Life-Cycle of Structures and Infrastructure Systems – Biondini & Frangopol (Eds)

A Markovian framework to model life-cycle consequences of infrastructure systems in a multi-hazard environment

Kenneth Otárola
Scuola Universitaria Superiore (IUSS) Pavia, Pavia, Italy

Leandro Iannacone, Roberto Gentile & Carmine Galasso
University College London, London, UK

ABSTRACT: Existing frameworks for multi-hazard life-cycle consequence (LCCon) analysis typically disregard the interactions between multiple hazards and obtain the total LCCon as the sum of the consequences caused by the individual hazards modelled independently. This practice leads to inaccurate life-cycle consequence estimates and ineffective risk-informed decision-making for disaster-mitigation strategies and/or resilience-enhancing policies. In addition, most available LCCon formulations fail to accurately incorporate the damage-accumulation effects due to incomplete (or absent) repairs between different hazard events. To address these challenges, this paper introduces a Markovian framework for efficient multi-hazard LCCon analysis of deteriorating structural systems, appropriately accounting for complex interactions between hazards and their effects on a system's performance. The changes in the system's performance level (e.g., damage or functionality state) are quantified with transition probability matrices following the Markovian assumption and the expected LCCon estimates are obtained by combining the performance level distribution with suitable system-level consequence models, which can include direct asset losses as well as socio-economic consequences. To showcase the framework applicability, a simple road network with a single case-study ordinary reinforced concrete bridge subject to earthquake-induced ground motions and environmentally-induced corrosion deterioration is investigated, estimating consequences in terms of community welfare loss.

1 INTRODUCTION

Many existing risk modelling frameworks independently analyse and aggregate the expected consequences due to multiple hazards (e.g., Dong & Frangopol, 2016). However, it has been demonstrated that multiple, often interacting, hazards can lead to consequences greater than the sum of those related to individual hazards (e.g., De Angeli et al., 2022). As such, it is imperative to account for hazard interactions when quantifying the potential impacts of the events on the performance of critical assets and the communities they serve for risk-informed decision-making on future disaster-mitigation strategies and resilience-enhancing policies. The frameworks for multi-hazard life-cycle consequence (LCCon) analysis that have gained considerable attention over past years neglect such interactions. In addition, they assume that systems sustaining structural/non-structural damage are either instantaneously repaired or do not receive any repair actions after an event (e.g., Fereshtehnejad & Shafieezadeh, 2018). Hence, dynamic changes in the performance of the systems during their service life are not adequately tackled, preventing the accurate quantification of the associated LCCon estimates.

To enable the optimal life-cycle management of structural systems (e.g., buildings or bridges) subject to multiple (and often interacting) hazard events, and of the infrastructure systems that rely on them (e.g., road networks), this paper proposes a Markovian framework for multi-hazard LCCon analysis, which explicitly accounts for the interacting consequences of the hazard events. Using the Markovian assumption (e.g., Bonamente, 2017), the framework can adequately

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model damage accumulation and, therefore, performance deterioration (i.e., reduction) while being computationally efficient (e.g., Iervolino et al., 2016). Markov processes have been extensively used for LCCon analysis of utility networks (e.g., Bocchini et al., 2013). They have also recently been used for life-cycle analysis of buildings, mainly in mainshock-aftershock-related applications (e.g., Shokrabadi & Burton, 2018). A comprehensive integration of the different types of hazard interactions is currently lacking in these formulations.

As such, the framework proposed in this paper advances the current knowledge by including the lifetime adverse impact of multiple hazard events and their interactions on the LCCon analysis of structural systems and associated infrastructure systems. It can also be integrated with suitable system-level consequence models to quantify the expected LCCon in terms of direct asset losses and socio-economic consequences. As an example, the proposed framework is applied to the LCCon analysis of a simplified transportation network with a single bridge subject to earthquake events and deterioration effects. Consequences are quantified in terms of welfare losses directly related to the increased travel time due to the actions taken on the bridge.

