Probabilistic life-cycle seismic resilience assessment of aging bridge networks considering infrastructure upgrading

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ABSTRACT
This paper presents a probabilistic framework for life-cycle seismic resilience assessment of aging bridges and transportation road networks subjected to infrastructure upgrade. The proposed framework accounts for the uncertainties in damage occurrence of vulnerable deteriorating bridges and restoration rapidity of the overall system functionality. The time-variant bridge fragilities and the damage combinations probability are evaluated considering different earthquake magnitudes and epicenter locations that define the seismic scenario. Traffic analyses are carried out to assess in probabilistic terms the network functionality profiles, the corresponding resilience levels, and a damage-based measure of life-cycle resilience. The effects of structural deterioration, seismic damage, and post-event repair actions under uncertainty are related to traffic restrictions applied over the network. The framework is applied to reinforced concrete bridges exposed to chloride-induced corrosion and simple road networks with a single bridge or two bridges in series under different earthquake scenarios. The effect of network upgrading is also investigated by adding road segments with a vulnerable bridge to strengthen the network connectivity and improve the lifetime system resilience. The results show the capability of the proposed resilience framework in quantifying the detrimental effects of structural deterioration at the network scale and the beneficial consequences of infrastructure investments, such as enhancing the network redundancy with the construction of an additional highway branch.

Introduction
Structures and infrastructure systems are exposed to detrimental effects of natural and man-made disasters along with aging and deterioration processes over the system lifetime (Biondini & Frangopol, 2016). Communities are hence called to cope with the impact of disruptive events, such as earthquakes, without suffering disproportionate sudden consequences and long-term effects with respect to the hazard exposure (Bruneau et al., 2003).

Road transportation systems are particularly critical to ensure quick deployments of relief aids and resources to repair the surrounding facilities in the post-event emergency response phase (Chang, Peng, Ouyang, Elnashai, & Spencer, 2012). Widespread and severe damage of bridges and other vulnerable system components can cause direct monetary losses associated with essential maintenance and repair interventions, as well as indirect economic consequences induced by lack of network connectivity and downtime (Zhou, Banerjee, & Shinozuka, 2010; Decò, Bocchini, & Frangopol, 2013; Titi, Biondini, & Frangopol, 2015; Capacci, Biondini, & Titi, 2016). It is hence necessary to ensure adequate levels of system resilience to withstand the impact of extreme events and recover promptly and efficiently the pre-existing performance and functionality (Chang, 2009).

The resilience of aging bridges and transportation networks exposed to sudden shocks such as earthquakes depends on the time of occurrence of the seismic event due to the long-term exposure to environmental hazards (Biondini, Camnasio, & Titi, 2015). As discussed in Capacci and Biondini, (2018a, 2018b, 2018d) for road networks and reinforced concrete (RC) bridges under chloride-induced corrosion, system functionality and seismic resilience should be formulated as time-variant probabilistic performance indicators in a life-cycle perspective. Several researchers exploited the concept of resilience to define quantitative performance indicators and optimal strategies for the management of deteriorating bridges and road networks. Among others, Padgett and DesRoches (2007) investigated the relationship between the damage induced by seismic events and the evolution in time of the expected level of allowable traffic carrying capacity for bridges. Bocchini and Frangopol (2011a, 2012a, 2012b) developed a stochastic computational framework for fragility analysis and optimal resilience- and cost-based prioritization of interventions on bridges spatially distributed in transportation networks under disruptive events. Decò et al. (2013) proposed a probabilistic approach for the pre-event assessment of seismic resilience of bridges considering uncertainties associated with expected damage, restoration process, and rebuilding/rehabilitation costs. Venkittaraman and Banerjee (2014) assessed the effectiveness...
of retrofit techniques on a single test-bed highway bridge with a resilience-based cost-benefit analysis during the bridge service life. Biondini et al. (2015a) investigated the role of aging and structural deterioration on the life-cycle seismic resilience of bridges. The time-variant formulation of seismic resilience has been extended to aging bridge networks and road infrastructure systems in Capacci et al. (2016). Alipour and Shafei (2016) investigated the recovery of congestion-based system functionality of a transportation network under seismic hazard with bridges affected by aging mechanisms. Capacci, Biondini, and Titi (2020) presented a general framework for life-cycle seismic resilience assessment of aging bridges and road networks considering the uncertainties associated with the time-variant seismic vulnerability of the bridges in the network.

Furthermore, major research efforts on the optimal management and upgrade of infrastructure systems and lifelines have been dedicated to the assessment of reliability and resilience of aging network components. Among the few works that tackled the problem of quantifying the beneficial impact of infrastructure upgrade in network reliability and lifeline resilience, the main focus is mainly put on planning optimal retrofit strategies to reduce the risk of network inoperability due to the failure of existing vulnerable assets, rather than proposing alternative design strategies based on large-scale infrastructure investments that can enhance the system functionality, such as building a new highway branch. Faturechi and Miller-Hooks (2015) provided a broad literature review on the assessment of anticipated transportation system performance, along with its management. Moghtaderi-Zadeh and Der Kiureghian (1983) addressed the need for efficient upgrade of lifelines by incrementally investing on critical components to satisfy system reliability targets for prescribed earthquake scenarios. Peeta, Salman, Gunnec, and Viswanath (2010) investigated a pre-disaster planning problem that seeks to strengthen vulnerable links within a benchmark highway network. Jalayer, Asprone, Prota, and Manfredi (2011) considered the expected life-cycle cost for a critical infrastructure under blast, earthquake and deterioration hazards as a benchmark variable in decision making problems involving retrofit and upgrading of a five-story RC frame structure. Bocchini and Frangopol (2011b) proposed a computational procedure for Pareto optimization of preventive maintenance of aging bridges within a highway network. Chang et al. (2012) presented a probabilistic framework for optimal bridge retrofit based on the maximization of the post-disaster evacuation capacity of a metropolitan road network. Zhang and Wang (2016) proposed a time-invariant resilience-based performance metric to rank different alternatives for the construction of new road segments enhancing the existing network resilience by altering its topology.

This paper extends the framework proposed in Capacci et al. (2020) to a fully probabilistic formulation of the resilience measure taking into account the uncertainties in the assessment of the recovery times and patterns affecting the resilience levels. Furthermore, the resilience framework is extended to incorporate the beneficial effects of upgrading the infrastructure. As previously discussed, most of the research work on life-cycle management of infrastructure systems is dealing with the impact of corrective interventions on structural facilities exposed to detrimental effects of damaging events, whilst little focus is put on the application of life-cycle performance indicators for the assessment of infrastructure investments such as the upgrade of the transportation system enhancing the network redundancy. To this purpose, the assessment of the immediate beneficial impact of the construction of new fast routes in existing infrastructure road networks, as well as the long-term decay of such benefit due to the progressive degradation of the newly built asset, is also investigated.

