PROBABILITY ANALYSIS OF EXTREME ENVIRONMENTAL CONDITIONS FOR OFFSHORE WIND TURBINES

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ABSTRACT

The development of renewable energy sources is a critical global need, and offshore wind energy is a particularly promising source. The Atlantic coast and Gulf of Mexico of the US, with large wind resources and proximity to major population centers, are natural places for such development, but so far the US still does not have a single utility-scale offshore wind turbine (OWT) in its waters. Europe, in contrast, installed its first OWT more than 30 years ago and currently has several gigawatts of installed capacity. Although experience in Europe provides important insight for the US, the presence of hurricane risk in the US means that new methods must be developed for assessing financial risk and designing/certifying OWTs for the hurricane-prone US coastal environment. This study presents research results and plans to advance understanding of the hurricane risk posed to OWTs.

The dissertation herein addresses two overarching themes. The first theme is structural modeling of OWTs. While performance-based structural modeling of infrastructure subjected to natural hazards is a well-established field, modeling of OWTs presents some interesting challenges since an OWT can be considered as both a machine and a structure. In particular, the structural characteristics of an OWT vary significantly depending on the operational condition of the turbine. One of these characteristics, aerodynamic damping, is examined in detail in this work, and a closed-form equation for estimating the magnitude of aerodynamic damping for use in structural analysis software is proposed. The second theme is probabilistic characterization of hurricane-induced offshore hazard relevant to design and risk evaluations of OWTs. The offshore environment is a fascinating example of a multi-hazard situation where the hazards of extreme hurricane-induced wind, wave height, and wave period
(among other hazards) are correlated to varying degrees. In this dissertation, the estimation of multi-hazard conditions relevant to OWTs is investigated and two approaches, one based on a jointly distributed model of multiple offshore hazards and another, simpler approach, based on independent distributions of multiple offshore hazards, are proposed to combine offshore hazards more realistically at recurrence periods relevant to design and risk assessment. As part of this second theme, probabilistic equations are statistically formulated for predicting wind speed and wave height during hurricanes. The equations are termed wind and wave prediction equations (WWPEs) and are analogous to ground motion prediction equations in probabilistic seismic hazard analysis. The equations are based on a statistical comparison between wind and wave measurements near the US Atlantic and Gulf of Mexico coastlines during hurricanes and two parametric models: Holland’s model to estimate hurricane winds and Young’s model to estimate hurricane waves.
RESEARCH PRODUCTS

Journal publications:


Publications under review:

Publications in preparation:


Conference papers:


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Nomenclature

AD: Aerodynamic Damping

OWT: Offshore wind turbine

PGA: Peak Ground Acceleration (g)

PGV: Peak Ground Velocity (m/s)

Sa: Spectral acceleration response (g)

V: Wind Speed (m/s)

$V_{N1,H1}$: Mean wind speed during $N1$ minutes at height $H1$ meters above sea surface (m/s)

$H_s$: Significant wave height (m)

$H_{s,50}$: Significant wave height for 50 years mean return period (m)

$T_p$: Wave peak spectral period (s)

TSR: Tip Speed Ratio

$R_{max}$: Hurricane Radius of Maximum Wind Speed (m)

$V_{max}$: Hurricane Maximum Wind Speed (m/s)

$V_{tr}$: Hurricane Translation Speed (m/s)

$V_w$: Wind Velocity at Hub Height (m/s)

$V_{50}$: Hourly mean wind velocity at for 50 years mean return period (m/s)

$P_c$: Hurricane central pressure (mb)

$P_a$: Hurricane ambient pressure (mb)

$r$: Distance from location to center of event (m)

M: Earthquake magnitude
\( \theta \): Angle clockwise positive from hurricane direction

IFORM: Inverse First Order Reliability Method

NOAA: National Oceanic and Atmospheric Administration (USA)

NREL: National Renewable Energy Laboratory (USA)

HAWT: Horizontal Axis Wind Turbine

R-LOS: R Largest order statistics

t\(_{lag} \): Time lag between the measurement of maximum V and the maximum Hs during an extreme event

CDF: Cumulative distribution function

GEV: Generalized extreme value

\( \mu \): Location parameter of GEV distribution

\( \sigma \): Scale parameter of GEV distribution

\( \xi \): Shape parameter of GEV distribution

g: Gravitational acceleration

T: Extreme wave period

N: Recurrence period

\( \beta \): Radius of the sphere in standard normal space used in IFORM

\( \Phi \): Cumulative distribution function for standard normal distribution

\( a \): Axial induction factor

\( a' \): Tangential induction factor

\( C_d \): Drag coefficient

\( C_l \): Lift coefficient

c: Blade chord length
$c_{ST}$ Structural damping coefficient
$c_{AD}$ Aerodynamic damping coefficient
$k_x$ Lateral stiffness at the hub for equivalent single degree of freedom wind tower in fore-aft direction
$k_y$ Lateral stiffness at the hub for equivalent single degree of freedom wind tower in side-to-side direction
$F_x$ Aerodynamic force at the hub in the fore-aft direction
$F_y$ Aerodynamic force at the hub in the side-to-side direction
$m$ Effective mass at the hub for equivalent single degree of freedom wind tower
$N_b$ Number of blades
$l$ Radial distance along the blade measured with respect to the blade root
$TSR$ Tip speed ratio, velocity of the blade tip with respect to $V_w$
$V_{rel}$ Velocity of the wind relative to the blade
$V_w$ Upstream wind velocity in the fore-aft direction
$V_x$ Wind velocity at the rotor in the fore-aft direction
$V_y$ Wind velocity at the rotor in the side-to-side direction
$\alpha$ Angle of attack, the angle between $V_{rel}$ and the blade chord
$\beta_0$ Blade pitch, the angle between the blade chord and the rotor plane
$\gamma_i$ The azimuth angle of the $i^{th}$ blade
$\zeta_{AD,x}$ Aerodynamic damping ratio in the fore-aft direction
$\zeta_{AD,y}$ Aerodynamic damping ratio in the side-to-side direction
$\rho$ Air density
$\phi$ The angle between $V_{rel}$ and the rotor plane
\[ \Omega \] Rotational speed of the rotor
1 INTRODUCTION

1.1 Motivation for this study

As the United States moves towards generating more of its energy demands with renewable sources, offshore wind energy will be a key component. The National Renewable Energy Laboratory (NREL) has stated that an optimal (i.e. least cost) strategy for the US to achieve its target of generating 20% of its electricity demand from wind energy by 2030 [1] should include the development of 54 gigawatts of offshore wind capacity. The Atlantic and Gulf coasts are natural places for such installations since the wind resource is rich and near population centers.

Despite approximately 20 proposed offshore projects along the US coast, there are currently zero utility-scale OWTs installed in US waters. Europe, in contrast, is the world leader in offshore wind power, with the first offshore wind farm being installed in Denmark in 1991 [2] and with thousands of OWTs currently generating multiple gigawatts of electric power. Since 1991, over 39 offshore wind farms have been installed off the shores of Belgium, Denmark, Finland, Germany, Ireland, the Netherlands, Sweden and the UK [3].

The growing demand for offshore wind energy is not limited to Europe. Current world-wide offshore wind capacity is 9.4 GW, but this number is projected to reach a total of 75 GW worldwide by 2020, with significant contributions from the United States and China [1]. The Chinese government has set an ambitious target of 5 GW of installed offshore wind capacity by 2015 [4]. In Japan, the goal
is 27 GW of wind energy by 2030, and 5.8 GW from OWTs [5]. India is also looking at the potential of offshore wind power, with a 100 MW demonstration plant being planned off the coast of Gujarat [6].

There are many signs indicating the world-wide rise of the offshore wind energy in the coming decades, however the installation of gigawatts of OWTs poses several challenges, one of which is the exposure to hurricane risk. Since offshore wind farms are a relatively recent technology and since most offshore wind farms so far have been located in Europe, a region not exposed to hurricane risk, there are no historical examples of damage to OWTs during hurricanes.

To increase the reliability of OWTs, international guidelines have been developed for the design and construction of such structures, however these guidelines have been focused on the European environment. In the United States, the presence of hurricane risk raises questions on whether loads on OWTs can be estimated using the prescriptive requirements of these international guidelines. A substantial portion of the technical expertise embedded in these guidelines can be applied in the US, however research is required to better understand the loads on OWTs caused by hurricanes.

In addition to needing a better understanding of the effect of hurricanes on OWTs installed in the US, obtainment of NREL’s recommendation of 54 gigawatts of offshore wind capacity in the US waters will also require a significant reduction in the Leveled Cost Of Energy of offshore wind energy which currently exceeds traditional, carbon-based energy sources by more than a factor of two [7]. Two ways to reduce this cost include reducing financing and underwriting costs and optimizing design requirements, both of which would reduce capital costs. A possible means to such reductions in capital costs can be
achieved by more realistically modeling the structural response as well as more realistic estimation of extreme environmental conditions and their associated loads on OWTs, thereby minimizing uncertainty in extreme loading and design conservatism in many cases.

One improvement to structural response modeling is to provide better tools for quantifying the effect aerodynamic damping on structural models. Aerodynamic damping is caused by the interaction of the velocity of a vibrating structure and wind velocity. It depends on the velocity term in the equation of motion and, for a linear model, is additive with traditional structural damping [8]. Specialized software exists for modeling and designing wind turbines (e.g. FAST and GH-Bladed). In such programs, aerodynamic damping is calculated explicitly and can significantly influence the dynamic response of wind turbines. However, in these programs the structure is usually modeled coarsely. For more realistic modeling of the structure, finite element programs with shell elements are preferable, however, most sophisticated structural analysis programs are usually not capable of explicitly modeling aerodynamic damping.

Another way to reduce the cost of OWTs is reducing the conservatism through more realistic modeling of hazard combinations during extreme events such as hurricanes. It many cases, the wind and wave hazard parameters during extreme conditions are modeled as being independent, however, in reality such parameters are correlated to varying degrees. A more realistic approach involves using the long term joint probability distribution of the metocean parameters to estimate combinations of wind and wave. Therefore, a possible way to reduce capital costs of OWTs is to more realistically model and estimate extreme metocean conditions and their associated hazards on OWTs (OWTs), thereby
minimizing uncertainty in extreme loading and design conservatism in most cases.

1.2 Objectives and scope

The overarching objective of this dissertation is to use risk-based engineering to promote the development of offshore wind energy resources. In support of this overarching objective, four specific objectives are studied in detail and organized into individual Chapters:

1- Accurate modeling of OWTs, including robust aerodynamic and hydrodynamic modeling and robust structural modeling is a challenge. In an effort to enable the use of robust structural software in the analysis of OWTs, this dissertation, formulates a closed form equation to estimate aerodynamic damping. This expression can then be used to include an important aerodynamic effect in robust structural analysis software which typically does not include explicit consideration of aerodynamic effects (Chapter 3).

2- The structural reliability analysis will be more realistic by understanding design metocean environment and the effect of simultaneity of extreme wind and wave hazards. A method for more realistically combining correlated wind and wave hazards is proposed. The proposed method is based on the inverse first order reliability method (IFORM) and uses joint measurements of three random variables representing the extreme environment to construct all combinations of these variables at a particular return period. The effect of the method is investigated by a series of structural analyses which seek the critical combination on these variables (Chapter 4).
3- Hurricanes are intense, non-frequent storms and prediction of hurricane hazard through the statistical analysis with observational data is not feasible because the historical record of hurricane activity is only ~100 year long. Because of this situation, it is common to augment the historical record with a set of synthetic hurricanes to estimate long term hazards. In most cases, environmental conditions for these synthetic hurricanes are estimated deterministically. The effect of uncertainty in these estimates is considered here through the development of wind and wave prediction equations (WWPEs) which consider modeling uncertainties in the estimation of wind and wave during hurricanes (Chapter 5).

4- In the design of an OWT, it is common practice to assume a range of peak spectral period associated with an extreme significant wave height. There is currently no consensus on how to calculate this range, and in this dissertation, an IFORM-based approach is proposed and applied separately to both normal and extreme conditions. For normal conditions, there is sufficient data to construct a conditional distribution directly from the data, however for extreme conditions, there is insufficient data to do this directly and so an approximate joint probability distribution approach is used instead to construct the environmental contour and create the 50-year combination of peak spectral period and significant wave height. This approach is then applied to 16 locations along the east coast of the US and an equation is proposed to obtain the worst combination of the peak spectral period and significant wave height to be applied in practice for design and analysis of OWTs (Chapter 6).
1.3 Organization and outlines

Motivated by risk and cost considerations of OWTs, this dissertation aims to develop methods for more realistic risk estimation for OWTs and contribute to the development of a formalized, rigorous and probabilistic hurricane risk framework. Within this context, this dissertation is organized as follows:

- Chapter 2 presents a literature review on current practices in the design, analysis and risk assessment of OWTs. In this Chapter, the available design provisions and guidelines for OWTs along with details of the dynamic structural modeling program FAST are summarized.

- Chapter 3 presents a derivation of a closed form expression to calculate the aerodynamic damping of a wind turbine for normal and parked conditions. The sensitivity of aerodynamic damping to various parameters and characteristics of wind turbines is studied.

- Chapter 4 presents the formulation of a method for more realistically combining metocean parameters at a mean return period appropriate for design. The method considers three jointly distributed metocean parameters (the wind speed, the significant wave height and the peak spectral period) and is based on the Inverse First Order Reliability Method. Examples are provided for three locations along the US Atlantic coast and the structural response using this approach is estimated and compared to other methods.

- Chapter 5 presents the formulation of wind-wave prediction equations which are probabilistic equations which estimate wind speeds and wave heights during hurricanes including uncertainty. Such equations are a
central part of the assessment of risk to offshore structures exposed to hurricane risk. In this Chapter, the available observational data as well as historical hurricanes are described along with a description of two physical models for estimating wind and wave during a hurricane. The physical models are then compared with measurements of wind and wave during hurricanes, and the wind-wave prediction equations are formulated. Use of the equation is demonstrated through a numerical example.

- Chapter 6 proposes a probabilistic model for combining peak spectral period with significant wave height for purposes of design. The model is proposed for normal (operational) and extreme sea conditions and a new equation is proposed to combine these parameters for a 50 year mean return period. Also, a numerical example compares the structural response of an OWT using the new equation with an equation which has been used in practice.

- Chapter 7 presents a description of future work with particular emphasis on the correlation of simultaneous extreme wind and waves during hurricanes. Additional study on the effect of hurricane joint probability of simultaneous wind and wave is proposed for more investigation in future research.
2 BACKGROUND

This Chapter provides background on the state-of-the-art for designing and analyzing OWTs. It starts with a review of design guidelines for OWTs, then provides a summary of the features and formulations of the open-source dynamic analysis program FAST which is freely distributed by the National Renewable Energy Laboratory, and finally provides a summary of probabilistic techniques to estimate multiple hazards and loads for the offshore environment. The Chapter is organized as follows:

- Section 2.1 reviews relevant design procedures for OWTs summarizes recommendations for designing OWTs for extreme offshore environmental conditions. The content in this section is a summary of that provided in a 2013 thesis by a Michael Harper. For more details, the reader is referred to this thesis [9]. Also, this section provides information about historical records for damaged wind turbines during storms.

- Section 2.2 explains modeling features within FAST, a program developed specifically for the design and analysis of wind turbines subject to simultaneous aero- and hydrodynamic loads. The theoretical formulation for turbulent winds, irregular waves, aero- and hydrodynamic loads and structural modeling within FAST are described. The program FAST is used to convert environmental conditions to structural loads throughout this dissertation. The content in this section is a summary of that provided in a 2013 thesis by a Michael Harper. For more details, the reader is referred to this thesis [9].
• Section 2.3 provides an overview of statistical techniques to estimate environmental hazard and design loads for OWTs at particular recurrence periods. These techniques are used in Chapters 4 and 6 to estimate realistic load combinations for extreme offshore conditions.

2.1 Code review, design commentary and historical record

Both the growth of the offshore wind energy industry and the growing size of OWTs motivate the need for more refined reliability and safety assessments of these structures. Design guidelines have been developed to promote consistency and legality for the development, design, implementation and operation of offshore wind farms. Among these design standards, IEC 61400-3 is the most widely used in practice. This standard is designed for the European environment, and, as such, does not include explicit methods for considering hurricanes in the estimation of design loads. In addition to this standard, several guidelines and reports have been published to address hurricane effects. In the following section, the general procedure, according to the IEC 61400-3 standard, for designing and analyzing an OWT for extreme conditions is reviewed, and the limitations of this standard are outlined with emphasis on limitations related to designing OWTS exposed to hurricanes. Following this, reviews are provided for three guidelines which explicitly address the calculation of hurricane hazards for OWTs. Finally, the historical records of collapsed or damaged wind turbine are listed.

2.1.1 IEC 61400-3 design procedure for OWTs

The International Electrotechnical Commission (IEC) is a worldwide standardization organization. IEC 61400-3 outlines minimum design requirements for OWTs. This standard proposes a minimum set of hazard
combinations, termed design load cases (DLCs), consisting of conditions such as operational, parked (during extreme loads), start up and shut down, transport, assembly and maintenance. Among these design load cases, this dissertation is focused on extreme load cases during which the OWT is in parked condition (i.e. the rotor is stationary and the blades are feathered). According to the standard, during extreme conditions, the ultimate loads shall be determined such that the global extreme environmental action has a combined mean return period of 50 years. The IEC standard allows that, in the absence of information defining the long-term joint probability distribution of extreme wind and waves, the extreme 50-year mean wind speed can be assumed to occur simultaneously with the extreme sea state with a 50-year mean return period. The extrapolation method described in Section 2.3 can be used to obtain 50-year values for wind speed and significant wave height from appropriate measurements and/or hindcast data.

The extreme sea state is defined in terms of the significant wave height and the peak spectral period. Although IEC 61400-3 provides a range of wave periods for the extreme wave (Equation 10 in the standard), no recommendation is made for obtaining the range of the peak spectral period, despite language requiring that “the designer shall take account of the range of peak spectral period, $T_p$ appropriate to $H_{50}$ and $H_{1}$ respectively” and that “design calculations shall be based on values of peak spectral period which result in the highest loads acting on an offshore wind turbine.” API-2A-WSD proposes a range of coefficients to convert the wave period to the peak spectral period; however, this approach may lead to an unrealistic extreme sea state. In Chapter 6, a more appropriate combination of peak spectral period and significant wave height is proposed to represent the 50-year sea state, more realistically.
Two structural analysis approaches are allowed in the IEC standard: the turbulent inflow combined with the stochastic sea state or the steady wind model with deterministic design waves. In the first approach, which is used in this dissertation, the turbulent extreme wind model is combined with extreme sea state conditions. The response is estimated using a full dynamic simulation based on at least six 1-hour realizations for each combination of extreme wind speeds and extreme sea states. In this case, the hub-height mean wind speed, turbulence standard deviation and significant wave height are calculated for a 50-year mean return period. The average of the maximum response during each 1-hour simulation will be used to determine design loads.

An important omission in the IEC 61400-3 standard is explicit consideration of the effect of hurricanes. To consider the effects of hurricanes, several guidelines have been published and these are listed in the following sections. The estimation of hurricane loads is an important part of this dissertation and is also discussed in Chapter 5.

2.1.2 ISO 2394

In IEC 61400-3, the combination of independently-calculated values of the extreme wind speed and significant wave height is allowed; however, this assumption can lead to unrealistic and, in many cases, unnecessarily severe design conditions. Various studies have been conducted on how to assess multiple conditions for a common mean return period, and some of this research is summarized in ISO 2394, Annex F. In the case of two variables, the Annex recommends taking one load (the dominant one) at the extreme (say corresponding to a probability level $P = \Phi(-\beta)$), where $\beta$ is reliability index, and the other (the accompanying one) at a reduced level $P = \Phi(-0.4\beta)$. In this
approach, a dominant metocean parameter is selected (either V or Hs as wind speed and significant wave height, respectively) and a 50-year value of this parameter is calculated and combined with a reduced value of the other parameter (either V or Hs). The dominant metocean parameter is defined as the parameter that makes the largest contribution to structural load effects. This method aims to avoid the conservatism of combining independent wind speed and significant wave height for a 50-year mean return period while maintaining the convenience of modeling only the marginal distributions of V and Hs. In other words, regardless of the correlation of two random variables, the marginal distribution of each random variable is used to obtain independent values of V and Hs for a 50 year MRP and these are then combined as described above.

Although this approach is more realistic than simply combining independent extreme wind and wave without any reduction, it has two important limitations: (1) the extreme response of the structure does not always occur at the extreme of the dominant load case (i.e. a more severe combination of dominant and non-dominant loads that is not located at the extreme dominant load might exist) and (2) the need to determine a dominant load always ties environmental conditions to the structural properties, and there are clear benefits to assessing environmental conditions independent of the structure, as is the case for hazard maps of wind and seismic hazards [10]. Chapter 4 of this dissertation considers instead using environmental contours which define multiple hazards at a common recurrence period without the need to consider structural effects.

2.1.3 Other reports and guidelines

The American Bureau of Shipping (ABS) published two sets of guidelines in 2010 and 2011 to address the design, construction and installation of OWTs in

In 2011, the ABS published the final report on design standards for OWTs [14]. The report reviews OWT design procedures, shows outputs of OWT case analysis and makes suggestions on design provisions for OWTs in hurricane prone areas.

