Bridge Network Decisions with Mobile Technology Integration

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ABSTRACT: The interconnectedness between structural failure probabilities and systemic features is crucial in civil infrastructure safety and integrity assessment in post-disaster applications. The combination of systemic reliability with transportation and health services demand can aid in optimizing the response strategies of the bridge population and planning effective disaster-related decisions. This paper aims to improve upon the conventional bridge health monitoring solutions by upscaling the monitoring paradigm into urban regions and transportation networks and applying mobile and smart sensing techniques together with an innovative reconnaissance procedure.

Structural health monitoring (SHM) systems have various applications (Brownjohn, 2007) including damage prognosis (Farrar & Lieven, 2007), residual life assessment (Chan, 2001; Li, 2001), decision-making (Hughes et al., 2021; Neves et al., 2019), and system-scale implementations (Addabbo et al., 2019; Alipour & Harris, 2020). However, these systems are often expensive (Lynch, 2007) and require significant labor, making them primarily used in structures with research incentives. However, following disastrous events, i.e., earthquakes, a global picture of the infrastructure asset conditions is required for making timely and effective mitigation problems, for example, conjunct risk of transportation system under bridges subject to seismic hazard (Kiremidjian et al., 2007; Lee et al., 2011; Padgett & DesRoches, 2007; Shiraki et al., 2007).

Recent advancements in SHM have integrated smart and mobile technologies, such as smartphones, to address certain needs (Malekloo et al., 2021; Sony et al., 2019). These low-cost solutions have enabled smartphones to play a key role in rapid system identification opportunities (Ozer, 2016) together with crowdsourcing-based (Mei & Gül, 2019), multisensory (Ozer et al., 2017), and model-engaged (Ozer & Feng, 2019) models, which have enhanced the foundations of the next generation of SHM.

Although smartphone-based SHM solutions have significant potential, they have been limited in scale in recent years. Prior research has primarily focused on testing sensor accuracy for signal or identification purposes. This paper represents the first effort to expand smartphone-based SHM to include computation and performance at both signal and identification levels. Additionally, the proposed computational scheme goes beyond damage assessment or prediction for high-end products and systematizes sensing platforms and data computation. This unified approach makes SHM available for population-scale analytics, enables SHMcalibrated bridge-specific fragilities to be integrated into the seismic performance of transportation networks, and allows for easy integration with client-side and server-side platforms (Ozer, Feng, & Feng, 2015).

This paper presents a method of using publicly accessible smart technologies as a tool for monitoring structural vibrations in a portable and cost-effective manner. The authors monitored twenty bridges in a region using smartphone accelerometers to identify their modal characteristics. Identification results are used for finite element models (FEMs) updating which are then used for bridge reliability estimation. The multiple bridge SHM results are fed into the performance assessment process which reveals systemic behavior expressing connected effects of failure probabilities. Eighteen post-event disaster mitigation scenarios are defined in accordance with the region-scale SHM findings from a decision maker's perspective. It is worth noting that the framework is flexible in terms of adopting alternative post-event decision processes other than emergency actions, such as retrofit and reconstruction actions.

1. METHODOLOGY

The evaluation process begins with a traditional reconnaissance process, which is followed by the use of rapid vibration monitoring applications. The data collected during the site visits are used to develop FEM, and the vibration data serves as the basis for modal identification, followed by FEM updating.

The updated model is then used to estimate the reliability of each bridge individually under seismic exposure. The functional role of each bridge is taken into account to assess the connectivity features of the network, considering post-disaster seismic scenarios and mitigation actions. Using the structural performance at a systemic level along with transportation and hospital configurations, optimal decision-making can take place.

1.1. Field Surveys and Data Acquisition

To conduct a structural reconnaissance procedure, this approach involves gathering important information such as bridge dimensions and transportation-related metrics including road network demand and capacity features. This information can be obtained through various means including digital sources like the Google Maps API. In addition, vibration samples are collected from bridges using smartphone accelerometers, which are then used to perform modal identification.

1.2. Seismic Response Analysis

To establish bridge-specific fragility curves, this study uses fiber section models in OpenSees to conduct nonlinear time history analysis. Material section characteristics are updated using a scheme similar to the one presented in (Priestley et al., 1996) that accounts for stiffness degradation and calibration with mobile vibration data. The analysis focuses on standard bridge profiles that are bearing-free frame-type integral bridges, where bridge piers and decks are potential sources of damage.

