Assessment of resilience of highway–bridge networks by considering interaction

Abstract: Restoration of damaged highway-bridge networks is to the recovery of networks' functionality in support of recovery actions. restoration actions to different bridges undertaken simultaneouslynetworks' . his paper investigate restoration interactions in post- highway–bridge networkssuch interactions' impact on restoration scheduling. A hybrid genetic algorithm that combines a genetic algorithm with a specifically designed heuristic approach is developed to improve the proposed integer program's computational efficiency. The results of a case study using the proposed method and data from the 2008 Wenchuan Earthquake show that the downtime due to restoration interactions can delay the recovery the networks' , and thus that neglecting such interactions can lead to the overestimation of the networks' resilience.

Keywords: Disaster recovery; restoration scheduling; seismic risk; transportation downtime, transportation network resilience\

1. Introduction

Highway–bridge networks play vital roles in the post-earthquake recovery of communities by transporting relief supplies, reconstruction materials and equipment, and supporting commercial activities as well as people's daily lives. However, the damage to bridges, which are commonly considered the most seismically vulnerable components of a highway–bridge network (Shinozuka et al., 2003), can lead to the disruption of highways, thereby hindering the recovery of communities. Thus, efficient restoration of damaged bridges in highway–bridge networks is of paramount importance to the recovery of such networks' functionality in support of recovery actions. The key to efficient restoration is optimal scheduling of bridge restoration tasks to recover those networks' functionality to the pre-disaster levels, and the concept of resilience has recently been widely used to measure infrastructures' ability to recover functionality within a given time.

Post-disaster long-term restoration-scheduling models for highway–bridge networks have been widely studied, with the aim of maximizing such networks' resilience (Bocchini and Frangopol, 2012, Karamlou and Bocchini, 2017, Zhang et al., 2017, Li et al., 2019, Kameshwar et al., 2020). Though differing in various respects, the long-term restoration schedules generated by these studies have tended to assume that all damaged bridges were reachable for restoration crews, and restoration crews could reach these damaged bridges without any hamper whenever they intend to restore these bridges. However, such an assumption may be impractical especially in mountainous areas where transportation networks consist of only a few highways. For example, after the 2008 Wenchuan Earthquake, bridges on the only two highways that connected Caopo city with other cities within the highway network were seriously damaged, leading to the isolation of Caopo city for two months (OSLR, 2018). These damaged bridges on such two highways could only be restored one by one in series because there was no other access for restoration crews to reach these bridges before recovering the passability of the highways to these bridges.

Therefore, when more than one bridge restoration activity is undertaken at the same time, restoration interactions resulted from the blockage or unblockage of bridges as a result of restoration works may occur among restoration crews on a highway–bridge network. Specifically, on one hand, the restoration of damaged bridges that are still passable after an earthquake will block the highway segments where these bridges are located, and thus other restoration crews should take a detour to bypass these highway segments containing bridges undergoing restoration or would stop working and wait until the bridges have been restored if there is no other way for these crews to detour. On the other hand, impassable bridges due to seismic damages can become passable after restoration, quite possibly changing the accessibility of bridges to restoration crews and leading to adjustments in the following restoration activities. Such restoration interactions may significantly affect the conduction of restoration activities on highway–bridge networks; nonetheless, the discussion of such restoration interactions is generally neglected in current methods for scheduling post-disaster long-term bridge restoration activities, and systematic approaches to accounting for such interaction in bridge restoration scheduling appear to be lacking altogether.

To address the aforementioned gaps in the existing post-disaster highway–bridge network restoration scheduling methods, the present study proposes an integer program with recursive functions for modeling post-earthquake restoration-scheduling problems for a highway–bridge network, with the aim of maximizing highway–bridge network resilience. Unlike traditional restoration-scheduling models, which assume that restoration crews are able to reach their destinations within a highway–bridge network without considering the restoration processes of other restoration works, the proposed model is intended to reveal the impact of restoration interactions on the overall restoration-scheduling process. Moreover, since uncertainty always exists in bridge restoration times, this paper also develops an optimization model for the stochastic case. Additionally, in support of this modeling, this paper proposes a hybrid genetic algorithm (GA) that combines a proposed early-termination test methodology to resolve the computational issues arising from the proposed restoration-scheduling problem involving restoration interactions. The proposed model will be tested using data from the 2008 Wenchuan Earthquake in China. It is hoped that the present research will serve as a basis for further studies of post-disaster long-term restoration-scheduling problems, with a wider aim of providing support for decision-makers tasked with drafting post-earthquake restoration strategies for highway–bridge networks.

2. Literature review

This section presents a brief review of the literature on post-disaster restoration scheduling and resilience quantification for transportation networks.

2.1. Post-disaster restoration scheduling for transportation networks

Generally, post-disaster restoration of transportation networks can be categorized into two types (ODOT, 2017, Li et al., 2019): emergency restoration (or short-term restoration), and long-term restoration. The former emphasizes the speedy and often aims at partially recovering damaged transportation networks in several days, primarily in support of emergency-response actions, such as rescuing victims from damaged properties, whereas the latter aims to fully restore damaged transportation networks to their pre-disaster conditions and thus can take months or years (ODOT, 2017). Though differing in terms of system functionality (e.g., travel time or traffic capacity), a majority of emergency restoration-scheduling studies have shared the general objective of quickly and partially restoring some critical network components (e.g., bridges and road segments) to efficiently improve transportation networks' functionality within limited times (Yan and Shih, 2009, Zhang and Miller-Hooks, 2015, Zhang and Wei, 2021).

Long-term restoration scheduling studies, on the other hand, have tended to focus on identifying the optimal restoration sequences of all damaged components in transportation networks when damages to all components are known. For example, Bocchini and Frangopol (2012) developed a computational procedure for the optimization of both schedules and funding allocation of restoration interventions to bridges, assuming that all damaged bridges within a highway–bridge network could be restored simultaneously. Zhang et al. (2017) presented a resilience-based framework to optimize the scheduling of the post-disaster recovery actions for road–bridge networks, considering the uncertainties in bridge restoration times. Li et al. (2019) investigated the optimization of recovery strategies for a post-disaster freight transportation network, with the aim of identifying the maximum-resilience restoration schedules for the network under budget and resource constraints. Though differing in various respects, the long-term restoration schedules generated in the above-cited studies have tended to proceed from an assumption that all damaged bridges were reachable for restoration crews. In other words, restoration crews could reach the bridges they intended to restore without considering the damage states and restoration processes of other bridges, and thus all damaged bridges could be restored simultaneously if adequate restoration resources and budget were available.

In reality, however, when restoration activities for different bridges in a highway–bridge network are undertaken at the same time, restoration interactions resulted from the blockage and unblockage of bridges may occur and may significantly affect the recovery process of the network. On one hand, as bridges will become impassable during the restoration of them and will be reopened after restoration, restoration crews should bypass these bridges undergoing restoration or would stop working and wait until these bridges have been restored if no other way is available for the crews to reach the bridges they intend to restore, quite possibly leading to the delay in the restoration processes. On the other hand, some bridges can become unreachable for restoration crews after earthquakes due to the blockage of highways that contain impassable bridges in severe damage, and thus, restoration of unreachable bridges cannot commence until these severely-damaged bridges on the highways to these unreachable bridges have been restored and become passable. Such restoration interactions were commonly seen in post-earthquake mountainous areas where transportation networks consist of only a few highways (Zhao, 2011, OSLR, 2018, Zhang and Wei, 2021). Given that restoration interactions may significantly affect the conduction of restoration activities on a highway–bridge network, it is necessary to explore such interactions' impacts on the restoration-scheduling processes and network resilience.

2.2. Transportation network resilience

The definition of resilience dates back to 1973 when Holling (1973) first defined the resilience of an ecological system as a measure of the system's ability to absorb disturbance and still maintain an equilibrium state. Then, the concept of resilience has been introduced to the field of infrastructure systems, and various definitions of infrastructure resilience have been developed (Cimellaro et al., 2006, Cimellaro et al., 2010a, b, 2011, Cimellaro et al., 2015, Domaneschi and Martinelli, 2016, Domaneschi et al., 2017, Zhang et al., 2017, Banerjee et al., 2019, Argyroudis et al., 2020, Kammouh et al., 2020). A widely accepted definition of infrastructure resilience was proposed by Bruneau et al. (2003), where resilience consists of four dimensions: robustness, describing the ability to resist disasters and still operate a service, redundancy, reflecting the number of substitutable components to keep the system's serviceability, resourcefulness, expressing the capability to identify problems, establish priorities, mobilize resources, and provide applicable budget after a disaster, and rapidity, defining the recovery time of the investigated system from a disaster to its normal level of performance. Based on such a definition, Bruneau et al. (2003) proposed a quantitative framework for infrastructure resilience, where resilience loss is defined as the size of the degradation in the quality of functionality over time. Specifically, infrastructure functionality could drop to a low level after a disaster and gradually recover to its pre-disaster level with the implementation of restoration interventions to infrastructures, and resilience loss is the cumulative system-functionality deficiency relative to its pre-event level until full recovery. Furthermore, Frangopol and Bocchini (2011) defined transportation network resilience as the normalized cumulative network functionality in a given time horizon. In the same study, the functionality of a highway–bridge network was represented by a monotonically increasing, stepwise function, where network functionality remains unchanged during the restoration of bridges and jumps to a higher level once bridges are restored.

Instead of using monotonically increasing functions, some studies used fluctuate, stepwise functions for representing highway–bridge networks' functionality, considering that network functionality may fluctuate during the implementation of restoration interventions (Lam and Adey, 2016, Hackl et al., 2018). Specifically, network functionality will fall when some highways are blocked for the restoration of damaged bridges on them, then remain unchanged while this restoration is ongoing (i.e., restoration downtime), and jump to a higher level when highways are unblocked due to the accomplishment of bridge restoration works on them. Accordingly, the proposed study will develop a fluctuant, stepwise function for accurately capturing the evolution of highway–bridge network functionality over time, thereby promoting the accurate quantification of highway–bridge network resilience.

