Structure and Infrastructure Engineering
Maintenance, Management, Life-Cycle Design and Performance

ISSN: 1573-2479 (Print) 1744-8980 (Online) Journal homepage: http://www.tandfonline.com/loi/nsie20

Resilience-based post-disaster recovery strategies for road-bridge networks

Weili Zhang, Naiyu Wang & Charles Nicholson

To cite this article: Weili Zhang, Naiyu Wang & Charles Nicholson (2017): Resilience-based post-disaster recovery strategies for road-bridge networks, Structure and Infrastructure Engineering, DOI: 10.1080/15732479.2016.1271813

To link to this article: http://dx.doi.org/10.1080/15732479.2016.1271813

Published online: 04 Jan 2017.

http://dx.doi.org/10.1080/15732479.2016.1271813

Taylor & Francis
Taylor & Francis Group

Resilience-based post-disaster recovery strategies for road-bridge networks

Weili Zhang[a], Naiyu Wang[b] and Charles Nicholson[a]

[a]Department of Industrial and Systems Engineering, University of Oklahoma, Norman, OK, USA ; [b]School of Civil Engineering and Environmental Science, University of Oklahoma, Norman, OK, USA

ABSTRACT

This paper presents a novel resilience-based framework to optimise the scheduling of the post-disaster recovery actions for road-bridge transportation networks. The methodology systematically incorporates network topology, redundancy, traffic flow, damage level and available resources into the stochastic processes of network post-hazard recovery strategy optimisation. Two metrics are proposed for measuring rapidity and efficiency of the network recovery: total recovery time (TRT) and the skew of the recovery trajectory (SRT). The TRT is the time required for the network to be restored to its pre-hazard functionality level, while the SRT is a metric defined for the first time in this study to capture the characteristics of the recovery trajectory that relates to the efficiency of those restoration strategies considered. Based on this two-dimensional metric, a restoration scheduling method is proposed for optimal post-disaster recovery planning for bridge-road transportation networks. To illustrate the proposed methodology, a genetic algorithm is used to solve the restoration schedule optimisation problem for a hypothetical bridge network with 30 nodes and 37 bridges subjected to a scenario seismic event. A sensitivity study using this network illustrates the impact of the resourcefulness of a community and its time-dependent commitment of resources on the network recovery time and trajectory.

ARTICLE HISTORY
Received 31 August 2015
Revised 18 November 2016
Accepted 24 November 2016

KEYWORDS
Decision optimisation; network recovery; resilience; restoration schedule; transportation networks; uncertainty modelling

1. Introduction and Background

Transportation networks play a vital role in ensuring the economic and social well-being of a community and the condition of such networks following the occurrence of an extreme hazard (e.g. earthquake, extreme wind storms, flood, terrorism, etc.) has a significant impact on the recovery of the community. Highway bridges are vulnerable components in road transportation system, and robustness and recovery of the transportation network as a whole highly depends on their performance. Large-scale hazards can damage many bridges in a transportation system simultaneously, and the loss that results from this damage can be classified into two categories: initial direct loss caused by structural damage and indirect loss caused by downtime of the network before its full recovery. The initial loss is determined by the vulnerability of the network to the hazard event (Bruneau et al., 2003; Chang & Shinozuka, 2004). The indirect loss due to downtime, which often is long-term and equally significant, largely depends on the overall recovery time and trajectory of the network. This paper investigates bridge-road transportation network restoration schedules that minimise the recovery time and optimise the recovery trajectory of the network as a whole; such optimal schedules ultimately lead to reduced indirect economic losses resulting from the downtime of damaged road systems.

A well-accepted definition of infrastructure system resilience is presented in Bruneau et al. (2003), as illustrated in Figure 1, where resilience is defined with four dimensions: robustness (ability to withstand extreme events and deliver a certain level of service after events), rapidity (speed of recovering from a disaster), redundancy (substitutable components within the system) and resourcefulness (availability of resources to respond to a disaster). Several approaches to quantifying resilience can be found in Bruneau et al. (2003), Bocchini, Frangopol, Ummenhofer, & Zinke (2013), Chang and Shinozuka (2004), Cimellaro, Reinhorn, and Bruneau (2006, 2010a, 2010b), and Zobel (2011). Numerous studies have been focused on the post-hazard restoration of physical networks. For example, Chang and Nojima (2001) utilised network coverage and transport accessibility to quantify the post-disaster performance of a transportation network and applied these concepts to a rail and highway transportation system in Kobe, Japan.

Shinozuka et al. (2003) discussed the restoration curve in terms of robustness and rapidity in which the recovery indicator is associated with the service level (e.g. power supply for electric networks or water supply for water systems) and the rapidity is measured by the average recovery rate, expressed in percentage recovery/time. Wang, Sarker, Mann, and Triantaphyllou (2004) constructed a depot location model to minimise the total inter-cell transportation cost for the electric power restoration process. Çağnan, Davidson, and Guikema (2006) compared the alternative restoration strategies for the electric power transmission systems with respect to the expected duration of power outages in Los Angeles using a discrete-event simulation model.

CONTACT Naiyu Wang naiyu.wang@ou.edu

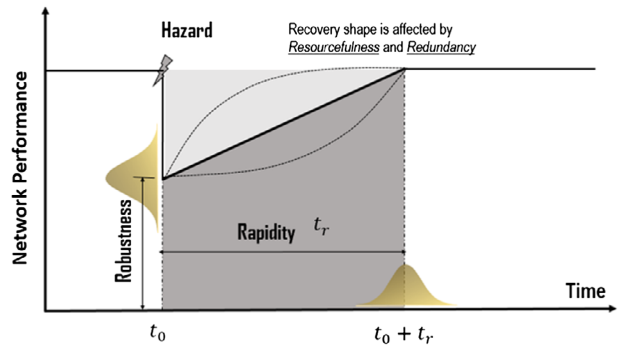

Figure 1. Illustration of resilience concept.

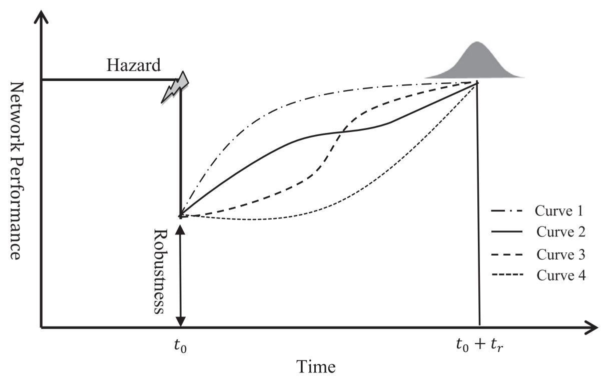

Figure 2. Recovery trajectories.

The study by Xu et al. (2007) of an electric system was aimed at minimising the area *above* the restoration curve; this area, shown in Figure 1 as the light-shaded triangular area, is named the resilience triangle in Bruneau et al. (2003). Miles and Chang (2006) proposed one of the first comprehensive concept models of post-disaster community recovery using an object-oriented design technique, in which the variables and relationships between different sectors were clearly defined. Their model provides a common basis for developing computer models of socio-economic recovery from disasters and its flexibility allows for the incorporation of various indicators and algorithms within the framework and was implemented successfully in a prototype computer simulation with a graphical user interface. Karlaftis, Kepaptsoglou, and Lambropoulos (2007) developed a three-stage approach to allocate available resources to the restoration of a transportation system in terms of the contribution of each bridge to the operation of the network.

