

STRUCTURAL RELIABILITY ASSESSMENT OF OFFSHORE WIND TURBINE JACKET CONSIDERING CORROSION DEGRADATION

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Abstract. In this paper, an approach is proposed to conduct reliability analysis on an offshore jacket considering corrosion degradation under extreme load cases. Corrosion degradation is considered as thickness wastage of the jacket element, which is seen as time-dependent variables. One probabilistic corrosion in literature is adopted by using different distribution models. Also, three different inspection cases (environmental conditions) of the corrosion are studied. The reliability assessment is evaluated by Crude Monte Carlo simulation based on the trained surrogate model. Deep neural networks are used to train the surrogate model, because they are not limited by the distribution and dimension of variables. The results show that using different corrosion distribution model, the probabilities of failure of the jacket are different, even though they have the same mean and standard deviation values. In addition, with same assumption of the distribution model in corrosion, the reliability of the jacket changes a lot concerning different inspection cases. Furthermore, it is noted that the inspection cases have more influences on the reliability analysis of jacket than different corrosion distribution assumptions. At the end, two recommendations are derived from this work.

1 INTRODUCTION

In the last decade, wind energy is considered one the strong competitors of the conventional fossil fuels, due to the technology improvements. The role of wind energy in renewable energy utilization is becoming more and more important. Compared to land-based wind energy, there is more space and more stable and higher wind speed for offshore wind energy. More and more offshore wind turbines are currently

under construction or planned. These offshore wind turbines has been installed in deep water. Steel jacket structures have been the main support structures, due to their higher stiffness at the footprint and the smaller surface facing ocean loads compared to the monopiles.

Many studies have been conducted with steel jacket structures. The long-term fatigue of offshore jacket is investigated in [1]. The fatigue of the jacket under three different load cases is evaluated. Ultimate strength assessment of offshore jacket can be found in [2]. However, the corrosion effect is not included in the above works. Corrosion can result in the reduction of member thickness and lead to the failure of the jacket structure. In [3], it proposes a framework to assess the corrosion effect on the offshore jacket. The jacket structures with corrosion effect under seismic loads is studied in [4]. Also, the time-dependent reliability assessment of the offshore jacket is investigated in [5] considering jacket shear capacity. In [6], the fatigue of offshore jacket with a simple corrosion model is studied. While, the jacket with corrosion effect under extreme load cases have not yet been considered. Moreover, multi-physics simulation models (aerodynamics, fluid-structure interaction, corrosion degradation, etc.) are involved in offshore wind jacket simulation and that makes the reliability analysis difficult. The reliability assessment based on Monte Carlo simulation (MCS) is much time-consuming and the use of approximation methods like (FORM/SORM) is also difficult, where these methods are gradient-based and the gradients of responses are difficult to evaluate. Hence, the first solution to deal with this is to substitute the numerical model with a metamodel, which is easier to estimate. There are many approaches like Kriging [7] and PCE [8] but they are limited by the distribution or dimension of random variables. Therefore, deep neural networks (DNN) are applied in this work, which have a good ability to conduct reliability assessment [9, 10]. Thus, the reliability of jacket model considering corrosion effect under extreme load cases are studied in this paper based on DNN.

The overview of the proposed approach is showed in Fig.1. There mainly two parts (green and blue). The green part is to train the surrogate surrogate model with three type parameters using DNN. Latin hypercube sampling (LHS) is used to generate the training data. The blue part is to evaluate the reliability based on the trained surrogate model. The probabilities of failure are estimated by Crude Monte Carlo simulation. In addition, the jacket model used in this study is referenced in Offshore Code Comparison Collaboration Continuation (OC4) [11] as showed in Fig.2. The paper is organized as follows. In the section 2, the corrosion model and multi-layer perception are introduced. The design load case, loads on the jacket and limit state function are given in the section 3. The parameters selected for metamodel and the results of training surrogate model are in the section 4. The reliability analysis results are listed in the section 5. Conclusions and recommendations are given in the section 6.

