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Real-Time Prediction of Storm Surge and Wave Loading on Coastal Bridges

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16. Abstract
Coastal bridges exhibit significant susceptibility to damages caused by storm surges and waves, which requires probabilistic models to quantify the bridge vulnerability for risk assessment and mitigation activities. This study presents an efficient risk analysis framework integrating hazard analysis and fragility analysis for coastal bridges under storm surges and waves. For hazard analysis, the synthetic 10,000-year hurricane records, together with a deep neural network (DNN)-based surrogate model for surge and wave response, are utilized to obtain the statistical characteristics of the surge elevation and wave height at the bridge site. For fragility analysis, a computationally efficient methodology is utilized to obtain the conditional failure (deck unseating) probability for each combination of the two intensity measures (i.e., surge elevation and wave height). To demonstrate the proposed framework, a case study on simply-supported coastal bridges in New York state is conducted for risk assessment of deck unseating subjected to storm surges and waves.

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DESCRIPTION OF THE PROBLEM

Almost 40 percent of the US population, corresponding to 127 million, lives in coastal areas and the trend is increasing (NOAA, 2013). The coastal areas (e.g., US East Coast and Gulf of Mexico) may suffer severely from hurricane-induced losses. For example, Hurricane Sandy, which made landfall on Brigantine in New Jersey in 2012, caused catastrophic damages ($70 billion worth of damage) to the densely developed areas such as New Jersey and New York (Blake et al., 2013). Bridges, which are among the most important components in the transportation network, are vulnerable to high surges and large waves during hurricane events. In addition to substantial direct and indirect economic losses, the nonfunctioning bridges in the transportation system may significantly affect post disaster emergency response and recovery activities for a region (Mosqueda et al., 2007). As a result, it is of great importance to investigate the performance of coastal bridges subjected to hurricane-induced surges and waves. Considering the uncertainties from both hazards and structures, a probabilistic framework is necessary to appropriately quantify the bridge vulnerability for hurricane risk assessment and mitigation activities.

APPROACH

This study presents an efficient risk analysis framework integrating hazard analysis and fragility analysis for coastal bridges under storm surges and waves. Regarding the hazard analysis, the synthetic 10,000-year hurricane records, together with a deep neural network (DNN)-based surrogate model for surge and wave response, are utilized to obtain the statistical characteristics of the surge elevation and wave height at the bridge site. For fragility analysis, a computationally efficient methodology is utilized to obtain the conditional failure (deck unseating) probability for each combination of the two intensity measures (i.e., surge elevation and wave height).

METHODOLOGY

The proposed framework in this study essentially originates from the methodology of performance-based earthquake engineering (PBEE), which could be mathematically formulated as (Moehle and Deierlein, 2004; Yeo, 2005):

$$\lambda(DV) = \int_{DM}\int_{EDP}\int_{IM} G(DV|DM)\mathrm{d}G(DM|EDP)\mathrm{d}G(EDP|IM)|d\lambda(IM)| \tag{1}$$

where λ (*DV*) is the annual exceedance rate of a decision variable *DV* (e.g., financial losses); *DM* represents damage states (e.g., minor, moderate and severe) for the structure under investigation; *EDP* denotes engineering demand parameters (e.g., displacement, drift and acceleration); *IM* is intensity measures of the hazard (e.g., surge elevation and significant wave height); λ (*IM*) is the annual rate of exceedance for a given level *IM* of hazard events; $G(\cdot|\cdot)$ is a complementary cumulative distribution function and $\mathrm{d}G(\cdot|\cdot)$ is its derivative. The PBEE framework is composed of four modules. The hazard analysis module targets on estimating the occurrence frequency of hazards at the structural site, which is usually in the form of annual rate of exceedance for hazard *IM*s. The structural analysis module is used to generate the probabilistic description of structural response in terms of *EDP* conditional upon different *IM*s. In the damage analysis, *DM*s are described as a function of *EDP* through a probabilistic comparison of capacities and demands. It is noted that structural analysis module and damage analysis module are often combined as the fragility analysis module to generate the fragility curves (or surfaces), which directly express the probability of *DM*s conditioned on *IM*s. As the final step, decision analysis could be conducted to calculate, for example, the financial losses due to the hazards and further propose retrofitting/repair strategies.

It is noted that hazard analysis for coastal bridges involves accurate modelling of the complex air-sea system for hurricane-induced surges and waves through high-fidelity numerical modes. With emerging publicly available dataset generated by high-fidelity simulations, attempts have been made to construct surrogate models for rapidly predicting wave and surge response under hurricanes (e.g., Jia and Taflanidis, 2013; Taflanidis et al., 2013; Kim et al., 2015; Jia et al., 2016; Zhang et al., 2018). Considering the rapid development in deep learning (LeCun et al., 2015), it is promising to use DNN for reduced-order modelling of the complex air-sea system dynamics due to its high function approximation ability, which will be adopted in this study. With the DNN-based surrogate model together with the generated long-term hurricane records, statistical analysis for storm surges and waves could be conveniently conducted. Following hazard analysis, fragility analysis using simplified hydrodynamics model and static structural analysis is further conducted to finally obtain the damage rate of the bridge. The proposed framework for risk analysis of coastal bridges subjected to hurricane-induced surges and waves is shown in Fig 1. It is noted that, although not included in the present study for the sake of brevity, the proposed framework could be further extended to include decision analysis such as determination of financial losses and optimization of retrofitting/repair strategies (e.g., Mondoro et al., 2017).

