A System Reliability Analysis Method for Offshore Wind Turbine Foundation

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ABSTRACT

Offshore wind energy is one of the most attractive sources of renewable energy. During the last decade, offshore wind turbines were extensive application throughout Europe. However, the reliability of offshore wind turbines especially foundations is one of the currently challenges. Simulation based methods are often used to calculate an accurate value for the reliability of structures, one of the major disadvantages however is the large number of simulations required to obtain an accurate estimate of the failure probability. To meet this disadvantage, a new simulation method based on support vector machine (SVM) is proposed in this paper, SVM is a relatively new computational learning method, it is especially efficient in classification problem. In the proposed method, Latin hypercube sampling (LHS) is adopted for the preliminary samples and the SVM response surface indicator is refined by adaptively increasing the sample points, then the MCS scheme is implemented. The objective of this paper is to further increase the efficiency of simulation based reliability methods. The overall performance of the technique is addressed referring to a benchmark example.

KEYWORDS: Renewable energy ;Offshore wind turbines; Foundations; Reliability; Support vector machine; Monte Carlo Simulation;

INTRODUCTION

Over the past decade, continually growing energy demands as well as global warming and other pollution concerns have drawn considerable attention to the need for alternative, free, and renewable sources of energy—offshore wind energy. offshore wind turbines are costly and complex, usually working in severe environment on a long term basis, as many source of uncertainty are inherent in structural design, absolute safety cannot be achieved. An important part of the analysis of structure is to calculate the probabilities of failure or of unacceptable structural performance. While expressing the limit state function in a closed-form is often not possible in the reliability analysis of complex structures.

In principle, any algorithm used for structural reliability evaluation may be adapted to handle implicit limit state functions. When the gradients of the limit state function are required, which is the case for first order and second order reliability methods (FORM and SORM), the performance is affected when direct or analytical differentiation are not available [1, 2]. Furthermore, these methods are very difficult for system reliability. Standard Monte Carlo Simulation (MCS) provides the most robust way for computing the failure probability, but it is well known to be inefficient when the failure probability is small, several techniques have been proposed to reduce this large figure, such as importance sampling (IS) [3], directional simulation [4], conditional simulation [5], antithetic variates [6] and others. Despite these methods require much less samples than MCS, in some cases their quantity can still be considered as large, especially when it may involve nonlinear finite element solutions and the computation of each sample is very costly .

The use of a response surface in combination with a simulation method to increase the efficiency is widely spread [1, 7–10], that is the response consisting of a complex function of input variables is approximated by a simple function of the input variables.

As we known in reliability analysis, it is the sign of the limit state function value, but not the actual function value that is useful, so in this paper we would propose a new method based on SVM that can reduce this calculation cost greatly. The idea of the proposed method is to construct a response surface indicator, i.e., response surface of the indicator function, instead of constructing a response surface of the limit state function itself. After the response surface of the indicator function is constructed and refined, MCS simulation is implemented.

THE BASIC THEORY OF SVM

SVM is a relatively new computational learning method based on the statistical learning theory developed by Vapnik [11], that has recently emerged as a general mathematical framework for estimating (learning) dependencies from finite samples.

SVM is based on the structural risk minimization (SRM) principle rooted in the statistical learning theory. It gives better generalization abilities, which are why it is noticed to be especially efficient in large classification problem.

Let us have a set of samples $\{y_i\} \in R^n, i = 1, 2, ..., l$, each of which is associated to a class $c_i \in \{-1, 1\}$. Suppose the samples are linearly separable by means of an *n*-dimensional hyperplane. The available set will be employed for calculating the equation of an optimal hyperplane, i.e., that allowing a minimum risk for classifying future samples, such optimality can be defined as finding the hyperplane that grants the maximum margin with respect to training samples located in either side.