2 MULTI-LAYER PERCEPTION AND CORROSION MODEL

2.1 Multi-layer perception

The multi-layer perception (MLP) is one common type structure in deep neural networks. The basic structure is showed in the Fig.4. It is composed of three or more layers of neurons. The neurons of the neighboring layers are connected by weights and the output of each neuron is as follows:

$$H_i^{(l)} = f \left(\sum_{j=1}^n w_{ij}^{(l)} H_j^{(l-1)} + b_i^{(l)} \right) \quad (1)$$

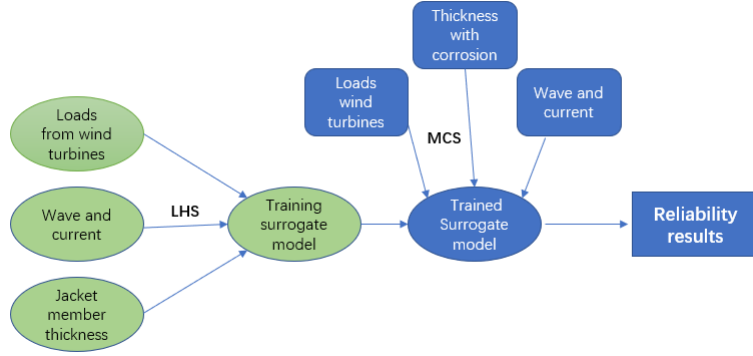


Figure 1: Overview of reliability assessment of the jacket

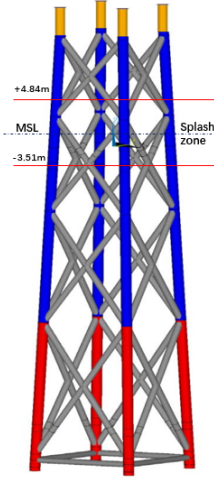


Figure 2: OC4 Jacket model

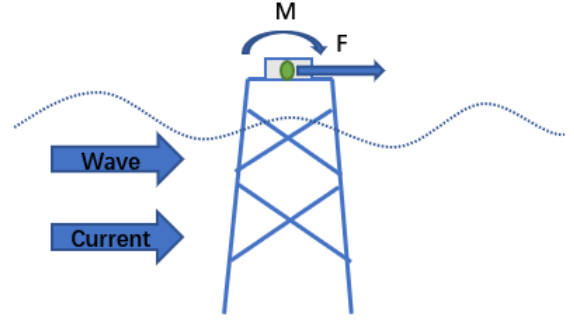


Figure 3: Loads on the jacket

where $H_i^{(l)}$ is the output of the i th neuron of the l th layer, $w_{ij}^{(l)}$ are the weights of the j th input, $b_i^{(l)}$ is the bias, n is the number of the neurons of the $(l-1)$ th layer, and $f(\cdot)$ is the activation function. In this paper, MLP trains the surrogate model using back propagation algorithm and the square errors are used as the loss function. As for the activation function in hidden layers, the solver, the neurons in hidden layers and the number of hidden layers, they are optimized by using hyperparameter optimization tools [12].

2.2 Corrosion model

In this work, the uniform corrosion is considered, which is most common form of corrosion and is uniformly distributed on the surface. The uniform corrosion can be simulated with a good approximation by a nonlinear function according to the studies [13, 14, 15]. The nonlinear function can be defined as following:

$$W(t) = A(t - t_{pt})^B \quad (2)$$

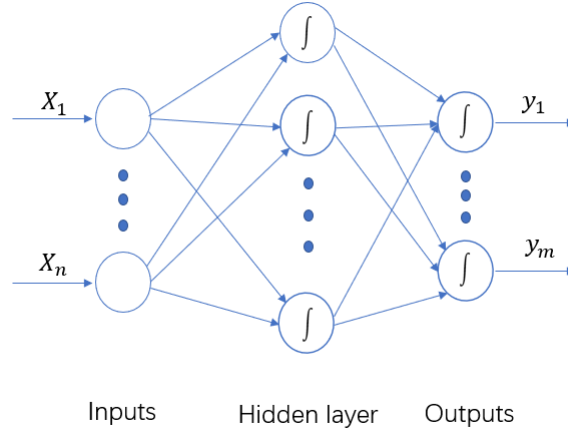


Figure 4: Multi-layer perceptron structures

where $W(t)$ is the thickness wastage in millimetres, t is the lifetime and t_{pt} is the corrosion protection time in years. A and B are two parameters that depend on the marine and environmental conditions. Our focus is mainly on the time after corrosion protection. Therefore, the protection time is ignored in this study. Additionally, the standard deviation of the thickness wastage is given by [15, 16].

