Probabilistic resilience model for management of road infrastructure systems subject to flood events

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ABSTRACT: Road infrastructure systems play a critical role in economic development by facilitating access to markets, jobs, and social services. However, they are vulnerable to various natural hazards and threats that have led to infrastructure failures and significant economic losses in the past. As a result, there is growing awareness of the need to build more resilient transportation systems. This paper addresses the challenge of modeling and assessing the risk and resilience of road infrastructure systems for optimal decision-making. This is facilitated by the generic system modeling framework for decision analysis proposed in Faber et al. (2017), which accounts for both the generation of benefits and losses. By using this scenario-based modeling approach, it is possible to gain a thorough understanding of the infrastructure failures that have the most significant impact on the expected total consequences at the road network level. In addition, the application of the modeling framework allows the comparison of different decision alternatives, such as decisions on the level of preparedness and decisions on the percentage of benefit to be saved as reserves. The modeling approach is illustrated for a roadway network, with bridges being considered the most vulnerable assets. The effect of climate change on the probabilistic life-cycle performance of the bridge network is investigated, and the probability of resilience failure is assessed through the event where reserves are insufficient for re-establishing the functionality of the transportation systems after a flood event.

1. INTRODUCTION

There are numerous socio-economic benefits of resilient road infrastructure systems. When modeling and assessing the resilience of these systems, great attention has been paid to defining a measure that adequately describes the system functionality (or performance or level of service) over time after a disruptive event. Several metrics have been proposed, such as connectivity, centrality, throughput, travel time, among others (Vishnu et al., 2018). If the network functionality is defined in terms of accessibility, it may contribute to identifying the loss of access to critical facilities. Whereas if it is defined in terms of total travel time, it may facilitate the quantification of monetary losses of users due to trip delays, rerouting costs, amongst others. The majority of studies select the most suitable functionality metric according to their main goal and quantify resilience as the loss of that metric after a disturbance event until the system is fully recovered. However, the choice of the functionality metric influences the measured resilience itself (Vishnu et al. (2018)). Then, if multiple functionality metrics are defined, it becomes difficult to compare the effects of decision alternatives in different functionality recovery curves and to select the most optimal strategy. In this paper, a probabilistic decision analysis framework is introduced (Faber et al., 2017, 2020), to facilitate the modeling of risk and resilience of roadway networks subject to flood events. This framework allows comparing different decision alternatives, including decisions on the level of preparedness and decisions on the percentage of benefit which should be accumulated to address adaptation and recovery after disruptive events. The methodology is demonstrated for a roadway network where bridges are assumed the most vulnerable assets. Their life-cycle performance is represented probabilistically, and the effects of climate change are incorporated into the probabilistic hazard representation through the increase in the annual rate of occurrence of flood events. The probability of resilience failure, formulated as the exhaustion of the road network's capacity to restore functionality, is calculated for different decision alternatives to analyze their potential to increase system resilience.

2. PROBABILISTIC RISK AND RESILIENCE FRAMEWORK FOR DECISION SUPPORT

When providing decision support for the management of systems, it is crucial to identify and

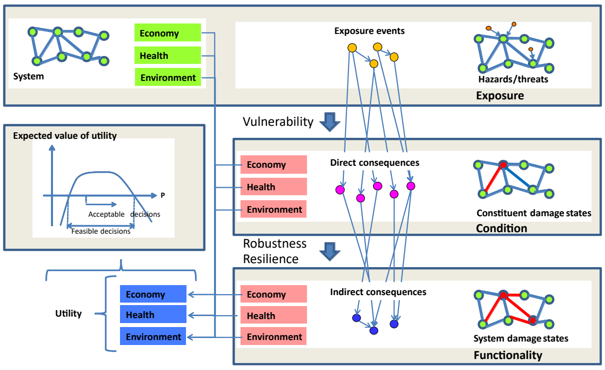

Figure 1: Illustration of systems modeling framework for decision analysis. Source: Faber et al. (2020)