Frangopol and Bocchini (2011) optimised the post-disaster restoration schedule for a transportation system with respect to total cost and resilience, the definition of which is the area *below* the recovery trajectory (the dark-shaded trapezoid shown in Figure 1) using total travel time and total travel distance as the network performance metrics. In a later study (Bocchini & Frangopol, 2012), the authors added the time required to recover a certain level of network functionality (less than complete recovery) as another objective in optimising the network restoration schedule. More recently, Karamlou and Bocchini (2014) proposed a multiobjective optimisation model to maximise the network resilience and minimise the required time to connect critical nodes (e.g. healthcare facilities and operations centres) in the network.

The network performance metrics used in post-disaster recovery in the studies as reviewed above include rapidity (recovery time), monetary loss (user cost), service performance (travel time and travel distance), and area under the recovery curve; however, no methods could be located which focus on the shape of the recovery trajectory. The shape, however, provides additional information and a novel perspective on the efficiency of the network restoration process. For example, as shown in Figure 2, the four recovery trajectories share the same rapidity, that is, recovery time. Assuming equal levels of community investment, curve 1 represents the best recovery strategy and curve 4 is the worst among all the alternatives.

Furthermore, recovery curve 2 is better than curve 3 due to its more efficient early-stage recovery which reduces early losses caused by network service disruption. This efficiency in early phase of recovery could also facilitate the recovery of other infrastructure systems whose service capabilities highly depend on the functionality of transportation network (e.g. emergency response and rescue immediately following hazard event). To the best of our knowledge, the existing network recovery scheduling frameworks are generally not capable of distinguishing recovery trajectories 2 and 3. While Bocchini and Frangopol (2012) proposed to use the time required for network to recovery to a pre-defined level of functionality as an additional measure to evaluate the efficiency of the recovery process that proposal still leaves curves 2 and 3 indistinguishable if the prescribed function level is close to the intersection point of the two curves.

In this paper, firstly, a novel metric for evaluating the relative efficiency of alternative network recovery strategies is introduced. Subsequently, a restoration scheduling methodology for network post-disaster recovery that minimises the overall network recovery time and optimises the recovery trajectory is developed, which ultimately will reduce economic losses due to network service disruption. In the proposed method, the number of simultaneous repair interventions (actions) is constrained by the available resources in the community throughout the recovery period. In addition, this model dynamically updates the damage level of each individual bridge and the corresponding overall performance of the network during the recovery process until all the damaged bridges are restored.

The restoration scheduling model is stochastic in nature because the uncertainties associated with parameters that are critical for network recovery, e.g. the restoration intervention duration for each damaged bridge and traffic flow on roads and bridges, are propagated throughout the analysis. The optimisation problem in this study is formulated as a version of the dynamic job shop problem, which is known to be NP-hard (Gonçalves, de Magalhães Mendes, & Resende, 2005). A genetic algorithm (GA) is used to search for near-optimal solutions in an efficient manner. Monte Carlo Simulation (MCS) is employed to sample the stochastic parameters to quantify the uncertainties associated with network recovery process.

The remainder of the paper is organised as follows. Section 2 introduces the resilience-based transportation network performance metric used in this study. In Section 3, we define the metrics for measuring the efficiency of the network recovery process and then develop the mathematical formulation for resilience-based network recovery optimisation. In Section 4, a hypothetical bridge network comprised of 30 nodes and 37 bridges is generated to illustrate the implementation of the developed methodology in a context of a considered scenario earthquake. A sensitivity study using this network illustrates the impact of the resourcefulness of a community and time-dependent commitment of resources on the network recovery time and trajectory. Conclusions and future work are summarised in Section 5.

2. Resilience-based performance metric of road networks

Many performance metrics for transportation networks, such as maximum traffic flow capacity and minimum travel time or distance, can be used to measure network performance under normal operational conditions but are not directly applicable to the analysis of post-disaster recovery following severe natural hazards. Immediately following an extreme event, people typically are more concerned about whether they are able to travel from one place to another than the distance or the speed at which they can travel. Connectivity reliability, as a network performance measure, could address the above-mentioned deficiencies but does not reflect the different levels of importance in the roles that different roads and bridges play in the functionality of the network.

Hence, connectivity reliability does not fully support resilience-based decisions on engineering interventions that are directly implemented at the network component (roads and bridges) level. A network performance metric recently introduced by Zhang and Wang (2016) and formulated in the context of community resilience to natural hazards, uses the weighted average number of reliable independent pathways between all origin-destination (O-D) pairs, denoted WIPW, as a performance measure of transportation networks. In this study, we adopt the WIPW as the network performance metric (the vertical coordinate of the resilience curves illustrated in Figures 1 and 2) for optimising post-event network recovery scheduling.

Let $G = (V, A)$ denote the road network, where $V = \{1, 2 \ldots n\}$ is the set of nodes, which is partitioned into a set $E = \{1, 2 \ldots e\}$ of emergency nodes (including critical emergency response facilities, e.g. fire stations and hospitals) and a set $N = \{e+1, e+2 \ldots n\}$ of normal nodes (representing major destinations, e.g. residential areas, economic hubs, and major road intersections); and $A = \{1, 2 \ldots m\}$ is the set of arcs (links) that represent roads without or with a maximum of one bridge.[1] The network performance metric, WIPW, is written as (Zhang & Wang, 2016):

$$\mathrm{WIPW}(G) = \mathcal{R}(G) = \sum_{i=1}^{n} w_i \frac{1}{n-1} \sum_{j=1, j\neq i}^{n} \sum_{k=0}^{K_{(i,j)}} w_k(i, j) \cdot R_k(i,j) \tag{1}$$

where $K_{(i,j)}$ is the total number of independent pathways[2] (IPW) between node $i \in V$ and node $j \neq i \in V$; $P_k(i,j)$ represents the kth IPW between node $i \in V$ and node $j \neq i \in V$, and $R_k(i,j)$ represents the reliability (probability of surviving a hazard) of $P_k(i,j)$. The weighting factor $w_k(i,j)$ is applied to $P_k(i,j)$, which is a function of the average daily traffic (ADT, denoted as F_{ij} in the subsequent sections) and the length (denoted as L_{ij} in the subsequent sections) of each arc that is a portion of the $P_k(i,j)$; weighting factor w_i is applied to node $i \in V$, which is a function of the distance from node i to its nearest emergency response facilities represented by emergency node $i \in E$. The detailed formulation of each item in Equation (1) and the complete algorithm to evaluate WIPW can be found in Zhang and Wang (2016).

This resilience-based network performance measure encompasses the following four important characteristics of network resilience: (1) the *network redundancy*, encapsulated in the term $K_{(i,j)}$ in Equation (1), reflects the number of alternative or back-up independent paths between all possible O-D pairs. (2) the *network component reliability*, encapsulated in the term $R_k(i,j)$, relates to the probability of bridges (and roads) being functional (fully or partially) after a given hazard event. For example, bridges with a higher reliability are likely to have less damage and require less time and resources to recover following a disaster; such attributes should be considered in effective network risk mitigation and recovery strategies. (3) *the importance levels of network components,* encapsulated in the term $w_k(i,j)$ (as a function of arc ADT and length) in Equation (1), reflect the different service levels of bridges and roads in terms of the roles that they play in supporting the overall network functionality. The ADT describes the historical traffic flow on each roadway. It is more accurate as a roadway importance measure than the traffic pattern predicted by existing traffic assignment models (Davis, 1997) because the user pattern of the road system is affected by many factors, including distribution of origins and destinations, distance and travel time of paths, congestion, facilities along the path, user preferences, etc. (4) *the role of the transportation network in post-disaster emergency response* is considered in the performance metric, through the term w_i in Equation (1), by applying heavier weights on roads and bridges that are topologically in close proximity to emergency facilities, as they likely play important roles in community emergency response and rescue immediately following the hazard event.