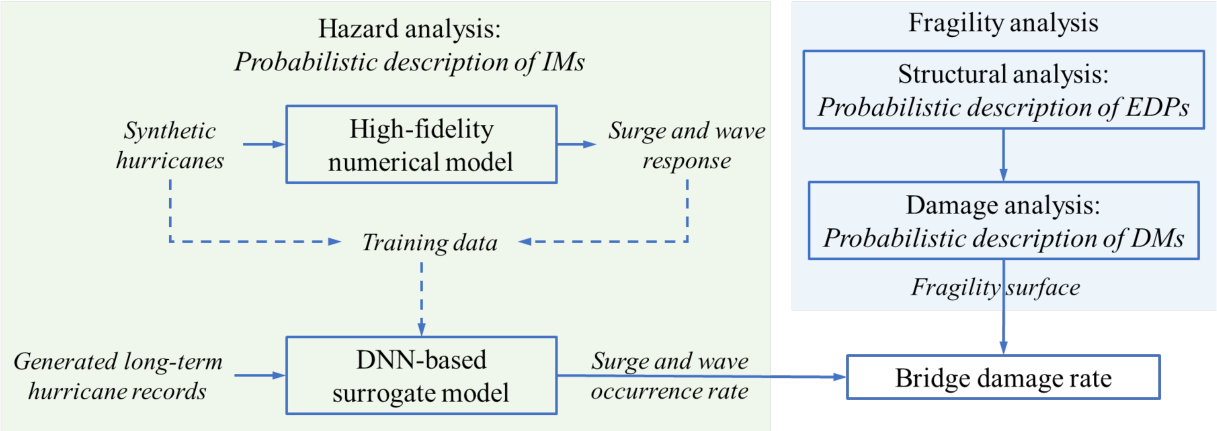


Figure 1. Proposed framework for damage analysis of coastal bridges under storm surges and waves

To construct the DNN-based surrogate model for surge and wave prediction, this study takes advantage of the database of North Atlantic Coast Comprehensive Study (NACCS) (Nadal-Caraballo et al., 2015; Cialone et al, 2015) built for identifying flood risk and mitigation strategies for North Atlantic Coast. A total of 1050 synthetic hurricanes are used as the input to a high-fidelity coastal modelling system for the computation of the storm surge and wave response. The coastal storm modelling system, as shown in Fig. 2, is composed of four coupled models. Specifically, planet boundary layer (PBL) model is used to calculate the wind velocity and pressure fields as the driving input to the subsequent hydrodynamic modelling (Oceanweather, Inc., 2014); the Wave Model (WAM) is used to generate the offshore deep-water wave estimation (Komen et al., 1994) while steady state spectral wave (STWAVE) is applied for the nearshore shallow-water wave modelling (Massey et al., 2011). For surge modelling, advanced circulation (ADCIRC) model is utilized to predict the water level elevation (ADCIRC, 2014). These modules are tightly coupled to accurately model the complex air-sea system dynamics. For example, the wave characteristics in deep water output by the WAM is used as the boundary condition for the show water wave modelling using STWAVE; ADCIRC and STWAVE are coupled through the interdependence on water level and wave forces. The high computational cost of the modelling system limits its application in real-time surge/wave prediction and statistical analysis that involves a large amount of hurricane inputs.

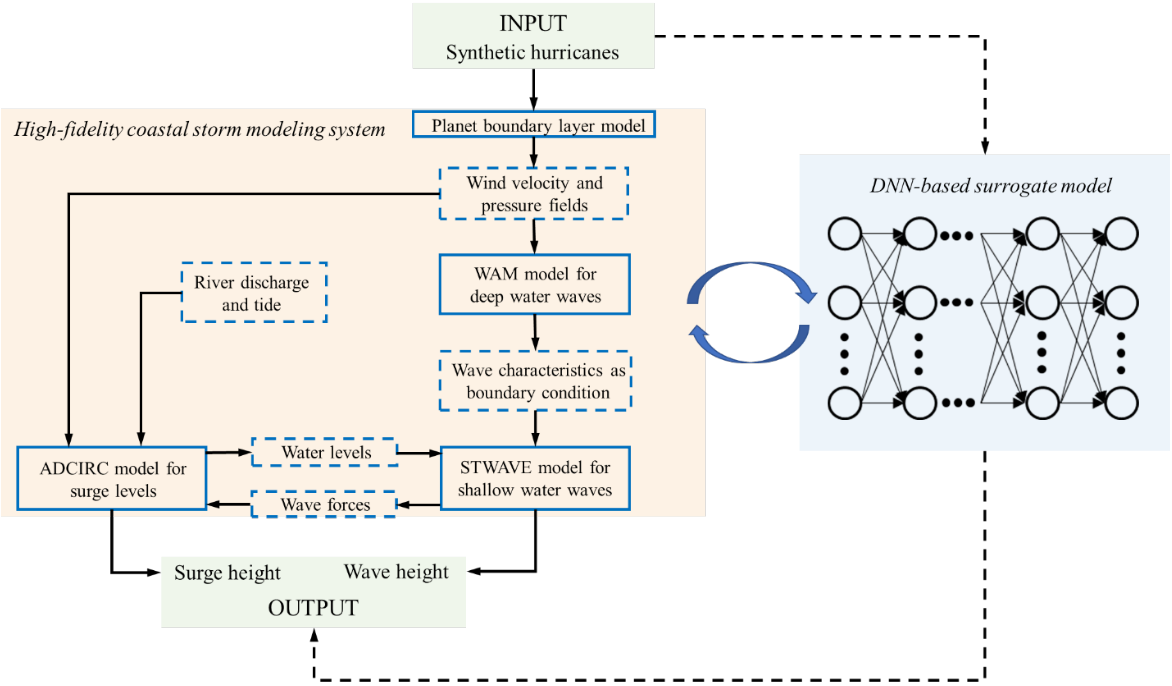


Figure 2. DNN-based surrogate model for the high-fidelity coastal storm modelling system used in NACCS