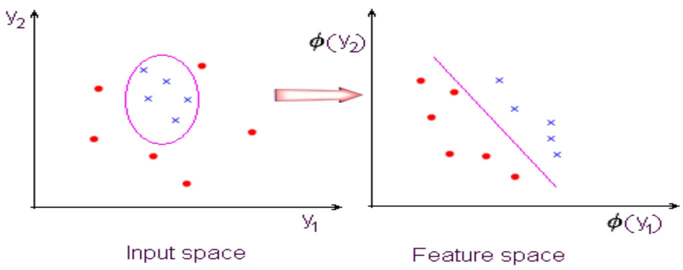


Figure 1 Mapping from input to feature space

However, since classes commonly found in reliability analysis exhibit a nonlinear frontier, it is necessary to have to resort to a more sophisticated classification criterion while maintaining at the same time the mathematical advantages of a linear form. To this end Vapnik [12] proposed to make the nonlinear mapping $\phi : R^n \mapsto D$, illustrated in Figure1. In fact, the possibilities of this classification method are enhanced by defining the kernel in a suitable reproducing kernel Hilbert space (RKHS) [13]. There are different kernel functions used in SVM, such as polynomial, radial basis and multilayer perceptron, here radial basis kernel function is adopted, $K(y, u) = \exp(-\frac{\|y-u\|}{2\sigma^2})$

METHOD PROPOSED IN THIS PAPER

This section provides a step-by-step description of the proposed procedure.

The proposed method can be divided into two major parts: SVM response surface indicator construction, and Monte Carlo simulation.

In the first part, a SVM response surface is constructed and refined by adaptively increasing the sample points. The procedure of this first part is described as follows:

Step 1 Identify the sampling region, here the region $(\mu_i - 6\sigma_i, \mu_i + 6\sigma_i)$ is considered.

Step 2 Use the first group of the LHS samples as initial samples，(The first group must consist of a few failure and a few safe samples, this can be obtained by means of engineering judgment.) calculate the responses (indicator function values) of the initial samples by calling the expensive performance function; Fit the 1st SVM response surface indicator using the initial samples and their responses.

Step 3 Use the 1st response surface indicator to filter the remaining LHS samples, and identify samples that are lying inside the current margin, here, samples lying beyond the margin need not be given to the solver in the Step 4.

Step 4 Fit the 2nd SVM response surface indicator using the first group of LHS samples plus samples lying inside the current margin and their responses (actual function evaluations) till the end value of the margin is very small (If necessary, predict the indicator function values of the remaining LHS samples using the 2nd response surface. Then build a new version of the SVM response surface. This option may be repeated a few times.)

The second part of the proposed method is MCS based on the response surface derived from the first part. The procedure is as follows:

Step 5 Set the desired number of samples N for MCS, using Eq. (1), with an error bound of l0%, and a confidence level a = 0.05.

$$10\% = 196\% \sqrt{\frac{(1-P_f^T)}{NP_f^T}} \tag{1}$$

Step 6 Filter the entire N MCS samples that have been generated according to the statistical distribution of the random variables, using the response surface of the indicator function from Step 4.

Step 7 Assign the final indicator function values for samples whose indicator function values are success or failure state region to be 1 and -1, respectively.

Step 8 Calculate the failure probability by counting the number of ones in the final indicator function values:

$$\text{Failure probability} = \frac{\textit{Number of} \;\; \text{failure state region}}{N} \times 100\% \tag{2}$$

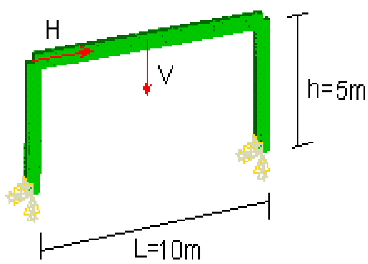
BENCHMARK EXAMPLE

A simple steel portal frame is shown in Figure 2 [14]. In this example, all joints are rigid moment-resisting joints. All structural elements have the same Material properties. Random variables: V (vertical load) ~ Normal (45, 4.5) *KN*, H (horizontal load) ~Normal (55, 5.5) *KN*.

Table 1: Material properties of the steel portal frame

Cross-sectional area (A, m^2)	Elastic modulus (E, *Pa*)	Inertia moment (I, m^4)	Density (ρ, Kg/m^3)	Poisson's ratio (ν)	Plastic bending moment (R, $KN \cdot m$)
0.459×10^{-2}	0.21×10^{9}	0.579×10^{-4}	7850	0.3	135

The analytical limit state functions are derived from plastic hinge theory. The potential locations of plastic hinges are indicated by ''·'' and Three most possible collapse mechanisms are plotted in Figure 3.



