Proceedings of the 26th International Conference on Offshore Mechanics and Arctic Engineering
OMAE2007
June 10-15, 2007, San Diego, California, USA

OMAE2007-29556

PROBABILISTIC FATIGUE RELIABILITY OF LARGE DIAMETER STEEL CATENARY RISERS (SCR) FOR ULTRA-DEEPWATER OPERATIONS

U. O. Akpan, T. S. Koko and **P. A. Rushton**
Martec Limited, 1888 Brunswick Street, Halifax, NS, Canada B3J 3J8

A. Tavassoli
INTEC Engineering Partnerships, Ltd., Houston, TX

M. Else
US Department of Interior, Minerals Management Service, 381 Elden Street, MS-4021 Herndon, VA 20170-4817, USA

ABSTRACT

For deepwater development in the Gulf of Mexico, steel catenary risers (SCRs) supported from both SPAR and semi-submersible platforms have proven to be successful solutions for in-field flowlines, tie-backs, and export systems. It is envisaged that this will continue to be a promising solution in ultra deep-water applications, up to and beyond 10,000 ft. The study, commissioned by the Mineral Management Service (MMS), investigated the reliability of large-diameter SCRs in ultra-deepwater operations. The primary damage mode considered is fatigue failure. A probabilistic methodology for fatigue reliability is developed, which utilizes deterministic cumulative fatigue damage indicators, namely the stress levels and cycles associated with the various sea states and the fatigue strength of the members. Uncertainties in structural load and material properties are accounted for by assigning probability distributions and standard deviations to the deterministic stress levels. Furthermore, fatigue strength parameters, Miner's indices, and capacities are modeled as random variables. First order reliability method (FORM) is employed for estimating fatigue reliability. The methodology is applied to three deterministic case studies presented by Intec Engineering (2006a, 2006b). The case studies involved either a SPAR or a semi-submersible platform. For the sake of brevity, a case study involving only a SPAR platform is presented in this paper. The effect of uncertainties in parameters on fatigue reliabilities is investigated. It is observed that the fatigue reliability estimates followed similar trends as the deterministic cumulative damage results, and hence can be used to complement deterministic estimates. Additional benefit and insight gained from the probabilistic study, which can be used for design decisions, include information regarding probabilistic importance and probabilistic sensitivity analysis. For case study presented here, it is seen that in general, uncertainty in the fatigue strength exponent (m) has the highest impact on fatigue reliability of SCRs. The second most important random variable is the stress range (S), which captures uncertainties in parameters such as loads and material properties. Parametric sensitivity studies on the fatigue strength parameters indicate that SCR reliability is sensitive to both the standard deviation and probability distribution of the parameters, thus highlighting the need for accurate probabilistic calibration of the random variables.

INTRODUCTION

In recent years, offshore reservoirs have been moving towards ultra-deepwater environments, where floating production, storage, and off-loading (FPSOs), semi-submersibles, and spars are considered to be the most economically viable platforms. Large diameter steel catenary riser (SCR) solutions are being considered for these floating production units in deepwater developments such as in the Gulf of Mexico (GOM). The study, commissioned by the Mineral Management Service (MMS), investigated the reliability of large-diameter SCRs in ultra-deepwater operations. The primary damage mode considered was fatigue failure. A variety of uncertainties are associated with material behavior, environmental loading, hydromechanic modeling, structural modeling, and fatigue/corrosion/wear characteristics, especially at hang-off and tie-in joints. In order to systematically account for such uncertainties, a rational framework needs to be established.

Existing approaches for SCR design and analysis are typically based on deterministic methods. Significant effort has been spent on these methods with the aim of improving them for ultra-deepwater operations. The outcome of the deterministic research effort for ultra deep-water applications has been presented in INTEC Engineering (2006a). In order to account for uncertainties associated with the deterministic fatigue predictions, a probabilistic reliability framework was developed and investigated. The result of the probabilistic study was reported in INTEC Engineering (2006b), and is the subject of this paper.

The paper begins with a formulation of the fatigue reliability problem in the context of offshore structures. It uses deterministic fatigue results as a basis for reliability analysis. The solution strategy for the fatigue reliability problem is then developed and applied to an SCR case study. Summarizes and conclusions from the study are discussed.

