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Reliability assessment of marine floating structures using Bayesian network

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ABSTRACT

Marine floating structures are widely used in various fields of industry from oil and gas to renewable energy. The predominant dynamic responses of these structures are controlled by mooring lines. In recent years, a number of high-profile mooring failures have highlighted the high risk of this element in floating structures. A reliable design of mooring liness is necessary to improve the safety of offshore operations. This paper proposes a novel methodology to conduct reliability analysis of moored floating structures using Bayesian network (BN). The long-term distributions of extreme responses of the floating object are estimated using analytical frequency domain method, while mooring failure probability is estimated using limit state function in the proposed BN framework. Application of the methodology is demonstrated by estimating the failure probabilities of a floating cylinder with tensioned mooring system. The proposed study also explains how the hydrodynamic and reliability analysis could be integrated with BN to assess the overall safety of the offshore structures. The methodology presented can be employed to mitigate associated risk with marine structures brought about by stochastic hydrodynamic loads.

1. Introduction

Marine floating structures are widely used in the oil and gas industry, marine transportation and exploration areas, and renewable energy applications. Conceptual design scenarios for each of these structures are based on environmental loads such as wave, wind and currents. Due to the stochastic behaviour of the sea environment, different types of failures are expected to occur, however it is necessary to improve the safety of marine structures during their lifetime. In the past few years, there has been an increasing focus on analysis of the extreme loads on oil and gas platforms [1–3], and have growing investigations on human reliability assessment in marine harsh environment [41,42]. To explain the complexity of the problem and the various factors involved in the field of marine engineering, a review of marine reliability analysis adopted from previous research is schematically illustrated in Fig. 1.

Previously, in order to conduct mooring failure analysis, traditional reliability methods were applied, such as the first order reliability method (*FORM*) and second order reliability method (*SORM*) applied by Gao [4], and Frosing and Jansson [5], and Nazir et al. [40]. Siddiqui and Ahmad [6] suggest that failure probability of a mooring system may increase when one mooring system has to be replaced or repaired due to partial or complete damage. With emphasis on the importance of progressive failure, or the entire collapse of the floating system, they investigated reliability of the mooring system of a Tension Leg Platform (*TLP*). Li et al. [7] analysed the effect of downstroke on the reliability of tendon unlatching using FORM and SORM, rather than considering the loss of tendon tension.

Although there are a number of methods in the literature for reliability analysis of marine structures, Bayesian statistics is recommended by Sørensen [8]. An extensive review of BN and probabilistic tools including a wide range of BN applications are provided by Nielsen et al. [57]. Among the current probabilistic models for risk and reliability analysis, Bayesian approach is a promising tool that allows reflection of available knowledge on the process (Abaei et al. [9], Groth et al. [52], Khakzad et al. [54], Musharraf et al. [55], Montewka et al. [56], Trucco et al. [59]). Since Bayesian approaches are capable of considering continuous variables in a discrete format [9–11], it is possible to conduct the inference of more complicated stochastic relationships among random variables in the network, i.e. each variable may have more values than true or false (such as different level of storm conditions), and not all the dependencies have to be deterministic (such as utilities for decision making [33]). In comparison, other probabilistic models such as FORM and SORM are not well suited to conduct risk and reliability analysis efficiently [10]. Recent research has applied BN to engineering fields such as corrosion on steel structure and condition

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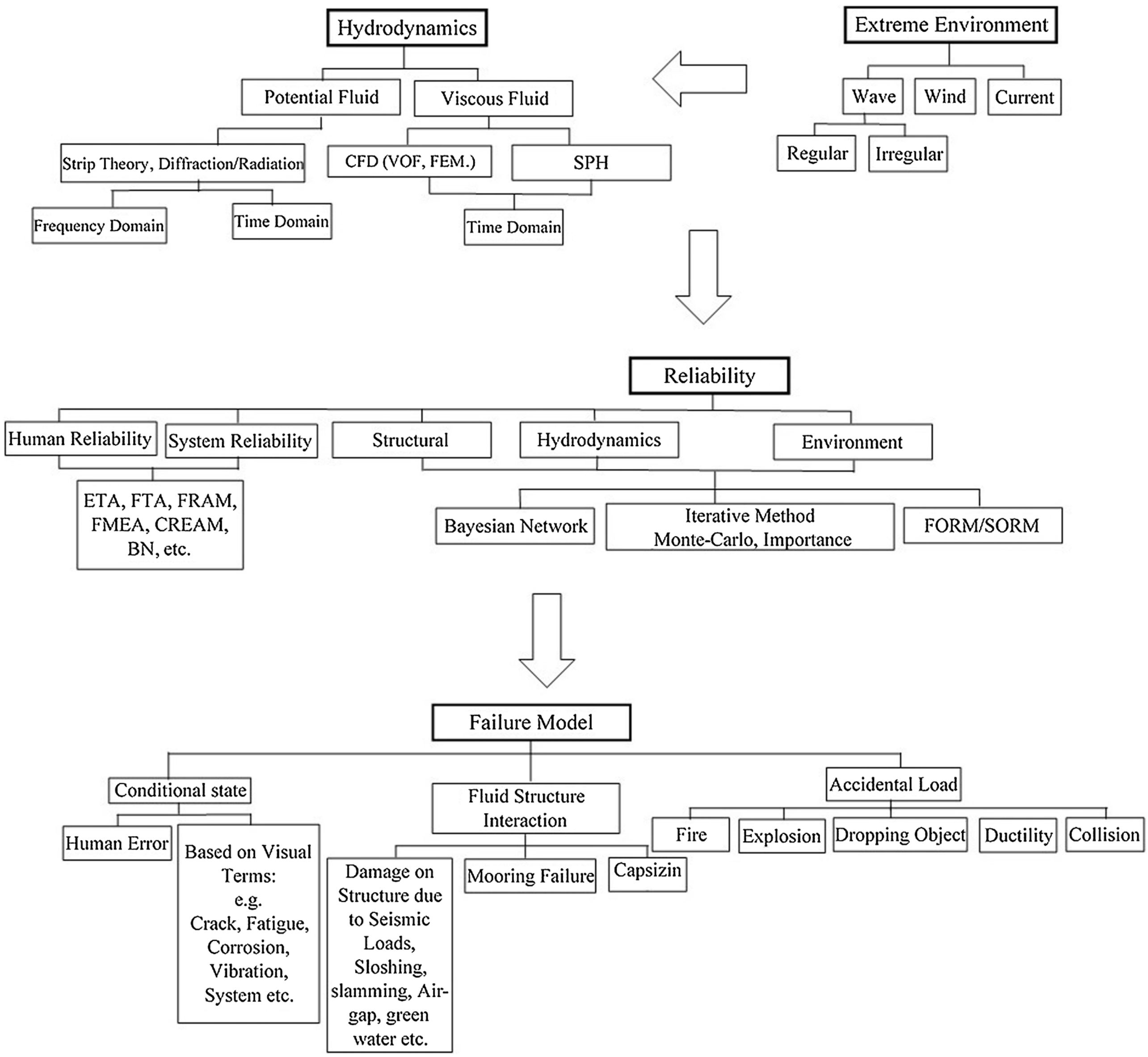

