ESTIMATING STRUCTURAL RELIABILITY UNDER HURRICANE WIND HAZARD: APPLICATIONS TO WOOD STRUCTURES

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Abstract

A stochastic nonparametric framework to estimate structural reliability under hurricane wind hazard is proposed. Scenarios of maximum sustained wind speeds are simulated using nonparametric density estimators based on the historical wind speed data. Nonparametric methods are data driven and need no prior assumption as to the form of the underlying probability density function. They are "local" methods in that estimates at any desired point is based on a small number of data points and thus have the ability to capture any arbitrary (skewed, bimodal, etc.) underlying density function. The generated wind scenarios are convoluted with fragility curves for the different types of wood structures to obtain the failure probability and consequently, the reliability. This is annually performed for the assumed life of the structure, thus, providing time varying estimates of structural reliability. It was found that the sustained wind speeds are related to a large-scale climate phenomenon in the tropical Pacific Ocean, El Nino Southern Oscillation (ENSO). Therefore, the wind scenarios had to be simulated conditioned on this large-scale climate phenomenon. The utility of the proposed framework in estimating the structural reliability of different wood structures over the coastal region of North Carolina is demonstrated. Significant differences in structural reliability relative to the state of the large-scale climate phenomenon ENSO were observed. This underscores the need for interdisciplinary approach to structural reliability estimation.

Introduction and Background

Natural hazards in general and hurricanes in particular, lead to loss of life and tremendous property damage and indirect economic loss for the United States annually (Mileti, 1999). Over the years several climate researchers have identified large-scale climatic factors, such as the El Nino Southern Oscillation (ENSO) phenomenon in the tropical Pacific Ocean and the Atlantic Sea Surface Temperatures (SSTs), rainfall over Africa's Sahel region that appear to affect the year-to-year variability in the hurricane activity (e.g., Gray, 1984, 1990; Shapiro and Goldenberg, 1998; Bove et al., 1998). The preceding winter state of the North Atlantic atmosphere has also been shown to impact the occurrence and steering of hurricanes in the following summer (e.g., Elsner and Kocher, 2000). Mechanistically, all these climatic phenomena are believed to regulate tropical storm formation via their effects upon upper tropospheric wind shear (Landsea, 1998). Events that increase shear lead to a weaker hurricane season (i.e., fewer hurricanes) while events that lower wind shear make for an active hurricane season. Consequently, the infrastructure risk too would be modulated from year-to-year by these large-scale climate phenomena. Therefore, for realistic simulation of hurricane tracks and consequently, the risk estimates, these climate features have to be appropriately included (or conditioned upon) in generating wind scenarios.

Infrastructure risk and damage prediction due to winds is an active area of research, with implications to emergency planners and insurers that focus on assessing the vulnerability of structures and probabilistic models for hurricane damage prediction (Leicester 1981; Sparks et al., 1994; Holmes, 1996; Huang et al., 2001; Stewart et al., 2003; Cope et al., 2003; Li and Ellingwood, 2003). However, these models suffer from the following drawbacks: (i) Often, structural reliability is estimated in isolation of realistic likelihood estimates of hurricane frequencies and magnitudes, (ii) Knowledge of year-to-year variability in occurrence and steering of hurricanes in the Atlantic basin (described earlier in this section) is not incorporated in structural reliability estimation. In particular, this information can be very useful in probabilistic forecast of storm tracks and magnitudes in any given year, (iii) the estimation of losses is purely empirical, based on the wind speed and no consideration of structural information. For example, a new structure and a 25 year old structure are assumed to have the same probability of failure for a given wind speed. The life-cycle cost of structures is also not considered. These can lead to substantial misrepresentation of losses and consequently far from optimal decision making.

Clearly, to address these deficiencies an integrated interdisciplinary framework is required. Such a "holistic" approach is recognized and recommended by professional agencies like ASCE (IBHS, 2001) and also by the U.S. House of Representatives in their bill H.R. 2020 also known as the *"Hurricane, Tornado and Related Hazards Research Act"*. In this paper we present our initial efforts at developing an integrated framework that combines the large-scale climate information, to better capture the hurricane risk, with a structural failure model. We demonstrate the utility of this framework by applying it to single-storied wooden structures in coastal region of North Carolina. The proposed framework and the steps for implementation are first presented, followed by a brief description of the data sets used. Results from applications to coastal region in North Carolina conclude the paper.