To establish the DNN-based surrogate model for efficient prediction of hurricane-induced surges and waves, the appropriate parameterization of hurricanes is required to provide the model inputs. Considering the hurricane intensity/size changes along the hurricane tracks, the surge elevation η_s and significant wave height H_s of a particular location at time *t* should be dependent on hurricane features (e.g., storm location, intensity and size) of both current time step and previous histories. Accordingly, η_s and H_s could be expressed as:

$$[\eta_s(t), H_s(t)] = F[x_{lat}(t), x_{lon}(t), \theta(t), V_f(t), \Delta p(t), R_m(t), x_{lat}(t-\Delta t), x_{lon}(t-\Delta t), \theta(t-\Delta t), V_f(t-\Delta t), \Delta p(t-\Delta t), R_m(t-\Delta t), \ldots, x_{lat}(t-n\Delta t), x_{lon}(t-n\Delta t), \theta(t-n\Delta t), V_f(t-n\Delta t), \Delta p(t-n\Delta t), R_m(t-n\Delta t)] \tag{2}$$

where x_{lat} and x_{lon} is the latitude and longitude of the hurricane center; θ and V_f represent the heading direction and translational speed, respectively; central pressure deficit Δp determines the intensity while the radius to maximum wind speed R_m characterizes the hurricane size; Δt is the time step size; *n* determines the length of time dependence; the general nonlinear function *F* captures the complex dynamics of the air-sea system during a hurricane event. Constructing an accurate surrogate model for surge and wave prediction requires datapoints to span the input parameter space, which results in an extremely large amount of data and is not available for existing databases. Specifically, NACCS assumes constant intensity/size of hurricanes before the landfall and the hurricane tracks are generated from a single genesis point with an idealized tracking pattern. Following this approach, the storm parameters at current time step could fully distinguish storms from one another in the NACCS database of idealized hurricanes. Hence, the DNN-based surrogate model (denoted by π_{DNN}) using NACCS database could be simplified as:

$$[\eta_s(t), H_s(t)] = \pi_{DNN}[x_{lat}(t), x_{lon}(t), \theta(t), V_f(t), \Delta p(t), R_m(t)] \tag{3}$$

The above formulation actually simplifies the system with "memory" into a "quasi-steady" system, which is acceptable for hurricanes with slow intensity/size changes. However, this assumption needs to be further validated for general hurricane events in future work. With the surrogate model available, long-term synthetic storms generated with the procedure in Snaiki and Wu (2020a and

2020b) are utilized as input to the DNN-based surrogate model to calculate the surge and wave response for statistical analysis. Based on the statistics of historical hurricane data [e.g., Hurricane Database version-2 (HURDAT2)], the hurricane generation procedure in Snaiki and Wu (2020a and 2020b) involves genesis model, track model and intensity model to obtain the 10,000-year realistic hurricanes affecting US East Coast. It is worthwhile to point out that utilizing the surrogate model trained by idealized hurricanes in NACCS to predict surge and wave response induced by realistic hurricanes may introduce inaccuracies considering that the effect of intensity/size variation along the realistic hurricane tracks is not included in the current database. This issue could be addressed in future work by constructing new databases or enriching existing databases using sampled realistic hurricanes to enhance surrogate modelling (Zhang et al., 2018), which, however, is outside the scope of current study.

Based on the hazard analysis of the bridge site, the structural fragility analysis can be conducted to investigate the bridge damages caused by the hazards. In this study, vulnerability of a typical coastal bridge under storm surges and waves is investigated following a similar approach as in Ataei and Padgett (2013). Bridge deck unseating, among other failure modes, is chosen as the damage indicator considering its prevalence in coastal bridges of United States during hurricanes (FHWA, 2010). Specifically, deck unseating is considered to occur when the structural demand (the surge and wave-induced vertical load on the bridge deck) is larger than the structural capacity (i.e., vertical resistance due the dead weight and strength of connections if used). By comparing with results from dynamic analysis, this efficient static approach showed good accuracy for the fragility analysis of coastal bridges with weak connection between sub and superstructure (Ataei and Padgett, 2011). The schematic of the fragility analysis is shown in Fig. 3, which is discussed in detail in the following.