More specifically, in the proposed approach the time-variant fragilities and damage probabilities with reference to several limit states from damage limitation up to collapse of the deteriorating bridges in the network are assessed through nonlinear incremental dynamic analysis and Monte Carlo simulation considering uncertainties on structural modeling and ground motion. The role of the seismic scenario is considered in terms of earthquake magnitude and source-to-site distance within a prescribed seismic area source. The post-event seismic damage and the progressive restoration of bridge seismic capacity due to repair actions are related to traffic limitations and vehicle restrictions considering the uncertainty in the recovery process. Traffic analysis is hence carried out for each combination of bridge traffic restrictions over the network to assess in probabilistic terms the network functionality profiles, the corresponding resilience levels, and a damage-based measure of life-cycle resilience.

The analytical formulation of lifetime seismic resilience is presented with emphasis on the probability of bridge damage combination and the cumulative distribution functions (CDF) of the resilience measure given the bridge damage combination. The proposed framework is applied to RC bridges exposed to chloride-induced corrosion and simple road networks with a single bridge or two bridges in series under different earthquake scenarios. Finally, the lifetime resilience is defined for an evolving road network characterized by the construction of a new road segment with a bridge in order to strengthen the network connectivity. The results show the detrimental effects of structural deterioration at the network scale and the long-term benefits of infrastructure investments for network upgrading. The applications show the importance of a life-cycle-oriented approach to probabilistic assessment of seismic resilience of aging infrastructure systems.

**Analytical formulation of lifetime resilience measure**

The resilience of road networks depends on their capability to sustain the impact of extreme events and to recover promptly the pre-event traffic capacity. Therefore, the definition of quantitative measures of seismic resilience should be informed by the relevance of the bridges within the infrastructure system, their vulnerability to major earthquakes and the rapidity to overcome the potential impairment of traffic capacity.
Resilience can be quantified based on the definition of an overall measure of the system performance, i.e. functionality $Q$. The physical damage suffered by the set of vulnerable bridges within the road network may cause an initial drop of functionality after the occurrence at time $t_0$ of a sudden disruptive event. The functionality drop depends on the combination of damage states of each bridge in the aftermath of the seismic event, which can be collected in vector $s$ characterized by a number of rows $N_b$ corresponding to the total number of vulnerable bridges in the network. Based on a set of damage states of each bridge, the repair activities lead to the progressive restoration of the structural capacity of the bridges and, in turn, of the system functionality.

The seismic resilience levels for a given combination of bridge damage states can be quantified based on the integral mean of the functionality profile from the time of event occurrence $t_0$ up to a fixed horizon time $t_h$ (Bocchini & Frangopol, 2012b):

$$R(s) = \frac{1}{\Delta t_b} \int_{t_0}^{t_h} Q(t;s)dt$$

where $\Delta t_b = t_h - t_0$.

In the aftermath of major earthquakes, the probability that the network suffers a specific combination of bridge damage states depends on the uncertainties related to structural response and environmental deterioration. Additional uncertainties should be considered in resilience assessment regarding the recovery process of bridges that suffered structural damage, with focus on the traffic capacity downtime. The time-variant measure of network resilience should be formulated in probabilistic terms to account for several uncertainties characterizing damage occurrence and recovery process.

The CDF of the resilience measure can be defined as the weighted sum of the CDFs of the resilience levels conditioned on the occurrence probability of a bridge damage combination:

$$F_R(r|\eta_0, t_0) = \sum_s P[s|\eta_0, t_0] \cdot F_{R(s)}(r|s)$$

This formulation is based on the total probability theorem (Ang & Tang, 2007). The bridge damage combinations represent a set of $N_r$ mutually exclusive and collectively exhaustive events, where $N_r$ is the number of all the possible permutations of the entries in vector $s$. In particular, $r$ represents the outcomes of the resilience measure random variable and vector $\eta_0$ collects the parameters affecting the seismic hazard expressing the information on seismic intensities and seismogenic sources, such as epicenter location and earthquake magnitude. The resilience measure distribution also depends on the earthquake occurrence time $t_0$, since the detrimental effects of aging and the benefits of infrastructure upgrading have a critical impact on the damage combination probabilities.

The proposed formulation of seismic resilience allows aggregating the uncertainties involved in the post-earthquake of the bridge damage combination with the recovery pattern of network functionality related to the repair activities. The following sections are devoted to a thorough discussion on the assessment of the probabilistic quantities that allow defining the distribution of the resilience measure $F_R$; the damage probability $P[s]$ and the conditional seismic resilience $F_{R(s)}$. Figure 1 represents a synthetic conceptual flowchart highlighting the key aspects of the proposed methodology. The components of this flowchart are discussed in the next sections.

**Bridge network seismic damage assessment**

**Corrosion damage**

The seismic response of RC structures in aggressive environments is impaired in time by chloride-induced deterioration that affects the mechanical properties of steel reinforcement and concrete cover (Bertolini, Elsener, Pedeferrì, & Polder, 2004; Biondini, Bontempi, Frangopol, & Malerba, 2004, 2014). The time-variant percentage loss of steel resistant area of a corroded reinforcing bar can be represented as a function of a dimensionless damage index $\Delta_s = \Delta_s(t) \in [0,1]$. Based on experimental evidence, the amount of mass loss is also informative of the reduction of steel ductility induced by the corrosion process (Apostolopoulos & Papadakis, 2008). The damage index may also be related to delamination and spalling of the concrete cover surrounding corroded bars due to the formation of oxidation products (Cabrera, 1996; Zhang et al. 2010; Al-Harthiy, Stewart, & Mullard, 2011). Both effects can be effectively modeled based on suitable functional relationships between the damage index $\Delta_s$ and both the ultimate steel strain $\varepsilon_{um}$ of each corroding bar and the compression strength $f_c$ of the surrounding concrete, as shown in Biondini and Vergani (2015).

The corrosion rate can be related to chloride concentration $C = C(\eta_0, t_0)$ at point $\eta_0$ and bridge age $t_0$ by means of the following relationship (Biondini et al., 2004):

$$\frac{\partial \Delta_s(t_0)}{\partial t} = q_s C(\eta_0, t_0), \quad t_0 \geq t_{cr}$$

where $q_s$ is a damage rate coefficient based on available data for chloride attacks (Bertolini et al., 2004). The critical time $t_{cr}$ is associated with corrosion initiation occurring when chloride concentration attains a prescribed critical threshold $C_{cr}$. Given the chloride concentration $C_0$ along the surface of the exposed structural members, the ingress of chlorides in concrete can be effectively studied using the Fick’s diffusion equation based on cellular automata (Biondini et al., 2004, Biondini, Bontempi, Frangopol, & Malerba, 2006; Titi & Biondini, 2016).

