	3	11.55	12.08	10.20	2991.21
	6	10.75	11.62	9.22	2976.97
Average		**5.20**	**5.44**	**4.61**	**1564.59**

deviation of each rule from the best solution for $C_{\max}$ and for $CI(t)$ in all scenario settings.

In Table 5, we observe that with regard to the $C_{\max}$ criterion, the relative performance of the rules change only slightly based on the type of scenario used. Rule 3 provides the best performance in all scenarios but one (with 5% blockage intensity and 1 dozer), where Rule 1 outperforms Rule 3 by an average of 0.2%. On the other hand, Rule 1 appears to be a close second with respect to $C_{\max}$ for all blockage intensity–dozer combination scenarios. Performance of Rules 2 and 4 are much worse than Rules 1 and 3 for all combinations. In terms of the relative performance, we also observe a more pronounced difference among the rules as blockage intensity increases. On the other hand, the performance difference among the rules is less pronounced across different dozer settings.

As displayed in Table 6, the relative difference among rules is much larger for all scenario settings in terms of the $CI(t)$ criterion in comparison to $C_{\max}$. We see that Rule 4 outperforms the other rules

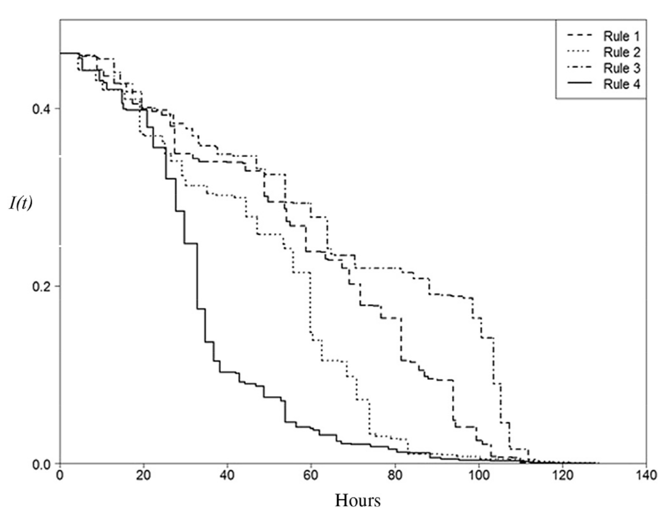

Fig. 6. Network inaccessibility resulting from applying four rules to a Caddebostan scenario.

in all scenarios based on average performance. The performance difference is especially emphasized for the 5% and 25% blockage intensity scenarios. In low-intensity blockage scenarios, dozers have to travel more and the decision on which blockage to pick next becomes more tricky in terms of assessing its impact on all shortest paths. Therefore, non-intense blockage scenarios prove to be more difficult to solve with regard to $CI(t)$. For instance, picking up the road with the least amount of work (Rule 2) does not help $CI(t)$ as much in less intense networks. As for Rule 1, most blocked edges on shortest paths have zero or one blocked links in less intense networks and Rule 1 has difficulty in differentiating among tasks. Networks with less number of blockages are more tricky for all rules except for Rule 4, which considers the shortest path impacts explicitly. As for the number of dozers, the performance difference among rules decreases as the number or dozers increase. For higher number of equipment, shorter sequences of tasks are constructed for each dozer and the problem becomes less complex. Thus, using a more sophisticated rule does not bring as much benefit for scenarios with higher number of dozers.

As displayed in Table 4, the type of scenario solved also has a serious impact on the CPU time. While the computational requirement of Rule 4 is much higher than the other rules for all scenarios, we see that the relative difference is less pronounced as the blockage intensity increases. However, the CPU times of Rule 4 can be too demanding on the planner when the network structure is complex or the damage in a region is extreme (such as 50% blockage intensity scenarios in Table 4, especially for the more complicated Fatih network). In such situations, Rule A can be applied to smaller segments within a neighborhood instead of the whole neighborhood. On the other hand, the impact of the number of dozers on the solution time appears to be quite limited.