establish a representation of the system which enables the ranking of different decision alternatives, consistent with the available knowledge, and coherent with the objectives and preferences of decision-makers and stakeholders (see JCSS (2008)). A modeling framework that facilitates decision analysis of systems is proposed in Faber et al. (2017, 2020), and it is illustrated in Figure 1. This decision support framework takes into account both risks in the sense of the expected value of losses of various metrics (e.g., loss of lives, damages to the environment, and economic losses), as well as benefits associated with decision alternatives. Thereby, this framework can be applied to rank different decision alternatives for the design and management of systems according to their expected value of utility in accordance with the Bayesian decision analysis (Schlaifer and Raiffa, 1961).

The modeling framework from Figure 1 utilizes the scenario-based system representation proposed by the JCSS (2008). This generic system representation subdivides scenarios of events into three parts: *i)* the exposure events acting on the constituents of the system (e.g., natural hazards, operational loads), *ii)* direct consequences that are associated with damages or failures of the constituents, and *iii)* indirect consequences that are related to the loss of functionality of the system as a result of one or more constituent failures. In general, a system is comprised of an ensemble of n constituents interacting jointly to provide the desired functionality. In the case of roadway networks, the system can be modeled at different spatial scales.

At a network level, different infrastructure assets, namely bridges, tunnels, pavements, among others, interact with each other to provide their intended service, i.e., transportation for people and goods. At the asset level, each infrastructure is a system that provides connectivity at one specific location in the network. The asset system is comprised of several interacting constituents, namely structural components (e.g., bridge components might be deck, piers, abutments, foundation), and non-structural components. Each component can be considered a subsystem itself. For instance, in a bridge system, the superstructure subsystem provides support for transferring the operating loads from cars and trucks, while the foundation subsystem provides support to the superstructure subsystem and transfers the loads to the soil. The definition of the scale of the system is especially relevant for risk-informed decision-making. Depending on the decision alternatives at hand, the appropriate scale of the system, which facilitates differentiating the expected value of benefit associated with the distinct decision options, should be chosen. In the present paper, the decision alternatives investigated in Section 3, correspond to decisions to be made at the network level scale.

2.1. *Flood hazard under climate change*

The flood hazard assessment is comprised of the characterization of the hazard process to determine the probability and magnitude of flood events in time and space, and the modeling of the flood action (load intensity measured through indices such as water depth, flow velocity, discharge) impacting the infrastructure system. The occurrence of flood events is commonly modeled via a homogeneous Poisson process, i.e., a process with independent and stationary increments (Shane and Lynn, 1964). According to this model, denoting with λ_0 the rate of flood events of magnitude $Q > q_0$, the probability that the number N of event occurrences during time t equals n is:

$$Pr[N(t) = n] = \frac{(\lambda_0\, t)^n}{n!} exp(-\lambda_0\, t), n = 0, 1, 2, ... \quad (1)$$

Nevertheless, there is evidence that the frequency and intensity of floods are likely to increase due to changes in precipitation patterns, sea level rise, early snow melt, and extreme cyclonic events, as a consequence of the warming of the climate system due to anthropogenic emissions of greenhouse gases (GHG) (Seneviratne et al., 2021). In this manner, flood event occurrences may follow a non-stationary behavior which may be better described by a non-homogeneous Poisson process where the occurrence rate is a function of time $\lambda(t)$ (Lin and Shullman, 2017):

$$\lambda(t) = \lambda_0(1 + r_{\mathrm{H}} \cdot t) \quad (2)$$

Equation 2 assumes a linear increasing relationship over time, where r_{H} is the annual percentage of increment of the initial stationary occurrence rate λ_0. The linear assumption is made for reasons of simplicity in modeling and lack of information supporting other assumptions.