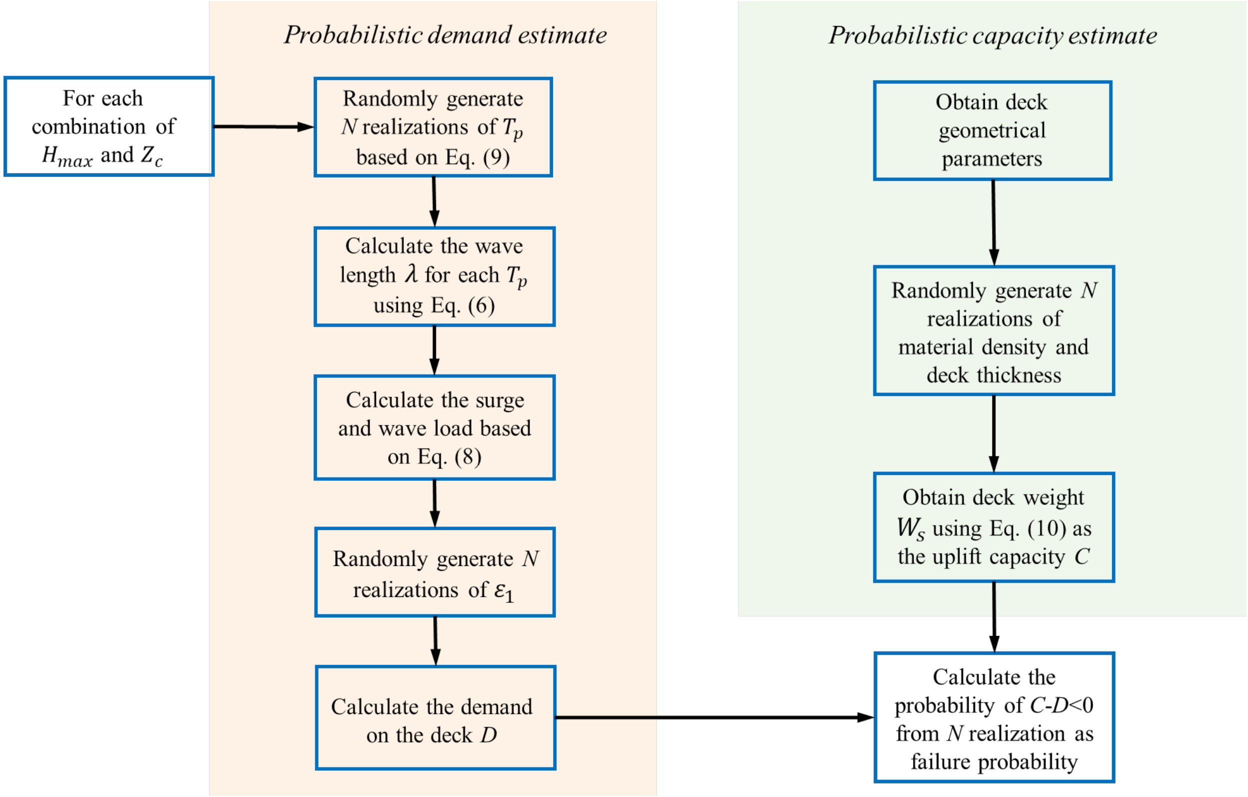


Figure 3. Schematic of the bridge fragility analysis

The vertical load on the bridge deck could be decomposed into quasi-static force and impulse-like force. The maximum of quasi-static force is composed of drag force, inertia force and buoyant force, which is given by (AASHTO, 2008):

$$F_{V,\max} = \gamma_w \bar{W} \beta \left(-1.3\frac{H_{\max}}{d_s} + 1.8\right) \times \left[1.35 + 0.35\tanh\left(1.2T_p - 8.5\right)\right]\left(b_0 + b_1 x + \frac{b_2}{y} + b_3 x^2 + \frac{b_4}{y} + \frac{b_5 x}{y} + b_6 x^3\right) \times (\mathrm{TAF}) \tag{4}$$

where γ_w is the unit weight of water; $H_{\max}$ denotes the maximum wave height, which could be related to the significant wave height H_s by $H_{\max} = 1.8H_s$; T_p is the wave period; d_s represents the total water depth during the storm surge; the coefficient β is used to consider the relative position of the wave crest with respect to bridge deck; the parameters b_0 to b_6 depends on the geometry of the bridge deck; TAF is a factor that is used to adjust the quasi-static force considering that effect of the entrapped air on the vertical force. The definitions of $\bar{W}$, *x* and *y* are given by (AASHTO, 2008):

$$\bar{W} = \begin{cases} \lambda - \frac{\lambda}{H_{\max}}\left(Z_c + \frac{H_{\max}}{2}\right) \text{ if } \bar{W} \geq 1.5W \\ 1.5W \text{ if } \overline{W} < 1.5W \end{cases} \tag{5}$$

where Z_c is the relative surge elevation with respect to the bridge deck (positive when water level is below the deck bottom); *W* is bridge width; $x = \frac{H_{\max}}{\lambda}$ and $y = \frac{\bar{W}}{\lambda}$; λ is the wave length, which is usually calculated based on the wave period using the following equation:

$$\lambda = \frac{gT_p^2}{2\pi}\sqrt{\tanh\left(\frac{4\pi^2 d_s}{T_p^2 g}\right)} \tag{6}$$

where g is gravitational acceleration. In addition to the quasi-static load, the impulse-type load on the deck per unit length is computed by (AASHTO, 2008):

$$F_s = A\gamma_w H_{\max}^2 \left(\frac{H_{\max}}{\lambda}\right)^B \tag{7}$$

where *A* and *B* accounts for the relative position of the wave crest with respect to the deck. The total maximum uplift force F_{vt}, considering the underlying uncertainty, could be calculated by (Ataei and Padgett, 2013):

