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

Smart resilience: Capturing dynamic, uncertain and evolving lifecycle conditions

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ABSTRACT: Modern cities are becoming increasingly smart and interconnected, with the capacity to gather unprecedented amounts of information. However, available methods for resilience quantification lack agility to cope with the ever-changing conditions and data that underpin disaster resilience and lifecycle performance analysis. In this paper, we discuss the limitations in the models themselves, i.e. even though frameworks predict uncertain and temporally evolving system performance, they are unable to learn from new data. To address these limitations, we pose a 'smart resilience modeling concept' which presents the ability to update model estimations and to efficiently estimate the lifecycle resilience as new data emerges. Hypothetical examples on community infrastructure affected by deterioration effects and punctuated events are presented. This conceptualization is expected to lay a foundation for smart resilience models capable of capturing the dynamic, uncertain, and evolving characteristics of future environmental demands, societal characteristics, and infrastructure conditions.

1 INTRODUCTION

The exposure of the built infrastructure to disruptive events demands a comprehensive way to measure its resilience. The importance of its quantification lies in the need of communities to set a baseline, define resilience goals and actions, quantify progress, and to estimate the social benefits and losses of resilience-related decisions (Committee on Increasing National Resilience to Hazards and Disasters *et al.* 2012). Modeling techniques are needed to establish such measurement in a prospective way; we need to predict communities and systems' capacity to withstand, adapt to and progressively recover after a disruption (Bruneau *et al.* 2003, Cimellaro *et al.* 2010). This requires interdisciplinary work and, although it has been a field of active research in the past decade, gaps and questions about measuring resilience still exist.

In the engineering community, there are difficulties in measuring resilience because of its multidimensional nature, the lack of evidentiary data and the uncertain and evolving conditions that underpin disaster resilience (National Academies of Sciences, Engineering, and Medicine 2019). Different efforts have been made to improve resilience estimation; for example, considering time-affected conditions of the engineering systems (Ghosh and Padgett 2010, Rokneddin *et al.* 2014, Jia and Gardoni 2019, Capacci *et al.* 2020); acknowledging the absorptive capacity of the system to accommodate or reduce the events' impacts (Ouyang and Dueñas-Osorio 2012, Decò *et al.* 2013); take account of the availability of resources needed for recovery processes (González *et al.* 2016); the multi-hazards conditions and cascading effects (Hernandez-Fajardo and Dueñas-Osorio 2013); the varying demand-supply of infrastructure services after events (Ouyang and Dueñas-Osorio 2012, Blagojević *et al.* 2022), among others. However, existing resilience modeling paradigms are designed with constrained inputs and model settings, and therefore easily become outdated over time.

To solve this limitation, we pose the idea of a 'smart resilience modeling approach'. We consider the infrastructure systems' resilience as a dynamic and uncertain quantity that evolves as

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data and new modeling approaches emerge. A 'smart' resilience model should be able to continuously learn from new data gathered, cope with shifts in environmental demands, consider variations in social needs and infrastructure uses, handle new monitoring parameters from emerging technologies, and others, adapting to the dynamic conditions of the systems. This paper presents the needs of such a framework using hypothetical examples. It is shown that lacking flexibility for coping with the emerging sources mentioned above may hinder the community spatial resilience, reduce their ability to identify and adaptively learn from varying threads and dimmish the ability to understand the community progress towards resilience goals, with probable worser impacts within the most vulnerable populations.

