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Optimal Post-disaster restoration schedule of transportation networks considering Resilience

Abstract

Transportation network is of vital importance for city maintaining and reconstruction especially after extreme events. Decision-making on the post-disaster restoration plan of transportation network has to take into account resource constraints and multiple preferences of stakeholders. Therefore, it is necessary to establish an approach to obtain a set of alternative general optimal restoration schedules for further selection. This paper explains the essential problems in network restoration scheduling, and presents a novel resilience-based universal optimization model for urban transportation network post-disaster restoration to reduce indirect loss. In the methodology, a new metric is introduced to measure the performance of transportation network, and three normalized independent resilience indicators are developed to characterize the functionality of a network in one disaster. Furthermore, a bi objective optimization model based on recovery trajectories is recommended to search for non-dominated optimal solutions. To illustrate the proposed method, Heuristic algorithms are used to solve the restoration schedule optimization problem of a hypothetical transportation network.

1. Introduction

Transportation network, which is the basis of social and economic activities in a society, plays a vital role in emergency rescue and reconstruction support after extreme events (e.g. earthquake, tsunami, storm, terrorism, etc.). However, transportation network itself is vulnerable to natural disasters that damage in one critical component (e.g. bridge, tunnel, etc.) influences the functionality of the entire network (Kilanitis & Sextos, 2018). Prior historical data indicates that the damage of transportation network due to extreme hazards, especially earthquake, can cause enormous socio-economic loss. For example, the Northbridge earthquake in 1994 caused approximately 140 road closures and over $40 billion in economic loss (Dong, 2014). The Wenchuan earthquake in 2008 caused about 69000 deaths and more than $100 billion in economic loss (Yuan, 2008). The loss caused by the disruption of transportation network can generally be classified into direct loss and indirect loss. The former is mainly determined by infrastructure damages related to the fragility of network components. While indirect loss, that usually overwhelmingly dwarfs direct loss (Bocchini, 2013), is induced by a decline in the service level of post-disaster network and mainly related to the restoration investment and disaster management.

Urban infrastructure resilience has become a research trend. A broadly accepted definition originated from a paper by Bruneau et al. (2003), in which the concept of resilience can be summarized as “ability of a system to withstand hazards when they occur, and recover quickly that minimizing socio-economic disruption”. A graphical expression is illustrated in Figure 1, where the resilience loss (R_L) is defined as the size of the degradation in the quality of functionality over time (light-shaded area, also known as the resilience triangle), and four properties—Robustness, Redundancy, Resourcefulness, Rapidity (4R) are used to measure resilience. Another widely used definition was proposed by Cimellaro et al. (2010), where the resilience within control time (R_{CT}) is normalized as the average residual functionality as shown in Figure 1 (dark-shaded area). Numerous contributions to urban infrastructure resilience include studies at the community level (Miles & Chang, 2006; Cimellaro, 2016), on lifeline systems (Chang & Shinozuka, 2004; Bocchini, 2013; Ouyang & Fang, 2017), on health-care systems (Bruneau & Reinhorn 2007; Isayama & Shaw, 2016), et al.

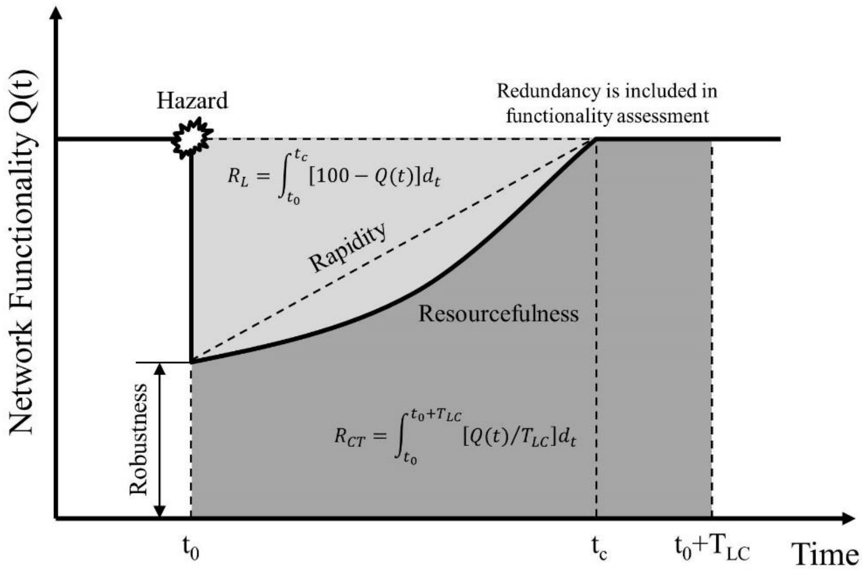


Figure 1. Resilience definitions (adapted from Bruneau et al. 2003)

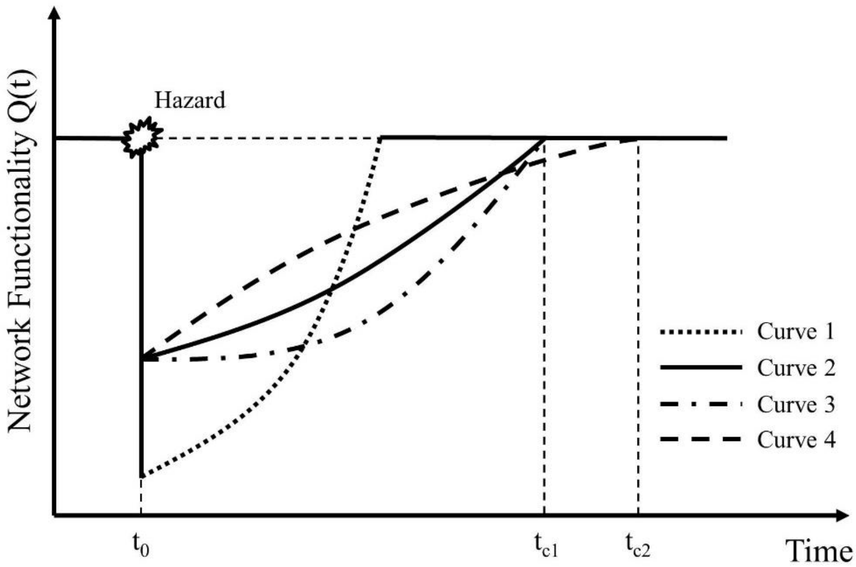


Figure 2. Recovery trajectories

For transportation network, Chang and Nojima (2001) utilized network coverage and transport accessibility to measure post-disaster performance of transportation network, and applied them to the urban rail and highway networks in Kobe, Japan. Grubesic, et al. (2008) examined various approaches in accessing facility importance and network vulnerability, and significant different results were obtained using these methods. Zhang and Miller-Hooks & Denny (2015) investigated the role of network topology and characteristics in coping with the resilience of transportation network by using three measurements—throughput, OD connectivity, and average reciprocal distance. Kim and Yeo (2016) proposed an evaluation method for the resilience of urban road network based on macroscopic fundamental diagram, and applied the concept to the road network of Gangnam district in Seoul, South Korea. Kilanitis and Sextos (2018) established a comprehensive, multi-criterion framework for seismic resilience assessment of roadway network composed of time-variant and cumulative indicators.