1.3. Mobile Technology Integration for Calibration (Model Updating)

This paper introduces a novel method for characterizing bridge stiffness using mobile accelerometers. This approach is particularly effective for bridges with simple geometry, as the stiffness features can be linked to the material characteristics (such as concrete class) and can be extracted from the dynamic response measurements obtained through modal identification and model updating procedures, subject to certain assumptions to limit the complexity of the bridge.

The FEM updating process is initiated when the objective function reaches its minimum value. By defining a stiffness parameter EI, the optimization function can then search for the optimal value of FEMs and their modal frequencies within a certain range. The objective function can be expressed using a generalized formula

$$Obj(EI_i) = \sum_{n=1}^{N} k_{fr_n} \frac{\left((f_i - f_m)^2\right)^{1/2}}{f_m} + k_{ms_n}(1 - MAC) \qquad (1)$$

where f_m and f_i are identified modal frequency from the measurements and the natural frequency of i^{th} finite element model, respectively. MAC corresponds to the modal assurance criteria between the identification-based and the finite element-based mode shapes. According to the generalized expression, n represents a particular mode and N represents the total number of modes considered within the updating framework. It should be noted damping ratio is excluded from the scheme due to its relatively less identifiable nature. k_{fr_n} and k_{ms_n} can be quantified accounting for confidence in identified parameters as well as the role of the constraints set by them. In some cases, beamlike models can be updated using only modal frequencies, with no consideration of mode shapes (e.g., Oh et al., 2015). In this study, the identification process is simplified by setting k_{fr_1} equal to unity and all other coefficients to 0. This minimizes the equipment node number and duration of the field tests.

This paper emphasizes the significance of boundary conditions in bridge dynamics and includes three different boundary condition scenarios: fixed-fixed, simply supported, and fixed-pinned. These conditions represent a wide range of possible restraint uncertainties.

In order to obtain the optimal value for the stiffness parameter, a gradient descent search technique is employed. This technique estimates the next step increment or decrement of the stiffness term based on the reduction or increase of the objective function during subsequent computations. A parameterized FEM is used to conduct a dense computation of the objective function and identify its features.

$$EI_{i+1} = EI_i - \gamma \nabla Obj(EI_i) \tag{2}$$

where γ is the step size. The proposed optimization scheme is expected to be efficient in case of extensions into multiparameter identification to achieve minimal computational expenses.

1.4. Transportation and Hospital Network Demand

The travel time delay due to reduction in the bridge capacities in different damage states can result in traffic congestion, and hence affect the post-earthquake emergency operation. In this study, total travel time is calculated based on the free-flow travel time on each link, i.e., the time taken by a user to travel a path when the traffic density (flow) is zero (i.e., the normal duration).

Furthermore, it is important to determine the health service capacities assigned to each node in the network and the demand after a seismic event. The number of casualties in a region can be estimated as a function of the seismic intensity to which the infrastructure is exposed, using an empirical approach (Jaiswal et al., 2009).

This approach can also be used to estimate injuries by applying a mortality to morbidity ratio of approximately one third for a typical Richter magnitude range of 6.5-7.4 (Alexander, 1985). Accordingly, the probability of not failing to receive medical services at a particular location following an earthquake can be defined as.

$$Sh^{w} = P(Mb < b_n) \tag{3}$$

1.5. Ground Motions for Fragility Curve Development

The process of simulating ground motions can involve generating synthetic ground motions that mimic the characteristics of actual earthquakes recorded at a specific location. By using the non-stationary Kanai-Tajimi model (Fan & Ahmadi, 1990; Lin & Yong, 1987) a range of ground motions with similar frequency content and duration to the target earthquake can be produced at different intensities.