2 LIFECYCLE RESILIENCE MODELING

Infrastructure lifecycle and resilience assessments are commonly separate analyses given the differences in their temporal scale. Lifecycle analyses typically evaluate the system time-dependent performance in which progressive and punctuated events can affect the infrastructure during decades of service (Sanchez-Silva *et al.* 2011). On the other hand, resilience assessments are usually related to the recovery phase after a punctuated disturbance occurred, often framed in a scale from days to years (see Figure 1). Recent emphasis has been given to the joint evaluation of lifecycle and resilience aiming to capture the increased vulnerability in aging infrastructure, shifts in user-demands over time and the adaptation of communities after shock-based events. However, lifecycle resilience modeling paradigms still lack flexibility to include these variations as new knowledge about the system becomes available at any point at time. This makes the lifecycle resilience modeling challenging to be repeatable, generalizable and, sometimes, impractical to be applied (National Academies of Sciences, Engineering, and Medicine 2019).

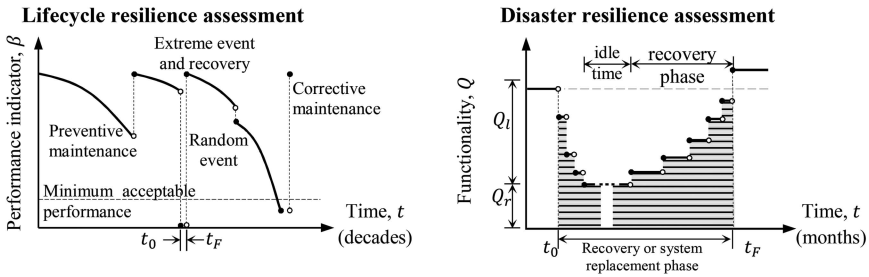

Figure 1. Lifecycle resilience analysis and resilience assessment time scales.

2.1 *Smart resilience modeling*

"Smart resilience" has appeared recently as a concept to depict the use of emerging technologies and intelligent practices (e.g. models, algorithms or tools) to enhance the system's capacity to handle, absorb, react and recover from any disturbance (DesRoches and Taylor 2018, Kumar *et al.* 2019, Padgett *et al.* 2022). Different examples in the literature demonstrate these smart technologies has permeated the resilience lifecycle assessment, including real-time health monitoring, physical and social sensors, IoT, and digital twins (Li and Pozzi 2019, Fan *et al.* 2021, Panakkal and Padgett 2022, Yabe *et al.* 2022). Also the evaluation of the benefits obtained from introducing these smart technologies for infrastructure monitoring purposes and the adaptability gained by the possibility of on-time decision-making have seen a tremendous increase of interest from researchers (Rabiei and Modarres 2013, Malings and Pozzi 2016, Zuluaga and Sánchez-Silva 2020). However, most of the recent contributions tend to focus on specific and individual portions of the infrastructure resilience lifecycle, i.e. they concentrate on introducing data acquisition techniques for characterization of exposed inventory, definition of system parameters to be monitored, or estimation of system performance during the post-disaster response phase.

To address the measurement and estimation of infrastructure resilience we pose a 'smart modeling paradigm'. We focus on the modeling paradigm itself to tackle the dynamic, uncertain and evolving lifecycle conditions over time. Smart resilience modeling refers to algorithms able to infuse existing modeling techniques with the ever-changing conditions measured or observed on the systems' dynamics (social, environmental, physical, and others). Hence, these must be flexible algorithms able to evolve as new knowledge and innovative approaches arise in the infrastructure lifetime horizon (see Figure 2).

Figure 2 depicts, conceptually, the system resilience estimations influenced by potential sources of data such as periodic or continuous observations (red stars and lines, respectively). For example, with the vast advances in smart technologies, shifts in the functionality of the system could be suddenly observed. On the other hand, performance estimates of the system are predicted by means of existing algorithms, which may include the effect of degradation stressors (blue lines) or the estimation of recovery trajectories after a shock event (green line). One key goal of the smart resilience concept is to continuously fuse these different knowledge sources to inform future resilience models. The outcomes of such approaches result in mean estimates of the system performance with bounds that show the varying uncertainty and its relationship with data collection efforts (black solid and dashed lines). Such a modeling paradigm requires intelligent algorithms to estimate, efficiently and confidently, the actual resilience of the system as time evolves. Recursive Bayesian algorithms, active learning, and transfer learning techniques, among others, are envisioned for this purpose. Such methods can help to limit the resources required for computation and data gathering, overcome data limitations and introduce the heterogeneous gathered knowledge into the assessment of future systems' resilience.