2.2. *Vulnerability of roadway infrastructures*

As illustrated in Figure 1, the relationship between exposure or hazard events and the direct consequences is termed vulnerability. Essentially, the vulnerability of a system indicates the degree to which exposures generate direct consequences. The vulnerability of roadway networks can be defined as the risk due to all direct consequences from all infrastructure assets in the system (R_{D}), and may be assessed through the expected value of the conditional risk due to direct consequences, over all possible hazard events and all asset damage states as (Bayraktarli and Faber, 2011):

$$R_{\mathrm{D}} = \sum_i \sum_j P(D_j|H_i)\; P(H_i)\; C_{\mathrm{D},ij} \quad (3)$$

where $P(H_i)$ is the probability of hazard H_i, with $i = 1, 2, ..., n_s$ possible different scenarios of hazard events; $P(D_j|H_i)$ is the probability of damage D_j given the hazard H_i, with $j = 1, 2, ..., n_{csta}$ possible set of infrastructure damage states; and $C_{\mathrm{D},ij}$ is the expected consequences (costs) of damage D_j due to hazard H_i.

2.3. *Functionality loss in roadway networks*

Indirect consequences in roadway networks are associated with the loss of functionality of the system caused by the effect of one or more infrastructure failures. Functionality can be measured by several metrics which relate to the different functions provided by the transportation system. Traffic flow capacity, travel time, and connectivity are among the most common metrics to describe the functionality of transportation systems and estimate the indirect monetary consequences. Essentially, in the case of failure of infrastructure assets, there will be a prolongation of travel since traffic flow is no longer possible through failed links. This will result in increased costs due to longer travel times for users, as well as additional vehicle operating costs as a result of fuel consumption and vehicle maintenance. These indirect costs due to the prolongation of travel ($C_{\mathrm{ID,pt}}$) can be estimated using Equation 4, where U_{tt} is the value of travel time, U_{ov} are the vehicle operating costs, $t_{\mathrm{l,0}}$ and $x_{\mathrm{l,0}}$ are the travel time and the traffic flow at link l, respectively, when the network is fully functional, and $t_{\mathrm{l,t}}$ and $x_{\mathrm{l,t}}$ are the travel time and the traffic flow at link l, respectively, at time t after a disturbance event, for each given network system scenario k (Hackl et al., 2018):

$$C_{\mathrm{ID,pt}}(k) = (t_{\mathrm{l,t}}(k) \cdot x_{\mathrm{l,t}}(k) - t_{\mathrm{l,0}} \cdot x_{\mathrm{l,0}}) \cdot U_{\mathrm{tt}} + (x_{\mathrm{l,t}}(k) - x_{\mathrm{l,0}}(k)) \cdot l \cdot U_{\mathrm{ov}} \tag{4}$$

In addition, the failure of certain infrastructure assets in the network may lead to a loss of connectivity between origin and destination (OD) pairs. This unsatisfied demand causes indirect costs due to decreased labor productivity during a time period, which can be estimated as (Hackl et al., 2018):

$$C_{\mathrm{ID,lc}}(k) = \sum_{P_{\mathrm{od}} \in P^{\mathrm{lc}}_{\mathrm{od,t}}(k)} OD_{\mathrm{m,n}}(k) \cdot U_{\mathrm{lt}} \tag{5}$$

where $P^{\mathrm{lc}}_{\mathrm{od,t}}(k)$ represents the OD-paths where no flow is possible (i.e., loss of connectivity between OD-pairs) for a given network system scenario k; $OD_{\mathrm{m,n}}$ is the travel demand from origin m to destination n; U_{lt} is the monetary loss due to the missed trips.

Based on the quantification of indirect consequences, it is possible to assess the risk due to indirect consequences (R_{ID}) through the expected value of the indirect consequences in regard to all possible hazard events and all asset damage states as:

$$R_{\mathrm{ID}} = \sum_k \sum_i \sum_j P(S_k|D_j \cap H_i) P(D_j|H_i) P(H_i) C_{\mathrm{ID},ijk} \tag{6}$$

where $P(S_k|D_j \cap H_i)$ is the probability of different network system states S_k given the damage of infrastructure assets D_j due to hazard event H_i; and $C_{\mathrm{ID},ijk}$ is the expected consequences (costs) of indirect damages due to system state S_k.