The WIPW was originally introduced as a network performance metric for pre-event risk mitigation decisions. In adapting the WIPW in this study for network post-disaster recovery scheduling optimisation, its formulation in Equation (1) need to be modified. Specifically, the pre-event reliability of IPW, $R_k(i,j)$, must be replaced by its post-event serviceability. The post-event service level of an arc (a road segment or a bridge) is a function of its damage level denoted as q_a for all $a \in A$, which can be measured on a 0 to 4 scale, corresponding to the damage levels of none, slight, moderate, extensive and complete (HAZUS MH-2.2, 2015). The service level of each arc $a \in A$ is ideally set $(1 - \frac{q_a}{4})$ (Bocchini & Frangopol, 2012); i.e. if an arc is fully damaged ('complete' damage state), q_a is set to be 4, and the corresponding service level is 0; otherwise, the arc service level ranges from 0 to 1. Subsequently, the service level of the IPW $P_k(i,j)$ is approximated as the product of the service levels of all arcs $a \in P_k(i,j)$. Accordingly, the WIPW for a damaged transportation network can be computed as:

$$\mathrm{WIPW}(G) = \mathcal{R}(G) = \sum_{i=1}^{n} w_i \frac{1}{n-1} \sum_{j=1, j\neq i}^{n} \sum_{k=0}^{K_{(i,j)}} w_k(i,j) \prod_{\forall a \in P_k(i,j)} \left(1 - \frac{q_a}{4}\right) \tag{2}$$

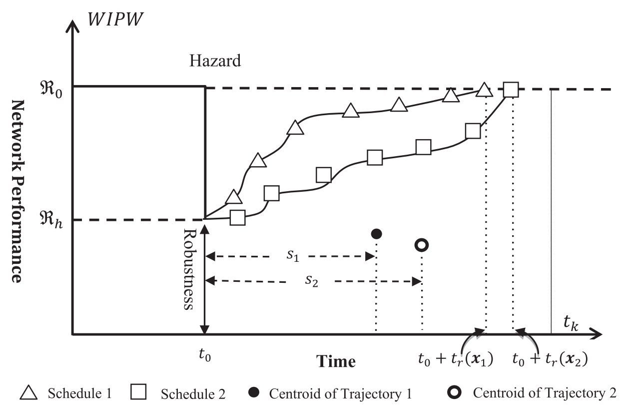

Figure 3. Skew of network recovery trajectory.

For post-event recovery scheduling investigated in this study, a damaged transportation network is considered as fully recovered if the network WIPW computed using Equation (2) returns to its pre-disaster level (without damaged network components).

3. Optimisation of network recovery scheduling

In this study, two metrics for resilience-based network recovery planning are introduced. The first metric is the total recovery time (TRT), t_r, after which the network is restored to its 'undamaged' condition (damage level for all arcs equals to 0 and network WIPW resumes to its pre-disaster value). As discussed previously, the TRT alone is not sufficient to evaluate the efficiency of network recovery strategies, which is partially encapsulated in the shape of the recovery trajectory. For example, Figure 3 shows two recovery trajectories as a function of time resulting from two different network restoration schedules, where the network performance (vertical axis) is measured by WIPW; $\mathcal{R}_0$ and $\mathcal{R}_h$ denote, respectively, the network WIPW before and immediately after the extreme event.

It is obvious that while restoration schedules 1 and 2 lead to approximately the same network recovery time, schedule 1 is notably more efficient than schedule 2 with respect to the economic losses incurred due to interrupted network service during recovery. Therefore, a second metric is introduced for evaluating the effectiveness of network restoration schedules – the skew of the recovery trajectory (SRT), defined as the centroid of the area below the recovery trajectory (from t_0 to t_k) with respect to $t = t_0$. The SRT associated with schedules 1 and 2 are marked in Figure 3 as s_1 and s_2, respectively. If the recovery were instantaneous, s would be equal to 0. This two-dimensional recovery metric, i.e. TRT and SRT, defines the objective functions in finding the optimal scheduling for the network recovery.

Although the scheduling framework introduced in this study applies to any arc within the network, i.e. both bridges and road segments, the subsequent discussion is focused on bridges as they are the most vulnerable arcs in the transportation network. Let $B = \{1, 2 \ldots m\}$ denote the set of network bridges. The recovery scheduling problem then is to determine an optimal schedule $\boldsymbol{x} = \{x_1, x_2, \ldots, x_d\}$ for the repair of all $d \le m$ damaged bridges, where $\boldsymbol{x}$ is the time at which restoration is initiated for bridges $b = 1, \ldots, d$, such that both the network TRT and SRT are minimised. Let D_b denote the duration of restoration intervention for each bridge $b = 1, \ldots, d$. The network TRT associated with the schedule $\boldsymbol{x}$, $t_r(x)$, is then:

$$t_r(\boldsymbol{x}) = \max_{b=1,2\ldots d} (x_b + D_b) - t_0 \tag{3}$$

The network SRT associated with the scheduling plan $\boldsymbol{x}$, $s(\boldsymbol{x})$, the centroid of the area under the recovery trajectory as shown in Figure 3, can be calculated by Equation (4), which requires the integrals of WIPW, i.e. $\mathcal{R}(t)$, as a function of time. As discussed previously, computing WIPW involves using Dijkstra's algorithm (Skiena, 1990) to search for IPWs for all O-D pairs, which cannot be performed in closed-form. Therefore, WIPW is estimated at discrete points in time; consequently, the recovery trajectory (expressed in terms of WIPW) is discretised into step functions. In addition, $T = \{t_0, t_1, \ldots, t_k\}$ is set such that $t_0 \le t_1 \le \ldots \le t_k$, in which the difference between any adjacent time points is a constant time increment Δt. The SRT can then be approximated by:

$$s(\boldsymbol{x}) = \frac{\int_{t_0}^{t_0+t_k} \mathcal{R}(t) \cdot (t - t_0) \mathrm{d}t}{\int_{t_0}^{t_0+t_k} \mathcal{R}(t) \mathrm{d}t} \approx \frac{\sum_{i=0}^{k} t_i \mathcal{R}(t_i) \Delta t}{\sum_{i=0}^{k} \mathcal{R}(t_i) \Delta t} \tag{4}$$

Table 1. Summary of the realised optimisation formulation.