FORMULATION OF FATIGUE RELIABILITY PROBLEM

The primary failure mode for offshore structures is fatigue. This failure mode must be considered in the design and analysis of these structures. Various steps are involved in the fatigue analysis of an offshore structure. They can be summarized as:

(i) Data collection and characterization, which involves compilation and statistical representation of ocean wave data and other environmental conditions applicable to a particular offshore structural location. This step is the basis for computation of offshore structural loads, which are typically random in nature. The wave, wind, and current data used for the current study are based on information taken from Deepstar JIP (1996) or obtained from MMS;

(ii) Computation of structural responses, such as stresses and strains, through application of the random loads computed in Step (i) above to a representative structural model. In this study, the load effects are computed using ultra-deepwater offshore structural models developed in INTEC Engineering (2006a);

(iii) The resulting stress and strain cycles are then used to compute some measure of fatigue damage, and;

(iv) Structural reliability is then estimated based on the computed measures of fatigue damage.

Fatigue damage resulting from random or variable amplitude loading is of primary concern here, as this loading is the most applicable to offshore structures. Fatigue damage may be computed using a number of methods. Fundamental to all is the assumption that fatigue behavior (under constant amplitude loading) can be described as some form of the relation

$$N(S)^m = K \tag{1}$$

where N is the number of stress cycles required to produce fatigue failure at an applied stress level, S denotes the applied stress level, typically described in terms of a stress range (or stress amplitude), and 'K' and 'm' represent the fatigue strength coefficient and fatigue strength exponent (respectively), both empirical material constants. For a specific stress range S_i (i=1,2,3,…,NSR_j), where NSR_j is the number of applied stress ranges during sea state 'j':

$$N_i(S_i)^m = K \tag{2}$$

from which it follows that the corresponding number of cycles to failure is given by

$$N_i = \frac{K}{(S_i)^m} \tag{3}$$

This relationship is commonly referred to as the 'stress-life' or 'S-N' curve approach. The S-N curve approach is commonly used in conjunction with the Palmgren-Miner rule, a linear damage accumulation rule which suggests that the accumulated damage fraction, D_i, resulting from the application of n_i cycles of stress range S_i is given by

$$D_i = \frac{n_i}{N_i} \tag{4}$$

For applied stresses below a material's endurance limit (S_{end}), it is assumed that damage will be negligible. Consider an offshore structure subjected to loads during a sea state 'j' of timeframe T_j. The total number of applied stress cycles during sea state 'j' is given by $(N_T)_{,j}$, where

$$(N_T)_j = \sum_{i=1}^{NSR_j} n_i \tag{5}$$

From the above equations, it follows that the total damage accumulated during sea state 'j' is given by

$$D_j = \sum_{i=1}^{NSR_j} D_i = \sum_{i=1}^{NSR_j} \frac{n_i (S_i)^m}{K} = \frac{(N_T)_j}{K} \sum_{i=1}^{NSR_j} \frac{n_i (S_i)^m}{(N_T)_j} \tag{6}$$

Defining f_i as the probability that a single stress range within sea state '*j*' will have magnitude S_i (i.e., the fraction of the total stress cycles of a given sea state that are applied at stress range S_i),

$$\left(f_i\right)_j = \left(\frac{n_i}{N_T}\right)_j \quad , \quad where \sum_{i=1}^{NSR_j}\left(f_i\right)_j = 1 \qquad (7)$$

It follows from Equation (4) that the total damage accumulation during sea state '*j*' can also be computed using the following relation

$$D_j = \frac{N_{Tj}}{K}\sum_{i=1}^{NSR_j}\left(f_i\right)_j\left(S_i\right)_j^m \qquad (8)$$

The function $\phi = f_i \ \left(i = 1,2,3,\ldots,NSR_j\right)$ essentially defines the probability density curve (or histogram) for the applied stress range associated with each sea state. The accumulation of fatigue damage throughout a series of relevant sea states is dependent not only on the distribution of applied stresses within each sea state but also on the relative frequency of occurrence of individual sea states. The fatigue damage accumulated at a given structural location within timeframe T_T can thus be expressed as

$$D_{Tot} = \sum_{j=1}^{NSS} p_j D_j = \sum_{j=1}^{NSS} p_j\left(\frac{\left(N_T\right)_j}{K}\sum_{i=1}^{NSR_j}\left(f_i\right)_j\left(S_i\right)_j^m\right) \qquad (9)$$