The document considers the terms of the operational and extreme design criteria which is provided by API and recommends that these terms are not directly applicable to OWTs in hurricane situations, as the operational modes have large influences on the structural responses of such structures. Therefore, it is recommended that strength criteria should be based on the operational modes and not only on the intensity of the environmental conditions.

To consider hurricane conditions for design of OWT support structures, the ABS recommends increasing the return period beyond the requirements in IEC 61400-3 [15]. This report also says that a large number of research is required for the approach to address the effects of regional variations in environmental conditions, characteristics of support structures and foundations.

Several suggestions on the design of fixed-bottom OWTs in hurricane-prone regions are also provided by the ABS. Among those, the ABS suggests that the effects of yaw misalignment be taken into account in design. Also in 2012 the AWEA released a report that reviewed current standards for the design [16]. This report recognizes that hurricane hazard may control the design of OWTs. It is recommended that the environmental hazard factors or mean return period for design be according to site-specific environmental conditions [16].
In 2011, TRB released a report [3] that discusses deficiencies in the current standards of OWT design for sited in hurricane-prone areas. It indicates that the design for OWT based on IEC 61400 may not be sufficient enough for OWTs to withstand the extreme wind gusts that happen in high-intensity hurricanes. TRB indicates that the IEC standards do not estimate maximum wind and wave conditions, or extreme directional wind variations as really happen due to hurricanes.

2.1.4 Historical records for damaged wind turbines

Although the wind resource provides optimism for reaching the DOE’s goal, the installation of gigawatts of OWTs poses several challenges, one of which is the threat of storm events and hurricanes. Since the offshore wind farms are more recent than on-land wind turbines and limited to the European sea, no catastrophic damage has been reported to OWTs, however, there has been many instances of structural damage to wind turbines due to the storms. In 1998, among 315 installed wind turbines, 129 destroyed due to a cyclone in Gujarat, India. A year later, in 1999, storm destroyed 8 wind turbines due to brake failure and rapid rotation in Jutland, Denmark. In 2002, a 28-m wind turbine tower completely destroyed during storm in Husum, Germany. At the same year, in Goldenstedt Ellenstedt, Germany, a Turbine completely toppled in storm and concrete base pulled out of ground. In 2003, in, a spring storm destroyed a turbine due to failure in automatic shut down and rotor blade points computed to reach speeds of 800 km/hr in Reinsberg, Germany. In 2004, a 30 m turbine collapsed during a storm in Loon Plage, France.

In 2003, Hurricane Maemi hit the Miayokojima Island in Japan and destroyed several wind turbines. Maemi stuck the island with gust wind speed of 74.1 m/s.
All six wind turbines operated by Okinawa Electric Power Company were extensively damaged and two of them collapsed due to the buckling of the towers (Figure 2-1).

![Damage to wind turbines](image)

**Figure 2-1.** Damage to wind turbines on Miayokojima Island in Hurricane Maemi, 2003.

Although the failure of OWTs due to major storms and hurricanes has not been reported yet, it is expected that an OWT is more vulnerable to the storms and hurricanes due to the influence of wave loads during a storm. Therefore, realistic estimation of loads on OWTs during extreme events is necessary. Therefore, guidelines have been developed by European countries to design OWTs according to operational and environmental loads, including the storm events.

### 2.2 Modeling OWT response

Throughout this dissertation, all numerical examples of the dynamic structural response of OWTs are provided for two OWTs defined by NREL. The first, the 1.5 MW NREL wind turbine, is used in Chapter 4 to estimate aerodynamic damping, and the second, the 5 MW NREL wind turbine, is used in Chapters 5, 6 and 7 to assess the effect of hazard estimation on dynamic structural response.
Both wind turbines are analyzed using FAST, a software program developed specifically to analyze onshore and OWTs. This section provides the theoretical background to modeling wind turbines with FAST.

Many computer software and programs have been developed to response analysis and design of offshore structures, however, majority of them can only be applied in oil and gas industry, such as design and analysis of offshore platforms. Since, OWTs are flexible structures and due to sophisticated mechanical structures, special attention is required for modeling dynamic response of such structures under simultaneous wind and wave. Also, operation of an OWT will produce additional dynamic load. Due to needs for special software for analysis of WTs, a special program, called “FAST” is developed by NREL. In this program, the dynamic response of OWTs can be modeled. In the following section, the specifications of this program as well as some theoretical background are described.

In FAST the rotor blades, tower and drive system, resulting in a total of up to 24 degrees of freedom (DOFs) are considered as flexible bodies. Three DOFs are translational motions (surge, sway and heave) of the support platform and three degrees of freedoms are rotational DOFs as roll, pitch and yaw of the support platform. The tower is modeled as the combination of the first two side-to-side and fore-aft modes, which accounts for four DOFs. The base of the tower is fixed. Yaw position is another DOF of the rotor which can be free or constrained with a torsional spring. Two DOFs account for the generator azimuth angle and teeter motion. Each blade has three degrees of freedom each, two for flap-wise modes and one edgewise mode. The other 2 DOFs are rotor and tail furling [17]. Also, FAST considers the geometric nonlinearities from structural deformations by
using “radial shortening” approach. It is comparable to $P-\delta$ effects in structural engineering concept [18].

In FAST the two-dimensional aerodynamic loads (i.e., drag, lift and pitching moment) are obtained from AeroDyn, which considers turbine operating conditions, geometry, blade-element speed and location. Blade Element Momentum (BEM) model, which is the most practical theory in aerodynamics used in wind turbine analysis and design, is applied in Aerodyn for this dissertation. Bets and Glauert introduced BEM in 1935 which comes from two different theories: blade element theory and momentum theory. This method is used in Chapter 3 to obtain aerodynamic damping of WT. For more information refer to [19].

Wind profile is generated through TurbSim which is a preprocessor program to calculate stochastic wind time histories [20]. It uses wind speed spectrum. The variance of wind speed in TurbSim is calculates through the following equation

$$\sigma^2 = \int_0^\infty S(f) df$$

(2-1)

Where, $S$ is velocity spectra and $f$ is frequency.

For this dissertation, the IEC Kaimal spectrum is used which is defined by the following equation,

$$S_K(f) = \frac{4\sigma^2 L_K/\bar{u}_{hub}}{\left(1+6fL_K/\bar{u}_{hub}\right)^{2/3}}$$

(2-2)

where $K$ is the three wind components in two horizontal and one vertical directions and $f$ is the frequency. $L_K$ is the turbulence integral scale parameter.
\( \sigma_K \) is the standard deviation of the wind velocity in the \( K^{th} \) direction, and \( \bar{u}_{hub} \) is defined as hub-height mean wind velocity. The integral length scale parameter is defined in IEC 61400-1 standard as:

\[
L_K = \begin{cases} 
8.10 \Lambda_U, k = u \\
2.70 \Lambda_U, k = v \\
0.66 \Lambda_U, k = w,
\end{cases}
\]

(2-3)

where the turbulence scale parameter \( \Lambda_U \) is defined as:

\[
\Lambda_U = \{0.7 \text{ min}(60m, Hub \ height)\}
\]

(2-4)

\[
\sigma_v = 0.8 \sigma_u \quad \text{(2-5)}
\]

\[
\sigma_w = 0.5 \sigma_u \quad \text{(2-6)}
\]

A turbulence model needs also to be determined in TurbSim. There are several models which reflect the IEC 61400-1 models such as the Normal Turbulence Model (NTM), Extreme Wind Model (EWM) and Extreme Turbulence Model (ETM) [16].

Turbulence intensity (TI) is the root mean square of wind speed fluctuation to the mean wind speed. This parameter needs to be defined in TurbSim. For different turbulent conditions the user should input different TI. For example, for the extreme turbulent model, the TI will be defined based on the wind turbine Category (See Table 1 in [22] for TI values for turbulence categories A, B and C).

To generate the wind speed profile through TurbSim first, the number of grid points to generate wind in vertical and horizontal direction is specified. In the models presented in this dissertation, 13 grid points are considered in both the horizontal and vertical directions, with a time step of 0.05 seconds and
turbulence characteristics for category “A”, as defined in IEC 61400-1. The turbulent wind speed generation is shown in Figure 2-2.

![TurbSim Input File](image)

Figure 2-2. Turbulent wind speed generation flowchart using TurbSim

HydroDyn is a preprocessing program for hydrodynamic force modeling to be applied in FAST. Wave spectrum, stretching, direction, structural properties are used in Morison equation through HydroDyn [23]. FAST includes several wave spectral models such as the Combined Joint North Sea Wave Project (JONSWAP) spectrum and Pierson-Moskowitz spectrum (which are both for irregular waves). The JONSWAP spectrum is a more expanded version of the Pierson-Moskowitz spectrum and is can applied to fully developed seas, but the Pierson-Moskowitz spectrum is used mostly for limited fetch scenarios. In HydroDyn, these spectra are adapted as they are in the IEC 61400-3 standard [15]. It is noticed that the use
of the JONSWAP spectrum alone is not sufficient to model the wave profile due to a hurricane. In other research, more sophisticated computational efforts were used to model wave profiles for hurricane[14, 24, 25].

In this dissertation, waves are modeled as linear irregular wave (Airy Wave Theory) which results in the wave surface as a Gaussian process. Non-Gaussian wave surface is more appropriate model to model shallow water wave which are known to have non-zero skewness [26,27].

It is noticed that the Airy Wave Theory has limitations [28]. This theory becomes invalid for shallow water due to change in wave dimension and shape [29].

2.3 Statistical techniques in extreme hazard estimation

Throughout this dissertation, statistical techniques are extensively applied to estimate long-term offshore conditions. These methods have been used in the literature for different statistical applications, and are employed in Chapters 4, 5 and 6 of this dissertation. These methods, along with relevant background, are provided in this section.

2.3.1 Extreme value distribution theorem

Most design applications are concerned with the estimation of extreme hazards. Therefore, attention should be directed towards the tails of the distribution of these loads and hazards. An extreme may be defined as the largest or smallest value drawn from a sample of all available data which is called “parent data”. In other words, extreme value modeling requires the selection of individual extreme values from parent data and discarding the majority of non-extreme data. Because the parent data are collected as a series of values (e.g. wind speed) over time, it is convenient to define the size of the sample in terms of time span,
which can be called an observation period. Monthly maxima are therefore the largest value in a 1-month observation period and annual maxima are the largest values in a 1-year observation period.

The theory of extreme values was first developed by Fisher and Tippett and extended by Gumbel. Fisher and Tippett showed that extreme values from all parent distributions converge asymptotically towards one of only three forms as the observation period increases. These are called Fisher-Tippett Type I, Type II and Type III distributions. For example, the CDF of extremes drawn from any Weibull parent will always converge to the Type I distribution. These extreme value distributions are explained in detail in [30].

Assuming that maxima are abstracted from a record of independent events over observation periods each comprising N numbers. For example, if 10 years of hourly wind speed is available, if N = 1, then all hourly wind speed is selected, if N = 24 then, daily maximum value of wind speed is collected from all data, if N = 24 × 7 = 168, then weekly maximum value of recoded wind speed is considered, for annual maxima N = 24 × 365 = 8,544). Therefore, maxima accumulate to form a new population of values, described by its own probability distribution. In the trivial case of N=1, this procedure would result in a CDF identical to that of the parent data. As N increases, then the choice of the maximum from each sample will result in a CDF that shifts to higher values of the random variable, and the resulting CDF moves further to the right from the CDF of parent data which contains all observational data. As long as the values in the parent are statistically independent, the CDF of the maximum in the observation period is:

\[ F_{\text{max}\{T\}} = F^N, \quad (2-7) \]
where $F$ is the CDF of the parent data.

Clearly, as the observation period becomes longer, a larger extreme is likely to occur during that time. If the original observation period used to extract the extreme from the parent is long enough to ensure the statistical independence of the extreme, then the resulting CDF is related to other observation periods by the following equation:

$$F(T_1) = F(T_0)^{T_1/T_0}, \quad (2-8)$$

where $T_0$ and $T_1$ are original and new observation periods.

In this dissertation, another extreme value distribution function, which combines the previous functions into a single function, is used. This single function is termed the Generalized Extreme Value distribution, and is explained in the following section.

2.3.2 Generalized Extreme Value (GEV) distribution function

Like the extreme value distributions, the generalized extreme value distribution is often used to model the smallest and the largest values among a large set of independent, identically distributed random variables that represent measurements or observations (i.e., the parent data). This distribution combines the three previous simple distributions into a single form, allowing a continuous range of possible shapes that includes all three simpler distributions. In other words, the GEV enables the data rather than the analyst to determine which of the three extreme value distributions is most appropriate [31].

22
The probability density function for the GEV is defined with the location parameter \( \mu \), scale parameter \( \sigma \), and shape parameter \( \xi \). The generalized extreme value distribution is defined as:

\[
F_X(x; \mu, \sigma, \xi) = \exp \left\{ - \left[ 1 + \xi \left( \frac{x-\mu}{\sigma} \right) \right] \right\}^{-\frac{1}{\xi}} \quad \text{for} \quad 1 + \frac{\xi(x-\mu)}{\sigma} > 0, \xi \neq 0 \quad (2-9)
\]

\[
F_X(x; \mu, \sigma, \xi = 0) = \exp \left\{ - \exp \left( - \frac{x-\mu}{\sigma} \right) \right\} \quad \text{for} \quad \xi = 0 \quad (2-10)
\]

When \( \xi = 0, \xi > 0 \) or \( \xi < 0 \) the resulting distribution will be the Gumbel, Frechet and Weibull (extreme value Type I, II, III), respectively.

2.3.3 Mean Return Period (MRP)

The CDF of extremes for a given observation period describes the probability of a certain magnitude not being exceeded. Similarly, the difference between CDF and one is the probability of exceedance of that value in the observation period. Neither the CDF nor (1-CDF) provides any information about the return period of extremes of a given magnitude in various intervals of time. This requires that attention be shifted to the time domain.

Consider the process of extracting annual maxima from the parent data. Every year a new value is added to the distribution of annual extremes, and if this process were to continued indefinitely, one in every 50 values, on average, would be greater than the value at \( P=0.98 \), that is, the annual rate of exceedance is 0.02. Exceedances are usually preferred to be expressed in terms of rates rather than in terms of probability, because computing probabilities involves an assumption of the nature of underlying event occurrence, (e.g. Poissonian). Moreover, the probability and mean rate are numerically almost equal for rare
conditions (e.g., those with 50 year or 100 year mean return periods). The MRP can be obtained from following equation:

\[
M_{RP} = \frac{1}{r(1-P)} \tag{2-11}
\]

where MRP is the mean return period in years, \( r \) is the rate of extreme occurrence and \( P \) is the CDF of the extremes observed at rate \( r \).

2.3.4 Joint probability distribution function, NATAF model

In this dissertation, the environmental conditions are defined by three random variables, sustained wind speed, significant wave height, and peak spectral period, defining turbulent winds and irregular waves. Unlike many regular structures, the hazards of the offshore environment are correlated, for example, high wind is usually accompanied by high waves. Therefore, the parameters defining the conditions may not be appropriately modeled as independent. The extreme value approach can be used to obtain the marginal distribution of each parameter; however, to consider combinations of these parameters at different mean return periods, the conditional probability of the parameters, or joint probability distribution of the parameters, must be calculated. The joint probability distribution function becomes more important in situations with limited data when the direct conditional distribution of the parameters cannot be estimated. In presence of sufficient data, the conditional probability function can be easily constructed by dividing the first random variable into the bins and collecting the second random variable, associated with each bin, then the conditional probability function can be estimated by analyzing the collected data within each bins. This method is not appropriate for limited data, because there is not sufficient data for the joint random variable within each bin. In the case of
limited data, the joint probability distribution function can be constructed by using marginal distribution of each random variable and the correlation of two or more random variable which can be estimated even for limited number of data. Having the joint probability distribution function, one can construct the conditional probability function by using Equation 2-12.

\[ f_{y|x}(y, x) = \frac{f_{y,x}(y, x)}{f_x(x)} \]  

(2-12)

Where \( x \) and \( y \) are two random variables, \( f_{y,x}(y, x) \) is joint probability distribution of \( x \) and \( y \), \( f_x(x) \) is marginal distribution of \( x \) and \( f_{y|x}(y, x) \) is conditional distribution function of variable \( y \) for given random variable \( x \). This is a common case for offshore data, where there is typically a sparsity of joint data measurements available.

The joint probability distribution of random variables can be estimated through different models. In this dissertation, the so-called NATAF [32] model or Gaussian copula [33] is used to construct joint probability distribution of random variables. This model describes the joint probability density function of random variables \( X_i \) based on their individual (marginal) distributions and their correlation \( \rho \). The basic concept of the NATAF model is to transform the original variables \( X_i \) into Gaussian variables \( Y_i \) whose joint density is assumed to be multidimensional Gaussian. This model can be estimated in three steps. First, map all random variables \( X_i \) individually to normally distributed random variables \( Y_i \) with zero mean and unit standard deviation:

\[ Y_i = \Phi^{-1}[F_{X_i}(X_i)] \]  

(2-13)

Then, assume a jointly normal distribution for all random variables \( Y_i \) with the statistical moments:
\[ E[Y_i] = 0; \quad E[Y_i^2] = 1; \quad E[Y_iY_k] = \rho'_{ik} \]  

(2-14)

Note that at this point, the correlation coefficients \( \rho'_{ik} \) are not yet known. The joint pdf for the components of the random vector \( Y \) can be found by:

\[
 f_Y(y) = \frac{1}{(2\pi)^{n/2}\sqrt{\det(R_{YY})}} \exp\left(-\frac{1}{2} y^T R_{YY}^{-1} y\right),
\]  

(2-15)

where \( R_{YY} \) denotes the matrix of all correlation coefficient \( \rho'_{ik} \). From this relation, it follows that:

\[
 f_X(x) = f_Y(y(x)) \prod_{i=1}^{n} \left| \frac{dx_i}{dy_i} \right| = f_{YY}(y(x)) \prod_{i=1}^{n} \frac{f_{x_i}(x_i)}{\varphi[y_i(x_i)]} \quad (2-16)
\]

Finally, the correlation coefficients \( \rho'_{ik} \) can be computed by solving the following equation:

\[
 \sigma_{x_i} \sigma_{x_k} \rho_{ik} = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} (x_i - \bar{x}_i)(x_k - \bar{x}_k) f_{x_i,x_k}(x_i,x_k,\rho'_{ik}) dx_i dx_k \quad (2-17)
\]

In the above equation, the correlation coefficients can be usually calculated by iteration. A known problem of the NATAF model is that this iteration may produce a non-positive definite matrix of correlation coefficients in which case the model is not applicable. A set of semi-empirical formulas relating \( \rho \) and \( \rho' \) based on numerical studies for various types of random variables is given in [34].

2.3.5 **Inverse First Order Reliability Method and structural reliability**

The First Order Reliability Method (FORM) is a reliability analysis approach to obtain probability of failure which is corresponds to exceeding demand from a known capacity of structure. The optimization process is used to obtain the probability of failure, associated with the reliability index. When the joint probability of random variables (known as loads in structural analysis) is known, FORM estimates (by approximating linear estimation of limit state function) the
probability of failure of structure; however, when this load combination is not known, an alternative method, the Inverse First Order Reliability Method can be used. This technique was first introduced by Winterstein in 1993 [35] and subsequently used in different design problems [36]. This method is based on the use of environmental contours that uncouple environmental random variables from the structural response. Using examples related to offshore structures, Winterstein showed how this method may be applied to offshore structures to estimate design loads associated with specified target reliability levels.

To explain the IFORM, consider the three random variables $X_1, X_2, X_3$ with joint probability distribution represented as $f_{X_1X_2X_3}(x_1x_2x_3)$. The probability of failure can then be written as:

$$P_f = \int_{g(x_1x_2x_3) \leq 0} f_{X_1X_2X_3}(x_1x_2x_3)dx_1dx_2dx_3$$

where $g(x_1x_2x_3) \leq 0$ is the limit state function, and $f_{X_1X_2X_3}(x_1x_2x_3)$ is the joint probability distribution of random variables. According to this equation, at each combination of random variables, the probability of failure can be calculated. In this case, the limit state function will depend on the structure, and the random variables will be coupled with the structural characteristics to estimate the probability of failure.

Now consider a sphere with a radius, equal to the reliability index $\beta$, in a 3D space, see Figure 2-3. If, a tangent hyperplane were drawn at any point on this sphere, the probability of occurrence of points on the side of this hyperplane away from the origin is $\Phi(-\beta)$, where $\Phi()$ is the Normal CDF and $\beta$ is the reliability index. It follows that each point on the sphere has same reliability index or mean return period. Then this sphere can be transformed into 3D
surface in original space of random variables. This transformation can be achieved through Rosenblatt transformation [37]. Therefore, all points on the 3D surface, representing all combinations of original random variables with reliability index $\beta$, can be searched to find the combination of variables resulting in the largest load combination. This search is can be performed through structural analysis under load combinations on this 3D surface. More detail is provided by numerical example in Chapter 4.

![3D standard normal space with reliability index $\beta$](image)

Figure 2-3. Representation of 3D standard normal space with reliability index $\beta$ [47].

In this dissertation, the target reliability is specified in terms of a return period, and the radius $\beta$ can be defined according to the following equation:

$$\Phi(\beta) = 1 - 1/(r \cdot N),$$

(2-19)
where \( r \) is the rate of annual occurrence and \( N \) is the mean return period. For example, if the recorded data is over every 3 hours, then \( r = 365 \cdot \frac{24}{3} = 1095 \); therefore, for \( N=50 \) years and \( \beta = 4.35 \).