Fig. 1. Accident modeling framework applied to marine environment.

monitoring [11–13]. Wang et al. [14] used Object Oriented Bayesian Network (OOBN) to investigate the failure probability of different types of Australian bridges in terms of both structural reliability and conditional-based reliability. Morales-Napoles et al. [15] applied BN as a tool for assessing the failure risk of earth dams providing a conceptual framework for implementation of continuous stochastic variables in BN.

While the application of BN in reliability analysis of marine application is shown by previous researchers [[19],10,16–18,36,46], it is still necessary to integrate the probabilistic and hydrodynamic analysis of marine floating structures for risk assessment purpose. The risk assessment of systems or components such as moorings requires a probabilistic damage model or inspection and monitoring database. Referring to previous studies, BN is a promising and efficient approach in reliability analysis compared to the traditional methods developed by Vazquez-Hernandez et al. [19], Montes-Iturrizaga et al. [20] and Vázquez-Hernández et al. [21]. In this study, a new methodology for assessing the reliability of floating offshore structures using BN and frequency domain analysis is developed. The strength of the framework is its computational efficiency when performing Bayesian updating integrated with hydrodynamic response of the structure for estimating reliability of the operation and determining optimum design point of critical components such as mooring lines. To demonstrate the application of the developed methodology, a floating renewable energy substructure with tensioned mooring is considered as the case study. A limit state function for critical surge response is derived analytically based on the Potential theory and Hooks law. The response based stochastic variables induced by hydrodynamic wave forces are computed for various sea states. The aim of this study is to argue an interpretation of using *BN* for marine structural reliability analysis in terms of extreme condition scenario and allocate it as a tool for future research on interdisciplinary study for structural reliability analysis, system failure detection, human error estimation and decision making. This will enable the risk assessment to improve the safety of the offshore structures' operation during their lifetime. The framework enables robust reliability updating for determining the best design point of the maximum excursion in the mooring line. By robust it is understood that the reliability updating can be performed in an automated manner using the developed BN. That is, the performance of the structure itself is employed to estimateing the reliability of the structure that encounters sea environments such as wave components. In brief, the conceptual framework, the scope of the study in each section of Environment, Hydrodynamics, Reliability and Failure model is shown in Fig. 1. The

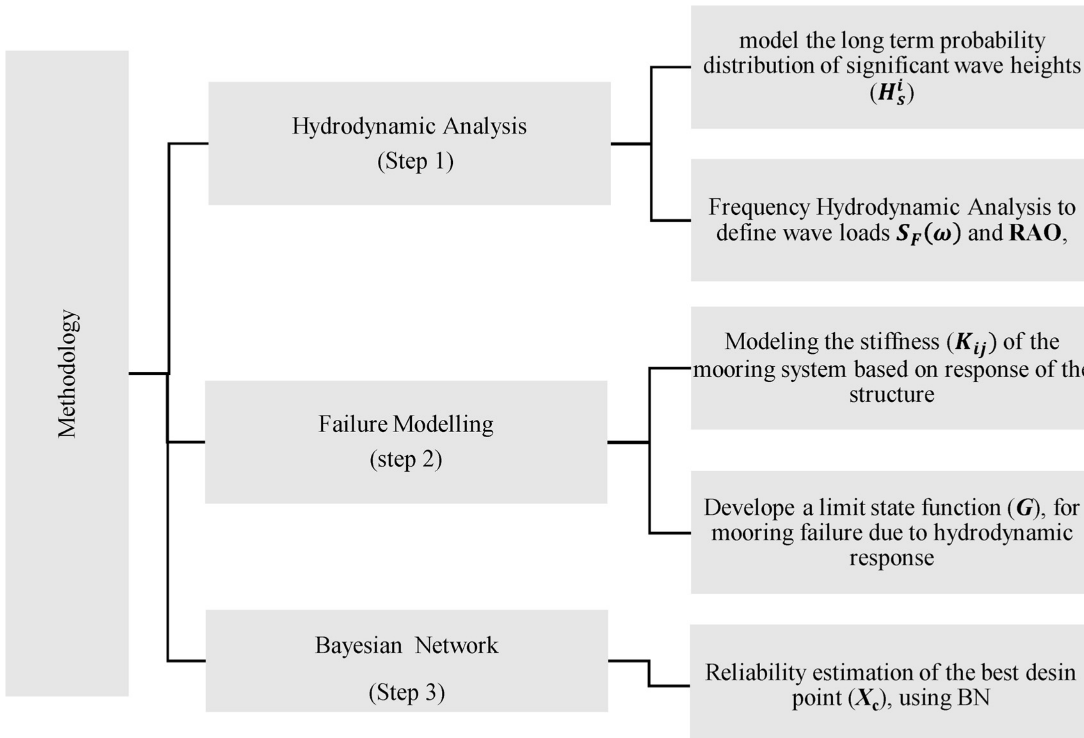

Fig. 2. Overview of developed methodology for reliability assessment of marine floating structures.

highlighted box in the figure represents a figurative description of different steps that are considered in this paper to integrate BN and Hydrodynamic of marine floating structures. For example, the “Potential Fluid” Box means that Potential theory is applied to investigate the hydrodynamic response of the structure, and “Mooring Failure” is highlighted as a failure model for this study. Additionally, each hierarchical diagram in this figure represents the previous research conducted to improve the reliability of the marine structures.