The deterioration process is characterized by several sources of uncertainty. The variability of the environmental hazard scenario can be taken into account based on a probabilistic modeling of the involved random variables (Biondini et al., 2006, 2014). Aleatory uncertainties of environmental aging should account for the randomness of diffusion of chlorides (e.g. concrete diffusivity $D$), corrosion initiation (e.g. initial and critical chloride concentrations $C_0$,
and $C_{cr}$, respectively) and deterioration process (e.g., damage rate $q_s$). Therefore, the CDF of the damage index $\Delta_s$ should be expressed as a time-variant function as follows:

$$F_{\Delta_s}(\delta_s | t_b) = \int_{R^N} F_{\Delta_s}(\delta_s | \eta_s, t_b) \cdot f_{\eta_s}(\eta_s) \cdot d\eta_s$$  

where $\delta_s$ represents the outcomes of the random variable $\Delta_s$, vector $\eta_s$ collects the $N_s$ random variables characterizing the environmental hazard scenario and $f_{\eta_s}$ represents the joint PDF of the $N_s$-dimensional multivariate distribution of the random variables collected in $\eta_s$.

**Time-variant bridge fragility**

The lifetime seismic capacity of RC bridges is investigated under uncertainty based on the assessment of time-variant fragility curves, representing the exceedance probability of a given damage state $s_b$ due to the occurrence at time $t_0$ of a seismic event of intensity $i_b$. Time-variant fragility curves rely on limit states informed by damage limitation associated with the accumulation of excessive plastic strains in critical regions, such as the pier ends in girder bridges under seismic loading. Bridge performance levels can therefore be defined with respect to inelastic displacement demand ratios similarly to the typical common practice for buildings (SEAOC, 1995).

Depending on the type of structure and failure conditions, multiple critical members and related damage measures can be incorporated in the proposed framework for the definition of the limit states. In this paper, $s_b$ is associated with the exceedance of a single damage measure as follows:

$$\{S_b \geq s_b \} = \{ \bar{\theta}_b(s_b, t_b) - \Theta_b(i_b, t_b) \leq 0 \}$$

where $S_b$ is a discrete random variable representing the damage state of the $b$-th bridge after the earthquake occurrence, the continuous random variable $\Theta_b$ is the damage measure of the aging bridge given the seismic demand, and the time-variant parameter $\bar{\theta}_b$ defines the limit state threshold.

The attainment of the damage states $s_b$ is associated with the following drift thresholds (Capacci, 2015):

- Slight Damage (SD, $s_b=1$): $\bar{\theta}_b(1, t_b) = \theta_{yb}(t_b)$;
- Moderate Damage (MD, $s_b=2$): $\bar{\theta}_b(2, t_b) = \theta_{yb}(t_b) + 0.3 \theta_{yp}(t_b)$;
- Extensive Damage (ED, $s_b=3$): $\bar{\theta}_b(3, t_b) = \theta_{yd}(t_b) + 0.6 \theta_{yp}(t_b)$. 

with $\theta_{yd} = \theta_{ub} - \theta_{yb}$ and where $\theta_{yb}$ and $\theta_{ub}$ are the drift at first yielding and ultimate bending curvatures, respectively, at the base of the bridge piers. In particular, the ultimate bending curvature is conventionally reached when either the outer concrete core fiber in compression or the outer steel reinforcement bar in tension attain their respective ultimate strains. In addition, the bridge is assumed to suffer No Damage (ND, $s_b=0$) if $\theta_{ub} < \theta_{yb}$, and to reach the limit...
state of Structural Collapse ($SC_s=4$) when the dynamic equilibrium under ground motion is no longer fulfilled, i.e. drift increases substantially with a small increment of intensity measure (Vamvatsikos & Cornell, 2002). The reference values $\Theta_{b}(i_b,t_b)$ and $\Theta_{a,b}(t_b)$ are set based on the mean values of a probabilistic time-variant non-linear static (pushover) analysis evaluated at different bridge ages $t_b$ (Capacci et al., 2016).

The time-variant fragility associated with a given damage state $s_b$ at bridge age $t_b$ is defined as follows:

$$P[s_b \geq s_b | i_b, t_b] = \int_0^{+\infty} I[\Theta_b(i_b, t_b) - \Theta_b(i_b, t_b) < 0] \cdot f_{\Theta_b(i_b,t_b)}(\Theta_b | i_b, t_b) d\Theta_b$$  

where $f_{\Theta_b(i_b,t_b)}$ is the PDF of the seismic damage measure conditioned by seismic demand $i_b$ and bridge age $t_b$. The distribution of the damage measure and the time-variant fragility curves can be obtained by coupling Monte Carlo simulation techniques with suitable structural analysis tools for the evaluation of the bridge response for different levels of seismic demand, such as Incremental Dynamic Analysis (IDA, Vamvatsikos & Cornell, 2002).

Due to the uncertainties associated with the seismic response of the structural system, suitable random variables should be considered to model the most sensitive mechanical parameters, such as the material strengths or the damping ratio (Biondini et al., 2006, 2014). Nonetheless, the deterioration process induced by the environmental exposure can severely affect in time the damage measure distribution. Assuming that a single damage index $\Delta$ is informative of the environmental damage suffered by the bridge, the PDF of the seismic damage measure $\Theta_b$ is defined as follows:

$$f_{\Theta_b | i_b, t_b}(\Theta_b | i_b, t_b) = \int_0^{+\infty} f_{\Theta_b | i_b, \Delta}(\Theta_b | i_b, \Delta) \cdot f_{\Delta | i_b, \Delta}(\Delta | i_b) \cdot d\Delta$$  

where $\Theta_b$ is the outcome of the damage measure random variable and $f_{\Theta_b | i_b, \Delta}$ is the PDF of the environmental damage index given the bridge age.