2.4 Conclusions

In this Chapter, background is provided on several important topics which are used throughout this dissertation. Those topics include (1) an overview of the relevant design documents and standards for OWTs with particular emphasis on any limitations for applying these standards in the US offshore environment which is exposed to hurricane risk, (2) structural response modeling of OWTs using the program FAST, and (3) the theory behind extreme value distributions and behind the Inverse First Order Reliability Method (IFORM). The IFORM approach is used in this dissertation when calculating MRPs for combined wind and wave conditions. In the next Chapter, a formulation for estimating aerodynamic damping is proposed and its influence on the dynamic behavior of wind turbines is investigated. In the following Chapters, the concepts provided in this Chapter are applied to the offshore environment along the US Atlantic coast and the Gulf of Mexico.
3 AERODYNAMIC DAMPING FOR HORIZONTAL AXIS WIND TURBINES

The material presented here is published in the following paper:


3.1 Introduction

The reliability of OWTs is a combination of fragility which directly corresponds to structural behavior and hazard evaluation for the site of interest. While this proposal mostly focuses on hazard aspect of risk analysis, to realistic analysis of wind turbines under long term wind and wave hazards, it is important to understand and apply the most influential parameters into analysis. One of the important parameters in dynamic analysis of wind turbines is the effect of aerodynamic damping. In this Chapter, the new formulations are proposed to predict the aerodynamic damping of a wind turbine more realistically to be applied in dynamic analysis.

In the current study, a closed-form solution based on Blade Element Momentum (BEM) theory for estimating the magnitude of aerodynamic damping of a HAWT tower responding dynamically in the fore-aft and side-to-side directions is proposed. The derivation of the closed-form solution is based on several simplifying assumptions, most notably a rigid rotor and a steady, uniform wind oriented perpendicular to the rotor plane.
3.2 Literature review

A few recent studies have examined the dynamic response of HAWTs [38]. Witcher (2005) [39] stated that operational wind turbines can experience total damping (aerodynamic plus structural) close to 5% and noted that, conveniently, this is commonly the same value prescribed by the seismic design spectra within many building codes.

Several prior studies have derived formulations for estimating aerodynamic damping of HAWT blades [40,41], but few studies have derived formulations of aerodynamic damping for HAWT towers. Some exceptions are work by Garrad in 1990 [42] and Kuhn in 2001 [43]. Garrad derived aerodynamic damping for a HAWT tower structure with a rigid rotor and a flexible tower and Kuhn simplified the derivation by Garrad and formulated aerodynamic damping in terms of the derivative of lift coefficient with respect to angle of the attack, geometric characteristics of the blades and dynamic characteristics of the tower. The derivation presented here extends these studies by including contributions to aerodynamic damping from the wind speed and by presenting equations for aerodynamic damping in the side-to-side direction.

3.3 Derivation of aerodynamic damping

The derivation for aerodynamic damping of an operational HAWT is based on a cantilever beam model with two degrees of freedom, lateral displacement at the hub height in the fore-aft (x-direction, perpendicular to the rotor plane) and side-to-side (y-direction, horizontal and within the rotor plane) directions. Figure 3-1 shows a schematic of the model and defines the coordinate system and several geometric parameters used in the derivation. The figure shows a generic three-
blade HAWT with its rotor spinning at a rotational speed \( \Omega \) and subject to a uniform upstream wind speed \( V_w \) in the fore-aft (x) direction. The figure also includes an image of a blade cross-section located a radial distance \( l \) from the rotor hub. The cross-section is subjected to a relative wind velocity \( V_{rel} \) that is comprised of a component normal to the rotor plane \( V_x = V_w(1-a) \), where \( a \) is the axial induction factor, and a component within the rotor plane \( \Omega l(1+a') \), where \( a' \) is the tangential induction factor. The axial induction factor defines the wind speed at the rotor \( V_x \) relative to the upstream wind speed \( V \) and the tangential induction factor defines the ratio between the angular velocity imparted to the air flow after passing through the rotor and the rotational speed of the rotor [44]. The relative wind on the cross-section induces lift and drag forces that can be decomposed into components in the fore-aft \( (F_x) \) and side-to-side \( (F_y) \) directions. The figure also defines the chord length \( c \) and several angles including the angle of attack \( \alpha \), the pitch angle \( \beta_0 \), and the angle of the relative wind \( \phi \).

Figure 3-1. Schematic representation, indicating coordinate axes and variables for (a) a HAWT in elevation view, (b) a HAWT rotor in elevation view and (c) blade cross-section.
For the derivation presented in this Chapter, the rotor blades are modeled as rigid and the mass of the rotor nacelle assembly and the equivalent modal mass of the tower are modeled as an equivalent mass $m$ concentrated at the turbine hub. The tower is modeled as a cantilever beam with lateral stiffness $k$ in x and y directions. Rotational degrees of freedom are not considered. The equations of motion for the fore-aft (x) and side-to-side (y) directions are provided below,

$$m\ddot{x} + c_{ST}\dot{x} + k_x x = dF_x$$  \hspace{1cm} (3-1)

$$m\ddot{y} + c_{ST}\dot{y} + k_y y = dF_y$$  \hspace{1cm} (3-2)

Where $c_{ST}$ is the structural damping coefficient and $dF_x$ and $dF_y$ are incremental changes in aerodynamic forces at the rotor hub induced by lateral motion. Aerodynamic forces are estimated based on Blade Element Momentum (BEM) theory [45].

The total aerodynamic force $F_x$ acting at the hub of the rotor is equal to the aerodynamic force in the x-direction acting at each blade cross-section, integrated over the radial length of each blade and multiplied by the number of blades $N_b$ in the rotor as shown below,

$$F_x = \frac{1}{2} \rho N_b \int [V_{rel}^2 [C_L \cos (\phi) + C_D \sin (\phi)] c(l)] dl$$  \hspace{1cm} (3-3)

where $\rho$ is the density of air, $C_L$ and $C_D$ are the coefficients of lift and drag for the blade, $c$ is the chord length of the blade, and $V_{rel}^2$ is the square of the relative wind defined as,

$$V_{rel}^2 = V_x^2 + (\Omega l)^2(1 + a')^2$$  \hspace{1cm} (3-4)
A rotor with a hub that is moving in the fore-aft direction with velocity \( \dot{x} \) will experience a change in the relative fore-aft wind velocity between the rotor and the air, as shown in Equation (3-5).

\[
dV_x = V_w (1 - a) - \dot{x}
\]  

(3-5)

This change in the relative fore-aft wind velocity induces a change in the fore-aft aerodynamic force on the rotor \( dF_x \). The relationship between \( dF_x \) and \( dV_x \) is provided below,

\[
\frac{dF_x}{dV_x} = \frac{\partial F_x}{\partial V_x} + \frac{\partial F_x}{\partial \phi} \frac{d\phi}{dV_x} 
\]  

(3-6)

where,

\[
\frac{\partial F_x}{\partial V_x} = \rho N_b \int V_x [C_L \cos(\phi) + C_D \sin(\phi)] c(l) dl 
\]  

(3-7)

\[
\frac{\partial F_x}{\partial \phi} = \frac{1}{2} \rho N_b \int [V_w^2 \cos(\phi) + \frac{\partial C_L}{\partial \phi} \sin(\phi) + C_D \cos(\phi) - C_L \sin(\phi)] c(l) \right] \frac{1}{2} \frac{1+a}{V_{rel}} 
\]  

(3-8)

\[
\frac{d\phi}{dV_x} = \frac{\Omega (1+a')}{V_{rel}^2} 
\]  

(3-9)

Note that, because the variables \( \phi \) and \( \alpha \) differ by a constant, the derivatives of \( C_L \) and \( C_D \) with respect to \( \phi \) are equivalent to the derivatives of \( C_L \) and \( C_D \) with respect to \( \alpha \). Equations 3-7 and 3-9 can be substituted into Equation (3-6) and rearranged as in Equation 3-10 below,

\[
dF_x = N_b (A + B)dV_x
\]  

(3-10)

where \( A \) represents the portion of \( dF_x \) generated by the upstream wind \( V_w \), see Equation 3-11, and \( B \) represents the portion generated by \( \Omega \), see Equation 3-12.

\[
A = \rho \int V_w (1 - a) [C_L \cos(\phi) + C_D \sin(\phi)] c(l) dl
\]  

(3-11)
\[ B = \frac{1}{2} \rho \int \Omega l (1 + a') \left[ \left( \frac{\partial C_L}{\partial a} + C_D \right) \cos(\phi) + \left( \frac{\partial C_D}{\partial a} - C_L \right) \sin(\phi) \right] c(l) dl \]  

Equations 3-5 and 3-10 can be substituted into Equation 3-1 and, upon rearranging of terms, the equation of motion is expressed as,

\[ m\ddot{x} + [c_{ST} + N_b(A + B)]\dot{x} + kx = N_b(A + B)V_w(1 - a) \]  

The damping in this equation is composed of two components, the structural damping \( c_{ST} \) and the aerodynamic damping \( c_{AD} \) which is defined in the equation below.

\[ c_{AD} = N_b(A + B) \]  

The aerodynamic damping ratio in the fore-aft direction \( \xi_{AD,x} \) is provided in Equation 3-15 and is a linear combination of two terms, one representing the effects of \( V_w \), Equation 3-11, and the other representing the effects of \( \Omega \), Equation 3-12.

\[ \xi_{AD,x} = \frac{c_{AD}}{2\sqrt{k_m}} = \frac{N_b(A + B)}{2\sqrt{k_m}} \]  

Following the same procedure for side to side direction, the aerodynamic damping ratio in the side-to-side direction \( \xi_{AD,y} \) is provided in Equation 3-16 and is a linear combination of two terms, one representing the effects of \( V_w \) and the other representing the effects of \( \Omega \).

\[ \xi_{AD,y} = \frac{N_b(B' - A')}{4\sqrt{k_m}} \]  

where \( A' \) represents the portion of \( dF_y \) generated by \( V_w \) and \( B' \) represents the portion generated by \( \Omega \).
B' = \rho \int \Omega r (1 + a') [C_L \sin(\phi) - C_D \cos(\phi)] c(l) dr \tag{3-18}

Given the aerodynamic damping in the fore-aft and side-to-side directions of a HAWT, the aerodynamic damping in any direction can be obtained using a transformation matrix. A similar procedure has been proposed by Peterson to obtain aerodynamic damping of a blade in any direction [40].

### 3.4 Numerical example – The 1.5-MW NREL baseline HAWT

The specifications of the 1.5-MW baseline turbine are provided in Table 3-1[46]. This wind turbine is used for calculating the aerodynamic damping of wind turbines. Each blade of the baseline turbine is composed of three segments, each with a different airfoil designation: S818, S825 and S826.

<table>
<thead>
<tr>
<th>Power output</th>
<th>1.5 MW</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hub Height</td>
<td>84 m</td>
</tr>
<tr>
<td>Rotor Diameter</td>
<td>70 m</td>
</tr>
<tr>
<td>Number of Blades</td>
<td>3</td>
</tr>
<tr>
<td>Max Rotational Speed</td>
<td>20 rpm</td>
</tr>
<tr>
<td>Cut in wind speed</td>
<td>5 m/s</td>
</tr>
<tr>
<td>Cut out wind speed</td>
<td>25 m/s</td>
</tr>
<tr>
<td>Nacelle Mass</td>
<td>51 Ton</td>
</tr>
<tr>
<td>Hub Mass</td>
<td>15 Ton</td>
</tr>
<tr>
<td>Tower Mass</td>
<td>123 Ton</td>
</tr>
<tr>
<td>Rotor Mass</td>
<td>12 Ton</td>
</tr>
<tr>
<td>Active Pitch Control</td>
<td>Yes</td>
</tr>
</tbody>
</table>

All three airfoils have nearly the same drag and lift characteristics which are shown in Figure 3-2 for the S818 airfoil. The considered 1.5-MW turbine is a variable speed, variable pitch machine and so the pitch and rotor speed are controlled to optimize power output for any wind speed.
At wind speeds above rated wind speed, the blades pitch increases while the rotor speed is held constant at the maximum speed, 20 rpm, to maintain rated power output. Below the rated wind speed, rotor speed decreases while blade pitch is held constant to maximize power output. For steady state conditions, the dependence of rotor speed and blade pitch on wind speeds between cut-in and cut-out is shown in Figure 3-3.

The current section is divided into two parts, both of which consider the 1.5-MW baseline turbine developed by NREL. In the first part, results from the derivation are compared to those from FAST program for the baseline turbine. The comparison is made under parked and operational conditions. In the second part, the relative importance of terms within the closed-form solution is examined to assess assumptions inherent to previous derivations which have assumed high tip speed ratios and thus have ignored contributions to aerodynamic damping from the wind speed.
Figure 3-3. Values of rotor speed $\Omega$, blade pitch and tip speed ratio (TSR) versus wind speed for operational conditions between cut-in (5 m/s) and cut-out (25 m/s) for the 1.5-MW baseline turbine.

All results presented for operational conditions are based on combinations of wind speed, rotor speed, and blade pitch as specified in Figure 3-3, while all results presented for parked conditions are based on a stationary rotor condition.

### 3.5 Verification of aerodynamic damping with FAST

To evaluate the accuracy of the proposed closed-form solution, a model of the 1.5-MW baseline wind turbine is analyzed with FAST under operational and parked conditions with and without the same simplifying assumptions inherent to the closed-form solution. Estimates from the closed-form solution are compared with results predicted by FAST for aerodynamic damping in the fore-aft and side-to-side directions. The FAST results are predicted at 21 different steady wind speeds, evenly spaced between cut-in and cut-out. The method to calculate aerodynamic damping in FAST starts with a model of the 1.5-MW baseline turbine with no structural damping so that all damping of the displacement response may be attributed to aerodynamic effects. This model is first subjected to a steady wind and then subjected to an impulse acceleration at
the base of the model. Following the impulse, the decay of displacement time history at the hub is recorded in the fore-aft and side-to-side directions and the magnitude of aerodynamic damping in each direction is calculated by applying the logarithmic decrement method in Figure 3-4.

![Figure 3-4. Tower top displacement to impulse load for 1.5 MW baseline HAWT.](image)

Seven FAST analyses, with varying degrees of simplification, are conducted at each wind speed to thoroughly investigate the accuracy of the closed-form solution. The features of each analysis are listed in Table 3-2.

Table 3-2. Features for each of the seven analyses conducted in FAST for comparison with predictions from the closed-form solution for the 1.5-MW baseline HAWT.

<table>
<thead>
<tr>
<th>Analysis Number</th>
<th>Wind Shear</th>
<th>Rotor</th>
<th>Yaw Error</th>
<th>Shaft Tilt</th>
<th>Pre-cone</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>$\alpha = 1/7$</td>
<td>Flexible</td>
<td>0°</td>
<td>-5°</td>
<td>-5°</td>
</tr>
<tr>
<td>2</td>
<td>None</td>
<td>Flexible</td>
<td>0°</td>
<td>0°</td>
<td>0°</td>
</tr>
<tr>
<td>3</td>
<td>$\alpha = 1/7$</td>
<td>Rigid</td>
<td>0°</td>
<td>0°</td>
<td>0°</td>
</tr>
<tr>
<td>4</td>
<td>None</td>
<td>Rigid</td>
<td>5°</td>
<td>0°</td>
<td>0°</td>
</tr>
<tr>
<td>5</td>
<td>None</td>
<td>Rigid</td>
<td>0°</td>
<td>-5°</td>
<td>0°</td>
</tr>
<tr>
<td>6</td>
<td>None</td>
<td>Rigid</td>
<td>0°</td>
<td>0°</td>
<td>-5°</td>
</tr>
<tr>
<td>7</td>
<td>None</td>
<td>Rigid</td>
<td>0°</td>
<td>0°</td>
<td>0°</td>
</tr>
</tbody>
</table>
Wind shear based on power law. The exponent $\alpha = 1/7$ for open terrain (Simiu 2011).

See FAST manual (NWTC 2013) for definition. Negative $5^\circ$ is the prescribed value for the 1.5-MW baseline turbine.

The first analysis is designed to most closely replicate realistic conditions, while the last analysis (#7) is designed to most closely replicate the simplifying assumptions of the closed-form solution. The intermediate analyses are designed to investigate the impact of each simplifying assumption individually. It is important to emphasize that, although analysis #7 is intended to most closely resemble the assumptions of the closed-form solution, there still remain many differences between the formulation of FAST and the closed-form solution. For example, for the fore-aft and side-to-side directions, FAST considers two mode shapes which include the effects of distributed mass and stiffness, whereas the closed-form solution is based on a cantilever beam model with lumped mass at the hub. Perhaps more importantly, the inflow model in FAST is based on the Generalized Dynamic Wake model and considers many features not considered in the closed-form solution, which is based on Blade Element Momentum theory. For example, the inflow model in FAST considers the dynamic wake effect and hub and tip losses.

In Figure 3-5, aerodynamic damping is estimated in the fore-aft direction based on Equation 3-15 and on FAST for the seven analyses specified in Table 3-2. The estimates are provided as a function of wind speed for both parked and operational conditions. Overall, Equation 3-15 gives a reasonable but generally lower estimate of aerodynamic damping compared to all seven FAST analyses.

The agreement between results is strongest for parked conditions and for wind speeds greater than the rated wind speed. For operational conditions, the mean
value of predictions per Equation 3-15 is 4.6% and the range is between 3.7% and 5.4%. As seen in Figure 3-5, for the range of analyses considered, the most influential assumption is that of a rigid rotor which tends to lower the estimates compared to those with a flexible rotor (Analyses #1 and #2).

![Figure 3-5. Aerodynamic damping in the fore-aft direction during parked and operational conditions for the 1.5-MW baseline HAWT.](image)

On average, the aerodynamic damping predictions from Analysis #1, the most realistic of the considered simulations, are 0.6% higher than those from Equation 3-15 for operational conditions and nearly identical for parked conditions. Comparing the results from Equation 3-15 with those from Analysis #7, which is designed to most closely replicate the simplifying assumptions of Equation 3-15, shows that predictions based on Equation 3-15 are, on average, 0.7% lower for operational wind speeds between cut-in and rated and 0.1% lower for operational wind speeds between rated and cut-out. For wind speeds between cut-in and rated, the FAST predictions including pre-cone and wind shear are shown to have similar effects with predictions averaging 0.7% higher than Equation 3-15.
The assumption of a steady wind (i.e. no turbulence) is another important simplification of the closed-form solution. To assess the impact of this simplification, Analysis #1 was repeated fifteen times with a turbulent wind history and a mean wind speed equal to the rated wind speed. The turbulent history is calculated based on the Normal Turbulence Model with a turbulence intensity of 0.15. For this particular case, the aerodynamic damping in the fore-aft direction was estimated as 5.7% for steady conditions and, for turbulent conditions, the mean and standard deviation of the fifteen simulations are 6.0% and 2.1%, respectively. It is further noted that, in an average sense, the plots of the displacement response at the hub following the application of the impulse load for the steady and turbulent conditions are nearly identical, except that the response for the turbulent conditions contains some small-amplitude, high-frequency oscillations.

Analysis with aerodynamic damping in side to side direction shows that for all conditions considered, the aerodynamic damping predicted by both FAST and Equation 3-16 never exceeds 0.5%. For operational conditions, the mean value of aerodynamic damping per Equation 3-16 is 0.1% and the range is between ~0.0% and 0.3%.

3.6 Simplification of closed-form solution

The derivation presented in this Chapter does not assume that wind speed is negligible compared to rotor tip speed, and the result is that the predicted aerodynamic damping depends on two components, the first, presented in Equation 3-11 and labeled component A, depends on the wind speed, and the second, presented in Equation 3-12 and labeled component B, depends on the
rotor speed. Figure 3-6 shows predictions of aerodynamic damping in the fore-aft direction for the baseline turbine under parked and operational conditions.

The figure shows that the component of the total aerodynamic damping that is attributed to the wind speed (A component) increases nearly linearly with increasing wind speed. At cut-in, 6.7% of the total damping is due to this term, while at cut-out, the proportion increases to 41%. The figure also includes a plot indicating the proportion of the rotor speed component of damping (B component) that is attributed to the derivative of the lift coefficient with respect to the angle of attack. This plot shows that the B component of damping is completely dominated by contributions from the lift coefficient derivative. The implication is that, for the considered turbine, predictions of aerodynamic damping will remain virtually unchanged in Equation 3-12 is simplified to,

\[
B = \frac{1}{2} \rho \int \Omega l (1 + a') \frac{\partial C_L}{\partial \alpha} \cos(\phi) c(l) dl
\]  

(3-19)
The simplification of term B in Equation 3-12 makes the proposed equations more practical in estimating aerodynamic damping and apply to dynamic analysis of wind turbines with advanced finite element programs.

3.7 Summary

The aerodynamic damping of an operational HAWT responding dynamically in the fore-aft and side-to-side directions is derived in closed-form based on Blade Element Momentum theory. The estimated results from the derivation are compared with those from FAST for the 1.5-MW baseline HAWT under parked and operational conditions and the comparison shows reasonable agreement. Under operational conditions and for the same turbine, the derivative of the lift coefficient of the blades with respect to the angle of the attack is shown to contribute most to aerodynamic damping, however, the contribution lessens as wind speeds approach the cut-out wind speed.

