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Application of DSI Techniques to Monopile Foundations of Offshore Wind Turbines Reliability Problems

Zhang Jing, Yugang Li, and Haigui Kang

School of Civil and Hydraulic Engineering, Dalian University of Technology, Dalian, China

ABSTRACT

The monopile foundations of offshore wind turbines are subject to combined wind and wave loading which must be taken into account for the reliability problems. The pile-soil structure system is complicated and the performance functions of piles under inclined loads are implicit. For failure probability estimates of the monopile foundations, the numerical expensive evaluations of the limit state function have to be replaced by suitable approximations. The common approach is to use the response surface method (RSM) based on the least square regression. However, the application of the discrete smooth interpolation (DSI) techniques to structural reliability problems has not been realized until recently. This paper investigates the use of DSI techniques that can be used to construct response surface approximation. Example is given in the paper by comparing with the most common RSM and the result shows that this method is compared well with those obtained by the RSM and is applicable to offshore wind turbines foundation reliability analysis involving implicit performance functions such as monopile foundations.

KEYWORDS: Offshore wind turbines; Monopile foundations; Response surface method; Reliability; Discrete Smooth Interpolation;

INTRODUCTION

Since installation of the first offshore wind farm in 1991 more than 330 offshore and near-shore wind turbines have been erected. Most projects have been realized with mono-towers on monopile based foundations. However, due to the inherent uncertainties in nature, it is difficult to determine the parameters precisely such as soil properties, pile properties and load properties, because of such uncertainties, it is logical to adopt a probabilistic approach in pile analysis and an important part is to calculate the probabilities of failure or of unacceptable structural performance.

In the reliability analysis of foundation structure, the limit state function is often implicit, Monte Carlo Simulation (MCS) can give an accurate estimation of the failure probability, but for structures with high reliability, a large number of mechanical computations will make the computational cost prohibitory high. This quite naturally leads to approximation procedures, one of these being the so-called response surface method (RSM) then was introduced to reliability analysis[1-3] and have been developed in recent years[4-10]

The most classical response surface method is to construct a metamodel of polynomial function to approximate the (unknown) limit-state function in the neighborhood of design point. The experiments points are chosen by statistical design of experiments (DOE) such as star shaped DOE[2] and Central Composite DOE[4]. Repeated deterministic finite-element analyses at selected points and subsequent regression analysis can be used to obtain an expression for the response surface. When the fitted surface becomes the explicit, it is now to apply directly one of the available methods（FORM/SORM or Monte Carlo Simulation）to find the design point corresponding to the reliability index. However, it has been shown[6] that the obtained results are highly dependent on these choices of the polynomial and on the shape of the actual failure hyper-surface, there is no guarantee that the fitted surface is in fact a sufficiently close fit in the region of interest. According to Hurtado and Alvarez[7], this is due to the rigid and non-adaptive structure of the meta-model implemented by response surface methods.

Recent research seems to be moving towards developing more flexible and generic meta-modeling approaches. Ideally, no functional form is preset and a ‘universal estimator’ is used, three main meta-models have been proposed instead of the quadratic polynomial RS for reliability analysis: Neural networks (NN)[7][9]. Splines[8][9] and Kriging[10].

Another alternative approximation method is DSI techniques which are not biased by the choice of a predefined regression model and can model complex and non-linear behaviors, however, to our knowledge, no study has been carried out to reliability analysis with DSI techniques, therefore, the aim of this paper is to:

(1) Present an new response surface approach for reliability analysis based on DSI techniques;

(2) Give a example demonstrate that this approach is feasible by comparing with classical RSM;

(3) Analysis the monopile foundations reliability problems of offshore wind turbines

DESIGN OF EXPERIMENTS

In the RSM technique, there are two important steps that require special attention: (1) The choice of meta-models type to represent the RS ; (2) The selection of a convenient DOE to give accurate RS. When meta-model type has been known, the main difficulty is to choose adequately a DOE, in this paper, for compare with classical RSM, only Central Composite DOE is adopted.

Fig. 1 shows the experiment design used in the present study with two random variables. A central composite DOE is a two level (2^n) factorial design, augmented by n_0 center points and two 'star' points positioned at $\pm\alpha$ (setting $\alpha = 1$ in this paper) for each factor. For n random variables, the number of numerical experiences is: $2n+1$ for the star shaped DOE and 2^n+2n+1 for the central composite DOE.

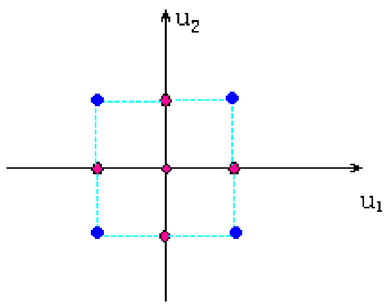

Figure 1: Central Composite Design (n=2)

APPLIED META-MODELS IN RESPONSE SURFACE

Classical RSM

In the RSM, the actual limit state function $g(x)$ is replaced by a polynomial type of function $\tilde{g}(x)$, typically a quadratic polynomial function without mixed terms:

$$\tilde{g}(x) \approx a + \sum_{i=1}^{n} b_i x_i + \sum_{i=1}^{n} c_i x_i^2 \tag{1}$$

where n is the number of random variables X, and a, b_i, and c_i are the least square regression coefficients.