**Probability of bridge damage combinations**

The probability of occurrence of a specific bridge damage combination depends on several factors affecting the seismic demand, such as earthquake magnitude and epicenter location (Biondini, Capacci, & Titi, 2017), as well as the deteriorating seismic capacity of each bridge and their mutual correlation (Capacci & Biondini, 2018c). Based on a Ground Motion Prediction Equation (GMPE), the seismic demand $i_b$ at the site $s_b$ of the $b$-th bridge in the network can be defined in terms of magnitude $M$ and source-to-site distance $d_{s-b}$. Given the 2-D vector collecting the bridge site coordinates $x_b$, the focal distance can be defined by the Euclidian norm $d_{c,b} = \|x_c - x_b\|$, where $x_c$ represents the 2-D vector collecting the epicenter location coordinates. The selection of the most appropriate GMPE should be informed mainly by the selected measure for the seismic demand $i_b$ and by the characteristics of the site of interest, since these prediction models are generally calibrated based on statistical regression on observations from libraries of observed ground motion intensities (Baker, 2009).

The time-variant probability of occurrence of the damage state $s_b=0,...,4$ on the $b$-th bridge can be represented as follows:

$$P[s_b = s_b | i_b, t_b] = P[s_b = s_b | i_b, t_b] - P[s_b = s_b + 1 | i_b, t_b]$$  

where $P[S_{b>0}]=1$ and $P[S_{b=5}]=0$. The joint probability of the bridge damage combination associated with the $N_b$-row vector $s$ collecting the damage states of the bridges in the network can be conveniently expressed as follows:

$$P[s | \boldsymbol{\eta}, t_0] = P[s_1 = s_1, s_2 = s_2, ..., s_{N_b} = s_{N_b} | \boldsymbol{\eta}, t_0]$$  

where the earthquake occurrence time $t_0$ can be related to the age of each bridge based on their construction time $t_{cb}$, i.e. $t_b = t_0 - t_{cb}$.

Seismic reliability assessment of bridge networks can be tackled by exploiting analytical techniques relying on suitable mathematical formulations (Kang, Song, & Gardoni, 2008) or numerical simulation (Ghosh, Rokneddin, Padgett, & Dueñas-Osorio, 2014). Relevant sources of uncertainty can be taken into account also in the seismic hazard prediction model of spatially distributed structures. These uncertainties are related to the scatter in observed ground motion intensities for a given magnitude and source-to-site distance, as well as the within-event spatial correlation and the related site-to-site variability of the seismic demand (Heresi & Miranda, 2019). In the applications of this paper, these uncertainties are not considered and the seismic intensity $i_b$ at the $b$-th bridge site is expressed in deterministic terms.

**Damage-dependent resilience measure**

**Congestion-based network performance**

Road networks are characterized by road segments and vulnerable bridges connecting nodes that originate and attract trips of the infrastructure users. A road arc $i-j$ is defined by nodes $i$ and $j$, where traffic flows get into and get out of the arc, respectively. The arc travel time $c_{ij}$ depends on the traffic flow of vehicles $f_{ij}$ and several parameters either peculiar to each road arc (such as its length $L_{ij}$ and the number of open lanes $n_l$) or representative of the road class (such as minimum allowed distance $d_{min}$ between vehicles, critical capacity $c_r$, and speed limit $v_{lim}$). More details on the traffic model used in the present paper can be found in Capacci et al. (2020).

According to the Wardrop’s gravitational model (Wardrop, 1952), the traffic flow response and Origin-Destination (OD) traffic demand of road users can be identified by minimizing the total travel time $TTT$, i.e. the time spent by all users to reach destination nodes from origin nodes departing in a fixed time window (Bocchini & Frangopol, 2011a):

$$TTT = \sum_{i \in I} \sum_{f \in F} \int_0^{f_i} c_{ij}(f) df$$  

where $f$ is a dummy integration variable, $I$ is the set of all
the generic nodes in the network and \( J \) is the subset of nodes connected to node \( i \) by a road segment. More details can be found in Bocchini and Frangopol (2011a) and Capacci (2015).

**Bridge traffic limitations and network functionality**

When road arcs include vulnerable bridges, the users travel time depends on the post-earthquake conditions of each damaged structural system and on traffic restrictions applied to regulate the transit (Mackie & Stojadinović, 2006). In order to guarantee the safety of road users in the aftermath of hazardous events, the road arc practicability may be impaired by traffic restrictions that the owner of the infrastructure would impose to either partially regulate or strictly prevent the passage of road users.

Three types of road users are considered in this paper: light vehicles \( f_l \), heavy vehicles \( f_h \), and emergency vehicles \( f_c \). Traffic limitations to each type of vehicle are applied on the \( b \)-th bridge depending on the bridge damage state. They are identified by a decision variable \( d_b \) based on the following limited traffic restrictions (Biondini, Capacci, & Titì, 2015):

- No Restrictions \((d_b=0)\): the traffic on the bridge is regular and the speed limit \( v_{\text{lim}} \) corresponds to the maximum allowed speed \( v_{\text{max}} \).
- Weight Restriction \((d_b=1)\): heavy vehicles are forbidden, i.e. \( f_h=0 \), and the speed limit is reduced to \( v_{\text{min}} \).
- One Lane Open Only \((d_b=2)\): light and emergency vehicles can transit on only one lane, i.e. \( n_l=1 \).
- Emergency Access Only \((d_b=3)\): the transit of emergency vehicles only is allowed, i.e. \( f_c=0 \).
- Closure \((d_b=4)\): no vehicles can transit over the bridge, i.e. \( f_l=0 \) or \( n_l=1 \).

Each restriction \( d_b=k \) with \( k>1 \) is inclusive of the traffic limitations associated with \( d_b<k \).

Bridges may suffer a loss of structural capacity due to the occurrence of an intense seismic event and network traffic restrictions in the immediacy of the earthquake occurrence are informed by the attainment of limit states for each vulnerable bridge. The set of transit limitations along each bridge can be collected in the \( N_b \)-row vector \( \mathbf{d} \), defining the combination of network traffic restrictions. The functionality \( Q_{\text{d}}(\mathbf{d}) \in [0;1] \) of the road network associated with the combination \( \mathbf{d} \) of traffic restrictions is defined as follows (Capacci, 2015):

\[
Q_{\text{d}}(\mathbf{d}) = \frac{\text{TTT}\text{d}}{\text{TTT}0},
\]

where \( \text{TTT}\text{d} = \text{TTT}(\mathbf{d}) \) is the total travel time under the restriction combination \( \mathbf{d} \), and \( \text{TTT}0 = \text{TTT}(\mathbf{d} = \mathbf{0}) \) is associated with no traffic restrictions applied to any bridge in the network, i.e. \( Q_\mathbf{0} = Q_\mathbf{0} = 100\% \).

A restriction \( d_b=k \) is applied to the \( b \)-th bridge attaining a damage state \( s_b=k \). Traffic limitations on the set of bridges in the network cause a sudden drop of functionality from 100% to \( Q_d(\mathbf{d} = \mathbf{s}) \) due to the limitation imposed with the initial damage combination \( \mathbf{s} \).