The aerodynamic damping in the fore-aft direction for the 1.5-MW turbine is estimated by the closed-form solution to be between 0.0% and 0.6% for parked conditions and between 3.7% and 5.4% under operational conditions. For the side-to-side direction, the estimates are ~0.0% for parked conditions and between ~0.0% and 0.3% for operational conditions. An analysis of the impact of the simplifying assumptions inherent to the derivation shows that the most influential assumption is that of a rigid rotor and that this assumption can reduce predictions of aerodynamic damping for operational conditions in the fore-aft direction by an average of ~1.0%. 
4 MULTIVARIATE EXTREME VALUE ANALYSIS

The material presented here is published as the following paper:


4.1 Introduction

It is known that any structure is subjected to various external loads. In buildings, the external loads, such as earthquake and wind, due to different events are considered independent; however for wind turbines in offshore environment, the wind turbine is subjected to several correlated hazards such as wind load, storm surge and wave height which can be defined based on significant wave height and peak spectral period. Two of most important hazards are wind and wave hazards. Three parameters define the wind and wave hazards, wind speed (V), significant wave height (Hs) and peak spectral period (Tp). For reliability analysis of OWTs appropriate combination of wind and wave hazard is necessary.

Wind speed (V) is hourly mean wind speed at 10 m reference height. Significant wave height (Hs) is the area under the wave spectrum curve, which represents four times of standard deviation of wave elevation (or the average of the highest 1/3 of the waves) and Peak Spectral Period (Tp) represents the frequency at which the power in the wave elevation is the greatest.

In this Chapter, two methods to estimate the 50-year extreme values of V, Hs and Tp are discussed. The first, termed herein as “1D Exceedance,” is a univariate method, commonly used in practice, wherein 50-year values of V and Hs are
calculated independently and a range of $T_P$ is deterministically conditioned on the 50-year $H_s$. The second method is multivariate analysis approach, considers the long term joint probability distribution of $V$, $H_s$ and $T_P$, and is referred to herein as 3D Inverse First Order Reliability method or “3D IFORM” [35]. IFORM is a general method for extrapolation of metocean parameters and is usually applied to joint distributions of two random variables. The result is an “environmental contour,” which defines, in a sense, combinations of the two random variables that have a particular return period. In this Chapter, IFORM is applied to three jointly distributed random variables resulting in an “environmental surface” which provides, in a sense, combinations of three random variables which have a particular return period, IFORM has been applied in three dimensional form by other researchers [47] who have used this method to generate an environmental surface of wind speed, turbulence intensity and bending moments for calculating the design moment at the root of a wind turbine blade. In that case of 3D IFORM, which is based on plentiful 10 min measurements of the joint data, the joint distribution of the three random variables can be expressed through a series of conditional distributions which can be estimated directly from the measured data. The application of 3D IFORM presented here is novel since it is based on sparse sets of extreme value data and therefore requires an approximation of the joint distribution, which, in this case, is approximated using the Nataf model.

As an example, results for both methods at three investigated sites are presented. For each of the three sites, both methods are compared by searching all combinations of $V$, $H_s$ and $T_P$ that are associated with a 50-year recurrence period to find the critical combination, defined as the combination resulting in the maximum structural effect.
4.2 Research review

The extreme hazards for OWTs are defined as the 50-year magnitudes of two metocean parameters: the V and the H_s. There are different approaches to obtain the long term structural response. The “structure variable” method identifies, prior to analysis, that function of the observed variables which best represents the loading on the specific structure of interest. Multivariate observations are then converted to univariate loadings, and univariate extreme value theory used to estimate the probabilities, or equivalently the return periods, associated with extreme events [48,49]. One major shortcoming of structural variable approach is that the load (e.g. bending moment at mudline of OWT) must be completely identified before statistical analysis. This approach will be very difficult and time consuming for complex structure, since every single combination of hazard needs to be analyzed to obtain the load on the structure. This issue causes significant difficulties for design and analysis. The alternative approach, is to use multivariate extreme value theory to estimate directly (the extremes of) the joint distribution of the variables of interest. One method to approximate the combination of wind and wave for different mean return periods is through Inverse First Order Reliability Method, or “IFORM”. IFORM, proposed by Winterstein in 1993 [35] is a general method for extrapolation of metocean parameters and is usually applied to joint distributions of two random variables. The result is an “environmental contour,” which defines, in a sense, combinations of the two random variables that have a particular recurrence period. In this study, IFORM is applied to three jointly distributed random variables resulting in an “environmental surface” which provides, in a sense, combinations of three random variables with particular recurrence period. IFORM has been applied in 3D by other researchers [47] who have used this
method to generate an environmental surface of wind speed, turbulence intensity and bending moments for calculating the design moment at the root of a wind turbine blade. In that case of 3D IFORM, which is based on plentiful 10 min measurements of the joint data, the joint distribution of the three random variables can be expressed through a series of conditional distributions which can be estimated directly from the measured data. However, their approach is only appropriate when sufficient data is available, therefore their approach is not suitable for extreme events with insufficient data.

4.3 Methodology
This section describes the method that was employed to identify extreme events from the wind and wave measurements obtained from NOAA buoys. Two methods, 1D Exceedance and 3D IFORM, to generate 50-year combinations of $V$, $H_s$ and $T_p$ are explained.

4.3.1 Identification of extreme events and extreme values
Extreme value analysis of metocean parameters requires identification of extreme events (i.e. storms) from either a hindcast or environmental conditions. Each event then provides a set of extreme values, in this case, values of $V$, $H_s$ and $T_p$, which are used to define the joint probability characteristics of the extreme values. R-Largest Order Statistics is applied with an R of 7, meaning that 7 extreme events are considered per year [50,51]. Specifically, the method employed here for identifying extreme events starts by finding the 7 largest measurements of the $V$ during each year of measurement. The wind speed is chosen here to identify intensity of storms because not only this parameter has been used previously and well known as the intensity of storms but also, storm wave height is dependent on wind intensity, i.e. in general higher wind causes
higher wave. The 7 measurements of V from each year are ensured to be from independent events by requiring that each measurement be spaced more than 72 hours apart. Next, the maximum Hs occurring within +/- 36 hours of each of the 7 largest wind measurements and the Tp occurring simultaneously with the Hs are paired with the V measurement. These seven triplets of V, Hs and Tp determine the coupled extreme values for the 7 extreme events per year. The process is then repeated for each year of available measurements, resulting in a set of 7 times the number of years of data of V, Hs and Tp coupled values.

4.3.2 Calculation of 50-year extreme environmental conditions

In this section, two methods are described for using measurements of extreme values of V, Hs and Tp to calculate combinations of these values that have a particular recurrence period. The first method is based on univariate or 1D distributions of the extreme value data and the second method is based on a multivariate or joint (in this case, 3D) distribution of the extreme value data.

• Univariate – 1D Exceedance

In this approach which is commonly used in practice, V and Hs are calculated independently, with GEV distribution function, Equation 2-9, 2-10 and a range of Tp is deterministically conditioned on Hs according to Equation 4-1.

\[
11.7 \sqrt{\frac{H_s}{g}} \leq T_p \leq 17.2 \sqrt{\frac{H_s}{g}}
\]  

(4-1)

where \(\mu\) is the location parameter, \(\sigma\) is the scale parameter \(\xi\) is the shape parameter. The three GEV parameters are selected to best-fit the data using a maximum likelihood approach [31].
Thus, this method results in scalar 50-year values for $H_s$ and $V$ and a corresponding range of $T_p$ defined by Equation 4-1.

- **Multivariate – 3D IFORM**

In contrast to previous section, the method described here considers the joint distributions of extreme values of $V$, $H_s$, and $T_p$. Because extreme value data is characteristically sparse, it is unlikely that sufficient data will exist to directly calculate the joint distribution of the data using approaches such as those recommended by the IEC standard. Rather, the joint distribution should be estimated approximately. One model for creating a joint distribution of multiple random variables is the Nataf model [34,32], which approximates the joint distribution of variables by matching their distributions and covariance [52].

After calculation of an approximate joint distribution of $V$, $H_s$, and $T_p$, the next step is to associate combinations of these variables with a mean return period. One method for associating return periods with joint random variables is the inverse first order reliability method, or IFORM [35], which is also described for two random variables in Annex G of the IEC standard. The environmental surface is calculated by transforming spherical surfaces with a constant radius $\beta$ in uncorrelated standard normal space to the physical joint random variable space using methods such as the Rosenblatt transformation [37]. The recurrence period ($N$) associated with each surface is calculated as,

$$N.R = \frac{1}{1-\Phi(\beta)}$$  \hspace{1cm} (4-2)

Where $\beta$ is the radius of the sphere in standard uncorrelated normal space from which the surface in physical space transformed. For $N = 50$ and $R=7$, $\beta = 2.76$. More details are available in Annex G of the IEC standard.
4.4 Site selection for numerical example

The investigated sites are selected based on a combination of geographic features and the availability of environmental data. Specifically regarding geographic criteria, sites have been selected along the Atlantic Coast of the US with added attention being given to the mid-Atlantic and Northeastern coasts where the wind resource is rich and where many current proposed sites for offshore wind farms in the US are located. Regarding data availability, sites have been selected to correspond to the location of environmental data buoys deployed and maintained by National Oceanic and Atmospheric Administration (NOAA) that have at least 20 years of data available. Given these considerations, three sites have been selected that lie off the coasts of the states of Maine, Delaware, and Georgia. In the remainder of this study the sites are identified by their two letter postal abbreviation codes ME, DE, and GA.

Table 4-1 gives the general characteristics of the sites including their latitude and longitude, distance from shore, water depth, NOAA site identifier, abbreviation and the duration of measurements. The sites have water depths ranging from 20 m to 30 m which covers the range of moderate depths for which monopile support structures are expected to be suitable. With the exception of the ME site, the locations are about 30 km offshore, with the closer ME site being reflective of the steeper bathymetry of ME compared with the remainder of the Atlantic coast.

Table 4-1. Site characteristics for structural analysis of 5 MW OWT

<table>
<thead>
<tr>
<th>Site</th>
<th>Postal Abbrev</th>
<th>NOAA ID</th>
<th>Lat</th>
<th>Long</th>
<th>Water Depth (m)</th>
<th>Dist. to Shore (km)</th>
<th>Duration (Years)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Maine</td>
<td>ME</td>
<td>44007</td>
<td>43.53° N</td>
<td>70.14° W</td>
<td>24</td>
<td>5.60</td>
<td>31</td>
</tr>
<tr>
<td>Delaware</td>
<td>DE</td>
<td>44009</td>
<td>38.46° N</td>
<td>74.70° W</td>
<td>30</td>
<td>30.3</td>
<td>27</td>
</tr>
<tr>
<td>Georgia</td>
<td>GA</td>
<td>41008</td>
<td>31.40° N</td>
<td>80.87° W</td>
<td>20</td>
<td>32.3</td>
<td>20</td>
</tr>
</tbody>
</table>
The measured data consists of the \( V \) measured at 5 m above sea level, the \( H_s \) and \( T_p \). Wind speed measurements reflect the 8 minute average wind speed and are reported hourly. The significant wave heights are determined based on a 20 minute time interval and are also reported hourly. Before applying the wind data to OWT design, corrections must be made to account for the higher elevation of the rotor hub and the different averaging periods [53].

### 4.5 Numerical examples

In this section, the methods described in the previous section are applied to each of the three NOAA buoy locations and the results are summarized. First, statistics of the measured data are provided for each of the three sites. Table 4-2 lists the best-fitting GEV distribution parameters and the correlation coefficients for \( V \), \( H_s \) and \( T_p \) at each of the three stations. For all sites, the largest correlation coefficient is between \( H_s \) and \( T_p \) (0.68 for ME, 0.80 for DE and 0.65 for GA), the second largest correlation coefficient is between \( H_s \) and \( V \) (0.29 for ME, 0.43 for DE and 0.54 for GA) and the smallest correlation coefficient is between \( V \) and \( T_p \) (0.22 for ME, 0.36 for DE and 0.27 for GA). Figure 4-1 shows projections of the joint distributions approximated by the Nataf model for all investigated sites.

<table>
<thead>
<tr>
<th>Stations</th>
<th>( \xi )</th>
<th>( \sigma )</th>
<th>( \mu )</th>
<th>Correlation Coefficient</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>( V )</td>
</tr>
<tr>
<td>ME</td>
<td>0.09</td>
<td>1.50</td>
<td>16.2</td>
<td>1.00</td>
</tr>
<tr>
<td></td>
<td>-0.13</td>
<td>1.45</td>
<td>3.23</td>
<td>1.00</td>
</tr>
<tr>
<td></td>
<td>-0.29</td>
<td>2.05</td>
<td>8.39</td>
<td>1.00</td>
</tr>
<tr>
<td>DE</td>
<td>0.01</td>
<td>1.41</td>
<td>16.7</td>
<td>1.00</td>
</tr>
<tr>
<td></td>
<td>0.10</td>
<td>0.95</td>
<td>2.99</td>
<td>1.00</td>
</tr>
<tr>
<td></td>
<td>0.21</td>
<td>1.34</td>
<td>6.91</td>
<td>1.00</td>
</tr>
<tr>
<td>GA</td>
<td>0.03</td>
<td>1.31</td>
<td>14.8</td>
<td>1.00</td>
</tr>
<tr>
<td></td>
<td>-0.13</td>
<td>0.74</td>
<td>2.29</td>
<td>1.00</td>
</tr>
<tr>
<td></td>
<td>0.04</td>
<td>1.29</td>
<td>5.89</td>
<td></td>
</tr>
</tbody>
</table>

Table 4-2. Best-fitting GEV marginal distribution parameters and correlation coefficients for \( V \), \( H_s \) and \( T_p \) at the three NOAA buoys.
Figure 4-1. Projections of the 3D joint distributions of $V$, $H_s$ and $T_p$ based on the Nataf model for Maine NOAA site, a)ME, b)DE, c)GA

Figure 4-2 shows 50-year recurrence combinations of $V$, $H_s$ and $T_p$ based on the 1D Exceedance and 3D IFORM methods. The combinations are projected onto $H_s$-$V$ space. In this space, the 50-year combinations from 1D Exceedance are
The 50-year environmental surfaces from 3D IFORM are represented as $H_s$-$V$ contours with constant $T_p$. Several critical points are indicated on these contours including the maximum and minimum $T_p$, the maximum $V$ and the maximum $H_s$. Both the location and shape of the projections of the environmental surfaces vary significantly from site to site, as expected based on the variability observed in the joint distributions presented in Figure 4-1. As seen in the figure, the projection of the 50-year environmental surface is required to be circumscribed by a rectangle defined by $V$ and $H_s$, and the point defined by $V$ and $H_s$ is required to be contained within an environmental surface that has a longer mean return period than 50 years. In general, the range of $T_p$ included on the environmental surface is much larger than the range provided in Equation 4-1.
Figure 4-2. 50-year recurrence combinations of $V$, $H_s$ and $T_p$ based on 1D Exceedance, indicated with a black circle and text defining the $T_p$ range, and 3D IFORM, indicated with contours of constant $T_p$, for a) ME, b) DE and c) GA.

To evaluate the effect of multivariate extreme value analysis, the 50-year mudline moment is estimated for each site, for yaw positions of 0° and 8°, and for the environmental conditions defined by the 1D Exceedance Method and the 3D IFORM method. In this study, the structural effect considered is the mudline
base moment which is estimated by analyzing a structural model of the 5 MW National Renewable Energy Laboratory (NREL) reference OWT supported by a monopile foundation.

The reference wind turbine, used in this study, is 5MW NREL offshore turbine, supported by a monopile foundation [54]. Key specifications of the 5 MW NREL reference OWT are provided in Table 4-3. The height of the monopile is set equal to the water depth at each of the three NOAA buoy locations. The first period of the structure is 3.7 s, 3.9 s and 3.6 s for ME, DE and GA, respectively.

<table>
<thead>
<tr>
<th>Table 4-3. Properties of 5MW NREL OWT.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rotor Orientation, Control</td>
</tr>
<tr>
<td>Rotor, Hub Diameter</td>
</tr>
<tr>
<td>Hub Height (relative to MSL)</td>
</tr>
<tr>
<td>Monopile Diameter, Thickness</td>
</tr>
<tr>
<td>Cut in, Rated, Cut out Wind</td>
</tr>
<tr>
<td>Rotor, Nacelle, Tower Mass</td>
</tr>
<tr>
<td></td>
</tr>
</tbody>
</table>

The structural analyses of both wind turbines in this analysis are conducted by FAST program to calculate mudline moments for specific combinations of $V$, $H_s$ and $T_p$. FAST is an open source program developed by NREL for the analysis of onshore and OWTs. For analyses in extreme hazard condition, the turbine is modeled in a parked condition (i.e. the rotor is stationary and blades are feathered) as is prescribed by the IEC standard for extreme conditions. The details of the turbulent wind model and irregular sea surface profile are provided in Section 2.2. For this structural analysis, the Turbsim program is, assuming a Kaimal spectrum and a turbulence intensity of 0.15. The irregular sea surface is generated based on a JONSWAP spectrum (see Section 6.1, for more details). The variance of the JONSWAP spectrum is determined by the significant wave height, which is defined as four times the standard deviation of
the sea surface elevation. The significant wave height is taken from the buoy measurements, but the turbulence intensity and spectral characteristics of the wind are taken from the IEC standard.

For the 1D Exceedance Method, a structural analysis is conducted for wind and wave times series defined by $V_{50}$, $H_{s,50}$ and the associated range of $T_p$ specified by Equation 4-1. In all cases the mudline moments are, on average, the highest for the lower bound of the period range which is closest to the first period of the structure for each location, thus the critical point for the 1D Exceedance Method is $V_{50}$, $H_{s,50}$ and $T_{p,\text{lower bound}}$. For the 3D IFORM method, a structural analysis is conducted for all combinations of $V$, $H_s$ and $T_p$ defined by the environmental surfaces provided in Figure 4-2. The combination of $V$, $H_s$ and $T_p$ resulting in the highest mudline moment is termed the critical point on the environmental surface. Searching the entire environmental surface for the critical point can computationally expensive, however, in this case, only a portion of the surface needs to be considered when determining the critical point because it is obvious that mudline moments will be higher, on average, for higher values of $V$ and $H_s$ and for peak spectral periods closer to the first structural period, which in this case means a lower $T_p$. Specifically, the search for the critical point can be reduced by first defining a plane that passes through the points on the environmental surface corresponding to the maximum wave height, maximum $V$ and minimum $T_p$, and then limiting the search for the critical point to the portion environmental surface on the side of the plane with more severe conditions (in this case, higher wind, higher wave and lower $T_p$).

Table 4-4 provides the values of $V$, $H_s$ and $T_p$ for the critical point for each site and yaw position and both methods.
<table>
<thead>
<tr>
<th>Station</th>
<th>Critical Point – 1D</th>
<th>Critical Point – 3D IFORM</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$V_{50}$ (m/s)</td>
<td>$H_{s,50}$ (m)</td>
</tr>
<tr>
<td>ME</td>
<td>25.7</td>
<td>10.5</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>DE</td>
<td>23.0</td>
<td>9.2</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>GA</td>
<td>23.1</td>
<td>5.3</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Regarding Table 4-4, several interesting observations can be made. First, for all three sites, the critical point on the environmental surface does not correspond to the point with the maximum $V$ or $H_s$. This is because the $T_p$ plays an important role in determining the location of the critical point. The influence of the $T_p$ can be seen clearly for site GA, Yaw = 0°, where the critical point is located at a $T_p$ close to the first period of the structure, even though this point corresponds to relatively small wind speeds and significant wave heights. Second, a yaw position of 8° increases the contribution of loading due to wind compared to a yaw position of 0°. This can be seen by comparing the critical point between the two yaw positions and noting that, for all sites, the critical point shifts to a higher $V$ for a yaw position of 8°. Specifically, for site GA, the critical point shifts from a $V$ close to the minimum value on the environmental surface to a $V$ close to the maximum value on the surface. For the DE and ME sites, which have larger water depths than the GA site, the loading due to waves is dominant. This can be seen by noting that the critical point moves minimally between the 0° and 8° yaw positions and noting that the wave height of the critical point is close to $H_{s,50}$. In general, the critical point moves toward the extreme of the parameter with the strongest influence on the structural response. Third, for every case except for the
ME site and an 8° yaw position, the $T_p$ of the critical point based on 3D IFORM is lower than the lower bound $T_p$ considered in 1D exceedance. For both yaw positions and the ME and DE sites, the difference between these $T_p$ s is less than 12%, however, for the GA site and a 0° yaw position, the $T_p$ of the critical point from 3D IFORM is more than 50% lower than the lower bound.