Description	Equations	Equation No.
Input parameters	Network topology: $G = (V, A)$ ADT: $F_{ij}(\xi)$; arc Length: $L_{ij} \forall (i,j) \in A$ Damage level of bridges: $q_b \in \{0,1,2,3,4\} \forall b \in B$ Bridge restoration duration: $D_b(\zeta_b) \forall b \in B$	
Decision variables intervention time for bridge b	$x = \{x_1, x_2, x_3, \ldots, x_d\}$	
Global Objective 1 Minimise total recovery time	$\min t_r(x) = \max_{b=1,2\ldots d} (x_b + D_b(\zeta_b)) - t_0$	(3)
Global Objective 2 Minimise skewness	$\min s(x) = \frac{\sum_{i=0}^{k} t_i \mathcal{R}(t_i) \Delta t}{\sum_{i=0}^{k} \mathcal{R}(t_i) \Delta t}$	(4)
Global Constraint 1 Network performance metric at time t	$\text{WIPW} = \mathcal{R}(G) = \sum_{i=1}^{n} w_i \frac{1}{n-1} \sum_{j=1, j \ne i}^{n} \sum_{k=0}^{K_{(i,j)}} w_k(i,j) \prod_{\forall a \in P_k(i,j)} (1 - \frac{q_a}{4})$	(2)
Local Constraint 2 Bridge damage level after repair	$q_b^t(x_b) = q_b[x_b + D_b(\zeta_b) > t], \quad b = 1, 2, \ldots, d, \forall t \in T$	(5)
Local Constraint 3 Simultaneous interventions cannot exceed maximum	$\sum_{b=1}^{m} [t \ge x_b][t \le x_b + D_b(\zeta_b)] \le N_{\text{SI}}^{\max}, \quad \forall t \in T$	(6)
Local Constraint 5 Complete recovery time	$t_r(x) \ge x_b + D_b(\zeta_b), \quad b = 1, 2, \ldots, d$	
Local Constraint 4 Variable interval	$x_b \ge 0, \quad b = 1, 2, \ldots, d$	

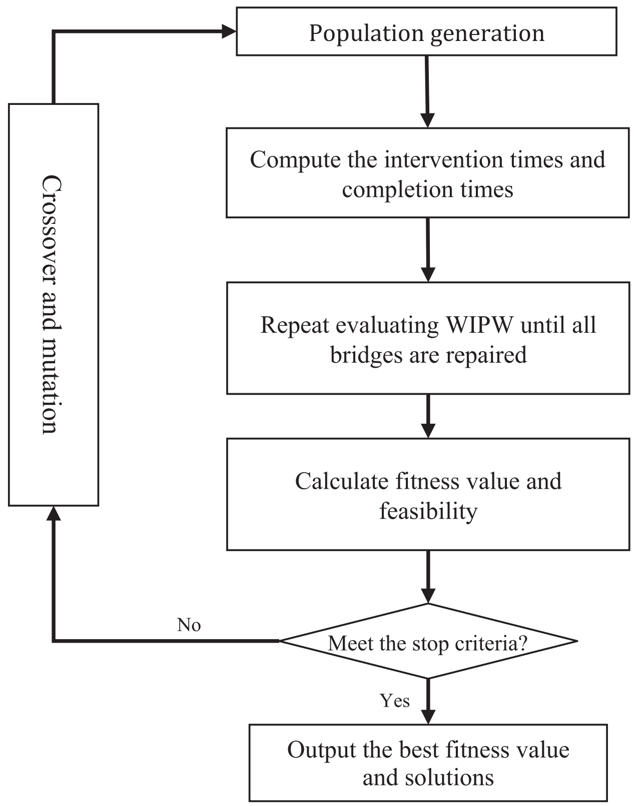

Figure 4. Flow chart of the GA.

in which t_k, set to be larger than any possible TRT, represents a common reference timeframe for computing SRT for different strategies. During the recovery phase, the damage level of each bridge b at any time $t \in T$ is:

$$q_b^t(x_b) = q_b \cdot [t < x_b + D_b] \tag{5}$$

where $[P]$ is the Iverson bracket, which returns 1 if P is true, and 0 otherwise.

Equation (5) ensures that the bridge b remains at its initial damage level q_b until its scheduled restoration intervention is completed; its damage level then becomes 0 after the completion of the intervention (i.e. when $t \geq x_b + D_b$). This assumption implies that selected lane closure during a bridge restoration project is not considered. That is, a bridges is not treated as a feasible link in searching for IPWs in the estimation of WIPW (i.e. $\mathcal{R}(t)$ in Equation (4)). At any given time $t \in T$, the number of simultaneous restoration interventions within the entire network, denoted by N_{SI}^t, can be computed as:

$$N_{\mathrm{SI}}^t = \sum_{b=1}^{m} \left[t \geq x_b\right]\left[t \leq x_b + D_b\right] \leq N_{\mathrm{SI}}^{\max} \tag{6}$$

where $[P]$ is the Iverson bracket as introduced above; $N_{\mathrm{SI}}^{\max}$ denotes the maximum number of simultaneous restoration interventions in the network allowed by the human and financial resources available in the community for the recovery of the road network following the hazard event. Accordingly, $N_{\mathrm{SI}}^{\max}$, imposes a constraint to the restoration scheduling, and thereby can impact the overall network recovery characteristics expressed in terms of TRT, $t_r(\boldsymbol{x})$, and SRT, $s(\boldsymbol{x})$.

The optimal restoration sequence for all damaged bridges and the time at which restoration is initiated for each bridge are obtained by minimising the network TRT (as defined by Equation (3)) and SRT (as defined by Equation (4)), under the constraint that only a prescribed maximum number of simultaneous restoration actions are possible at any given time (as expressed by Equation (6)). The complete optimisation model is summarised in Table 1. The ADT of each roadway [used in calculating the term $w_k(i, j)$ in estimating the WIPW for the damaged network as expressed in Equation (2)] and the duration of restoration intervention for each bridge are treated as random variables denoted, respectively, as $F_{ij}(\hat{\xi})$ for all $(i, j) \in A$ and $D_b(\hat{\zeta}_b)$ for all $b \in B$, where $\hat{\xi}$ and $\hat{\zeta}$ are stochastic variables. The distribution of $F_{ij}(\hat{\xi})$ can be derived from historical ADT measurements which are readily available from federal, state or local bridge owners. $D_b(\hat{\zeta}_b)$is assumed to have a normal distribution with a mean that is a function of both the damage level (q_b) and deck area of the bridge (A_b) (Fragkakis & Lambropoulos, 2004). Realisations of these random variables are denoted as $F_{ij}(\xi)$ and $D_b(\zeta_b)$.

The decision problem under investigation, as formulated in Table 1, is closely related to the NP-hard parallel machine scheduling problem (Cheng & Sin, 1990; Lenstra, Rinnooy Kan, & Brucker, 1977; Ullman, 1975). We assume bridge repair scheduling is non–pre-emptive, that is, once a crew has begun repair on a given bridge, they must complete their work before moving to another bridge. Additionally, the problem under investigation is further complicated by the necessary estimation of WIPW which, as discussed, is computed iteratively through a series of weighted shortest path problems. Approximation approaches are commonly utilised for addressing complex scheduling problems (e.g. Cheng & Gen, 1997).