2. Developed methodology

During the conceptual design phase, it is necessary to find an efficient approach for estimating probability of failures to be used for safety analysis of marine structures. A comprehensive probabilistic study of different phenomena in marine structures hydrodynamic aspect of the design are requisite for the development of any risk mitigation strategies. With this objective, it is necessary to precisely estimate the occurrence of the long-term response of the structures describing them probabilistically to account for uncertainties. In this study, an integrated methodology is developed based on frequency domain analysis along with BNayesian network for hydrodynamic and structural reliability analysis respectively. The methodology is divided into five steps. Firstly, the long term probability distribution of sea waves is estimated. Secondly, for each significant wave height, Hs, Pierson-Moskowitz spectrum is considered to calculate the wave force and response of the structure. Wave forces are computed based on frequency domain method determining response amplitude operator (ayesian network*RAO*). In the third step, the response spectrum is used to estimate the expected value of surge response. Rayleigh distribution was applied to evaluate the highest 1% of the responses , $\overline{X}_{0.01}$, for each spectrum. This distribution is the most suitable probability density function to predict the maximum response in different sea states (Kamphuis [53]). The major causes of failure in floating structures are the responses of the structure due to extreme loads [43–45]. It is necessary to predict the highest possible responses that structure encounters, i.e. determining the best design point. In this study, mooring disconnection was considered as the failure scenario. Expected value and standard deviation of $\overline{X}_{0.01}$ responses are fitted to a Gumbel distribution to model the long term performance of a floating structure. Other related design parameters such as the elasticity and strength of materials are assumed to have a normal distribution. This is a valid assumption as it has previously been considered by several researchers [10,22]. Geometric variables such as the mooring and object diameter, and length of mooring line are defined as deterministic values. In the fourth step, a suitable limit state function was developed to model the failure of the mooring system. Lastly, to implement the structural reliability analysis, the failure function is mapped into a BN. The network assists in predicting the probability of failure identifying the best design points for the structure. The steps of the developed methodology are illustrated in Fig. 2.

2.1. Hydrodynamic analysis (steps 1)

In this study, a tension cylinder is considered for assessing the reliability of the mooring system. To replicate the environmental loads, a three-parameters Weibull distribution explained in Eq. (1), and recommended by Karadeniz et al. [23], Siddiqui and Ahmad [6], is used to model the long term probability distribution of significant wave heights:

$$f(H_s) = \frac{C}{B}\left(\frac{H_s - A}{B}\right)^{C-1} e^{-(H_s - A/B)^C} \tag{1}$$

Where A is the location parameter, and B and C are the scale and shape parameters of the Weibull distribution. These parameters need to be obtained from the scatter diagram of any sea location. In the present paper, sea state data are adopted from a study by Siddiqui and Ahmad [6] based on the North Sea location, to estimate the long-term occurrence probability of the extreme wave height. According to Siddiqui and Ahmad [6], corresponding to a known significant wave height H_S, zero crossing period T_Z can be obtained assuming the same probability of occurrence for T_Z as H_S. That is, to consider the long term probability of wave period, the wave height and period (Hs, Tz) are taken in a correlated fashion as per an empirical relation defined as:

$$T_Z = \sqrt{\left(\frac{32\pi H_s}{g}\right)}. \tag{2}$$

The frequency domain method is applied for predicting extreme responses with regards to each sea state. The structure encounters a wide range of wave heights and wave periods. The wavelength, λ, is assumed to be 5 times larger than the diameter of the structure, so that the diffraction problem is neglected. Using strip theory, the added mass coefficient is derived analytically. Mooring line stiffness coefficient is defined based on Hook's law. The dynamic equation computed is using frequency domain method to find the response amplitude operator (RAO). In this study, hydrodynamic loads on the structure are computed analytically using frequency domain method. Frequency domain method is extremely fast for computing hydrodynamic loads and is therefore suitable to integrate with reliability analysis of marine floating structures [24]. To conduct linear stochastic analysis, there is no significant difference between using strip theory or Morison equation for the consumption time of numerical calculation. However, in this study, the hydrodynamic loads have been computed analytically based on strip theory for slender body as presented by Abaiee et al. [25]. The stochastic dynamic analysis of the structure is performed for 12 sea states then referring to the i^{th} sea state, H_s^i (significant wave height of the i^{th} spectrum) and T_P^i (Peak period of the i^{th} spectrum), the 1% of highest response value is computed to predict extreme value responses. To compute the highest 1% of surge motions, a linear stochastic analysis of the structure is performed with the assumption that the wave heights and response followed Rayleigh distribution. The extreme value of the linear response for the highest 1% calculated is based on the exceedance probabilities. Therefore, all ranges of wave height and wave period are considered in this approach to predict the reliability of the structure.

To compute the wave forces on the structure, it is assumed that the fluid is incompressible, irrational and non-viscous [26]. Therefore, the linear potential theory is applied to model wave velocity for deep water, given as:

$$\phi = \frac{g\xi_a}{\omega} e^{kz} \cos(\omega t - kx) \tag{3}$$

Where, g is the acceleration due to gravity, ξ_a is wave amplitude, ω is wave frequency and k is the wave number with regards to Bernoulli equation and the assumption that the velocity of particles is relatively small. It should be noted that Eq. (3) is simplified to describe wave potential regarding linear wave-structure-interaction problem to obtain response of the system. Therefore, a linear stochastic approach is considered to evaluate the hydrodynamic response of the structure, since the main objective of this study is to demonstrate a framework to assess the reliability of marine structures using Bayesian Approach with integrating hydrodynamics. The hydrodynamic pressure and force on the structure are defined using Eqs. (4) and (5), [26]:

$$P = \rho \frac{\partial \phi}{\partial t} \tag{4}$$

$$F = \iint P.\, n\, dA \tag{5}$$

Where, ρ is sea water density, t is time, P is the fluid pressure, n is the normal vector on the structure in an outward direction and dA is the element of area on the structure where wave pressure is exerted. To demonstrate the application of the developed methodology, a tensioned cylinder is considered for integrating the hydrodynamic analysis of the structure with the proposed probability model which is discussed in the next section. As suggested by Abaiee et al. [25], surge and roll motions, among 6 DOFs, are the most critical responses that play a major role in exerting significant tension on the mooring line. Therefore the dynamic equation for the coupled degrees of surge and roll motion are adopted from recent study conducted by Abaiee et al. [25] and defined as:

$$(m + m_{11})\ddot{X}_{11} + c_1\dot{X}_{11} + k_{11}X_{11} = F_{11}(\mathrm{t}) \tag{6}$$

$$(I + m_{12})\ddot{X}_{12} + c_2\dot{X}_{12} + k_{12}X_{12} = F_{12}(t) \tag{7}$$

Where m_{11} and m_{12} are added mass, k_{11} and k_{12} are the stiffness coefficients, F_{11}(t) and F_{12}(t) are wave forces, m and I are mass components of surge and coupled roll respectively. As suggested by Abaiee et al. [25], the hydrodynamic damping coefficient (C_1 and C_2) has less importance and can be neglected for this structure. A detailed discussion on the analytical solution of the dynamic equation and the parameters are provided by Abaiee et al. [25].