For the measurement of transportation network functionality, various network performance metrics have been developed, mainly including topological metrics and functional metrics, as reviewed by Faturechi and Miller-Hooks (2015). Topological metrics, such as connectivity, centrality, and betweenness, emphasize the relative locations of nodes and links in a network and are commonly used in the optimization of pre-disaster network planning (Berche et al., 2009, Peeta et al., 2010, Reggiani et al., 2015). Functional metrics, on the other hand, focus on the inherent serviceability of transportation networks, such as total travel time, total travel distance, traffic capacity, and weighted average travel speed, and are often used in the optimization of post-disaster recovery strategies (Zhou et al., 2010, Frangopol and Bocchini, 2011, Zhang and Miller-Hooks, 2015, Liu et al., 2020). Among these metrics, weighted average travel speed proposed by Liu et al. (2020) is considered a comprehensive performance metric for a post-disaster highway–bridge network not only because this metric is applicable in the cases with significant changes in traffic demand before and after a disaster, which are quite common under seismic conditions (Chang et al., 2012, Liu et al., 2020), but also because this metric itself involves consideration of travel time, travel distance, and traffic capacity. Therefore, the present study adopts weighted average travel speed as the performance metric of a highway–bridge network and uses the ratio between post- and pre-disaster network performance to measure the quality of network functionality.

3. Problem description

This section defines the proposed post-disaster long-term restoration-scheduling problem for highway–bridge networks, and such a problem involves interactions among restoration activities for different bridges. By explicitly investigating the restoration interactions, this study optimizes the long-term restoration schedules for a post-earthquake highway–bridge network to achieve maximum network resilience. Specifically, this study adopts weighted average travel speed as the network performance metric and develops a fluctuant, stepwise functionality curve for capturing the evolution of network functionality over time. In the post-earthquake recovery phase when information about bridge damages has been collected via a thorough post-disaster inspection and the required restoration activity for each bridge has been determined, restoration crews depart from repair centers and commence to conduct restoration activities on the highway–bridge network. Restoration crews will stop working when all damaged bridges have been restored.

3.1. Network definition

As shown in Figure 1, a highway–bridge network system is abstracted as a network graph , consisting of a number of nodes and highway segments, where is the set of nodes, including city nodes and bridge nodes , and is the set of highway segments connecting city nodes. Bridge nodes are distributed along highway segments, and each highway segment is divided into a set of links (i.e., the line connecting adjacent two nodes) by the bridge nodes on the segment. Time is discretized into small increments of equal duration, i.e., , where a disaster occurs at , and is the investigated time horizon for restoring all damaged bridges in the network. The time required for collecting bridge damage information is neglected in this study, and long-term restoration interventions are assumed to start at . Decision variables and parameters to be calculated within the proposed mathematical formulation are tabulated in Appendix (Table A.1). The notations used in this study are listed as follows:

Set of network nodes, representing cities and bridges

Set of highway segments

Set of links connecting with ,

Set of bridge nodes

Set of city nodes

Set of bridges on ,

Set of bridge restoration times

Bridge damage index of bridge after an earthquake,

Length of highway segment ,

Design speed of highway segment ,

Traffic capacity of highway segment ,

Ground motion in the Modified Mercalli Intensity scale

Sample size of the Latin Hypercube Sampling method

Number of bridges within the highway–bridge network

Number of cities within the highway–bridge network

Number of highway segments within the highway–bridge network

Number of restoration crews

Time horizon

Time required for restoring bridge ,

Pre-earthquake travel demand between city and city ,

<Figure 1.>

3.2. Damage assessment for highway–bridge networks

Post-disaster damage states of bridges that can be obtained by a thorough inspection are generally classified into five levels: no, slight, moderate, extensive, and complete damage (FEMA, 2012). Bridges' damage states can be quantified by the bridge damage index () proposed by Chang et al. (2000), in which the values of corresponding to no, slight, moderate, extensive, and complete damage were suggested to be 0, 0.1, 0.3, 0.75, and 1.0, respectively, based on the statistical information of bridge damages in the 1994 Northridge earthquake in the U.S.

It is noted that the structure of a highway segment itself is assumed to not be subjected to damage, and the damage of the highway segment is caused by the damage of bridges on that segment. In other words, bridges within the network are the only elements that can be affected by structural damages and can undergo restoration interventions. As such, this study adopts the link damage index () proposed by Guo et al. (2017) to classify the damage state of highway segments into one of five levels: no, slight, moderate, extensive, and complete damage. The of a highway segment is determined by the of all bridges along that segment, as follows:

(1)

where is the number of bridges on the highway segment, and is the of bridge on that segment. Adopting the same study of Guo et al. (2017), the damage state of a highway segment can then be determined according to the five damage states' corresponding ranges of : no damage (), slight damage (), moderate damage (), extensive damage (), and complete damage (). It is noted that Equation (1) suggests that a highway segment is considered to be in complete damage state if it contains at least one impassable bridge. Specifically, bridges in extensive or complete damage are deemed to be impassable after earthquakes because such bridges are considered structurally unsafe (FEMA, 2012).

3.3. Post-earthquake traffic analysis

Post-disaster travel demand of cities, which are origins and destinations of traffic flows on a transportation network, can deviate significantly from the normal conditions due to the damages of buildings and transportation networks (Shinozuka et al., 2008, Chang et al., 2012, Liu et al., 2020), and therefore, establishing appropriate traffic analysis models is a fundamental step in evaluating network performance. First, to estimate dynamic changes in the post-earthquake travel demand of each city, the present study adopts the trip reduction and recovery models proposed by Shinozuka et al. (2008), in which travel demand was considered to reduce immediately after an earthquake and to gradually recover as restoration proceeded. In (Shinozuka et al., 2008), the post-earthquake trip reduction was measured by the initial trip reduction rate , the value of which ranges from 0 to 1 and is dependent on the ground motion intensity, whereas the post-earthquake trip recovery was modeled as a linear process based on the 1996 southern California origin-destination (OD) survey data (SCAG, 1997), as follows:

(2)

(3)

where is the period for the full recovery of travel demand; is the ground motion intensity in the Modified Mercalli Intensity scale, and ; is the trip reduction rate at time (), and its value ranges from 0 to . It is noted that if , indicating that travel demand is recovered to the pre-disaster level after time .

Accordingly, the post-earthquake travel demand between city and city at time can be calculated as follows:

(4)

where is the pre-earthquake travel demand between city and city .

Finally, this study adopts the Frank-Wolfe algorithm (Florian and Hearn, 1995) to assign travel demand to form traffic flow on highway segments within the highway–bridge network and thereby to calculate the post-earthquake travel time on each highway segment. The principles for traffic assignment are based on the user equilibrium (UE) model and Wardrop's second principle proposed by Wardrop (Wardrop, 1952), which are particularly suitable for the analysis of users' behavior on a post-disaster transportation network (Frangopol and Bocchini, 2012). The UE model states that every user tends to choose the optimal route according to the following principle: travel times in all routes actually used are equal and less than those which would be experienced by a single vehicle on any unused route. Wardrop's second principle states that the system is in optimal condition when the total network travel time is a minimum. Furthermore, to calculate the travel time on highway segment , this study adopts the Bureau of Public Roads function proposed by Martin and McGuckin (1998), as follows:

(5)

where is the length of ; and are the residual free-flow driving speed and traffic capacity of , respectively; is the traffic flow on ; the function parameters and can be obtained from traffic counting in the work zone, and their values are typically 0.15 and 4, respectively (Shinozuka et al., 2008). Considering that and of a highway segment will reduce depending on the damage states of the highway segment (i.e., in Equation (1)), the present study adopts Guo et al.'s study (2017) for determining and of highway segments with no, slight, moderate, extensive, and complete damage, being and , and , and , and , 0 and 0, respectively, where and are the pre-disaster design speed and traffic capacity of , respectively. Such suggestions on the values of and can be seen reasonable because they will decrease in line with damage states of highway segments, as zero values of and of a highway segment in complete damage indicate that such a highway segment is impassable.

Accordingly, the Frank-Wolfe algorithm can be explained as follows. In the initialization, the total travel demand is assigned to the network to form the initial traffic flow distribution using an all-or-nothing assignment, in which the shortest path (i.e., the path with the shortest travel time) for each OD-pair is calculated, and the travel demand of each OD-pair is assigned to the shortest path. The travel time of each highway segment is calculated based on zero traffic demand. Then the first iteration starts, and every iteration consists of three steps. First, the travel time of each highway segment is recalculated based on the traffic flow from the previous iteration. Thereafter, an all-or-nothing assignment is performed based on the new travel time, and this yields new traffic flow distribution. This step is also referred to as direction finding, meaning there will be some traffic flow shifted in this new 'direction'. Third, via a line search, it is determined how much traffic flow is to be shifted from the old to the new traffic flow distribution, and the move is made. By following these three steps, the final traffic flow distribution at the end of the iteration can be determined. The iterative process is repeated until a stop criterion is met.

3.4. Network resilience

The present study adopts weighted average travel speed () proposed by Liu et al. (2020) as the performance metric of the highway–bridge network to explicitly capture the impact of the dynamic changes in post-disaster travel demand on network functionality. is calculated as follows:

(6)

(7)

where is the average travel speed on highway segment at time and is computed as the length of divided by the travel time (Equation (5)) on ; is the weighting factor of and is a function of the pre-disaster traffic capacity and the length of highway segments, reflecting the importance level of . Equation (7) indicates that the summation of of all highway segments in a network is 1, and the highway segments with large and are more important than the highway segments with small and .

As defined by Liu et al. (2020), the quality of network functionality at time , denoted , is measured by the ratio between post-disaster network performance at time , i.e., , and pre-disaster network performance, i.e., , as follows:

(8)

where ranges from 0 to 1, and the value of 1 indicates that the performance of the network has been recovered to the pre-disaster level. Figure 2 illustrates the proposed fluctuant, stepwise functionality curve of a post-disaster highway–bridge network. An earthquake occurs at time and damages the highway–bridge network. As a result, network functionality drops to a low level in the immediate aftermath of the earthquake. Then, network functionality starts to recover with the implementation of restoration interventions, during which network functionality may drop due to the blockage of highway segments for the restoration of bridges on them, remain unchanged during the restoration of bridges, or jump after the accomplishment of bridge restoration works and the reopening of highway segments. In other words, network functionality only changes at time (i.e., vertical dashed lines in the shaded area in Figure 2) when a restoration crew starts or completes the restoration of a bridge; on the other hand, at time (), i.e., during a restoration crew's restoration of a bridge, network functionality remains unchanged. Accordingly, network functionality must be recalculated recursively at each time , hereafter referred to as the identified time, to capture the change of network functionality over time.

