Prioritizing transportation network recovery using a resilience measure YuanChi Liua\*, Sue McNeila, Jürgen Hacklb, Bryan T. Adeyb

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Prioritizing transportation network recovery using a resilience measure

How and when transportation networks are restored following a natural hazard event plays a key role in post-event recovery. Determination of the optimal repair program and schedule to restore large networks with consideration of user costs is, however, computationally intensive, making it difficult post-event to determine how to proceed. For example, developing detailed simulation models may lead to delays in the restoration of the network and, therefore, recovery. This paper uses a modified network robustness index (MNRI), a measure of resilience, to prioritize the order of repair to minimize total costs including the repair cost and the travel cost during the recovery. For each link, the repair program is selected from multiple options using incremental benefit cost analysis. To test the efficiency and effectiveness of the method, the method is used to determine the restoration program for a realistic network that has been damaged due to a hypothetical extreme event. The network modelled is in the region around Chur, Switzerland. Three scenarios with different resources in terms of repair budgets and crew availability are investigated. The results demonstrate that the approximations obtained using the proposed method are close to the results using a near optimal heuristic algorithm, and reduce the computational effort and the time needed, making the application possible in practice.

Keywords: resilience, transportation network recovery;

# Introduction

The concept of infrastructure resilience has attracted attention in academic research and disaster management practice in the United States after several disasters and catastrophes, including hurricanes Katrina, Irene, and Sandy (Faturechi and Miller-Hooks 2014; Henry and Ramirez-Marquez 2012). Infrastructure resilience is often defined as the ability to withstand or remain functional (the attribute referred to as robustness) during and following a disaster, and the ability to recover back to the initial status after the disaster (the attributes referred to as resourcefulness and rapidity) (Bruneau et al. 2003). Resilience can be measured as a composite of these three attributes, or the individual attributes. The first attribute of resilience, robustness, is the inherent ability, design or strength to resist, tolerate, or withstand actual or possible disturbances and the availability of redundant alternatives as components or systems functionally fail. The second and third attributes, resourcefulness and rapidity, change as activities that involve human operations and resources assignments are undertaken to restore or recover functionality.

Various studies attempt to quantify and improve on these definitions. Some focus on the functionality remaining or loss during the events related to vulnerability analysis (Balijepalli and Oppong 2014; El-Rashidy and Grant-Muller 2014; Kurauchi et al. 2009); others focus on the recovery speed after the events involving resource coordination and the sequencing of infrastructure repair (Adams et al. 2013; Adjetey-Bahun et al. 2014; Henry and Ramirez-Marquez 2012; Renschler et al. 2010; Twumasi-Boakye and Sobanjo 2019). Some focus on all three (Adey et al. 2019).

Although there are a number of similar concepts, like risk management, vulnerability and redundancy, the concept of resilience provides a more holistic perspective of transportation network performance during and following a sudden event, such as a disaster, to direct capital investments not only to mitigate potential disruptions, but also to accelerate the recovery process.

The transportation system, a critical infrastructure system, plays a major role in the subsequent recovery of other disrupted facilities, as well as the inherent importance of minimizing the disruption of the transportation network itself following a disaster. The objective of this paper is to propose a solution to determine a quick and approximate way to prioritize the order of repair interventions to maximize resilience, taking into consideration repair cost and travel costs during the recovery. Recovery strategies based on actual damage are going to be more resilient but require computation after the event when there is pressure to deploy resources as quickly and effectively as possible. The paper explores decision methods that allow much of the computational effort to be expended prior to an event and compares the recovery plan with more computationally intense near-optimal plans and simple, less computationally intense methods that use actual damage data. The strategy draws on experiences that suggest that there are many near optimal solutions.

In alignment with the United States Federal Emergency Management Agency’s (FEMA) recovery continuum phases, the recovery process in this paper focuses on short-term (days) to intermediate (weeks/months) (Department of Homeland Security 2011). Therefore, the recovery of the transportation network should be expeditious (minimizing the time to recovery), and efficient (minimizing the cost of recovery). It is most likely beneficial to prioritize links that contribute to both improving connectivity and reducing disruption as some damaged links may result in an isolated subnetwork with significant travel demand.

Related research explores different algorithms to find the optimal or near optimal solutions including identifying the repair activity and scheduling repairs both with and without budgetary and labour resource constraints (El-Anwar et al. 2016a; Hackl et al. 2018a; Orabi et al. 2009). With multiple disrupted links and repair alternatives, the solution space is large. Furthermore, the evaluation of alternative repair programs has to account for the user delays requiring a traffic model that models the changes in network flow and travel time at each time step once a link is repaired. As a result, the computational effort needed has impeded further application in practice, especially for a large-scale post-event transportation network.