Proposed Approach

The proposed framework is outlined in the flowchart below (Figure 1).

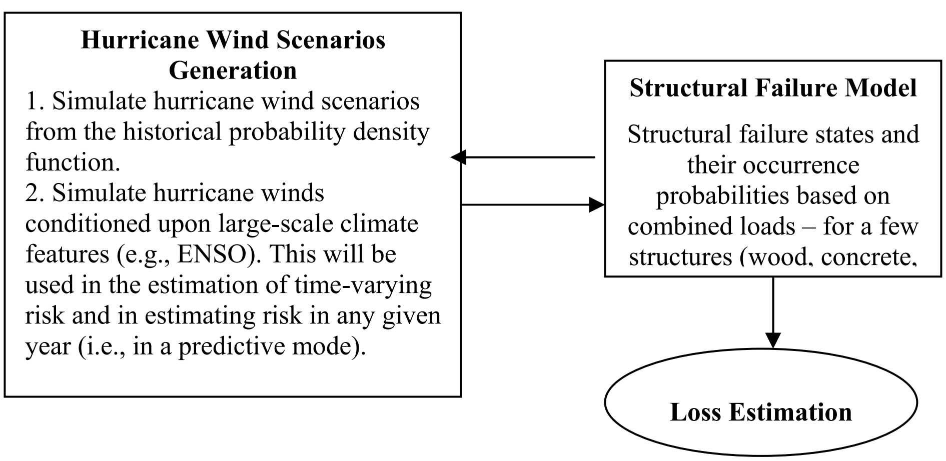

Figure 1: Flowchart of the proposed framework

The key elements are generating scenarios of winds from probability density functions (PDFs) of the historical data estimated by nonparametric techniques (Rajagopalan and Lall, 1999; Bowman and Azzalini, 1997; Loader, 1999). The scenarios are generated conditioned upon the state of the large-scale climate (in this case the state of ENSO). The simulations are then used in conjunction with fragility curves to estimate the infrastructure reliability estimates. Based on the structural failure model it was found that characteristics of hurricanes such as the three-second gust are important (as will be shown later) in the scenario generation, hence, the two-way arrow. Presumably further studies will indicate other characteristics, such as frequency regions with strong power spectral density function content, that are important for such wind-sensitive structures as tall buildings and towers. The implementation algorithm is described later in this section.

Data Sets Used

The annual maximum wind speed within 2.5o latitude by 2.5 ^{o} longitude grid box was obtained. This grid encompasses the North Carolina sea coast, from the Atlantic hurricane track data available from NOAA (http://www.nhc.noaa.gov) for the 1886-present period. The widely used Tropical Pacific ocean sea surface temperature based index of ENSO phenomena, called the NINO3 index (Diaz and Markgraf, 2000) was obtained from the data library at (http://iri.ldeo.columbia.edu). Typically, values of the index greater than 0.5 imply El Nino conditions that tend to inhibit the formation and sustenance of hurricanes, while the values less than -0.5 indicate La Nina conditions (e.g., Gray, 1990). ENSO has profound impacts on the world's climate and weather including the hurricane activity in the Atlantic, and is actively studied (Diaz and Markgraf, 2000).

Algorithm for Implementation

Single story light-frame structures without overhangs and a design life time of 25 years were assumed. The aim was to investigate the impact of large-scale state variables on structural risk estimates. The following steps were performed to obtain the time-varying structural reliability estimates:
(i) Assume the 25-year life time to be El Nino active.
(ii) Bootstrap a NINO3 index from the historical values greater than 0.5 (to simulate El Nino state), say, x_i
(iii) Generate maximum wind speed from the conditional PDF, $f(MAX\ Wind\ speed \mid x_i)$. This involves finding the K-nearest neighbors (K-NN) of x_i from the historical record (i.e. K years from the past that are similar to the current index value x_i). One of the K-NN is bootstrapped via a weight function that gives high probability to the nearest neighbor (i.e. year) of x_i and low to the farthest. The corresponding maximum wind speed of the bootstrapped neighbor forms the simulated value. Instead of re-sampling the neighbors, polynomials can be fit to the K-NN that can then be used to estimate the wind speed corresponding to x_i. Nonparametric estimators are data-driven, flexible and have the capability to capture any arbitrary characteristics (e.g., nonlinear, bimodal distribution) exhibited by the data. Nonparametric estimators have been applied successfully in a variety of hydroclimate and other applications involving simulating from multivariate PDFs, spatial interpolation and extreme value analysis (e.g., Lall, 1995; Rajagopalan and Lall, 1999; Bowman and Azzalini, 1997, Loader, 1999).
(iv) Step (iii) is repeated to generate an ensemble of 250 maximum wind speed scenarios. The annual maximum hurricane wind speeds are converted to 3-second gust using gust correction factor (~1.5) suggested by Simiu et al. (1996).