**Recovery processes and life-cycle seismic resilience**

Post-event repair activities of the \( b \)-th bridge in the network are carried out from the idle time \( T_{I,b} \) up to the time of repair completion \( T_{r,b} \). The structural recovery profile depends on many uncertain factors, including type of system and components, magnitude and location of damage, and restoring techniques (Kafali and Grigoriu, 2005; Cimellaro, Reinhorn, & Bruneau, 2010; Bocchini, Decò, & Frangopol, 2012; Decò et al., 2013; Titi et al., 2015; Karamlou & Bocchini, 2017a, 2017b; Sharma, Tabandeh, & Gardoni, 2018). In this paper, the initial traffic limitations \( d_b=k \) with \( k>0 \) are partially released through a progressively decreasing sequence of less severe restrictions \( d_b=h \) with \( k<h \). Finally, full serviceability of the bridge, i.e. \( d_b=0 \), is assumed to be reached at time \( T_{r,b} \).

The network functionality profile over the horizon time interval \( \Delta t_h \) between the occurrence time \( t_0 \) and a given horizon time \( t_h \) is hence defined in stepwise form as follows:

\[
Q(t) = Q_j = Q_{\text{d}}(\mathbf{d}_j), \quad T_j \leq t < T_{j+1} \forall j \in [0, N_j] \tag{12}
\]

where \( T_j \) is the time instant associated with a partial or total recovery time of a bridge in the network, defined up to \( T_{j+1} = t_h \) for \( j=N_j \) with total number of time steps in the network recovery process \( N_j = \sum_i N_{j,i} \). The functionality \( Q_j \) at the \( j \)-th recovery step corresponds to the functionality with traffic restrictions combination \( \mathbf{d}_j \).

Based on the stepwise form of the recovery profile, seismic resilience associated with the network damage combination \( \mathbf{s} \) over the horizon time interval \( \Delta t_h \) can be expressed as follows:

\[
R(\mathbf{s}) = \frac{1}{\Delta t_h} \sum_{j=0}^{N_j} Q_j \cdot \Delta T_j \tag{13}
\]

The resilience measure is a random variable that depends on network layout, seismic vulnerability of bridges with key topological importance and the set of variables affecting the recovery from the given damage state combination. Severe restrictive traffic limitations and late restoration can substantially reduce the network resilience, forcing traffic flows to be detoured to secondary roads for the time interval required to carry out the necessary repair activities.

Finally, the distribution of the random variable characterizing the resilience measure conditioned by the damage state combination \( \mathbf{s} \) can be assessed by means of simulation techniques typical of probabilistic frameworks. This allows retrieving numerically the CDFs \( P_{R|s}(r|\mathbf{s}) \) necessary to define the distribution of the seismic resilience measure.

**Applications**

**Lifetime probabilistic structural analysis of RC bridge**

The four-span continuous RC bridge analyzed in Capacci et al. (2020) is considered. Each bridge span is 50 m long...
and the bridge deck has a box girder cross-section. Each bridge pier is 14 m high with circular cross-section. The piers are exposed to a constant chloride concentration $C_0$ uniformly distributed on the external surface.

Seismic analyses are carried out by considering a uniform gravity load equal to 315 kN/m, including self-weight, dead loads and a 20% of live loads, applied on the deck. Non-linear time-history dynamic analyses of the RC bridge are performed using OpenSees (Mazzoni, McKenna, Scott, & Fenves, 2006). The structural model is based on elastic beam elements for the deck and beam elements with lumped plasticity for the piers, where plastic hinges are expected to develop at the ends under transversal loading.

Shear failure is neglected, assuming that the transverse steel reinforcement is sufficient to prevent such collapse mode based on lifetime capacity design criteria (Titi & Biondini, 2014).

The deteriorating function of steel ultimate strain $\varepsilon_{su} = \varepsilon_{su}(\Delta_0)$ adopted in this study for the damage model and the numerical validation against experimental results can be found in Biondini and Vergani (2015). Deterioration of the concrete cover is neglected in this application since its contribution to the member capacity is limited compared to the contribution of the confined concrete core of the solid circular cross-section. Further details concerning with structural modeling and environmental aggressiveness parameters are reported in Capacci et al. (2020).

Peak Ground Acceleration (PGA) is assumed as measure of seismic demand $i_b$. A key aspect in the seismic assessment of bridges is to account for the variability of the ground motion. This can be based either on the automatic generation of synthetic acceleration time-histories compatible with code design spectra (SIMQKE 1976), which may lead to overestimation of the seismic demand, or on the adoption of accelerograms from historical databases, whose selection procedure should rely on an accurate definition of the seismogenic sources characterizing the seismic hazard at the bridge site (Bazzurro & Cornell, 1999). In the application of this paper, dynamic analyses are carried out based on ten artificially generated acceleration time-histories compatible with the elastic response spectrum given by Eurocode 8 for soil type B (CEN-EN 1998-1, 2004).

The aleatory uncertainties associated with structural system and aging process are modeled based on a set of random variables related to the main mechanical and structural parameters of the pristine structure (i.e. concrete compressive strength $f_c$, steel yielding strength $f_{ys}$, viscous damping $\zeta$) and to the environmental exposure and material properties affecting the aging process (i.e. diffusivity coefficient $D$; damage rate $q_{si}$; chloride concentration along the pier circular cross-section $C_0$; critical concentration $C_{cr}$). The analytical models for the distribution of the considered random variables are presented in Capacci et al. (2020). Given the involved aleatory uncertainties, a set of 100 statistically independent realizations of deteriorating structural system has been generated based on Latin Hypercube Sampling and analyzed for each artificial ground motion, leading to a sample of $100 \times 10 = 1000$ realizations. This sample size is selected as a trade-off between computational effort and representativeness of the uncertainties involved in the problem (Capacci, 2015).

The results of the life-cycle fragility analysis are shown in Figure 2 in terms of median, 16% and 84% fractiles for increasing bridge ages: from the pristine structure with no corrosion ($t_b=0$, Figure 2a) to $t_b=30$ years (Figure 2b) and $t_b=60$ years (Figure 2c). The dashed lines indicate the time-variant drift threshold values for the definition of intermediate damage states (slight, moderate and extensive). The progressive reduction of the drift thresholds associated

![Figure 2. RC bridge Probabilistic IDA capacity curves (median, 16% and 84% fractiles): (a) $t_b=0$, (b) $t_b=30$ years, and (c) $t_b=60$ years (The dashed lines indicate the time-variant drift threshold values for the definition of intermediate damage states, i.e. slight, moderate and extensive).](image-url)
with moderate and extensive damage ($s_b=2$ and $s_b=3$, respectively) is due to the reduction in the expected ultimate drift caused by the corrosion process.