2 GENERAL FRAMEWORK

The proposed Markovian framework for multi-hazard LCCon analysis efficiently computes expected LCCon estimates of a structural system subject to multiple hazard events causing state changes. The performance of the system is modelled as a discrete-time, discrete-space Markovian process (i.e., treating the state of the process as a discrete variable; e.g., Iervolino et al., 2016). Namely, the system's performance domain is partitioned into mutually exclusive and collectively exhaustive performance states/levels. Such states should be represented using a single harmonised scale valid for different hazard types since specific hazards can cause different types of performance impairment to a system. Thus, for instance, a valid (hazard-agnostic) scale could be defined in terms of the system's functionality. For example, the adopted functionality states (FSs) for a bridge could be defined as: 1) no restrictions; 2) weight restrictions; 3) one lane open only; 4) emergency access only; 5) closure (e.g., Capacci et al., 2020). If the considered hazards can cause similar damage mechanisms to a system (i.e., a consistent damage scale can be used), the performance can also be defined directly in terms of damage states (DSs).

The transition probabilities between FSs (i.e., the probabilities that after one event, the system is in the m-th FS given that it was in the n-th FS before the event) are derived employing state-dependent functionality models (defining the probability of exceeding a FS given a hazard intensity and the FS achieved during a prior event; e.g., fragility relationships) and hazard models (defining the probability of exceeding a hazard intensity measure –IM– given the hazard characteristics; e.g., hazard curves). The transition matrices (i.e., the stochastic square matrices used to describe the FS transitions) are assembled by collecting each (n,m) transition probabilities between FSs, also characterising the system's performance deterioration. The resulting expected consequences are obtained from suitable system-level consequence models (i.e., linking the FSs to a consequence metric of interest).

In the following section, an analytical formulation is presented to compute the expected LCCon estimates. This formulation is based on classical hypotheses for performance-based engineering and is divided into two modelling stages (Zaghi et al., 2016). The first stage, hazard modelling, considers Level I interactions that are independent of the presence of a physical system (e.g., a landslide triggered by an earthquake event). The second stage, consequence modelling, considers Level II interactions resulting from the impact of hazards on a physical system, such as functional impairment due to the accumulation of damage during a seismic sequence.

For modelling purposes, the Level I interactions can be subclassified in (Iannacone et al., 2023): 1) *non-interacting*: hazards whose co-occurrence is purely coincidental (e.g., earthquakes and hurricanes); 2) *concurrent*: hazards that co-occur or have a significant joint probability of occurrence in a period of time (e.g., storm surge, sea waves, and strong wind that co-occur during a hurricane); 3) *successive*: hazards with a causal relationship. Two broad categories can be identified within successive hazards based on their causal relationship: *Type A* (i.e., when a secondary hazard is triggered by the occurrence of a primary hazard) and *Type B* (i.e., the rate of occurrence of a secondary hazard increases following the occurrence of a primary hazard).

Level II interactions are related exclusively to the impairment of a physical system's performance, described by damage or functionality states, given the occurrence of hazard events. In general, the system's performance deterioration can be caused by shock deterioration processes associated with hazard events occurring at a point in time (e.g., an earthquake-induced ground motion) or gradual deterioration processes associated with ageing and/or deteriorating mechanisms (e.g., steel rebars corrosion). System performance can also be recovered (i.e., improved) due to potential repair actions executed in between hazard events. However, such actions are typically intended to recover from shock deterioration processes rather than those due to gradual deterioration.

3 ANALYTICAL FORMULATION

The total expected LCCon estimates associated with a structural system subject to multiple hazard events can be obtained by summing the expected hazard-induced consequences during its service life, obtained as in Equation (1).

$$E[C] = \sum_{i=1}^{\infty} P(i, t_{LC}) \sum_{j=1}^{i} \boldsymbol{F_{S_j}} E[\boldsymbol{C_{F_S}}]^T \tag{1}$$

In Equation (1), $\boldsymbol{F_{S_j}}$ is the 1xN_{F_S} probability mass function (PMF) of the system's FSs after the j-th hazard event, $E[\boldsymbol{C_{F_S}}]$ is the consequence model (i.e., a 1xN_{F_S} vector with the expected consequences associated with each FS), N_{F_S} is the total number of FSs, and $P(i,t_{LC})$ is the probability of having i hazard events during the service life (t_{LC}), obtained as in Equation (2).

$$P(i, t_{LC}) = \frac{(\nu_T t_{LC})^i e^{-(\nu_T t_{LC})}}{i!} \tag{2}$$

In Equation (2), v_T is the total rate of occurrence (in a selected time unit) of N_h hazards, regardless of their type and event characteristics. It is assumed that hazard events of the same type (h) occur according to a homogeneous Poisson process with a rate of occurrence equals v_h ($h = 1, \ldots, N_h$). Therefore, v_T can be computed as in Equation (3).