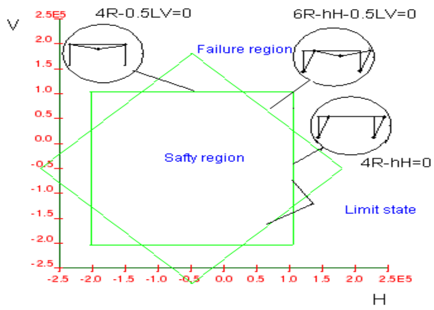


Figure 2: Simple frame structure

Figure 3: Plastic hinge limit state functions in the space of basic variables

For the purpose of validating the proposed method A basic MCS with 100,000 samples (equivalent to 300,000 function evaluations) is first performed to calculate a benchmark failure probability estimate, which is found to be 4.5317×10^{-5} and is considered to be accurate.

For comparing the efficiency with other simulation methods, here we also gave the results of importance sampling and directional simulation, however since the MPP information is required for the two methods, the standard FOSM is first utilized to search for the most probable point (MPP) for each of the three limit states.

Table 2 lists the safety indices and the corresponding failure probabilities for the 3 failure modes.

Table 2: Failure probabilities for the three possible failure modes

Mode no.	Failure function	Safety index (β)	Failure probability (P_i)
1	$g_1 = 4R - 0.5LV$	5.94	1.4251×10^{-9}
2	$g_2 = 4R - hH$	4.52	3.092×10^{-6}
3	$g_3 = 6R - hH - 0.5LV$	3.92	4.4090×10^{-5}

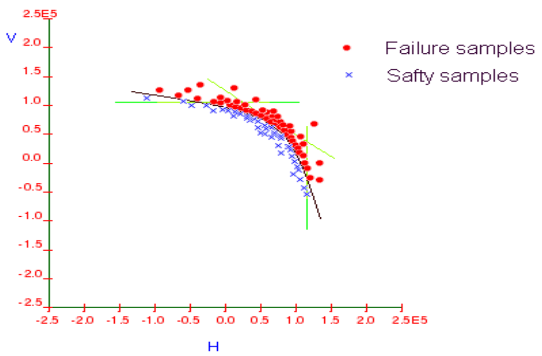


Figure 4: Samples lying inside the margin in simulation process

Table 3: Obtained results compared with other simulation methods

	P_f	No. of Function Evaluations	Error (P_f)
Monte Carlo Simulation	4.5317×10^{-5}	300,000	--
Importance sampling	4.6440×10^{-5}	842	2.48%
Directional simulation	4.4763×10^{-5}	664	1.22%
Proposed method	4.5189×10^{-5}	261	0.28%

The reliability analysis results are shown in Table 3 as well as Figure 4. The numbers of actual function evaluations are also given. It noticed that the proposed method is very close to the basic Monte Carlo method (error =0.28%), while the error of importance sampling and directional simulation is 2.48% and 1.22% respectively. Proposed methods greatly improve the efficiency compared with the basic MCS, importance sampling and Directional simulation.

SYSTEM RELIABILITY ANALYSES FOR OFFSHORE WIND TURBINE FOUNDATION

Description of an offshore wind turbine with tripod foundation

A number of different foundation types can be used for offshore wind turbines. Here, we focus on the tripod foundations, as this foundation type is likely to be one of the most dominant types used in the near to midterm future [15].

The researched offshore wind turbine has hub heights of approximately 90 m and rotor diameters of approximately 90 m (Figure 5). Moreover, the wind farms shall be installed in areas far away from the coast. At these locations, water depths from 20 m to 40 m are expected. The design parameters are given in Table 4 and are treated as uniformly distributed variables

Table 4: Design parameters (m)

Design parameters	d_1	d_2	d_3	d_4	d_5	t_1	t_2	t_3	t_4	t_5
Upper bound	5.500	4.000	3.000	3.000	2.000	0.100	0.050	0.050	0.050	0.050
Lower bound	3.500	1.500	1.000	0.500	0.500	0.010	0.010	0.010	0.010	0.010
values	4.500	3.000	2.000	1.500	1.000	0.050	0.030	0.025	0.025	0.020

Structure-Soil Interaction

The axial and lateral resistance of the soil against displacements of the pile is often modeled with springs. Commonly, three types of springs [16] are considered as shown in Figure5. The Winkler assumption states that each spring acts independently of the other springs and of pile displacements at other locations. The models for the spring behavior of the soil that are used in this study are based on the recommendations of the API [17].