<Figure 2.>

Finally, adapting the transportation network-resilience qualification model proposed by Frangopol and Bocchini (2011) to the proposed fluctuant, stepwise network functionality curve, the present study defines highway–network resilience as the normalized area below the network functionality curve in a given time horizon , as follows:

(9)

where ranges from 0 to 1, and a larger value of indicates a higher level of network resilience.

4. Model formulation

4.1. Model assumptions

The present study has made several assumptions for the sake of easing the modeling of its focal problem.

1) A number of cities are set as repair centers, where restoration crews depart.
2) The bridges undergoing restoration work will be blocked for repair, and thus they cannot be crossed by any restoration crew for the duration of that work.
3) Bridges in extensive or complete damage are impassable for restoration crews until such bridges have been fully restored.
4) Bridges' damage states decrease to no damage after restoration.

5) Restoration scheduling is non-preemptive (i.e., once a restoration crew has begun repair on a given bridge, it must complete its work before moving to another bridge.)

4.2. Deterministic optimization model formulation

Bridge restoration times are deterministic parameters if every damaged bridge can be restored in the planned restoration time. Accordingly, the proposed restoration-scheduling problem in the deterministic case can be formulated as ():

() (10)

subject to

(11)

(12)

(13)

(14)

(15)

(16)

(17)

(18)

(19)

(20)

(21)

The objective function (10) seeks the maximum network resilience that can be achieved within a given time horizon . Constraints (11) and (12) ensure that each bridge is restored by one restoration crew for one time. Constraints (13) and (14) ensure that a restoration crew can commence restoring only one bridge at a time. Constraint (15) builds the relationship between non-independent decision variables and : specifically, if bridge is restored by restoration crew , ; otherwise, Constraint (16) establishes the relationship between the start times of two adjacent restoration works for each restoration crew. Such a constraint indicates that a restoration crew cannot move to the next bridge for restoration until the restoration crew has finished the ongoing restoration work. Constraint (17) calculates the time-varying bridge damage index at time , indicating that a bridge's remains unchanged before restoration and is decreased to 0 after the bridge is fully restored, while a bridge undergoing restoration is blocked with its being set as 1. Constraint (18) calculates the time-varying link damage index of each highway segment based on the time-varying of bridges on the highway segment. Constraint (19) captures the passability of the paths between node pairs at time . Constraint (20) formulates the interactions among restoration activities. Specifically, a restoration crew can move to a bridge for restoration on condition that at least one path to the bridge is passable; otherwise, restoration crews temporarily terminated their works if the bridges they needed to restore were unreachable for them due to the blockage of the highway segments that contain bridges either undergoing restoration or in extensive or complete damage. Finally, constraint (21) enforces binary-value requirements on decision variables.

4.3. Stochastic optimization model formulation

In practical circumstances, post-earthquake bridge restoration times tend to be uncertain for many reasons, such as the unpredictable weather, the change of work proficiency of restoration crews, the fluctuation of available funds and equipment, etc. (Li et al., 2019). Consequently, the uncertain restoration times can render the recovery process of the network functionality uncertain, and eventually render network resilience uncertain. Adopting the probabilistic distribution function of bridge restoration times proposed by Shinozuka et al. (2003), in which the restoration times of bridges in different damage states were suggested to follow uniform distributions based on the bridge restoration data in the 1994 Northridge earthquake in the U.S., the present study formulates the stochastic optimization model for the proposed restoration-scheduling problem as ():

() max (22)

subject to constrains (11) – (21)

(23)

The objective function (22) maximizes the expectation of network resilience . Constraint (23) defines the uniform distributions of based on bridges' damage states (i.e.,). The proposed stochastic optimization model is summarized in Appendix (Table A.2).

5. Solution methodology

5.1. Hybrid genetic algorithm

Restoration-scheduling problems are usually seen as NP-hard problems, and thus it is impractical to obtain the exact solution of such problems on a regional transportation network within a limited time (González et al., 2016, Li et al., 2019, Liu et al., 2020). Although existing studies have proven the superiority of GAs in solving restoration-scheduling problems (Toklu, 2002, Senouci and Eldin, 2004, Furuta, 2006, Aksu and Ozdamar, 2014), the specific problem to be solved in the present study, which involves accounting for restoration interactions within a highway–bridge network of multiple restoration crews, is self-evidently more computationally complex than similar problems without considering such interactions. Accordingly, this study proposes a hybrid GA to efficiently solve the proposed integer programs.

Figure 3 shows the solution algorithm for the stochastic case. First, samples of bridge restoration times are randomly generated based on constraint (23) using Latin Hypercube Sampling method, which can effectively recreate population distribution through a small number of samples and will be explained in detail in the next subsection. Then, chromosomes, each of which consists of a set of decision variables and represents a solution for the proposed integer program, are randomly generated to form the initial population with the population size being . The present study follows Xie and Xing's (1998) recommendation that the population size should be set to between and , where is the number of genes on a chromosome, to obtain a higher computational efficiency of the hybrid GA. Given that and are non-independent decision variables, and can be calculated using constraints (15) and (16) if is known, a chromosome needs only to include to form candidate scheduling solutions.

The fitness value of each chromosome, defined as the average resilience level (Equation (22)) under the samples of via the implementation of such candidate scheduling solutions, can be calculated by following the steps in the shaded area in Figure 3 (Equations (1) to (9)). Then, using the roulette-wheel method, which has been proved effective in selecting useful chromosomes in GA (Goldberg, 1989), () chromosomes are then selected from among the initial population as elite chromosomes for crossover and mutation. When those chromosome operations (i.e., crossover and mutation) are applied to the elite chromosomes, new offspring are generated. Next, to accelerate the chromosomes' evolution, an early termination test is applied. This test, a heuristic approach specially designed for the present study's proposed integer programs, is explained in detail in the next subsection. Based on the results of the early termination test, the fitness values of the offspring can be obtained, and those with high fitness values are selected to update the population. Finally, if the stopping criterion, i.e., the maximum number of generations, is met, the hybrid GA will output the best fitness value and its corresponding solution.

Additionally, the solution algorithm for the deterministic model is similar to the aforementioned solution algorithm for the stochastic model, and the only differences are that only one sample of is used, and that the fitness of a chromosome is network resilience calculated by Equation (9).

<Figure 3.>

5.2. Latin Hypercube Sampling in Monte Carlo simulation

In the stochastic case, the present study uses Monte Carlo simulation to characterize the uncertainty associated with bridge restoration times by first generating a number of samples of bridge restoration times according to constraint (23) and then using the mathematical expectation of the restoration results calculated based on these samples as the approximation results of the stochastic case. Given that Monte Carlo simulation uses a random sampling method, where new samples are randomly generated without taking into account the previously generated samples, a large number of samples are needed to ensure that the generated samples can well represent the distribution of the population, leading to the high computational complexity of the Monte Carlo simulation method (Keramat and Kielbasa, 1999). Therefore, to decrease the computational complexity of the Monte Carlo simulation method, this study adopts the Latin Hypercube Sampling method proposed by Mckay et al. (2000), which has been proved to be effective in recreating population distribution through a small number of samples (Matala, 2008, Deco et al., 2013).

The Latin Hypercube Sampling method starts by dividing the cumulative distribution curve of each variable (i.e., in the present study) into a number of strata of the equal interval and then randomly takes a sample from each stratum. Specifically, in the restoration time sampling, the interval of cumulative probability of each bridge' restoration time, i.e., [0,1], is divided into non-overlapping strata of equal probability , i.e., [0,], (,], (,],…, (,1]. From each stratum, one number is randomly taken according to the uniform distribution of the stratum, and the numbers taken from strata form a vector , indicating restoration scenarios of a bridge. For example, as shown in Figure 4, the interval of cumulative probability of the restoration time of a bridge in complete damage is divided into four strata (i.e.,), and four numbers are randomly taken from these four strata to form a vector , indicating four restoration scenarios of the bridge, with its restoration time being , , , and , respectively. Then, the numbers in are paired with numbers in at random (Figure 5), these pairs are further paired similarly with numbers in , and so on, until all of samples of bridges' restoration times are formed.

<Figure 4.>

<Figure 5.>

With the implementation of the Latin Hypercube Sampling method, samples of bridge restoration time for Monte Carlo simulation can be generated. Moreover, the ratio between the number of samples and the number of variables (i.e., in the present study) was suggested by Jia et al. (2007) to be larger than 15.6 to get reliable results for Monte Carlo simulation using the Latin Hypercube Sampling method.

5.3. Solution encoding

A chromosome in a GA is considered as a feasible solution for the proposed integer program if it satisfies all constraints. An encoding scheme that allows feasible chromosomes to be created and updated while maintaining their feasibility is critical to efficient computation. The proposed encoding scheme for this study's integer programs is shown in Figure 6. A chromosome consists of genes, representing the sequence of bridges for restoration by all given restoration crews (i.e.,). Each chromosome is divided into elements, which respectively indicate the restoration sequences of restoration crews (). For example, as shown in Figure 6, the genes on Element_1 indicate the sequence of bridges to be restored by restoration crew .

<Figure 6.>

5.4. Early-termination-based heuristic approach

This study's early-termination test is designed to deal with possible situations in which all restoration crews terminate their restoration activities before finishing the restoration of all damaged bridges in the highway–bridge network, and such situations can lead to the slowing of the evolution of the population's fitness. The early-termination problem results from restoration interactions and the inaccessibility of bridges within the highway–bridge network. Specifically, restoration crews will terminate their works if the bridges they need to restore are unreachable due to the impassable bridges on the highway segments that they need to traverse.

As illustrated in Figure 7, this test begins with inputting a chromosome, whose first identified time is 0 when a disaster occurs and all restoration crews in repair centers are ready for work. The following is calculated recursively by searching for the earliest end time of the current restoration tasks. At , if the next bridge to be restored by restoration crew is reachable, the program can move to the next identified time; otherwise, if bridge is unreachable, the end time of the ongoing work for restoration crew is set as infinite (). The early-termination test continues until all bridges have been restored or the value of is . If is , early termination is enacted because restoration crews terminate restoration works before finishing the restoration of all bridges; otherwise, the chromosome is deemed normal.