8. Analysis of rule robustness under uncertain road cleanup times

So far, we have analyzed the performance of the four edge selection rules assuming that all information is deterministic and known to the decision maker. However, the amount of uncertainty is quite high during a disaster recovery operation and this can adversely affect the quality of the optimization decisions made based on imperfect information. In debris cleanup planning, the most uncertain type of data are the debris cleanup times, w_e, which have to be estimated immediately after the disaster based on limited information. As the cleanup effort continues, these estimates are updated by the actual debris cleanup times as reported by the cleanup crews. It is important to assess how these imperfect debris clearing durations affect the performance of edge selection rules in order to find out whether their performances compare differently under uncertainty. In order to evaluate the impact of imperfect cleanup times, we have simulated the process of updating the debris cleanup times as they become known after each cleanup task is completed. First, we created "actual" cleanup times as follows. We generated probabilistic actual w_e values by accepting the estimated w_e's as expected values for each of the 10 Caddebostan instances of a selected scenario with a blockage intensity of 25% and 3 dozers. Then, we generated 10 sets of normally distributed random variates for each blocked road in the district using the 15%, 30% and 45% of its expected value as three standard deviation settings, respectively. Thus, we created 30 new instances of each of the 10 Caddebostan problems, making a total of 300 problems. Using this extensive test bed, we investigate the robustness of the rules under different variability conditions. In terms of the solution approach, we adjusted the basic algorithm as follows. During the course of the heuristic, each time an edge is to be selected, the selection rule is implemented based on the expected w_e of

Table 5
Average percent deviation from the best solution with respect to the C_{max} criterion.

		Caddebostan				Fatih			
		Rule 1	Rule 2	Rule 3	Rule 4	Rule 1	Rule 2	Rule 3	Rule 4
Blockage intensity	5%	0.94%	8.83%	1.13%	5.41%	1.54%	17.56%	2.28%	7.73%
	25%	2.77%	17.49%	0.26%	16.21%	3.63%	12.25%	0.00%	10.54%
	50%	3.60%	16.35%	0.00%	15.08%	2.04%	12.54%	0.00%	10.25%
Dozer	1	1.72%	14.56%	0.19%	13.68%	2.10%	10.14%	0.00%	9.83%
	3	2.81%	16.54%	0.45%	13.10%	1.88%	13.47%	0.65%	9.78%
	6	2.77%	11.57%	0.75%	9.92%	3.22%	18.74%	1.63%	8.91%

Table 6
Average percent deviation from the best solution with respect to the *CI(t)* criterion.

		Caddebostan				Fatih			
		Rule 1	Rule 2	Rule 3	Rule 4	Rule 1	Rule 2	Rule 3	Rule 4
Blockage intensity	5%	66.87%	103.45%	50.94%	0.00%	244.02%	107.07%	196.57%	0.00%
	25%	104.99%	71.65%	127.85%	0.00%	93.31%	76.05%	141.24%	0.00%
	50%	29.73%	12.27%	50.83%	0.00%	33.01%	16.98%	58.20%	0.06%
Dozer	1	106.19%	97.94%	101.26%	0.00%	174.82%	86.85%	156.26%	0.06%
	3	53.22%	55.19%	68.13%	0.00%	116.67%	66.85%	141.87%	0.00%
	6	42.18%	34.24%	60.23%	0.00%	78.85%	46.40%	97.89%	0.00%

candidate blocked edges. However, once an edge is selected, its debris cleanup time becomes its randomly generated "actual" w_e, and, the completion time of the task is adjusted accordingly.

To observe the impact of imperfect information on rule performance, we have solved the 300 new instances using the modified heuristic described above. Tables 7 and 8 illustrate the impact of imperfect information on the selected Caddebostan instance with a blockage intensity of 25% and 3 dozers. In both tables, the first column displays the problem instance solved, the next four columns titled "Perfect information" display the results that correspond to the original problem, where the expected and actual cleanup times are equal, therefore the rule is operated with perfect information. The next four columns titled "Imperfect Information" provide the average value of the performance criterion ($\boldsymbol{C_{max}}$ or *CI(t)*) over the 10 stochastic instances of that problem instance created under the indicated standard deviation setting (15%, 30%, or 45%).

As summarized in Table 7, usage of imperfect information in the edge selection process causes some variability in the resulting $\boldsymbol{C_{max}}$ values. However, this variability is quite limited. In fact, we observe that the variability occurs in both directions, especially for instances with lower standard deviation. Moreover, the ranking of the four rules based on the deterministic and stochastic data are the same. Consequently, we can say that the makespan performance of four rules under uncertain debris cleanup times are quite similar to that of the deterministic case, under the assumption of normally distributed cleanup times. In order to evaluate the statistical significance of the rule performance under different standard deviation settings, we performed an ANOVA with three independent variables (rule, standard deviation setting and problem instance solved) and $\boldsymbol{C_{max}}$ as the response variable where each cell of the full factorial design is replicated 10 times (Please refer to Table 2A in the Appendix). This analysis indicated that each variable is significant at 95% confidence level; however the two- and three-way interactions are insignificant. Therefore, we can also conclude that all rules are affected similarly by the magnitude of the error in estimating the w_e values.