Three studies using different methods and networks demonstrate that if a damaged network is already modelled and coded, the time required to develop a recovery strategy is unacceptable. Orabi et al. (2009) use a genetic algorithm (GA) to seek the optimal reconstruction program and resource utilization to minimize the impact of the disruption on overall network performance in terms of additional user travel time, and reconstruction cost needed under limited resources and potential conflicts between reconstruction projects. The algorithm is applied to a real highway network of twenty-nine nodes and forty-one links in Shelby County, TE, with a hypothetical earthquake resulting in seven damaged bridges needing repair. In addition to prioritizing repair projects, Orabi et al. also considered assignments among three contractors and six different work paces (representing overtime policies) resulting in a large solution space. The GA seeks near optimal solutions and trade-offs between reconstruction costs and additional travel time during recovery. The problem took 4-5 days to solve using the computer technology at that time. In 2016, using the Sioux Falls, South Dakota network, El-Anwar et al. (2016b) employed mixed-integer linear programming to reduce the solution space assuming five damaged links by clustering the prioritization and eliminating inefficient solutions in advance. This method required about 11 hours to find the solutions. A similar result, in terms of the efficiency of the solution, was obtained by Hackl et al. (2018a) using a simulated annealing algorithm to schedule the best activity for twenty-nine damaged links under the network composed of 2,153 segments and 37 by 37 origin-destination pairs in Chur, Switzerland.

Building on the concept that recovery is connected to resilience, this research develops a rapid decision-making method for resource assignment and recovery scheduling for a network with multiple disrupted links. Following the work of Hackl et al. (2018a), the objective is to develop a recovery program that minimizes total costs defined as repair cost and travel cost including user delay, vehicle operation , and loss of connectivity over a planning horizon for three different scenarios representing crew constraints, budget constraints and both budget and crew constraints. The method uses incremental benefit cost analysis to select the repair alternative and prioritizes links for repair on the basis of a modified network robustness index (MNRI), a measure of resilience. The method is applied to the case study for Chur, Switzerland that has also been solved using a near optimal heuristic algorithm based on simulated annealing (Hackl et al., 2018a). The results are compared.

The paper is organized as follows. The following section describes the data and methods. The subsequent section presents the case study. A discussion of the results highlights the efficiency and effectiveness of the approximate method. Finally, the conclusions summarize the strengths of the method and opportunities to generalize the results.

# Data and Methods

To improve the resilience of a transportation network facing any kind of natural hazard event, the following strategies are used: mitigate the possible performance loss by strengthening and protecting facilities in the pre-event phase; enhance preparedness and response during the event by allocating and deploying temporary equipment or facilities to reduce the possible performance loss; and accelerate the recovery in order to reduce the impacts of the disruptions by optimizing the use of resources and the scheduling of recovery projects in the post-event phase. This paper focuses on the recovery of the transportation network following an infrequent natural hazard event that results in multiple damaged links in a transportation network needing repair and serious consequences in terms of delays and disruptions. Due to the low recurrent frequency of the event, the focus is on how to accelerate the post-event recovery rather than the pre-event mitigation. The unexpected event may result in competition for scarce available resources. Therefore, an effective and efficient decision-making process is needed to accelerate the recovery. This decision-making process needs to identify the priority of damaged links for repair and the appropriate repair program given resource constraints. That information can then be used to evaluate alternative programs by computing the overall additional travel cost, disruption cost and repair cost through the recovery period.

In order to reduce the computational effort involved in prioritizing the repairs and assigning resources for each repair to restore or partially restore the capacity of each link (either road segments or bridges), this paper proposes a two-stage method. The first stage uses a measure of resilience, the network robustness index to identify the critical links throughout the whole network to determine the repair order. The second stage uses an incremental benefit cost analysis to determine the best intervention method.

## Repair order

While the repair order for damaged links can be formulated as an optimization problem, the solution is computationally intractable and heuristics are computationally intensive. Immediate repairs are expected to facilitate search and rescue and other disaster response activities, and eventually support recovery. Damaged links can be prioritized and then repaired as soon as resources are available. Hackl et al. (2018a) investigated the effects of different intervention programs (that is, restoring a road segment or bridge) on user impact in terms of additional travel cost and compared the results with prioritized road segments or bridges based on average traffic volume. Other link attributes used for prioritization include expected damage (highest damage, highest priority) (Buckle et al. 2006), and the importance of the network link to the overall network, referred to as the Network Robustness Index (NRI) and defined as the change in travel-time cost due to rerouting as the studied link is closed or removed. (Scott et al. 2006). Traffic volume alone does not account for connectivity, and damage status does not account for user costs, but link importance (NRI) considers lost connectivity and user costs.

This paper uses the Network Robustness Index (NRI) because it considers the increase of travel cost resulting from rerouting. The NRI was first proposed by Scott et al. (2006) to evaluate the criticality of a studied link to the overall network. The NRI is computed for each link by setting the capacity of that link to zero and then computing the increase in travel-time cost on the network resulting from detours and congestion. The criticality of each studied link is in order of increasing travel-time cost. Moreover, the removal of certain links may result in isolated subnetworks and making the travel time cost on these links infinite and the evaluation of network-wide cost impossible. To solve this, this paper uses the approach of Hackl et al. (2018) to assign an economic cost to the loss of connectivity when trips cannot be completed because a damaged link results in an isolated network. These are defined as lost trips. For completeness, the modified network robustness (MNRI) is computed based on the change in total travel costs including travel time cost, travel distance cost and the cost of lost trips.

In addition to a network model, the calculation of the MNRI requires a link performance function (Bureau of Public Roads 1964) for each link, and the origin destination matrix for the network. The origin destination matrix for the network is assumed to remain unchanged after the event. Nicholson and Du (1997) provide a summary of how travel patterns might change after an event. Such changes could be incorporated in these models. Our results are conservative assuming a uniform reduction in travel across a region. Given the origin destination matrix, a method for assigning traffic to the network, such as the Frank-Wolfe algorithm for deterministic user equilibrium traffic assignment (Bell and Iida 1997), is used to obtain the travel-time cost reflecting the effect of traffic flow on each route.