Discrete smooth interpolation[11]

The DSI framework[12] aims at interpolating a function *z*, at each node β of a discrete model. The interpolation is carried out by computing a solution that honors, in the least square sense, a set of linear relationships between function values, also called "constraints". DSI constraints are classified into three main groups: The roughness constraint ensures the smoothness of the results; The control node constraint specifies the value of the function at a given node of the discrete model; The fuzzy equality constraints specify some linear relationships between the function values at several nodes of the discrete model. These constraints are resolved the least square sense and can be balanced with weighting coefficients.

They can are usually written in the following form

$$\sum_{\beta\in\Omega} A_c(\beta)z(\beta)b_c \qquad (2)$$

where β is a node of the underlying discrete model, Ω is the set formed by all the nodes while $A_c(\beta)$ and b_c are coefficients specific to the constraint c.

More details can be obtained in the reference [11]

ITERATIVE PROCEDURE

As seen from Fig. 2, the approach can be divided mainly into two stages as in the classical RSM. The following explanation can be extended for the second stage as well. First a design of experiment method such as central composite design can be selected to form the necessary experimental points. Instead of choosing the RSF type for the first stage, the DSI model is selected, and an approximate limit state function is formed. Then, one of the structural reliability methods such as FORM/SORM or MCS can be chosen to find the design point corresponding to the reliability index. Based on the design point found in the first stage, a new center point which is proposed by Bucher and Bourgand[2] is calculated as

$$\mathbf{x}_M = \bar{\mathbf{x}} + (\bar{\mathbf{x}}_{D1} - \bar{\mathbf{x}})\frac{g\bar{\mathbf{x}}}{g\bar{\mathbf{x}} - g(\bar{\mathbf{x}}_{D1})} \qquad (3)$$

where $\bar{\mathbf{x}}$ is the mean value of the random variables, $\bar{\mathbf{x}}_{D1}$ is the design point of the first stage.

The experimental points for the second stage are formed based on the new center point, applying one of the design of experiment methods. The same procedure explained above is followed for the second stage. In this study the comparison of the classical RSM and the DSI method is carried out based on the approach explained in this section.

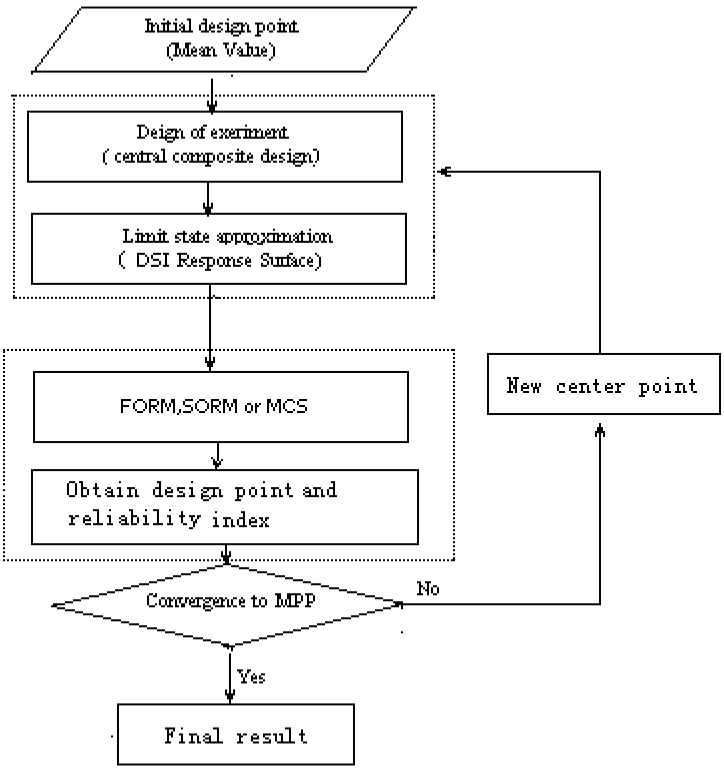

Figure 2: Flowchart of the DSI technique modified for the use of structural reliability problems.

EXAMPLE: A HIGHLY NONLINEAR LIMIT STATE FUNCTION

This example, which is taken from the study by Zou[13], behaves highly nonlinearly around the design point as illustrated in Fig. 3. The performance function is given as

$$g_X(X_1, X_2) = X_1^3 + X_2^3 - 18.0$$

Table 1: Random variables

variable	PDF	Mean	Standard deviation
X1	Normal	10	5.0
X2	Normal	9.9	5.0

Table 2: Result

	MCS	Classical RSM	DSI RSM
Reliability index	2.53	2.33	2.49
Failure probabilities	0.00570	0.00990	0.00639
Error	0	73%	12%