The average maximum mudline moment for the critical point based on 1D Exceedance and 3D IFORM is presented in Figure 4-3 for the three sites and two yaw positions. For the ME and DE sites, the 1D Exceedance method results in a higher moment (7 to 12% higher) than 3D IFORM for both yaw positions. However, for the GA site, the 3D IFORM method results in a higher moment (0.4 to 8% higher), even though 1D Exceedance considers a more severe combination of $V$ and $H_s$ than any of the combinations on the environmental surface. For the ME and DE sites, as shown in Table 4-4, the critical point on the environmental surface has a $T_p$ that is much closer to the lower bound of the range considered in 1D Exceedance. So, at these sites, the more severe combination of $V$ and $H_s$ inherent to 1D Exceedance increases mudline moments by more than the lower peak spectral periods possible with 3D IFORM. However, for the GA site, the $T_p$ for 3D IFORM is much lower than the lower bound of the range considered in 1D Exceedance, and so, in this case, the lower peak spectral periods possible with 3D IFORM increase mudline moment by more than the more severe combination of $V$ and $H_s$ inherent to 1D Exceedance. This result is completely conditioned on the simple method applied in this study for estimating the range of $T_p$ for the 1D Exceedance method. Certainly, a more rigorous method could result in a more appropriate range which would avoid the non-conservative behavior shown here. Nevertheless, if a method similar to 1D Exceedance is used, the result emphasizes the importance of appropriate consideration of the $T_p$ range.
Figure 4-3. Average of the six maximum mudline bending moments from six one hour simulations of turbulent winds coupled with a linear irregular waves defined by the critical point determined by either 3D IFORM (blue) or 1D Exceedance (red) with numerical percentage values indicating the difference between the average moments calculated with each method.
5 PROBABILISTIC HURRICANE HAZARD ANALYSIS

The material presented here is under review with the Journal of Coastal Engineering:


5.1 Introduction

It is well-known that the hurricane effect in the east coast of the US is an important hazard which needs to be considered in the design of structures in hurricane prone regions. Building design standards and hurricane wind speed maps provide an important comparison for inland structures. For example, ASCE 7-10 [10] provides the basic wind speed map for hurricane regions. This map is defined for different categories of building occupancies. The hurricane wind speed for the design of buildings has been recently updated and is based on a Monte Carlo simulation model which has been used by Vickery [79, 80, 88]. The updated data used in the simulation is an improved version of the hurricane wind field which includes the model for sea-land transition effect and hurricane boundary layer and hurricane weakening after landfall. Also, consideration of the Holland B parameter has also been improved. This new hurricane hazard model resulted in lower wind speeds than in ASCE 7-05, however the overall rate of intense storms is larger compared to previous version of ASCE 7.

Although standards are available to provide wind speed for design of buildings, they don’t provide any information about offshore conditions during a
hurricane. Also, all wind speed maps are only valid for inland structures and no offshore wind speed is provided according to standards.

The method of probabilistic seismic hazard analysis (PSHA) has evolved significantly over the past several decades since its inception with Cornell’s seminal paper in 1968 [55]. An integral component of PSHA is the ground motion prediction equation (GMPE, formerly referred to as an attenuation relationship) which predicts ground motion shaking intensity (e.g. peak ground acceleration or spectral acceleration) and its uncertainty as a function of earthquake characteristics (e.g. magnitude, site-to-source distance). GMPEs were first proposed in 1964 [56], but have evolved many times since then (e.g. [57,58,59,60,61,62]). In contrast, probabilistic offshore hurricane hazard analysis (POHHA) and its onshore counterpart are more recent endeavors of engineering research, and, overall, receiving less research attention than PSHA.

Traditionally, POHHA has considered realizations of hurricane recurrence probabilistically using a stochastic catalog of synthetic hurricanes [63] to augment the ~150 year long record of Atlantic hurricane activity and provide tens of thousands or probabilistic realizations of one year of potential hurricane activity. Risk assessments usually include the estimation of hazard intensity measures, such as sustained V and Hs, for various realizations of hurricanes. In most cases, these relationships have been modeled deterministically [64,65,66], however, for onshore applications, there have been exceptions, notably [67,68] who considered uncertainty in the relationship between hurricane realizations and sustained wind speed. Furthermore, for offshore applications, no researchers have considered uncertainty in the relationship between hurricane realizations and wind or wave. Such relationships are termed here as wind and wave prediction equations (WWPEs) and are a direct analog to GMPEs. In summary,
the literature has produced no systematic approach to account for uncertainties related to offshore $V$ or wave height. For these reasons, it is helpful to consider POHHA in light of the extensive earthquake engineering literature on PSHA.

This Chapter reviews basic concepts of PSHA and then discusses similarities and differences between PSHA and POHHA with particular emphasis on the comparison between GMPEs and WWPEs. Following this comparison, the chapter details the collection of wind and wave measurements for buoys during historical hurricanes and lists the specifications of these hurricanes. Next, the chapter introduces two parametric models that form the basis of the WWPEs and compares their results to measured data. The two parametric models are the Holland model to estimate sustained hurricane winds [64] and Young’s model to estimate the $H_s$ during hurricanes [66]. The chapter then formulates the WWPEs after assessing model biases and quantifying uncertainty. The chapter concludes by demonstrating the application of WWPEs through numerical examples at three sites off the coasts of Maine, Delaware and Georgia. The examples are based on a 100,000 year stochastic catalog of synthetic hurricanes, the development of which is outlined by Liu [69]. At each of the three sites, sustained wind speeds and significant wave heights are calculated for several MRPs to assess the significant of including uncertainty in the WWPEs.

5.2 Formulation of POHHA

The idea of POHHA originated in response to Probabilistic Seismic Hazard Analysis (PSHA), which was first proposed by Allin Cornell in the 1960s [70,55]. Cornell proposed the idea that aggregate seismic hazard can be estimated by summing hazards from multiple contributing sources. Cornell focused primarily on the aleatoric uncertainty (randomness) of ground motions; however the
The discussion has expanded since then to include the epistemic uncertainty, which considers modeling uncertainties related to the ground motion prediction equations themselves. The objective of a PSHA is to estimate a probability distribution in either scalar or vector form for ground motion intensities at a particular site. Based on this distribution, probabilities of exceedance and mean return periods can be calculated for particular values of the ground motion intensity [71]. The formulation of PSHA is shown generically here as,

\[ F_X(x) = \int F_{X|\bar{Y}}(x|\bar{y})f_{\bar{Y}}(\bar{y}) \, d\bar{y} \quad (5-1) \]

Where \( F_{X|\bar{Y}}(x|\bar{y}) \) is the conditional cumulative probability distribution function for random vector \( X = x \) conditioned on random vector \( \bar{Y} = \bar{y} \), \( f_{\bar{Y}}(\bar{y}) \) is the probability density function of \( \bar{Y} \), \( X \) is a variable characterizing ground motion intensity (e.g. spectral acceleration at a particular period), \( \bar{Y} \) represents a vector of parameters characterizing an earthquake event (e.g. the magnitude of earthquake, the source to site distance, and other parameters defining rupture characteristics and soil conditions) and \( F_X(x) \) is the CDF of random variable \( X \).

The GMPE is represented in Equation 5-1 as \( F_{X|\bar{Y}}(x|\bar{y}) \), and the focus of this chapter is the development of WWPEs, which are the corresponding equations for POHHA. The WWPEs probabilistically estimate sustained wind speeds, \( H_s \) and their uncertainty as a function of hurricane parameters.

Page and Boore in 1972 [57] first used records from 6 earthquakes to estimate ground motion accelerations and velocities for earthquakes with different magnitudes. Since then, GMPEs have been consistently updated to include an ever widening earthquake database and with additional parameters such as soil conditions and fault mechanisms [58-62]. In most instances, PSHA measures the intensity of the ground shaking with a scalar variable such as spectral
acceleration, however, in 2002; the PSHA framework was expanded to include vector measures of ground shaking intensity. In 2005, Baker [72] suggested a multivariate measure of ground motion intensity by defining a second intensity measure, epsilon, which was defined as the maximum difference between the spectral acceleration of an individual record and the mean spectral acceleration of a ground motion prediction equation at a particular period. Vector-valued probabilistic hazard analysis is important when multiple intensity measures are used to estimate damage and when those measures are not perfectly correlated. This is the case for POHHA because damage to offshore structures depends on both wind and waves intensities.

For POHHA, the parameters characterizing a hurricane event are typically hurricane eye location, central pressure, maximum wind speed, radius of maximum wind speed, hurricane translation speed and hurricane translation angle. Since the location and characteristics of a hurricane are not stationary in time, probabilistic distributions of hurricane parameters are not usually modeled explicitly as in common in PSHA, but rather realizations of hurricane parameters are considered through a stochastic catalog of synthetic hurricane events which characterizes these parameters at regular intervals over the duration of the hurricane. The stochastic catalog is, in effect, a discrete set of realizations of hurricane events that is calibrated to be consistent with the historical record and physical understanding of hurricanes. The objective of POHHA is to estimate a probability distribution of wind and wave intensities at a particular site. While, the wind and wave intensities and their uncertainty are correlated, here, for simplification, the distribution of intensities resulting from a POHHA are modeled as independent, and, specifically in this chapter, the wind intensity is represented with the variable $V$, the 1-minute sustained wind speed at an
elevation of 10 m, and the wave intensity is represented with the variable $H_s$. Schematically, the POHHA procedure is illustrated in Figure 5-1. The WWPEs are represented in Figure 5-1b.

Figure 5-1. Schematic illustrating probabilistic offshore hurricane hazard analysis.

The stochastic catalog approach originated in 1971 by Russell [73], since then several researchers improved the technique to simulate synthetic hurricanes for the Atlantic basin [74,75,76,77,67]. In most cases, the motivation of these studies was to calculate wind speeds along the US Atlantic coast at a mean return period appropriate for building design. In these studies, the statistical distributions and correlations of hurricane parameters (e.g. $R_{max}$, Central pressure) are assigned on a site-specific basis. Hurricane parameter realizations are considered through a
Monte Carlo approach and for each realization a wind speed is estimated with parametric wind field models; however none of these studies validated the accuracy of the wind field model with measurements. In 1985, Georgiou was the first to use a numerical model of the hurricane wind field assessment when he used the Holland model at gradient height. In his studies, he constrained $B$ to be 1 [87]. Then, in 2000, Vickery et al [78] used hurricane wind field model from Georgiou (1985) but not constraining $B$ to the unity. They performed validation analysis and extended the comparison of wind speed to examine both the mean and gust wind speeds, comparing model predictions with measurements from 16 offshore and 35 onshore sites, and found that the model provides an accurate representation of the hurricane wind field with error with standard deviation between 4.25% to 11.23% for $|r/R_{max}| \leq 2$ and standard deviation of 1.08% for $2 \leq |r/R_{max}| \leq 4$. This level of accuracy was considered sufficient and uncertainties in in the wind field model were not considered explicitly in the estimation of long return period wind speeds in this study. Research interest in evaluating the uncertainty in the wind field models for hurricanes has increased more recently. In 2009, Vickery et al [79,80] considered the uncertainty in both realizations of hurricane parameters and the wind field model. Based on a comparison with measurements which is 245 comparisons in total (165 land-based and 80 marine-based measurements), the study found that uncertainty in the Holland model could be characterized with an additive, normally distributed error term with zero mean and a standard deviation of 10%. Their study also included correlated uncertainty in the distributions of hurricane parameters and the wind field uncertainty was modeled as being independent of the hurricane parameter uncertainty. The study found that consideration of both hurricane parameter and wind field uncertainty resulted in a coefficient of variation in the 100-year mean return period wind speed of 6% in the Gulf of Mexico and 15% off
the coast of Maine. In 2010, Jayaram [81] considered two hurricanes (Hurricanes Jeanne and Frances, both in 2004) and quantified the uncertainty in the Batt’s wind field model [67] by comparing model predictions with onshore wind speed reanalyses from the H*Wind database. In this work, a linear bias was identified wherein the Batt’s model tended to overestimate the values reported by H*Wind for locations near the hurricane track and underestimate the values for locations far from the hurricane track. After correcting for this bias, Jayaram found that the uncertainty in the wind speed predictions could be modeled with normally distributed random variable with 0 mean and standard deviation of 15% representing the difference between the logarithm of predicted and observed values. This research has made important advances in the understanding of the uncertainty in parametric models to predict onshore winds during hurricanes, however, there has been considerably less research effort on understanding uncertainty in the prediction of offshore wind and waves during hurricanes using parametric models.

5.3 Metocean observational data

For Probabilistic Hurricane Hazard Analysis, three different sources of data are used. NDBC (National Data Buoy Center) has a number of Buoys, located off the east coast of the US and the Gulf of Mexico. The buoys directly measure 8 minutes average V at 5 m above the surface and Hs during 20 minutes and report them hourly (some buoys report each 30 minutes); other data, measured by buoys include average wave period, dominant wave period, wind direction and pressure. In this Chapter, wind speeds and Hs are used as observations.

The buoy selection is based on several parameters. First, the data for both V and Hs must be available, therefore the fixed stations which only measures V will opt
out from the selection. Second, the buoys data must be independent; therefore the distance between buoys must ensure the independency of observations. The stations are divided into 4 categories based on water depth. The distribution of buoys along the east coast of the US and Gulf of Mexico is shown in Figure 5-2 and the buoys characteristics are listed in Table 5-1. In this figure the solid circles identifies the buoys in the East Coast and hollow circles are used for buoys located in Gulf of Mexico.

As can be seen in Figure 5-2, the stations are uniformly distributed along the coast; therefore, no major region is removed from the analysis. Furthermore most of the buoys are located in medium and deep water and there are only three stations located in the shallow water. Since offshore wind farms are installed mostly in shallow and medium waters, getting more data in shallow and medium water is of more interest. The same issue had arisen in earthquake engineering, however, the first GMPEs were formulated based on limited data, for example in 1972, Page and Boore [57] formulated the GMPE with only 5 earthquakes and few record observations. Later they improved their equations.
by adding more ground motion data. In this investigation, the idea of WWPE is developed by having sufficient data to formulate WWPE; however, the equation can be updated by using more recent data from hurricanes.

Table 5-1. NDBC (NOAA) stations and available data.

<table>
<thead>
<tr>
<th>Category</th>
<th>NOAA Station ID</th>
<th>Latitude</th>
<th>Longitude</th>
<th>Dist. to shore (km)</th>
<th>Water Depth (m)</th>
<th>Observation length (yrs)</th>
<th># of observation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Shallow (d &lt; 20 m)</td>
<td>41008*</td>
<td>31.40° N</td>
<td>80.87° W</td>
<td>35</td>
<td>20</td>
<td>21</td>
<td>3</td>
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<tr>
<td></td>
<td>42007</td>
<td>30.10° N</td>
<td>88.77° W</td>
<td>10</td>
<td>15</td>
<td>29</td>
<td>3</td>
</tr>
<tr>
<td></td>
<td>42035</td>
<td>29.23° N</td>
<td>94.41° W</td>
<td>29</td>
<td>13</td>
<td>21</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td>44007*</td>
<td>43.53° N</td>
<td>70.14° W</td>
<td>6</td>
<td>24</td>
<td>31</td>
<td>0</td>
</tr>
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</table>

*Station considered in the numerical example.

5.4 Historical hurricane data

Hurricanes are selected from H*Wind database [82]. Most researchers have applied hurricane data from HURDAT database, the only missing parameter being the radius of maximum wind (R_{max}) speed. Since R_{max} plays an important role in WWPE, the most accurate value for this parameter is of interest which is available directly from observations in H*Wind database. Therefore, H*Wind database is used to collect hurricanes with all required information. H*Wind
provides the hurricane parameters, required to estimate V and Hs. These parameters are central pressure, R_{max}, V_{max}, location of eye and direction of the hurricane. From H*Wind, 29 hurricanes from 1999 to 2012 are selected with proper distance to NDBC Buoys in the Atlantic coast and Gulf of Mexico. Figure 5-3 illustrates the hurricanes, used in the analysis. As shown in Figure 5-3, the only effective parts of the hurricanes on the wind and waves at buoy locations are considered.

Figure 5-3. Twenty nine historical hurricane tracks considered in this study occurring between 1999 and 2012. Markers indicate eye positions when data is available from the H*Wind project.

The investigated Hurricanes and their characteristics are listed in Table 5-2. The hurricane parameters are obtained from H*Wind data mainly at 3 hour time steps. For wind and wave analysis, one hour time steps are used for consistency with observations, therefore linear interpolation for hurricane parameters is used to obtain hurricane characteristics in each 1 hour.
Table 5-2. Characteristics of the 29 historical hurricanes considered in this study.  
AC = Atlantic coast. GoM = Gulf of Mexico. TS = Tropical Storm.

<table>
<thead>
<tr>
<th>No.</th>
<th>Year</th>
<th>Hurricane</th>
<th>Hurricane Category</th>
<th>Location</th>
<th># of Measurements</th>
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5.5 Physical models

While in GMPE, “multiple regression” approach is used to formulate the ground motion parameters; in WWPE the physical models are used to estimate the hurricane hazard parameters. There are several physical models for this purpose. Most of the models are proposed for V [66,83], and a few models are proposed to estimate H [66]. Also rigorous finite element models are available for wind and wave modeling with high accuracy, for instance ADCIRC uses the vertically-integrated continuity equation for water surface [84] and SWAN is developed from a model based on Eulerian formulation of the discrete spectral balance of
action density that accounts for refractive propagation over arbitrary bathymetry and current fields [85]. In 2001, the atmospheric model was coupled with a high-resolution version of the Princeton Ocean Model. This incorporated the effect of the tropical cyclone–ocean interaction into the forecast system [86]. The finite element models, however, are not suitable for Monte-Carlo simulation technique due to time limitations. In the PHHA, using a hurricane catalog, the wind and wave estimation due to large number of hurricane is necessary which prevents using high resolution finite element models. Therefore in this investigation two simple wind and wave models are used in hurricane wind and wave prediction equations. The wind model, used in this study, is obtained from Holland in 1980 [65] and Georgiou in 1985 which proposed an equation for asymmetric V at different azimuthal directions [87], and the applied wave model in this study is Young’s model [66]. These two models are selected in this study. Because they both are widely accepted and used in previous research; and due to the simplicity of these methods, simulation with a hurricane catalog with a large number of hurricanes is straightforward and reasonably fast. These two physical models are described in the following sections:

5.5.1 Holland’s model

In the Holland model, the tangential wind field is given by the pressure field via
cyclostrophic flow balance and expressed as,

\[ V_g(r) = \left[ \frac{B}{\rho} \left( \frac{R_{\text{max}}}{r} \right)^B (P_n - P_c) e^{-\left( \frac{R_{\text{max}}}{r} \right)^B} + \frac{1}{4} (V_{tr} \cdot \sin(\theta) - r \cdot f_c)^2 \right]^{0.5} + \frac{1}{2} (V_{tr} \cdot \sin(\theta) - r \cdot f_c) \]  

\[ V_g(r) = \left[ \frac{B}{\rho} \left( \frac{R_{\text{max}}}{r} \right)^B (P_n - P_c) e^{-\left( \frac{R_{\text{max}}}{r} \right)^B} + \frac{1}{4} (V_{tr} \cdot \sin(\theta) - r \cdot f_c)^2 \right]^{0.5} + \frac{1}{2} (V_{tr} \cdot \sin(\theta) - r \cdot f_c) \]  

(5-2)

where \( V_g \) is the 10-minute averaged gradient V at distance \( r \) along the maximum V from the eye of hurricane, B is the Holland B parameter, \( R_{\text{max}} \) is the radius of
maximum wind speed, \( V_{Ir} \) is the hurricane translation speed, \( \theta \) is the angle defining the hurricane translation direction, \( \rho \) is air density, \( P_c \) is the central pressure, \( P_n \) is the ambient pressure and \( f_c \) is the Coriolis parameter [87]. The Holland B parameter represents the shape of the decay of hurricane winds with increasing distance from the hurricane eye. This parameter has an important influence on the prediction of wind speeds and is not provided by the H*Wind database of historical hurricanes. Two approaches for estimating this parameter were applied by Vickery and Wadhera in 2008 [88]. In the first approach, the parameter is selected which minimizes the root mean square error, where error defined as the difference between theoretical central pressure and measured pressure over a range of 0.5 \( R_{max} \) to 1.5 \( R_{max} \). The second approach is to select a value of \( B \) which matches the maximum \( V \) at 10 m predicted by the Holland model with the maximum \( V \) from H*Wind. For the present study, spatially distributed measurements of the central pressure are not available for most of the considered hurricanes so a variant of the second method is used to estimate the best \( B \) parameter. Specifically, \( B \) is selected by minimizing the root mean square error between the \( V \) predicted by the Holland model and the \( V \) provided by H*wind over a range of 0.5 \( R_{max} \) to 1.5 \( R_{max} \), with comparisons made at a resolution of roughly 6 km.