Table 1
Stochastic variables considered in hydrodynamic analysis.

Variable		Distribution	
x_{11}	Surge response	Gumbel	$P(X_{11}) = exp\left[exp\left[\frac{-(x_{11}-a)}{b}\right]\right]$
E	Modulus of elasticity	Normal	$Z_R = +1.28$
T_o	Pre-tension of tendon	Normal	$Z_R = +1.28$
A	Cross section of tendon	Deterministic	$Z_R = 0$
L	Length of tendon	Deterministic	$Z_R = 0$
I	Moment Inertia for Cylinder	Deterministic	$Z_R = 0$
σ_V	Von-Mises stress (for axial load only)	Normal	$Z_R = -1.28$[a]
H_s	Significant wave height	Weibul	Eq. (1)

[a] $\boldsymbol{Z_R}$ is the normal standard deviation and defined as $Z_R = \frac{x - E(x)}{\sigma}$. The number -1.28 means that the random variable is with 0.9 probability lower than its mean value.

2.2. Failure modelling (step 2)

In this study, mooring rupture is considered as a failure mode. It is assumed that if the axial tension exceeds the allowable yield stress caused by the large response of the structure in a harsh environment, then the rupture will occur in the mooring line. The mooring force incurred by environmental load is modelled by Hook's Law assumption and the maximum surge response as recommended by [27]. All variables that are implemented to derive the failure function are presented in Table 1 along with the specified probability distribution function. It is essential to determine the most realistic random variable distributions for tendon characteristic. The reason being that during the lifetime of the floating object, the material properties of the mooring lines, as well as its geometry, may change. As recommended by [28] for tensioned floating structures, Tendon Tension Monitoring System (*TTMS*) should be installed to obtain the actual tension during the operation. This requires suitable and reliable tendon tension monitoring devices and a precise monitoring program. However, condition monitoring for equipment such as renewable energy systems is not applicable, since most of these new devices have yet to be installed. Any changes in material of tendon, leads to changes in the natural frequency of the system which is an important parameter in damage detection. However, in this study, it is assumed that these characteristics have normal distribution as recommended by Kamphuis [22], and it has a value lower than the mean value. As a result, its normal standard parameter, *Z*, has a negative amount. Fundamentally, the mooring failure depends on hydrodynamic parameters (surge response, x_{11}, wave height, H_s, Wave period, T_z), material characteristics (elasticity, E, yield strength, σ_v), the geometry (Cross section, A, Length of mooring, L) and the pre-tension, T_0. The relationship between these variables is modelled by introducing a suitable failure function defined as $G(x_{11}, H_s, T_Z, E, T_0, A, L, \sigma_v)$.

The limit state function will determine whether the system is in safe or fail mode. The developed function is:

$$G(F_T(X) > F_T(X_c)) = F_T(X_c) - F_T(X) \tag{8}$$

where $F_T(X) = k_{11}X_{11}$ is the tendon force due to surge and roll responses, X_c is the critical surge response that represents a design parameter and is defined as any break or disconnection in tendon, k_{11} is nonlinear stiffness due to the unique hydrodynamic load in surge direction. The inequality $F_T(X) > F_T(X_c)$ shows the limit if the forces on the mooring line, $F_T(X)$ exceed the critical loads, $F_T(X_c)$. The surge force in tendon is linear with respect to the wave height Faltinsen [51], then the limit state function defined in Eq. (8) is truncated on the mean value of surge response, X_{11}. Since the response of X_{11}^i in long-term is fitted to a Gumbel distribution, the mean value is $E[X_{11}] \neq 0$. The super index i represents i^{th} sea state. The design load, $F_T(X_c)$ is defined according to the flexibility and strength of the material which is based on the design criteria. Mooring force is $F_T(X)$ estimated based on *Hook's* linear elastic equation as $F_i = k_{ij}X_i$ in 6° of freedom (DOF) [27]. K_{ij} is an array of the stiffness matrix defined by applying a unit displacement on the structure in j^{th} direction, equal to the resultant mooring force experienced in i_{th} direction [27]. The stiffness coefficient of tendon in surge direction is derived as [27]:

$$\begin{aligned} k_{11}x &= (T_0 + \Delta T)sin\theta \simeq \\ &= \left(T_0 + \frac{(\sqrt{x^2+L^2} - L)AE}{L}\right)sin\theta \\ &= \left(T_0 + \frac{(x^2)AE}{(\sqrt{x^2+L^2}+L)L}\right)sin\theta \\ &\simeq \left(\frac{T_0 x}{L} + \frac{AE}{2L^3}x^3\right) \end{aligned} \tag{9}$$

and,

$$k_{12}X_{12} = -(KGX_{11})X_{12} \tag{10}$$

where T_0 is the tendon pre-tension, ΔT is the extra tendon tension, θ is the angle between tendon line and its initial vertical position, i.e. $\sin\theta \approx \theta = \frac{x}{L}$. Therefore Eq. (8) is truncated over $X_{11} = E[X_{11}]$ to define linear failure function:

$$G \approx F_T(X_c) - \left(\left(\frac{T_0 E[X_{11}]}{L} + \frac{AE}{L}E[X_{11}]^3\right) + \left(\frac{T_0}{L} + 3\frac{AE}{L}E[X_{11}]^2\right)(X_{11} - E[X_{11}])\right) \quad , \quad \begin{Bmatrix} if\ G > 0\ ;\ Safe\ Mode \\ f\ G \leq 0\ ;\ Fail\ Mode \end{Bmatrix} \tag{11}$$

$$E[X_{11}] = \sum_{i=1}^{m} f(H_s^i).\ \overline{X}_{0.01}^i \tag{12}$$

where $\overline{X}_{0.01}$ is the average of highest 1% of structure's linear responses, supposing that the maximum response in each sea state follows a Rayleigh distribution:

$$\overline{X}_{0.01} = 6.67\sigma \tag{13}$$

where σ is the standard deviation of structural responses. To find a suitable probability distribution, ($P(X_{11})$ in Table 1), for long-term occurrence of structural responses, MLE method is applied to estimate distribution properties such as the shape and scale parameter for each case. When failure due to extreme condition is of interest, (such as extreme surge response in this study), then special attention is needed to predict the parameters that are highly unlikely to occur. In previous studies by Diznab et al. [29] and Chen and Moan [30], it has been recommended that Generalized Extreme Value (GEV) and Gumbel distributions are two of the most suitable distributions for modelling long-term performance of marine floating structures under extreme loads. For this study, Gumbel distribution is considered to correctly predict the stochastic time-response data.