2.4. Resilience modeling and quantification

Following the decision analytical framework proposed by Faber et al. (2017), systems resilience models and assessments should concern not only the loss of functionality and recovery but also the generation of the system recovery capacity, which is critical for successfully and rapidly reorganizing, adapting, and recovering from disturbance events. Essentially, socio-technical systems such as roadway networks generate a benefit over time that favors economic growth. A percentage of that benefit should be collected as an economic reserve to respond to disturbances. Thus, the economic capacity R_{r} of the road infrastructure system over time may be described as the accumulation of the reserves (Liu et al., 2022):

$$R_{\mathrm{r}}(\mathbf{X}, \mathbf{a}, \chi, t) = R^0_{\mathrm{r}} + \int_0^t \frac{\chi\, b(\mathbf{X}, \mathbf{a}, \tau)}{(1 + r_\gamma)^\tau}\, d\tau \tag{7}$$

where R^0_{r} represents the starting capital reserve, which may be assumed to correspond to some percentage of the expected value of total benefits generated during the service life of the road infrastructure system; χ represents the percentage of benefit savings; $b(\mathbf{X}, \mathbf{a}, \tau)$ corresponds to the benefit generation over time; r_γ is the discount rate. The quantification of benefits of a roadway network should be based on considerations of the relationship between the choice of quantity and quality of transportation infrastructure and its impact on society's economic growth. In Nishijima and Faber (2009), this relationship was established using macroeconomic production functions to determine the optimal investments in infrastructures exposed to natural hazards that would ensure sustainable societal development.

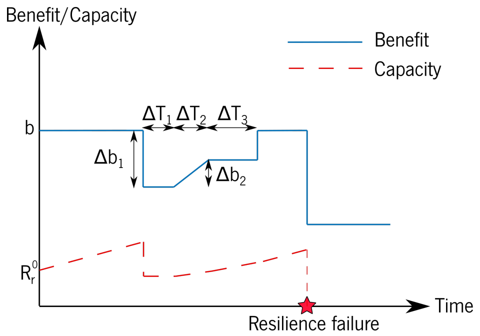

Figure 2: Resilience model in terms of benefit generation and economic capacity

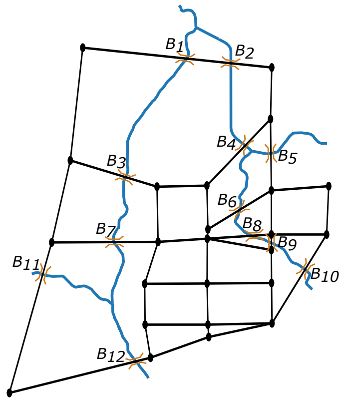

Figure 3: Application example of a roadway network

Figure 2 illustrates a realization of benefit generation and the accumulated economic capacity. For simplicity, the evolution of benefit generation is assumed to be constant over time when the transportation network is fully functional. When the occurrence of a disturbance event at time τ results in damage or failure of infrastructure constituents in the network, both the benefit generation and the economic capacity of the transportation system will be reduced. The economic demand S_r caused by a disturbance event at time t may be expressed as (Liu et al. (2022)):

$$S_\mathrm{r}(\mathbf{X},\mathbf{a},t) = \sum_{\tau \in \{\mathrm{t_F} \cap (0,t)\}} \frac{C_\mathrm{T}(\mathbf{X},\mathbf{a},\tau)}{(1+r_\gamma)^\tau} \quad (8)$$