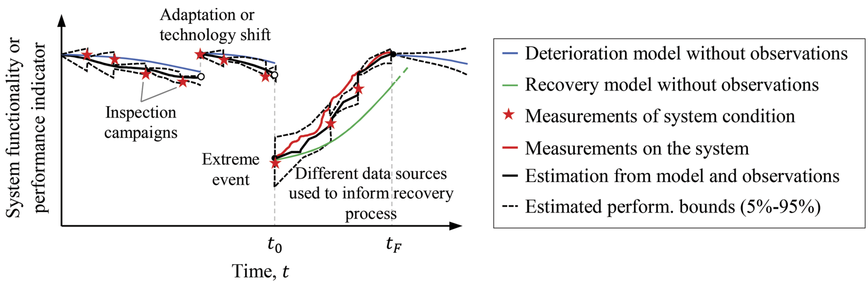

Figure 2. Resilience modeling of infrastructure performance over time and potential to leverage different data sources in a smart resilience framework.

3 ILLUSTRATIVE EXAMPLE

3.1 *Problem definition*

A rather simple transportation network is selected to explain the smart resilience approach (Figure 3). It consists of seven cities connected through 10 roads which condition depends on bridges' availability. Multi-span simply supported concrete bridges (assumed as representative of the bridges in the network) are affected by deterioration processes related to chloride ingress (Ghosh and Padgett 2010). The bridges' capacity to sustain service loads (i.e. live loads) and extreme loads (represented by seismic events) are affected. The live loads crossing the bridges are represented probabilistically by a three parameter Weibull distribution following Chowdhury *et al.* (2013), and seismic loads by a point of fault rupture that generates events whose magnitude follows a truncated Gutenberg-Richter model ($M_{w,min}$ = 5, $M_{w,max}$ = 8, b = 1). The loads and magnitude probability distributions are considered fixed in this study.

Bridges in this network are the only components considered susceptible to failure producing a complete road closure. Failure events related to live loads occur when a live load exceeds the bridge's moment capacity or the reliability index (β) reaches a value of β = 2.6 (Vishnu 2019). Besides, when a seismic event occurs leading to extensive damage is also considered as bridge failure (or if β = 1.5). It is assumed that a failure condition always requires a complete bridge closure for intervention purposes.

Inspection campaigns, information about failure events and data collected during repair activities are documented in Table 1. Bridge deterioration affected components are examined (using intrusive approaches) every 5 years. Deck or total bridge replacements are reported if the moment capacity has been exceeded on the bridge's deck or a seismic event damaged structures within the network. Finally, field observations of the progress and used times are collected during bridge interventions. These sources of information are used to update model inputs, model parameters or to infuse authoritative data within the predicted model estimations.

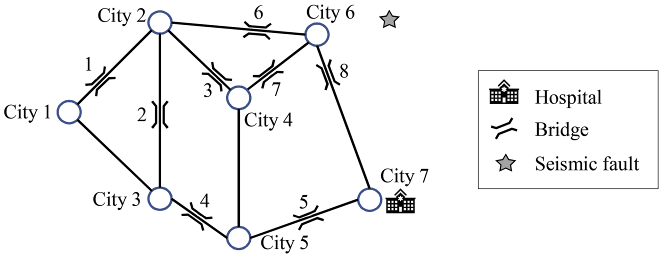

Figure 3. Hypothetical transportation network.

Table 1. Timeline of data collected and event occurrence.