Furthermore, the availability of redundant routes may be reflected in the change in total travel cost. That is, a link assumed to be disrupted in an undisrupted network before an event or a link assumed to be repaired in a disrupted network with multiple damaged links after the event, may result in changes in travel cost throughout the network. These changes are used to determine criticality of the link. By considering four alternative circumstances, this paper uses four calculations of MNRI (defined as types) to determine the repair priorities. These are partial/full removal of the studied link before the event and partial/full restoration of the studied link after the event. Although this paper focuses on prioritizing links for network recovery, Type I and II analysis (without any damage) permits comparison with Type III and IV (requiring information on damage) to determine the value of information about damage with respect to network recovery. The four types of MNRI calculations are described as follows:

Type I: pre-event, no disruption, set the capacity of only the studied link to zero representing a fully closed link due to the damage;

Type II: pre-event, no disruption, set the capacity of only the studied link as partially closed due to the damage;

Type III: post-event, the damage degrees on all damaged links are assumed to be known to specify the capacities of the damaged links and only the studied link is assumed to be restored to full capacity;

Type IV: post-event, the damage degrees on all damaged links are assumed to be known to specify the capacities of the damaged links and only the studied link is assumed to be restored to partial capacity due to resource constraints.

## Selection of repair alternatives

Incremental benefit cost analysis is commonly used to select the best alternative when more than one mutually exclusive alternative is available (Khisty et al. 2012). This method determines if added initial cost generates the equivalent or greater monetary benefit. The method starts with arranging all alternatives in order of initial cost and choosing the least cost alternative first. Assuming the least cost alternative, is economically feasible (benefits exceed costs over the planning horizon), the next ranked alternative is selected. For the candidate alternative, the potential incremental benefit is compared with the incremental cost. If the incremental benefit cost ratio (B/C) is greater than one, the candidate alternative is selected in place of the previous alternative. The procedure continues to examine the incremental benefit cost ratio for each of the ranked alternatives.

As the benefit (in this case, decrease in travel cost), measured in generic monetary units (mu), is a function of the planning horizon, this paper explores the impact of alternative planning horizons. The planning horizon is a function of the recovery period, which in this case is relatively short, therefore, the analysis does not take account of the time value of money. An example of the selection of an intervention is shown in Figure 1, Table 1 and Table 2, assuming there are three interventions. As Figure 1 shows, different interventions selected will result in various recovery paths and durations taken to complete the repair. In this case, Intervention 1 reduces indirect costs (travel time, travel distance and loss of connectivity) from 763,377 mu/day after 7.5 days to 728,980 mu/day (initial status); Intervention 2 reduces indirect costs by the same amount but only after 15.5 days; and Intervention 3 reduces indirect costs from 763,377 mu/day to 741,546 mu/day after 12.5 days. The range of possible planning horizons may be quickly estimated by assigning either the fastest or the slowest intervention method to all the damaged segments. To illustrate the computation of the incremental benefits and costs, this example uses a planning horizon (that is based on the expected recovery period) of 30 days. The area between the path and initial status is computed as the change of indirect cost. For example, for Intervention 3, the additional indirect cost is shown in Figure 2 and computed as 12.5 days times the reduction in indirect cost (763, 377 – 728,980 mu/day) plus 17.5 days times the additional indirect cost (741,546 – 728,980 mu/day) as the link is not fully repaired. All the direct costs for repair and indirect costs are shown in Table 1. The results from the incremental benefit cost analysis are shown in Table 2. As the incremental B/C for Intervention 2 compared with Intervention 3 is greater than one, the more expensive alternative (Intervention 2) is selected, Intervention 2 is then compared with Intervention 1. In this example the incremental B/C is not greater than one, so Intervention 2 is the final selection.

## Recovery strategy

The recovery strategy is the repair order and the selected repair alternative for each link subject to any constraints, such as crew availability and budget. A simple algorithm, shown in the flow chart in Figure 4, is used to develop the schedule.

# Case study

The case study is based on the paper by Hackl et al. (2018a) to facilitate the comparison of the results for the proposed recovery strategy and a near optimal solution based on simulated annealing. The example road network is located in the Rhine Valley around the city of Chur, Switzerland, shown in Figure 3. This area is exposed to recurrent floods and landslides that affect the traffic throughout the region (Hackl et al. 2018b). To simplify the analysis, the studied network is assumed to consist only of the national road (51 km), main roads (165 km), and minor roads (395 km) and modelled as a graph composed of 1,520 nodes (37 centroids, 1056 junctions, and 427 changes in road geometric features) and 2,153 links (representing road segments and bridges). For further details of the network refer to Hackl et al. (2018a). The study area is divided into 37 traffic analysis zones (TAZs), and traffic demand is represented by a 37 by 37 origin-destination (OD) matrix estimated by Hackl et al (2018a) using a gravity model. A hypothetical 500-year return period flood event is simulated by Hackl et al (2018b) to determine the 29 disrupted segments based on fragility and loss functions. The 29 disrupted segments consist of 24 road segments and 5 bridge elements that are to be restored. The level of damage and the associated loss in capacity on the links are shown in Table 3. Three damage states (State 0, no damage; State 1, minor damage; and State 2, major damage) represent the loss of capacity that vehicles experience travelling over the damaged segments.