Resilience-based decision-making support during disaster management is one of the most promising fields for engineering practice (Bocchini, 2013). Frangopol and Bocchini (2011) proposed an optimization model for post-disaster restoration schedule of transportation network with respect to total present cost and R_{CT}, using both total travel time and total travel distance as the network performance metrics. In their later study (Bocchini & Frangopol, 2012), the time required to reach a target functionality level was added as another objective in the optimization model. In addition to the long-term resilience indicator, Karamlou and Bocchini (2016) introduced a connectivity-based resilience indicator to optimize the restoration priorities during medium-phase disaster management. Zhang and Wang (2017) presented a framework to optimize the restoration schedule for post-disaster road network based on the total recovery time and skew of recovery trajectory, where the network performance is measured by weighted average number of reliable interdependent routes over all origin-destination (OD) pairs. Unal and Warn (2017) developed a set-based optimization model to comprehensively take into account various restoration decision criteria of transportation network according to the design by shopping paradigm.

Various transportation network performance metrics have been used in previous studies as above (e.g. connectivity, travel time and travel distance). However, most of them focused on the performance changes in a specific network, but cannot be applied to compare the performance states between different networks. For example, the accessibility of a damaged complex network may still be higher than a complete simple network. Furthermore, current optimization methods as reviewed generally take R_L minimization or R_{CT} maximization as the main objective, and other preferences of decision-makers as secondary objectives to support decision-making, such as outcome values (e.g. total present cost and total recovery time) and mid-stage constraints (e.g. functionality-based and time-based). However, using R_L or R_{CT} alone cannot describe the resilience characteristics of a network, for example, R_L and R_{CT} are equal for curve 1 and curve 2 as illustrated in Figure 2, but with significant differences in functionality reduction and recovery. In real cases additionally, it is impossible to quantify all the preferences of stakeholders as objective functions, which may result in excessive computational effort. Therefore, it is necessary to establish a method to broadly explore alternative general optimal solutions, so that decision-makers could make a final choice from a limited number of optimal restoration schedules by weighting multiple preferences (Balling, 1999).

Functionality curve is an efficient way in accessing resilience, whereas few studies have been done in distinguishing recovery trajectories. As shown in Figure 2, the recovery trajectories of curve 2, 3 & 4 share the same starting point after the disaster, but with different recovery trajectories. Assuming equal resources available, you can tell that curve 2 is better than curve 3 because of a higher efficiency with the same recovery time, but no existing methods could distinguish curve 2 and curve 4. While the optimization model proposed by Zhang and Wang (2017) focused on the shapes of recovery trajectories, but the two metrics (TRT and SRT) were merged in one fitness function due to their high positive correlation.

Hence, it still leaves curve 2 and curve 4 indistinguishable if SRT of curve 4 is smaller than that of curve 2, as the weighting factor of the two objectives is difficult to determine.

In the field of decision-making, the set-based approach is recognized to have more advantages than traditional point-based method, because a set-based approach could explore the entire solution space for decision-makers to satisfy their preferences (Unal & Warn, 2017). This study aims to investigate the essential problems to be solved in post-disaster restoration scheduling from the point of view of recovery trajectories, and develop an optimization method to search for alternative general solutions for decision-making support accordingly. In this paper, first, a novel performance metric is defined for the analysis of post-disaster transportation network, which is suitable for performance comparisons between different networks. Subsequently, a three-indicator framework located which focus on the functionality curve is introduced to comprehensively describe the resilience characteristics of a network. Lastly, a bi-objective optimization methodology that maximizes the rapidity and efficiency of recovery is developed for post-disaster restoration scheduling, which could reduce the indirect loss ultimately. In the proposed method, the damage states of critical components and corresponding network functionality are dynamically updated until complete recovered, considering resource constraints. Since the optimization of restoration schedule is actually a dynamic job shop problem that is NP-hard (Gonçalves, et al., 2005), GA and NSGA-II are employed to search for the near-optimal solutions in an efficient manner.

The remainder of the paper is organized as follows. Section 2 introduces the performance metric of transportation network used in this study. In section 3, a three-indicator framework is defined for network resilience assessment. Section 4 explains the mathematical formulation of the optimization models for resilience-based post-disaster restoration scheduling. In section 5, a hypothetical transportation network comprised of 17 nodes, 24 arcs and 10 bridges is generated to illustrate the implementation of the proposed methodology considering a scenario earthquake. Conclusion and discussion are summarized in Section 6.

2. Performance metric of transportation network

Connectivity-based and traffic flow-based approaches are widely used in accessing transportation network performance under extreme events. For network with limited detour routes, such as rural transportation network, connectivity-based metrics appear reasonable.

However, when more detour routes are available, for urban transportation network, connectivity-based metrics are not applicable to reflect the impact of damages. In traffic flow-based approaches, total travel time and travel distance are the most common used network performance metrics to reflect post-disaster travel delays (Frangopol & Bocchini, 2012). However, these two metrics are mainly used to track the performance changes within a specific network with fixed traffic demand, and cannot reflect the importance levels of different roads and facilities in the network.

The post-disaster performance of a transportation network should be determined by the relationship between its remaining traffic capacity and dynamic traffic demand. Hence, a novel resilience-based network performance metric is defined in this study, using weighted average travel speed of all the roads in a network, denoted *WATS*. Unlike the above metrics, *WATS* fluctuates within a limited range (smaller than the speed limit), making it especially suitable for comparing the service levels between different transportation networks. In addition, as an easy-to-obtain metric after disasters, *WATS* can be collected by Remote Sensing and Vehicle-mounted GPS, using to estimate the real-time network performance and to modify the restoration schedule if necessary.

Introducing the terminology of graph theory (Czumaj & Jansen, 1985), let G = (V, A) denote the transportation network, where V= {1, 2 … n} is the set of nodes, and A= {1, 2 … m} is the set of arcs (links). Then the *WATS* of a transportation network and the quality of network functionality can be measured as:

$$WATS = \sum_{i=1}^{m} w_i S_i = \sum_{i=1}^{m} \frac{w_i L_i}{T_i} \tag{1}$$

$$w_i = \frac{C_i L_i}{\sum_{i=1}^{m} C_i L_i} \tag{2}$$

$$Q(t) = \frac{WATS(t)}{WATS(pre)} \tag{3}$$

where m is the total number of arcs in the network; A_i represents arc(i) in the network and S_i represents the travel speed of A_i, which is computed as arc length (L_i) divided by its average transit time (T_i). The weighting factor w_i applied to A_i, which reflects the importance level of an arc in the network, is a function of arc length (L_i) and its initial traffic capacity (C_i). It is noted that the sum of the weighting factors of all the arcs in a network is 1. The quality of network functionality at time t, denoted $Q(t)$, is estimated as its real-time weighted average travel speed, i.e. $WATS(t)$, divided by that before disaster, i.e. $WATS(pre)$. Therefore, a damaged network is considered as complete recovered if $Q(t)$ returns to 1 (all damaged components have been restored).