Accordingly, the GA for the scheduling problem described in Gonçalves et al. (2005) is modified to be applicable for the purposes of this study, i.e. to identify the near-optimal solutions. The classical weighted-sum method (Deb, 2001; Kim & De Weck, 2005) is applied to the two objectives, TRT and SRT, to form a fitness function as follows:

$$\min[c \cdot t_r(x) + (1 - c) \cdot s(x)] \tag{7}$$

where $c \in [0, 1]$ is introduced as a weighting factor to impose the relative importance between the two objectives. A community (or government decision makers) can use different weighting factors based on their preferences, value and tolerances to different risks in order to obtain the 'best' strategy to their specific situation. For the example presented in the subsequent section, we simply apply equal weights to the two objectives for illustration. It is worth to note that even though the GA is implemented with one fitness function in the way we choose to perform the optimisation, there are alternative approaches to keep the objectives separate, e.g. non-dominated sorting GA II (Deb, Pratap, Agarwal, & Meyarivan, 2002). The optimisation process is summarised in Figure 4. The stochastic variables (i.e. $F_{ij}(\hat{\xi})$and $D_b(\hat{\zeta}_b)$) are realised using MCS.

Note that the two objectives, TRT and SRT, represent two very distinct characteristics of the network recovery. Summing the two objectives to form a fitness function is simply the way we choose to solve the optimisation problem efficiently, which is independent of the multiobjective optimisation formulation for the recovery as shown in Table 1. There are alternative

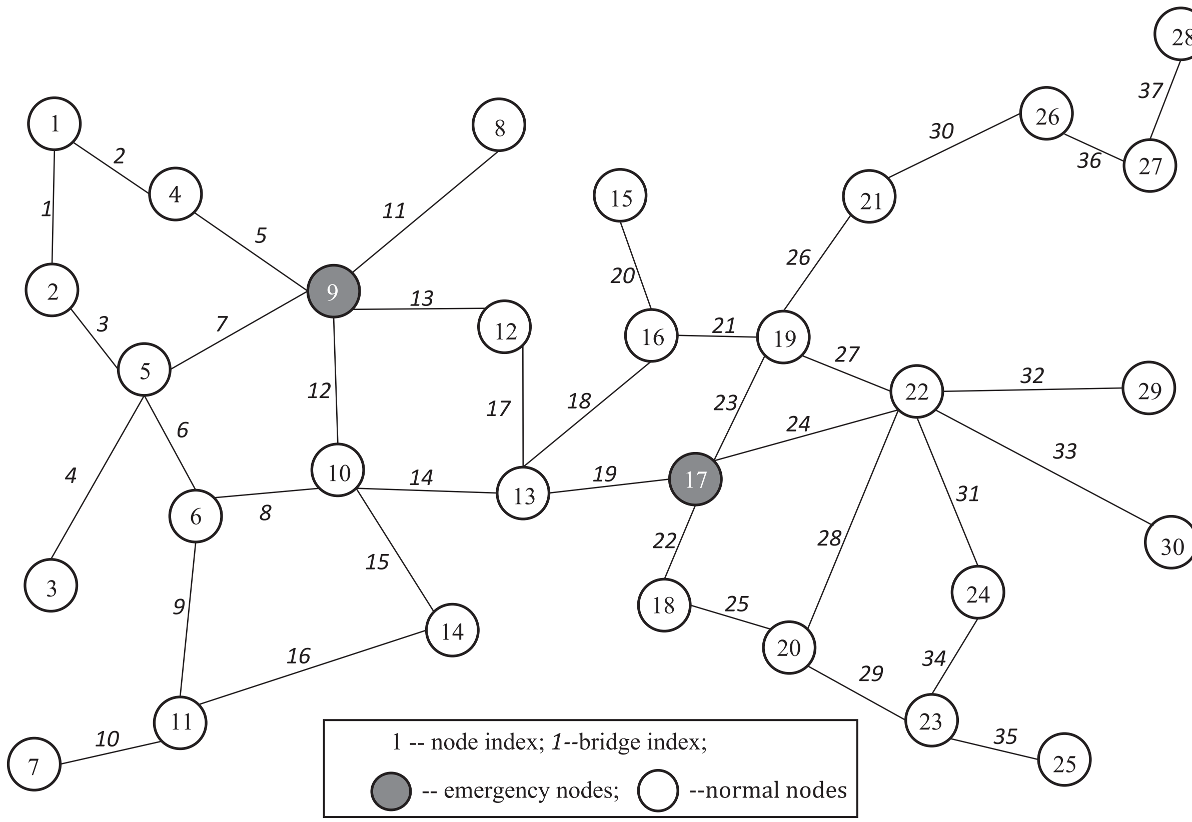

Figure 5. Hypothetical bridge network.

approaches to keep the objectives separately, e.g. non-dominated sorting genetic algorithm II, if preferred.

4. Numerical application

4.1. Bridge network characteristics

The proposed methodology is illustrated using a hypothetical road transportation network, shown in Figure 5, in which there are 37 arcs and 30 nodes. The gray nodes (Node 9 and 17) represent emergency nodes and other nodes represent normal nodes. For simplicity, each arc is assumed to be associated with exactly one bridge; out of the 37 bridges, 19 are steel (S) bridges and 18 are reinforced concrete (RC) bridges. A scenario earthquake with a magnitude 7.0 and an epicentre distance of 40 km from the centroid of the network is considered for this illustration. The network parameters used in this illustration, including bridge type and ADT, are tabulated in Table 2. The initial damage levels for all bridges for the stipulated hazard event are tabulated in Table 3.

Among the 37 bridges, 15 bridges sustained negligible damages, while the other 22 suffer damage at different levels: six have major (complete or extensive) damages, five are moderately damaged and 11 have slight damages. These initial damage levels are assigned inversely proportional to the bridge reliabilities (Zhang & Wang, 2016), and are used as a starting point for recovery scheduling. The restoration duration of each damaged bridge is also presented in Table 2. The uncertainty models that we assumed for the parameters $F_{ij}(\xi)$ and $D_b(\zeta_b)$ are summarised in Table 4.

The network WIPW prior to and immediately following the scenario event are 1.74 and 0.62, respectively, representing a 64.4% sudden drop in network performance (the vertical coordinates of the resilience curve). In the subsequent network recovery optimisation, it is assumed that the bridges with a damage levels 2–4 cannot carry traffic until the completion of their scheduled repair; furthermore, the limited available resources for recovery, representing a mid-income (average) community, only allow a maximum number of four bridges to be repaired and restored simultaneously, i.e. $N_{SI}^{t} \le 4$.

4.2. Optimal schedule for network restoration

The optimal bridge restoration schedule is determined using the GA summarised in Figure 4. The specific tuning parameters and stopping criterion play a critical role in the efficacy of the algorithm. These parameters include population size, crossover rate, mutation rate, and elitist mechanisms (see, e.g. Davis (1991)). A generation in the GA refers to one complete cycle as depicted in Figure 4. Table 5 summarises the GA parameters used in this illustration, which were determined after extensive experimentation.

In total, 500 random instances were generated using MCS and optimise the restoration of each of the 500 instances using the aforementioned GA. Figure 6 illustrates the distribution of optimal network recovery time under stochastic conditions. Considering the uncertainties associated with restoration duration and ADT for each bridge, the mean network recovery time is 21.3 months and the standard deviation is approximately 20 days. The Δt and t_k in Equation (4) are set to be 1 day and 50 months,

Table 2. Mean values of network parameters.