OD pairs, transportation network attributes (connectivity, link capacity, and free flow travel time), and intervention methods and required resources (Table 4) are drawn from Hackl et al. (2018a). The travel related cost, which is referred to as indirect costs, contains three parts: travel-time cost, travel distance cost (that is, vehicle operation cost), and lost trips cost. This paper uses indirect cost to account for unfulfilled trips instead of simply using overall travel cost (time and distance) only. The cost calculations are shown in equations (1) - (3):

Travel-time cost: (1)

Travel distance cost: (2)

Lost trips cost: (3)

*Flow* (va vehicles per hour) is the flow on the link,

*travel time* (hours per trip) is the time to travel a link,

*traveldistance* (km per trip) is the length of the link, and

*Losttrips* (vehicles per hour) are the number of trips that cannot be completed due to loss of connectivity.

These values are obtained from the network model. In the network model, travel time is computed using the link performance function (Bureau of Public Roads 1964):

,

t0 is the free flow travel time,

ca is the capacity of link a. corresponding to level of service (LOS) C

Unit cost data are assumed to be:

*usertravelcosts*: 29.50 mu/hour;

*vehicleoperation costs*: 31.04 mu/km;

*economiccost*: 666.32 mu/day

The unit cost data is in monetary units (mu).

To account for the number of hours in the day, the variable *dayfactor* is assumed to be 9.

For MNRI (Type I to IV), the capacity setting is described as:

Type I: the capacity of the studied link (includes road and bridge) is 0%.

Type II: the capacity of a road link is 60% of the original capacity for minor-damage (based on 70% loss of capacity from Table 3, and then restoration of 30% of capacity for Level 3 Intervention from Table 4) and 10% for major-damage (based on 100% loss of capacity and then restoration of 10% of capacity Level 3 Intervention); the capacity of a bridge is 70% of the original capacity for minor-damage (based on 50 % loss of capacity and then restoration of 20%) and 10% for major-damage (based on 100% loss of capacity then restoration of 10%).

Type III: the capacity of minor-damaged road and bridge recovers from 30%, and 50%, respectively to 100%, and major-damaged roads and bridges from 0% to 100%.

Type IV: the capacity of minor-damaged roads and bridges recover from 30% to 60%, 50 % to 70% respectively and major-damaged roads and bridges from 0% to 10%).

The case study uses three scenarios to illustrate different types of constraints assuming up to three crews (a, b and c) are available (Hackl et al. 2018a):

Scenario 1: Crew b is not available until day 5 and Crew c is not available between days 10 and 15.

Scenario 2: Crew b is not available until day 5 and Crew c is not available between days 10 and 15, and repair budget is 3,630,000 mu.

Scenario 3: No constraints

# Results and Discussion

The recovery strategy combines the method to select the repair order and the method to select the repair alternative, subject to constraints. The results are tabulated in Table 5 for the following assumptions assuming no resource constraints:

* Repair order
  + Pre-event MNRI
    - Type I - full link closure; Type II – partial link closure
  + Post-event MNRI
    - Type III – link fully restored; Type IV – link partially restored
* Repair alternative
  + Pre-event
    - 30-day, 40-day, and 50-day planning horizons
  + Post-event
    - 30-day, 40-day, and 50-day planning horizons

The segments are sorted according to the priority determined by Hackl et al (2018a) for Scenario 3 (no constraints). The repair order, based on the MNRI, as shown in Table 5 also assumes no constraints. The second column shows the segment ID, which is also shown on the map in Figure 3.

Comparing the repair order for Type I and Type II, reveals that fifteen of the links have the same repair order; they are the last and next to last to be repaired. In the case of Type III and Type IV repair order, the results are the same for each link. These results are not surprising. Using the pre-event MNRI, the criticality of the link for low priority links is going to be the same whether the link is fully closed or partially closed. These links carry low volumes of traffic. In the case of the post-event MNRI for this network, fully or partially restoring any link has the same impact on the network because the traffic volume is relatively low in this network. These observations are supported by Spearman rank-order correlations shown in Table 6. The correlations also show that the repair order using the MNRI are modestly correlated with the near optimal repair order determined by Hackl (2018a).

Differences in the repair order determined using different methods are glaring for some links. For example, link ID 1095 is ranked 6th by Hackl et al. and 16th, 16th, 15th and 15th using the Type I, II, III and IV MNRI methods. However, the overall similarity based on the rank correlation suggests further evaluation of the repair schedule is warranted. This line is pursued in the following paragraphs. As noted above, of the 29 segments in the network, approximately half the segments (14 segments for Type I and II MNRI calculations, and 15 segments for Type III and IV MNRI calculations) are assigned as the last to be repaired. These segments may not contribute to the reduction of additional travel cost and prolong the repair after other repairs are done. In the pre-event study, the criticality varies among the remaining segments through partial or full closure of each segment. This result may also be helpful to prioritize routine maintenance or long-term mitigation during the normal status. In contrast, for the post-event analysis, the order of criticality remains the same independent of partial or full recovery of each link. The post-event analysis reveals that during the recovery period, partial or full recovery does not make a difference in the reduction of additional indirect cost (these results are perfectly correlated as shown in Table 6). It is attributed to the small demand of the studied region.