Establishing appropriate traffic analysis model is a basic step in estimating network performance. Travel behavior and demand can change significantly following a natural disaster. In the proposed method, the dynamic post-disaster traffic demand could be taken into account by assigning a step-wise OD matrix to the recovery process. Chang, et al (2012) summarized the post-earthquake traffic demand modification models for emergency analysis. As the prediction of OD transformation in long-time recovery involves multiple social and behavioral aspects that it is not addressed definitely (Kilanitis & Sextos, 2018). However, *WATS* could provide a good access to the network performance coupling both residual network capacity and dynamic traffic demand. Travel activities of network users are distributed by means of the Gravity Model (Casey, 1955), which suggests that the travel attraction between two traffic zones is proportional to their trip generation and attraction, but inversely proportional to the traffic impedance. User equilibrium (UE) model is used for traffic assignment (Wardrop, 1952), which is particularly suitable for the analysis of transportation network subjected to extreme events (Frangopol & Bocchini, 2012). The performance function of arcs used in this study is the Bureau of Public Road (BPR) equation (Martin, et al., 1998).

$$T_i = T_i^0 \left[1 + \alpha \left(\frac{V_i}{C_i}\right)^{\beta}\right] \tag{4}$$

where T_i^0 is the time spent to cover A_i at free flow, considering the limitations of the damaged critical components. V_i and C_i are the traffic volume and traffic capacity of A_i, in which the detrimental impact of the damaged components is also considered. α and β are parameters of the model, in general, α=0.15 and β=4.

This study is performed under the assumption that bridges are the only vulnerable components of transportation network as they are considered as most fragile in case of natural hazards (Frangopol & Bocchini, 2012; Zhang & Wang, 2017). The damage states of an individual bridge, which can be obtained by post-disaster inspection or pre-disaster simulation, are generally divided into five levels: none, slight, moderate, extensive and complete damage (FEMA, 2012). For a network arc consisting of several bridges, its damage state can be deduced according to the bottleneck model or associated model. The former holds that the damage state of an arc depends on its most damaged bridge (Shinozuka, 2006; Zhou, 2010), while the latter takes into account all damaged bridges in the arc. A commonly used associated model is illustrated in Chang, Shinozuka & Moore (2000), where the arc damage index (ADI) is computed using Equation (5). One thing should be mentioned is that arcs without bridges are assumed to be restored in a short time following the disaster, so they are not considered in the long-term recovery.

$$ADI = \sqrt{\sum_{i=1}^{N} BDI_i^2} \tag{5}$$

where N is the number of bridges contained in the arc. BDI_i is the damage index of bridge(i), using discrete values to quantify the damage states. Table 1 summarizes the values of BDI and ADI. Moreover, a conservative relationship between damage levels and residual performance indexes of arcs is defined in Table 2, including the reduction of traffic-carrying capacity and free-flow speed (FEMA, 2012; Guo, Liu, Li & Li, 2017). Arcs that exceed extensive damage are considered out of service.

Table 1. Definition of bridge damage index and arc damage index

Bridge damage level	None	Slight	Moderate	Extensive	Complete
BDI	0.0	0.1	0.3	0.75	1.0

Arc damage level	None	Slight	Moderate	≥Extensive
ADI	ADI≤0.5	0.5≤ADI<1.0	1.0≤ADI<1.5	ADI>1.5

Table 2. Damage level and residual rate of performance indexes of arcs

Damage Level	Residual percentage (%)	
	Traffic-carrying capacity	Free-flow speed
None	100	100
Slight	70	75
Moderate	30	50
≥Extensive	0	0

3. Resilience indicators of network

As discussed previously, the single-indicator assessment method using R_L or R_{CT} cannot comprehensively describe the resilience characteristics of a network. In this study, a three-indicator framework is introduced to characterize network resilience in one disaster, which can be better understood from the functionality curve in Figure 3. The first indicator is the residual ratio of functionality (*RRF*) after an extreme hazard, which can be computed as:

$$RRF = \frac{Q(t_0)}{Q(t_{pre})} \tag{6}$$

where $Q(t_{pre})$ and $Q(t_0)$ are the quality of network functionality before and after the disaster, respectively. Generally, $Q(t_{pre})$ is set to be 1, as the pre-disaster network is considered to be fully functional. *RRF* not only quantifies the network instantaneous loss, it also determines the starting point of recovery. The other two indicators are used to characterize the post-disaster recovery trajectory, which is determined by the restoration schedule of damaged bridges in this study. The second indicator is the rapidity of restoration schedule (*RRS*) normalized as the position of the recovery time within its feasible range, and the calculation formula is:

$$RRS = \frac{TRT_{max} - TRT}{TRT_{max} - TRT_{min}} \tag{7}$$

where *TRT* is the total recovery time of the schedule. TRT_{max} and TRT_{min} are the upper and lower limit of feasible network recovery time. The former is computed as the sum of the restoration durations of all damaged bridges, that is, the bridges in the network are restored one by one, considering minimum resources available. While the latter is equal to the longest restoration duration among the damaged bridges, indicating that all the bridges are restored simultaneously, with infinite resources available.

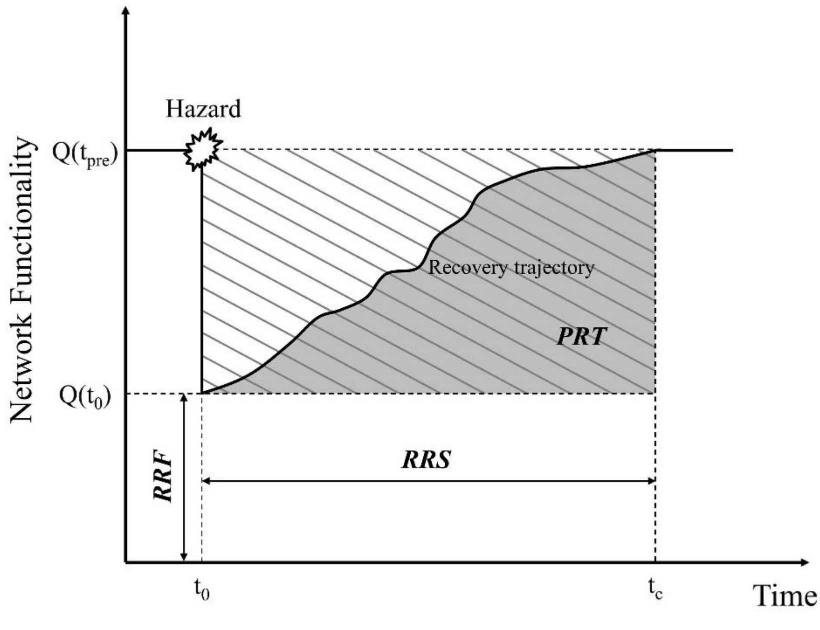


Figure 3. resilience indicators of network

In real cases, the restoration schedule is always conditioned by human and material investments during network recovery, so only a limited number of bridges could be restored simultaneously. The resource constraint in this study is considered as the number of identical engineering teams available throughout the recovery phase. Therefore, the restoration scheduling is defined as an allocation and sequence problem in terms of the damaged bridges. *RRS* determined by Equation (7) is only related to the allocation of bridges to be restored, but has nothing to do with the restoration sequence, so it is absolutely a Combination problem. This is also the reason why *RRS* alone is not sufficient to evaluate the restoration activities of a network. Consequently, a third indicator is defined to access the restoration priorities of the damaged bridges, computed as the ratio of the restored functionality over time (dark shaded area) to the entire functionality recovery zone (slash shaded area) in Figure 3, denoted as the plumpness of recovery trajectory (*PRT*).