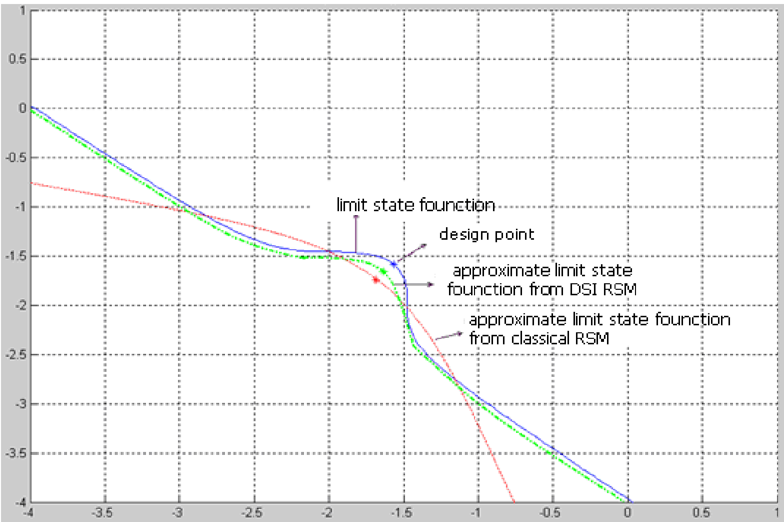

Figure 3: Two RSFs from classical and DSI with the central composite design around the design point.

For the numerical example (nonlinear behavior is high), with the central composite design, DSI response surface technique gives a better results than that of the classical RSM(Table2). The reason is that the DSI technique can capture the shape of the performance function as can be seen from Fig. 3. The result indicates the advantage of using DSI method for structural reliability when the original problem performed highly nonlinear behavior.

RELIABILITY ANALYSES FOR THE MONOPILE FOUNDATION OF AN OFFSHORE WIND TURBINE

Here, we focus on the monopile foundation of an offshore wind turbine, the researched offshore wind turbine has a hub height of approximately 90 m and rotor diameter of approximately 100 m (Fig. 4), the wind farms was installed in areas far away from the coast. At these locations, water depths from 10 m to 20 m. The design parameters are given in Table 3 and Fig. 4

The reliability analysis is conducted for two different failure modes: (i) The pile head displacement ≥ 0.05 m, (ii) the maximum bending moment in the pile ≥ 230 kN•m.

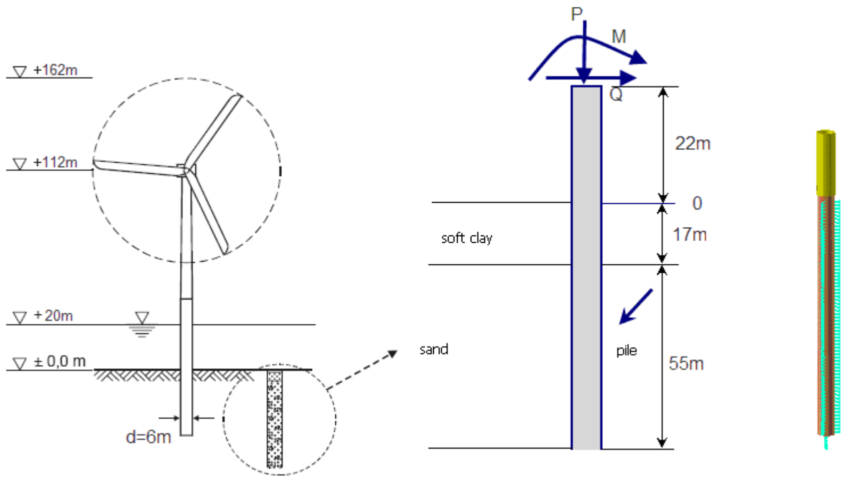

Figure 4: the offshore wind turbine with its soil profiles and ANSYS model

Table 3: Random variables

Notation	Random variables	Type	Mean value	S.D	COV
X_1	Applied vertical load, P	Normal	2 MN	400 kN	0.2
X_2	Applied lateral load, Q	Extreme type I	1.5 MN	300 kN	0.2
X_3	Applied top moment, M	Extreme type I	80 MN·m	16 MN·m	0.2
X_4	Sand angle of internal friction, φ	Normal	30°	3°	0.1

X_5	Soft clay unit weight, γ_1	Normal	20kN/m^3	4 kN/m^3	0.2
X_6	Sand unit weight, γ_2	Normal	25 kN/m^3	5 kN/m^3	0.2
X_7	Pile unit weight, γ_3	Normal	78 kN/m^3	15.6kN/m^3	0.2
X_8	Soft clay cohesion, c	Normal	18kPa	1.8 kPa	0. 1
X_9	Pile diameter, d	Normal	6m	0.3	0.05
X_{10}	Pile modulus of elasticity, E	Normal	2.1×10^{11} kPa	4.2×10^{9} kPa	0.02

Table 4: Results

	β	P_F
Failure mode (i)	3.17	0.00076
Failure mode (ii)	3.09	0.00100

CONCLUSIONS

This paper developed a new RSM method based on DSI technique, its efficiency was demonstrated through a benchmark example. The main advantage is its flexibility to adapt to more complex limit state functions that might not be represented well by means of a low order polynomial. It is applicable to offshore wind turbines foundation reliability analysis involving implicit performance functions such as monopile foundations.

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