$$F_{vt} = \left(F_{V,\max} + F_s + \Delta_b\right)\varepsilon_1 \tag{8}$$

where Δ_b is introduced to account for the bias in the estimation of wave load; ε_1 is a random variable with lognormal distribution introduced to capture the model error. The Δ_b and ε_1 are obtained by comparing with experimental results, which is given by Ataei and Padgett (2013). Wave period T_p and maximum wave height $H_{\max}$ are related based on the joint probability distribution (Longuet-Higgins, 1983):

$$f(\xi,\eta) = L(\xi/\eta)^2 \exp\{-\frac{\xi^2}{2}[1 + \left(1 - \frac{1}{\eta}\right)^2 \frac{1}{v^2}]\} \tag{9}$$

where ξ and η are the nondimensional wave height and wave period defined as $\xi = H_{max}/\sqrt{m_0}$ and $\eta = T_p/\bar{T}$; $L = [1 + (v^2/4)](1/\sqrt{2\pi v})$; m_0 is the first spectral moment, i.e., the area under the wave spectrum, which is computed by $m_0 = (\frac{H_s}{4})^2$. The value $v = 0.3$ is the bandwidth of the wave spectral density; $\bar{T}$ is the mean wave period usually chosen as 6.125s (Ataei and Padgett, 2013).

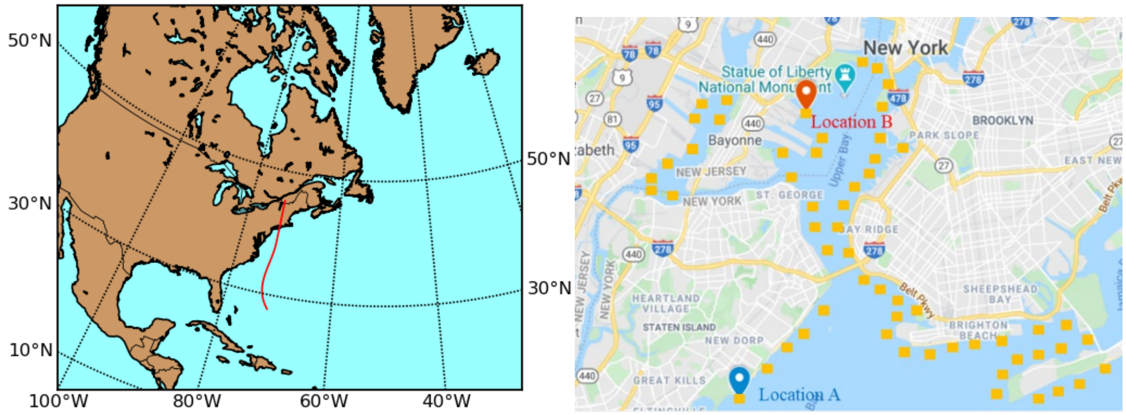
For conservative estimates, the vertical resistance of the bridge comes only from dead weight of the deck while the connection between superstructure and substructure is not considered. The weight of the deck per unit length W_s is calculated based on:

$$W_s = \left(d_b W + A_g \times n_g\right)\gamma \tag{10}$$

where d_b represents the deck thickness; A_g is the area of girder cross-section; n_g is the number of girders; γ denotes the unit weight of the materials. Uncertainties from materials and workmanship could be considered, e.g., using the recommended distributions given by Ataei and Padgett (2013).