$$PRT = \frac{\int_{t_0}^{t_c}[Q(t)-Q(t_0)]d_t}{[Q(t_{pre})-Q(t_0)]\cdot(t_c-t_0)} \tag{8}$$

where t_0 and t_c is the start and completion time of the network recovery. $Q(t)$ can be computed using the traffic analysis model discussed in section 2. Equation (8) indicates that normalized *PRT* is a relatively independent indicator to depict the shape of recovery trajectory in relation to the efficiency of restoration. For restoration schedules with identical allocation, i.e. *RRS*, *PRT* is determined by nothing but the restoration sequence of the damaged bridges, which is a Permutation problem.

The resilience assessment framework as illustrated above utilizes three independent indicators to characterize the functionality curve of one breakdown and recovery of a network. Normalized *RRF*, *RRS* and *PRF* make it possible to compare the resilience between different disasters and networks from a multidimensional prospective. Beyond that, R_L defined in Bruneau, et al (2003), which is considered to be closely related to the indirect loss (Kilanitis & Sextos, 2018), is employed for comparative analysis in this study. R_L can be converted by the three introduced indicators using Equation (9) based on the geometric relation. Accordingly, *RRF*, *RRS* and *PRF* are all linearly negative correlated to R_L, so they can be considered equally significant in determining indirect loss.

$$R_L = (1-RRF)(1-PRT)[TRT_{max} - (TRT_{max} - TRT_{min})\cdot RRS] \tag{9}$$

4. Optimization of network restoration schedule

The optimization purpose of this study is to search for general optimal restoration schedules without considering any preference of decision-makers. Therefore the overall optimization objective is set to be reducing indirect loss, which is also a main purpose in any resilience research. Normally, *RRF* can be determined by damage inspection, which is of great priority following a disaster (Chang & Nojima, 2001). Therefore, the problem to be solved is to optimize the restoration schedules for known damage scenarios. Two optimization models are established with respect to *RRS* & *PRF* and R_L, respectively. A detailed mathematical model is depicted as follows. It should be noted that, R_{CT} (as shown in Figure 1) is not selected in this study because of a lower comparative sensitivity in the results of different restoration schedules due to the intervention of the control time (T_{LC}). However, R_{CT} can be obtained by a simple conversion of R_L without affecting the conclusions of this paper.

Let $B = \{b_1, b_2 \cdots b_n\}$ denote the set of damaged bridges to be restored in the transportation network, and $D = \{d_1, d_2 \cdots d_n\}$ denote the restoration durations of the bridges, where d_i can be estimated as a function of both the damage level and desk area of bridge $b_i \epsilon B$ (Fragkakis & Lambropoulos, 2004). The restoration schedule is determined by $X = \{x_1, x_2 \cdots x_n\}$, where x_i is the time when restoration is initiated on bridge $b_i \epsilon B$. *RRS* associated with schedule *X* can be computed as:

$$RRS(X) = \frac{\sum_{i=1}^{n} d_i - \left[\max_{b \epsilon B}(x_b + d_b) - t_0\right]}{\sum_{i=1}^{n} d_i - \max_{b \epsilon B} d_b} \tag{10}$$

Because of the increase of the network functionality is driven by the restoration of bridges, the recovery trajectory can be discretized into step functions and $Q(t)$ can be estimated at discrete time points. Let $T = \{t_1, t_2 \cdots t_n\}$, in which $t_1 < t_2 \cdots < t_n$, denote the time points when any bridge restoration completed in the recovery trajectory. *PRT* and R_L in terms of schedule *X* can be computed as:

$$PRT(X) = \frac{\sum_{i=1}^{n-1}(t_{i+1} - t_i)[Q(t_i) - Q(t_0)]}{(t_n - t_0)[Q(t_{pre}) - Q(t_0)]} \tag{11}$$

$$R_L(X) = \sum_{i=0}^{n-1}(t_{i+1} - t_i)\left[Q(t_{pre}) - Q(t_i)\right] \tag{12}$$

During the recovery phase, it is assumed that a bridge remains at its initial post-disaster damage level until it is completely restored, and the restoration does not affect its passage. Let $I = \{i_1, i_2 \cdots i_n\}$ denote the damage indexes of bridges $b \epsilon B$ from the post-disaster damage inspection. Then the damage index of each bridge $b_i \epsilon B$ at any time $t \epsilon T$ is:

$$i_b^{t}(X) = \begin{cases} i_b, & t < x_b + d_b \\ 0, & t \geq x_b + d_b \end{cases} \tag{12}$$

The number of bridges under restoration simultaneously at any time $t \epsilon T$, denoted N_{rs}^t, is conditioned by:

$$N_{rs}^t(X) = \sum_{b=1}^{n}[t \geq x_b][t < x_b + d_b] \leq NT^{max} \tag{13}$$

where $[P]$ is the Iverson bracket, that returns 1 if it is true and 0 otherwise. NT^{max} is the number of identical engineering teams available throughout the recovery phase. It is assumed that an engineering team must complete the restoration of one bridge before moving to another. As discussed in Equation (7), If $NT^{max} = 1$, RRS is equal to 0 that the bridges have to be restored one after another. That is, the restoration schedule is wholly determined by the repair sequence, i.e. PRT.

The complete optimization models are summarized in table 2. The decision-making variable X, related to the combination and permutation of the bridges to be restored, is a NP-hard parallel machine scheduling problem (Cheng & Sin, 1990) with dimension n!. Therefore, Heuristic algorithms are used to search for near-optimal solutions in efficiency. Genetic Algorithm (Holland, 1984) and Non-dominated Sorting Genetic Algorithm-II (Deb, 2000) are modified to be applicable for this study. A detailed optimization process is illustrated in Figure 4. Note that, the two models share the same overall objective, i.e. indirect loss minimization. The set-based optimization model 1 will be further discussed in the following numerical application, while the point-based optimization model 2 is mainly for comparative analysis.