where $C_\mathrm{T}(\mathbf{X},\mathbf{a},\tau)$ represents the total costs accrued during the recovery phase after the failure event; $\mathrm{t_F}$ corresponds to the time domain when disturbance events happened within the service life of the infrastructure system (0,t). If, at some point in time, the economic capacity is insufficient for re-establishing the functionality of the transportation system, i.e., reserves are exhausted, this can be defined as a resilience failure event (dashed line from Figure 2). Thus, the probability of resilience failure P_RF may be defined and assessed probabilistically as (Faber et al., 2017):

$$P_\mathrm{RF}(\mathbf{a},\chi,t) = 1 - P\big[\, \{R_\mathrm{r}(\mathbf{X},\mathbf{a},\chi,t) - S_\mathrm{r}(\mathbf{X},\mathbf{a},t)\} > 0, \forall\, \tau \in [0,t] \,\big] \quad (9)$$

3. PRINCIPAL EXAMPLE

In the following, an example of a roadway network exposed to flooding events is presented to illustrate the framework outlined in Section 2. The considered network is shown in Figure 3, which is a benchmark example adapted from the roadway network in Sioux Falls, South Dakota, that has been widely used to test traffic assignment models (see Stabler et al. (2022) for network input data). The roadway network consists of 24 nodes, 76 links, and it is assumed that the critical infrastructures to be considered are twelve reinforced concrete bridges ($N_\mathrm{B} = 12$) located at the river intersections as depicted in Figure 3. It is further assumed that the demands in the traffic model correspond to daily origin-destination (OD) trips.

The probabilistic performance of the roadway network is assessed for a life cycle equal to 50 years. The realization of flood events over time is assumed to follow a non-homogeneous Poisson process with an initial annual occurrence rate $\lambda_0 = 0.01$. The load intensity of the flood event acting on each bridge from the roadway network is modeled by a random vector log-normally distributed with the expected value $E[I_H] = 1$ and $COV[I_H] = 0.4$. The realizations of I_H are assumed independent from time to time, but the load intensities acting on each bridge at a given time are assumed correlated with correlation coefficient $\rho_H = 0.8$, since all bridges given their geographical proximity are considered to be located within the same small catchment. To investigate the impacts of different possible scenarios of climate change, the annual rate of increase r_{H} is varied from 1%-5 %. For the most extreme case, i.e., annual increase rate of 5%, the value of $\lambda(t = 50)$ would correspond to 0.035. To compute the risks associated with this flood hazard event, only the complete failure of bridges is considered, i.e., only one damage state. The time-dependent limit state equation which describes the failure of bridges with respect to the flood load intensity is given by:

$$g_{\mathrm{B_i}}(\mathbf{X},t) = z \cdot R_{\mathrm{B_i}} \cdot d(t) - i_{H_{\mathrm{Bi}}} \tag{10}$$

where $R_{\mathrm{B_i}}$ is the resistance of each bridge $i = 1,..,12$ with respect to the flood event intensity, modeled by a normal random variable with expected value $E[R_{\mathrm{B_i}}] = 1$ and $COV[R_{\mathrm{B_i}}] = 0.2$; z is the safety design parameter which is set to 4 for all bridges to achieve an annual probability of bridge failures in the order of 10^{-4}; $d(t)$ is a resistance degradation function; and $i_{H_{\mathrm{Bi}}}$ is the flood load intensity at bridge i. The structural capacity of the portfolio of bridges exhibits some correlation influenced by various factors, including structural typology, construction period, design standards (Bayraktarli and Faber, 2011; Yang and Frangopol, 2020). Thus, it is assumed that the correlation coefficient between the structural capacities of bridges is ρ_R = 0.3. Finally, a simplified resistance degradation function for reinforced concrete bridges subjected to corrosion is adopted in the following from (Enright and Frangopol, 1998):

$$\begin{aligned} &d(t) = 1 - k_1\,t + k_2\,t^2 \\ &\text{Low det}: \mathrm{k_1} = 0.0005,\ \mathrm{k_2} = 0,\ \mathrm{T_i} = 10\mathrm{yr} \\ &\text{High det}: \mathrm{k_1} = 0.01,\ \mathrm{k_2} = 0.00005,\ \mathrm{T_i} = 2.5\mathrm{yr} \end{aligned} \tag{11}$$

where k_1 and k_2 are coefficients defining the deterioration rate. The values for these coefficients and the time of corrosion initiation T_{i} are given for two scenarios, namely low and high deterioration conditions.