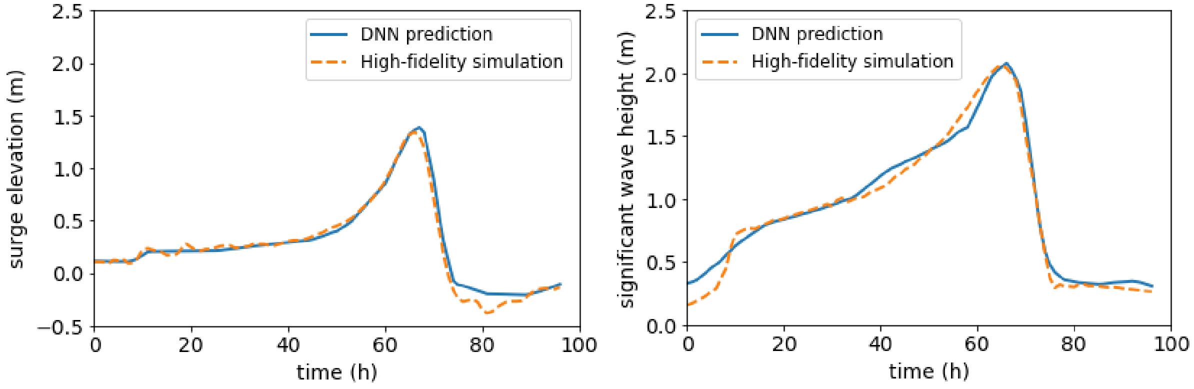
FINDINGS

To demonstrate the proposed framework, a case study on simply-supported coastal bridges in New York state is conducted for risk assessment of deck unseating caused by storm surge and wave events. After a quality check, a total of 1031 synthetic hurricanes and the associated surge/wave responses are used as the dataset for training the DNN-based surrogate model, where the datapoints during a hurricane event are given at 1-hour interval. The training, validation and testing dataset are 70%, 15% and 15% respectively of the whole dataset. A fully connected feedforward neural network is constructed for surge and wave prediction. Specifically, there are three hidden layers with 30, 60 and 30 neurons for each layer while the activation function is chosen as the rectified linear unit (RELU). The learning algorithm is chosen to be ADAM with the batch size of 2000. The learning rate is 0.0001. Among the approximate 2,000 coastal save points near New York City given by NACCS, two locations are chosen to consider different hazard characteristics. Specifically, location A is near the coastline while location B is in the Hudson river. For the landfall hurricane indicated in Fig. 4(a) and the two locations presented in Fig. 4(b), the trained DNN could capture the surge and wave responses with high accuracy, as shown in Figs. 4(e)-(f). The root mean square testing error is less than 0.05 for surge and wave of both locations. It is noted that under same hurricane event, the surge elevation at location A is slightly larger than that at location B while the significant wave height shows much larger response at location A, which may be due to the dissipation effect of the wave propagation from sea to rivers.



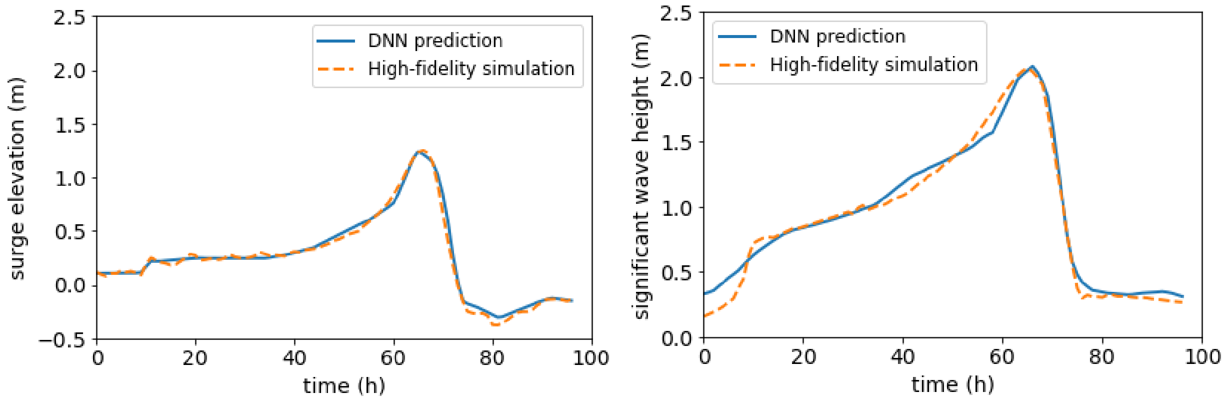
(a) A typical landfall hurricane track

(b) Selected two locations near New York City



(c) Surge prediction at location A

(d) Wave prediction at location A



(e) Surge prediction at location B (f) Wave prediction at location B

Figure 4. Results of surge and wave prediction using DNN-based surrogate model

The design of a typical simple-supported coastal bridge is used for the fragility analysis. The deck width W is sampled from a normal distribution with mean of 8m and standard deviation of 0.5m. The deck thickness d_b is chosen to be normal distribution with mean of 0.25m and standard deviation of 0.01m. The area of a girder A_g is chosen to be 0.025m^2 with uniform distribution bounded by 5%. The girder number n_g is 6. The concrete density γ of the deck is chosen to be normal distribution with mean of 24 kN/m^3 and standard deviation of 1 kN/m^3. A total of 5000 Monte Carlo simulations are conducted to generate the probability of failure for each combination of the two intensity measures. The fragility surface for the coastal bridge is shown in Fig. 5, where there is a sharp increase of failure probability when the surge/wave level is larger than a threshold.