$$\sigma_{W(t)} = 0.67 W(t) \quad (3)$$

Furthermore, the two parameters, A and B should be precisely determined. The following Table.1 adopted from [3] gives three inspection cases. In this paper, only the corrosion in the splash zone is considered, where the corrosion is the most severe. The splash zone are defined following the reference [17] as depicted in Fig.2.

Table 1: Corrosion inspection cases and parameters

Inspection case (IC)	Splash zone area	
	A(mm)	B
1. Not performed	0.3	1
2. Severe corrosion	0.3	0.823
3. No significant corrosion	0.252	0.823

3 DESIGN LOAD CASES, LOADS AND LIMIT STATE FUNCTION

3.1 Design load cases

In the standard codes IEC 61400-3 [18], 32 DLCs (design load cases) are defined covering various operational modes of the turbine such as normal operation, shut down and 50-years extreme conditions. They can be mainly categorized into two major groups namely ultimate and fatigue DLCs. Basically, the typical load cases applied in structural design of OWT is the fatigue load under normal sea conditions and the ultimate load under 50-year extreme condition [19]. All the DLCs should be carefully considered in

design of the jacket. While, in this paper, our focus is mainly on the ultimate DLCs. The 50-year return period is generally considered as a critical ultimate load case as showed in Table.2, which is mostly considered to correspond to the parked turbine, under the 50-year EWM (extreme wind model) with a 50-years RWH (reduced wave height) and ECM (extreme current model) as described in DLC6.1b IEC 61400-3 [18].

Table 2: Design load case

Load cases	Wind condition	Wave conditions
Ultimate load case DLC.6.1b	EWM: V_{g50}	RWH: $1.32 * H_{s50}$ ECM: $V_{c,ex}$

3.2 Loads

OWT jacket support structures are generally exposed to complex and variable loads. These loads can roughly categorized into two groups as illustrated in Fig.3. The loads applied on the top of jacket are from wind turbine including aerodynamic loads and inertia / gravitational loads. The others are the hydrodynamic loads including the wave and current loads. The details are listed in the following subsection.

3.2.1 Loads from wind turbine

The loads from wind turbine mainly consist of aerodynamic and inertia loads. Aerodynamic loads are transferred from the rotor. Inertial load is mainly due to the mass of the RNA (rotor-nacelle assembly). The above loads are among the most important load sources to be considered in the reliability assessment of the support structure. They can be simulated from the wind turbine tools like FAST [20] and HAWC2 [21]. In this study, the loads applied on the top of jacket top are directly extracted from the WindPACT (Wind Partnership for Advanced Technologies) report on Turbine Rotor Design Study [22] as listed in Table.3.

Table 3: Loads applied on the top of the jacket

Load case	Thrust force (kN)	Inertia/gravitational force (kN)	Bending moment(kN-m)
Ultimate load case	12440	1928	223500

3.2.2 Hydrodynamic loads

Hydrodynamic loads mainly consist of wave and current loads. It is critical to properly estimate the wave load, because waves will cause a significant force on the jacket. The choice of wave theory to apply to the model depends on the site characteristics. The decision of wave theory is also dependent on the ratio of the height to diameter of the structural member. When the diameter of the structure is less than one fifth of the wave length, Morrison's equation can be applied for the wave force estimation [23]:

$$F_{\text{wave}}(z) = \frac{1}{4} \rho_w \pi D^2 C_M \dot{u}(z, t) + \frac{1}{2} \rho_w D C_D u(z, t) |u(z, t)| \quad (4)$$

where D and ρ_w are the diameter of jacket members and the density of the water with a typical value of 1025 kg/m^3 , C_M and C_D are the coefficient of inertia and drag of the jacket members respectively, and

their corresponding values are 1.6 and 1.0 respectively, according to [24]. $\dot{u}(z, t)$ and $u(z, t)$ are respectively horizontal acceleration and velocity of water particles, which can be obtained from linear/Airy wave theory. z and t are respectively the reference depth and time.