$$v_T = \sum_{h=1}^{N_h} v_h \tag{3}$$

It is worth noting that $P(i,t_{LC})$ can also be obtained through a simulation-based approach (e.g., Iannacone et al., 2023). The PMF of the system's FSs after the j-th hazard event only depends on the current PMF of the system's FSs and can be estimated as in Equation (4).

$$\boldsymbol{F_{S_j}} = \boldsymbol{F_{S_{j-1}}} \boldsymbol{T_{F_S}} \tag{4}$$

In equation (4), $\boldsymbol{F_{S_{j-1}}}$ is the 1xN_{F_S} PMF of the system's FSs after the ($j-1$)-th hazard event, and $\boldsymbol{T_{F_S}}$ is the N_{F_S}xN_{F_S} transition matrix quantifying the probability of transitioning between the FSs given an event, obtained as in Equation (5).

$$\boldsymbol{T_{F_S}} = \sum_{t_j=0}^{t_{LC}} \sum_{t_{j-1}=0}^{t_j} f\left(t_{j-1}, t_j | i, t_{lc}\right) \boldsymbol{T_S} \boldsymbol{T}_{\boldsymbol{G},\Delta t_j} \boldsymbol{T}_{\boldsymbol{R},\Delta t_j} \tag{5}$$

In Equation (5), $\boldsymbol{T_{F_S}}$ accounts for possible repair actions and gradual deterioration in the time between the occurrence of the ($j-1$)-th hazard event and the j-th hazard event (i.e., interarrival-time), denoted as Δt_j. The quantity $f\left(t_{j-1}, t_j | i, t_{lc}\right)$ is the PDF of two hazard events occurring at a time t_{j-1} and t_j, conditioned on the occurrence of i hazard events during the nominal lifetime of the system (details on how to obtain this PDF are shown in Fereshtehnejad & Shafieezadeh, 2018), $\boldsymbol{T_S}$ is the

N_{F_S}xN_{F_S} transition matrix associated with a shock deterioration process accounting for the possible hazard events (e.g., earthquake- and flood-related events), $\boldsymbol{T}_{\boldsymbol{G},\Delta t_j}$ is the N_{F_S}xN_{F_S} transition matrix associated with a gradual deterioration process occurring in Δt_j (e.g., deteriorating mechanisms), and$\boldsymbol{T}_{\boldsymbol{R},\Delta t_j}$ is the N_{F_S}xN_{F_S} transition matrix associated with the repair actions occurring in Δt_j. The matrix $\boldsymbol{T_S}$ can be obtained combining the N_{F_S}xN_{F_S} transition matrices for individual, non-interacting, hazard types $\boldsymbol{T}_{\boldsymbol{S}_h}$, as in Equation (6).

$$\boldsymbol{T_S} = \sum_{h=1}^{N_h} \frac{v_h}{v_T} \boldsymbol{T}_{\boldsymbol{S}_h} \tag{6}$$

A significant challenge in using Equation (1) is linked to the high computational cost of integrating all the possible outcomes for the occurrence of the hazard events and the total number of hazard events during the selected time horizon. Such a drawback is exacerbated by $\boldsymbol{T}_{\boldsymbol{G},\Delta t_j}$ and $\boldsymbol{T}_{\boldsymbol{R},\Delta t_j}$ being a function of Δt_j. Nonetheless, Equation (1) can be significantly simplified by modelling the expected LCCon estimates as the sum of the expected consequences in N_t fixed time intervals of length Δt, where $N_t = \lfloor t_{LC}/\Delta t \rfloor$. Selecting a sufficiently small Δt such that only one (primary) hazard event is likely within each interval, the expected LCCon estimates can be computed with Equation (7).

$$E[C] = \sum_{m=1}^{N_t} \boldsymbol{F}_{\boldsymbol{S}_{t+m\Delta t}} E[\boldsymbol{C}_{\boldsymbol{F_S}}]^T \tag{7}$$

In Equation (7), $\boldsymbol{F}_{\boldsymbol{S}_{t+m\Delta t}}$ is the 1xN_{F_S} PMF of the system's FSs at time $t + m\Delta t$, computed as in Equation (8). F_{S_t} is the 1xN_{F_S} PMF of the system's FSs at time t.

$$\boldsymbol{F}_{\boldsymbol{S}_{t+m\Delta t}} = F_{S_t} \prod_{i=1}^{m} [\nu_T \boldsymbol{T_S} \boldsymbol{T_G} + (1 - \nu_T) \boldsymbol{T_R} \boldsymbol{T_G}] \tag{8}$$