Year	Event type	Data gathered		Unit
0	Exposed assets	Bridges ages: 45, 24, 26, 12, 47, 37, 19, 37		years
5	Bridge inspection	Deterioration affected parameters*		cm
15	Bridge inspection	Deterioration affected parameters*		cm
17	Seismic event, M_w=5.7	Damaged condition	0,0,0,0,1,0,1,0	1: failure, 0: safe
25	Bridge inspection	Deterioration affected parameters*		cm
35	Bridge inspection	Deterioration affected parameters*		cm
36	Exceeded moment capacity on a bridge	Damaged condition	0,0,0,0,0,1,0,0	1: failure, 0: safe
38	Seismic event, M_w=7.8	Damaged condition	0,1,0,1,0,1,0,1	1: failure, 0: safe
40	Bridge inspection	Deterioration affected parameters*		cm

* Deterioration affected parameters correspond to rebars' diameter measured on columns, deck and elastomeric bearing dowels (data not shown here for brevity).

3.2 *Lifetime reliability and resilience assessment*

Given the small size of the network, the system failure evaluation is performed through matrix-based approaches (Kang *et al.* 2008). This method enumerates the m possible 'network states' into a matrix of system events **C**; i.e. the entire sample space of mutually exclusive and collectively exhausting (MECE) bridge states combinations or 'network states'. The probability of occurrence of each MECE events, arranged in vector **P(t)**, is obtained using individual bridges' failure probabilities; these are time-dependent functions conditioned on seismic intensities *im* or live loads w, p_S (im,t) and $p_L(w,t)$ respectively. Finally, the probability of disconnection $Pr(\mathbb{D}|t)$ of any source-terminal pair can be obtained using this method combined with network science algorithms (see details in Kang *et al.* 2008). In the present study, the probability of losing connection between any city and City 7 is defined as a network-level reliability metric of interest.

Additionally, the method has been extended to obtain the probability of network disconnection $N_{\mathbb{D}}$; a vector **D** is created using the indicator function over the connectivity of the system for the MECE events (0 if the network is connected, and 1 otherwise). Then, $N_{\mathbb{D}}$ is computed as:

$$Pr(N_{\mathbb{D}}|t) = \mathbf{D}^{\top}\mathbf{P}(\mathbf{t}) \tag{1}$$

For seismic events, the bridge's failure probability $p_S(im)$ is computed from the bridge fragility functions proposed by (Rokneddin *et al.* 2014) and the intensity measure obtained from the (Atkinson and Boore 1995) ground motion model. Hence, the network states probability vector **P** is also conditioned on the magnitude of the event. The analysis of the unconditional failure probability of the system $P_{sys,s}$ requires the integration of the network failure events over the joint probability density function of the event magnitudes (Kang *et al.* 2008). In this study, $P_{sys,s}$ is computed for each time t of analysis obtaining a lifetime metric useful for decision making.

The system failure probability for extreme live loads depends on $p_L(w,t)$, which is obtained from the surrogate model presented by Vishnu (2019) for exceeding the allowable moment in a bridge deck. To consider the uncertainty on the bridge structural parameters and in live loads w (inputs required of the surrogate model), p_L is computed using 10,000 Monte Carlo (MC) simulations. Mean failure probability p_L for each year t is obtained by updating the deck reinforcement bar diameter on the MC analysis; then, p_L is used for the lifetime network reliability analysis.

In addition to reliability metrics, average network resilience is computed from the network states. Each network state, represented by one MECE event, indicates a unique network condition, thus MC analysis is used to simulate the bridge recovery processes. The recovery simulation of each damaged bridge follows the approach proposed by Decò *et al.* (2013) and simultaneous repairs are assumed to occur if the number of available crews (n_{crews}) is larger than one. The simulated repair schedule defines the time at which functionality at the road level is recovered, resulting in a stepwise network recovery profile. The 'network functionality' η is assumed to be equivalent to the 'global network efficiency' (weighted version) often used in network science (LiYing Cui *et al.* 2010). The time-dependent efficiency computed during the repair phase is normalized by the unperturbed network functionality η_0, canceling out the normalization factor:

$$Q(t_r) = \frac{\eta(t_r)}{\eta(t_{r0})} = \frac{\cancel{n(n-1)}\sum_{j\neq i}\frac{1}{d_{ij}(t_r)}}{\cancel{n(n-1)}\sum_{j\neq i}\frac{1}{d_{ij}(t_{r0})}} \tag{2}$$

where $d_{ij}(t_r)$ refers to the distance between ij pairs considering all the available roads at recovery time t_r. The resilience metric is computed using Equation 3, with $Q(t)$ as the functionality metric, T_R assumed as the total time required to finish repair activities within the network, and a target functionality TQ, commonly assumed as 100% (Ouyang and Dueñas-Osorio 2012). This proposed metric depicts the evolution of the global system functionality (in terms of distance traveled by the users), between the nodes of the network, relative to the original system state.

$$R(t_r) = \frac{\int_0^{T_R} Q(t_r)dt_r}{\int_0^{T_R} TQ(t_r)dt_r} \tag{3}$$

The average network resilience obtained for each MECE event is arranged in vector **U**. It is used to obtain the time-dependent mean network resilience N_R:

$$N_R(t) = \mathbf{U}^\top \mathbf{P}(\mathbf{t}) \tag{4}$$

4 RESULTS: SMART TIME-DEPENDENT RESILIENCE ASSESSMENT

New knowledge that emerges at a certain time t are denominated here as 'learning events'. If a certain learning event occurs during time t, the subsequent step should consider the knowledge acquired through a fusion process. For example, bridge mean failure probabilities for extreme live loads are initially predicted using a deterioration model without introducing any observation (see Figure 4a). These, translated into reliability indexes β, can help to define the expected year when bridge deck replacement must take place. Following a recursive Bayesian estimation approach, specifically the Kalman filter algorithm (Kalman 1960), lifetime predictions are updated by infusing the knowledge obtained from the inspection cycles defined in Table 1. The first inspection is clearly depicted by a large shift on the predicted values for β towards the "true performance" (i.e. when complete knowledge is available); beyond that point the recursive Bayesian approach improves the model predictions, increasing its accuracy with every new observation. If after each updating process large computational efforts are needed, then smart algorithms can also be used to reduce the burden. For example, active learning reliability estimation methods, e.g. using gaussian process regression and MC analysis (Echard *et al.* 2011), are possible solutions for recomputing the large MC analysis. In addition to enhancing individual performance indicators, infusing the knowledge from observations clearly influences the computed mean network total restoration time T_R (i.e. the estimated performance) as depicted in Figure 4b. Annual expected T_R is relatively small considering that the failure associated to live loads, for this particular example, presents a low failure probability.

Observations about bridge deterioration on column and elastomeric bearing dowel rebars affect the expected seismic response of bridges. The model for parameterized seismic fragility functions (Rokneddin *et al.* 2014) is suitable for time-dependent analysis and it is easily updated as new information about the components' conditions is collected. However, although directly measured, data gathered is only representative of the real (yet uncertain) structural state. The probability of extensive damage predicted by the fragility functions is also updated indirectly as new information from the rebar condition is considered in the recursive Bayesian estimation. Figure 5a depicts the evolution of approximate seismic reliability index and the impact of new data introduced to the model. The implications of the observations on the bridge's conditions are propagated to the network reliability N_R as observed in Figure 5b. After some sequential observations the model greatly improves its guesses about the future resilience, reducing the error between the predicted and the 'true' system performance indicators.