3.1. Risk-informed decision-making

Monte Carlo (MC) simulations are used for the probabilistic representation of the different bridge failure scenarios. Given that only survival or complete failure of bridges is considered, the expected direct costs for each scenario may be computed as:

$$C_{\mathrm{D}}(k) = \sum U_{\mathrm{r}} \cdot N_{\mathrm{BF}}(k) \tag{12}$$

where $N_{\mathrm{BF}}(k)$ corresponds to the number of bridge failures in the network system scenario k; and U_{r} is the unit cost for reconstruction of a bridge, which is obtained by assuming that building a new bridge network corresponds to the benefit generated over a period of 15 years. In the case of a bridge failure, it is assumed that traffic flow is not possible through the link. Thus, a traffic assignment model is used to simulate the traffic flow conditions under the failure scenarios by removing the corresponding link(s). The transportation network model was created using AequilibraE (Camargo, 2014), an open-source Python package for transportation modeling. The static traffic assignment method is used to estimate the travel time and traffic flow at each link, as well as the OD-paths where no flow is possible, for each damage scenario. It should be noted that the traffic assignment is run only once for the same failure scenario (same bridge failures) since they are stored to avoid higher computational costs in the MC simulation. Based on the results from the traffic assignment, Eq. 4 and Eq. 5 are used to estimate the indirect losses by assuming the unit costs as U_{tt} = 10 MU/hour, U_{ov} = 10 MU/km, U_{lt} = 20 MU/trip, and a month factor of 20 to account for the number of days per month to compute the total losses during the recovery period. The benefit realization path from Figure 2 illustrates the shape of the recovery curve adopted. The duration ΔT_1 denotes the time required to evaluate the damages and plan provisional measures, which are executed and become fully operational after a time ΔT_2, resulting in a gain in functionality. Finally, permanent measures to re-establish functionality are fully implemented after a period of ΔT_3. These recovery times are assumed to be proportional to the number of failed bridges in the scenario and are modeled by log-normal distributed random variables. In order to investigate how decisions on the level of preparedness may affect the risk and resilience of the roadway network, two levels of preparedness are considered, namely low and high. The expected values E[·] (in months) and coefficients of variation COV[·] for the random variables are given in Table 1.

Table 1: Probabilistic model for functionality recovery

Preparedness level	Variable	Distribution	E[·]	COV[·]
Low	ΔT_1	Log-normal	N_{BF}	0.2
	ΔT_2	Log-normal	$5N_{\mathrm{BF}}$	0.2
	ΔT_3	Log-normal	$20N_{\mathrm{BF}}$	0.2
High	ΔT_1	Log-normal	$0.5N_{\mathrm{BF}}$	0.1
	ΔT_2	Log-normal	N_{BF}	0.1
	ΔT_3	Log-normal	$10N_{\mathrm{BF}}$	0.1