In equation (8), $\boldsymbol{T_S}$ is the transition probability due to the gradual deterioration in the time interval Δt, $\boldsymbol{T_R}$ is the transition probability due to the recovery actions in the time interval Δt, $v_T \boldsymbol{T_S} \boldsymbol{T_G}$ corresponds to the transition probability due to shock and gradual deterioration, multiplied by the probability of observing a shock-type hazard event in a selected Δt (equal to the rate v_T under the small-interval assumption). (1-v_T)$\boldsymbol{T_R} \boldsymbol{T_G}$ corresponds to the transition probability due to repair actions and gradual deterioration, multiplied by the probability of not observing a shock-type hazard event in a selected Δt (equal to 1-v_T under the small-interval assumption). It is assumed that only a transition due to a hazard event or a repair action occurs in a unit of time since, commonly, repair actions will be interrupted after a significant event. Nonetheless, such an assumption can be relaxed. In this case, $v_T \boldsymbol{T_S} \boldsymbol{T_G}$ can be written as $v_T \boldsymbol{T_S} \boldsymbol{T_R} \boldsymbol{T_G}$. The following subsections describe the derivation of the described transition matrices.

3.1 *Shock deterioration transition matrix*

The shock-type deterioration transition matrix $\boldsymbol{T_S}$ only has diagonal and upper-triangular entries corresponding to the probabilities of transitioning from a given FS to a higher FS (i.e., a transition between progressively worse FSs) or staying at the same FS after a hazard event. It is obtained from the transition matrix of the individual hazard types $\boldsymbol{T}_{\boldsymbol{S}_h}$ using Equation (6). Otárola et al. (2023) detail how to assemble each $\boldsymbol{T}_{\boldsymbol{S}_h}$ accounting for Level I and II interactions in the four following cases: 1) hazard type h does not interact with other hazards; 2) hazard type h induces the simultaneous occurrence of other multiple concurrent hazards; 3) hazard type h is the primary hazard of a successive Type A interaction; 4) hazard type h is the primary hazard of a successive Type B interaction.

3.2 *Gradual deterioration transition matrix*

Before the gradual deterioration initiation time (t_i), there is no transition between FSs. Thus, the gradual-type deterioration transition matrix (i.e., $\boldsymbol{T_G}$) is numerically equal to the identity matrix ($\boldsymbol{T_G} = \boldsymbol{I}$). After t_i, the system starts transitioning from a given FS to a higher FS (i.e., a transition between progressively worse FSs) or staying at the same FS, and $\boldsymbol{T_G}$ becomes an upper-triangular matrix whose entries correspond to the probability of transitioning in Δt, as in Equation (9) (which is valid for $t > t_i$). Several probabilistic models can be used to model the system's gradual deterioration (e.g., Duracrete, 2000, Iannacone & Gardoni 2019) and, thus, to obtain the (n,m) entry of the matrix $\boldsymbol{T_G}$. In the described procedure, gradual deterioration is treated for modelling purposes as the impact of non-monitored, yet frequent, small shocks.

$$\boldsymbol{T_G}(n,m) = \begin{cases} P(FS_m|FS_n, \Delta t) & \text{if } n < m \\ 1 - \sum_{i=1}^{N_{P_S}} \boldsymbol{T}_G(n,i) & \text{if } n = m \\ 0 & \text{if } n > m \end{cases} \tag{9}$$

3.3 *Repair actions transition matrix*

The repair-type recovering transition matrix (i.e., $\boldsymbol{T_R}$) only has diagonal and lower-triangular entries relating to the probabilities of transitioning from a given FS to a lower FS (i.e., a transition between progressively better FSs) or staying in the same FS as the structural system recovers with time. The repair actions are modelled through a Poisson process. The daily rate of occurrence of an event where the system is recovered from a worse FS to a better FS is assumed as the inverse of the difference between the repair times of each FS ($T_{n,m}$). This time difference does not necessarily correspond to the repair times associated with each state-dependent FSs; however, this is the simplest approximation to a potential recovery path between the FSs. The values of $T_{n,m}$ are defined if $n > m$, and can be found in the literature (e.g., HAZUS, 2003). The (n,m) entry of the matrix $\boldsymbol{T_R}$ is obtained as in Equation (10). The Δt should be expressed in the same units than $T_{n,m}$.