**Time-variant bridge seismic fragility**

The outcomes of time-variant structural analyses can be suitably described by a statistical model that relies on a log-normal distribution to represent the exceedance probabilities for each limit state:

$$P[S_b \geq s_b | i_b, t_b] = \Phi \left( \log \left( \frac{i_b - \lambda_{s_b,b}(s_b, t_b)}{\sigma_{s_b,b}(s_b, t_b)} \right) \right)$$

where $\Phi$ is the CDF of the univariate standard normal distribution. The time-variant mean $\lambda_{s_b,b}$ and standard deviation $\sigma_{s_b,b}$ of the natural logarithm of the intensity measure leading to exceedance of a given damage state can be obtained based on the method of moments (Ang & Tang, 2007) and the corresponding fragility curves for the studied model are reported in Capacci et al. (2020).

The occurrence probabilities of each bridge damage state can be computed for a given age and seismic intensity based on the time-variant fragility curves. The results shown in Figure 3a refer to the pristine structure: the probability of occurrence of severe damage increases along with the seismic intensity. Figure 3b and c represent the damage occurrence probabilities for bridge ages $t_b=30$ and 60 years, respectively. These graphs highlight that environmental aging narrows in time the range of seismic intensities that lead to significant probability of suffering intermediate seismic damage levels ($0<s_b<4$).

**Highway network with a single bridge**

A simple road network characterized by one origin and one destination is assumed to be connected by a three-lanes 15-km main highway with a single bridge $B_1$ built at time $t_{c,b}=0$ (Capacci & Biondini, 2018d). The OD nodes are also connected by a two-lanes 60-km secondary road to detour the traffic flows with a user demand of $f_t=7000$ cars/h, $f_b=1000$ cars/h and $f_e=700$ cars/h. The maximum speed limit for the main highway and the side road are $v_{\text{max}}=130$ and $90$ km/h, respectively. The speed limit is reduced to $v_{\text{min}}=70$ km/h when the bridge is damaged. For both roadways, the critical velocity and the minimum allowed distance are $v_{\text{cr}}=65$ km/h and $d_{\text{min}}=30$ m/cars, respectively.

Figure 4 represents the functionality levels $Q_d$ given the decision variable $d_b$. The network functionality is reduced when bridge traffic restrictions of increasing severity are applied, inducing a progressive increase of the total travel time with respect to the unrestricted condition. For example, restrictions to heavy vehicles ($d_b=1$) and open lanes ($d_b=2$) induce an increase of total travel time of about 50%, whilst the transit of light vehicles ($d_b=3,4$) reduces the functionality down to almost 15%.
Traffic restrictions are applied to bridges according to the initial damage state and progressively released based on the post-event recovery allowing for stepwise increments of network functionality. The following recovery model 

\[ r_b = r_b(t) \in [0;1] \]

is adopted over the bridge recovery time interval \( \Delta T_{r,b} = T_{r,b} - T_{i,b} \) (Titi et al., 2015):

\[ r_b(t) = \begin{cases} 
0 & , \tau \leq 0 \\
\omega^{1 - \rho} t^\rho & , 0 < \tau \leq \omega \\
1 - (1 - \omega)^{1 - \rho} (1 - t)^\rho & , \omega < \tau \leq 1 \\
1 & , \tau > 1 
\end{cases} \]  

(15)

where \( \tau = (t - T_{i,b}) / \Delta T_{r,b} \in [0,1] \) is a normalized time variable.

The role of the shape parameters \( \omega \in [0,1] \) and \( \rho \geq 0 \) is graphically presented in Figure 5. In particular, parameter \( \omega \) governs the inflection point of the recovery curve (Figure 5a) and \( \rho \) influences its curvature (Figure 5b). The advantage of this model is that a proper probabilistic definition of each shape parameter can effectively reproduce different patterns of the recovery processes, since it can represent cases in which structural capacity restoration after the repair initiation is quick (\( \omega = 0 \) and \( \rho > 1 \)), slow (\( \omega \approx 1, \rho > 1 \)) or gradual in time (\( \rho \approx 1 \)).

The uncertainties involved in the bridge recovery process are taken into account by considering idle time, total recovery intervals, and shape parameters of the recovery profile as uncorrelated random variables. Uniform distribution is assumed for idle time, total recovery intervals \( \Delta T_{r,b} \) and shape parameter \( \rho \). Beta distribution is assumed for the shape parameter \( \omega \). The minimum and maximum values for the idle time are 5 and 30 days, respectively. The statistical parameters of the probability distributions of the recovery model random variables for different damage states \( r_{p,b} \) listed in Table 2. In each diagram, the continuous line represents the recovery process defined by the mean values of all the involved random variables, whilst the dotted lines represent the lower and upper bounds of each profile. The bridge traffic restrictions are progressively released, increasing the functionality as the bridge recovery curve reaches the capacity targets (horizontal dashed lines in Figure 6).

Based on Monte Carlo simulation for each seismic damage state, Figure 7 shows the empirical CDF of resilience conditioned by the bridge damage states \( s_b \) for horizon time \( t_b = 1 \) year. These largely dispersed and weakly skewed conditional distributions are bounded by the minimum and maximum values associated with the recovery profiles represented by dotted stepwise lines in Figure 6. These values decrease with the severity of the initial damage due to the larger post-earthquake decay of functionality and longer maximum and minimum repair times.

The probabilistic assessment of seismic resilience is based on the conditional CDFs for each bridge damage state weighted by their time-variant probabilities of occurrence. Figure 8 displays three descriptors of the network resilience vs. the seismic intensity \( i_b \) for different bridge ages \( t_b \), namely median (continuous thick line) and the fractiles at 16% and 84% (dotted thin lines). The resilience fractiles monotonically decrease from 100% down to the levels associated with the reference fractile of the resilience conditional CDF of the structural collapse state \( s_b = 4 \). A more complete representation of the resilience measure is given by the CDFs shown in Figure 9. The effects of corrosion exacerbate the resilience decay, since the probability of occurrence of severe damage increases not only with seismic demand, but also with the bridge age.

### Table 1. Statistical parameters of the probability distributions of the recovery model random variables for different damage states \( s_b \) : Beta(\( a, b \)) distribution of shape parameter \( \omega \in [0;1] \); Uniform distribution of shape parameter \( \rho \geq 0 \); Uniform distribution of total recovery interval \( \Delta T_{r,b} \).