Current can induce a drag load acting on the jacket structure. The current velocity can be estimated using an exponential profile as follows [18]:

$$u_c(z) = u_{MSL} \left(\frac{d+z}{d} \right)^{\frac{1}{7}} \quad (5)$$

where u_{MSL} is the current velocity at mean sea level (MSL), d is the depth of water and z is the reference depth. Usually, for simplicity, the direction of current and wave are assumed to be aligned. In this paper, both wave and current loads are defined in ANSYS ocean loading module [25] by giving the related wave and current parameters such as wave height, wave period and current velocity at MSL.

3.3 Limit state function

As mentioned above, this work focuses on the ultimate load case. Hence, only ultimate limit state is considered in this paper. The performance function of the ultimate state based on the Vons-Mises stress is given by:

$$g_u(x) = \sigma_{\text{allow}} - \sigma_{\text{max}} \quad (6)$$

where σ_{allow} is the allowable stress with a value of 323 Mpa for steel S355 considering safety factor of 1.1 in [23] and σ_{max} is the maximum Von-Mises stress simulated or calculated by the finite element analysis tools. x represents all the random parameters.

4 PARAMETER SELECTION AND SURROGATE MODEL

4.1 Parameter selection

For the random parameters, there are mainly three types as showed in the Table.4. The first is the loads (F_x, F_z, M_y) from the wind turbines. The second is the wave (H_s, T_p) and current parameters (C_{msl}). The third type is the thickness parameters (T_{grey}, T_{blue}) of jacket members. Here, the mean values of wave and current parameters in 50-year return period are referenced in [17]. The loads from wind turbines and wave and current parameters are assumed to follow normal distribution with standard deviation equal to 10% of their mean values as done in [26]. As for the thickness parameters T_{grey} and T_{blue} , they represents respectively the thickness of braces in splash zone with grey color and the thickness of legs in splash zone with blue color as showed in Fig.2. Here, the thickness of members are considered as random variables instead of the corrosion wastage, because different corrosion distributions will be considered. In addition, the original thickness of braces and legs in the splash zone are 20 mm and 35 mm. Corrosion degradation will cause the thickness wastage of jacket members. Therefore, for training the surrogate model process, it is better to assume that the thickness parameters follow the uniform distribution with lower bound (open interval) equal to 0 and upper bound equal to original thickness. In this case, the trained surrogate model may have good capacity to predict the corrosion effect.

Table 4: Stochastic parameters in reliability assessment

Stochastic variables	Mean (Lower bound)	Standard deviation (Upper bound)	Distribution
F_x –Thrust force (kN)	12440	1244	Normal
F_z –Inertia force (kN)	1928	192.8	Normal
M_y –Bending moment ($kN * m$)	223500	22350	Normal
H_s –Wave height (m)	10.34	1.034	Normal
T_p –Wave period (s)	10.87	1.087	Normal
C_{msl} –Current velocity (m/s)	1.2	0.12	Normal
T_{grey} –Thickness of braces (mm)	0	20	Uniform
T_{blue} –Thickness of legs (mm)	0	35	Uniform

4.2 Surrogate model

For training process with MLP, all the parameters as listed in Table.4 are considered as inputs and the maximum stress in static analysis simulated by ANSYS is the output. Moreover, one criterion is used to evaluate the surrogate model. That is the mean absolute percentage error ($MAPE$), given by:

$$MAPE = \frac{1}{n} \sum_{i=1}^{i=n} \left| \frac{y_i - \hat{y}_i}{y_i} \right| * 100\% \quad (7)$$

where y_i and \hat{y}_i are the actual value and predicted value and n is the total number of samples. The training process is by increasing training data set until the criterion $MAPE$ is less than the predefined value (0.1 in this paper). In this study, total 5000 training samples are used to training the surrogate model. The number of test data equals to 10% of that in the training data. Other 3 validation data sets (each including 1000 simulations) are used for validation process. The training results and validation results are showed in Table.5. The predicted values and true values of test data set and validation data set 1 are plotted in Fig.5.

