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DRAFT: RELIABILITY ANALYSIS OF FLOATING OFFSHORE WIND TURBINE SYSTEM BASED ON POLYNOMIAL CHAOS METHOD

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ABSTRACT

In reliability analysis, the objective is to evaluate the probability of failure of a system corresponding to a predefined reference period with respective to some performance functions. Various methods have been proposed to solve this problem efficiently, like Monte Carlo based sampling methods, approximation based FORM/SORM and surrogate models. However, the efficiency of these methods will decrease exponentially as the dimension of the problem increases. Even though the dimension-free property of Monte Carlo based methods are attractive, the slow convergence rate ($\propto 1/\sqrt{N}$) makes those approaches particularly inefficient. For an offshore system, the dimension of the random variables could easily be hundreds or thousands due to the existence of random phases when applying wind and/or wave spectrum. In this paper we propose to isolate the uncertainties induced due to environment random variables and random phases. Phase-conditioned meta-models, which are inexpensive to evaluate in contrast to the original model, are constructed based on Polynomial Chaos Expansion (PCE) under the framework of Uncertainty Quantification (UQ). The uncertainty of random phases will then be taken into account by bootstrapping from phase-conditioned meta-model pools. Since it is impossible to quantify the error made with surrogate model, this approach is first applied to a single DOF dynamic system with external wave loads. A few metrics are compared to assess the accuracy of this method against crude Monte Carlo method. The 50-year return loads of the SNL 13.2 MW semi-submersible floating offshore wind turbine model is eventually obtained with the constructed PCE surrogate models

NOMENCLATURE

A You may include nomenclature here.
α There are two arguments for each entry of the nomemclature environment, the symbol and the definition.

meta model for structural reliability and UQ [**?**]

The accuracy of Polynomial chaos approximation [**?**]

Three possible sources of discrepancy between simulation and experimental observations may be distinguished: Model inadequacy, Numerical Error and Input parameter uncertainty. Only the uncertainty in input parameters is addressed in this work. Probabilistic methods based on the representation of uncertain input parameters by random variables or random fields.

Non intrusive method, which only make use of a series of calls to the deterministic model. Also minimize the number of calls to the model.

Alternative is response surface method or metamodels. PCE: spectral methods provide a polynomial metamodel onto a basis that is well suited to post-processing in uncertainty and sensitivity analysis. Cons: Metamodeling reveal efficient and accurate for a moderate number of input parameters. Besides, Difficult in estimation of the approximation error, which directly depend on the goodness-of-fit of the metamodel. Reliable error estimate allow to design an adaptive refinement of the metamodel

Let(Ω, F, P) be a probability space, where Ω is the event space equipped with σ-algebra and probability measure P. Throughout this work, random variables are denoted by upper case letters $X(\omega):\Omega\rightarrow D_X\in R$, while their realizations are denoted by the corresponding lower case letters. Moreover, bold upper and lower case letters are used to denote random vectors and their realizations, respectively.

Standard methods for uncertainty propagation.

Statistical point view: Unbiased Estimator, However slow convergence rate. could be improved by LHS and QMC. By definition, could also be viewed as integration. Quadrature rule could be applied. Curse of dimensionality. Could be improved by sparse quadrature schemes.

SDOF system

Single DOF system defined by natural frequency and damping ratio. $\omega_n = 0.15Hz, \zeta = 0.1$.

System transfer function as following

$$H(\omega) = \frac{1}{\sqrt{(1-\frac{\omega}{\omega_n})^2 + (2\zeta\frac{\omega}{\omega_n})^2}}$$

External loads are assumed to be wave loads. JONSWAP wave spectrum is used as recommend by standard IEC 61400-3

Pierson-Moskowitz (PM) spectrum $S_{PM}(\omega)$ is given by:

$$S_{PM}(\omega) = \frac{5}{16}\cdot H_s^2\omega_p^4\cdot\omega^{-5}\exp\left(-\frac{5}{4}\left(\frac{\omega}{\omega_p}\right)^{-4}\right) \tag{1}$$

where $\omega_p = 2\pi/T_p$ is the angular spectral peak frequency.

JONSWAP Spectrum:

$$S_J(\omega) = A_\gamma S_{PM}(\omega)\gamma^{\exp\left[-0.5(\frac{\omega-\omega_p}{\sigma\cdot\omega_p})^2\right]} \tag{2}$$

where $S_{PM}(\omega)$ is pierson-Moskowitz spectrum, $\gamma = 3.3$ is non-dimensional peak shape parameter. σ is spectral width parameter, $\sigma = \sigma_a = 0.07$ for $\omega \leq \omega_p$ and $\sigma = \sigma_b = 0.09$ for $\omega > \omega_p$. $A_\gamma = 1 - 0.287\ln(\gamma)$ is a normalizing factor.