1.6. Systemic Reliability and Risk Estimation

Bridge-specific fragility curve can be generated based on lognormal cumulative distribution function fitting the failure and survival data such that

$$F(a) = \varphi\left(\frac{ln\frac{a}{c}}{\sigma}\right) \tag{4}$$

where a, c, and σ corresponds to the ground motion intensity, mean, and standard deviation. The curve fitting operation can be conducted through

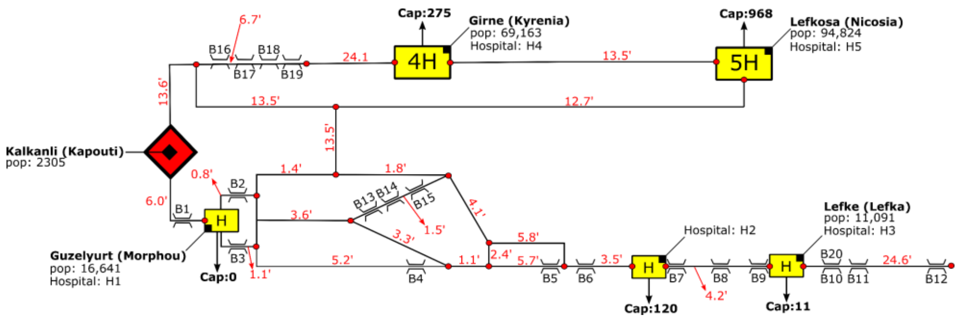

Figure 1. Abstract network connecting Kalkanli with adjacent regions denoting travel time and hospital capacity.

maximum likelihood estimation. One can also reinterpret the seismic fragility of an individual bridge's reliability as

$$R(a) = 1 - F(a) \tag{5}$$

which is further extended to series and parallels bridge systems. Accordingly, the reliability of a transportation path L_{qw} connecting vicinities q and w can be linked to the collective behavior of series and parallel alignment of bridge nodes such as

$$R_{L_{qw}}([a_{j=1:m}]) = R_{sys}([a_{j=1:m}]) \tag{6}$$

where a_j refers to the ground motion intensity imposed on bridge j.

Risk minimization or utility maximization objectives include minimizing the travel time (t_{qw}) and maximizing the probability of receiving health services, i.e., Sh^w at vicinity w, which follows as

$$U_{qw} = R_{L_{qw}} Sh^w \frac{1}{t_{qw}} \text{ given } t_{qw} > 0 \tag{7}$$

2. CASE STUDY

This study showcases the systemic reliability problem and the suggested solution of integrating SHM in the transportation network of Kalkanli (Kalo Chorio Kapouti) located in the western part of Northern Cyprus. To model the 20 bridges in the region, a field survey was conducted, which included creating a 3D model of each bridge and collecting vibration measurements via smartphones for model calibration. The transportation network, along with the bridges, hospitals, and neighboring areas, is presented in Figure 1.

2.1. *Regional Seismicity and Bridge-Specific Fragilities with SHM Calibration*

A total of 18 earthquake scenarios in three districts with magnitudes M=5.5, 6.5 and, 8.0 each with two different depths, 10 km and 60 km are used in this study. The intensity measure at each bridge is simulated with ShakeMap (U.S. Geological Survey, 2017). Three ground motion prediction equations (GMPEs) developed by Boore & Atkinson (2008), Campbell & Bozorgnia (2014), and Akkar & Bommer (2010) with weight of 0.4, 0.4 and 0.2, respectively, are used (Cagnan & Tanircan, 2010).

Bridge vibration data is collected via two types of phones (Samsung Galaxy S8 and LG G6) for vibration measurements during field visits with a variety of settings. Five tests addressing the Ath configuration, another one addressing Bth configuration, and a final one on Cth option are developed and applied during each bridge visits as shown in Figure 2.

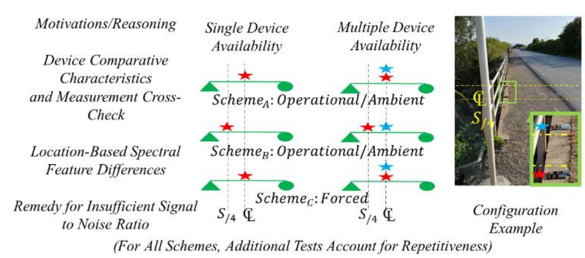

Figure 2. Instrumentation template and demonstration

Prior to the tests, both devices are tested in a laboratory environment, with known input and reference output data through small-scale shake table tests and confirmed their accelerometer fidelity. Figure 3 demonstrates an example of the vibration signal features from a under the first setting.