Table 5: Surrogate model training results

Validation data set	Traning data MAPE (%)	Test data MAPE (%)	Validation data MAPE (%)	Pf_pre	Pf_actual
1	0.0261	0.025	0.0443	0.017	0.017
2			0.0428	0.001	0.001
3			0.0253	0.103	0.103

As showed in Table.5 and Fig.5, the trained surrogate model achieve to predict the unknown validation data set. All the $MAPE$ s of three validation data sets are less 0.1%. Also, the predicted probabilities (Pf_pre) of failure of validation data sets are equal to the true probabilities (Pf_actual) of failure of validation data sets.

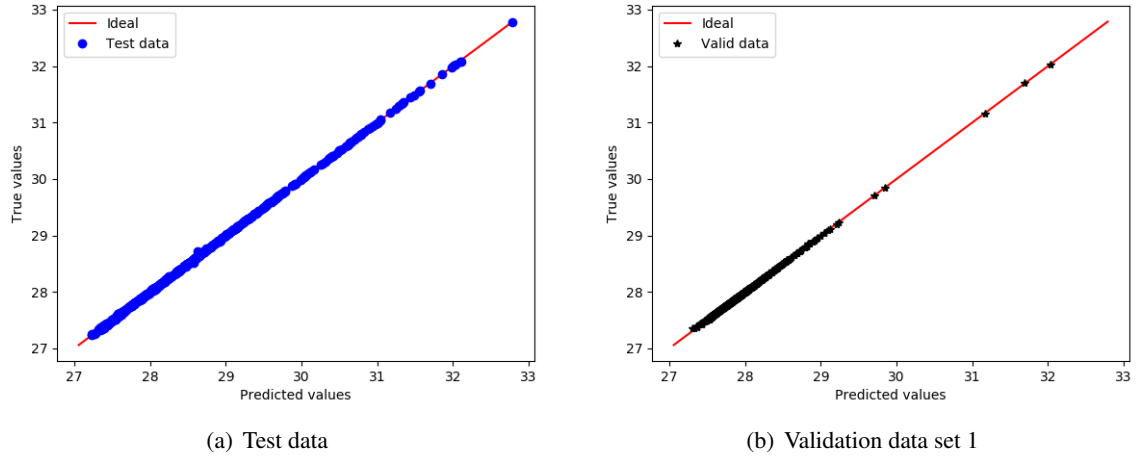


Figure 5: Comparison results between predicted values and true values

5 RESULTS AND COMPARISONS

The design life of the OC4 jacket is about 20 years. The 20 years are divided into 20 time nodes with each interval equal to one year. A reliability analysis is performed each year. Due to a lack of corrosion measurement, two probabilistic corrosion models are considered, *Gamma* and *Lognormal* distributions respectively. For these two distributions, the mean and the standard deviation take the same values, as shown in Table.1. Additionally, the three inspection cases of corrosion in the table are also investigated. To evaluate reliability of the jacket in each year, one million samples are generated for each year and each inspection case (IC) with each corrosion model by using Monte Carle simulation. The maixmum stresses of jacket are estimated by the trained surrogate model in section 4.2. The probabilities of failure (Pfs) are evaluated based on the limit state function in section 3.3.