<Figure 7.>

For a chromosome with the early-termination problem, the gene on each element that leads to early termination is extracted and moved to the end of that element, deprioritizing the restoration of the particular bridge associated with that gene (Figure 8). The researchers' preliminary study indicated that the evolution of the population was significantly improved after several generations when the proposed early-termination test was applied, as compared to when it was not.

<Figure 8.>

6. Illustrative case study

6.1. Experimental design and parameter settings

A highway–bridge network including 19 cities, 27 highway segments, and 112 damaged bridges in central Sichuan, China was selected as a case study to illustrate the proposed methodology, as shown in Figure 1. The lengths, design speeds, and traffic capacity of these highway segments at the time of the 2008 Wenchuan Earthquake were referred to Zhuang and Chen (2012) (see the Appendix for Table A.3). Due to the lack of real information about the locations and numbers of repair centers and restoration crews, we assumed that four repair centers were located in cities (C) C1, C8, C13, and C15, and the numbers of restoration crews in these repair centers were four (, , , and), two (and), one (), and three (, , and), respectively.

The 2008 Wenchuan Earthquake was selected as the disaster scenario, and the ground motion intensity in the studied area was nine, i.e.,9 in Equation (2), as recorded in *Relief Records in the Wenchuan Earthquake* (OSLR, 2018). The initial trip reduction rate (Equation (3)) for 9 was 7% according to (Shinozuka et al., 2008), and the pre-earthquake travel demand (Equation (4)) was used the data reported in Li et al. (2008) (see the Appendix for Table A.4). The post-earthquake damage states of bridges were recorded in (Zhuang and Chen, 2012) (see the Appendix for Table A.5). The deterministic bridge restoration times adopted in the present study for typical Chinese bridges were referred to (OSLR, 2018), which records the historical bridge restoration information after the 2008 Wenchuan Earthquake (see the Appendix for Table A.5).

The present study calculated network resilience and the corresponding optimal restoration schedules for 2500 days after the earthquake because the researchers' preliminary studies revealed that all damaged bridges in Figure 1 could be generally restored within such a time horizon. Three additional tests were also performed, based on the same network and earthquake scenario. These were: 1) a comparison of network resilience resulted from the proposed restoration-scheduling model and from a traditional restoration-scheduling model without considering restoration interactions; 2) sensitivity analysis to investigate the impact of the number of restoration crews, considered as resource limitations, on network resilience; and 3) a comparison of the computational efficiency and accuracy of the proposed hybrid GA against a traditional GA without the proposed early termination test.

The parameters of the proposed hybrid GA that were found to result in optimal computational efficiency were found to be a population size of 200 (i.e., 200); 20 elite chromosomes (i.e., 20); 200 generations; a crossover probability of 0.9; and a mutation probability of 0.3. The MATLAB2014b language was used to program the mathematical model. All tests were performed on an Intel® Core™ i7-7700 CPU@ 3.6GHz with 32 GB RAM in a Microsoft Windows 10 environment.

6.2. Results of the deterministic case

The average weighted travel speed on the highway–bridge network was 61.67 km/h before the earthquake, i.e., 61.67 km/h, and it decreased to 42.28 km/h in the immediate aftermath of the earthquake, i.e., 42.28 km/h at 0. As shown in Figure 9, network functionality calculated by Equation (8) dropped to 0.6855 at time 0 when the earthquake occurred. It can also be observed that the optimal network resilience in 2500 days was 0.8722, and network functionality returned to the pre-earthquake level after 2024 days of the implementation of restoration interventions.

<Figure 9.>

The optimal restoration schedules for each of the ten restoration crews generated by the proposed restoration-scheduling model are shown in Figure 10(a). The results indicate that restoration interactions could significantly increase the complexity of restoration schedules and lead to long waiting times of restoration crews. The restoration of bridges (B) B83 and B84 on the highway segment (S) S19, as shown in Figure 1, is taken as an example to explain such restoration interactions. B83 was in slight damage, and B84 was in extensive damage. As shown in Figure 10(a), after restoration crew finished the restoration of B92, it should have immediately departed to B83 on S19; however, the impassability of the paths from B92 to B83 due to the ongoing restoration of B84 on S19 and the extensively-damaged B81 and B82 on S19 had stopped at B92 for 146 days to wait for the completion of the restoration of B84 by . Once B84 had been restored, and the path from B92 to B83 became passable on day 670, could depart from B92 to B83 for restoration.

Another example of restoration interactions is the restoration of extensively- or completely-damaged bridges B22 to B30 on S5 and S6. Specifically, these bridges could only be restored one by one in order by one restoration crew, i.e., from B22 to B30, because all these bridges were impassable, and could, for example, restore B23 only after it restored B22 and recovered the passability of B22, and it could restore B24 only after it restored B22 and B23 and recovered the passability of B22 and B23. The results indicate that impassable bridges due to seismic damages may affect the restoration process for other bridges, and thus the computational complexity of restoration scheduling may significantly increase if there are many extensively- or completely-damaged bridges on the network.

Moreover, the results of the optimal restoration schedules indicate that the restoration downtime of highway segments for the restoration of bridges on them can lead to significant drops in network functionality. For example, network functionality dropped by 42.4% on day 0, from 0.6855 to 0.3949 (Curve 1 in Figure 9), when restoration crews started to work because the highway segments S1, S21, and S23, which were passable immediately after the earthquake, were blocked on day 0 for the restoration of bridges B3, B91, B101, and B106 on these highway segments (Figure 10(a)). Similarly, the blockage of S25 on day 309 for the restoration of B110 led to the decrease of network functionality by 17.4%, from 0.7497 to 0.6194.

Network resilience and the optimal restoration schedules were also calculated from a traditional restoration-scheduling model where all bridges were assumed to be reachable for restoration crews, and restoration works could be conducted simultaneously without considering restoration interactions. Under this condition, network resilience was 0.9326 in 2500 days, and the network functionality curve generated by the traditional model (Curve 2 in Figure 9) was generally above the network functionality curve generated by the proposed model (Curve 1 in Figure 9). Thus, it can be concluded that neglecting the interactions among bridge restoration activities can lead to the overestimation of the optimal network resilience by 6.9% in the case study. Additionally, the optimal restoration schedules generated by the traditional model showed that all damaged bridges could be restored in 1657 days (Figure 10(b)). However, it should be noted that the restoration schedules generated by the traditional model were inapplicable to the real situation due to the neglect of restoration interactions. For example, Figure 10(b) suggested that should commence the restoration of B101 on day 1, and B16 and B17 could be restored simultaneously by and , respectively; however, in practice, B16 was unreachable for on day 1, and B17 could not be restored until B16 had been fully restored and become passable. Accordingly, it could be concluded that the proposed restoration scheduling model could promote the highway–bridge network system resilience in terms of resourcefulness by correctly identifying restoration interactions within the bridge restoration scheduling problem and establishing effective and efficient restoration schedules.

<Figure 10.>

6.3. Results of the stochastic case

The sample size of the Latin Hypercube Sampling method in the stochastic case was set as 2000 (i.e., 2000) according to the research proposed by Jia et al. (2007), in which the ratio between the number of samples and the number of variables (i.e., 112 in the present case study) was suggested to be larger than 15.6 to get reliable results. The optimal bridge restoration sequences in the stochastic case are tabulated in Table 1. Figure 11 shows the histograms of network resilience for these 2000 samples, and the expected network resilience (Equation (22)) in 2500 days was 0.8592. It can be observed that the results of the optimal restoration sequences in the stochastic case are largely different from the results in the deterministic case, indicating that uncertainty associated with bridge restoration times can significantly affect the optimal restoration schedules.

<Table 1.>

<Figure 11.>

Although this study assumed that the probabilistic distributions of restoration times of bridges in different damage states were known prior to conducting restoration works, obtaining the actual distributions of bridge restoration times could be a difficult task in real projects, which could further affect the distribution of network resilience (Li et al., 2019). Accordingly, to analyze the reliability of the probabilistic restoration results in the stochastic case without assuming the distribution of network resilience, the present study adopted the non-parametric bootstrap method proposed by Efron (1977), in which a resampling method was developed to generate bootstrap samples for inferring the population statistics without assuming the probabilistic distribution of the population. The standard error, mean square error, and 95% confidence interval of the bootstrap estimations of are 7.4797e-04, 5.8733e-

07, and [0.8566, 0.8618], respectively. The results indicate that there is a 95% probability that the calculated confidence interval, i.e., [0.8566, 0.8618], encompasses the true value of in the proposed stochastic case.

The average computational time was 8.3 minutes for the deterministic case and 13264.6 minutes for the stochastic case. Therefore, the proposed solution methodology is efficient in solving the deterministic case. Future work may develop more advanced solution algorithms such as a parallel algorithm to improve the computational efficiency in solving the stochastic case.

6.4. Results of sensitivity analysis and performance of the hybrid GA

Sensitivity analysis of the impact on network resilience of the number of restoration crews, considered as resource limitations, proceeded via five scenarios: scenario 1 (i.e., the scenario used in the aforementioned deterministic case) with a total of ten restoration crews; scenario 2 to scenario 5 with 5, 20, 30, and 50 restoration crews, respectively. Comparison of network resilience in 2500 days under all five scenarios shows that decreasing the number of restoration crews from ten to five could lead to a sharp decrease in network resilience by 5.27%, from 0.8722 to 0.8263, whereas network resilience was increased by 6.15%, from 0.8722 to 0.9259, if the number of restoration crews was increased from ten to 50 (Figure 12). These five scenarios indicate that the restoration capacity can affect network resilience to a certain degree, and the results have important implications for decision-makers seeking to optimally allocate restoration crews to achieve specific network-resilience outcomes.

<Figure 12.>

Figure 13 depicts network resilience in 2500 days along with numbers of generations in the deterministic case, as per both the proposed hybrid GA and a traditional GA that does not incorporate the proposed heuristic approach. As this figure indicates, the maximum network resilience of 0.8722 calculated by the proposed hybrid GA converges at 131 generations, as compared to a network resilience of 0.8379 at 175 generations in the case of the traditional GA. In other words, the proposed hybrid GA's performance is superior to the traditional GA in terms of computational efficiency, i.e., 1.34 times faster, as well as providing a better solution to the problem.