Table 5 also shows the intervention method for three different planning horizons. As discussed, the planning horizon is determined by the fastest and longest period of time required to repair all links. In this case study, the planning horizon for completing the repair of 29 segments ranges between 30 to 50 days. Therefore, to compare the interventions, this paper considers planning horizons of 30, 40, and 50 days. For the selection of intervention method, the study periods make no difference in the pre-event repair order but the post-event repair order analysis differs between the 40- and 50-day planning horizons for two segments. For the pre-event selection of interventions, the incremental benefit cost analysis for most of the segments suggests the least cost intervention method. Segments using the most expensive method are IDs 1803, 2052, 1802, 1706, 2069 and 1913, which either result in lost trips due to loss of connectivity or significant travel time increases if the segment is fully closed. The analysis implies that the benefits of full repair with the highest investment are greater than the additional cost input. The only segment utilizing the highest cost intervention for all the methods is Segment ID 2052. This segment results in lost trips if it is fully closed. This implies that the cost of lost trips dominates the increase of the indirect cost. For the post-event analysis, the selection of the intervention method for segments with IDs 554, 2042, and 2131 changes according to the planning horizon. It can be inferred that the incremental benefit cost analysis applied may be influenced by the length of the planning horizon. However, given only three segments change the results are relatively insensitive to the analysis period.

The recovery strategy is based on a combination of the method to select the repair order and the method to select the intervention method. However, using pre-event MNRIs and post-event intervention selection is unrealistic as disruptions cannot be predicted before the event. Therefore, only five heterogeneous pairs analysed to represent recovery strategies as listed in Table 7. These five recovery strategies are used to schedule the interventions and crews based on different crew and repair budget constraints.

The results, based on data and methods for determining costs from Hackl et al. (2018a), are shown in Table 8 and the discussion follows.

In scenario 2, the suggested intervention methods above need to be adjusted to account for the budget constraint. There are two alternatives to be considered: either apply intervention 3 for all damaged links or not to repair all damaged links. The first option is shown here. The repair order also requires minor adjustments to accommodate the actual availability of crews. For example, segment ID 554 is suggested as 4th to be repaired with two crews, however, this segment has to wait until two crews become available. Therefore, that available crew will be assigned to the highest priority segment without disrupting the overall assigned order. This is why segment ID 332 is repaired prior to segment ID 554 although it is planned to be the 10th repaired. One of the actual schedules for Scenario 3 using Intervention Strategy III/IV.3 (Post event prioritization with a 50-day planning horizon) is shown in Table 9.

Table 8 also compares the results using the five strategies with the results from Hackl et al (2018a) for a benchmark and a heuristic algorithm based on simulated annealing (SA) using the total cost consisting of the repair cost and indirect costs. The benchmark used travel volume of each segment during normal status to assign the repair order followed with the assigned intervention method by SA. The heuristic algorithm uses simulated annealing to find a near optimal solution. Overall, the results for the five strategies and Hackl et al.’s solution methods provide some insights into the decision process. The results arranged by pre-event MNRI (Type I and Type II) are significantly costlier (18.82% more for Scenario 1, 19.65% more for Scenario 2, and 28.42% more for Scenario 3) than the heuristic (SA) results. In contrast, the results arranged by post-event order (Type III and Type IV) are relatively comparable to the heuristic results (0.45% more for Scenario 1, 0.60% more for Scenario 2, and 1.05% more for Scenario 3). Using knowledge of the actual damage (Type III and Type IV) to determine the criticality of each segment is constructive information that enhances the solution. In this case study, the results are within 1% of the heuristic.

Compared with the heuristic algorithm, determining the criticality of the order is computationally efficient assuming the network is already modelled. The repair order requires running the traffic network assignment for each disrupted segment to determine the MNRI. Hackl et al. (2018a) reports that the solution of the heuristic takes approximately 10 hours, where our solution is determined in a matter of minutes making the method feasible for near real-time decision support.

Table 9 shows the scheduling for Scenario 3 using the post event priority and a 50-day planning horizon. The table provides implementable details for the agency to manage the network recovery and communicate with other stakeholders, including, for each damaged segment, the state, remaining capacity, repair cost and durations needed, and crew assignment. For example, segment ID 2052 repair (Intervention 1) would begin immediately and be completed after 11 days using crews a and b.

# Conclusion

Transportation networks play a major role in post-event rescue, restoration and recovery as a community experiences an unexpected event. There are different ways to increase the resilience of transportation networks. For example, mitigate the potential damage through the design of transportation infrastructure recognizing the frequency and the intensity of historical events. However, infrequent extreme weather events shift the focus to rapid and efficient recovery involving decisions and trade-offs recognizing recovery budgets and resource allocation, which is another way to improve the transportation resilience. This paper explores a two-stage method to facilitate the rapid decision-making process of resource allocation and prioritization for a damaged transportation network, including four types of prioritization, based on a resilience measure, and intervention selected using three different recovery planning horizons. The resilience measure is intended to capture usage and network connectivity, appropriate measures of accessibility and mobility. The different types of resilience measures are used to demonstrate the value of knowing which links are damaged. The modified network robustness index (MNRI) is based on the reduction in travel costs if a damaged link in a disrupted network is repaired and the other links are still disrupted. While the measure does not capture dependencies, such as damaged links in serial, the lack of redundancy and loss of connectivity is captured, as well as the relative importance of highly travelled links.