2.3. Probabilistic analysis: Bayesian approach (step 3)

BN is a graphical model for reasoning under uncertainty that uses causal relationships (represented by directed edges) among components of a system (represented by chance nodes). BN estimates the joint probability distribution of a set of random variables based on the conditional independencies and the chain rule, as stated in Eq. (3). An extensive review of BN and probabilistic knowledge elicitation including its applications in risk and reliability analysis is provided by Barber [48], Scutari et al. [58] and Benson [49].

$$P(X_1, X_2, ..., X_n) = \prod_{i=1}^{n} P(X_i|pa(X_i)) \tag{14}$$

where $pa(X_i)$ is the parent set of variable X_i. In case new information becomes available for one or more chance nodes, BN is able to update the joint probability based on the Bayes' theorem:

$$P(X|E) = \frac{P(X, E)}{\sum_X P(X, E)} \tag{15}$$

This advantage of the BN will be adopted to estimate the optimum design point of the structure's mooring system assisting in failure modelling (see Eq. (11)). Friis-Hansen [10] provides a more detailed explanation of BN concepts. The application of BN in the field of risk and reliability is explored by many researchers. A few recent examples include [9,31]; Abbassi et al. [47], Bhandari et al. [50], Yeo et al. [60]. Inserting continuous variables in *BN* is not an easy task and many approaches have been adopted by previous researchers to develop approximating models, however the approaches are applicable for normally distributed variables. The alternative approach to consider continuous variables in *BN* is to discretise them into n states with univariate intervals. This method is defined as the univariate discretization given that the states are all mutually exclusive for these n states [10]. The optimum number of intervals is estimated by compiling different numbers of discretization in the network using *GeNIe* Software.

2.3.1. Discretization of the continuous variables

In a BN-based reliability model ($X \rightarrow Z \longleftarrow Y$), X and Y are continuous nodes with arbitrary probability distributions and Z is deterministically defined by its parent nodes using failure function. The continuous variables are discretized into a set of mutually exclusive states. Univariate discretization scheme and Monte Carlo simulation is used to find the uniform interval and the final probability of failure as recommended by Friis-Hansen [10] and Daniel [11]. Using the limit state function, each configuration of the stochastic variables will be sampled to define the safety mode of the structural behaviour. The conditional probability distribution of the failure node is computed by sampling the intervals of the parent nodes for all the configurations. For each sample, values "one" and "zero" are assigned to the cases whether the structure is in fail or safe state respectively [10]. Finally, using Monte Carlo method, the probability of failure for the limit state node will be computed in the network. The numbers of discretization intervals for all the continuous variables considered for reliability analysis are shown in Table 2. The rest of the variables such as significant wave height, H_s, sea wave spectrum $S(\omega)$, and wave force spectrum $S_F(\omega)$ are

Table 2
Discretization of continuous variables in BN model.

Continuous Variables	Type of Distributions	Number of discretization intervals	Interval size
σ_v (N/m)	Normal	10	2×10^7
T_0 (t)	Normal	9	70
E (N/m)	Normal	10	10^9
X_{11}(m)	Gumbel	22	1.0

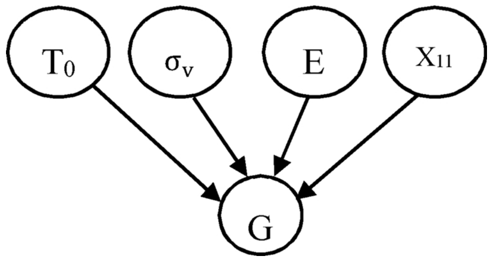

Fig. 3. Established BN model for assessment of tendon failure.

implicitly considered in the failure function and they should not be regarded as the parent nodes in *BN*.

The network presented in Fig. 3 shows the probabilistic model for the reliability of tendon. Node *G* in the figure contains binary variable with two states of "Fail" as $G < 0$ and "Safe" as $G > 0$. It then holds the probability of failure due to increasing tendon forces given values of the input variables σ_v, T_0, E and X_{11}. The conditional probability distribution $P(G|\sigma_v, T_0, E, X_{11})$ should be implemented for each of the $10 \times 9 \times 10 \times 22 = 19800$ configuration of parent variables using the failure function (Eq. (11)). The probability of failure, P(G) is defined by marginalizing the joint distribution of the stochastic variables in the *BN* using *GeNIe* software.

3. Application of developed methodology: case study

3.1. Geometry details

A floating cylinder is considered as the case study to demonstrate the application of the developed methodology. The structure is connected to a single tensioned line to evaluate the reliability of the mooring system as a result of extreme responses incurred by the wave loads. Fig. 4 provides a schematic illustration of the structure used in the case study, in which B is centre of buoyancy, G centre of gravity, L is the length of the cylinder, d is the draft, dz, dF and dM are strip elements for vertical deformation, force and moment, respectively, a_{ij} is the added mass in i^{th} direction due to unit deformation of object in j^{th} direction, K is the stiffness of the tendons, E is the modules of elasticity and l is the length of the tether. The stiffness coefficients of tether are defined based on *Hook*'s law [27]. Discretised strip terms for wave force and added mass are presented in Fig. 4 for two degrees of freedom, surge and roll. All required loads and response variables involved in the case study are presented in Table 3.

3.2. Hydrodynamic responses

Physical parameters applied in the hydrodynamic and reliability analysis are illustrated in Table 4. Pierson-Moskowitz spectrum density is used to compute the hydrodynamic forces and responses [22]. The highest 1% of surge responses are derived from each *RAO* to predict extreme value of horizontal excursion of mooring line. The Surge responses spectrum for each sea state are illustrated in Fig. 5. The probability of occurrence for each significant wave height is selected such that the whole area under cumulative distribution of $\sum f(Hs)\Delta Hs$ equals unity. The product of $f(Hs)\Delta Hs$ then provides the magnitude of the corresponding occurrence probability of the sea state. The final results for the extreme surge response obtained from RAO response of each sea states are reported in Table 5.