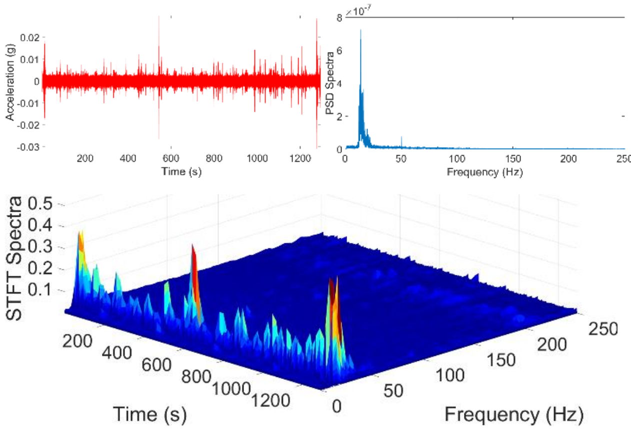

Figure 3. Time and frequency features of vibration signals from Bridge B2 (Test Scheme A, Operator 2).

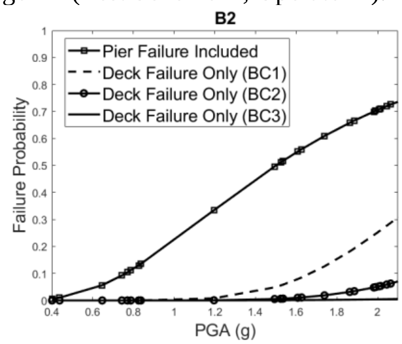

Figure 4. Ductility values for an exemplary bridge and fragility curves under different boundary condition

Most bridge models can be created using beam elements, with only a few exceptions such as arch-type and irregular/skewed bridges requiring alternative modeling approaches. Updated finite element models of the bridges are used in nonlinear time history analyses with a series of ground motions constructed from 50 records of three real earthquakes (M=5.5, 4.0, and 4.5) with epicenters in the Mediterranean Sea. Each bridge model is subjected to 100 ground motions with different boundary conditions, and the parameters of the fragility curves, including mean and standard deviation values, are identified. Ductility values are then converted into fragilities with different failure criteria and boundary conditions, as shown in Figure 4, which presents fragility curves for individual bridges up to a 2g intensity measure.

In this study, eighteen different scenarios are created to investigate the behavior of the transportation network under various circumstances. The seismic demand on each bridge is estimated for each event using the GMPEs and the PGA of the shaking intensity maps. A lognormal probability distribution is then generated for each bridge and scenario, consisting of 10,000 samples, which is later used for a Monte Carlo Simulation to propagate the uncertainty into route selection and produce a discrete probability range for the alternative routes.

Additionally, Google Maps API is used to generate four different travel times for each link, including normal, best guess, optimistic, and pessimistic durations, which introduces another level of uncertainty analysis in travel time estimation. By combining the intensity measures, travel times, and hospital capacities in the network, one can compare alternative routes and identify those with a higher likelihood of successful and timely evacuation to essential medical facilities. The probability of morbidity being less than hospital capacity can be expressed to indicate the probability of receiving service from the hospital in that vicinity, which can then be used to estimate the fatality rates and morbidities.

2.2. *Systemic Reliability for Optimal Post-Event Routes*

To ensure the overall performance of the bridge populations in the study area, a decision tree scheme is utilized, which takes into account travel time, path reliability, and the probability of receiving hospital service as shown in Figure 5. The expected inverse travel time is computed and represented as utilities, which are visualized in Figure 6. Interestingly, the utilities are found to be the same across all earthquake scenarios.

2.3. *Hypothetical Extensions for Optimal Post-Event Routes*

To further investigate the systemic behavior, modifications can be made to the bridge reliability components, hospital capacities, and transportation network. Table 1 presents four hypothetical cases that overwrite the existing optimization scheme to test deviations from the actual behavior. Case 1 refers to the closure of Bridge 1 due to

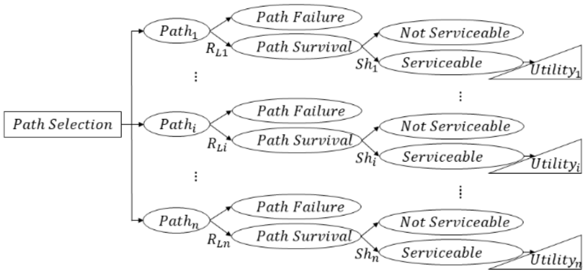

Figure 5. Decision tree identifying optimal path to hospitals in consideration of bridge population behavior.