<table>
<thead>
<tr>
<th>Damage State</th>
<th>( a )</th>
<th>( b )</th>
<th>( \rho )</th>
<th>( \Delta T_{r,b} [\text{days}] )</th>
</tr>
</thead>
<tbody>
<tr>
<td>( s_b = 1 )</td>
<td>2</td>
<td>8</td>
<td>1.0</td>
<td>3.0, Min:5, Max:120</td>
</tr>
<tr>
<td>( s_b = 2 )</td>
<td>4</td>
<td>6</td>
<td>1.5</td>
<td>4.5, Min:15, Max:170</td>
</tr>
<tr>
<td>( s_b = 3 )</td>
<td>6</td>
<td>4</td>
<td>2.0</td>
<td>6.0, Min:55, Max:220</td>
</tr>
<tr>
<td>( s_b = 4 )</td>
<td>8</td>
<td>2</td>
<td>2.5</td>
<td>7.5, Min:75, Max:270</td>
</tr>
</tbody>
</table>

Figure 5. Recovery model and influence of the shape parameters (a) \( \omega \) and (b) \( \rho \).
Highway network with multiple bridges

The previously investigated road network is modified considering two identical bridges in series along the main highway (Capacci et al., 2020). Bridges B1 and B2 built at time $t_{c,b} = 0$ at a relative distance of 10 km. Table 3 provides the functionality for each combination $d$ of traffic restrictions. For a highway network with bridges in series, redundancy is given only by the detour: any damage scenario in which at least one bridge suffers significant damage would increasingly affect the road network functionality with the severity of the related traffic limitation. In this network layout, both bridges have the same topological importance; therefore, functionality is predominantly affected by the most damaged bridge.

The seismic demand $i_b$ is related to earthquake magnitude $M$ and source-to-site distance $d_{c,b}$ in terms of median value of the PGA based on the attenuation model proposed by Bindi et al. (2011) calibrated on the strong motion database for Italy:

$$\log_{10} i_b = 3.672 + F_D(d_{c,b}, M) + F_M(M) + F_S + F_{sof}$$

$$F_D = [-1.940 + 0.413(M-m_{ref})] \log_{10} \left( \frac{d_{c,b}^2 + h^2}{d_{ref}} \right) - 0.000134 \left( \frac{d_{c,b}^2 + h^2 - d_{ref}}{d_{ref}} \right)$$

$$F_M = \begin{cases} -0.626(M-m_{ref}) - 0.0707(M-m_b)^2 & \text{for } M \leq m_b \\ 0 & \text{otherwise} \end{cases}$$

where $i_b$ is given in cm/s$^2$, distances are expressed in km, and $F_D(d_{c,b}, M)$, $F_M(M)$, $F_S$, and $F_{sof}$ are the distance function, the magnitude scaling, the site amplification factor, and the style-of-faulting correction. Reverse faulting is assumed with $F_S=0.162$, $F_{sof}=0.105$, $h_c=10.322$ km, $d_{ref}=1$ km, $m_{ref}=5$, and $m_b=6.75$.

Figure 10 shows the 3-D surface and 2-D contour map of different resilience fractiles (16%, 50%, 84%) for a seismic event with magnitude $M = 6.5$ occurring at time $t_0=0$ based on a square grid of possible epicenters with grid size of 0.2 km. The vertical axis of the surface represents the reference descriptor of the resilience measure CDF for the given epicenter locations in the map grid, which govern the source-to-site distance for each vulnerable bridge in the network and, therefore, the seismic intensity $i_b$ and the damage probabilities. From this graphical representation of the resilience measure, it is evident that the most detrimental seismic scenarios are with epicenters close to one of the two bridges, with a sharp attenuation of the effects of seismic damage for epicenters far away from both bridges.

Figures 11 and 12 depict the resilience maps for seismic events occurring at occurrence times $t_0=40$ and 80 years, respectively. The resilience decay induced by corrosion is exacerbated as the epicenter approaches the location of one of the two bridges, particularly for the 16% fractile (Figures 10a and 11a). This occurs within circular areas of radius 3 and 5 km for $t_0 = 40$ and 80 years, respectively. The results presented in Figures 10–12 are based on the assumption of perfect statistical dependency of bridge capacities.

Table 2. Capacity targets for each damage state.

<table>
<thead>
<tr>
<th>Damage</th>
<th>$r_{p=1}$</th>
<th>$r_{p=2}$</th>
<th>$r_{p=3}$</th>
<th>$r_{p=4}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$s_b=1$</td>
<td>1.00</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>$s_b=2$</td>
<td>0.50</td>
<td>1.00</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>$s_b=3$</td>
<td>0.20</td>
<td>0.50</td>
<td>1.00</td>
<td>-</td>
</tr>
<tr>
<td>$s_b=4$</td>
<td>0.05</td>
<td>0.20</td>
<td>0.50</td>
<td>1.00</td>
</tr>
</tbody>
</table>

Figure 6. Bridge capacity recovery model and network functionality recovery profiles given the bridge damage state: (a) $s_b=1$; (b) $s_b=2$; (c) $s_b=3$; (d) $s_b=4$ (expected recovery process with continuous line; “slowest” and “fastest” recovery processes with dotted lines).
Additional results for different levels of bridge capacity correlations are available in Capacci et al. (2020) in terms of expected seismic resilience. It is shown that high correlation levels have a detrimental impact in networks with bridges in parallel and a beneficial impact in networks characterized by bridge-in-series layouts.

The seismic hazard could be analyzed at the regional scale to account for the uncertainties in the epicenter location of future major earthquakes. For example, area sources are often used in practice to account for “background” seismicity characterized by lack of information on the local active faults (Baker, 2009) or when the complex spatial distribution of the epicsens of historical earthquakes discourages the choice of hazard models that attribute them to their causative fault (Barani, Spallarossa, & Bazzurro, 2009).

Figure 13 presents the fractiles 16%, 50%, 84%, of the resilience \( R_A \) averaged over a 10-km radius circular area source centered at midspan between the bridges versus the occurrence time \( t_0 \) over 100-year lifetime for earthquake magnitude \( M = 6.0, 6.5, 7.0 \). The epicsens within the prescribed area source are assumed to represent equally likely epicenter locations of a seismic event with given magnitude. Despite being affected by the dimensions and geographical location of the seismogenic area source (Capacci & Biondini, 2018b), this representation provides a more synthetic measure of the time-variant network resilience for a prescribed hazard scenario with respect to the 3-D maps for each resilience fractile.
Evolving highway network

The road network shown in Figure 14 is characterized by a 10-km highway and a 40-km detour route (Capacci & Biondini, 2018a). The OD user demand and the road class parameters are the same as the application previously presented. A single-lane 1-km re-entry link with the same road class parameters as the detour road provides a connection between both main highway and side road at their third quarters (i.e., 7.5 km and 30 km for highway and detour road, respectively). Two identical bridges B1 and B2 built at $t_{c,B1}=t_{c,B2}=0$ are located on the main highway at $x_{b,B1}=[-5;0]$ and $x_{b,B2}=[5;0]$.