Table 8 also displays similar results for the *CI(t)* measure. We see that the results remain relatively unchanged under uncertainty: while the variance of the results is quite low for the stochastic case, the ranking of the four rules also remain unchanged with respect to the deterministic case. In the stochastic case, Rule 4 emerges as the best performer for all problem instances across all scenario settings. Therefore, we can safely suggest the usage of Rule 4 for minimization of *CI(t)* even in the existence of data uncertainty. We have also performed an ANOVA for the *CI(t)* criterion as we did for $\boldsymbol{C_{max}}$.

Table 7
Impact of imperfect information on the performance of selection rules on C_{max}.

Problem	Perfect information				Imperfect information			
	Rule 1	Rule 2	Rule 3	Rule 4	Rule 1	Rule 2	Rule 3	Rule 4
15% standard deviation								
1	106.24	120.56	104.12	122.87	107.96	120.46	104.55	120.92
2	108.10	125.09	101.18	119.56	106.76	123.27	101.14	118.90
3	109.72	125.70	106.24	122.13	111.31	126.56	107.39	123.49
4	109.06	126.60	106.88	123.48	110.05	127.39	106.31	124.15
5	106.73	119.96	103.34	121.83	107.75	121.79	103.61	121.10
6	113.62	129.58	108.68	123.68	111.05	127.39	107.13	123.43
7	108.55	128.71	104.44	123.25	109.79	127.66	105.26	123.31
8	104.86	123.22	100.91	121.42	105.55	122.09	100.44	120.76
9	109.45	121.09	104.61	124.76	108.69	121.82	105.12	122.65
10	105.65	125.41	103.85	122.70	105.13	124.44	103.73	121.81
Average	**108.20**	**124.59**	**104.43**	**122.57**	**108.40**	**124.29**	**104.47**	**122.05**
30% standard deviation								
1	106.24	120.56	104.12	122.87	106.65	119.81	103.93	120.99
2	108.10	125.09	101.18	119.56	108.06	123.02	103.07	120.58
3	109.72	125.70	106.24	122.13	110.79	125.79	106.68	122.73
4	109.06	126.60	106.88	123.48	109.28	126.67	106.37	123.60
5	106.73	119.96	103.34	121.83	109.32	121.88	104.18	122.30
6	113.62	129.58	108.68	123.68	110.01	127.66	106.60	124.29
7	108.55	128.71	104.44	123.25	107.85	124.48	104.56	121.96
8	104.86	123.22	100.91	121.42	105.32	123.06	100.38	120.86
9	109.45	121.09	104.61	124.76	108.11	124.38	104.49	122.61
10	105.65	125.41	103.85	122.70	105.35	123.03	102.97	120.30
Average	**108.20**	**124.59**	**104.43**	**122.57**	**108.08**	**123.98**	**104.32**	**122.02**
45% standard deviation								
1	106.24	120.56	104.12	122.87	110.62	124.12	106.28	124.92
2	108.10	125.09	101.18	119.56	108.34	123.87	104.95	121.54
3	109.72	125.70	106.24	122.13	109.60	124.00	105.86	122.44
4	109.06	126.60	106.88	123.48	115.39	131.03	110.92	128.19
5	106.73	119.96	103.34	121.83	109.27	124.82	104.97	121.95
6	113.62	129.58	108.68	123.68	107.53	124.36	104.17	121.18
7	108.55	128.71	104.44	123.25	113.85	128.78	108.01	126.43
8	104.86	123.22	100.91	121.42	110.74	128.29	105.74	128.18
9	109.45	121.09	104.61	124.76	107.89	122.43	103.47	120.75
10	105.65	125.41	103.85	122.70	103.18	120.38	100.91	118.98
Average	**108.20**	**124.59**	**104.43**	**122.57**	**109.64**	**125.21**	**105.53**	**123.46**

Table 8
Impact of imperfect information on the performance of edge selection rules on $CI(t)$.