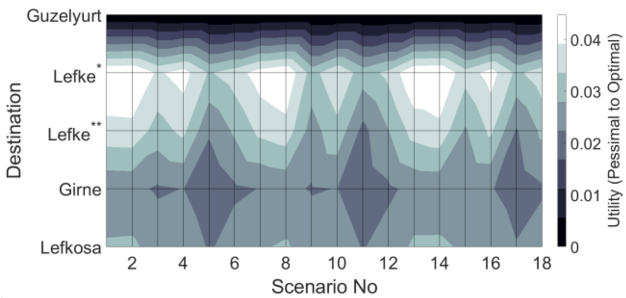

Figure 6. Utility surface identifying optimal routes per scenario (*, ** stands for the two hospitals in the region).

Table 1. Suppositional cases impacting the network and evacuation actions.

Case	Description
1	Temporary functionality loss concerning
2	Hospital capacity reduction in Lefke region
3	Bed extension in Guzelyurt Hospital
4	Bridges retrofitted in the Guzelyurt-Girne line

maintenance works. Case 2 corresponds to the capacity reduction in Lefke region due an ongoing additional demand reducing hospital serviceability by 50%. Case 3 follows a minor investment scenario adding bed capacities to the hospital in Guzelyurt, bringing hospital service probability only to 50%. Case 4 expresses complete capacity maximization of the bridges connecting Kalkanli and Girne due to retrofitting efforts. Figure 7 presents a snapshot of the utilities observed in each hypothetical cases.

3. RESULTS AND DISCUSSION

It is important to highlight that the identified modal frequencies, all above 10 Hz, are exceptionally high compared to typical bridge infrastructure. This is because the entire population of structures

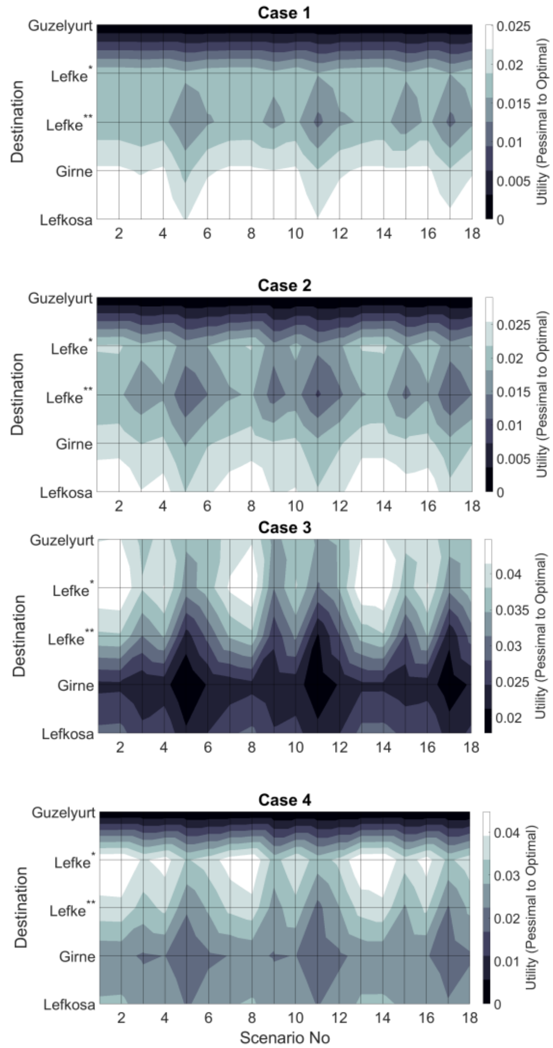

Figure 7. Utility surface identifying optimal routes per scenario under given suppositional cases.

consists of super short-span bridges with a maximum of 10-meter spans. As a result, the bridge reliabilities are very high (medians above 1g excitation) and have a negligible impact compared to other emergency response parameters such as travel time and hospital capacities. Therefore, the Lefke hospitals, with their high bed capacity and relatively close distance to the origin vicinity, dominate the destination selection criteria in all seismicity scenarios.