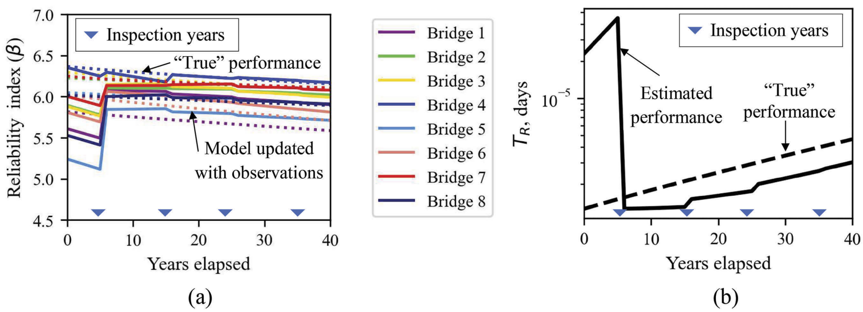

Figure 4. Model estimations and updated predictions for a) bridge-level reliability index and b) time-dependent mean network downtime for extreme live loads.

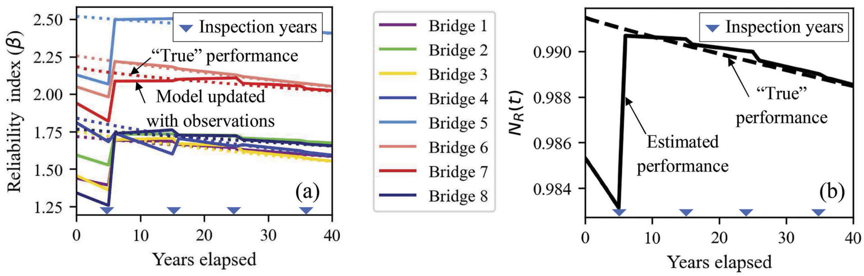

Figure 5. Model estimations and updated predictions for a) bridge-level reliability index for an event of Mw=6 and b) time-dependent mean network resilience for seismic events.

Finally, the occurrence of seismic events in years 17 and 38, and the failure of bridge N° 6 in year 36 require the total replacement of some bridges. Once these replacements are done, the recursive Bayesian estimation must be initiated again on those bridges using the information of the new conditions (e.g. new column rebar area). The introduction of renewed conditions is depicted as an abrupt positive modification on the mean network downtime and mean network resilience (see Figure 6). Note that this change influences both the 'true' and estimated performance; it occurs considering that the 'true' network vulnerability is also diminished with newer bridges. Repair times measured during the intervention efforts could also be used to additionally improve the distributions of the model inputs (not included for brevity). This illustrative example shows that the model predictions sequentially updated with observations tend to represent more accurately the performance metrics at the component (bridge) and system (network) level.

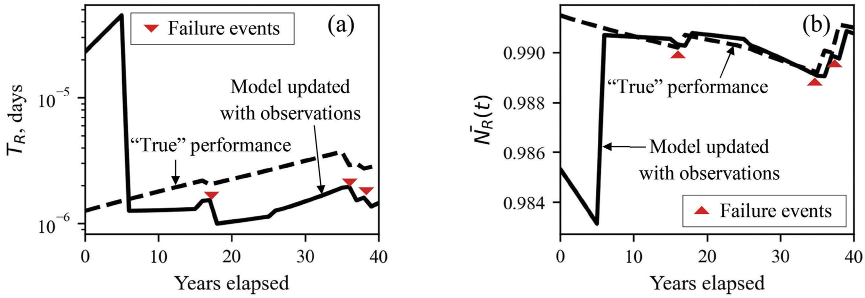

Figure 6. "True" and updated prediction of a) mean network downtime for live loads and b) mean network resilience for seismic demands, both including failure events occurred.