(v) Structural fragility curves developed by Li and Ellingwood (2003) were then used to study two example states of structural failure, that of roof panel uplift and roof-to-wall separation for single story light-frame homes without overhangs, subjected to ASCE 7 Exposure Category B. The panels were 4' x 8', attached with 8d and 6d nails. This construction is typical of houses in the Southeast United States.
(vi) Conduct a convolution of the fragility curve with the simulated wind speeds to compute the structural failure risk as a function of duration of exposure (i.e., cumulative failure probability).The simulations assume that there is at least one hurricane occurrence each year. To correct for this, in the convolution process the probability of at least one hurricane from the historical data is multiplied by the probability that any particular year is hurricane-active.
(vii) Repeat steps (ii) to (vi) for all the years in the 25 year life horizon.
(viii) Repeat steps (ii) to (vii) to simulate La Nina conditions and all years.
Other relevant large-scale climate information can be easily included in this framework. Furthermore, this approach can incorporated in a stochastic hurricane track simulation model.

Results

The joint PDF of maximum wind speed and NINO3 index estimated by nonparametric estimators (Bowman and Azzalini, 1997) is shown in Figure 2. Non-Gaussian features are apparent. To illustrate this further, the conditional PDFs of maximum wind speed conditioned at NINO3 values of -1 and 1 are shown in Figure 3.

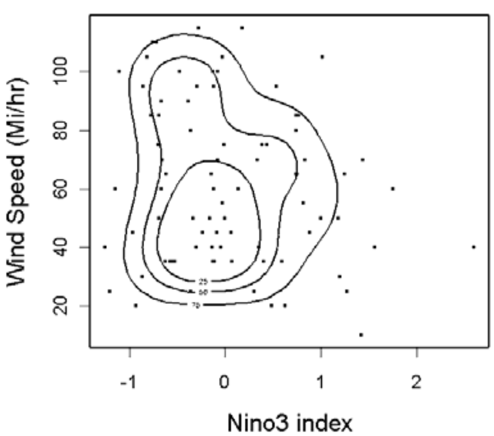

Figure 2. Joint Probability density of NINO3 index and maximum wind speed

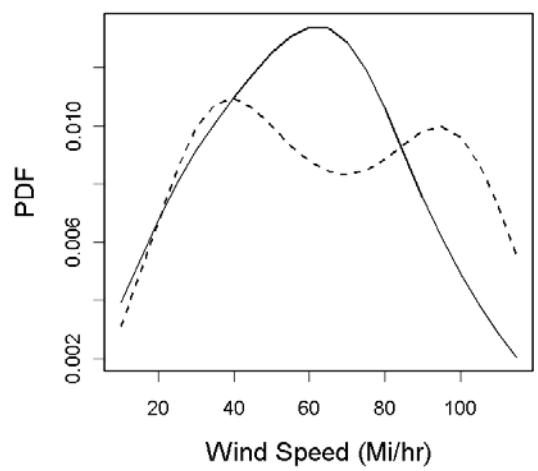

Figure 3. PDF of maximum wind speed conditioned upon NINO3 index value of -1 (solid line) and 1 (dotted line), respectively.

It can be seen that El Nino conditions tend to have higher probability of lower wind speeds and vice-versa. This is further confirmed in Figure 4. In this figure, boxplots of Cumulative Distribution Function (CDFs) of maximum wind speeds from simulations conditioned on El Nino state, following the steps above, are shown, along with the CDFs of maximum wind speeds of historical data from El Nino (red line) and La Nina (blue line) years. The boxes represent the interquartile range of the CDFs from the simulations and the whiskers are the 5th and 95th percentiles. Notice that the simulations capture the historical CDF of El Nino years very well (as the red line is within the boxes). Structural failure probabilities are shown for the 25 year life horizon for two failure states – panel uplift (Figure 5) and roof-to-wall separation (Figure 6), for two nail types (6d and 8d) and for the three climate states (El Nino active, La Nina active and all years that has the climate variability similar to the historical record).