The impact of bridge population reliability can be further examined by examining the hypothetical cases described in the previous section. For instance, the performance of a critical bridge located at the Guzelyurt/Lefkosa-Lefke intersection can dramatically alter population behavior, as seen in Case 1, while improving the entire bridge series linking Guzelyurt and Girne cannot reverse the optimal decisions (Case 4). Bridge performance alone has a limited effect on emergency services following a disaster, and additional information is required to develop an improved understanding of systemic performance, such as transportation metrics and hospital proximity, to develop an effective post-disaster strategy. Finally, in remote areas, it may be more urgent to invest in minor hospitals to increase mitigation capabilities, and similarly, reducing hospital services can have significant adverse effects on optimal evacuation routes, as seen in Case 2 versus Case 3.

4. CONCLUSIONS

The authors of this study introduce a novel approach to assess the bridge network by using scalable mobile sensing data. The results indicate that if the seismic demand-capacity ratio is low, the bridge conditions have less influence on the transportation network's systemic performance. However, if a single bridge is lost, the impact could be much greater than the loss of multiple bridges, depending on the location's remoteness. The authors note that this study serves as a starting point for future research, which will focus on propagating errors from various sources of uncertainties, such as seismic hazard and environmental frequency variations, requiring long-term monitoring. In the future, automation attempts and multi-algorithmic approaches (Tran et al., 2020, Tran et al., 2021) will be integrated into the procedure for improvements in the identification process, and accordingly, in the fidelity of the decisions. Interested readers can refer to (Ozer et al., 2022) for more in-depth details for the presented work in this paper.

5. REFERENCES

Addabbo, T., Fort, A., Mugnaini, M., Panzardi, E., Pozzebon, A., & Vignoli, V. (2019). A city-scale IoT architecture for monumental structures monitoring. *Measurement*, *131*, 349–357.

Akkar, S., & Bommer, J. J. (2010). Empirical Equations for the Prediction of PGA, PGV, and Spectral Accelerations in Europe, the Mediterranean Region, and the Middle East. *Seismological Research Letters*, *81*(2), 195–206.

Alavi, A. H., & Buttlar, W. G. (2019). An overview of smartphone technology for citizen-centered, real-time and scalable civil infrastructure monitoring. *Future Generation Computer Systems*, *93*, 651–672.

Alexander, D. (1985). Death and injury in earthquakes. *Disasters*, *9*(1), 57–60.

Alipour, M., & Harris, D. K. (2020). A big data analytics strategy for scalable urban infrastructure condition assessment using semi-supervised multi-transform self-training. *Journal of Civil Structural Health Monitoring*, *10*(2), 313–332.

Boore, D. M., & Atkinson, G. M. (2008). Ground-Motion Prediction Equations for the Average Horizontal Component of PGA, PGV, and 5%-Damped PSA at Spectral Periods between 0.01 *s* and 10.0 *s*. *Earthquake Spectra*, *24*(1), 99–138.

Brownjohn, J. M. W. (2007). Structural health monitoring of civil infrastructure. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, *365*(1851), 589–622.

Cagnan, Z., & Tanircan, G. B. (2010). Seismic hazard assessment for Cyprus. *Journal of Seismology*, *14*(2), 225–246.

Campbell, K. W., & Bozorgnia, Y. (2014). NGA-West2 Ground Motion Model for the Average Horizontal Components of PGA, PGV, and 5% Damped Linear Acceleration Response Spectra. *Earthquake Spectra*, *30*(3), 1087–1115.

Chan, T. (2001). Fatigue analysis and life prediction of bridges with structural health monitoring data — Part II: Application. *International Journal of Fatigue*, *23*(1), 55–64.

Farrar, C. R., & Lieven, N. A. J. (2007). Damage prognosis: The future of structural health monitoring. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, *365*(1851), 623–632.

Hughes, A. J., Barthorpe, R. J., Dervilis, N., Farrar, C. R., & Worden, K. (2021). A probabilistic risk-based decision framework for structural health monitoring. *Mechanical Systems and Signal Processing*, *150*, 107339.