An important limitation of this work, is that our simple algorithm was only tested on one network. This network has relatively low traffic volumes but also had damaged segments that isolated subnetworks. Generalization on our conclusions requires extensive sensitivity analysis and testing on other networks.

In summary, the result shows the post-event information, the degree of damage in each segment together with resilience measures that capture network connectivity, is most valuable to construct the near optimal solution under the set constraints without requiring extensive computational effort, compared with other heuristic algorithms. Also, some of the disrupted segments that do not contribute to reduced travel cost (non-critical segments) may be deferred when available resources are limited. That is, a relatively simple two stage method for first, determining the intervention action, and then prioritizing the links for repair using a modified network robustness index is computationally efficient and delivers result that perform similarly in terms of costs to a near optimal heuristic based on simulated annealing. The algorithms also perform well (within 1% of the total costs associated with the near optimal solution) when simple rules are added to account for crew and budget constraints.

Although the hypothetical extreme event may never happen, it still helps agencies to review the resources required and explore if existing contingency resources or crews available for recovery are capable and have sufficient capacity. Further strategizing and developing plans to face the more unpredictable disasters will enhance the overall transportation network resilience. For future research, other different scale transportation networks may be used to test regional recovery plans and more realistic constraints. In addition, using the initial prioritization and then transitioning to a near optimal solution may be promising.

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Table 1 Cost details for each intervention (Assuming 30-day planning horizon)

|  |  |  |
| --- | --- | --- |
|  | Total Additional Indirect Cost  (mu) | Direct Cost  (mu) |
| Intervention 3 | 649,868 | 879,468 |
| Intervention 2 | 533,154 | 937,026 |
| Intervention 1 | 257,978 | 1,219,234 |

Table 2 An example of selection by incremental benefit cost analysis (Assuming 30-day planning horizon)

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | Δ Benefit  (mu) | Δ Cost  (mu) | ΔB/ΔC  (mu) | Result |
| 3 -> 2 | 116,714 | 57,558 | 2.0 | Select 2 instead of 3 |
| 2 -> 1 | 275,176 | 282,208 | 0.97 | Remain on 2 |

Table 3 State and capacity loss for the network due to flood

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| State | Description | Capacity Loss - (%) | | Number of damaged segments | |
| Road | Bridge | Road | Bridge |
| 0 | No damage | 0 | 0 | 1,987 | 111 |
| 1 | Minor damage | 70 | 50 | 20 | 3 |
| 2 | Major damage | 100 | 100 | 4 | 2 |

Table 4 Intervention types and associated recovery rate, resources and costs for bridge and road

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | State | Intervention type | Capacity recovery  (%) | Duration (1) | Required crews | Fixed costs  (2) | Variable costs  (3) | Resource costs  (4) |
| Bridge | 1 | Level 1 | 100 | 20 | 2 | 16 | 24 | 0.9 |
| Level 2 | 100 | 40 | 1 | 10 | 15 | 0.9 |
| Level 3 | 20 | 35 | 1 | 10 | 13 | 0.9 |
| 2 | Level 1 | 100 | 90 | 2 | 48 | 64 | 1.2 |
| Level 2 | 100 | 160 | 1 | 30 | 40 | 1.2 |
| Level 3 | 10 | 145 | 1 | 30 | 37 | 1.2 |
| Road | 1 | Level 1 | 100 | 1 | 2 | 5.25 | 22 | 0.5 |
| Level 2 | 100 | 3 | 1 | 3.5 | 16.5 | 0.5 |
| Level 3 | 30 | 3 | 1 | 3.5 | 14.5 | 0.5 |
| 2 | Level 1 | 100 | 6 | 2 | 14.4 | 110 | 0.7 |
| Level 2 | 100 | 12 | 1 | 9.6 | 82.5 | 0.7 |
| Level 3 | 10 | 10 | 1 | 9.6 | 78.5 | 0.7 |
| Note:   1. Duration: hours/element for bridge, hours/1,000 m2 for road 2. Fixed costs: in 1,000 mu 3. Variable costs: in 1,000 mu /element for bridge; mu / m2 for road 4. Resource costs: in 1,000 mu per resource crew hour | | | | | | | | |