<Figure 13.>

7. Conclusions

Post-earthquake long-term restoration scheduling for highway–bridge networks have generally not incorporated restoration interactions resulted from the blockage and unblockage of bridges for restoration works, but the results of the present study clearly demonstrate the necessity and the benefits of doing so. To understand the impact of restoration interactions on post-earthquake bridge restoration-scheduling problems, the present study proposed an integer program for such problems by modeling such interactions in the case of a post-earthquake highway–bridge network, with the aim of maximization of such a network' resilience. Furthermore, this study developed a stochastic model to take into consideration the uncertainty associated with bridge restoration times. Additionally, it reported on the development of a hybrid GA that combines a traditional GA with a specially designed heuristic approach to improve the integer program's computational efficiency.

The proposed methodology was tested using detailed data about a highway–bridge network in central Sichuan, China, and the effects of the 2008 Wenchuan Earthquake on it. By comparing network resilience calculated via the proposed restoration-scheduling model against that from a traditional restoration-scheduling model without considering restoration interactions, it became clear that neglecting the restoration interactions led to the overestimation of optimal network resilience, i.e., by 6.9% in this case study. It can also be observed that restoration interactions can lead to long waiting times of restoration crews and can delay the recovery process of the highway–bridge network, i.e., a 367-day delay in this case study. Additionally, comparing the optimal restoration sequences in the stochastic case against that in the deterministic case, one can conclude that uncertainty associated with bridge restoration times can significantly affect the optimal restoration sequences. Based on the results of sensitivity analysis of the network-resilience impacts of the number of restoration crews, considered as a resource constraint, it is clear that the restoration capacity can affect network resilience to a certain degree. Finally, the present case study shows that the proposed hybrid GA had 1.34 times faster computational efficiency than a traditional GA and provided a better optimal solution.

It is hoped that the present study will serve as a basis for further research on long-term restoration scheduling for post-disaster highway–bridge systems. Specifically, the proposed restoration scheduling model improves the current models by taking into consideration restoration interactions, which have been proved to significantly affect the restoration processes within a highway–bridge network. Moreover, the proposed methodology can help decision makers explicitly and practically appraise highway network resilience and establish efficient long-term bridge restoration schedules with optimal network resilience.

Nonetheless, it has some limitations that should be acknowledged. First, network resilience depends very much on the highway–bridge network's topology, and the results of the present case study were derived from a single selected highway–bridge network in Sichuan, China; thus, the proposed methodology could be tested using various network topologies with different network sizes. Second, this study used simplified restoration processes and did not consider the budget constraints; however, detailed restoration processes and the availability of budget could be included in future works. For example, different bridges may require different restoration resources, and restoration crews' productivity may fluctuate during the recovery process. Finally, given that the proposed hybrid GA may not be able to obtain a global optimum solution in the case study, and that the deviation from the exact solution was thus unknown, a small-size highway–bridge network, for which exact solutions can be computed, could be used to test the computational efficiency of the proposed methodology.

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Appendix

<Table A.1.>

<Table A.2.>

<Table A.3.>

<Table A.4.>

<Table A.5.>

Table

Table 1. Optimal bridge restoration sequences in the stochastic case

Table 1. Optimal bridge restoration sequences in the stochastic case

Restoration crew	Restoration sequences
	4→79→103→69→81→88→84→2→111→86→112→106
	16→17→22→23→24→25→26→27→28→29→30
	102→101→100→99→98→89→15→14→13→12→11
	104→5→6→7→8→9→10→18→19→20→21→108
	40→39→38→37→36→35→34→33→32→31→41
	70→42→43→44→45→47→48→49→50→51→52
	77→46→97→68→67→66→65→64→76→78→63
	62→53→54→55→56→57→58→59→60→61→75
	71→72→73→74→90→91→92→93→94→95→96
	105→87→83→80→85→82→110→107→109→3→1

Figures

Figure 1. Post-earthquake highway–bridge network in Sichuan, China

Figure 2. Proposed fluctuant, stepwise functionality curve of a highway–bridge network

Figure 3. Flowchart of the proposed solution algorithm for the stochastic model

Figure 4. Example of restoration-time sampling of a bridge in complete damage ()

Figure 5. Randomly pairing with ()

Figure 6. Encoding scheme for a chromosome (the numbers on the genes are bridge identifications (IDs))

Figure 7. Process of the early-termination test

Figure 8. Updating of a chromosome terminated early (the numbers on the genes are bridge IDs)

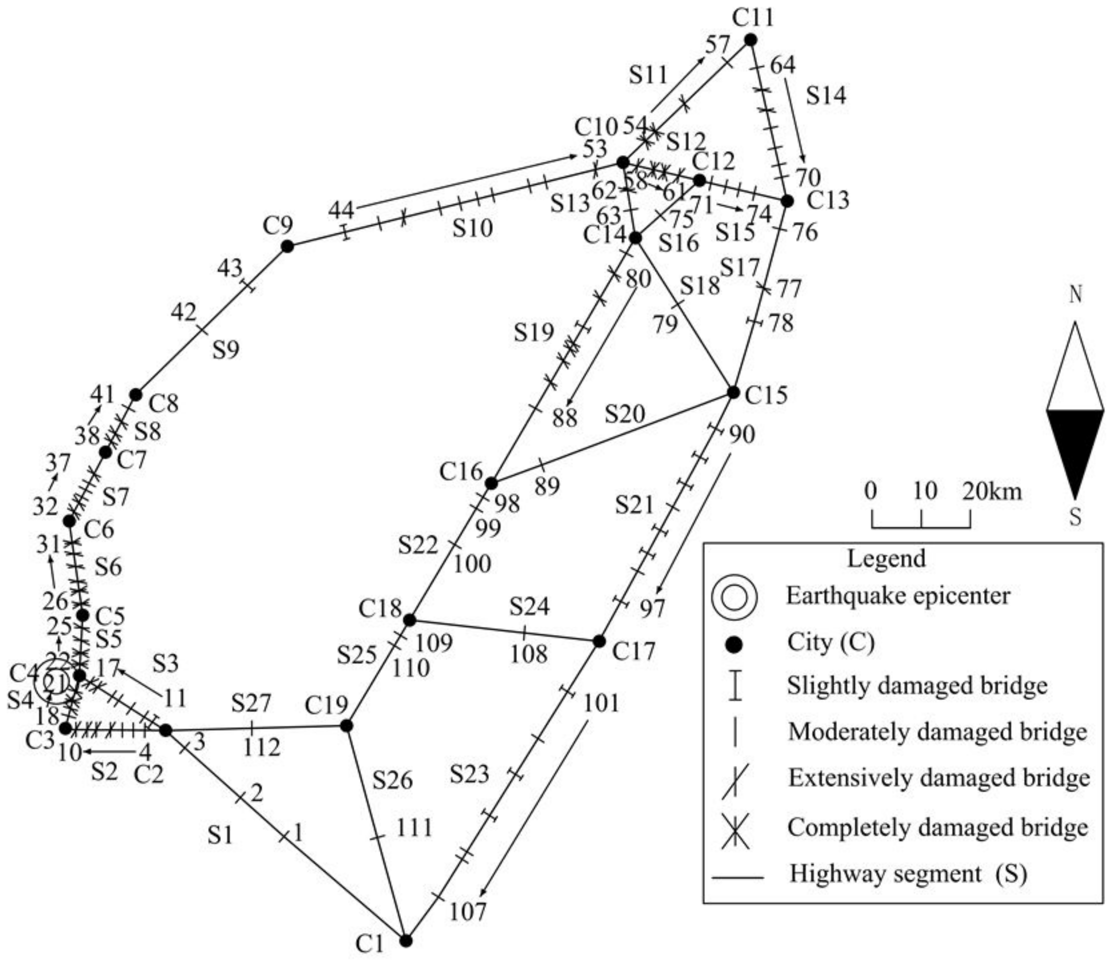
Figure 9. Network functionality over time

Figure 10. Optimal results for (a) restoration schedules generated by the proposed restoration-scheduling model, and (b) restoration schedules generated by a traditional restoration-scheduling model. The numbers on the bars are bridge IDs, and the length of each bar represents restoration time.