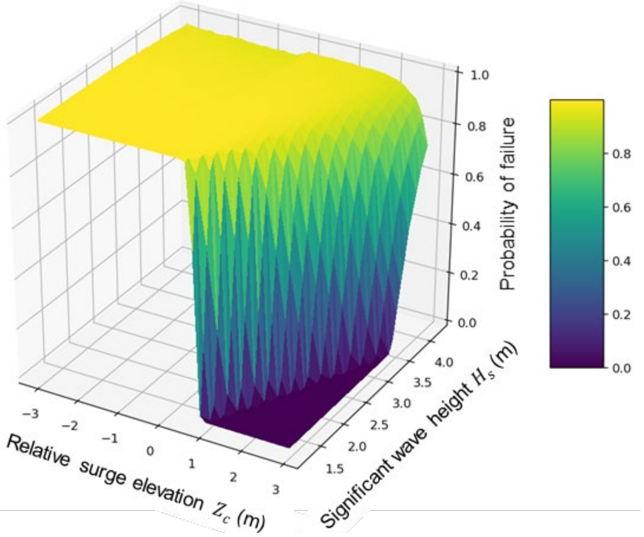
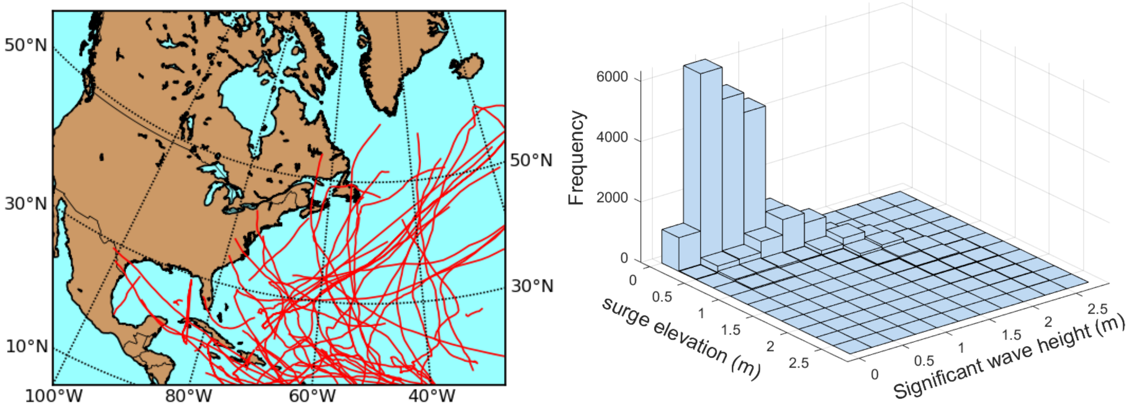
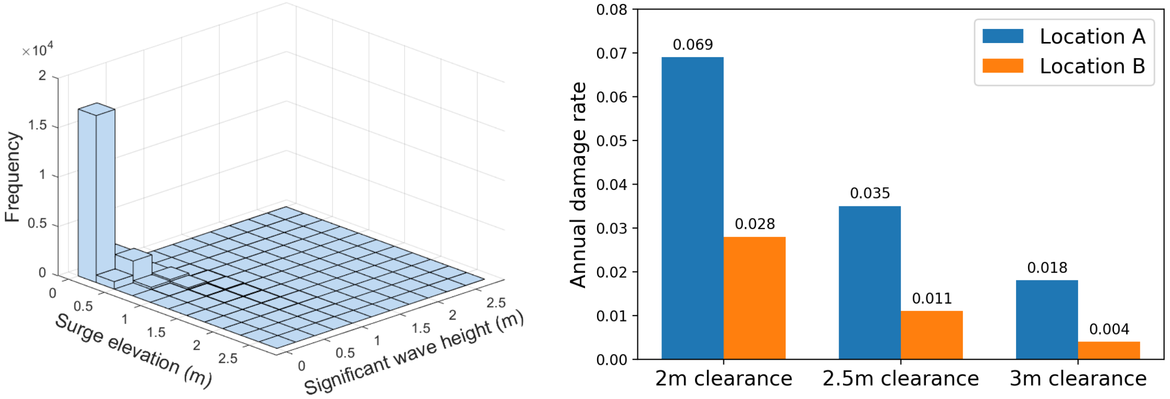


Figure 5. Fragility surface of a typical coastal bridge under storm surges and waves

With the results from hazard analysis available, real-time risk quantifications of coastal bridges could be conducted during a hurricane using DNN-based model with real-time hurricane forecasting as input. In addition, risk analysis could be performed with synthetic long-term hurricane records. Following the procedure given by Snaiki and Wu (2020a and 2020b), 10,000-year hurricane records, with 23,197 hurricanes in total, are generated for the US East Coast. The selected simulations are presented in Fig. 6(a). With the synthetic hurricanes as inputs to the trained DNN-based surrogate model, the 10,000-year surge and wave response could be calculated. The joint surge/wave histogram are shown in Fig. 6(b) and 6 (c) for location A and B respectively. It is clear that location A has a larger surge/wave response compared to that of location B. The statistical information of the surge/wave response could be straightforwardly utilized, together with the fragility surfaces, to obtain the annual damage rate of coastal bridges. Three different clearances of coastal bridges (the distance between deck bottom to the mean water level) are considered in the risk analysis and the result is shown in Fig. 6(d). It is clear that the annual damage rate decreases as the clearance increases, and the bridge at location A is more vulnerable to storm surges and waves than that at location B due to the larger surge/wave level under hurricanes.



(a) Synthetic hurricanes (50 realizations) (b) Histogram of surge and wave at location A



(c) Histogram of surge and wave at location B (d)Annual damage rate of bridges at location A and B

Figure 6. Results for risk analysis of coastal bridges

CONCLUSIONS

This study presented an efficient risk analysis framework for coastal bridges under storm surges and waves, which integrated hazard analysis and fragility analysis. For hazard analysis, the synthetic 10,000-year hurricane records, together with a deep neural network (DNN)-based surrogate model for surge and wave response, were utilized to obtain the statistical characteristics of the surge elevation and significant wave height at the bridge site. For fragility analysis, a computationally efficient methodology was utilized to obtain the conditional failure (deck unseating) probability for each combination of the two intensity measures (i.e., surge elevation and wave height). A case study on simply-supported coastal bridges with different clearance heights in New York state was conducted to demonstrate the simulation accuracy and efficiency of the proposed framework for risk assessment of deck unseating subjected to storm surges and waves. It was shown that the annual damage rate decreases as the clearance increases. In addition, the bridge at location near the coastline is more vulnerable to storm surges and waves than that at the location in the Hudson river.

RECOMMENDATIONS

The high risk of coastal bridges under storm surges and waves makes it necessary to investigate effective retrofitting methods before hurricanes as well as decision-making strategies (e.g., bridge closure) during hurricanes.

REFERENCES

AASHTO, 2008. Guide specifications for bridges vulnerable to coastal storms, AASHTO, Washington, DC.

ADCIRC, 2014. User's manual. http://adcirc.org.