Table 3. Illustration of optimization models

Description:	Optimization model 1	Optimization model 2
Given parameters:	Network topology $G = (V, A)$	
	Arc length L_i and capacity C_i	
	Residual functionality of bridges $F = \{F_1, F_2 \cdots F_n\}$	
	Restoration duration of bridges $D = \{d_1, d_2 \cdots d_n\}$	
Constraints:	Bridge functionality i_b^t	
	Simultaneous restored bridges cannot exceed NT^{max}	
	Complete recovery time $t_c = max[(x_b + d_b) - t_0]$, $b \epsilon B$	
Variable:	Bridge start restoration time schedule $X = \{x_1, x_2 \cdots x_n\}$	
Objectives:	Maximize *RRS*	Minimize R_L
	Maximize *PRT*	
Algorithm:	NSGA-II	GA

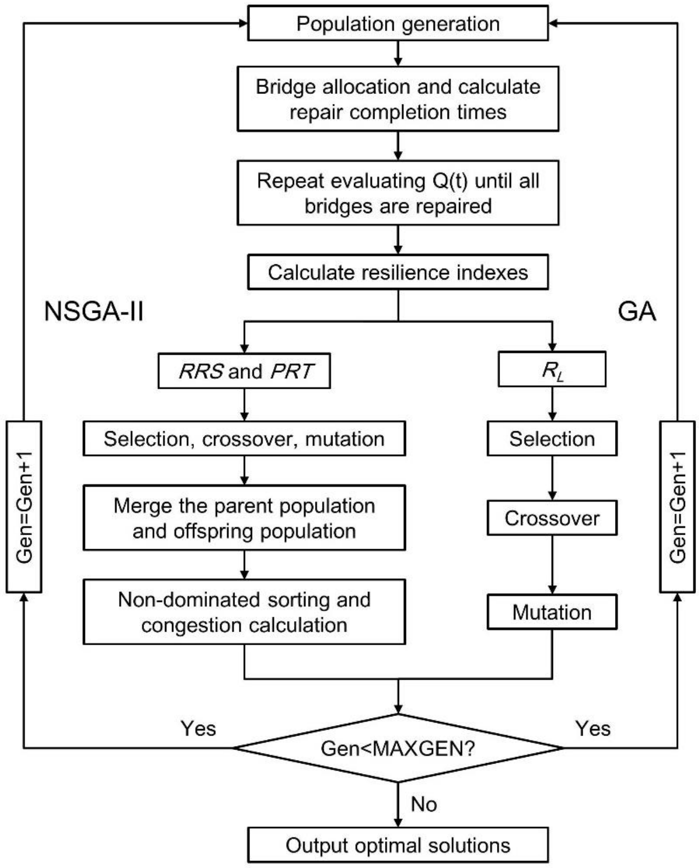


Figure 4. Flow chart of optimization

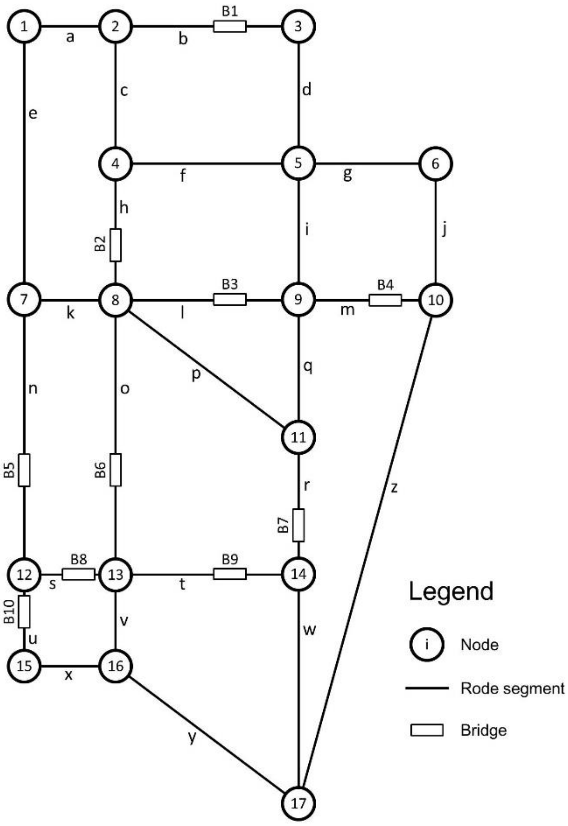


Figure 5. Hypothetical transportation network

5. Numerical application

5.1 Transportation network parameters

The proposed optimization method is applied to a hypothetical transportation network as shown in Figure 5, in which there are 17 nodes, 26 arcs, and 10 bridges. Table 4 summarizes the initial parameters of the network arcs, including length, capacity, and speed limit. 10 reinforced concrete bridges, which are the only vulnerable components in the network, are distributed on 10 different arcs. In this application, a magnitude 8.0 scenario earthquake near the center of the network is considered. Each of the 10 bridges suffered some level of damage that is determined by post-earthquake damage inspection as tabulated in Table 5, along with the estimated restoration durations. The traffic demand for network performance assessment in this application is stored in OD matrix as listed in Table 6. A capacity-limited incremental traffic assignment model (Toroslu & Üçoluk, 1990) is used to evaluate the functionality of the network to ensure a manageable number of iterations. This is a dynamic traffic assignment method that traffic demand is divided into several portions and gradually loaded to the network to approximate the UE result, and the commonly used model parameters are summarized in Table 7. Additionally, it is assumed that there are only three identical engineering teams available in the recovery process, i.e. $NT^{max} = 3$.

Table 4. Parameters of network arcs

Arc ID	Length(km)	Traffic Capacity(pcu/h)	Speed limit(km/h)
a	2	5050	50
b	4	5091	50
c	3	5229	50
d	3	5045	50
e	6	8349	50
f	4	7841	50
g	3	5045	50
h	3	9559	50
i	3	7841	50
j	3	3652	50
k	4	9599	50
l	2	15540	50
m	3	5229	50
n	6	8349	50
o	6	15540	50
p	5	7841	50
q	3	10000	50
r	3	10000	50
s	2	5045	50
t	4	9599	50
u	2	5059	50
v	2	15540	50
w	5	5059	50
x	2	5050	50
y	5	7841	50
z	12	5229	50

Table 5. Damage levels and restoration durations of network bridges

Bridge ID	Damage Level	Restoration duration (days)
B1	Extensive damage	204
B2	Collapse	210
B3	Slight damage	42
B4	Moderate damage	123
B5	Extensive damage	195
B6	Slight damage	63
B7	Collapse	240
B8	Moderate damage	105
B9	Slight damage	48
B10	Moderate damage	108

Table 6. OD traffic demand matrix of the network (pcu/h)