The results of the reliability assessment with two corrosion distribution models are plotted in Fig.6 and Fig.7. It is clear that inspection cases (environmental conditions) have great influence on the reliability assessment of the jacket. At the first 6 years, the inspection cases seems to have little influence on the reliability of the jacket. While, after the 6th year, the differences of Pfs with different inspection cases appear. In addition, the results of the two corrosion models are compared in Fig.8. It is noted that the probabilities of failure at the end of 20 years in two corrosion model are different in all the three inspection cases. In IC1, at the beginning, the probabilities of failure of the jacket are higher with the *Lognormal* distribution assumption of corrosion. However, after the 13th year, the probabilities of failure with *Gamma* distribution model are greater. In IC2 and IC3, the jacket model with corrosion assumption of *Lognormal* distribution always has bigger probabilities of failure but the differences between two corrosion distributions are not obvious compared with IC1. Meanwhile, it should be mentioned that the differences in different inspection cases have more effects on the reliability assessment of jacket, compared to different corrosion distribution assumptions as showed in Fig.8. At last, the 20th year probabilities of failure of the jacket in two corrosion models with three inspection cases are given in Table.6. The corresponding coefficient of variations and 95% confidence interval are also listed in the table. All the probabilities of failure in the 20th year are greater than the design probability of failure 0.01% [23].