5 CONCLUSIONS

Models for resilience estimation commonly focus on instantaneous infrastructure resilience, lacking the ability to introduce data gathered throughout the system lifecycle. Also, existing models may not be able to improve the model parameters, not being able to cope with real ever-changing conditions. This paper attempts to review the challenges of such modeling frameworks and provides the 'smart resilience' concept as a practical solution. Smart resilience modeling refers to algorithms able to continuously learn from new data gathered, cope with shifts in environmental demands, consider variations in social needs and infrastructure uses, handle new monitoring parameters from emerging technologies, and others, adapting to the dynamic conditions of the systems. Hence, it is essential to use 'smart' algorithms such as active learning schemes to improve information gain, transfer learning techniques to cope with heterogenous and changing conditions, or recursive Bayesian approaches for continuous updating processes, among others. An illustrative example using a hypothetical transportation network is presented. Deteriorated conditions of aging-bridge parameters (specifically steel rebars) are assumed to be collected as well as the dates of bridge replacements (after failure occurs). The introduction of sequential data gathered to update existing model predictions were shown to improve the accuracy of metrics of interest, such as the bridge-level reliability index and network-level annual expected recovery times and annual mean resilience, demonstrating the importance of working toward smart resilience approaches.

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REFERENCES

Atkinson, G.M. and Boore, D.M., 1995. Ground-motion relations for eastern North America. *Bulletin of the Seismological Society of America*, 85 (1): 17–30.

Blagojević, N., Hefti, F., Henken, J., Didier, M., and Stojadinović, B., 2022. Quantifying disaster resilience of a community with interdependent civil infrastructure systems. *Str. and Infr. Engineering*, 0 (0): 1–15.

Bruneau, M., Chang, S.E., Eguchi, R.T., Lee, G.C., O'Rourke, T.D., Reinhorn, A.M., Shinozuka, M., Tierney, K., Wallace, W.A., and von Winterfeldt, D., 2003. A Framework to Quantitatively Assess and Enhance the Seismic Resilience of Communities. *Earthquake Spectra*, 19 (4): 733–752.