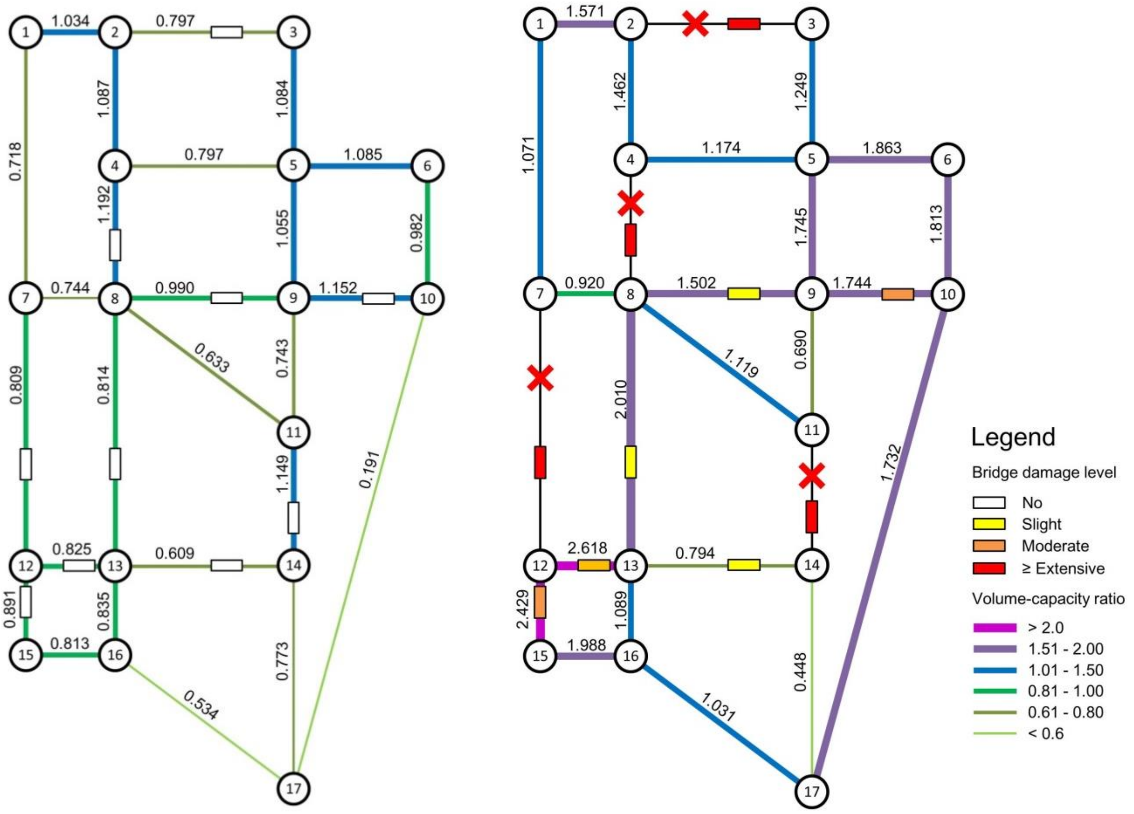
O \ D	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1	/	450	400	600	500	400	700	600	500	250	400	350	450	300	450	400	350
2	450	/	300	600	450	300	550	700	450	300	300	250	300	250	300	300	250
3	400	300	/	550	450	400	600	500	500	250	450	300	250	300	300	350	400
4	600	600	550	/	500	450	650	800	650	300	500	450	600	300	400	500	450
5	500	450	450	500	/	500	600	650	700	300	500	400	500	500	350	450	650
6	400	300	400	450	500	/	600	750	700	250	550	300	450	350	300	450	450
7	700	550	600	650	600	600	/	800	700	250	650	550	600	300	550	600	450
8	600	700	500	800	650	750	800	/	950	450	750	750	800	650	650	850	750
9	500	450	500	650	700	700	700	950	/	400	800	550	700	600	450	650	700
10	250	300	250	300	300	250	250	450	400	/	300	400	450	450	400	500	550
11	400	300	450	500	500	550	650	750	800	300	/	550	700	750	500	900	900
12	350	250	300	450	400	300	550	750	550	400	550	/	650	300	650	750	450
13	450	300	250	600	500	450	600	800	700	450	700	650	/	550	550	750	750
14	300	250	300	300	500	350	300	650	600	450	750	300	550	/	500	800	700
15	450	300	300	400	350	300	550	650	450	400	500	650	550	500	/	750	550
16	400	300	350	500	450	450	600	850	650	500	900	750	750	800	750	/	750
17	350	250	400	450	650	450	450	750	700	550	900	450	750	700	550	750	/

Table 7. Parameters of capacity limited increment traffic assignment

Step	1	2	3	4	5	6	7	8	9	10
Loading rate (%)	25	20	16	12	9	7	5	3	2	1

5.2 Post-earthquake network performance

According to Equation (1) and Equation (2), *WATS* prior to and immediately after the earthquake is 46.2 km/h and 24.5 km/h, respectively. *RRF* is equal to 0.53, representing a 47% sudden drop in the network functionality in terms of its pre-earthquake state. The traffic congestions before and after the earthquake measured by the volume-capacity (V/C) ratio (also known as level of service) are illustrated in Figure 6. Obviously, the post-earthquake network congestions are far more serious than those before the earthquake. In Figure 6(b), the aggravation of congestions in detour routes caused by out-of-service arcs is particularly significant. For example, serving as four trunk roads for vertical transportation of the network, the congestions in arc(o) and arc(z) increase dramatically as a result of the interruption of arc(n) and arc(r), which also indirectly leads to the high congestions in their adjacent arcs, such as arc(j) and arc(s).



(a) Pre-earthquake (b) Post-earthquake

Figure 6. Traffic congestion (volume-capacity ratio)

5.3 Optimization for network restoration

The restoration schedules for the above damage scenario are optimized using GA and NSGA-II as shown in Figure 4. The specific parameters and stopping criterion used in the application are listed in Table 8. Optimization model 1 and model 2, as illustrated in Table 3, were carried out 5 tests respectively, where 500 and 250 random instances generated by MCS were optimized using NSGA-II and GA. The discussion below is mainly focused on the set-based optimization model 1.

Figure 7 summarizes all feasible solutions obtained in the optimization process of model 1. These solutions are distributed in vertical stripes, that is, for a given *RRS*, there exist many alternative schedules with different *PRT*. This observation confirms the discussion in section 3 that *RRS* related to the allocation of the damaged bridges is not sufficient to determine an optimal restoration schedule. *PRT* associated with the restoration sequence ensures the optimal restoration efficiency among alternative solutions with the same recovery rapidity. However, not every allocation scheme, i.e. *RRS*, correspond to an optimal solution in the final result. NSGA-II eliminated the unreasonable allocation schemes, and end up with 29 non-dominated optimal solutions (also known as Pareto fronts) as depicted in Figure 7. According to the relationship between R_L and *RRS* & *PRT* as formulated in Equation (9), the unique optimal solution obtained by GA must be included in these Pareto fronts, and in this case, it refers to solution No.5 in Figure 7.