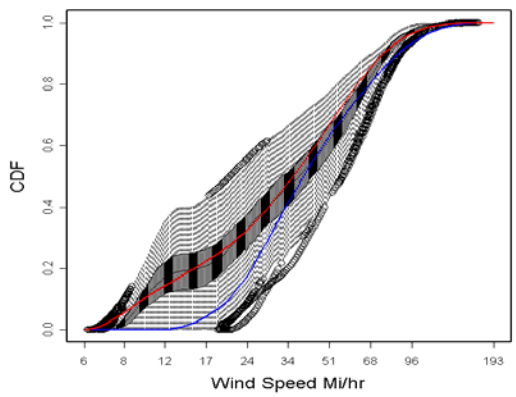

Figure 4. Boxplots of CDFs from the simulations conditioned upon El Nino state. CDF of the historical data from El Nino years (red) and La Nina years (blue)

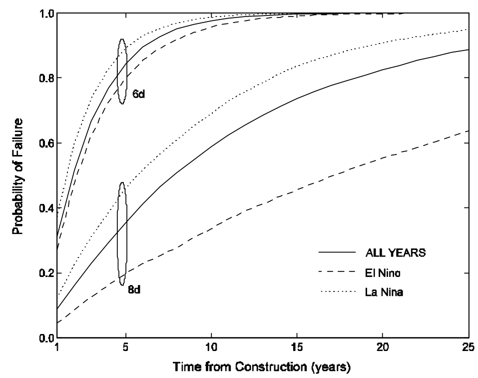

Figure 5. Structural failure probabilities due to panel uplift.

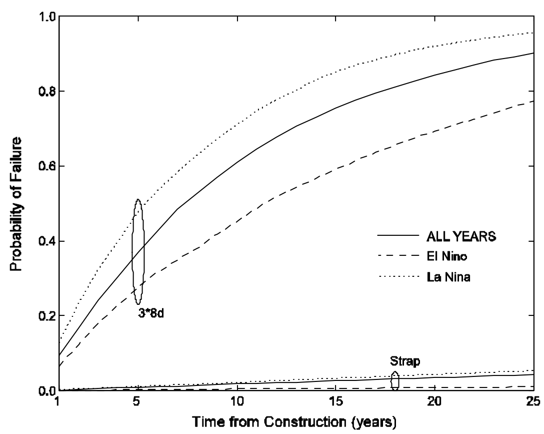

Figure 6. Structural failure probabilities due to Roof-to-Wall connection.

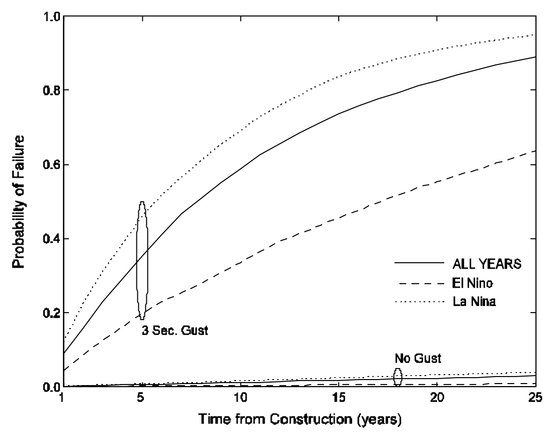

Figure 7. Structural failure probabilities due to Gust.

It can be seen that the risk during El Nino active period is substantially lower than during a La Nina active phase. Obviously, the 8d nails have a smaller risk than their 6d counterparts and the strapping of roof dramatically reduces the risk. The risk estimates appear to be much higher in general (e.g., a 0.8 failure probability at the end of 25-year period). This is probably due to the gust correction factor, which has historically come primarily from turbulence structure studies in extra-tropical winds. To test this, the failure probabilities are estimated without considering the gust correction (Figure 7) and a dramatic reduction can be seen. Clearly, the gust correction factor to be applied to hurricane winds needs to be further studied.

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