Figure 4 shows a histogram of the total risk, i.e., the expected value of total consequences, for a roadway network with high preparedness to recovery, exposed to low deterioration, and for an annual increase of the occurrence rate of flood events of 1%. In order to identify which failure events are contributing the most to the losses, a histogram of the frequency of each bridge failure for all scenarios and scenarios from the 90^{th}percentile of expected total losses is constructed (see Figure 5). It can be observed that the frequency of bridge failures for all scenarios is uniform (displayed with blue bars), which is consistent with the fact that the resistance of all bridges was assumed equal. However, when only the scenarios leading to greater total losses are analyzed, failure of bridges B10 and B12 are the most frequent (displayed with orange bars). These results indicate that their corresponding links are the most critical in the roadway network in terms of functionality loss and associated indirect consequences. In addition, the co-occurrence of bridge failures may also lead to critical scenarios with large total expected losses. Table 2 presents the most significant ten failure scenarios (in terms of total losses) from the 90^{th}percentile of risks. Besides the individual failure of bridges B10 and B12, it can be seen that their co-occurrence of failure with bridges B4, B6, B7, B8, and B9, is an event with a very low probability of occurrence but with very high consequences, which contributes substantially to total expected losses.

3.2. Resilience quantification and decision alternatives

Conditioning on the flood hazard event previously described, the resilience failure probability of

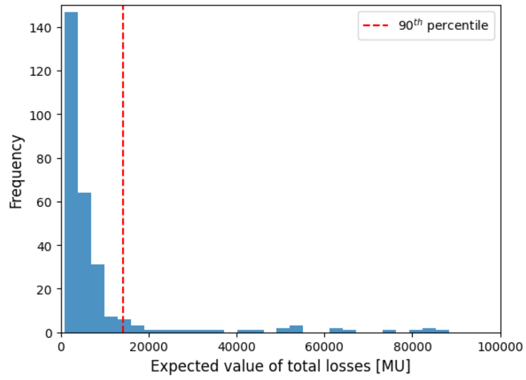

Figure 4: Histogram of total risk for low det. and high prep. for 1% annual increase of flood occurrence rate

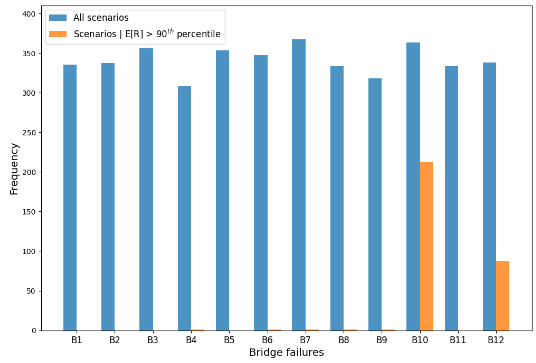

Figure 5: Frequency of bridge failures for all scenarios and scenarios from the 90^{th} percentile of risks

the roadway network can be defined as the event where the available reserves to recover within a specified time frame are exceeded, as expressed by Eq. 9. To estimate the economic capacity (Eq. 7), the benefit generated from the roadway network is assumed to be 10^8 MU/year. In the case where the roadway network is disrupted by failure events, the annual loss of benefit Δb_1 is assumed proportional to the number of failed bridges, i.e., $\Delta b_1 = N_{\mathrm{BF}}/N_{\mathrm{B}}$ (Figure 2). After time ΔT_2 where provisional measures are operational, there is a gain in the benefit generation Δb_2, which depends on the level of preparedness. For low preparedness, it is assumed that the benefit gain is 50%, while for high preparedness level is assumed equivalent to 80%. All benefits and expenditures for recovery occurring in the future are discounted assuming a discount rate of 2% which is assumed intergenerationally acceptable for sustainable decision-making (Rackwitz et al., 2005). Five decision alter-

Table 2: Failure scenarios contributing to larger risks

Failed bridges	Expected losses [MU]	Prob. Event
B4, B6, B7, B8, B9, B10, B12	211778.13	2.00E-06
B10	106396.25	4.22E-04
B12	87861.57	3.68E-04
B9	85083.95	3.50E-04
B7	84744.40	4.44E-04
B8	81758.93	3.72E-04
B3	73902.48	4.20E-04
B6	64636.99	3.80E-04
B5	64055.98	3.86E-04
B11	62446.48	3.82E-04