Figure 11. Histograms of network resilience in the stochastic case

Figure 12. Impact of the number of restoration crews on network resilience

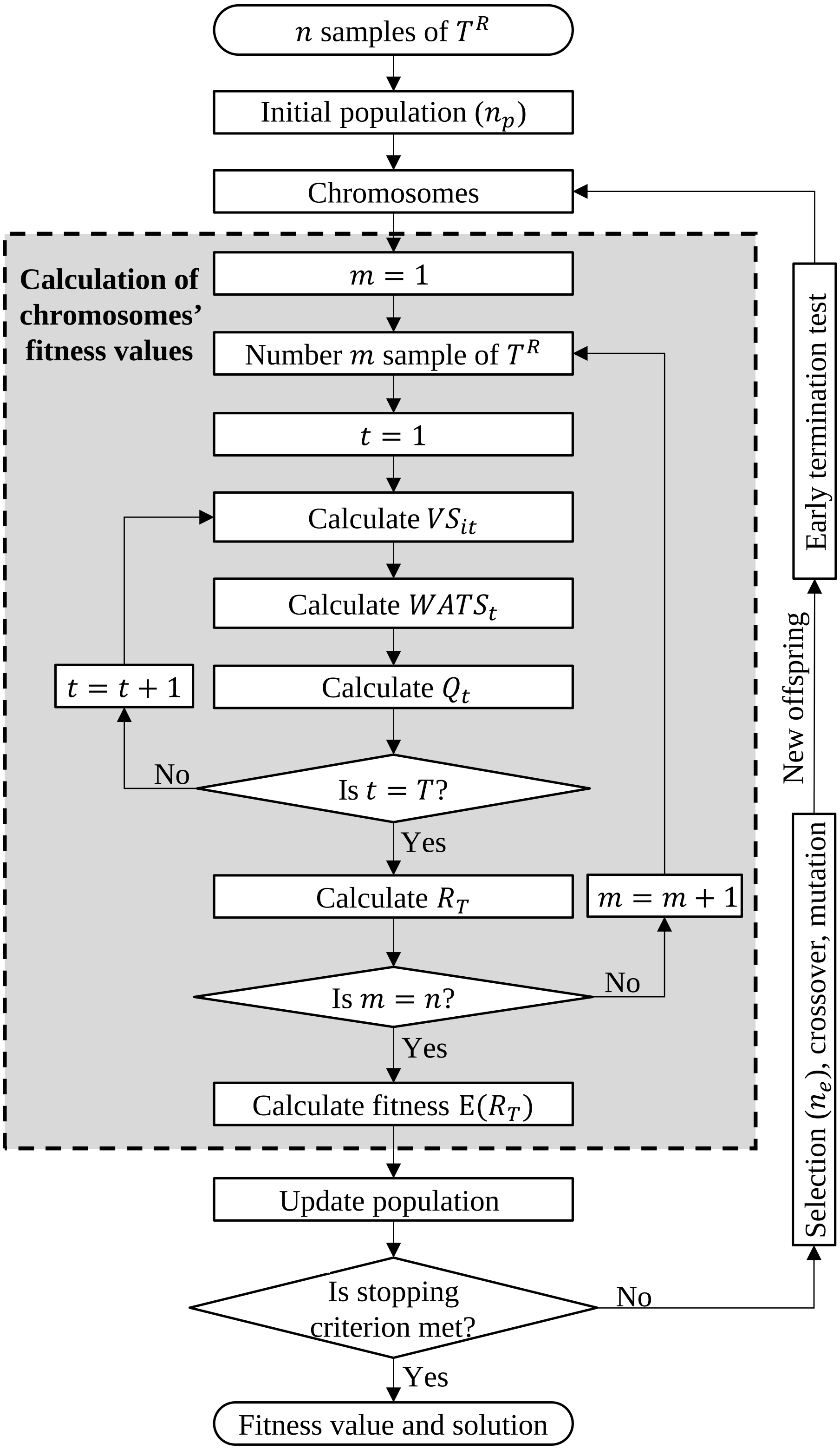
Figure 13. Evolution of resilience values across generations



C11
57
S11
64
S14
C10
54
S12
53
C12
70
C13
62
58
61
S13
71
74
44
63
75
C9
S10
C14
S16
S15
76
S17
43
80
77
S18
42
79
78
S9
S19
N
41
C8
C15
88
S20
90
38
S8
C7
37
C16
89
S7
0 10 20km
32
98
S21
C6
99
S
31
S22
Legend
S6
100
Earthquake epicenter
26
C5
C18
S24
97
25
109
City (C)
S5
C4
S25
108
C17
S3
Slightly damaged bridge
21
17
110
11
S27
S4
C19
101
18
Moderately damaged bridge
C3
3
112
10
4
S2
C2
S23
Extensively damaged bridge
S26
2
1
Completely damaged bridge
S1
111
Highway segment (S)
107
C1

Figure 1. Post-earthquake highway–bridge network in Sichuan, China

Figure 2. Proposed fluctuant, stepwise functionality curve of a highway–bridge network



n samples of T^R
Initial population (n_p)
Chromosomes
Calculation of chromosomes' fitness values
$m = 1$
Number m sample of T^R
$t = 1$
Calculate VS_{it}
Calculate $WATS_t$
Calculate Q_t
$t = t + 1$
No
Is $t = T$?
Yes
Calculate R_T
$m = m + 1$
Is $m = n$?
No
Yes
Calculate fitness $E(R_T)$
Update population
Is stopping criterion met?
No
Yes
Fitness value and solution
Early termination test
New offspring
Selection (n_e), crossover, mutation

Figure 3. Flowchart of the proposed solution algorithm for the stochastic model

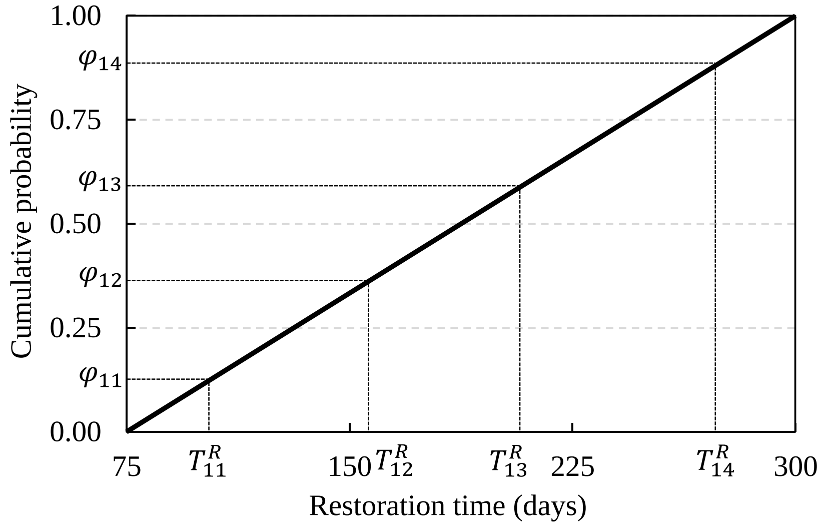


Figure 4. Example of restoration-time sampling of a bridge in complete damage ()

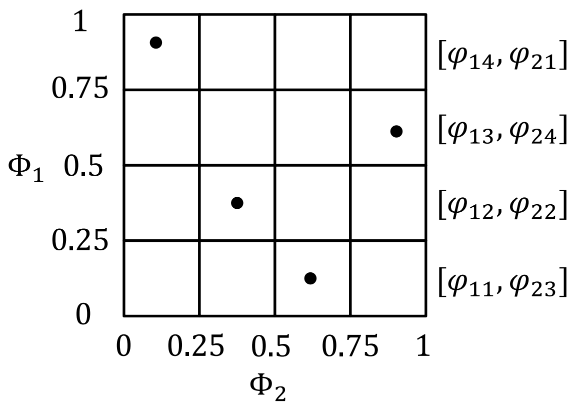


Figure 5. Randomly pairing with ()

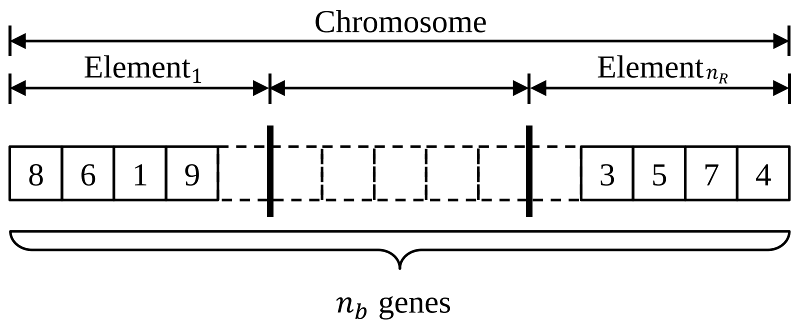
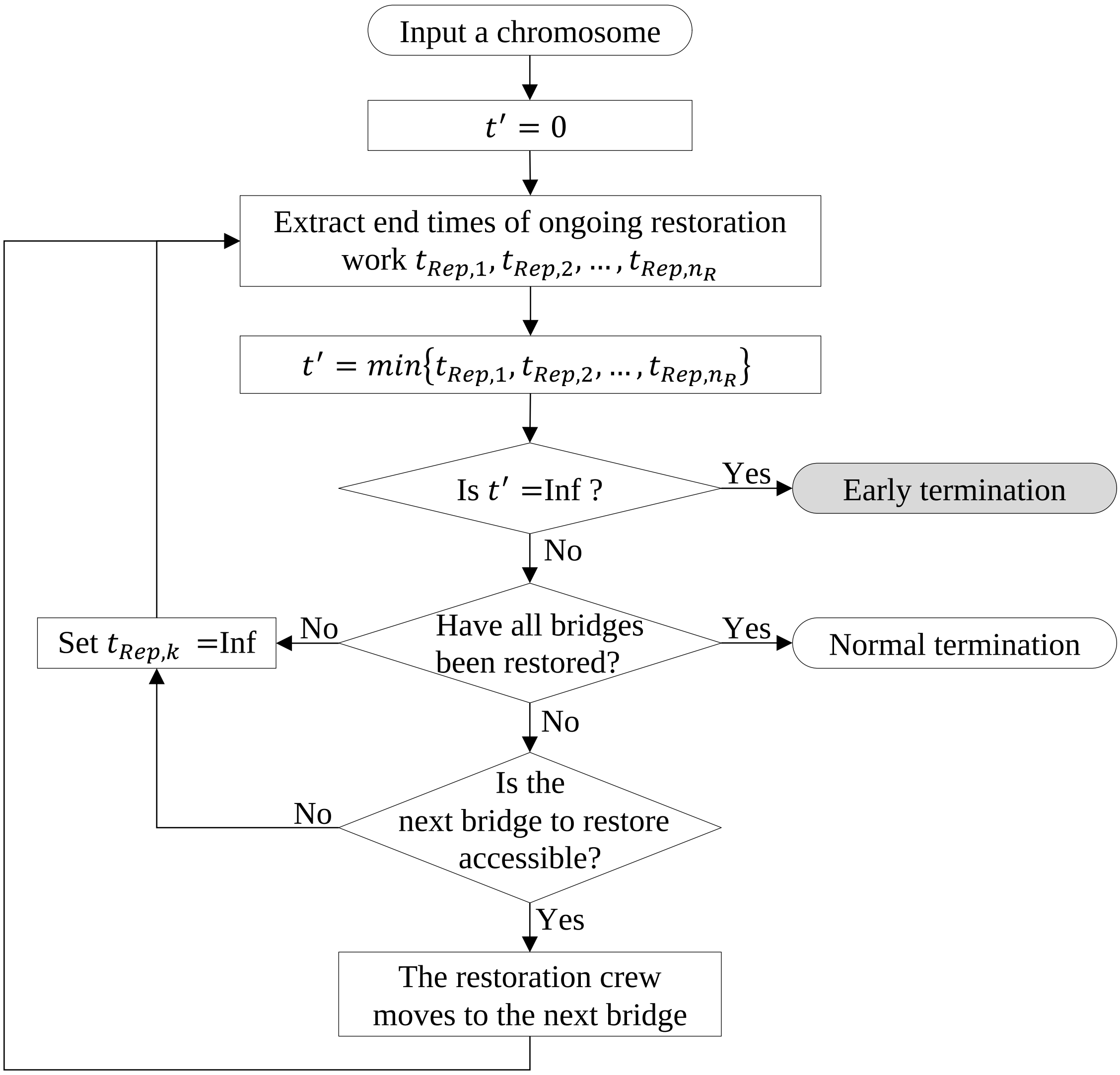