Table 5 Result of the repair order and intervention method on each segment

|  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Nr(\*) | ID  (\*\*) | Repair order | | | | Intervention method | | | | | |
| Pre-event | | Post-event | | Pre-event | | | Post-event | | |
| I | II | III | IV | (30 days) | (40 days) | (50 days) | (30 days) | (40 days) | (50 days) |
| 1 | **2042** | 14 | 12 | 2 | 2 | 3 | 3 | 3 | 1 | 1 | 2 |
| 2 | **2052** | 5 | 4 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| 3 | 554 | 11 | 10 | 4 | 4 | 3 | 3 | 3 | 2 | 2 | 1 |
| 4 | 1905 | 16 | 16 | 15 | 15 | 3 | 3 | 3 | 3 | 3 | 3 |
| 5 | 1913 | 3 | 3 | 3 | 3 | 1 | 1 | 1 | 3 | 3 | 3 |
| 6 | 1095 | 16 | 16 | 15 | 15 | 3 | 3 | 3 | 3 | 3 | 3 |
| 7 | **2069** | 6 | 2 | 14 | 14 | 1 | 1 | 1 | 3 | 3 | 3 |
| 8 | 471 | 16 | 16 | 15 | 15 | 3 | 3 | 3 | 3 | 3 | 3 |
| 9 | 1803 | 2 | 5 | 6 | 6 | 1 | 1 | 1 | 3 | 3 | 3 |
| 10 | 1706 | 8 | 7 | 8 | 8 | 1 | 1 | 1 | 3 | 3 | 3 |
| 11 | 1907 | 16 | 16 | 15 | 15 | 3 | 3 | 3 | 3 | 3 | 3 |
| 12 | 1279 | 16 | 16 | 15 | 15 | 3 | 3 | 3 | 3 | 3 | 3 |
| 13 | 461 | 10 | 14 | 11 | 11 | 3 | 3 | 3 | 3 | 3 | 3 |
| 14 | 1233 | 16 | 16 | 15 | 15 | 3 | 3 | 3 | 3 | 3 | 3 |
| 15 | 1802 | 4 | 6 | 7 | 7 | 1 | 1 | 1 | 3 | 3 | 3 |
| 16 | 562 | 7 | 1 | 12 | 12 | 2 | 2 | 2 | 3 | 3 | 3 |
| 17 | 1798 | 16 | 16 | 15 | 15 | 3 | 3 | 3 | 3 | 3 | 3 |
| 18 | 1692 | 15 | 15 | 15 | 15 | 3 | 3 | 3 | 3 | 3 | 3 |
| 19 | 332 | 1 | 11 | 10 | 10 | 3 | 3 | 3 | 3 | 3 | 3 |
| 20 | 1498 | 16 | 16 | 15 | 15 | 3 | 3 | 3 | 3 | 3 | 3 |
| 21 | **2131** | 12 | 8 | 5 | 5 | 3 | 3 | 3 | 2 | 2 | 1 |
| 22 | 460 | 13 | 9 | 9 | 9 | 3 | 3 | 3 | 3 | 3 | 3 |
| 23 | 1814 | 16 | 16 | 15 | 15 | 3 | 3 | 3 | 3 | 3 | 3 |
| 24 | 1703 | 9 | 13 | 13 | 13 | 3 | 3 | 3 | 3 | 3 | 3 |
| 25 | **2043** | 16 | 16 | 15 | 15 | 3 | 3 | 3 | 3 | 3 | 3 |
| 26 | 1237 | 16 | 16 | 15 | 15 | 3 | 3 | 3 | 3 | 3 | 3 |
| 27 | 1371 | 16 | 16 | 15 | 15 | 3 | 3 | 3 | 3 | 3 | 3 |
| 28 | 1276 | 16 | 16 | 15 | 15 | 3 | 3 | 3 | 3 | 3 | 3 |
| 29 | 1202 | 16 | 16 | 15 | 15 | 3 | 3 | 3 | 3 | 3 | 3 |

(\*) Nr: Repair order in Hackl et al. (2018a) for Scenario 3

(\*\*) Bridge are indicated in **bold**.

Table 6 Spearman's Rank Order Correlations for Prioritizations Order

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | Nr | I | II | III | IV |
| Nr | 1 | 0.32 | 0.39 | 0.51 | 0.51 |
| I |  | 1 | 0.84 | 0.64 | 0.64 |
| II |  |  | 1 | 0.68 | 0.68 |
| III |  |  |  | 1 | 1.00 |
| IV |  |  |  |  | 1 |

Table 7 Recovery strategies

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
|  | | Selection of intervention method | | | | | |
| Pre-event  (30/40/50 days) | | Post-event  (30/40 days) | | Post-event  (50 days) | |
| Selection of repair priority method | Pre-event (I) | | 🗸 (I.1) | | - | | - | |
| Pre-event (II) | | 🗸 (II.1) | | - | | - | |
| Post-event (III/IV) | | 🗸 (III/IV.1) | | 🗸 (III/IV.2) | | 🗸 (III/IV.3) | |

Table 8 Total cost (mu) using each method and scenario

|  |  |  |  |
| --- | --- | --- | --- |
| Intervention strategy | Scenario | | |
| 1  Crew constraint | 2  Crew & budget constraint | 3  No constraint |
| I.1 | 9,428,768 | 10,978,792 | 9,229,391 |
| II.1 | 14,432,066 | 12,735,845 | 11,165,718 |
| III/IV.1 | 8,856,184 | 9,230,736\* | 7,752,772 |
| III/IV.2 | 7,970,793 | 7,742,800 |
| III/IV.3 | 8,235,164 | 7,262,239 |
| Benchmark | 9,032,603 | 9,841,807 | 7,784,687 |
| Heuristic (SA) | 7,935,172 | 9,175,545 | 7,186,918 |
| Scenarios (Hackl et al. 2018b):  1: Crew b is not available [0,4], Crew c is not available [10,15]  2: Crew b is not available [0,4], Crew c is not available [10,15], repair budget limit 3,630,000 mu  3: No constraint  \*Under a budget constraint all interventions are set to level 3, the least cost option and all strategies result in the same cost. | | | |