natives are considered to investigate how the percentage of annual benefit χ, which is saved for financing the repair and replacement of bridges, may affect the resilience of the roadway network (i.e., $\chi = 0.02, 0.04, 0.06, 0.08, 0.1$). Correspondingly, the starting capital reserve is computed as the percentage χ of the expected value of total benefits generated during the service life of the roadway network. Figure 6 presents the probability of resilience failure as a function of the annual increase in the occurrence rate of the flood event, for different decision alternatives and deterioration levels. Unsurprisingly, P_{RF} increases with higher annual occurrence rates, with a more pronounced effect for the cases of high deterioration. Likewise, the effect of the level of preparedness is highly relevant for reducing P_{RF}, especially for conditions of high deterioration. It can also be observed that P_{RF} significantly decreases when the percentage of annual benefit χ is increased from 2% (continuous lines) to 10% (dashed lines). Figure 7 examines more closely the variation of P_{RF} as a function of the percentage of χ, where it is evidenced how resilience significantly depends on the maintenance of reserves. Yet, it can be seen that the most substantial reduction in the P_{RF} occurs from 2% to 4% of χ, and it becomes more stable after 6%. Thus, identifying this optimal value of χ is extremely important for resilience management and should account for all the trade-offs and constraints.

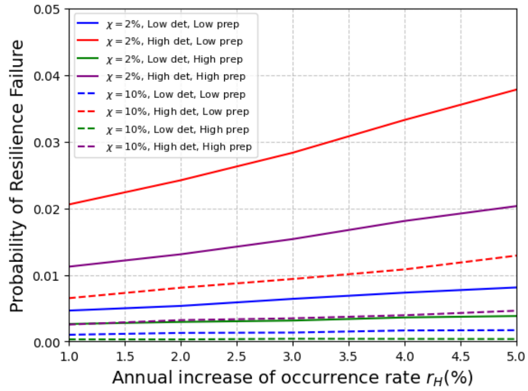

Figure 6: Probability of resilience failure under different deterioration and climate change scenarios

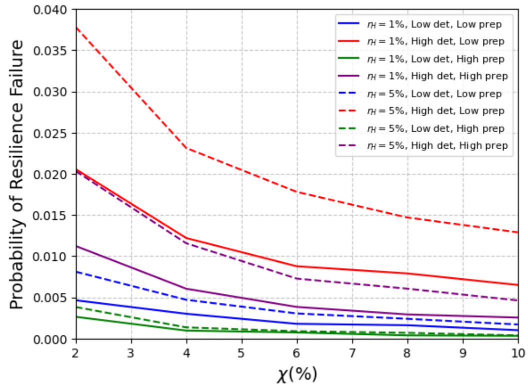

Figure 7: Probability of resilience failure for different percentages of benefit savings

4. CONCLUSIONS

This paper presents a probabilistic framework for risk and resilience modeling of roadway networks subject to flood events, which aims at facilitating the ranking of different decision alternatives with respect to their management. The scenario-based modeling approach enables a comprehensive understanding of which infrastructure failures are contributing the most to the expected total consequences, which is of high relevance in complex systems such as roadway networks. Moreover, the modeling of resilience implemented in this paper allows the consideration of all potential hazard events throughout the infrastructures' service life (rather than limiting the analysis to a single event), as well as explicitly accounting for the generation of capacity to recover from hazard events. An application example of a simple roadway network is presented, where bridges are considered the critical infrastructures subject to flooding events. The example demonstrates how critical bridges may be identified according to their contribution to the total risk. Based on the results, bridges may be ranked in the network, and decisions on their safety level can be made. In addition, the example investigates the impact of different decisions on the probability of resilience failure, namely decisions on the level of preparedness and decisions on the percentage of benefit savings χ. Decisions on improving the safety of infrastructures can also be introduced, including options for maintenance strategies aiming at mitigating the effect of deterioration which was deemed of relevance in the example presented. Finally, future work should focus on the optimization problem where costs for improving design reliability and preparedness should be in balance with the expected value of loss reduction and resilience improvement.

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