Bridge ID	Construction Type	ADT (Vehicle/ Day)	Duration of restoration intervention (Month)
1	RC	2200	4.10
2	RC	1900	1.71
3	S	2000	10.21
4	S	1500	0.00
5	RC	1900	6.52
6	S	2200	0.00
7	S	700	0.00
8	S	2400	0.00
9	S	2600	3.99
10	S	300	4.75
11	S	800	1.44
12	RC	900	2.38
13	S	2500	0.00
14	S	600	2.42
15	RC	2000	1.40
16	S	500	2.11
17	RC	2500	3.32
18	RC	2800	0.00
19	S	1300	2.49
20	S	1700	0.00
21	S	1500	9.04
22	S	1200	3.34
23	RC	1500	0.00
24	S	700	1.28
25	S	1800	0.00
26	S	900	5.02
27	S	600	5.25
28	RC	800	6.65
29	RC	1400	0.00
30	RC	2800	2.35
31	RC	1900	2.46
32	RC	2900	0.00
33	RC	1300	1.65
34	RC	900	0.00
35	RC	2200	0.00
36	RC	700	0.00
37	RC	3000	0.00

Table 3. Damage levels of individual bridges.

Damage Level	Condition	Number of bridges	Bridge ID
0	No damage	15	4, 6, 7, 8, 13, 18, 20, 23, 25, 29, 32, 34, 35, 36, 37
0–1	Slight damage	11	2, 11, 12, 14, 15, 16, 19, 24, 30, 31, 33
1–2	Moderate damage	5	1, 9, 17, 22, 27
2–3	Extensive damage	3	5, 10, 26
3–4	Collapsed	3	3, 21, 28

Table 4. Statistics of the stochastic parameters.

Parameters	Notation	Distribution	Mean	COV
Average daily traffic (ADT)	$F_{ij}(\xi)$	Uniform	As tabulated in Table 2	0.05
Duration of restoration intervention	$D_b(\zeta_b)$	Normal		0.05

respectively. In the remainder of this section, the discussion is focused on the optimal solution for a single instance of the simulation, $\tilde{x}$, where all the random variables are taken as their mean values. This discussion is applicable for all other simulated scenarios.

Figure 7 depicts the fitness values defined by Equation (7) over the CPU time with three random initial populations in genetic algorithm. GA is allowed to run up to 60 min and it is observed that GA converges in 30 min. Therefore, the maximum allowable running time is set as 30 min for all experiments in this section. The best fitness value in the initial GA population is 78.14 and decreases to 49.95 in 30 min (600 generations). The fitness value of 49.95 is the sum of the network TRT (21.42 months) and SRT (28.53 months).

Figure 8 illustrates the quality of the *near-optimal solution* from each generation of GA with respect to the fitness function, which shows that TRT and SRT are highly positively correlated. Note that this correlation will be much less if *all feasible solutions* are included in the Figure 8. Even with only the near-optimal solutions, Figure 8 indicates that for a given TRT there exist many alternative strategies with different SRT representing different recovery trajectories. This observation confirms that TRT alone, if used as the sole objective for recovery, is not sufficient to ensure the optimal recovery schedule with the 'best' trajectory. The SRT ensures the recovery efficiency among the alternative schedules that represent the same recovery time.

The optimal network restoration schedule is illustrated in Figure 9, which shows the times at which restoration intervention is initiated and completed for each damaged bridge. The length of the bar associated with each bridge is the duration of the intervention. This optimum schedule allows all damaged bridges in the network to be restored in less than 21 months, given that the maximum of 4 bridges can be repaired simultaneously. To evaluate the efficiency of this scheduling, we compare this optimal solution with a naïve network restoration schedule in which all the damaged bridges tabulated in Table 4 are repaired in a randomly selected sequence as shown in Figure 10. In this case, 23.5 months are required to completely restore the network.

Figure 11 illustrates that the network recovery trajectory associated with the optimal recovery plan is superior to that of the random restoration sequence. Note that these two recovery schedules employ the same amount of resources and the only difference between them is the sequence in which the damaged bridges are restored to their pre-event conditions. Although, the 2.5-month seems to be an insignificant improvement in this illustration, one that could be achieved by adding some common sense to the completely random strategy, the advantage of this scheduling algorithm would become more obvious when dealing with large, extensively damaged networks where the decision variables, possible alternative strategies and constraints create a complex decision problem where intuition may not apply.

Furthermore, if a short-term network recovery objective is to ensure that there is at least one path, on average, between each O-D pair (i.e. the performance metric WIPW is equal or greater than 1), then the optimal recovery scheduling achieves this objective 8 months earlier than the random scheduling. We note that the bridges selected in the early phase in the optimal solution, i.e. bridges 14, 24, 28, are the bridges with the highest impact on the overall network performance, as measured by WIPW, because they are shared by multiple O-D pairs and are close to the emergency facilities. These results demonstrate that the optimal scheduling of bridge restoration can greatly improve the efficiency of the transportation network recovery. Bridge authorities can use this information to allocate their limited resources intelligently to both minimise total network recovery time and to maximise the recovery efficiency.

Table 5. Parameters setting in the GA.

Parameter	Value
Population	50
Cross-over rate	0.9
Mutation rate	0.3
Elitist selection	20
Maximum generations	1000
Maximum time	1800 s

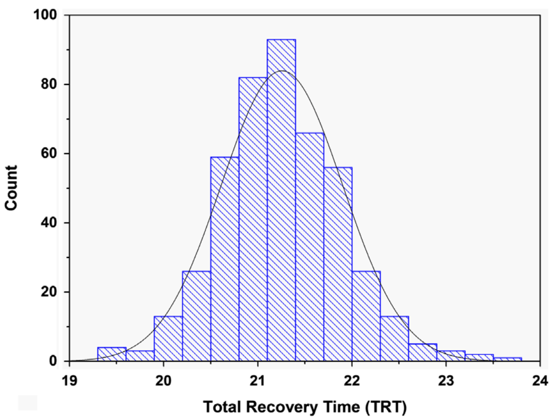

Figure 6. Probability density of the TRT.

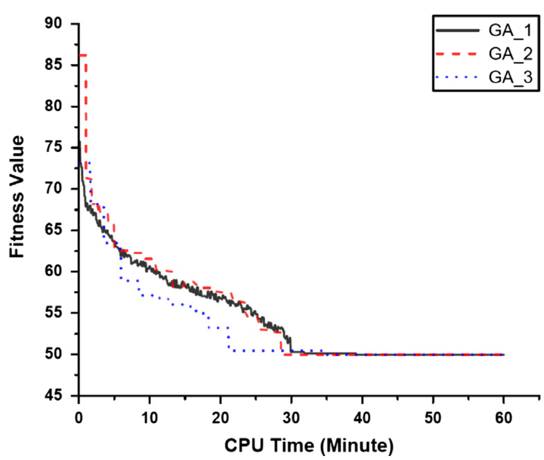

Figure 7. Fitness values over time with three random initial populations in GA.

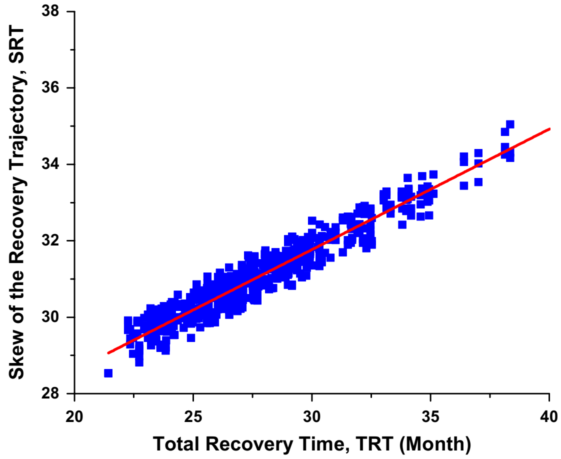

Figure 8. TRT and SRT of the optimal solutions.