Table 9 Result of Scenario 3 with III/IV.3 with a 50-day planning horizon

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Start  (day #) | End  (day #) | ID | Segment type | Damage state | Original Capacity  (veh/hr) | Capacity after damage  (veh/hr) | Repair order | Intervention method | Capacity after repair  (veh/hr) | Repair cost  (mu) | Duration  (days) | # of Crews | Crew(s) detail | Nr |
| 0 | 11 | 2052 | bridge | 2 major | 900 | 0 | 1 | 1 | 900 | 323200 | 11 | 2 | a,b | 2 |
| 0 | 5 | 2042 | bridge | 1 minor | 900 | 450 | 2 | 2 | 900 | 61000 | 5 | 1 | c | 1 |
| 5 | 14 | 1913 | road | 1 minor | 4000 | 1200 | 3 | 3 | 2400 | 387407 | 9 | 1 | c | 5 |
| 11 | 11.5 | 554 | road | 1 minor | 1200 | 360 | 4 | 1 | 1200 | 15416 | 0.5 | 2 | a,b | 3 |
| 11.5 | 14 | 2131 | bridge | 1 minor | 1200 | 600 | 5 | 1 | 1200 | 76000 | 2.5 | 2 | a,b | 21 |
| 14 | 15.5 | 1803 | road | 1 minor | 4000 | 1200 | 6 | 3 | 2400 | 59941 | 1.5 | 1 | a | 9 |
| 14 | 15.5 | 1802 | road | 1 minor | 4000 | 1200 | 7 | 3 | 2400 | 70300 | 1.5 | 1 | b | 15 |
| 14 | 16 | 1706 | road | 1 minor | 4000 | 1200 | 8 | 3 | 2400 | 83607 | 2 | 1 | c | 10 |
| 15.5 | 17.5 | 460 | road | 1 minor | 4000 | 1200 | 9 | 3 | 2400 | 87829 | 2 | 1 | a | 22 |
| 15.5 | 16 | 332 | road | 1 minor | 4000 | 1200 | 10 | 3 | 2400 | 26239 | 0.5 | 1 | b | 19 |
| 16 | 16.5 | 461 | road | 1 minor | 4000 | 1200 | 11 | 3 | 2400 | 33526 | 0.5 | 1 | b | 13 |
| 16 | 28.5 | 562 | road | 2 major | 4000 | 0 | 12 | 3 | 400 | 879468 | 12.5 | 1 | c | 16 |
| 16.5 | 18.5 | 1703 | road | 1 minor | 4000 | 1200 | 13 | 3 | 2400 | 83849 | 2 | 1 | b | 24 |
| 17.5 | 35.5 | 2069 | bridge | 2 major | 4000 | 0 | 14 | 3 | 400 | 239800 | 18 | 1 | a | 7 |
| 18.5 | 19 | 1095 | road | 1 minor | 850 | 255 | 15 | 3 | 510 | 17222 | 0.5 | 1 | b | 6 |
| 19 | 22 | 1692 | road | 2 major | 600 | 0 | 15 | 3 | 60 | 224657 | 3 | 1 | b | 18 |
| 22 | 22.5 | 1279 | road | 1 minor | 850 | 255 | 15 | 3 | 510 | 10856 | 0.5 | 1 | b | 12 |
| 22.5 | 23.5 | 1907 | road | 1 minor | 600 | 180 | 15 | 3 | 360 | 41954 | 1 | 1 | b | 11 |
| 23.5 | 24 | 1905 | road | 1 minor | 600 | 180 | 15 | 3 | 360 | 33646 | 0.5 | 1 | b | 4 |
| 24 | 26.5 | 1237 | road | 2 major | 850 | 0 | 15 | 3 | 85 | 177416 | 2.5 | 1 | b | 26 |
| 26.5 | 28 | 1276 | road | 1 minor | 600 | 180 | 15 | 3 | 360 | 63335 | 1.5 | 1 | b | 28 |
| 28 | 28.5 | 1202 | road | 1 minor | 850 | 255 | 15 | 3 | 510 | 30809 | 0.5 | 1 | b | 29 |
| 28.5 | 29 | 1233 | road | 1 minor | 600 | 180 | 15 | 3 | 360 | 10041 | 0.5 | 1 | b | 14 |
| 28.5 | 29.5 | 1798 | road | 1 minor | 850 | 255 | 15 | 3 | 510 | 47523 | 1 | 1 | c | 17 |
| 29 | 33.5 | 1814 | road | 2 major | 600 | 0 | 15 | 3 | 60 | 302468 | 4.5 | 1 | b | 23 |
| 29.5 | 34 | 2043 | bridge | 1 minor | 900 | 450 | 15 | 3 | 630 | 55400 | 4.5 | 1 | c | 25 |
| 33.5 | 37 | 1498 | road | 2 major | 600 | 0 | 15 | 3 | 60 | 245457 | 3.5 | 1 | c | 20 |
| 34 | 34.5 | 471 | road | 1 minor | 600 | 180 | 15 | 3 | 360 | 32999 | 0.5 | 1 | c | 8 |
| 34.5 | 35 | 1371 | road | 1 minor | 600 | 180 | 15 | 3 | 360 | 22313 | 0.5 | 1 | c | 27 |

Figure 1 An example of indirect costs by various interventions (Assuming a 30-day planning horizon)

Figure 2 Indirect cost for Intervention 3 (Assuming a 30-day planning horizon)



Figure 3 Studied network with damaged segments’ ID

Figure 4 Flowchart to develop the schedule