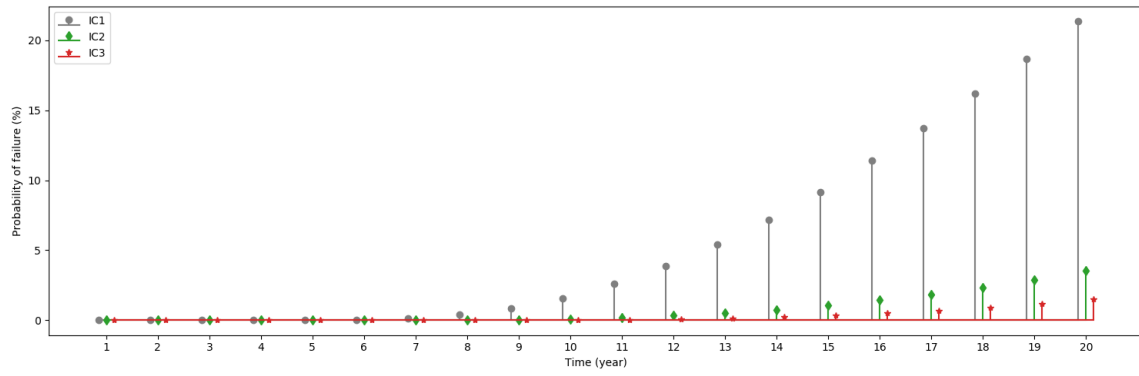


Figure 6: Reliability results with *Gamma* distribution corrosion model

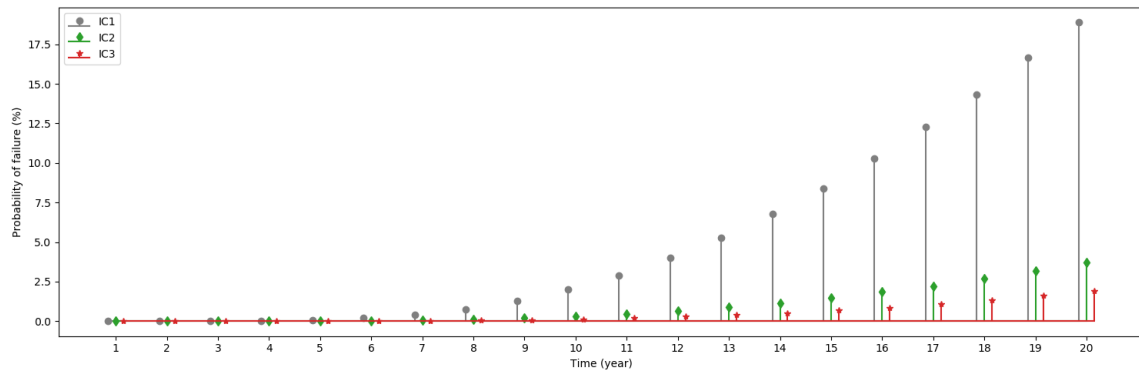


Figure 7: Reliability results with *Lognormal* distribution corrosion model

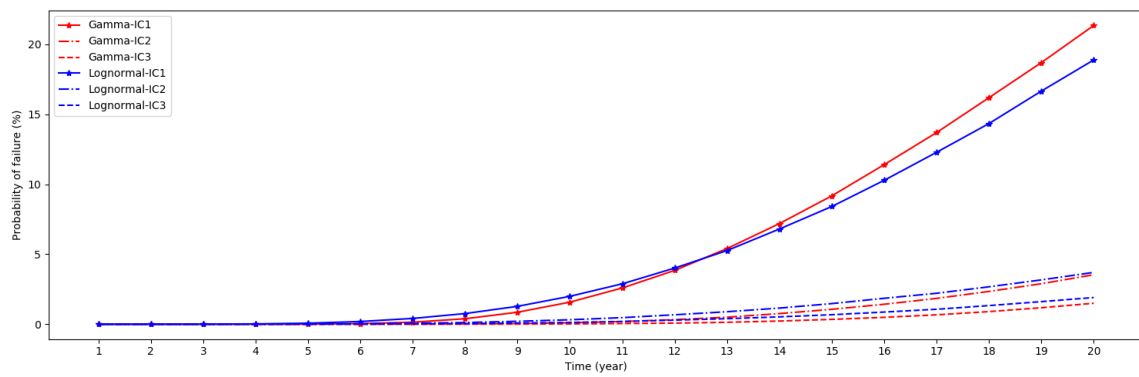


Figure 8: Comparison of reliability assessment results in two corrosion models

Table 6: Probabilities of failure in the 20th year with two corrosion models

Gamma distribution Inspection case(IC)	Pf in the 20th year (%)	Coefficient of variation (%)	95% confidence interval of Pf (%)
IC1	21.37	0.19	[21.29, 21.45]
IC2	3.54	0.52	[3.50, 3.58]
IC3	1.49	0.81	[1.47, 1.51]
Lognormal distribution Inspection case(IC)	Pf in the 20th year (%)	Coefficient of variation (%)	95% confidence interval of Pf (%)
IC1	18.88	0.21	[18.80, 18.96]
IC2	3.71	0.51	[3.67, 3.75]
IC3	1.89	0.72	[1.86, 1.92]

6 CONCLUSIONS AND RECOMMENDATIONS

In this paper, an approach is proposed to evaluate the reliability of failure of an OWT jacket considering corrosion degradation under extreme load cases. The reliability assessment is based on a surrogate model trained by deep neurons networks. The corrosion degradation is considered as time-dependant variables. The probabilistic corrosion model is adopted in this paper by using two probability distribution of the corrosion parameters, *Lognormal* and *Gamma* respectively. In addition, three inspection cases of corrosion are investigated. The results show that:

1. The probabilities of failure of the jacket are slightly the same for severe corrosion and no significant corrosion when the corrosion parameters are assumed *Lognormal* and *Gamma* probability distribution. However, when the inspection case is not-performed and the corrosion is severer, then the probability of failure is different regarding the gamma and lognormal distributions models.
2. With same assumption of corrosion distribution, the probabilities of failure of jacket will depend on the inspection cases (environmental conditions). In addition, in this paper, it is also noted that the inspection cases have more influences on the probabilities of failure, compared to different corrosion distribution assumptions (*Gamma* and *Lognormal* distribution in this paper).
3. With two corrosion distributions studied in this work, it is found that the probabilities of failure in the end of 20 years can reach up to 21.37% for the maximum value and 1.49% for the minimum value. More importantly, all the probabilities in the two corrosion distributions with three inspection cases at the end of 20th year are greater than design probabilities of failure 0.01% in [23].

From this work, two recommendations are proposed. Firstly, the extreme load cases with corrosion degradation should be considered in design of the offshore jacket, in the view of the effect of corrosion and the increase extreme weather conditions in recent years. Secondly, the corrosion model should be chosen carefully, if on-site corrosion data is not available or not sufficient to estimate the future corrosion.

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