Figure 6. Encoding scheme for a chromosome (the numbers on the genes are bridge identifications (IDs))



Input a chromosome
$t' = 0$
Extract end times of ongoing restoration work $t_{Rep,1}, t_{Rep,2}, \dots, t_{Rep,n_R}$
$t' = min\{t_{Rep,1}, t_{Rep,2}, \dots, t_{Rep,n_R}\}$
Is t' =Inf ?
Yes
Early termination
No
Have all bridges been restored?
Yes
Normal termination
No
Set $t_{Rep,k}$ =Inf
No
Is the next bridge to restore accessible?
No
Yes
The restoration crew moves to the next bridge

Figure 7. Process of the early-termination test

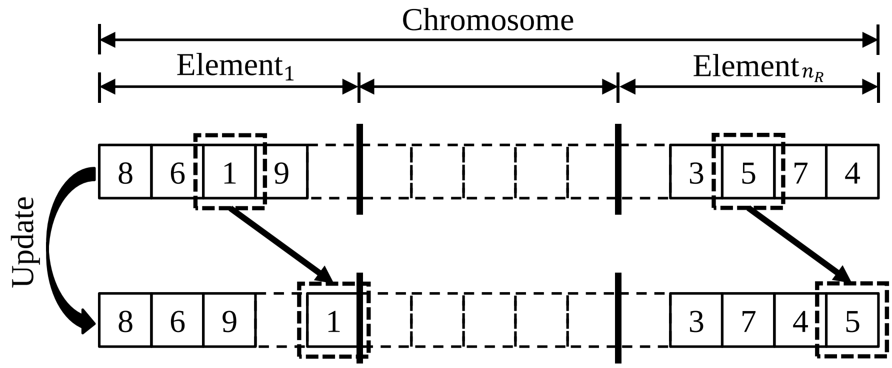


Figure 8. Updating of a chromosome terminated early (the numbers on the genes are bridge IDs)

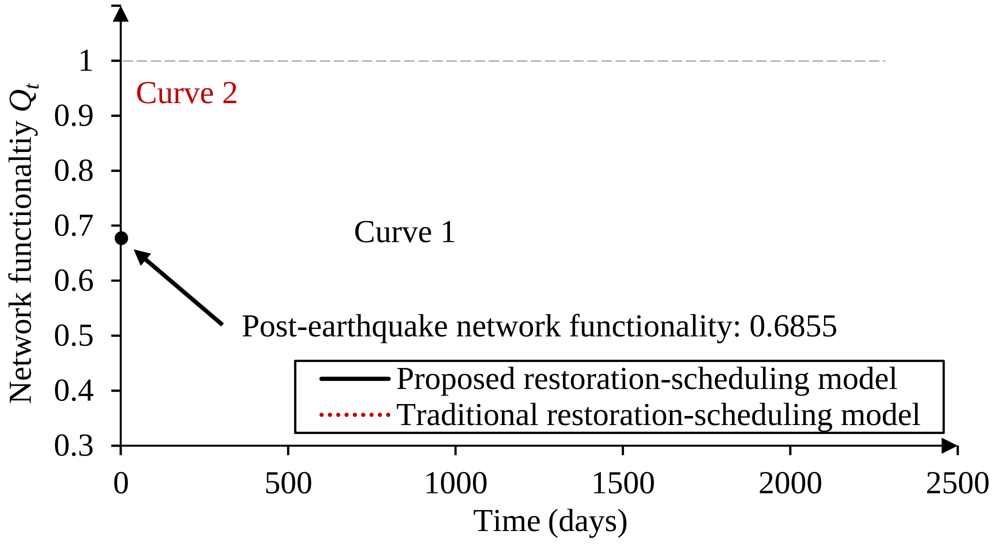
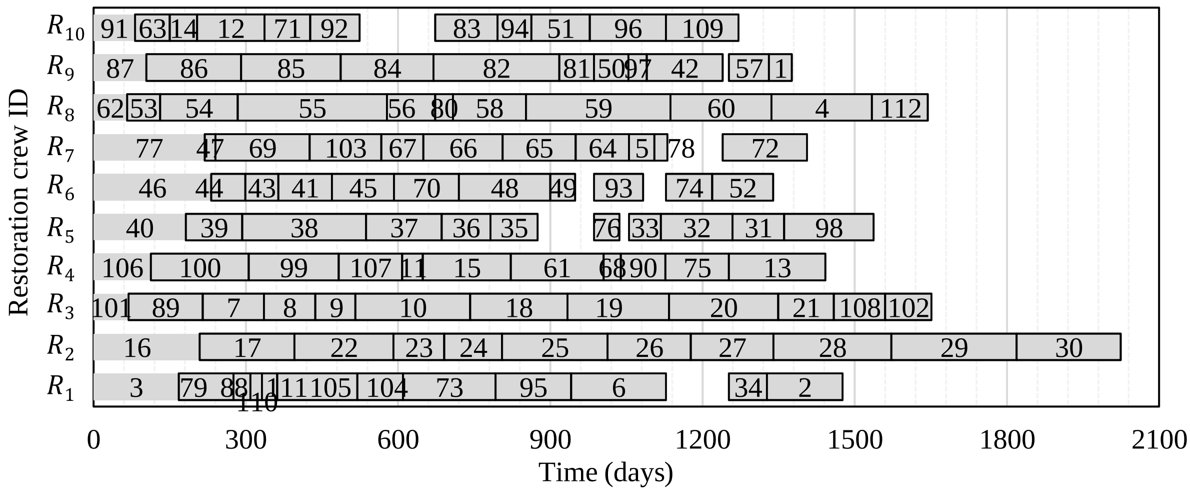
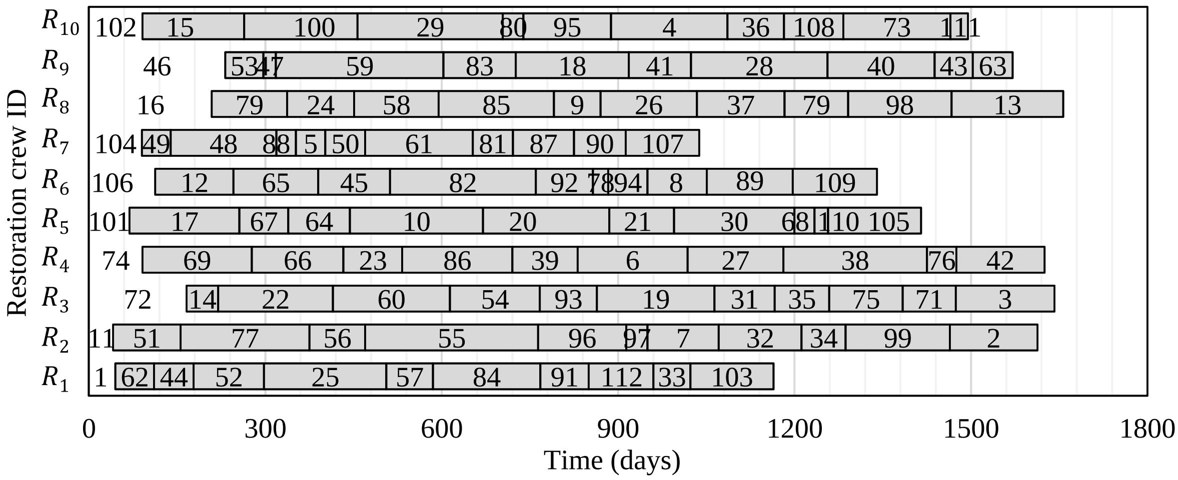


Figure 9. Network functionality over time



Restoration crew ID
R_{10}
R_9
R_8
R_7
R_6
R_5
R_4
R_3
R_2
R_1
0
300
600
900
1200
1500
1800
2100
Time (days)

(a)



(b)

Figure 10. Optimal results for (a) restoration schedules generated by the proposed restoration-scheduling model, and (b) restoration schedules generated by a traditional restoration-scheduling model. The numbers on the bars are bridge IDs, and the length of each bar represents restoration time.