Jaiswal, K., Wald, D. J., & Hearne, M. (2009). Estimating Casualties for Large Earthquakes Worldwide

Using an Empirical Approach. In *Estimating Casualties for Large Earthquakes Worldwide Using an Empirical Approach* (USGS Numbered Series No. 2009–1136; Open-File Report, Vols. 2009–1136). U.S. Geological Survey.

Kiremidjian, A., Moore, J., Fan, Y. Y., Yazlali, O., Basoz, N., & Williams, M. (2007). Seismic Risk Assessment of Transportation Network Systems. *Journal of Earthquake Engineering*, *11*(3), 371–382.

Lee, Y.-J., Song, J., Gardoni, P., & Lim, H.-W. (2011). Post-hazard flow capacity of bridge transportation network considering structural deterioration of bridges. *Structure and Infrastructure Engineering*, *7*(7–8), 509–521.

Li, Z. (2001). Fatigue analysis and life prediction of bridges with structural health monitoring data — Part I: Methodology and strategy. *International Journal of Fatigue*, *23*(1), 45–53.

Lynch, J. P. (2007). An overview of wireless structural health monitoring for civil structures. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, *365*(1851), 345–372.

Malekloo, A., Ozer, E., AlHamaydeh, M., & Girolami, M. (2021). Machine learning and structural health monitoring overview with emerging technology and high-dimensional data source highlights. *Structural Health Monitoring*, 147592172110368.

Mei, Q., & Gül, M. (2019). A crowdsourcing-based methodology using smartphones for bridge health monitoring. *Structural Health Monitoring*, *18*(5–6), 1602–1619.

Neves, A. C., Leander, J., González, I., & Karoumi, R. (2019). An approach to decision-making analysis for implementation of structural health monitoring in bridges. *Structural Control and Health Monitoring*, *26*(6), e2352.

Oh, B. K., Kim, M. S., Kim, Y., Cho, T., & Park, H. S. (2015). Model Updating Technique Based on Modal Participation Factors for Beam Structures. *Computer-Aided Civil and Infrastructure Engineering*, *30*(9), 733–747.

Ozer, E. (2016). *Multisensory Smartphone Applications in Vibration-Based Structural Health Monitoring* [Doctoral dissertation, Columbia University]. https://academiccommons.columbia.edu/doi/10.7916/D8TB175F

Ozer, E., Feng, D., & Feng, M. Q. (2017). Hybrid motion sensing and experimental modal analysis using collocated smartphone camera and accelerometers. *Measurement Science and Technology*, *28*(10), 105903.

Ozer, E., & Feng, M. Q. (2019). Structural Reliability Estimation with Participatory Sensing and Mobile Cyber-Physical Structural Health Monitoring Systems. *Applied Sciences*, *9*(14), 2840.

Ozer, E., Malekloo, A., Ramadan, W., Tran, T. T. X., & Di, X. (2022). Systemic reliability of bridge networks with mobile sensing-based model updating for postevent transportation decisions. *Computer-Aided Civil and Infrastructure Engineering*, mice.12892.

Padgett, J. E., & DesRoches, R. (2007). Bridge Functionality Relationships for Improved Seismic Risk Assessment of Transportation Networks. *Earthquake Spectra*, *23*(1), 115–130.

Shiraki, N., Shinozuka, M., Moore, J. E., Chang, S. E., Kameda, H., & Tanaka, S. (2007). System Risk Curves: Probabilistic Performance Scenarios for Highway Networks Subject to Earthquake Damage. *Journal of Infrastructure Systems*, *13*(1), 43–54.

Sony, S., Laventure, S., & Sadhu, A. (2019). A literature review of next-generation smart sensing technology in structural health monitoring. *Structural Control and Health Monitoring*, *26*(3), e2321.

U.S. Geological Survey. (2017). *ShakeMap* [Data set]. U.S. Geological Survey.

Tran, T. T., & Ozer, E. (2020). Automated and model-free bridge damage indicators with simultaneous multiparameter modal anomaly detection. Sensors, 20(17), 4752.

Tran, T. T., & Ozer, E. (2021). Synergistic bridge modal analysis using frequency domain decomposition, observer Kalman filter identification, stochastic subspace identification, system realization using information matrix, and autoregressive exogenous model. Mechanical Systems and Signal Processing, 160, 107818.