$$\boldsymbol{T_R}(n,m) = \begin{cases} \left(\frac{1}{T_{n,m}}\Delta t\right) e^{-\left(\frac{1}{T_{n,m}}\Delta t\right)} & \text{if } n > m \\ 1 - \sum_{i=1}^{N_{F_S}} \boldsymbol{T}_R(n,i) & \text{if } n = m \\ 0 & \text{if } n < m \end{cases} \tag{10}$$

4 ILLUSTRATIVE APPLICATION

The proposed framework is demonstrated using a simplified case-study road network with a single symmetric double-span box-girder seat-type bridge (Figure 1a). Such a bridge represents a typical bridge vulnerability class in Southern California and is located in downtown Los Angeles (Lat: 34.052, Lon: -118.257). The bridge is characterised by: deck width: 23 m; number of spans: 2; span lengths: 45.7 m; number of columns: 2; columns radius: 0.85 m; columns height: 6.70 m. It comprises seat-type abutments (which include an arrangement of nonlinear springs for shear keys, elastomeric bearing pads, soil backfill, and abutment piles), column bents (which include nonlinear fibre sectional models for columns and column foundational springs), and an elastic superstructure representing the box-girder deck, designed and detailed according to Caltrans Seismic Design Criteria 2.0 (Caltrans, 2019). The bridge is assumed to undergo earthquake-induced ground motions while experiencing environmentally-induced corrosion deterioration in a marine splash exposure. DSs are used as performance states (so FS = DS in the previous equations) since a unique shock-type hazard is investigated, as in common performance-based engineering practice. The time- and state-dependent fragility relationships developed in Otárola et al. (2022) are used to assemble $\boldsymbol{T_S}$ and HAZUS repair times are used to assemble $\boldsymbol{T_R}$ (HAZUS, 2003). Table 1 to 3 presents the transition matrices for the case-study bridge. In total, four DSs are adopted, corresponding to slight (DS1), moderate (DS2), extensive (DS3), and complete (DS4) structural damage. Although the entries for $\boldsymbol{T_S}$ and $\boldsymbol{T_R}$ are obtained from fragility and recovery models, respectively, values for $\boldsymbol{T_G}$ are ideal and are used for illustrative purposes, estimating its non-diagonal entries as those corresponding to $\boldsymbol{T_S}$ divided by 100 for a$\Delta t = 1$ month.

Table 1. $\boldsymbol{T_S}$ transition probability matrix.

DSs	DS0	DS1	DS2	DS3	DS4
DS0	0.9596	0.0297	0.0084	0.0009	0.0014
DS1	0	0.9893	0.0084	0.0009	0.0014
DS2	0	0	0.9969	0.0015	0.0016
DS3	0	0	0	0.9978	0.0022
DS4	0	0	0	0	1

Table 2. $\boldsymbol{T_G}$ transition probability matrix.

DSs	DS0	DS1	DS2	DS3	DS4
DS0	9.997e-1	2.471e-4	6.996e-5	7.517e-6	1.179e-5
DS1	0	9.999e-1	6.978e-5	7.343e-6	1.196e-5
DS2	0	0	9.999e-1	1.253e-5	1.340e-5
DS3	0	0	0	9.999e-1	1.833e-5
DS4	0	0	0	0	1

Table 3. $\boldsymbol{T_R}$ transition probability matrix.

DSs	DS0	DS1	DS2	DS3	DS4
DS0	1	0	0	0	0
DS1	0.3020	0.6980	0	0	0
DS2	0.1224	0.2180	0.6595	0	0
DS3	0.0746	0.1009	0.1927	0.6318	0
DS4	0.0858	0.0951	0.1156	0.1683	0.5351

The expected LCCon is estimated in terms of expected welfare loss ($E[\Delta W]$; i.e., a measure of the impact of road network disruption on the commuters' well-being, Silva-Lopez et al., 2022) and considering 80 years as the bridge's service life. A welfare-loss consequence model is developed, associating each DS to a restrictive action that causes an increase in the travel time of the members of the community, namely: 1) DS0: no restrictions; 2) DS1: speed restrictions; 3) DS2: one lane open only; 4) DS3: one lane open only and speed restrictions; 5) DS4: closure. The consequence estimates are obtained from analysing the road network performance given a restrictive action. The outcome of such analyses is the aggregated travel time of the commuters, T, from where the difference in the travel time is obtained as $\Delta T = T - T_0$, where T_0 is the travel time in the "no restrictions" case. To compute ΔT, a graph-based approach based on the shortest-path algorithm is implemented (Dijkstra, 2022) . In this regard, the road network is idealised as a directed graph (the travels are assumed to be directed to a unique destination, i.e., node 4 in this application) where nodes represent the locations of interest and edges represent the links between these locations. A demand of 500, 500, and 1000 vehicles/h is assumed to originate from nodes 1, 2, and 3, respectively. The links are assumed to be at full capacity with no congestion in the "no restriction" case (i.e., vehicles move at the free flow speed); the free flow speed is assumed as 40, 80, 40, and 80 km/h for the two-lane links 1-2, 1-3, 2-4, and 3-4, respectively. A speed restriction is assumed to reduce the free flow speed to 75% of the original value. A lane closure is assumed to reduce the capacity of the link to the value C^*, causing a congestion and changing the aggregated travel time associated with the link to