3.3. Reliability assessment results

In this study, GeNIe software was employed to conduct the reliability analysis of the mooring system for different critical surge excursion levels, *Xc*. This parameter represents a condition that the load will start to exceed the allowable design load, and defined as$X_c \frac{F_T(X_C)}{K_{11}}$. The numerical simulation was performed for 12 different X_c and summarized in Table 6 In order to determine the best design point, according to the intensity of wave excitation, the strength of mooring profile was

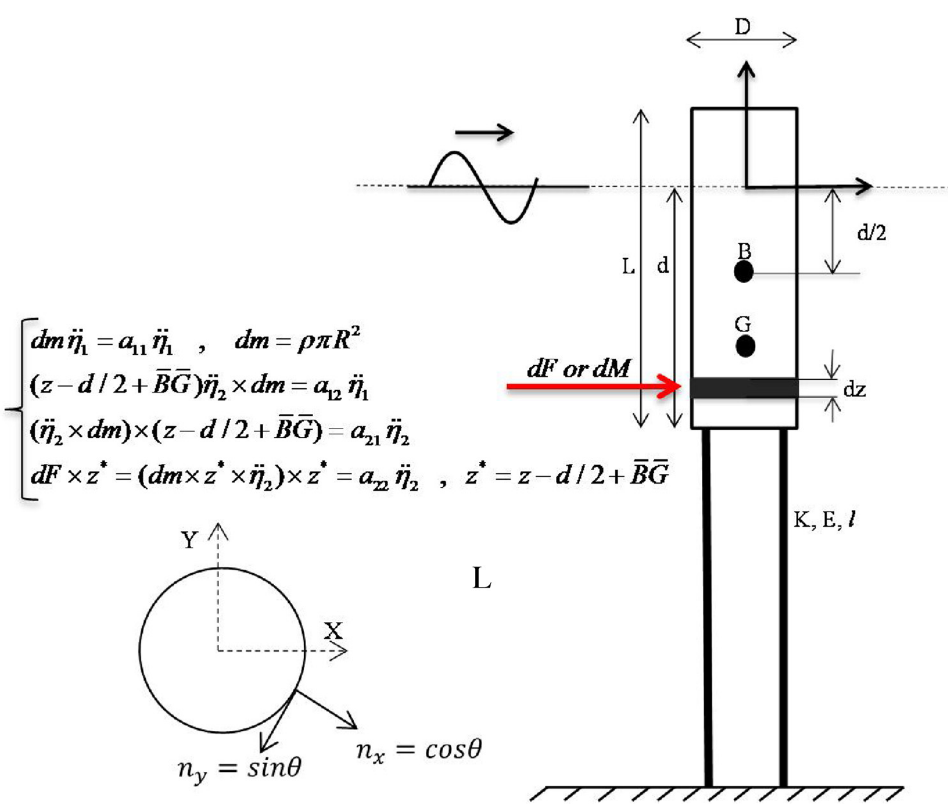

Fig. 4. Geometry details of a moored floating cylinder considered in the case study.

Table 3
Load and response functions derived from frequency domain analysis and Hook's law for reliability analysis.

Load function		Response function	
Surge Frequency Force	$S_{F11}(\omega) = 4\rho^2 g^2 A^2 S(\omega)$	Surge Response[a]	$X_{11} = \frac{1}{\mu_{12}}[(I + m_{12})\omega^2 + k_2 + \mu_{12}].\ H_{12}(\omega)$
Pitch Frequency Force	$S_{F22}(\omega) = 4\rho^2 g^2 A^2 \alpha^2 S(\omega)$	Pitch response due to surge force	$X_{12} = H_{12}(\omega)$
Surge Tendon Stiffness	$k_{11} = \frac{n\left(\frac{(T_0 x)}{L} + \frac{AE}{Lx^3}\right)}{X_{11}}$	Tendon Force	$k_{11}X_{11} = n\left(\frac{(T_0 x)}{L} + \frac{AE}{L}x^3\right)$

[a] $H_{12}(\omega) = \frac{\mu_{12}.2\rho g\pi R^2 \xi_a[1-e^{-kd}]}{\Lambda}$ called frequency transfer function.

Table 4
Geometry details of the floating cylinder and its mooring system.

Parameters	Value	Parameters	Value
Cylinder Radius (R), m	2	Pre-Tension (T_0), t ($0.7\ \nabla_{Bouyancy}$)	43.96
Water depth, m	50	Module of elasticity (E), GPa	73
Draft (*d*), m	5	Weight ($0.40T_0$), t	17.58
Height of cylinder (*L*), m	8	Yield Stress (σ_y), MPa	100
Tendon Diameter, mm	100	Gyration Radius (*I*), m	0.3 R
KG, m	$\frac{1}{3}$d	GM, m	$\frac{1}{6}$d
Surge added mass (m_{11}), t	62.8	Surge due to roll added mass (m_{12})	52 t

increased consistently at each simulation. As an example, the numerical result for the case$X_c = 2.4$ m is illustrated in Fig. 6. The CPT for failure node "G" is completed using Eq. (11) and given to the network for estimating probability of failure which is found as$P_f = 5.59E - 02$. To define the failure point, node "G" instantiated on "Fail" state. The network is shown in Fig. 7 and the results are summarized as E = 80 GPa, T = 490 t and σ_y = 100 MPa with allowable horizontal surge response of $X_c \geq 2.4$ m. The process continues until the probability of failure reaches a plateau of $p_f = 2.0E - 05$corresponding to the reliability index of β = 3.50. Parameter β is defined by a standard normal distribution, Φ corresponding to the reliability of the system in terms of $R = 1 - \Phi(\beta)$ represented in Fig. 8. It is found that for $X_C > 3.5$ m, the structure will not be affected by extreme waves and probability of failure remains constant at $p_f = 2.0E - 05$. That is, for $X_C \leq 3.5$ m, the structure is vulnerable to the sea environment, and otherwise it will be sufficiently flexible due to adequate stiffness of the mooring line in respect to different levels of wave forces. The structure can experience a larger horizontal surge response because of the fact that the mooring line is reliable enough to survive extreme loads. Also, the result confirms that it is well worth keeping the design point as $X_C = 3.5$ m to minimize the cost in designing mooring system. As recommended by Brindley and Comley [32], there is no necessary rule to demonstrate that increasing the mooring capacity is sufficient to

Table 5
The highest 1% of the surge responses for each sea state.