Equation 5-2 provides the gradient \( V \), which, for the present application, is then converted to the surface \( V \) at 10 m. Many methods exist to convert the gradient winds to surface winds [89,90], and the approach adopted here is based on results by Powell et al [91] in 2003. Powell et al found that the maximum \( V \) at 10 m during a hurricane is equal to 71% of gradient \( V \), averaged over the same duration. Vickery et al. in 2000a showed that for relatively intense hurricane with no air-sea temperature difference, near the eyewall the typical ratio of surface
wind to gradient wind are in the range of 0.7 to 0.72. Although this result was strictly stated only for converting the maximum V from gradient to the surface level, the non-maxima wind speeds were found to vary with V, distance from the wall, roughness. Vickery et al. in 2009 proposed the boundary layer model to convert gradient V to surface V [79]. For the present application, which seeks to calculate extreme hazard at long mean return periods, conversion accuracy is preferred for maximum wind speeds. For these reasons along with a preference for a straightforward approach that can be incorporated into practice, in the present study, all surface winds at an elevation of 10 m, including wind speeds that are not the maximum, are assumed to be 71% of the gradient wind during hurricanes. The effect of distance to the eye of the hurricane then can be found in terms of residuals as a function of $r/R_{max}$.

$$V = 0.71V_g$$  \hspace{1cm} (5-3)

5.5.2 Young’s model

Young’s parametric hurricane wave prediction model [66] generates a wave field during a hurricane. This model requires three wind field parameters as input: radius to maximum winds, maximum V, and forward speed of storm. Fetch is defined as the length of water over which wind blows, and equivalent fetch takes into account the speed of the wind and the speed of the storm. Higher wind speeds produce waves with higher velocities. If these waves move at speeds similar to the speed of the storm, then the high winds blow over the waves for an extended period of time, rather than instantaneously. The maximum equivalent fetch creates maximum wave conditions. An equivalent fetch, dependent on $R_{max}$, is calculated from translation speed and maximum V. Then, $H_s$ is estimated using standard JONSWAP fetch-limited growth relationships. Young used these
concepts to create a synthetic database of hurricanes, applying a wide range to the given parameters, and fit the results with a simple parametric model. Closed form equations determine the maximum $H_s$ at an instant along the duration of the hurricane. Young has provided spatial distribution plots, standardized by the direction of forward motion and in terms of the ratio between the distance from eye to point of interest ($r$) and the effective radius to maximum winds ($R'$) to determine the $H_s$ at a given point during this instant. Young’s equations are summarized below:

$$\frac{gH_s}{V_{max}^2} = 0.0016 \left( \frac{gF}{V_{max}^2} \right)^{0.5} \quad (5-4)$$

Where:

$$\frac{F}{R'} = aV_{max}^2 + bV_{max}V_{tr} + cV_{tr}^2 + dV_{max} + eV_{tr} + f \quad (5-5)$$

In 1988, Young proposed the coefficients in Equation 5-5 and years later, he used the actual data from altimeters to revise the coefficients in Equation 5-5 [92] as:

$$a = -2.175 \cdot 10^{-3}, \quad b = 1.506 \cdot 10^{-2}, \quad c = -1.223 \cdot 10^{-1}, \quad d = 2.190 \cdot 10^{-1}, \quad e = 6.737 \cdot 10^{-1}, \quad f = 7.980 \cdot 10^{-1}$$

Also, $R'$ is effective radius, defined as:

$$R' = 22500 \log R - 70800 \quad (5-6)$$

The spatial distribution of $H_s$ is provided through a series of plots indicating the ratio of $H_s$ at each location to maximum $H_s$, obtained from Equation 5-4.

Young’s model assumes that the hurricane is over deep water, open-ocean far from the influence of land, and has a linear path. Because this study is in regards to locations where offshore wind farms could be located, we are specifically
interested in shallow water points that are relatively close to land. The assumption of a linear hurricane track also does not necessarily hold true for all hurricanes that we are modeling. Since the assumptions of the model are not being met it is expected that there will be some error in the $H_s$ predictions.

The limited parameter in wave modeling, provided by Young, also poses difficulties in modeling the specifically selected hurricanes. Each of Young’s parameter ranges, for $R_{\text{max}}, V_{\text{max}}$, and $V_{tr}$, is exceeded during at least one of the hurricanes of interest, resulting in an inability to make wave height predictions at these times. Additionally, the wave height predictions are limited by the size of the spatial distributions provided by Young, which extend to less than 8 times the effective radius. These limiting factors mean that it is not possible to make $H_s$ predictions for all points along the East Coast.

5.6 Bias correction and uncertainty quantification in the parameteric models

In PSHA, the ground motion intensity measure is usually modeled with a lognormal distribution, meaning that the logarithm of the intensity measure follows a normal distribution [93]. Uncertainty is measured with the residual error, a normally distributed random variable with zero mean and defined as the logarithmic difference between measured and modeled ground motion intensity measures. In this chapter, the same approach is applied, and the uncertainty in the WWPEs is characterized by the residual error $\varepsilon_x$, the difference of the logarithms between buoy measurements $\hat{x}$ and predictions from models $x$,

$$\varepsilon_x = \ln(\hat{x}) - \ln(x) \quad (5-7)$$

where, in this case, the variable $x$ may be either the sustained $V$ or the $H_s$. In the former case, modeled values are determined by Holland’s model, while in the
latter case, modeled values are determined by Young’s model. The residuals are calculated independently for wind and wave AND are based on the maximum measured and on the maximum modeled value during the duration of the hurricane. In the following sections, biases, homoscedasticity and uncertainties of these models are assessed in terms of $\varepsilon_X$.

### 5.6.1 Biases and homoscedasticity

Two biases were identified and corrected in the residual measure $\varepsilon_X$. The first bias relates to the observation that the mean of $\varepsilon_V$ varies with $V$ as predicted directly by Holland’s model. Figure 5-4 shows a plot of $\varepsilon_V$ versus $V$, and a linear regression trendline is superimposed on the figure.

\[ \varepsilon_V = -0.007V + 0.2 \]

![Figure 5-4. Wind speed residual versus V with linear regression line superimposed. Marker colors indicate the water depth at the location of the measurement and marker fill indicates whether the measurement was taken at a location in the Gulf of Mexico or off of the Atlantic coast.](image)

A t-test is conducted on the hypothesis that the slope of the linear regression line is zero, and the resulting p-value is 1%. In statistical hypothesis testing, it is
common to reject the hypothesis for P-values less than 5%. The observed bias is influenced by the very simple approach employed here to convert gradient wind speeds to surface wind speeds. A bias corrected value for the modeled $V_c$ is calculated in terms of the uncorrected value $V$ based on the linear regression line in Figure 5-4 and expressed as,

$$\ln(V_c) = -0.007V + 0.2 + \ln(V)$$  \hspace{1cm} (5-8)

The second bias relates to the observation that the mean of $\varepsilon_{Hs}$ varies with water depth $d$ when $H_s$ is predicted directly by Young’s model. The equation proposed by Young for estimating the $H_s$ during hurricanes is developed assuming deep water conditions where the seafloor does not influence the wave height. Figure 6 presents the values of $\varepsilon_{Hs}$ versus water depth for each hurricane wave observation. The figure shows that model predictions are somewhat biased with respect to water depth, with Young’s model tending to overestimate the $H_s$ in shallow water. Superimposed on the figure is an exponential regression function which minimizes the root mean square of the error.

To remove the bias of Young’s model with water depth, a bias corrected value for the $H_{s,c}$ is calculated in terms of water depth $d$ based on the exponential regression function in Figure 5-5 and expressed as

$$\ln(H_{s,c}) = -e^{-0.06d} + \ln(H_s)$$  \hspace{1cm} (5-9)

Based on the bias corrected prediction of $V_c$, a residual $\varepsilon_{Vc}$ is calculated for each observation of the $\hat{V}$ and the mean value of $\varepsilon_{Vc}$ is 0.00 and the standard deviation is 0.13. Figure 5-6a-d present $\varepsilon_{Vc}$ and $\varepsilon_{\hat{V}c}$ versus $V_c$ and the radial position $r/R_{max}$. Linear regression lines are superimposed on all four plots. To evaluate the extent
of any remaining biases or heteroscedasticity, the slopes of the regression lines are evaluated with a T-test, the results of which are provided in Table 5-3.

![Figure 5-5. Uncorrected $H_s$ residual versus water depth. Marker colors indicate the water depth at the location of the measurement and marker fill indicates whether the measurement was taken at a location in the Gulf of Mexico or off of the Atlantic coast.](image)

Based on the bias correction for the $H_s$, a residual $\varepsilon_{Hs,c}$ is calculated for each observation of the $\tilde{H}_s$ and the mean value of $\varepsilon_{Hs,c}$ is 0.00 and the standard deviation is 0.25. Figure 5-7a-d present $\varepsilon_{Hs,c}$ and $\tilde{H}_s$ versus the corrected prediction of $H_{sc}$ and the water depth $d$ with linear regression lines superimposed on all four plots. Note that the horizontal axes of Figure 5-7b and Figure 5-7d are logarithmic and thus the linear regression lines superimposed on these figures appear nonlinear.
Figure 5-6. Evaluation of bias, (a) and (b), and homoscedasticity, (c) and (d), for wind speeds estimated by Holland’s model and compared to 62 buoy measurements during 29 historical hurricanes. Marker colors indicate the water depth at the location of the measurement and marker fill indicates whether the measurement was taken at a location in the Gulf of Mexico or off of the Atlantic coast.
Figure 5-7. Evaluation of bias, (a) and (b), and homoscedasticity, (c) and (d), for significant wave heights estimated by Young’s model and compared to 62 buoy measurements during 29 historical hurricanes. Marker colors indicate the water depth at the location of the measurement and marker fill indicates whether the measurement was taken at a location in the Gulf of Mexico or off of the Atlantic coast.

To evaluate the extent of any remaining biases or heteroscedasticity, the slopes of the regression lines are evaluated with a T-test, the results of which are provided in Table 5-3.
Table 5-3. Linear regression data and T-test results on the statistical significance of the slope of the regression line between the variables listed in the first two columns. The null hypothesis is that the regression slope is zero. The p-value is the probability of observing a slope at least as extreme as the regression slope calculated here given the null hypothesis.

<table>
<thead>
<tr>
<th>Y Variable</th>
<th>X Variable</th>
<th>Relevant Figure</th>
<th>Regression Slope (Y/X)</th>
<th>Regression Y-intercept</th>
<th>P-Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\varepsilon_{Vc}$</td>
<td>$V_c \ (m/s)$</td>
<td>14a</td>
<td>0 \ ((m/s)^{-1})</td>
<td>0</td>
<td>100%</td>
</tr>
<tr>
<td>$\varepsilon_{Vc}$</td>
<td>$r/R_{max}$</td>
<td>14b</td>
<td>0.008</td>
<td>-0.01</td>
<td>59%</td>
</tr>
<tr>
<td>$\varepsilon_{V_{sc}}$</td>
<td>$V_c \ (m/s)$</td>
<td>14c</td>
<td>0.0004 \ ((m/s)^{-1})</td>
<td>0.005</td>
<td>53%</td>
</tr>
<tr>
<td>$\varepsilon_{V_{sc}}$</td>
<td>$r/R_{max}$</td>
<td>14d</td>
<td>0.007</td>
<td>0.004</td>
<td>9%</td>
</tr>
<tr>
<td>$\varepsilon_{H_{sc}}$</td>
<td>$H_{sc} \ (m)$</td>
<td>15a</td>
<td>-0.02 \ m^{-1}</td>
<td>0.2</td>
<td>7%</td>
</tr>
<tr>
<td>$\varepsilon_{H_{sc}}$</td>
<td>$d \ (m)$</td>
<td>15b</td>
<td>-0.00003 \ m^{-1}</td>
<td>0.05</td>
<td>20%</td>
</tr>
<tr>
<td>$\varepsilon_{H_{sc}}^2$</td>
<td>$H_{sc} \ (m)$</td>
<td>15c</td>
<td>-0.009 \ m^{-1}</td>
<td>0.1</td>
<td>3%</td>
</tr>
<tr>
<td>$\varepsilon_{H_{sc}}^2$</td>
<td>$d \ (m)$</td>
<td>15d</td>
<td>-0.00001 \ m^{-1}</td>
<td>0.07</td>
<td>12%</td>
</tr>
</tbody>
</table>

Table 5-3 provides P-values resulting from a T-test on the null hypothesis that the linear regression slope of the Y-X data in Figure 5-6a-d and Figure 5-7a-d is zero. Based on the convention in hypothesis testing for rejecting the null hypothesis when P-values are less than 5%, only one of the eight cases in Table 5-3 is rejected. This particular case relates to the expected value of $\varepsilon_{H_{sc}}^2$ versus $H_{sc}$, see Figure 5-7c. In this case, the data shows that the expected value of $\varepsilon_{H_{sc}}^2$ decreases with increasing values of $H_{sc}$. While this results makes some intuitive sense, a linear bias correction is undesirable in this case because the expected value of the variance would become negative at large but plausible values of $H_{sc}$. For this reason, along with a desire to keep the WWPE equations as simple as possible, the linear bias observed in $\varepsilon_{H_{sc}}^2$ versus $H_{sc}$ is ignored.

5.6.2 Uncertainty quantification

The measured distribution of the residuals $\varepsilon_X$ is plotted with respect to normal distributions with identical means and standard deviations in Figure 5-8. Both distributions passed a KS-test of normality at 5% significance, however, it is
important to note that the data shows that the normality assumption appears to fit the worst in the upper tails of the distributions of both $\varepsilon_{Vc}$ and $\varepsilon_{H_{s,c}}$. Despite this observation, the normal distribution overall does reasonably well at representing the observed values, and this serves as the justification for modeling $\varepsilon_X$ as a normally distributed random variable with zero mean and standard deviation equal to 0.13 for $V_c$ and 0.25 for $H_{s,c}$. These distributions form the basis for the WWPEs, the PDFs of which can be expressed generically for intensity measure $X$ as.

$$f_{\ln(X)}(\ln(x) | \bar{y}) = \frac{1}{\sigma_{\ln(X)} \sqrt{2\pi}} \exp\left(-\frac{(\ln(x) - \ln(x|\bar{y}))^2}{2\sigma_{\ln(X)}^2}\right)$$  \hspace{1cm} (5-10)

The PDFs for $V$ and $H_s$ are plotted on logarithmic axes along with the measured data superimposed in Figure 5-9.

Figure 5-8. Normality plot for the distribution of $\varepsilon_{Xc}$ for $X = H_{s,c}$ and $X = V_c$. Marker colors indicate the water depth at the location of the measurement and marker fill indicates whether the measurement was taken at a location in the Gulf of Mexico or off of the Atlantic coast.
Figure 5-9. Probability density function and measured values for a) corrected $V_c$ and b) corrected $H_{s,c}$. Marker colors indicate the water depth at the location of the measurement and marker fill indicates whether the measurement was taken at a location in the Gulf of Mexico or off of the Atlantic coast.

5.7 Limitations of WWPE

The WWPEs proposed here are derived using 62 measurements of sustained $V$ and $H_s$ during hurricanes from NDBC buoys. Most of the observations correspond to lower intensities of $V$ (74% of the measured wind speeds are below 35 m/s) and wave height (76% of the measured wave heights are below 10 m) and more measurements at higher intensities could significantly change the character of the WWPEs. Characterizing the WWPEs at higher intensities is especially important since the hurricane risk to offshore structures is expected to be influenced strongly by intense, but infrequent hurricanes with corresponding higher wind and wave intensities. Another important limitation in the WWPEs formulated here is that they are derived independently and don’t provide any information on the correlation between wind and wave uncertainty. This is an important consideration when using these equations to evaluate the hurricane risk to an offshore structure. Moreover, the effect of simultaneity of wind and wave conditions is not considered here since wind and wave conditions are only
evaluated separately. Thus a risk assessment which considered the effect of both wind and wave would need to account for the fact that it is not likely that the maximum wave height will occur simultaneously with the maximum V at a particular site [94].

An additional limitation is that the bias correction for the V was only calibrated based on a range of V observations between 20 m/s and ~50 m/s. Beyond this range, the appropriateness of the correction has not been verified and, for very large wind speeds, the magnitude of the correction is quite large (e.g. for $V_c = 70$ m/s, the shift in $\varepsilon_{Vc}$ is 0.15). The authors do not recommend applying the correction to wind speeds significantly outside of the range considered here.

Another limitation in the method developed here is that there is no upper bound to the wind speeds and wave heights predicted with the WWPEs. This is particularly important for estimating wave height since it is known that there are physical stability limits to wave height and steepness beyond which a wave will break. Some consideration of the physical limits of wave heights should be added to the WWPE formulation.

5.8 Numerical example

In this section, numerical examples are provided following the POHHA procedure depicted schematically in Figure 5-10 to calculate hurricane wind speeds and significant wave heights at different MRPs using the WWPEs with and without the inclusion of uncertainty. The POHHA is conducted for three locations along the Atlantic coast of the US. The three sites correspond to locations of NDBC buoys. The NOAA station IDs for the three sites are 44007, 44009 and 41008. In this section these sites are referred to by the postal abbreviation of their closest state, ME for 44007, DE for 44009 and GA for 41008.
The first step in a POHHA is to develop a stochastic catalog of synthetic hurricanes for the location of interest. The specific stochastic catalog used here considers 100,000 years of hurricane activity in the Atlantic basin and was developed by Liu [69] in 2014. The catalog is developed following the same general approach originated by Vickery in 2000 [78]. The numerical examples provided in this chapter are based on a sampling of 1000 hurricanes among 100,000 years of hurricanes in the catalog, following an approach outlined in [69] wherein the catalog is first filtered to only include hurricanes passing within 250 km of the considered location and then, from this subset of hurricanes, 1000 hurricanes are selected based on a Latin Hypercube approach (or inverse CDF approach) to find a set of 1000 hurricanes for each site that closely approximates the CDF based on the entire 100,000 year catalog, for more information please refer to [69]. The wind speed at 10 m height can be estimated according to Equation (5-3). More information for converting the gradient wind speed to 10 m wind speed can be found in Section 5.5.1. Using the stochastic catalog, a hurricane arrival rate can be calculated for each of the three sites. The rates differ significantly among the three sites with the GA site estimated to have hurricanes passing within 250 km most frequently at 1.16 year\(^{-1}\). The DE and ME sites are estimated to annual hurricane frequencies of 0.79 year\(^{-1}\) of and 0.53 year\(^{-1}\) respectively. For this example, 100 realizations of wind speeds and significant wave heights are sampled from the WWPE distribution for each of 1000 hurricanes at each site, and the results are presented in Figure 5-10.
Figure 5-10. Results from a POHHA for WWPEs with and without uncertainty for (a) sustained wind speeds $V$ and (b) $H_{s,c}$. Thin solid lines indicate results from 100 realizations of $V$ and $H_{s,c}$ for each site with $\sigma_{V_{c}} = 0.13$ and $\sigma_{H_{s,c}} = 0.25$. Bold solid lines indicate the median of these realizations while dashed solid lines indicate predicted values without consideration of uncertainty in the WWPEs (i.e. with $\sigma_{V_{c}} = \sigma_{H_{s,c}} = 0$).

It can be seen from these figures that, in all cases, including uncertainty in the WWPEs causes a modest increase in the intensity for all MRPs shown (i.e. MRP > 10 years) with the magnitude of the difference increasing with increasing MRP. The effect of including uncertainty is greater for the $H_{s}$ than the $V$, reflecting the larger variance observed in the wave height prediction.

### Table 5-4. $V$ and $H_{s}$ for investigated sites for 50 and 500 years mean return periods.

<table>
<thead>
<tr>
<th>Site</th>
<th>MRP (years)</th>
<th>$V_{c}$ (m/s)</th>
<th>$H_{s,c}$ (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>No Uncertainty</td>
<td>Median</td>
<td>Difference</td>
</tr>
<tr>
<td>ME</td>
<td>50</td>
<td>26.7</td>
<td>27.7</td>
</tr>
<tr>
<td></td>
<td>500</td>
<td>35.5</td>
<td>38.2</td>
</tr>
<tr>
<td>DE</td>
<td>50</td>
<td>28.8</td>
<td>30</td>
</tr>
<tr>
<td></td>
<td>500</td>
<td>39.4</td>
<td>41.7</td>
</tr>
<tr>
<td>GA</td>
<td>50</td>
<td>33.6</td>
<td>35.4</td>
</tr>
<tr>
<td></td>
<td>500</td>
<td>42.7</td>
<td>46.1</td>
</tr>
</tbody>
</table>

Numerical results of this comparison are summarized in Table 5-4 and the average increase in $V$ when considering uncertainty, among all three sites, for a
50-year MRP is 4.7% and 6.2% for a 500-year MRP. The average increase in $H_s$ when considering uncertainty is 7.5% for a 50-year MRP and 24% for a 500-year MRP.
6 PROBABILISTIC MODEL FOR PEAK SPECTRAL PERIOD FOR GIVEN SIGNIFICANT WAVE HEIGHT

The material presented here is in preparation for publication as:


As mentioned in previous Chapters, $H_s$ and $T_p$, are two common parameters used to represent an irregular sea state in the design and risk assessment of OWTs. In many cases, only $H_s$ is considered as a random variable for modeling the seastate and $T_p$ is modeled as being dependent on $H_s$. In this Chapter, the effect of $T_p$ on structural response of an OWT is investigated, and it is shown that $T_p$ has a significant effect on the structural response estimation and that, based on observation from 16 offshore buoys spanning the Atlantic coast, the magnitude of $T_p$ appropriate for design can be estimated as a function of $H_s$. The function is calibrated using the Inverse First Order Reliability Method (IFORM) with separate environmental contours for normal and extreme conditions. An environmental contour represents the combinations of $H_s$ and $T_p$ that correspond to, in a sense, equal probability of occurrence, or inversely, equal mean return period.

This Chapter is divided into 5 sections. It starts with an introduction, motivation and overview of the current approach to combine $T_p$ and $H_s$. Then, a sensitivity analysis of the 5MW OWT is performed to show the variation of response with respect to $T_p$. After the sensitivity analysis is conducted, a probabilistic model for estimating the sea state environmental contour for both normal and extreme conditions is described. This is then followed by an example of the procedure for a specific location offshore of Georgia to obtain the environmental contour for 50
years mean return period. Lastly, this approach is applied to measurement from 16 offshore buoys and a power function is fit to the median values among the 16 sites. This function is compared with the current lower bound on the response of the 5MW NREL OWT in terms of bending moment at the mudline. The results show that the new equation is a more realistic model and it is recommended to be used in design and analysis.

6.1 Introduction

The most widely applied provision in design of OWTs is IEC 61400-3 [15]. This standard provides a set of design load combinations to estimate loads during different normal and extreme OWT conditions. Three environmental parameters, $V$, $H_s$, and $T_p$ are used to define loads according to this standard. The combination of these parameters is discussed in Chapter 4, however, in this Chapter, a simplified procedure is provided to estimate the sea state for a return period of 50 years.