$$T^* = \frac{C^*}{D} T_0 \tag{11}$$

In this case study, $C^* = C_0/2$ is assumed, where C_0 is the capacity of the link in the "no restriction" case. No reduction in the demand is assumed between cases.

The ΔT metric is then used to estimate the welfare loss (ΔW) as in Equation (12), using the same parameters presented in Silva-Lopez et al. (2022), where y is the commuter's wage rate, assumed to be 17.8 USD/h. Thereby, the consequence model E[$\boldsymbol{C_{FS}}$] = [0, 52.26,156.79, 261.32,522.63] is proposed in utils/h units.

$$\Delta W = \frac{1}{2y^{0.26}} \Delta T \tag{12}$$

Figure 1b Shows the expected life-cycle welfare loss for the case-study road network for the bridge starting in pristine conditions ($\boldsymbol{Fs}_0$ = [1,0,0,0,0]) as obtained by employing the proposed framework. Additionally, the expected life-cycle welfare loss of a structural upgraded bridge at t = 0 years (yr) is presented. Such an upgrade is assumed to ideally increase the median fragility values by 20% (i.e., to increase the lateral-resisting system structural capacity). As expected, an enhancement in the bridge's seismic lateral resisting system can significantly reduce its LCCon estimates, as also observed in Figure 1b. Given the flexibility and efficiency of the proposed framework, such improvements can be analysed at any point in time and utilised to showcase the value and/or significance of risk management and adaptation pathways.

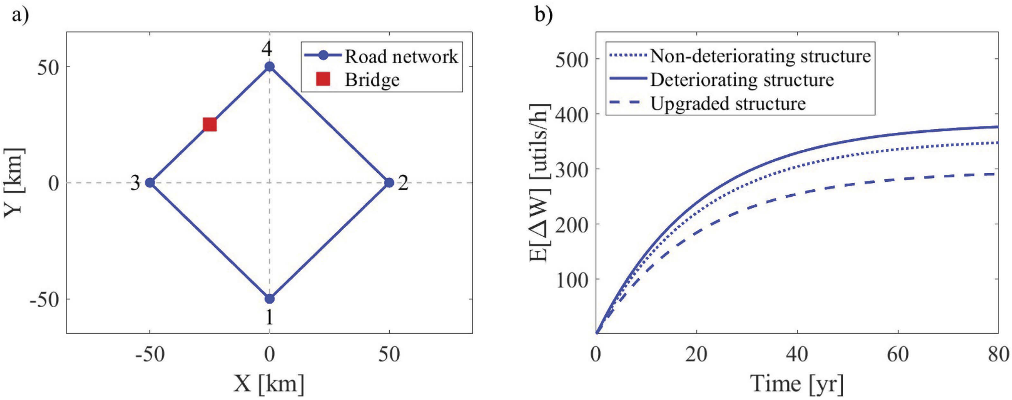

Figure 1. a) Case-study road network and b) expected life-cycle welfare loss.

5 CONCLUSIONS

The paper presented a Markovian framework for multi-hazard life-cycle consequence analysis of deteriorating structural systems. Transition matrices for shock deterioration, gradual deterioration, and repair actions were established to model the performance state change accounting for the possible interactions among hazards. Different unitary consequences (in terms of repair costs) were assigned to different performance states, allowing to obtain the expected Life Cycle Consequences of the system. The framework can be used to model the time- and state-dependent deterioration and recovery processes with significantly low computational demand. The proposed framework was applied for a simplified road network with a double-span box-girder seat-type bridge subject to earthquake-induced ground motions and corrosion-induced deterioration. The results showcase how the formulation can be implemented in actual risk modelling practice to adequately assess the life-cycle consequences of structural systems due to multiple hazards.

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