Table 8. Parameter settings in GA and NSGA-II

Parameters	GA	NSGA-II
Population	50	100
Maximum generations	50	100
Cross-over rate	0.9	0.9
Mutation rate	0.7	0.7
Generation gap	0.9	—
Elitist Strategy	Yes	Yes

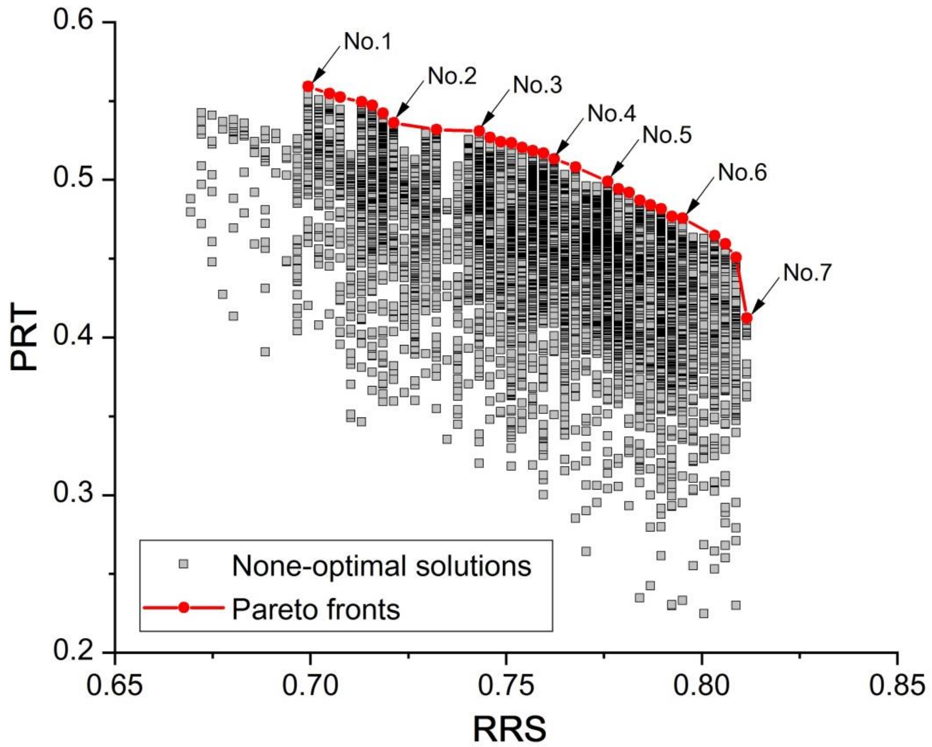


Figure 7. *RRS* and *PRT* of the NSGA-II optimal solutions

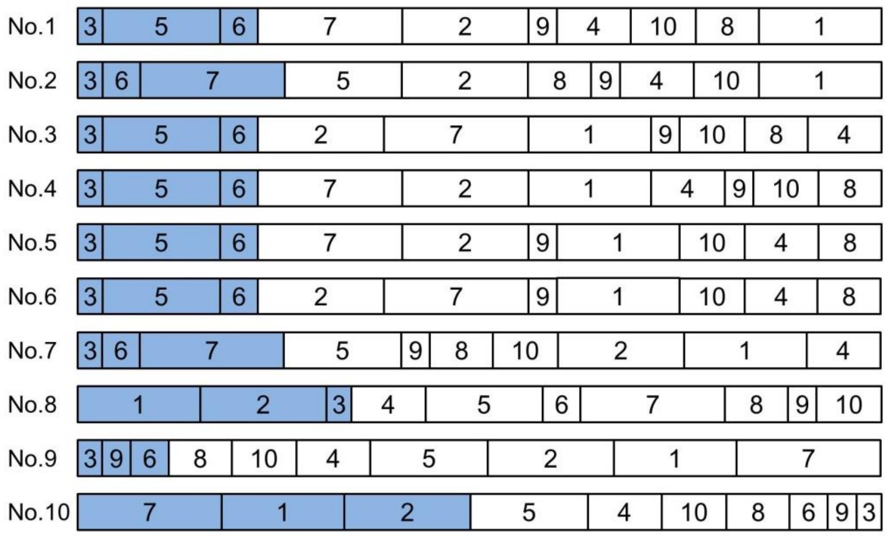


Figure 8. Restoration schedule of optimal and naïve solutions

Seven solutions are selected from the 29 Pareto fronts for further study as shown in Figure 7, and Figure 8 presents the restoration sequence of these seven optimal solutions, i.e. No.1 to No.7. In each solution, the restoration starts simultaneously for the first three bridges (shaded) as they have the highest priority, and then continues on the next bridge whenever an engineering team becomes available. B3 is selected as one of the top priorities without exception by the seven optimal solutions, because arc(k), that located in the center of the network, is one of the most important alternative roads after earthquake, and more importantly the restoration duration of B3 is the shortest. Other bridges of top priorities include B5, B6 and B7, which all located in the trunk roads for vertical transportation as discussed above, that the restoration of B5, B6 or B7 can relieve the congestions of arc(o), arc(z) and their adjacent arcs.

Three naive restoration sequences are also presented in Figure 8, where the bridges are restored in their numbered sequence for No.8 and in ascending and descending sequence of restoration durations for No.9 and No.10, respectively. Note that these ten restoration schedules in Figure 8 share the same initial condition and engineering teams available, and the only differences between them are the allocation and sequence in which the damaged bridges are restored. The calculation results of schedule No.1 to No.10 are summarized in Table 9, including resilience-based indicator *RRF*, *RRS*, *PRT*, R_L and the recovery time to specific percentage of the pre-earthquake functionality, which could be the preferences of decision-makers. R_L in optimal results are obviously less than those in naive results, indicating less indirect loss. Furthermore, there is a notable improvement in the recovery efficiency of the optimal results, where the average time required reaching 80% functionality is 120 days less than that of the naive results, and 90 days less in reaching 90% functionality. However, it is difficult to choose the best solution from these seven optimal results, because their values of R_L are close and each recovery schedule has its advantages. If using the GA solution, i.e. No.5, as a benchmark, the shaded numbers in Table 9 represent less time required to recover to specific functionality. For instance, the total recovery time of solution No.6 or No.7 is shorter, but more days are required in recovering to 90% or 95% of the pre-earthquake functionality. The same conclusion can also be obtained from the recovery trajectories of six selected restoration schedules as shown in Figure 9, that is, the Pareto optimal solutions are too close to call, but superior to naive solutions obviously.

From the above discussion, the proposed method in this study could significantly improve the recovery rapidity and efficiency, which results in indirect loss reduction. Optimization model 1 using NAGA-II is of higher recommendation, because it could provide a series of Pareto fronts with different allocation and sequence of the bridges to be restored. These optimal restoration schedules allow decision-makers to make a final choice considering also other socio-economic preferences and previous experience.