Random variables

The random variables are given in the following table.

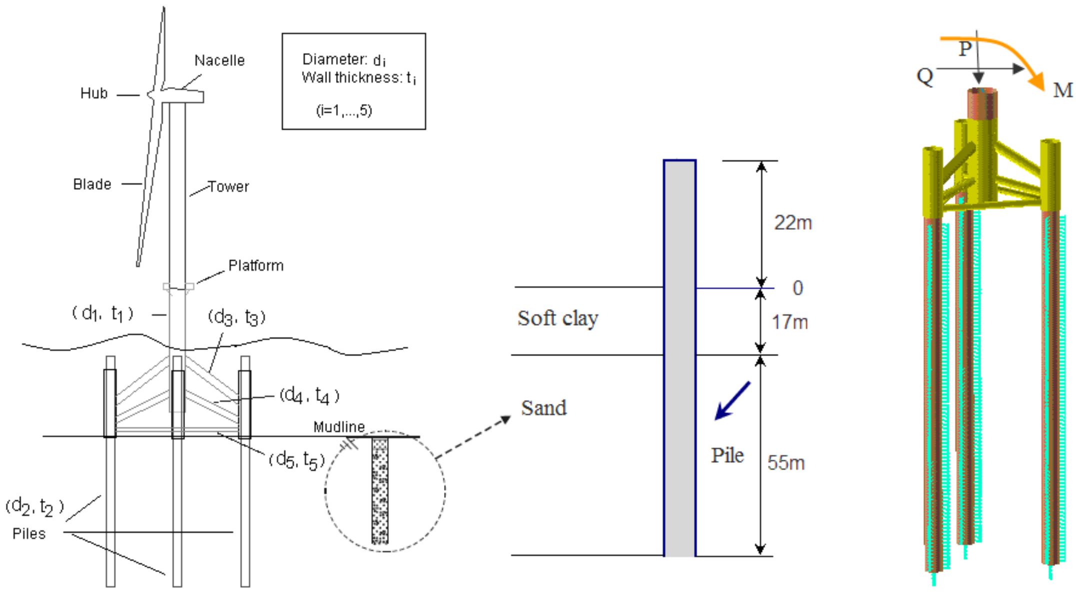


Figure 5: an offshore wind turbine with tripod foundation /soil conditions/ ANSYS model

Table 5: Random variables

Notation	Random variables	Type	Mean value	S.D	COV
X_1	Applied vertical load, P	Normal	2000 kN	400 kN	0.2
X_2	Applied lateral load, Q	Normal	1500 kN	300 kN	0.2
X_3	Applied top moment, M	Normal	80000 kN·m	16000 kN·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	20 kN/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	15.6 kN/m^3	0.2
X_8	Soft clay cohesion, c	Normal	18 kPa	1.8 kPa	0. 1
X_9	Pile modulus of elasticity, E	Normal	2.1E11 kPa	4.2E9 kPa	0.02

Limit states and reliability results

- yielding failure of the first support structure component

$$g_1 = \sigma_{c\max} - [\sigma_c] \tag{3}$$

- capsize failure of the first pile (the maximum axial pulling forces exceed the ultimate pulling resistance)

$$g_2 = S_{t\max} - [\underset{\sim}{Q}_u] \tag{4}$$

-failure of the first compression pile caused by exceeding ultimate load carrying capacity

$$g_3 = P_{t\max} - \left[\underset{\sim}{Q}_d \right] \quad (5)$$

Table 6: Reliability results

	g_1	g_2	g_3
Failure probability (P_i)	8.1×10^{-6}	3.0×10^{-6}	1.4×10^{-6}
System Failure probability (P_i^{system})		9.5×10^{-6}	

CONCLUSIONS

This paper developed a simple simulation method integrated with SVM in achieving a more efficient reliability assessment. Its efficiency was demonstrated through a benchmark example. Comparatively, the proposed method has a few distinctive features:

The proposed method does not call any MCS process directly on the expensive performance function. It only focuses on an accurate SVM model near the limit state rather than globally, therefore the cost of metamodel building is reduced.

The proposed method is applicable to both component and system level reliability problems with any statistical distribution.

The proposed method does not require any MPP information, and is ready to be applied to problems with non-normal variables without any transformations from non-normal to normal space.

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