Problem	Perfect information				Imperfect information			
	Rule 1	Rule 2	Rule 3	Rule 4	Rule 1	Rule 2	Rule 3	Rule 4
15% standard deviation								
1	29.51	25.16	32.33	13.50	29.81	25.24	32.07	13.48
2	30.29	23.29	32.52	15.08	29.69	22.84	32.20	15.00
3	30.63	24.65	33.82	13.06	30.65	24.97	33.84	13.15
4	31.71	25.00	32.18	15.43	30.30	25.57	32.26	15.62
5	29.24	20.35	30.75	15.08	28.93	20.68	31.19	14.78
6	31.10	25.86	33.66	14.45	31.03	25.82	33.44	14.43
7	29.83	27.71	33.58	14.19	30.23	27.77	33.80	14.16
8	28.51	24.52	30.81	13.15	28.61	24.56	30.65	13.36
9	29.19	23.89	31.38	13.52	29.86	24.06	31.38	13.48
10	30.16	23.02	29.32	13.34	29.17	23.05	29.30	13.26
Average	**30.02**	**24.35**	**32.04**	**14.08**	**29.83**	**24.45**	**32.01**	**14.07**
30% standard deviation								
1	29.51	25.16	32.33	13.50	29.43	24.81	31.93	13.65
2	30.29	23.29	32.52	15.08	29.46	22.46	32.66	15.17
3	30.63	24.65	33.82	13.06	30.71	24.88	33.30	13.12
4	31.71	25.00	32.18	15.43	30.02	25.71	31.39	15.31
5	29.24	20.35	30.75	15.08	29.01	20.74	31.46	14.54
6	31.10	25.86	33.66	14.45	31.04	25.66	32.87	14.30
7	29.83	27.71	33.58	14.19	29.68	27.09	33.14	13.79
8	28.51	24.52	30.81	13.15	28.26	24.38	31.12	13.20
9	29.19	23.89	31.38	13.52	29.14	23.92	31.20	13.79
10	30.16	23.02	29.32	13.34	28.58	22.11	28.49	12.82
Average	**30.02**	**24.35**	**32.04**	**14.08**	**29.53**	**24.17**	**31.76**	**13.97**
45% standard deviation								
1	29.51	25.16	32.33	13.50	29.93	24.98	32.46	13.19
2	30.29	23.29	32.52	15.08	29.62	23.26	32.63	15.13
3	30.63	24.65	33.82	13.06	29.08	24.78	32.68	12.66
4	31.71	25.00	32.18	15.43	31.24	25.92	32.85	15.44
5	29.24	20.35	30.75	15.08	29.11	20.94	31.07	15.33
6	31.10	25.86	33.66	14.45	29.51	25.04	32.12	14.07
7	29.83	27.71	33.58	14.19	30.03	28.00	34.81	14.65
8	28.51	24.52	30.81	13.15	29.22	24.53	31.84	13.60
9	29.19	23.89	31.38	13.52	29.17	23.91	30.70	13.81
10	30.16	23.02	29.32	13.34	27.60	21.50	28.60	13.07
Average	**30.02**	**24.35**	**32.04**	**14.08**	**29.45**	**24.29**	**31.98**	**14.10**

(Please refer to Table 2B in the Appendix) This ANOVA also indicated that the rule is a significant factor at 95% confidence level; however the standard deviation was not significant at the same level. The statistical analysis also supports our observation that the difference between rules is significant even if they are applied with imperfect information.

Overall, the results reported in Tables 7 and 8 suggest that the findings of the deterministic case reported in the previous section remain valid under the assumption of normal distributed cleanup times under uncertain debris cleanup times.

9. Conclusions

In this paper, we address an important problem that arises during the first phase of disaster response and recovery: the problem of coordinating debris cleanup operations in post disaster road networks. Fast access to survivors and speedy evacuation can be achieved if this problem is solved efficiently.

The problem consists of assigning a limited number of dozers to a number of blocked roads where travel times between consecutive cleanup tasks depend on the current blockage status of the entire network. Two goals are defined for this problem: minimizing the operation completion time (makespan) and maximizing network accessibility throughout the cleanup operation. Both objectives are important, the first one relates to the start of subsequent recovery activities while the second one enables relief traffic to all locations in the network and increases survival rate. A mathematical model of the problem presented is developed here. The model turns out to be a recursive MIP which is deemed as intractable for exact solutions. Subsequently, resorting to heuristics to deal with large impact disasters seems to be a logical course of action. In order to develop “good” rules, we first analyze the impacts of different priority rules on the behavior of the network inaccessibility function. This leads to two intuitive rules that favor this goal. A “shortest travel time” rule is also proposed to enhance the makespan related performance. Finally, a rule that considers clusters of blockages is proposed to achieve a balance between the two goals. All rules are embedded in a constructive heuristic and tested on several real road network blockage scenarios. Their ranking with regard to both performance criteria is observed. Computational results indicate that the ranking of each rule under the makespan and network accessibility criterion is significantly different, which suggests that using the right task selection rule can play an important role in achieving the performance goals in the first phase of disaster response and recovery. Robustness of the performance rankings is also shown under uncertain road cleanup times. Based on this computational analysis, we conclude that the proposed rules can be utilized for effective coordination of cleanup operations of road networks.