The network is upgraded at construction time $t_c$ by building a three-lanes 15-km highway branch (dashed line in Figure 14) with a bridge B3 located at $x_{b,B3}=[0;5]$. Bridge B3 is characterized by the same structural properties of bridges B1 and B2 and its time-variant fragilities are consistent with its age $t_{b,B3}=t_0-t_c$. In the present application, the idle time is assumed to be null and the statistical representation of the recovery process is defined based on the expected values of shape parameters and recovery times collected in Table 4 for each bridge damage state.

When the infrastructure upgrade is not carried out at the time of earthquake occurrence ($t_0<t_c$), the network is
characterized by two vulnerable bridges: B1 and B2. The integration of the expected functionality profiles for each of the $52 = 25$ bridge damage combinations allows evaluating the expected resilience values collected in Table 5. These results highlight the impact on system functionality and network resilience of the re-entry link, which enhances the network redundancy providing a bypass through road segments where traffic is impaired by damaged bridges. Being farther than bridge B2 from the re-entry link, bridge B1 is the most important between the two vulnerable elements in the infrastructure system: applying traffic limitations on bridge B1 with no damage on bridge B2 would force the road users to cover a longer distance on a slower road than vice versa.

Figure 15 illustrates the 3-D surface and 2-D contour map of the expected resilience for the studied network in the original configuration under a prescribed seismic event with magnitude $M = 6.75$ occurring at times $t_0 = 0, 30,$ and $60$ years. These results highlight the impact of the re-entry link on network redundancy with the development of corrosion damage. The lack of symmetry in the expected resilience surface is limited for $t_0 = 0$ (Figure 15a), since both bridges are not affected by aging. However, it becomes more evident for $t_0 = 30$ years (Figure 15b) and $t_0 = 60$ years (Figure 15c), when the structural capacity of both bridges is impaired by corrosion.

Tables 6–10 collect the expected values of seismic resilience for the $5^3 = 125$ possible damage state combinations related to the scenario in which the earthquake occurs after the upgrade ($t_0 \geq t_6$). Each table represents the expected resilience for a prescribed damage combination with a given state for bridge B3 (from No Damage $s_{b3} = 0$ in Table 6 to Structural Collapse $s_{b3} = 4$ in Table 10). When bridge B3 is open to traffic, the redundancy enforced by the possibility of rerouting the traffic flows to the new highway branch enhances the expected resilience for any damage combination of bridges B1 and B2. Nevertheless, also the newly built asset may undergo traffic limitations after the seismic event: the upgrade benefit on the expected resilience decreases as the damage severity on bridge B3 increases. These beneficial effects can be quantified based on the 3-D surface and 2-D contour map of the expected resilience in Figure 16. The upgrade at time $t_6$ provides an immediate significant gain in the expected resilience, especially when the epicenter location lies within the network area. This can be appreciated by comparing Figure 15b ($t_0 = 30$ years) to
Figure 16a ($t_0 = t_c = 30$ years), as well as Figure 15c ($t_0 = 60$ years) to Figure 16b ($t_0 = 2t_c = 60$ years). Nevertheless, the harmful development of corrosion damage can severely reduce in time the upgrade benefits, as shown in Figure 16c ($t_0 = 2t_c = 60$ years).

A more synthetic representation of these results can be obtained by averaging the resilience expectation over a 10-km radius circular area source centered at $x = [0; 0]$. Figure
17 presents the averaged expected resilience $R_A$ evaluated for occurrence times every 10 years over a 100-year lifetime for three earthquake magnitudes scenarios ($M = 6.0, 6.5,$ and $7.0$) with upgrade at construction times $t_c = 30$ and $60$ years. The thick lines represent the expected resilience with upgrade, whilst the thin lines represent the scenario assuming no deployment of infrastructure investments to enhance the road network with the new highway branch.

This representation can assist decision makers and infrastructure managers in planning key interventions on the vulnerable bridges of the network based on the attainment of resilience targets for different levels of seismic risk and environmental exposure. The results indicate that the short-term effectiveness of the upgrading increases with both earthquake magnitude and severity of corrosion damage. However, as already pointed out, aging and deterioration may reduce in the long-term the resilience gain induced by the investment on a road system that is more redundant, yet continuously aging.

Conclusions

The seismic resilience of road networks with vulnerable components can be severely harmed by late restoration of widespread damage due to the application of traffic limitations that would force road users to be detoured to secondary roads for prolonged time necessary to complete the repair activities. A probability-based approach to quantitative assessment of seismic resilience of aging bridges and road networks has been presented in order to assist decision makers in the definition of life-cycle multi-hazard probabilistic metrics to inform effective, reliable, and sustainable emergency management strategies.

The proposed formulation of seismic resilience measure takes into account the uncertainties associated with the time-variant seismic vulnerability of the bridges in the network, as proposed in Capacci et al. (2020), as well as the uncertainties in the assessment of the recovery times and patterns affecting the resilience levels for any combination of post-earthquake bridge damage states. Depending on the environmental aggressiveness, RC bridges may suffer significant reduction of structural capacity over time and exacerbate the impact of severe earthquake events at the network level. In particular, uncertainties associated with both seismic damage and recovery pattern tend to propagate along with the infrastructure age and the severity of the seismic event.

The detrimental effects of aging can be mitigated by upgrading interventions aimed at improving the network connectivity by means of new road branches and alternative travel paths, which may provide an immediate significant gain in seismic resilience. It has been shown that the construction of new fast routes in parallel to the old ones may ensure an immediate gain in seismic resilience, especially for increasing earthquake magnitudes and severity of the corrosion damage. However, the initial beneficial effects of the upgrading can be substantially reduced in the long-term by the detrimental impact of deterioration of bridges located along the new routes.

Further research is necessary to investigate the interaction between time-variant bridge seismic fragilities and traffic restrictions, as well as between direct monetary cost of repair actions and indirect economic losses induced by network downtime. Moreover, the time-variant resilience measure conditioned on both the hazard scenario and infrastructure age proposed in this paper should be extended to account for the actual rate of occurrence of seismic events at the regional scale and aggregation over time of network losses.

Disclosure statement

No potential conflict of interest was reported by the authors.

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