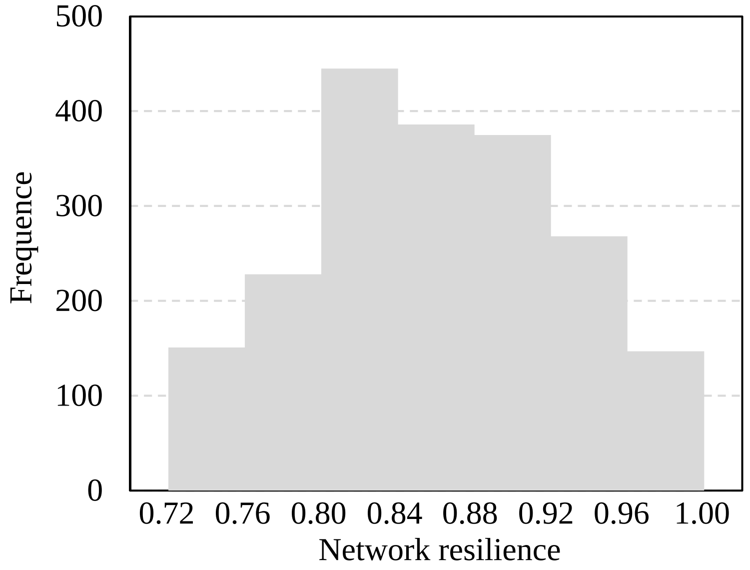


Figure 11. Histograms of network resilience in the stochastic case

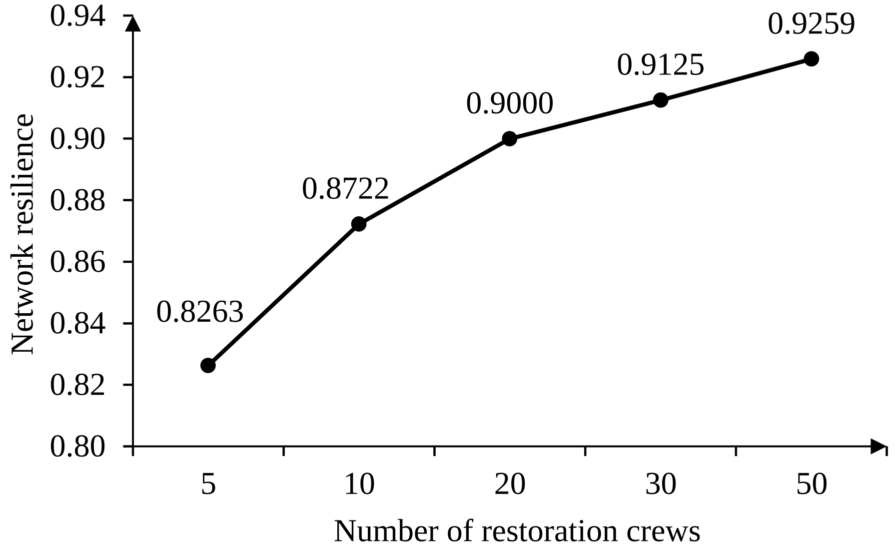


Figure 12. Impact of the number of restoration crews on network resilience

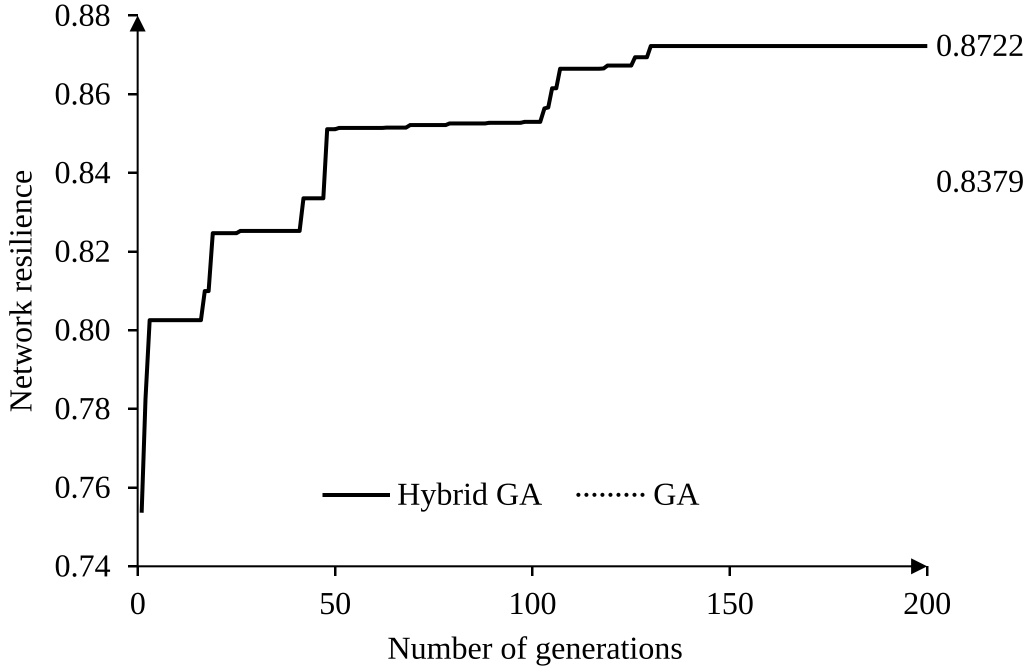


Figure 13. Evolution of resilience values across generations

Appendix

Table A.1. Decision variables and parameters to be calculated

Table A.2. Summary of the realized stochastic optimization formulation

Table A.3. Parameters of highway segments

Table A.4. Pre-earthquake travel demand between cities

Table A.5. Bridge damage states and deterministic bridge restoration times

Table A.1. Decision variables and parameters to be calculated

Notation	Description
Decision variables	
	A binary variable to indicate whether restoration crew starts to restore bridge at time
	A binary variable to indicate whether restoration crew restores bridge in sequence
Parameters to be calculated	
	Bridge damage index of bridge at time , ,
	Link damage index of highway segment at time , ,
	Residual free-flow driving speed on highway segment at time , ,
	Residual traffic capacity of highway segment at time , ,
	Traffic flow on highway segment at time , ,
	Passability of the path from node to node at time , ,
	Network functionality at time ,
	Highway–bridge network resilience
	Period for the full recovery of travel demand after a disaster
	Post-earthquake travel demand between city and city at time , ,

Table A.2. Summary of the realized stochastic optimization formulation

Description	Equations	Equation No.
Input Parameters	Network topology:	
	Attributes of highway segments: , ,	
	Bridge damage index:	
	Number of restoration crews:	
	Time horizon:	
	Pre-earthquake travel demand between cities:	
	Trip reduction rate:	
Decision Variables		
Restoration plans	, ,	
Objective		
		(5)
Maximize highway–bridge network resilience		(6)
		(7)
		(8)
		(9)
	max	(22)
Restoration Activity Constraints		
Each bridge is restored one time		(11)
		(12)
A restoration crew restores one		(13)
		(14)

bridge at a time	
Decision Variable Relationship Constraints	
Relationships of decision variables	(15)
Start times of two adjacent restoration tasks	(16)
Restoration Interaction Constraints	
Restoration activities affect passability of highway segments	(17)
	(18)
	(19)
	(20)
Binary Constraint	
Decision variables	(21)
Restoration Time Constraint	
Restoration time	(23)

Table A.3. Parameters of highway segments

Highway segment	City	City	Length (km)	Design speed (km/h)	Traffic capacity (pcu/day)	Bridges on highway segments
S1	C1	C2	60	80	115200	1-3
S2	C2	C3	27	30	16800	4-10
S3	C2	C4	23	80	115200	11-17
S4	C3	C4	13	40	26400	18-21
S5	C4	C5	12	40	26400	22-25
S6	C5	C6	27	30	16800	26-31
S7	C6	C7	20	30	16800	32-37
S8	C7	C8	21	40	24000	38-41
S9	C8	C9	51	40	24000	42-43
S10	C9	C10	90	40	24000	44-53
S11	C10	C11	24	40	26400	54-57
S12	C10	C12	30	40	26400	58-61
S13	C10	C14	19	40	24000	62-63
S14	C11	C13	49	40	24000	64-70
S15	C12	C13	24	30	16800	71-74
S16	C12	C14	25	40	24000	75
S17	C13	C15	45	30	16800	76-78
S18	C14	C15	53	30	16800	79
S19	C14	C16	61	40	24000	80-88
S20	C15	C16	68	30	16800	89

S21	C15	C17	68	30	16800	90-97
S22	C16	C18	31	40	24000	98-100
S23	C17	C1	48	80	115200	101-107
S24	C17	C18	27	40	24000	108
S25	C18	C19	38	80	115200	109-110
S26	C19	C1	48	80	115200	111
S27	C19	C2	73	40	26400	112

Note: pcu = passenger car unit.

Table A.4. Pre-earthquake travel demand between cities

City	City	Travel demand (pcu/day)	City	City	Travel demand (pcu/day)	City	City	Travel demand (pcu/day)
C1	C2	2000	C2	C6	200	C11	C13	500
C1	C3	200	C2	C7	200	C12	C13	400
C1	C4	300	C3	C4	300	C12	C14	300
C1	C8	1200	C4	C5	200	C13	C15	1000
C1	C9	800	C5	C8	200	C13	C16	300
C1	C10	500	C6	C8	200	C13	C17	600
C1	C13	1200	C7	C9	300	C14	C15	500
C1	C15	1500	C8	C9	500	C14	C16	800
C1	C16	1500	C9	C10	500	C15	C16	2000
C1	C17	4000	C10	C11	200	C15	C17	3000
C1	C18	1000	C10	C12	300	C15	C18	1400
C1	C19	1800	C10	C13	600	C16	C17	1400
C2	C3	400	C10	C14	300	C16	C18	800
C2	C4	500	C10	C15	200	C17	C18	2300
C2	C5	300	C10	C16	300	C18	C19	1800

Note: pcu = passenger car unit.

Table A.5. Bridge damage states and deterministic bridge restoration times

Bridge	DS	RT	Bridge	DS	RT	Bridge	DS	RT
1	M	45	39	E	111	77	E	219
2	M	149	40	E	182	78	S	26
3	M	168	41	M	106	79	M	108
4	M	198	42	M	150	80	M	35
5	M	50	43	S	65	81	E	68
6	M	187	44	S	67	82	E	248
7	E	121	45	M	122	83	S	123
8	E	101	46	E	232	84	E	183
9	E	79	47	M	21	85	E	196
10	E	226	48	M	180	86	E	187
11	S	41	49	M	49	87	E	104
12	M	133	50	M	68	88	M	33
13	M	190	51	M	115	89	M	146
14	M	54	52	M	120	90	S	88
15	M	173	53	E	65	91	S	82
16	E	209	54	C	153	92	S	97
17	E	187	55	C	294	93	M	97
18	M	192	56	E	95	94	S	67
19	E	200	57	M	79	95	S	149
20	C	215	58	E	144	96	M	150
21	E	110	59	C	285	97	S	36
22	C	195	60	C	199	98	M	176

23	C	100	61	E	183	99	M	177
24	E	114	62	E	66	100	M	193
25	E	208	63	M	68	101	S	69
26	C	164	64	M	105	102	M	91
27	C	163	65	E	144	103	S	141
28	E	232	66	E	156	104	S	90
29	E	247	67	M	83	105	M	158
30	E	205	68	M	34	106	M	113
31	C	102	69	M	186	107	M	125
32	E	141	70	M	128	108	M	101
33	E	63	71	M	90	109	M	143
34	M	75	72	M	166	110	M	23
35	M	93	73	M	182	111	M	30
36	M	96	74	M	91	112	M	110
37	E	149	75	M	125			
38	E	244	76	M	50			

Note: DS = bridge damage state; S = slight; M = moderate; E = extensive; C = complete; RT = bridge restoration time (days).