The seastate is defined by $T_p$ and $H_s$. The IEC standard recommends using a deterministic range of wave period, which is a function of $H_s$. This wave period can be transformed to $T_p$ by using statistical coefficient provided by API [11], however, the procedure has not clearly been defined by IEC or API. Therefore, the $T_p$ range, estimated by this approach, will be a vague estimation of $T_p$ for a given $H_s$.

The peak spectral period, abbreviated by $T_p$, is the wave period with highest energy. The significant wave height time history can be obtained from hourly buoy measurements, see Figure 6-1.a. For short time period, a typical sea surface is shown in Figure 6-1.b. The inversion of this frequency is the peak spectral period ($T_p$). The distribution of wave energy among different wave periods or
frequencies can be represented by a wave spectrum. In Figure 6-1.c, the frequency content of sea surface is shown. As can be seen in this figure the energy of the wave at some frequencies is higher and the frequency at which the energy is highest is the dominant frequency. This distribution of energy can be estimated by predefined spectrum. For example, the JONSWAP spectrum for the sea surface is shown in Figure 6-1.d. The JONSWAP and Pierson-Moskowitz spectra are the two most commonly used. The wave spectrum and \( T_p \), along with the \( H_s \), and, for the case of the JONSWAP spectrum, the peak enhancement factor, can be used to generate a time history realization of the irregular sea surface [26].

![Figure 6-1](image)

(a)

Figure 6-1. a) Significant wave height time history, b) typical sea surface, c) magnitude of wave power in frequency domain, and d) JONSWAP spectrum.
As such, accurate estimation of $T_p$, directly affects the sea elevation time history, and it follows that the $T_p$ also affects the loads on the structure. The IEC Standard requires consideration of a deterministic range of wave period $T$ of the wave in a sea state. The range is for up crossing period of a single extreme wave which is given by,

\[ 11.1 \sqrt{H_s/g} \leq T \leq 14.3 \sqrt{H_s/g} \quad (6-1) \]

Where, $g$ is gravity, and $T$ is the period of the wave. The design wave is the wave with period $T$ that leads to maximum loads on the structure. Although the range of $T$ provided by the IEC Standard is not referenced, the authors believe that the equation originated in Baltrop [95]. The physical reason can be explained as higher waves tend to require longer fetches and longer build up time to achieve that wave height. A fully developed seastate is the one at which the energy added by the incoming wind is equal to the energy lost by the waves due to breaking and whitecapping. The period of the wave, or wavelength at which this occurs is directly proportional to the speed at which the wind is blowing, and the $H_s$ is also proportional to wind speed. The actual distribution of power at each frequency is given by the wave spectrum, because ocean waves aren’t perfect. The peak frequency is a coarse representation of the equilibrium point of fully generated seas. The recommended practice, API-RP2A (2002), which is used to design oil and gas offshore structures in the US, provides a range of the expected ratio between the sea state $T_p$ and the period of the wave $T$,

\[ 1.05 \leq T_p/T \leq 1.2 \quad (6-2) \]

In addition, the API standard API 2INT-MET (2007) [12], which provides guidance on hurricane conditions in the Gulf of Mexico, states that the ratio of
the $T_p$ to the period of the maximum wave can be assumed to be between 1.08 and 1.12. In this Chapter, the range of maximum wave period provided in Equation 6-1 is converted to a range of $T_p$ by using Equation 6-2 and multiplying the lower bound of the range in Equation 6-1 by 1.05 and the upper bound of the range by 1.2, resulting in the range for the $T_p$ given as,

$$11.7 \sqrt{H_s/g} \leq T_p \leq 17.2 \sqrt{H_s/g}$$

(6-3)

This range is referred in the remainder of this chapter as the deterministic range of $T_p$. In the next section, Equation 6-3 is evaluated to see to what extent the provided range can represent measurements of the actual range of $T_p$ and in the following sections, the effect of $T_p$ on structural response is investigated.

### 6.2 Validity of deterministic range of $T_p$

The range in Equation 6-3 is compared to measurements for an offshore site off the coast of Georgia where NOAA buoy 41008 is located. This particular site was selected for this study because it had a long duration of data (24 years) and because it was located in a water depth that was sufficiently shallow (20 m) to be viable for the installation of a fixed-bottom OWT. The location of this site is indicated in Figure 6-4 as station 41008, along with the locations of other buoys, and specifications of the site are provided in Table 6-2, along with the specification of other buoys. The other buoys are considered later in this Chapter. The buoy measurements considered in this Chapter are $H_s$ and $T_p$, and both quantities are determined based on a 20 minute time interval and are reported hourly. To assess the extreme sea state described in the IEC Standard for station 41008 (shown on Figure 6-4), extreme values of $H_s$ and corresponding peak spectral periods are extracted from the hourly measured data, for station 41008, using the method of 7-Largest Order Statistics (7-LOS). An example of a similar
A scatter plot of the extreme values of $H_s$ and the corresponding peak spectral periods for station 41008 are provided in Figure 6-2. It is noticed that the extreme data is for both hurricane and non-hurricane events and the upper bond and lower bound are provided regardless of the source of extreme event. More hurricane data is required to provide the boundaries with respect to the source of the extreme events. Superimposed on this plot are two curves, indicating the upper and lower bounds of the deterministic range of $T_p$ presented in Equation 6-3.

![Figure 6-2](image_url)

Figure 6-2. Extreme value measurements of $H_s$ and corresponding $T_p$ extracted from NOAA buoy 41008. The upper and lower bounds of the deterministic $T_p$ range presented in Equation 6-3 are superimposed.

Comparing the measured extreme values with the upper and lower bounds of Equation 6-3, it is obvious that many measured values fall outside the upper and lower bounds. In total, 16% of the measurements are outside the range with 6%
of the measurements above the upper bound and 10% of the measurements below the lower bound. The variability of the measurements above the upper bound is much larger than the variability of measurements below the lower bound. For this particular site, it is clear that, over a duration of 24 years during which buoy 41008 was active, there are many instances where measurements are outside the deterministic range in Equation 6-3. A logical question is whether this observation has a significant influence on the structural demands on an OWT subjected to the extreme sea state, or, in other words, how sensitive is the response of an OWT to variation of $T_p$. The next section addresses this question for a specific 5MW wind turbine supported by a monopile foundation.

6.3 Sensitivity of hydrodynamic loads on OWTs to peak spectral period

In this section, a structural analysis is performed to find the sensitivity of the structural response of a specific OWT to variation in $T_p$ and $H_s$. The analysis is based on a structural model of the 5MW National Renewable Energy Laboratory (NREL) baseline OWT supported by a monopile foundation (Jonkman, 2009). Key specifications of this OWT are provided in Table 6-1. This model has a fundamental period of 3.5 s and is fixed at the mudline. In this analysis, the turbine is modeled in a parked condition (i.e. the rotor is stationary and blades are feathered) as is prescribed by the IEC Standard for extreme storm conditions. Since this analysis is focused only on the effect of the extreme sea state on the structural response, wind speed is neglected for all analyses. Waves are modeled as irregular and linear, following a JONSWAP spectrum defined by $H_s$ and $T_p$ and a peak enhancement factor of 1, following the procedure outlined by Agarwal and Manuel (2010). The JONSWAP spectrum is a description of the variability of the sea-surface at a given point in space with respect to time. If the wavelength expected is much greater than the diameter of the foundation, which
is the case for monopole-supported wind turbines, then the loads are correlated according to the Morison Equation. If the wavelength is on the same order of the diameter of the foundation (as would be the case for a floating platform), then the loads are more correlated according to diffraction theory. The integrated length-scale for wind speed according to Equations 2-2 to 2-4 can be estimated as 510.3 according to IEC 61400-1 standard. In FAST, these parameters are calculated by indicating the standard and wind spectrum.

Table 6-1. Properties of 5MW NREL OWT.

<table>
<thead>
<tr>
<th>Rotor Orient. Configuration</th>
<th>Upwind, 3 Blades</th>
</tr>
</thead>
<tbody>
<tr>
<td>Control</td>
<td>Variable Speed, Collective Pitch</td>
</tr>
<tr>
<td>Rotor, Hub Diameter</td>
<td>126 m, 3 m</td>
</tr>
<tr>
<td>Hub Height</td>
<td>90 m</td>
</tr>
<tr>
<td>Monopile Diameter, Thickness</td>
<td>6 m, 0.027 m</td>
</tr>
<tr>
<td>Cut in, Rated, Cut out Wind</td>
<td>3 m/s, 11.4 m/s, 25 m/s</td>
</tr>
<tr>
<td>Rotor, Nacelle, Tower Mass</td>
<td>110 t, 240 t, 347 t</td>
</tr>
</tbody>
</table>

The analyses are conducted within the program FAST (Jonkman, 2013), an aeroelastic and hydrodynamic simulator that couples wind and wave forces with the structural response of OWTs. In total, the structural model is analyzed for 240 combinations of $H_s$ (12 values) and $T_p$ (20 values). For each combination, 24 one-hour analyses are simulated and the maximum moment at the mudline for each of the 24 simulations is recorded. Although IEC requires only 6 one-hour analyses, 24 analyses are carried out to reduce discrepancies and have more reliable convergence of the average maximum response. The results of these analyses are presented in Figure 6-3, which shows the average of the maximum mudline moment from each of the 24 simulations for a water depth of 20 m.
It can be seen that the maximum bending moment occurs at peak spectral periods near those of the structure (3.5s), and that the bending moment decreases as $T_p$ moves away from fundamental period. According to Figure 6-3, the turbine response is sensitive to values of $T_p$ and thus, if the deterministic range presented in Equation 6-3 were used in the design for this turbine and location (for $H_s = 2$ m, $5.3 \text{s} < T_p < 7.8 \text{s}$, for $H_s = 6$ m, $9.1 \text{s} < T_p < 13.4 \text{s}$, for $H_s = 10$ m, $11.8 \text{s} < T_p < 17.4 \text{s}$), it is possible that a response-controlling and reasonably likely combination of $H_s$ and $T_p$ would not be considered in the design. Therefore, it is necessary to consider a more realistic range of $T_p$ to be combined with $H_s$ for the design mean return period. A more rational approach to determine the $T_p$ for design is to use site-specific data to probabilistically estimate an appropriate range for $T_p$ conditioned on the $H_s$ of the extreme sea state. In the following section, a methodology for calculating a more realistic combination of sea state parameters for the extreme seastate of design is described.
6.4 Probabilistic model for range of $T_p$ conditional on $H_s$

Design of OWTs should result in an appropriate structural reliability under a variety of environmental and normal conditions. In normal condition, the rotor is rotating and the blades are pitched to extract maximum energy from the wind. Under such conditions, aerodynamic loads on the rotor are much higher than when the rotor is parked and blades feathered, however, the wind speed for normal range is limited to steady winds between 3 and 25 m/s. Beyond this wind speed range, the wind turbine will be shut down with the rotor parked and blades feathered to minimize aerodynamic wind loads. These wind speeds occur during extreme events such as storms and hurricanes. To ensure appropriate structural reliability, an assessment of loads for design must be performed for both normal and extreme conditions. The following sections provide two different approaches to model the $T_p$ for normal and extreme conditions. Two separate approaches are suggested because the number of measurements in the normal condition range is much larger than the number in the extreme condition. The methodology used to make predictions for normal and extreme is different based because of this difference in the availability of the data. Following these two sections, an illustrative numerical example is provided wherein environmental contours associated with the design recurrence period of 50-years are calculated based on measurements at a buoy located near the New England coast (buoy 44007).

6.4.1 Assessment of peak spectral period for normal conditions

The normal condition in general refers to the range of wind speeds that a wind turbine is experiencing in most of its life span, e.g. no storm conditions. This situation is the environmental condition for most of the time and, when decades of hourly measurement of wind and sea condition are available, there are a
significant number of data to construct distributions of $T_p$ conditioned on $H_s$. This case, when number of observations is sufficient to construct the direct conditional distribution of $T_p$ given $H_s$ is referred to as normal condition in this Chapter. The NOAA buoys considered in this dissertation report hourly measurements of the wind speed and seastate. Therefore, for each year, a total of $365 \times 24 = 8760$ combinations of $H_s$ and $T_p$ are measured. Since, most of this data is measured during normal conditions and since most buoys have multiple years of data, there is sufficient data to directly estimate conditional probability distributions for $T_p$ given $H_s$. These conditional distributions can then be used along with the IFORM and the Rosenblatt transformation [35, 37], to estimate environmental contours of $H_s$ and $T_p$ at a recurrence period appropriate for design.

6.4.2 Assessment of peak spectral period for the extreme environmental condition

In contrast to buoy measurements during normal conditions, measurements during extreme conditions are characteristically sparse, and are not likely to have sufficient data to construct the conditional probability distribution directly. In this case, an alternative approach is used to obtain the conditional probability distribution, based on an estimation of the joint probability distribution of extreme value data using the so-called Nataf model (Liu & Kiureghian, 1986, Bucher, 2009) which estimates a joint probability distribution of $T_p$ and $H_s$ that matches the marginal distributions and covariance of the paired data. The Nataf model is based on a transformation of the original correlated variables to Gaussian variables whose joint density is assumed to be multi-dimensional Gaussian. To transform from original space to Gaussian space, the random variables are mapped individually to standard normal space per the transformation outlined below.
Having an estimate of the joint probability distribution of $H_s$ and $T_p$, the conditional distribution of $T_p$ given $H_s$ can be calculated as,

$$f_{T_p|H_s}(t_p, h_s) = \frac{f_{T_p,H_s}(t_p,h_s)}{f_{H_s}(h_s)} \quad (6-4)$$

Using Equation 6-4, the CDF and the probability density function (PDF) of $T_p$ given $H_s$ can be calculated. The application of this method is explained further in the numerical example in the following section.

6.4.3 Numerical example

A subset of 16 buoys is considered here. These buoys are selected from the NDBC. The subset is selected mainly based on data availability, specifically that the buoy must simultaneously measure both $V$ and $H_s$. The geographic distribution of the selected subset of NDBC buoys considered in this study is shown in Figure 6-4, with the color of the buoy marker indicating water depth and the buoy characteristics are listed in Table 6-2. The stations are divided into 3 categories, shallow, medium and deep, based on water depth.
Figure 6-4. Locations and water depths of 16 NOAA buoys considered in this study. d = water depth. AC = Atlantic coast.

Table 6-2. Characteristics of the NDBC buoys considered in this study. Shallow is less than 20m of water depth. Medium is between 20 and 60m of water depth and deep is greater than 60m of water depth.

<table>
<thead>
<tr>
<th>Category</th>
<th>NOAA Station ID</th>
<th>Latitude</th>
<th>Longitude</th>
<th>Dist. to shore (km)</th>
<th>Water Depth (m)</th>
<th>Observation length (yrs)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Shallow</td>
<td>41008</td>
<td>31.40° N</td>
<td>80.87° W</td>
<td>35</td>
<td>20</td>
<td>21</td>
</tr>
<tr>
<td></td>
<td>44007*</td>
<td>43.53° N</td>
<td>70.14° W</td>
<td>6</td>
<td>24</td>
<td>31</td>
</tr>
<tr>
<td></td>
<td>44025</td>
<td>40.25° N</td>
<td>73.16° W</td>
<td>45</td>
<td>40</td>
<td>28</td>
</tr>
<tr>
<td></td>
<td>44009</td>
<td>38.46° N</td>
<td>74.70° W</td>
<td>31</td>
<td>31</td>
<td>29</td>
</tr>
<tr>
<td></td>
<td>41013</td>
<td>33.44° N</td>
<td>77.74° W</td>
<td>50</td>
<td>24</td>
<td>9</td>
</tr>
<tr>
<td>Medium</td>
<td>41004</td>
<td>32.50° N</td>
<td>79.10° W</td>
<td>66</td>
<td>38</td>
<td>23</td>
</tr>
<tr>
<td></td>
<td>41012</td>
<td>30.04° N</td>
<td>80.53° W</td>
<td>74</td>
<td>38</td>
<td>11</td>
</tr>
<tr>
<td></td>
<td>41009</td>
<td>28.52° N</td>
<td>80.19° W</td>
<td>35</td>
<td>41</td>
<td>25</td>
</tr>
<tr>
<td></td>
<td>44005</td>
<td>43.20° N</td>
<td>69.13° W</td>
<td>79</td>
<td>206</td>
<td>35</td>
</tr>
<tr>
<td></td>
<td>44013</td>
<td>42.35° N</td>
<td>70.65° W</td>
<td>16</td>
<td>65</td>
<td>29</td>
</tr>
<tr>
<td></td>
<td>44018</td>
<td>42.13° N</td>
<td>69.63° W</td>
<td>35</td>
<td>228</td>
<td>11</td>
</tr>
<tr>
<td></td>
<td>44011</td>
<td>41.10° N</td>
<td>66.60° W</td>
<td>288</td>
<td>86</td>
<td>29</td>
</tr>
<tr>
<td></td>
<td>44008</td>
<td>40.50° N</td>
<td>69.25° W</td>
<td>102</td>
<td>66</td>
<td>31</td>
</tr>
<tr>
<td></td>
<td>44014</td>
<td>36.61° N</td>
<td>74.84° W</td>
<td>96</td>
<td>95</td>
<td>23</td>
</tr>
<tr>
<td></td>
<td>41025</td>
<td>35.01° N</td>
<td>75.40° W</td>
<td>28</td>
<td>68</td>
<td>10</td>
</tr>
<tr>
<td></td>
<td>41010</td>
<td>28.90° N</td>
<td>78.46° W</td>
<td>202</td>
<td>1873</td>
<td>25</td>
</tr>
</tbody>
</table>

*Station considered in the numerical example provided in this chapter.
In this section, as an illustrative example, environmental contours with a 50-year mean recurrence period are calculated for buoy 44007, which is located near the coast of New England. As shown in Table 6-2, the water depth at this buoy is 24 m and the duration of hourly measurements is 31 years. The hourly data for the entire duration is plotted in Figure 6-5, which shows that the data are concentrated at low values of $H_s$, and thus, the conditional probability of $T_p$ given $H_s$ can be estimated directly for the observational data. The data is sparser for high values of $H_s$, and the conditional distribution cannot be estimated directly from the data. In this situation, the Nataf model is used to approximate the joint distribution of the extreme values.

![Figure 6-5. All hourly observational data vs extreme value data for site 44007. Blue is continuous hourly data, red is extreme hourly data obtained from 7-ROS.](image)

As a result, the environmental contour for sea state random variables, depending on data availability, should be obtained according to different probability approaches. For normal conditions, as shown by blue asterisks in Figure 6-5, the
Hs data is divided into bins of Hs spaced every 0.6 m. Within each bin, the Pareto distribution function is applied to fit the upper and lower tails of the empirical CDF for measurements of Tp within each bin of Hs. Using these conditional distributions for the tail of Tp given Hs, IFORM along with the Rosenblatt transformation are applied to estimate the environmental contour, specifying combined 50-year conditions of Tp and Hs.

For extreme conditions, the R-Largest Order Statistic method is applied to select the extreme value data from 31 year of measurements. In this case, R=7 meaning that the data with 7 largest measurements of the Hs are selected each year, as shown by red circles in Figure 6-5. The GEV distribution function is fit to the extreme value data to obtain marginal distributions of the Hs and Tp. The correlation coefficient between Hs and Tp is 0.4 for this station. Having the marginal distributions and correlation coefficient, the joint probability distribution for extreme values of Hs and Tp can be approximated with the Nataf model. The correlation coefficient is obtained though integration method (Equation 2-17). The detailed procedure is described by Valamanesh et al., 2014 and also described in Chapter 4. Also, the assumptions and properties for the GEV distribution are described in Section 2.3.

Since the IEC design standard recommends the design of a structure for MRP=50 years, environmental contours for a 50-year MRP and for both extreme and normal conditions are shown in Figure 6-6. As can be seen, the upper bound in the low Hs which, calculated directly from the, data is not smooth. The reason for this feature is that for each bin of data, the upper tail of the Pareto distribution is heavily influenced by the large values of Tp and in this situation, the upper values of Tp are sparse. On the other hand, the observations of Tp for the lower range have much less variability, which makes the environmental contour
smoother. The upper bound of the environmental contour is shown by the dashed line. However the upper bound is less important than the lower bound as OWT loads tend to be larger for extreme conditions with low peak spectral periods than those with high. Therefore the focus here is on developing an equation for the lower bound of $T_p$ given $H_s$.

![Figure 6-6. Sea state 50-year environmental contour, site 44007.](image)

6.5 **Simplified lower bound equation for $T_p | H_s$ in the East Coast**

The range of $T_p$ given $H_s$ is generalized in this section by looking at 50 years lower bound of all 16 stations plotted in Figure 6-7. These 16 stations are categorized into three water depths, shallow, medium and deep water. For each station, the 50-year environmental contour of $H_s$ and $T_p$ for both extreme and normal conditions is constructed. Then, the lower bound is plotted for all 16 investigated sites in Figure 6-7. Therefore, the lower bound (as seen in Figure 6-6 for site 44007) is calculated for 50 years mean return period for all 16 investigated sites along the east coast of the US. The lower bound is shown with three
different colors, representing shallow, medium and deep waters. For example for site 44018, the water depth is 228 m, meaning deep water, therefore, the lower bound in Figure 6-7 is shown by blue color.