Check if the variance of system introduced due to random phases is comparable with wind turbine system.

To achieve 10^{-6} failure probability with $CV_{p_f} \leq 10\%$, requires about 10^8 simulations

1 PCE Structural Reliability

Xiu in [**?**] proposed and numerically demonstrated the optimal (exponential) convergence rate of each Wiener-Askey polynomial chaos expansion for its corresponding stochastic process.

TABLE 1. System variance indicator introuded by random phases

	quantile of $F_{T_p\|Hs}$							
$H_s(m)$	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8
1	1.12	1.17	1.12	1.16	1.22	1.21	1.28	1.32
2	1.16	1.32	1.27	1.26	1.45	1.17	1.4	1.25
3	1.24	1.39	1.23	1.13	1.2	1.12	1.08	1.27
4	1.3	1.21	1.24	1.29	1.29	1.28	1.1	1.47
5	1.21	1.14	1.35	1.29	1.17	1.15	1.1	1.19
6	1.11	1.2	1.22	1.23	1.12	1.26	1.32	1.13
7	1.25	1.29	1.27	1.26	1.19	1.24	1.24	1.08
8	1.1	1.19	1.25	1.27	1.2	1.16	1.33	1.17
9	1.21	1.12	1.35	1.15	1.36	1.19	1.26	1.36

Idealy, if the independent variable ζ in the polynomials $\Phi_i(\zeta)$ belong to the basic types as shown in Wiener-Askey scheme, the exponential convergence rate could be achieved. However, like the Weilbull and Lognormal distributions used in the current research, we often encounter distributions of random inputs not listed. A transformation could be used to map the target random variables to basic random variables.

The target is the 50-year return loads. Based on Possion process assumption etc, we can evalute the extreme loads based on the maximum load within simulation duration. If conditions ** meets, block maxima will follow generalized extreme value distributions.

Quantity of interest (QoI) could be defined as following

y^i_{max} represents the maximum response value of the i^{th} simulation with duration 400 seconds, $i = 1,\ldots 100$. $\max\left\{y^i_{max}\right\}/\text{mean}\left\{y^i_{max}\right\}$ is selected to indicate the random phases variance.

a standard uniform random variable is first chosen, $u \in U(0,1)$. The CDFs for physical random variable x and random variable ζ chosen from the list are F_X and F_Z. Then we can set $u = F_X(x) = F_Z(\zeta)$ Howver since we don't know what is the best for that distribution, this approximiation could be reasonable.

Random variables: X, Environmental Random variables. Θ: Random phases. $Y = f(X,\Theta)$: response with unknown marginal distribution F_Y. Note that Θ and X are independent.

$$\begin{aligned}\Pr(Y > y_0) &= \int \Pr\left(f(X|\Theta) > y_0\right) f_\Theta\left(\Theta=\theta\right) d\Theta \\ &= \iint \Pr\left(f(x,\theta) > y_0\right) f_X(X=x) dX f_\Theta\left(\Theta=\theta\right) d\Theta\end{aligned} \tag{3}$$

The idea to solve this problem is to seperate the uncertainty introduced by random phases and physical random vari-