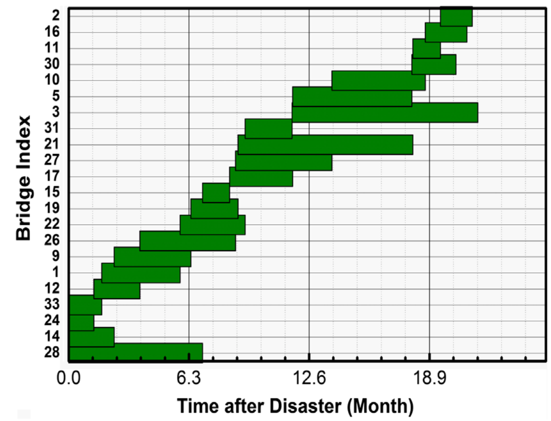

Figure 9. Optimal scheduling with times for initiation and completion of restoration for each damaged bridge.

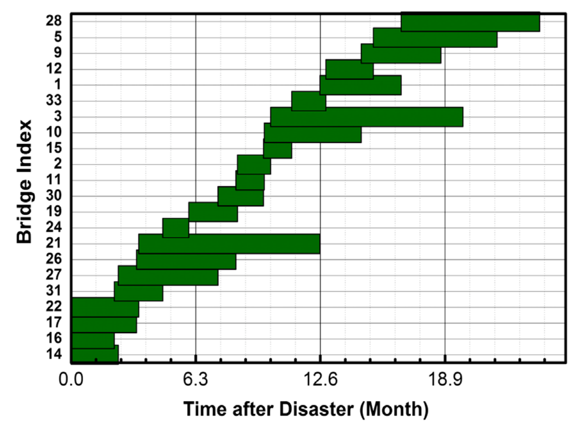

Figure 10. Naïve (random) bridge restoration sequence.

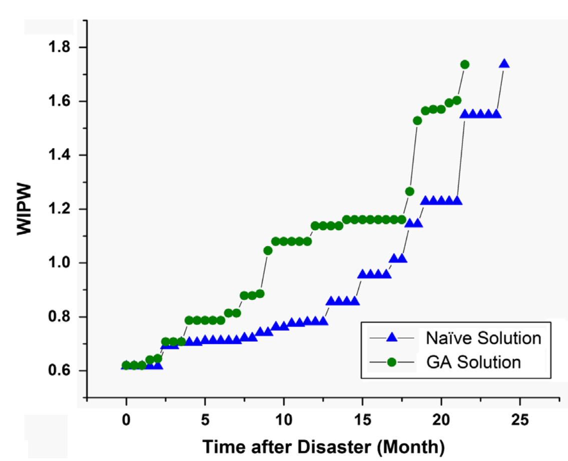

Figure 11. Network recovery trajectories with different restoration schedules.

To investigate the sensitivity of the scheduling to the resourcefulness of the community (an important characteristic of community resilience), rather than assuming a constant amount of recovery resources (i.e. $N_{SI}^{max} = 4$), it is now assumed that the maximum number of simultaneous restoration interventions, is a dynamic quantity, which changes the recovery process to

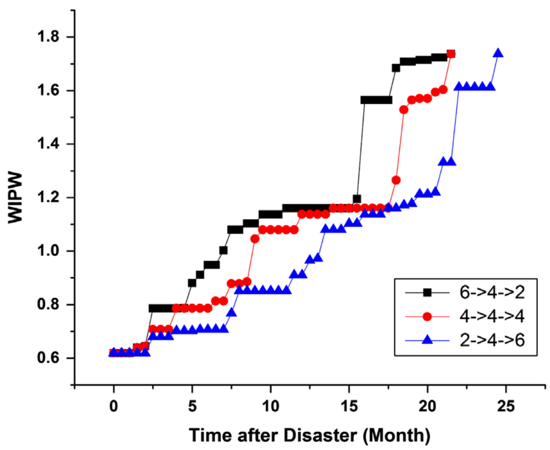

Figure 12. Resilience as a function of time under different recovery capability.

reflect different community social-economic structures and investment patterns. For instance, poorer communities may have fewer resources available immediately following the event and may depend on outside resources which take time to deploy. To address this case, we assume that the value of N_{SI}^{max} is 2 for the first 7 months, 4 from the 7th to 14th months, and 6 after the 14th month.

Conversely, a wealthy community might have more resources on hand to address the initial impacts of a disaster but may decrease the investment in recovery as the network resilience improves. To model such a situations, it is assumed that N_{SI}^{max} is dynamically decreasing from $N_{SI}^{max} = 6$ for the first 7 months, 4 for the following seven months, and then, 2 until all bridges are repaired. Figure 12 displays the associated resilience trajectories for the three communities with different resource investment patterns: wealthy (6- > 4- > 2), middle-income as considered previously with constant recovery resources (4- > 4- > 4) and poor (2- > 4- > 6). The recovery time of the wealthy and middle-income communities are approximately the same; however, the SRT of the wealthy community indicates a more efficient recovery schedule.

The network performance metric WIPW of the wealthy community achieves the value of 1 at month 7 which is two months earlier than is achieved by the average community. Furthermore, although the poor community has six simultaneous interventions in progress after 14 months, its TRT still is 3 months longer than that of both the wealthy and the average communities. It is evident that the resource allocation pattern as a function of time can significantly impact the efficiency of the network recovery.

5. Conclusions

This paper has presented a novel and dynamic model to optimise the restoration schedules of transportation networks following extreme events. The model incorporates a network resilience-based performance metric, recovery trajectory, community resourcefulness, and uncertainties relating to damage levels and restoration duration of damaged bridges in a quantitative resilience-based decision framework for road network recovery. An efficient metaheuristic approach was employed to find near-optimal solutions for recovery scheduling. The following three aspects of the restoration process have been addressed:

First, a two-dimensional metric – TRT was introduced, and the SRT – as measures for the network recovery planning, both of which are significantly affected by the restoration sequence when resources for post-disaster recovery are limited. This two-dimensional metric can be used collectively as the objectives in identifying the optimal post-event scheduling for the network recovery.

Second, according to Figures 11 and 12, simple functions (linear or nonlinear) for recovery trajectory apparently do not exist in even simple networks such as the one considered herein. Different prioritisation schedules can lead to significant changes in both TRT and SRT. The dynamic nature of available resources (immediately on-hand or delayed due to outsourcing) can have a notable impact on the network recovery time and trajectory. Even under circumstances in which the total amount of resources utilised in the recovery period is the same, the recovery trajectory is sensitive to the timing in which such resources are made available.

Third, both the scheduling framework and the GA used to obtain the optimal solutions can be extended to handle large and complex networks. This problem is NP-Hard (Lenstra & Kan, 1981); accordingly, the problem solving time may increase significantly with the size of the network. However, there is no limitation regarding network size on the mathematical formulation itself presented herein. Moreover, many advanced techniques can be employed to reduce the solving time, such as parallelised computing. Finally, the distribution of recovery time under stochastic conditions, the intelligent network restoration scheduling (intervention time and completion time) and the corresponding recovery trajectory can be visualised easily, which provides a wealth of information for bridge authorities to make decisions regarding the post-disaster recovery of transportation networks.