Table 9. Calculation results of optimal and naive schedules

No.	Type	*RRF*	*RRS*	*PRT*	R_L	Recovery time to specific functionality (days)			
						80%	90%	95%	100%
1	Optimal	0.530	0.699	0.559	117.9	273	282	387	570
2	Optimal	0.530	0.721	0.536	118.8	240	273	396	546
3	Optimal	0.530	0.743	0.531	114.8	252	303	399	522
4	Optimal	0.530	0.762	0.513	114.4	273	282	399	501
5	Optimal	0.530	0.776	0.499	114.2	273	282	447	486
6	Optimal	0.530	0.795	0.476	114.3	252	303	447	465
7	Optimal	0.530	0.811	0.412	123.2	240	444	447	447
8	Naive	0.530	0.781	0.364	143.2	360	408	450	480
9	Naive	0.530	0.689	0.465	146.1	366	390	582	582
10	Naive	0.530	0.806	0.312	146.2	399	399	411	453

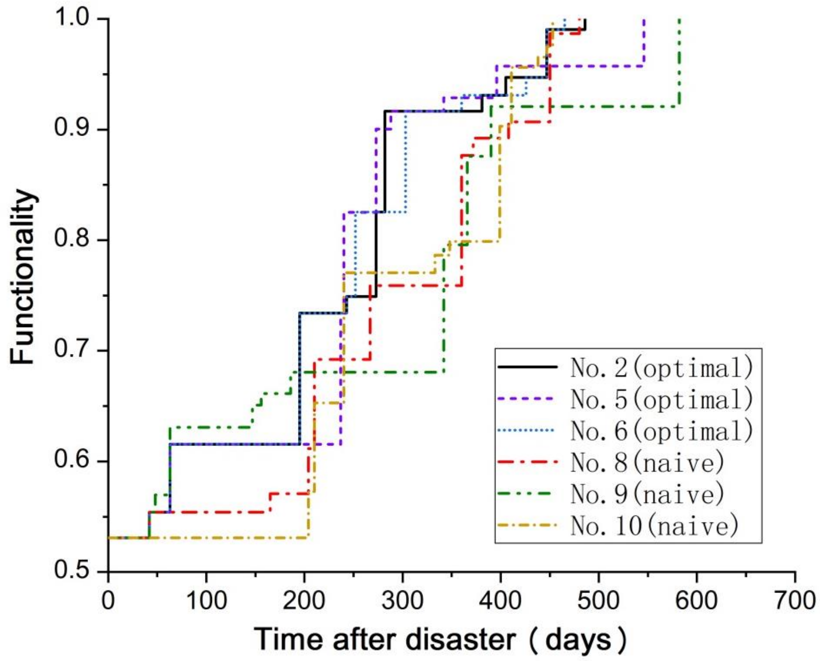
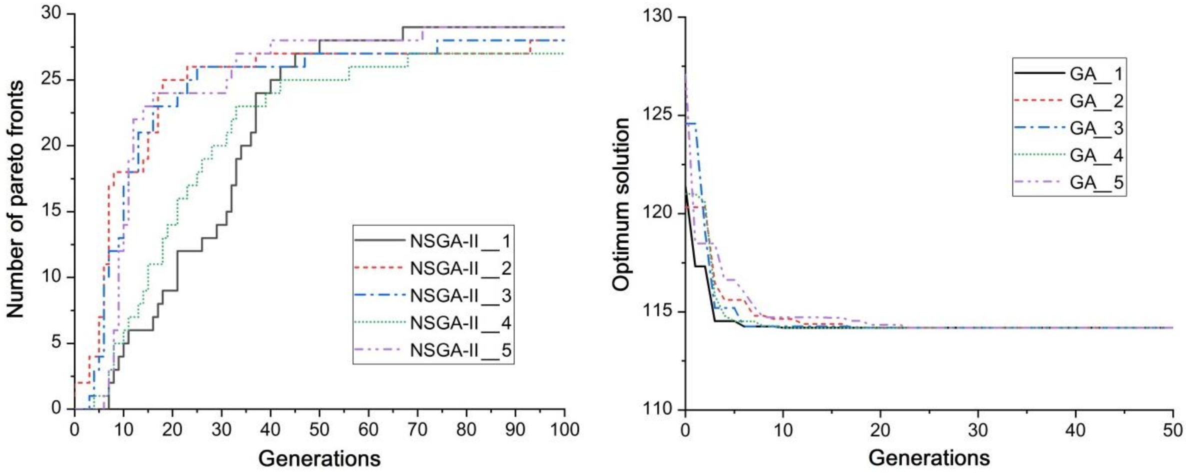


Figure 9. Recovery trajectories of optimal and naive schedules



(a) NSGA-II based optimization model 1

(b) GA based optimization model 2

Figure 10. Convergence of GA and NSGA-II

5.4 Computational efficiency and stability

The numerical application was performed on an ordinary desktop with Intel(R) Core(TM) i7-6700K CPU @ 4.00GHz CPU and 8GB memory. The proposed models were solved in MATLAB. The average computing time of optimization model 2 in 5 tests is 22.2min, and that of optimization model 1 is 94.6min, which is slightly more than 4 times that of model 2. As a matter of fact, the gap between the computing times of individuals in these two algorithms is small, considering the population and maximum generation of optimization model 1 are double those of model 2 as listed in Table 8. Figure 10 illustrates the convergence of optimization model 1 and model 2 over generations. In Figure 10(b), all five tests using GA converge to the same solution before the 25th generation, indicating a fast convergence and good stability. In contrast, there seem some gaps between the five tests using NSGA-II in Figure 10(a). However, all of them could obtain at least 25 of the final 29 Pareto optimal solutions before the 45th generation, which is already sufficient for decision-making. Therefore, a fast convergence and good stability make the proposed method have potential application prospect for post-disaster decision-making of large complex transportation network.

6. Conclusion and discussion

In this paper, a novel methodology has been presented to search for alternative general optimal restoration schedules for post-disaster decision-making of urban transportation network. The proposed method introduces a new network performance metric that takes into account the road weighting factor, dynamic traffic demand, and residual network capacity. A three-indicator framework for network resilience assessment was established to comprehensively characterize the functionality curve of a network in one disaster. Furthermore, two optimization models were developed for network restoration scheduling to reduce indirect loss, and Heuristic algorithms were used to search for near-optimal solutions. Finally, the proposed method was applied to a hypothetical transportation network. The numerical application indicates that the proposed method can significantly improve the rapidity and efficiency of network recovery and the set-based optimization model could provide multiple choices for decision-makers to make a final decision considering also other preferences. Additionally, the mathematical formulation illustrated in this study can be easily extended to deal with large transportation network restoration problems and the proposed optimization method is proved to have good convergence and computational efficiency.

In fact, the approach presented in this paper can also be applicable for other low-probability high-consequence events. Even if these events induce different infrastructure disruptions, their damage scenarios can be converted into network functionality loss, and the restoration schedule can be formulated accordingly. This study aims to provide decision-making support for post-disaster network restoration scheduling when the damage scenario is known, so uncertainty has not been discussed much. Uncertainties, which are mainly contained in the failure probabilities of network components and the hazard itself, will be further discussed in future studies about inherent resilience of different types of transportation networks.

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