Capacci, L., Biondini, F., and Titi, A., 2020. Lifetime seismic resilience of aging bridges and road networks. *Structure and Infrastructure Engineering*, 16 (2): 266–286.
Chowdhury, M., Putman, B., Pang, W., Dunning, A., Dey, K., Chen, L., and Clemson University. Dept. of Civil Eng., 2013. *Rate of deterioration of bridges and pavements as affected by trucks*. FHWA.
Cimellaro, G.P., Reinhorn, A.M., and Bruneau, M., 2010. Framework for analytical quantification of disaster resilience. *Engineering Structures*, 32 (11): 3639–3649.
Committee on Increasing National Resilience to Hazards and Disasters, Committee on Science, Engineering, and Public Policy, Policy and Global Affairs, and National Academies, 2012. *Disaster Resilience: A National Imperative*. Washington, D.C.: National Academies Press.
Decò, A., Bocchini, P., and Frangopol, D.M., 2013. A probabilistic approach for the prediction of seismic resilience of bridges. *Earthquake Engineering & Structural Dynamics*, 42 (10): 1469–1487.
DesRoches, R. and Taylor, J., 2018. The promise of smart and resilient cities. *The Bridge*, 48 (2).
Echard, B., Gayton, N., and Lemaire, M., 2011. AK-MCS: An active learning reliability method combining Kriging and Monte Carlo Simulation. *Structural Safety*, 33 (2): 145–154.
Fan, C., Zhang, C., Yahja, A., and Mostafavi, A., 2021. Disaster City Digital Twin: A vision for integrating artificial and human intelligence for disaster management. *Int. J. of Inf. Management*, 56, 102049.
Ghosh, J. and Padgett, J.E., 2010. Aging Considerations in the Development of Time-Dependent Seismic Fragility Curves. *Journal of Structural Engineering*, 136 (12): 1497–1511.
Ghosh, J. and Padgett, J.E., 2012. Impact of multiple component deterioration and exposure conditions on seismic vulnerability of concrete bridges. *Earthquakes and Structures*, 3 (5): 649–673.
González, A.D., Dueñas-Osorio, L., Sánchez-Silva, M., and Medaglia, A.L., 2016. The Interdependent Network Design Problem for Optimal Infrastructure System Restoration: The interdependent network design problem for infrastructure restoration. *Computer-Aided Civil and Infr. Engineering*, 31 (5): 334–350.
Hernandez-Fajardo, I. and Dueñas-Osorio, L., 2013. Probabilistic study of cascading failures in complex interdependent lifeline systems. *Reliability Engineering & System Safety*, 111: 260–272.
Jia, G. and Gardoni, P., 2019. Stochastic life-cycle analysis: renewal-theory life-cycle analysis with state-dependent deterioration stochastic models. *Structure and Infrastructure Engineering*, 15 (8): 1001–1014.
Kalman, R.E., 1960. A New Approach to Linear Filtering and Prediction Problems. *Journal of Basic Engineering*, 82 (1): 35–45.
Kang, W.-H., Song, J., and Gardoni, P., 2008. Matrix-based system reliability method and applications to bridge networks. *Reliability Engineering & System Safety*, 93 (11): 1584–1593.
Kumar, S.A.P., Bao, S., Singh, V., and Hallstrom, J., 2019. Flooding disaster resilience information framework for smart and connected communities. *Journal of Reliable Intelligent Environments*, 5 (1): 3–15.
Li, S. and Pozzi, M., 2019. Predicting the Condition Evolution of Controlled Infrastructure Components Modeled by Markov Processes. *South Korea*, 8.
LiYing Cui, Kumara, S., and Albert, R., 2010. Complex Networks: An Engineering View. *IEEE circuits and systems magazine (New York, N.Y. 2001)*, 10 (3): 10–25.
Malings, C. and Pozzi, M., 2016. Value of information for spatially distributed systems: Application to sensor placement. *Reliability Engineering & System Safety*, 154, 219–233.
National Academies of Sciences, Engineering, and Medicine, 2019. *Building and Measuring Comm. Resilience: Actions for Comm. and the Gulf Research Program*. Washington, D.C.: National Acad. Press.
Ouyang, M. and Dueñas-Osorio, L., 2012. Time-dependent resilience assessment and improvement of urban infrastructure systems. *Chaos: An Interdisciplinary Journal of Nonlinear Science*, 22 (3), 033122.
Padgett, J.E., Panakkal, P., and González, C., 2022. Chapter 12 – Infrast. impacts and vulnerability to coastal flood events. *In*: S. Brody, Y. Lee, and B.B. Kothuis, eds. *Coastal Flood Risk Red*. Els., 151–165.
Panakkal, P. and Padgett, J.E., 2022. OpenSafe Fusion [online]. *OpenSafe Fusion*. Available from: https://www.opensafefusion.com/# [Accessed 18 Apr 2022].
Rabiei, M. and Modarres, M., 2013. A recursive Bayesian framework for structural health management using online monitoring and periodic inspections. *Reliability Eng. & System Safety*, 112: 154–164.
Rokneddin, K., Ghosh, J., Dueñas-Osorio, L., and Padgett, J.E., 2014. Seismic Reliability Assess. of Aging Highway Bridge Networks with Field Instrum. Data and Correlated Failures, II: Application. *Earthquake Spectra*, 30 (2): 819–843.
Sanchez-Silva, M., Klutke, G.-A., and Rosowsky, D.V., 2011. Life-cycle performance of structures subject to multiple deterioration mechanisms. *Structural Safety*, 33 (3): 206–217.
Vishnu, N., 2019. Multi-threat Sust. Assessm. of Bridges and Bridge Networks. Rice University, Texas.
Yabe, T., Rao, P.S.C., Ukkusuri, S.V., and Cutter, S.L., 2022. Toward data-driven, dynamical complex systems approaches to disaster resilience. *Proc. of the National Acad. of Sciences*, 119 (8), e2111997119.
Zuluaga, S. and Sánchez-Silva, M., 2020. The value of flexibility and sequential decision-making in maintenance strategies of infrastructure systems. *Structural Safety*, 84: 101916.