Notes

1. In the WIPW formulation, a link is a segment that can only have one bridge at most, because the mitigation decision is made on individual bridges (links), each of which needs a unique identity in the network topology representation.
2. A pathway between a node-pair usually consists of multiple arcs connected in series. Independent pathways (IPW) are defined as the pathways between a node-pair that do not share any common arcs (road segments). Dijkstra's algorithm (Skiena, 1990) can be used to search for IPWs between any node pairs.

Acknowledgements

Any opinions, findings and conclusions or recommendations expressed in this paper are those of the authors and do not necessarily reflect NIST.

Disclosure statement

No potential conflict of interest was reported by the authors.

Funding

This work was supported, in part, by the Center for Risk-Based Community Resilience Planning, National Institute of Standards and Technology (NIST) [Federal Award No. 70NANB15H044].

ORCID

Charles Nicholson http://orcid.org/0000-0002-7023-8802

References

Bocchini, P., & Frangopol, D. M. (2012). Restoration of bridge networks after an earthquake: Multicriteria intervention optimization. *Earthquake Spectra, 28*, 426–455.

Bocchini, P., Frangopol, D. M., Ummenhofer, T., & Zinke, T. (2013). Resilience and sustainability of civil infrastructure: Toward a unified approach. *Journal of Infrastructure Systems, 20*, 04014004-1–04014004-16.

Bruneau, M., Chang, S. E., Eguchi, R. T., Lee, G. C., O'Rourke, T. D., Reinhorn, A. M., Shinozuka, M., Tierney, K., Wallace, W. A., & Winterfeldt, D. V. (2003). A framework to quantitatively assess and enhance the seismic resilience of communities. *Earthquake Spectra, 19*, 733–752.

Çağnan, Z., Davidson, R. A., & Guikema, S. D. (2006). Post-earthquake restoration planning for Los Angeles electric power. *Earthquake Spectra, 22*, 589–608.

Chang, S. E., & Shinozuka, M. (2004). Measuring improvements in the disaster resilience of communities. *Earthquake Spectra, 20*, 739–755.

Chang, S. E., & Nojima, N. (2001). Measuring post-disaster transportation system performance: The 1995 Kobe earthquake in comparative perspective. *Transportation Research Part A: Policy and Practice, 35*, 475–494.

Cheng, R., & Gen, M. (1997). Parallel machine scheduling problems using memetic algorithms. *Computers & Industrial Engineering, 33*, 761–764.

Cheng, T. C. E., & Sin, C. C. S. (1990). A state-of-the-art review of parallel-machine scheduling research. *European Journal of Operational Research, 47*, 271–292.

Cimellaro, G. P., Reinhorn, A. M., & Bruneau, M. (2006, April). Quantification of seismic resilience. In: *Proceedings of the 8th US National Conference on Earthquake Engineering. Presented at the 8th US National Conference on Earthquake Engineering* (p. 10). San Francisco, CA, USA.

Cimellaro, G. P., Reinhorn, A. M., & Bruneau, M. (2010a). Seismic resilience of a hospital system. *Structure and Infrastructure Engineering, 6*, 127–144.

Cimellaro, G. P., Reinhorn, A. M., & Bruneau, M. (2010b). Framework for analytical quantification of disaster resilience. *Engineering Structures, 32*, 3639–3649.

Davis, G. (1997). Accuracy of estimates of mean daily traffic: A review. *Transportation Research Record: Journal of the Transportation Research Board, 1593*, 12–16.

Davis, L. (Ed.) (1991). *Handbook of genetic algorithms* (Vol. 115). New York, NY: Van Nostrand Reinhold.

Deb, K. (2001). *Multi-objective optimization using evolutionary algorithms* (Vol. 16). John Wiley & Sons.

Deb, K., Pratap, A., Agarwal, S., & Meyarivan, T. A. M. T. (2002). A fast and elitist multiobjective genetic algorithm: NSGA-II. *IEEE Transactions on Evolutionary Computation, 6*, 182–197.

Gonçalves, J. F., de Magalhães Mendes, J. J., & Resende, M. G. (2005). A hybrid genetic algorithm for the job shop scheduling problem. *European Journal of Operational Research, 167*, 77–95.

FEMA/NIBS. (2015). *Multi-hazard loss estimation methodology earthquake model* (HAZUS-MH 2.2). Washington, DC: Technical Manual.

Frangopol, D. M., & Bocchini, P. (2011). Resilience as optimization criterion for the rehabilitation of bridges belonging to a transportation network subject to earthquake. In *Proceedings of the 2011 Structures Congress* (pp. 14–16). Las Vegas, NV.

Fragkakis, N. P., & Lambropoulos, S. (2004). A quantity and cost estimate model for concrete road bridges. *Technica Chronica I: Scientific Journal of Technical Chamber of Greece, 2–3*, 65–77.

Karamlou, A., & Bocchini, P. (2014). Optimal bridge restoration sequence for resilient transportation networks. In *ASCE Structures Congress 2014* (pp. 1437–1447). Boston, MA.

Karlaftis, M. G., Kepaptsoglou, K. L., & Lambropoulos, S. (2007). Fund allocation for transportation network recovery following natural disasters. *Journal of Urban Planning and Development, 133*, 82–89.

Kim, I. Y., & De Weck, O. L. (2005). Adaptive weighted-sum method for bi-objective optimization: Pareto front generation. *Structural and Multidisciplinary Optimization, 29*, 149–158.

Lenstra, J. K., Rinnooy Kan, A. H. G., & Brucker, P. (1977). Complexity of machine scheduling problems, In: P. L. Hammer, E. L. Johnson, B. H. Korte, & G. L. Nemhauser (Eds.), *Annals of discrete mathematics* (Vol. 1, pp. 343–362). Elsevier.

Lenstra, J.K., & Kan, A.H.G. (1981). Complexity of vehicle routing and scheduling problems. *Networks, 11*, 221–227.

Miles, S. B., & Chang, S. E. (2006). Modeling community recovery from earthquakes. *Earthquake Spectra, 22*, 439–458.

Shinozuka, M., Chang, S. E., Cheng, T. C., Feng, M., O'rourke, T. D., Saadeghvaziri, M. A., Dong, X., Jin, X., Wang, Y., & Shi, P. (2003). Resilience of integrated power and water systems. *Multidisciplinary Center for Earthquake Engineering Research, 155*, 22–43.

Skiena, S. (1990). Dijkstra's algorithm. In: M. A. Reading (Ed.), *Implementing discrete mathematics: Combinatorics and graph theory with mathematica* (pp. 225–227). Reading, MA: Addison-Wesley.

Ullman, J. D. (1975). NP-complete scheduling problems. *Journal of Computer and System Sciences, 10*, 384–393.

Wang, S., Sarker, B. R., Mann Jr., L., & Triantaphyllou, E. (2004). Resource planning and a depot location model for electric power restoration. *European Journal of Operational Research, 155*, 22–43.

Xu, N., Guikema, S. D., Davidson, R. A., Nozick, L. K., Çağnan, Z., & Vaziri, K. (2007). Optimizing scheduling of post-earthquake electric power restoration tasks. *Earthquake Engineering & Structural Dynamics, 36*, 265–284.

Zhang, W., & Wang, N. (2016). Resilience-based risk mitigation for road networks. *Structural Safety, 62*, 57–65.

Zobel, C. W. (2011). Representing perceived tradeoffs in defining disaster resilience. *Decision Support Systems, 50*, 394–403.