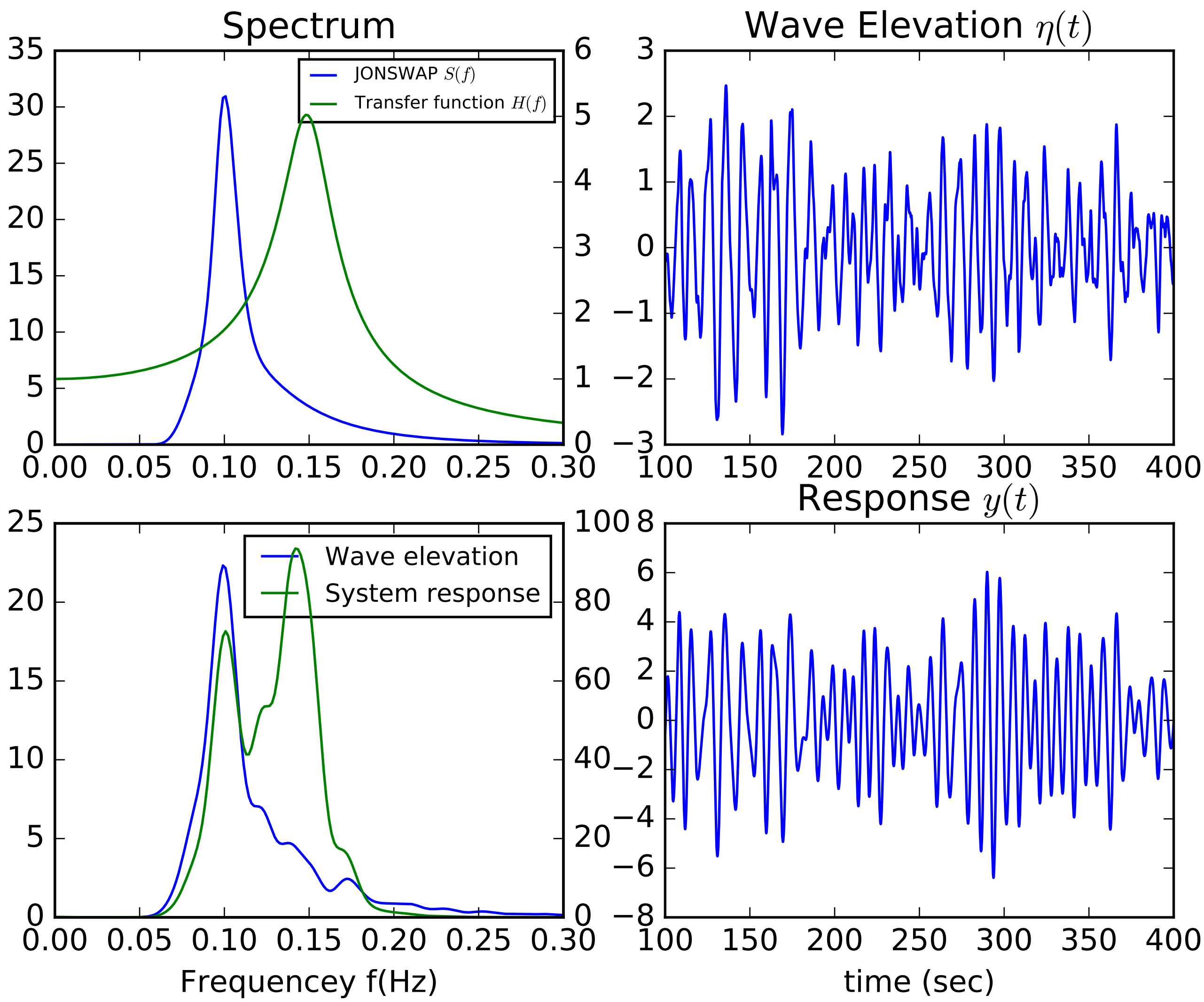

FIGURE 1. SDOF sysmtem properties

ables. According to TurbSim, the random numbers generated by the pRNG are used to create random phases (one per frequency per grid point per wind component) for the velocity time series. The difficulty to quantify the phase uncertainties comes from the large dimensions and the dimension changes as we create or apply different wind model. In addition, we can bearly control the random phases unless we know the pRNG. Thus the following alternatives are proposed. Say, our goal is 50-year return loads and simulation duration is 1-hour. Our QoI can either be the block maxima (assumptions here like possion process; POT works here?) or the time series itself.

Define the maxima in duration T is y_{max}. Then the QoI can be expressed with PCE as following:

$$y^K_{max}(x|\theta) = \sum_{k=0}^{K} \alpha_k \Phi_k(u) \tag{4}$$

If the QoI is the time series, then expression can be written as:

$$y^K(x,t) = \sum_{k=0}^{K} \alpha_k(t) \Phi_k(u) \tag{5}$$

The inner integral conditional on Θ in Eqn. 3 can be appxomiated as:

$$\Pr(Y > y_0|\Theta) = \int \Pr\left(y^K_{max}(x|\theta) > y_0\right) f_X dX \tag{6}$$

Or

$$\Pr(Y > y_0|\Theta) = \int \Pr\left(y^K(x,t|\theta) > y_0\right) f_X dX \tag{7}$$

The next step is to account for the outer integral, sampling from Θ space. One critical question is then to choose the proper number of samples N_θ to represent the distribution as well as to quantify the uncertainty."Repeat for N_θ times with different θ samples. (need a metric to determine)

Once this step is done, the following algorithm could be used to estimate the 50-year return load.

number of samples(numSamples) = 50 year / T

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for $i = 1:$ numSamples **do**
  $X_i \sim F_X$
  select θ from pre-runned θ pool ▷ Can pick θ uniformly from N_θ samples or add weight based on sampling results
  $y^i_{max} = y^K_{max}(X_i, \theta)$
end for
50 year return load = max $\left\{y^i_{max}\right\}$

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for $i = 1:$ numSamples **do**
  $X_i \sim F_X$
  select θ from pre-runned θ pool ▷ Can pick θ uniformly from N_θ samples or add weight based on sampling results
  $y^i_{max} = \max\left\{y^K(X_i, t, \theta)\right\}$
end for
50 year return load = max $\left\{y^i_{max}\right\}$

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Is the variance in SDOF model competible with wind turbine?

REFERENCES