Sea state Number	Significant Wave Height, $H_{s(m)}$	Probability of Occurrence of Wave Height	Standard Deviation for X_{11} (m)	Maximum of Response, $\bar{X}^{i}_{0.01}$
1	0.7500	0.2099	0.0001	0.0008
2	1.2500	0.3131	0.0007	0.0048
3	1.7500	0.3154	0.0023	0.0158
4	2.2500	0.2820	0.0058	0.0387
5	2.7500	0.2355	0.0120	0.0801
6	3.2500	0.1875	0.0224	0.1495
7	3.7500	0.1439	0.0391	0.2614
8	4.2500	0.1071	0.0692	0.4616
9	4.7500	0.0776	0.1674	1.1165
10	5.2500	0.0549	0.4096	2.7323
11	5.7500	0.0381	0.8375	5.5864
12	6.2500	0.0259	1.4059	9.3776
Fitted data to Gumbel Distribution of Maxima for Long-Term Surge response				$E[X_{11}] = 0.8539$ $\sigma[X_{11}] = 2.0133$
Gumbel Parameter				$a = 1.76$ $b = 1.5698$

Table 6
Estimated probability of mooring failure obtained from BN model.

Case.	Maximum allowable critical surge response (m)	Probability of mooring failure
1	$X_C \leq 1.9$	$1.58E - 01$
2	$X_C \leq 2.4$	$5.59E - 02$
3	$X_C \leq 2.8$	$2.27E - 02$
4	$X_C \leq 3.0$	$1.35E - 03$
5	$X_C \leq 3.2$	$1.01E - 04$
6	$X_C \leq 3.3$	$9.00E - 05$
7	$X_C \leq 3.5$	$2.00E - 05$
8	$X_C \leq 4.0$	$2.00E - 05$
9	$X_C \leq 4.5$	$2.00E - 05$
10	$X_C \leq 5.0$	$2.00E - 05$
11	$X_C \leq 6.0$	$2.00E - 05$
12	$X_C \leq 7.0$	$2.00E - 05$

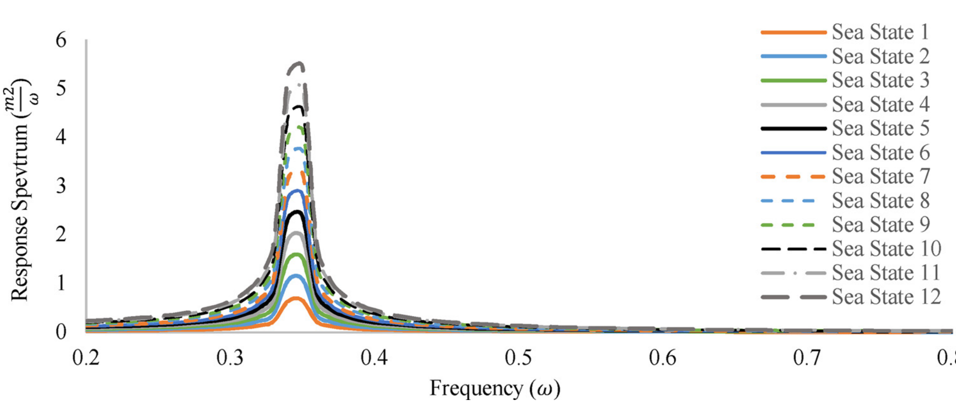

Fig. 5. Estimated Surge Response Spectrum for of floating structure with respect to different sea states.

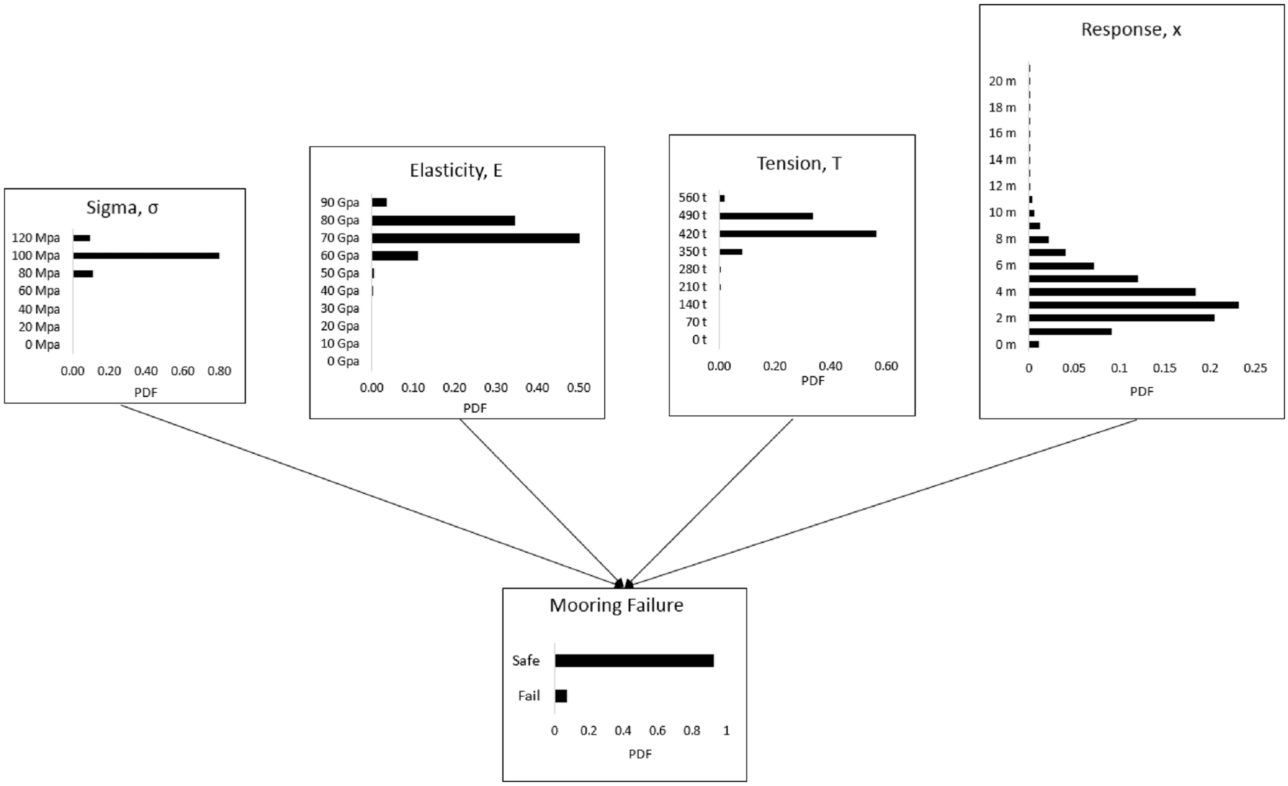

Fig. 6. Developed BN for reliability analysis of structure (critical surge excursion is considered as $X_c = 2.4\,\text{m}$).