It can be seen in Figure 6-7 that the water depth does not have a significant effect on lower bound of $T_p$ given $H_s$. Also, it can be seen that the lower bound for all stations are very close to each other, therefore, it is proposed that the lower bound equation can be estimated and extended to all stations. A power function is fit to the medians of the lower bounds using regression. The form the power function is kept the same as Equation 6-3 and the regression is based on optimizing the coefficient of this equation. The least square method is applied to find the best coefficient for the equation in this form. As can be seen in Figure 6-7, the coefficient of the proposed relationship is 9.5 which is lower than 11.7 as shown in Equation 6-3. This means that for combinations of $T_p$ and $H_s$ for mean return period of 50 years, the proposed equation represents a lower bound of $T_p$ for given $H_s$. This is expected to result in higher loads since, as shown in Figure 2, as $T_p$ becomes closer to the fundamental period of OWTs, the response tends to increase.
6.6 Effect of new model in structural response

To investigate the effect of a lower boundary for $T_p$ given $H_s$ for normal and extreme conditions, the 5MW NREL wind turbine is analyzed for different combinations of $H_s$ and $T_p$. Two different water depths, 10 m and 20 m, are considered and the results are shown in Figure 6-8, which shows the bending moments at mudline of 5MW OWT for various combination of $H_s$-$T_p$ as well as the measurements of these parameters for the 16 considered stations along the Atlantic coast.

Figure 6-7. Lower bound plots for 50-year sea state for sites along the US Atlantic coast.
Figure 6-8. Mudline moment (MN-m) response contour for 5MW NREL OWT for water depths of a) d=10 m, b) d=20 m.

The contours in these figures are the average of maxima from 24 one-hour simulations for the bending moment at mudline. As can be seen, the moment is maximum in range of 4s – 6s which is close to the fundamental period of
vibration of the structure. The bending moment decreases as $T_p$ increases beyond this range. Figure 6-8 also shows the recorded $H_s$ and $T_p$ for hourly recorded data for all buoys along the US Atlantic coast coast, shown by blue marker on the plots. It can be seen that, for low values of $H_s$, the $T_p$ is low (Figure 6-8 for $H_s < 4$ m) and falls within the range of maximum response ($4 \, s < T_p < 6 \, s$). For higher $H_s$, on the other hand, the $T_p$ conditioned on $H_s$ increases and it is no longer within the maximum response range (e.g. for $H_s > 4$ m, $T_p > 6$ s). So, at low $H_s$ it is important to not only consider the lower boundary of $T_p$ but also to consider different combination of $H_s$ and $T_p$ to ensure the maximum response of structure is captured. For higher $H_s$, the structure should only be analyzed for combinations of lower values of $H_s$ and $T_p$ to ensure the maximum response is captured.

This lower boundary of $T_p$ given $H_s$ is proposed in Figure 6-7 of this Chapter for 50 year mean return period. It can be seen in Figure 6-8 that not only the proposed equation with coefficient of 9.5 captures realistic combination of $T_p$ and $H_s$ as compared to Equation 6-3 with coefficient 11.7, but also, it comes with higher bending moment and structural response.

In Figure 6-9a, the bending moment which is obtained using $H_s$-$T_p$ combination along two lower boundaries, i.e. $C=11.7$ (representative of lower bound in Equation 6-3) and $C=9.5$ (representative of proposed equation in this Chapter) are shown for water depths of 10 m and 20 m. It can be seen at lower values of $H_s$, both equations capture the maximum moment, because both coefficients capture the range of $T_p$ close to structural period which results in the maximum response. With further increasing $H_s$, e.g., at $H_s=3$ m for water depth of 20 m and $H_s=4$ m for water depth of 10 m, the maximum response starts to deviate and the
difference between the bending moments obtained from two \( T_p \)-\( H_s \) equations increases, especially for a water depth of 20 m.

Figure 6-9. Comparison of Mudline bending moment of 5MW NREL OWT from two equations for \( T_p \mid H_s \) (e.g. \( T_p = 11.7 \sqrt{H_s/g} \) (\( C = 11.7 \)) and \( T_p = 9.5 \sqrt{H_s/g} \) (\( C = 9.5 \))). a) Bending moment comparison for two water depths, \( d=10 \) m and \( d=20 \) m, b) moment ratio (\( M_{9.5} \) is moment obtained by using \( C = 9.5 \) to calculate \( T_p \) and \( M_{11.7} \) is obtained by using \( C = 11.7 \) to calculate \( T_p \)).
As seen in Figure 6-9.b. at $H_s=8$ m and for a water depth of 20 m, the proposed $H_s-T_p$ combinations results in 11% higher bending moment than the $H_s-T_p$ relationship based on Equation 6-3. In other words, if the design is based on Equation 6-3, the bending moment will be underestimated by 11 percent.

6.7 Conclusions

In this Chapter, a deterministic approach to calculate the appropriate range of $T_p$ given $H_s$ for the east coast of the US offshore environment is proposed. Comparison of measurements with a previously proposed range, Equation 6-3, shows that there are many instances when measurements of $T_p-H_s$ are outside of this range. Sensitivity analyses of the 5MW NREL OWT show that the mudline moment is sensitive to change in $T_p$ conditioned on $H_s$. A probabilistic approach, which considers normal and extreme data differently, is proposed to calculate a more realistic lower boundary of $T_p$ conditioned on $H_s$. This approach applied to 16 buoys along the US Atlantic coast and a new relationship is proposed to calculate the lower boundary of $T_p$ given $H_s$. This new relationship modifies the coefficient from 11.7 in Equation 6-3 to 9.5.

The structural analysis shows that the maximum mudline bending moment for 5MW OWT for lower values of $H_s$ ($H_s < 3$ m for $d = 20$ m and $H_s < 4$ m for $d = 10$ m) is not sensitive to the lower boundary coefficient, however, for higher $H_s$, the new proposed coefficient results in higher bending moment than applying Equation 6-3. For $H_s = 8$ m, the difference is 11% for $d = 20$ m. For this condition, application of the previous approach to estimate the lower boundary of $T_p$, conditioned on $H_s$, will underestimate the loading on OWTs; the proposed
equation is suggested instead since it provides a safer margin for structural design.
7 SUMMARY, CONCLUSIONS AND FUTURE WORK

In this Chapter, the scope and conclusions from the study are summarized and topics for future work listed. The topics of future work are focused on ideas for how to consider the effect of joint probability of simultaneous wind and wave hazard into the design of OWTs. First, the challenges of this future work are summarized and then some preliminary thoughts on how to consider this effect are provided.

7.1 Summary and Conclusions

7.1.1 Summary

This dissertation aims to improve risk analysis of wind turbines in offshore environments. Improving methods for structural modeling and assessing hazard of the offshore environment are two primary objectives in this study. The work on hazard assessment is focused on the environment of the US Atlantic coast, a region exposed to hurricane risk.

Regarding structural modeling, an explicit formulation for estimating the magnitude aerodynamic damping is proposed. In Chapter 3 of this dissertation, a new formulation to estimate aerodynamic damping of wind turbines is proposed. Important parameters such as angle of attack, pitch angle, the wind speed, rotation speed, chord length, density, and the fundamental period of the structure are investigated and shown to be influential parameters on aerodynamic damping.

Regarding hazard modeling, this dissertation considers both measurements of offshore hazard along with estimate of hazard for synthetic storms. Chapter 4
discusses estimation of long term hazard conditions along the US coast. Generalized Extreme Value (GEV) distributions and the Nataf model are used to construct the joint probability distribution for the three random variables. Then, the Inverse First Order Reliability Method (IFORM) is used to construct the environmental surface for these three hazards at a MRP of 50 years. In Chapter 5 of this dissertation, the concept of Probabilistic Offshore Hurricane Hazard Analysis is introduced to estimate long term hurricane wind and wave hazard for the Atlantic coast of the US. The resulting equations, termed Wind and Wave Prediction Equations (WWPEs), are capable of making probabilistic estimates of hurricane wind and wave. Chapter 6 proposes a probabilistic lower bound for the peak spectral period of a seastate conditioned on the significant wave height. The lower bound is obtained by applying IFORM to extreme value measurements at 16 buoy locations along the US Atlantic coast. The method is proposed as a more rational way to consider peak spectral period than that employed in Chapter 4.

7.1.2 Conclusions

The main conclusions of this dissertation are as follows:

- The aerodynamic damping, estimated as the percent of critical damping, in the fore-aft direction for the 1.5-MW NREL reference turbine is estimated by closed-form solution to be between 0.0% and 0.6% for parked conditions and between 3.7% and 5.4% for operational conditions. For the side-to-side direction, the estimates are \( \sim 0.0\% \) for parked conditions and between \( \sim 0.0\% \) and 0.3% for operational conditions.

- A novel application of 3D IFORM, based on sparse sets of extreme value data which require an approximation of the joint distribution, is proposed.
The application is demonstrated for calculating combinations of wind speed, significant wave height and peak spectral period at a 50-year mean return period based on sparse buoy measurements of extreme values of these parameters.

- Three methods for calculating wind and wave conditions with a mean return period of 50-years are considered. Two of the three methods are based on calibrating independent probability distributions for wind and wave conditions, and the third method is based on calibrating a joint distribution of wind and wave conditions. It is found that the design loads associated with the conditions assessed with independent distributions are usually higher than those assessed with a joint distribution, however, in one case, where dynamic effects on the structure were significant, the design loads were higher for conditions assessed with a joint distribution.

- The probabilistic nature of the uncertainty in the predictions of hurricane wind with the Holland model and hurricane waves with Young’s model is found to be reasonably characterized by a zero-mean normally-distributed random variable representing the logarithmic difference between predicted and measured intensities.

- The uncertainty in wave height predictions with Young’s models is found to be considerably greater than the uncertainty in wind speed predictions with the Holland model with the former having a standard deviation of the logarithmic difference between prediction and measurement of 0.25 and the latter having a standard deviation of 0.13.
- The effect of including uncertainties in the estimation of hurricane wind and waves is shown to increase the estimate of the wind speed and the significant wave height, especially at higher MRPs.

- The lower bound equation, proposed in IEC is updated. While the format of the lower bound equation is the same as IEC, the coefficient 11.7 is changed to 9.5. The analysis shows that the new coefficient is better representative of lower bound equation for combination of Significant wave height and peak spectral period for 50 years mean return period event.

7.2 Future work

In Chapter 6, the maximum wind speed and significant wave height due to hurricanes at different mean return periods including uncertainty are calculated. This work led to an important question: do the maximum wind and maximum significant wave height during a hurricane occur simultaneously? If the answer is no, a logical next question is how the maximum wind and wave should be reasonably combined for design and risk?

In Chapter 4, a method for realistically combining wind and wave parameters based on sparse offshore measurements is proposed. In this section, the same approach is suggested, however the available data for hurricane events is much less than those from non-hurricane extremes, therefore, one important assumption in the method proposed here is that the joint probability distribution of simultaneous wind and wave is not dependent on the location and will not vary with hurricane events. The availability of more data may reveal variability of the joint probability distribution of simultaneous wind and waves by
hurricane and location, and, if so, the proposed procedure in this Chapter may be modified accordingly.

The suggested approach, which is based on IFORM and on temporally-distributed measurements of hurricane seastates and wind fields during hurricane, is described below.

7.2.1 Simultaneity of wind and wave during hurricanes

In Chapter 5, a framework termed Probabilistic Offshore Hurricane Hazard Analysis (POHHA) is proposed to estimate long term wind and waves due to hurricanes. Specifically, the Chapter presents a statistical formulation of probabilistic equations to predict wind speed and wave heights during hurricanes. The proposed approach is appropriate to estimate wind and wave hazard independently for the design mean return period (i.e., assuming that independent estimates of 50-year wind and wave conditions occur simultaneously), however this method does not provide any consideration of the timing of wind and wave during a hurricane. Obviously, assuming that the maximum wind speed and seastate occurs simultaneously during a hurricane will result in a higher estimate of overall environmental conditions. However, this assumption can be justified if the following two assumptions are reasonable:

1- The extreme wind and extreme wave both come from the same hurricane event. Since the POHHA is an event-based assessment using a catalog of synthetic events, this assumption means that the estimated wind speed and significant wave height for any mean return period are from the same hurricane with the same MRP.
2- The extreme wind and extreme wave are simultaneous during a hurricane (i.e. the most severe seastate and wind field during the hurricane, coincide in time).

To assess the first assumption, the maximum wind and wave from buoy measurements during historical hurricanes are shown in Figure 7-1. As can be seen, although there is a linear correlation between maximum wind and maximum waves during hurricane for each station, it is not always true to assume the extreme value wind and waves are coming from the same hurricane event.

![Figure 7-1. Maximum wind and maximum wave observed during historical hurricanes.](image)

Figure 7-2 shows an example relevant to the second assumption. Figure 7-2a shows continuously recorded hourly wind and wave for station ID#41010 during hurricane Frances in 2004. The data can be used to investigate three assumptions for combining wind and wave hazard: (1) the conservative approach, assuming that the maximum wind and maximum wave are simultaneous \( (V_{max}, H_{z,max}) \), (2) the max wind approach, assuming that design conditions can be modeled by
combining the maximum wind with the simultaneous significant wave height \((V_{max}, H_{s,i})\) and (3) the max wave approach, assuming that design conditions can be modeled by combining the maximum wave with the simultaneous wind \((V_j, H_{s,max})\). These three combinations for each station can be illustrated as shown in the lower figure, which consists of several triangles, representing four numbers, \(V_{max}, H_{s,max}, V_j, H_{s,j}\). These triangles illustrate both the magnitude and difference between the extreme seastate and the extreme wind field, as shown in Figure 7-2b. Based on this plotting scheme, a hurricane with the most severe seastate occurring simultaneously with the most severe wind field will be plotted as a point in the lower figure, while hurricanes with large differences between simultaneous conditions and extreme conditions will be plotted as a large triangle. In the case of a hurricane represented by a large triangle, assuming that the maximum wind and maximum wave is simultaneous, will be conservative.

According to Figure 7-2, the length of each side in triangle is defined as the difference between the maximum value and the joint value. The normalized difference, then, is obtained by dividing the difference by the maximum value.

Figure 7-3 plots the length of the triangle normalized with respect to the maximum value for each parameter according to following equation.

\[
\tau_V = \frac{dV}{V_{max}} \quad (7-1)
\]

\[
\tau_{H_s} = \frac{dH_s}{H_{s,max}} \quad (7-2)
\]
The joint variability of the simultaneity of wind and wave can be characterized based on the above equations. If $r_V$ and $r_{H_s}$ are close to 0, then the maximum wind and wave during a storm are more likely to be simultaneous, however, the data show that the maximum wind and wave are not simultaneous for almost all measurements. The ratio of simultaneous wind and wave with respect to the maximum values of wind and waves during each storm are shown in Figure 7-3 for all buoys and historical hurricanes considered in Chapter 5. In this figure, the
assumption of simultaneity is more reasonable the closer the points are to the origin.

![Figure 7-3. Ratio of simultaneous wind and wave with respect to the maximum values.](image)

Using this information, a probabilistic combination of simultaneous wind and wave is suggested here. First, the joint probability distribution of $r_V, r_{H_s}$ is obtained. Then, having the joint probability distribution function, IFORM is used to obtain the contours of combinations of wind and wave. The procedure is explained in detail in the following section. The procedure is similar to that in Chapter 4, but with different hazard parameters, which here are defined as ratio of simultaneous wind and waves to the maximum values and different probability distribution functions, exponential distribution functions are used here.

It can be seen from Figure 7-3 that the linear correlation coefficient between $r_V$ and $r_{H_s}$ is small and, based on the lack of pattern of the scatter, the two ratios can
be modeled as independent random variables. Therefore the joint probability distribution can be obtained according to the following equation:

\[ f_{VH_s}(v, h_s) = f_V(v) \cdot f_{Hs}(h_s) \quad (7-3) \]

Therefore, the joint probability distribution function of \( r_V \) and \( r_{H_s} \) can be generated based only on the marginal distributions of each random variable. In Figure 7-4, the exponential distribution function is fit to the data for the wind speed ratio \( r_V \) and the significant wave height ratio \( r_{H_s} \).

Figure 7-4. Probability plot for exponential distribution function for marginal distributions of wind and wave with respect to maximum values for a) \( r_V \) and b) \( r_{H_s} \).
Knowing the marginal distribution of wind speed and significant wave height, the joint probability distribution of the ratio is plotted in Figure 7-5. As can be seen in this figure, the probability contours are almost linear.

![Figure 7-5. Joint probability distribution of simultaneous wind and wave ratio.](image)

Using this joint probability distribution, the 50-yr environmental contour for $r_V$ and $r_{H_s}$ can be calculated using IFORM. The general procedure is described in Chapter 2, however the difference is that here, the exponential distribution of the defined ratios is used to transform from standard normal space to original space. The concept is illustrated with an example in the following section.

As an example, assume that annual maxima of wind and wave is only available for a duration of 20 years and that the objective here is estimating the combination of wind and wave for an MRP=1 year. The beta, corresponding to MRP=1 can be obtained from following equation:

$$\Phi(\beta) = 1 - \frac{1}{N+1}$$  \hspace{1cm} (7-4)
Where \( N \) in this case is the number of independent sea states in one year. For annual maxima data, then:

\[
\Phi(\beta) = 1 - \frac{1}{2} = 0.5 \quad \text{for} \quad \beta = 0
\]

In Chapter 5, a method is described to estimate the wind and wave conditions for any mean return period. The conditions are defined by two parameters: \( V_{50, H_{s,50}} \) for wind speed and significant wave height, respectively. Now, assume that there are \( S \) combination of 50 year wind speed and significant wave height. Therefore, we can assume we have \( S \) realizations of 50 years of wind and wave combination, and we can say the rate of occurrence is 1/50. In this case, for MRP=50 years according to Equation (4):

\[
N = (\text{MRP} \cdot \text{rate}) = 50 \cdot \frac{1}{50} = 1
\]

Therefore,

\[
\Phi(\beta) = 1 - \frac{1}{2} = 0.5 \quad \text{for} \quad \beta = 0
\]

By transforming the normal space to the original space, following the joint probability distribution of \( r_v, r_{H_s} \), the expected combination of wind and wave for 50 years mean return period can be obtained. As an example demonstrating how this approach can be used to estimate simultaneous conditions of wind and wave, assume that the maximum 50 years wind speed occurs. The simultaneous significant wave height ratio can be calculated according to the following equation:

\[
F(r_{H_s}) = \Phi(0) \rightarrow \tilde{r}_{H_s} = F^{-1}(0.5) = 0.096
\]
Using exponential distribution function for $r_{H_s}$, as suggested previously, the expected value of $\bar{r}_{H_s}$ = 0.096.

Following the same approach the combined wind speed ratio with maximum significant wave height can be obtained as:

$$F(r_V) = \Phi(0) \rightarrow \bar{r}_V = F^{-1}(0.5) = 0.064$$

Therefore the combined wind and wave for two important points are:

$$\left(V_{50}, 0.904H_{s,50}\right), \left(0.936V_{50}, H_{s,50}\right)$$

While the example just introduced was for considering conditions with an MRP of 50 years, the procedure can be extended to any MRP. Figure 7-6 provides combinations of simultaneous wind and wave for different mean return periods.

Figure 7-6 is produced to obtain combination of $H_s$ and $V$ for 50 years, 100 years and 500 years, when the independent $V$ and $H_s$ for 50 years is known. Let’s say,
instead of having V and Hs for 50 years, independent V and Hs are calculated for N years mean return period. When the maximum wind and wave for N years mean return period is given, then the plot in Figure 7-7 can be used to obtain combination factors to be applied to independent V and Hs for different mean return periods. For example if N = 200 years (independent V and Hs are known for MRP = 200), the blue line is a combination of V and Hs, that is proposed for 200 years, the red line is proposed for combination of Hs and V for 400 years and black line is proposed the combination factors for 2000 years. It is important to mention that this line is not representative of combination of load for 2000 years mean return period.

![Figure 7-7. Combination of simultaneous wind and wave for different mean return periods, when N years maximum wind and wave is available.](image)

For example, if the maximum value of hurricane wind and wave for 100 years is obtained, the blue line shows the combination for 100 years, the red line shows the combination for 200 years and the black line shows the combination for a 1000 year mean return period.
Simultaneity effect is evaluated through statistical analysis of all historical hurricane data. Since, the simultaneity distribution may vary by location and hurricane event parameters, more investigation is required to quantify the variability of simultaneous wind and wave more accurately. The goal in this Chapter is to propose a framework to consider the joint variability and spatial variability of extremes, and in the future this equation can be adjusted through validation process by having more observations.

In Chapter 4 the combination of wind and wave hazard proposed, however, this approach cannot be used to consider very long mean return period conditions, because the NATAF model does not consider the asymptotic correlation of random variables. Therefore, considering the asymptotic correlation to estimate very long mean return period condition is an objective for future studies. In Chapter 5, the POHHA is introduced to obtain the independent wind and wave hazard. In this Chapter, using the IFORM, a combination approach is proposed for different mean return period to account for simultaneity of hurricane wind and wave hazard.

Although the combination rule can be used to consider the simultaneity effect, there are several challenges which need to be addressed in future studies. The joint probability distribution of $r_Y$ and $r_{H_s}$ needs to be characterized by location and hurricane events, since this distribution may vary with location and hurricane parameters. Also, in this study it is assumed that both maximum wind and maximum wave are coming from the same hurricane, which may not be accurate, especially for low mean return period hazard.
REFERENCES


[29] Le Roux, J.P “Profiles of fully developed (Airy) waves in different water depths,” Departamento de Geología, Facultad de Ciencias Físicas y Matemáticas, Universidad de Chile, Casilla, unpublished.