Ataei, N. and Padgett, J.E., 2011. Coastal bridge reliability during hurricane events: Comparison of fragility curves by static and dynamic simulation. In *Structures Congress 2011*, Las Vegas, USA.

Ataei, N. and Padgett, J.E., 2013. Probabilistic modelling of bridge deck unseating during hurricane events. *Journal of Bridge Engineering*, 18(4), 275-286.

Blake, E.S., Kimberlain, T.B., Berg, R.J., Cangialosi, J.P., and Beven II, J.L., 2013. Tropical Cyclone Report-Hurricane Sandy (AL182012) 22 – 29 October 2012, National Hurricane Center.

Cialone, M.A., Massey, T.C., Anderson, M.E., Grzegorzewski, A.S., Jensen, R.E., Cialone, A., Mark, D.J., Pevey, K.C., Gunkel, B.L. and McAlpin, T.O., 2015. North Atlantic Coast Comprehensive Study (NACCS) coastal storm model simulations: Waves and water levels, US Army Engineer Research and Development Center, ERDC/CHL-TR-15-14.

FHWA (Federal Highway Administration), 2010. Highway Statistics 2010, https://www.fhwa.dot.gov/policyinformation/statistics/2010/

Jia, G. and Taflanidis, A.A., 2013. Kriging metamodelling for approximation of high-dimensional wave and surge responses in real-time storm/hurricane risk assessment. *Computer Methods in Applied Mechanics and Engineering*, 261, 24-38.

Jia, G., Taflanidis, A.A., Nadal-Caraballo, N.C., Melby, J.A., Kennedy, A.B. and Smith, J.M., 2016. Surrogate modelling for peak or time-dependent storm surge prediction over an extended coastal region using an existing database of synthetic storms. *Natural Hazards*, 81(2), 909-938.

Kim, S.W., Melby, J.A., Nadal-Caraballo, N.C. and Ratcliff, J., 2015. A time-dependent surrogate model for storm surge prediction based on an artificial neural network using high-fidelity synthetic hurricane modelling. *Natural Hazards*, 76(1), 565-585.

Komen, G. J., L. Cavaleri, M. Donelan, K. Hasselmann, S. Hasselmann, and Janssen P. A. E. M., 1994. *Dynamics and modelling of ocean waves*. United Kingdom, Cambridge University Press.

LeCun, Y., Bengio, Y. and Hinton, G., 2015. Deep learning. *Nature*, 521(7553), 436-444.

Longuet-Higgins, M.S., 1983. On the joint distribution of wave periods and amplitudes in a random wave field. *Proceedings of the Royal Society of London. A. Mathematical and Physical Sciences*, 389(1797), 241-258.

Massey, T. C., M. E. Anderson, J. M. Smith, J. Gomez, and R. Jones. 2011. STWAVE: Steady-state spectral wave model user's manual for STWAVE, version 6.0. ERDC/CHL SR-11-1, U.S. Army Engineer Research and Development Center.

Moehle, J. and Deierlein, G.G., 2004, A framework methodology for performance-based earthquake engineering. In *13th world conference on earthquake engineering*, Vancouver, Canada.

Mondoro, A., Frangopol, D.M. and Soliman, M., 2017. Optimal risk-based management of coastal bridges vulnerable to hurricanes. Journal of Infrastructure Systems, 23(3), 04016046.

Mosqueda, G., Porter, K. A., O'Connor, J., and McAnany, P., 2007. Damage to engineered buildings and bridges in the wake of Hurricane Katrina. *Structures Congress 2007: New Horizons and Better Practices*, Reston, Virginia.

Nadal-Caraballo, N.C., Melby, J.A., Gonzalez, V.M. and Cox, A.T., 2015. North Atlantic Coast Comprehensive Study–Coastal Storm Hazards from Virginia to Maine. US Army Engineer Research and Development Center, ERDC/CHL TR-15-5.

NOAA, 2013, National Coastal Population Report: population trends from 1970 to 2020. https://aamboceanservice.blob.core.windows.net/oceanservice-prod/facts/coastal-population-report.pdf

Oceanweather, Inc., 2014. Development of wind and pressure forcing for the North Atlantic Coast comprehensive study (NACCS). Submitted to U.S. Army Engineer Research and Development Center.

Snaiki, R. and Wu, T., 2020a. Revisiting hurricane track model for wind risk assessment. *Structural Safety*, 87, 102003.

Snaiki, R. and Wu, T., 2020b. Hurricane Hazard Assessment Along the United States Northeastern Coast: Surface Wind and Rain Fields Under Changing Climate. *Front. Built Environ*. 6:573054.

Taflanidis, A.A., Kennedy, A.B., Westerink, J.J., Smith, J., Cheung, K.F., Hope, M. and Tanaka, S., 2013. Rapid assessment of wave and surge risk during landfalling hurricanes: probabilistic approach. *Journal of waterway, port, coastal, and ocean engineering*, 139(3), 171-182.

Yeo, G.L., 2005. Stochastic characterization and decision bases under time-dependent aftershock risk in performance-based earthquake engineering, Doctoral dissertation, Stanford University.

Zhang, J., Taflanidis, A.A., Nadal-Caraballo, N.C., Melby, J.A. and Diop, F., 2018. Advances in surrogate modelling for storm surge prediction: storm selection and addressing characteristics related to climate change. *Natural Hazards*, 94(3), 1225-1253.