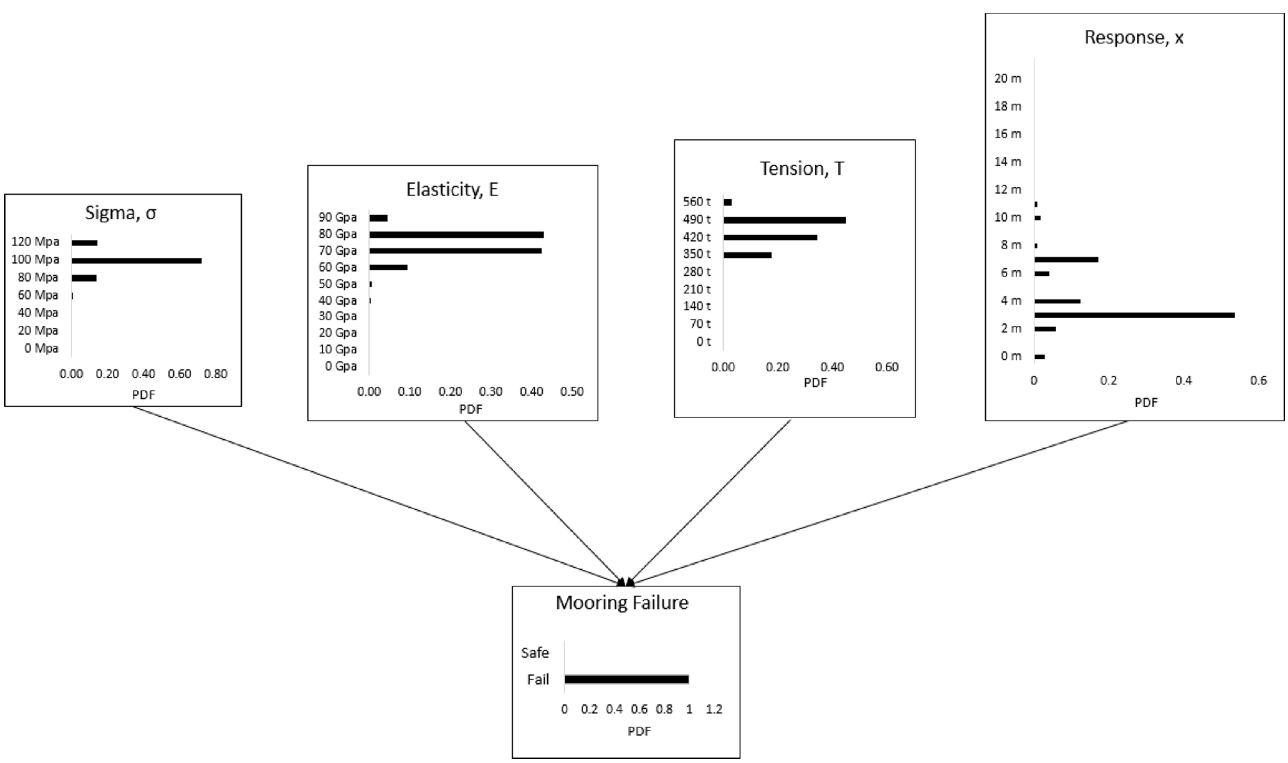

Fig. 7. Estimation of best design point for critical surge excursion of $X_c = 2.4\,\text{m}$.

optimize the reliability. Increasing the strength of the mooring line will also escalate manufacturing and maintenance costs. With this objective, this study has investigated the optimum design point resulting in the desired level of structural reliability while it can be regarded as having future cost minimizing strategies.

4. Conclusion

In this study, a methodology is developed to integrate Bayesian approaches with the hydrodynamics analysis of marine floating structures to improve their safety. For this purpose, the frequency domain

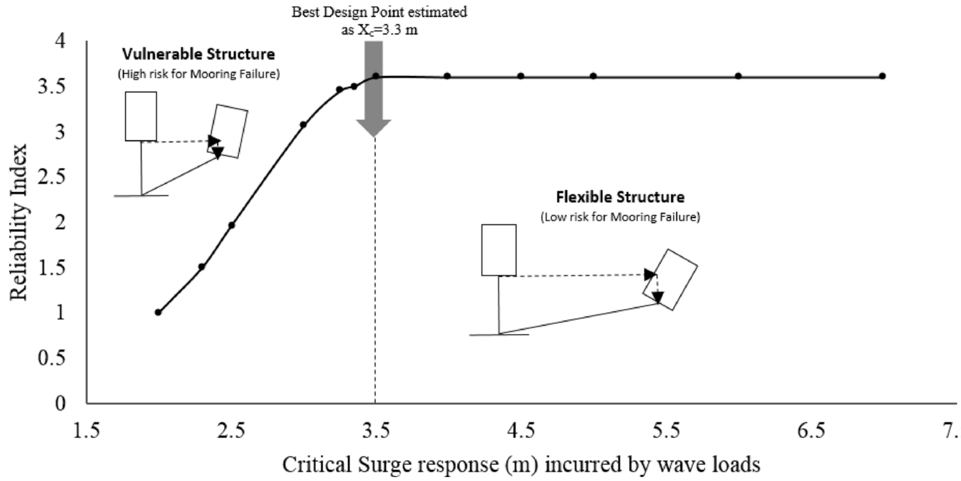

Fig. 8. Estimated reliability index of different critical surge response considered as the design point.

approach is applied for hydrodynamic analysis given that this method provides an efficient solution to compute, either numerically or experimentally, the stochastic wave loads on structures. BNayesian network is adopted for estimating the probability of failure to identify the best design point. A floating tensioned cylinder is considered as a case study to demonstrate the application of the methodology. The structure is subjected to 12 sea states and the reliability of the mooring system is examined with respect to the allowable horizontal elongation. It is found that the structure can tolerate the extreme wave height with optimum critical surge response of $X_C = 3.5$ m, corresponding to reliability index of almost $\beta = 3.50$. This methodology can be applied to effectively perform reliability analysis of a floating structure with tensioned mooring system. In order to use the proposed methodology for another type of failure, firstly it is necessary to develop a suitable limit state function for a particular failure scenario. The same approach should then be followed for developing the BN and estimation probability of the failure. For this purpose, a suitable limit state function, G, for a particular failure scenario (such as capsizing a vessel due to extreme roll angle) should firstly be developed and then follow the same approach proposed in Section 2.3 for developing related BN and estimation probability of the failure. Results of this research confirm that the methodology is successful in identifying the critical design point of the system with respect to hydrodynamic response of the structure in different sea states which can assist in maintaining an acceptable level of failure risk during the operational time.

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