This paper contributes to the relevant literature by developing a novel model that explicitly considers cumulative network accessibility as its goal and includes road status based dynamic dozer travel times in the routing constraints. The proposed heuristics have practical value, because they generate dozer routes for large scale road networks hit by high impact disasters. An important observation is that these heuristics are robust under damage assessment uncertainty. The proposed method also provides a viable way to insert new task selection rules for practitioners who might have different goals in mind.

In this work, we have developed easy to implement rules that can be used to create quick-and-dirty schedules that can be used in disaster recovery operations. While these rules provide initial solutions, future research can focus on improving the quality of these solutions by integrating them into meta/hyper-heuristics or other tailored improvement heuristics. However, one obvious shortcoming of most heuristic approaches is the lack of benchmark solutions that can be used to assess their solution quality. Unfortunately, development of exact solutions and/or lower bounds for this problem is a very challenging task for this problem due to its recursive nature. Another area of future research can focus on this issue.

Appendix

Table 1A
ANOVA for deterministic tests (C_{max}).

Dependent variable: C_{max}					
Source	Type III sum of squares	df	Mean square	F	Sig.
Corrected Model	41554017.973[a]	71	585267.859	14859.712	0.000
Intercept	33315449.500	1	33315449.500	845865.644	0.000
Rule	103650.281	3	34550.094	877.213	0.000
Dozers	16291993.370	2	8145996.685	206823.526	0.000
Block	16436080.606	5	3287216.121	83461.074	0.000
Rule* Dozers	52388.255	6	8731.376	221.686	0.000
Rule* Block	52753.116	15	3516.874	89.292	0.000
Dozers* Block	8588143.857	10	858814.386	21804.946	0.000
Rule* Dozers* Block	29008.488	30	966.950	24.550	0.000
Error	25522.270	648	39.386		
Total	74894989.743	720			
Corrected Total	41579540.243	719			

[a] R Squared = ,999 (Adjusted R Squared = ,999).

Table 1B
ANOVA for deterministic tests (*CI*).

Dependent variable: CI					
Source	Type III sum of squares	df	Mean square	F	Sig.
Corrected Model	12193771.949[a]	71	171743.267	2325.022	0.000
Intercept	5177940.583	1	5177940.583	70097.814	0.000
Rule	167927.835	3	55975.945	757.790	0.000
Dozers	2559074.415	2	1279537.207	17322.092	0.000
Block	6096599.440	5	1219319.888	16506.883	0.000
Rule* Dozers	79200.364	6	13200.061	178.700	0.000
Rule* Block	149524.482	15	9968.299	134.949	0.000
Dozers* Block	3070591.223	10	307059.122	4156.898	0.000
Rule* Dozers* Block	70854.190	30	2361.806	31.974	0.000
Error	47866.050	648	73.867		
Total	17419578.583	720			
Corrected Total	12241637.999	719			

[a] R Squared = ,996 (Adjusted R Squared = ,996).

Table 2A
ANOVA for stochastic tests (C_{max}).

Dependent variable: C_{max}					
Source	Type III sum of squares	df	Mean square	F	Sig.
Corrected Model	94307.731[a]	119	792.502	27.380	0.000
Intercept	15903134.978	1	15903134.978	549438.554	0.000
Rule	87172.027	3	29057.342	1003.904	0.000
StdDev	429.911	2	214.956	7.427	0.001
Block	3268.518	9	363.169	12.547	0.000
Rule* StdDev	9.398	6	1.566	0.054	0.999
Rule* Block	734.527	27	27.205	0.940	0.554
StdDev* Block	2459.577	18	136.643	4.721	0.000
Rule* StdDev* Block	233.773	54	4.329	0.150	1.000
Error	31259.885	1080	28.944		
Total	16028702.594	1200			
Corrected Total	125567.616	1199			

[a] R Squared = ,751 (Adjusted R Squared = ,724).

Table 2B
ANOVA for stochastic tests (*CI*).

Dependent variable: CI					
Source	Type III sum of Squares	df	Mean square	F	Sig.
Corrected Model	58942.481[a]	119	495.315	245.442	0.000
Intercept	748028.797	1	748028.797	370668.346	0.000
Rule	56849.288	3	18949.763	9390.116	0.000
StdDev	11.002	2	5.501	2.726	0.066
Block	1050.266	9	116.696	57.826	0.000
Rule* StdDev	5.542	6	0.924	0.458	0.840
Rule* Block	881.376	27	32.644	16.176	0.000
StdDev* Block	91.147	18	5.064	2.509	0.000
Rule* StdDev* Block	53.860	54	0.997	0.494	0.999
Error	2179.498	1080	2.018		
Total	809150.777	1200			
Corrected Total	61121.980	1199			

[a] R Squared = ,964 (Adjusted R Squared = ,960).

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