where D_j denotes the damage accumulation during sea state '*j*', f_i and S_i (i=1,2,3,…,NSR_j) defines the probability density curve for the applied stresses within each sea state, *NSR* denotes the number of applied stress ranges associated with each sea state, and T_j represents the duration of sea state '*j*' (usually expressed in terms of elapsed time or applied cycles). The probability of occurrence associated with sea state '*j*' is denoted by p_j and given

by the ratio T_j / T_T, where $T_T = \sum_{j=1}^{NSS} T_j$ (j=1,2,3,…,*NSS*) and *NSS* represents the number of relevant sea states. It is noted that *K* and *m* are empirical constants representing the fatigue strength coefficient and exponent (respectively), which may be treated as random variables to reflect the uncertainty in structural capacity, material properties, and the like. It is further noted that the stress S_i (taken here as the average of the applied stress range) is typically randomly distributed due to uncertainties in environmental parameters and structural loading

RELIABILITY SOLUTION STRATEGY

The limit state function for the fatigue reliability of ultra-deep offshore structures can be defined as

$$g\left(X\right) = B_R\Delta - B_S D_{Tot} \qquad (10)$$

This can be rewritten using Equation (9) as

$$g\left(X\right) = B_R\Delta - B_S\sum_{j=1}^{NSS} p_j\left(\frac{\left(N_T\right)_j}{K}\sum_{i=1}^{NSR_j}\left(f_i\right)_j\left(S_i\right)_j^m\right) \qquad (11)$$

where *X* is the vector of random variables, B_R denotes the modeling uncertainty factor applied to the fatigue resistance limit Δ (also known as Miner's index), and B_S represents the bias factor associated with the fatigue damage calculation itself. For the current study, it is assumed that in performing the reliability analysis using Equation (11):

(i) the design life for the offshore structural components is 20 years;

(ii) empirical constants *K* and *m*, representing the fatigue strength coefficient and exponent (respectively), are the same for all locations considered, and are based on the X' S-N curve provided in INTEC Engineering (2006a); and

(iii) the deterministic fatigue predictions from INTEC Engineering (2006a), obtained using Flexcom-3D/LifeTime software and presented in the form of stress levels and frequency of occurrence, can be used for reliability analysis.

Furthermore, it is noted that for the purposes of this analysis, the applied stress data supplied in INTEC Engineering (2006a) was discretized into stress ranges and cycles that affect cumulative damage ($\sigma \in [0,150]MPa$).

Once the limit state function has been defined, the reliability of offshore structural components can be defined as the likelihood of their functioning according to their designed purpose for a particular time period (e.g., an intended service life).

The fatigue reliability of an SCR structural component, may be computed using the limit state or performance function ($g(X)$) defined above. The failure domain (Ω) is defined by a negative performance function (i.e., $\Omega = \left[g\left(X\right) < 0\right]$), while its compliment ($\Omega' = \left[g\left(X\right) > 0\right]$) defines the safe region. The failure probability is defined as

$$P_f = \int_{\Omega} f\left(X\right)dX \qquad (12)$$

where $f(X)$ denotes the joint probability density function of the basic random variables (X) at time t. As the joint probability density function is generally unknown, evaluation of this convolution integral becomes rather arduous. Several practical approaches have been developed, including first-order reliability methods (FORM) and second-order reliability methods (SORM).

First-Order Reliability Methods (FORM), also known as Fast Probability Integration (FPI) schemes, are the most robust methodologies for computing instantaneous failure probability. The method uses the Hasofer-Lind (or H-L) formulation (or Advanced First Order Second Moment (AFOSM) model), the basic concept of which involves the transformation of Gaussian (i.e., normal) random variables to the standard form (i.e., with zero mean and unit standard deviation). The Hasofer-Lind reliability index, denoted by β_{HL}, is then computed as the minimum distance from the origin to the limit state surface. Although the H-L formulation is limited to cases involving Gaussian variables, the work represents an important milestone and has laid a solid foundation for the development of a class of procedures generically referred to as first-order reliability methods (FORM). FORM procedures are essentially optimization-based techniques that are used to evaluate the reliability index (β), from which the failure probability (P_f) can be computed using the following relationship:

$$\beta = \Phi^{-1}\left(P_f\right) \tag{13}$$

where Φ denotes the standard normal cumulative distribution function (CDF). FORM procedures utilize the full distribution information for all random variables included in the limit state function. Correlation between the random variables is permitted with FORM. Several techniques are available with which to complete FORM calculations. It is sufficient, however, to illustrate the basic features of the entire class via a description of a particular scheme called the HL-RF algorithm. This algorithm is named after Hasofer and Lind (1974), based on the work described above, and Rackwitz and Fiessler (1978), who first proposed the generalization of the H-L scheme to non-Gaussian random variables. The Hasofer-Lind and Rackwiz-Fisseler (HL-RF) algorithm has become one of the most popular FORM procedures employed today. The essential steps involved in FORM algorithms include:

(i) a transformation of the vector of basic random variables from the original X-space to the standard normal u-space;

(ii) a search (usually in u-space) for the point (u*) on the limit state surface (i.e., g(u)=0) that has the highest joint probability density. This point is commonly referred to as the design point, failure point, or the most probable point (MPP);

(iii) an approximation of the failure surface (in u-space) at the MPP; and

(iv) a computation of the distance from the origin to the MPP, referred to as the reliability index (β). This information can then be used to compute the associated failure probability (Pf).

The transformation from the original X-space to standard normal u-space is usually denoted by the transformation operator (T), such that:

$$U = T\left(X\right) \tag{14}$$

This probability transformation scheme has been verified to yield extremely accurate results in reliability analysis. The search for the most probable point is conducted via solution of an optimization problem. The optimization problem pertaining to the calculation of the Hasofer-Lind reliability index in u-space may be summarized as follows:

$$\begin{aligned} &\min imize\ D = \sqrt{u_i^T u_i} = \beta \\ &subject\ to\ g\left(u_i\right) = 0 \end{aligned} \tag{15}$$

The solution of this problem locates the MPP and the n-dimensional position vector locating this point (U^*) is given by

$$U^* = \alpha^* \beta \tag{16}$$

where α^* denotes the unit normal vector at the MPP. That is,

$$\alpha^* = \frac{\nabla g\left(U^*\right)}{\left|\nabla g\left(U^*\right)\right|} \tag{17}$$

in which ∇ represents the gradient operator. First Order Reliability Methods assume a linear approximation of the performance function at the MPP. The computed reliability index (β) has a one-to-one non-linear relationship with the failure probability.

The HL-RF algorithm is currently the most widely used method for solving the constrained optimization problem in structural reliability (Lui and Der Kiureghian, (1991)). The method is based on the following recursive formula:

$$U_{k+1} = \frac{1}{\nabla g^T\left(U_k\right)\nabla g\left(U_k\right)}\left(\nabla g^T\left(U_k\right)U_k - g\left(U_k\right)\right)\nabla g\left(U_k\right) \tag{18}$$

Experience shows that for most situations, the HL-RF algorithm converges rapidly. Alternatively, the Monte Carlo Simulation (MCS) technique, in which the failure set, g(X), is populated through generation of random samples, has proven to be a valuable instrument in reliability analysis. These capabilities are available in Martec's general-purpose reliability analysis tool COMPASS (Orisamolu et al., 1992), which is used for the reliability analysis in this study.

DEMONSTRATION EXAMPLE

Problem Description, Reliability Analysis and Result Presentation

The generic spar model shown in Figure 1 is used for both deterministic and reliability analysis. A detailed description of the problem configuration is provided in INTEC Engineering (2006a). For the sake of completeness, a summary of the hull and riser data is provided in Table 1 and Table 2. The purpose of this case study is to investigate fatigue reliability associated with various hang-off locations as well as the hang-off connections. Based on the deterministic fatigue results (INTEC Engineering, 2006a), uncertainties are assigned to the random variables, which are employed in a probabilistic fatigue analysis. The SCR hang-off locations are given in Table 2, while the associated coordinate system is shown in Figure 1. The origin is located at the keel at the platform center with the z-coordinate upwards. There are two alternative hang-off options, namely (i) soft tank, and (ii) hard tank. In both cases, the x and y coordinates of the hang-off locations are the same. There is a 3-meter separation between the hang-off points, and the riser headings differ by 5 degrees. A total of six random variables were used for the reliability analysis, their characteristics summarized in Table 3.

All reliability analyses were carried out based on the First-Order Reliability Method (FORM), the results of which are presented in Table 4 (Note: the following abbreviations apply: HT=hard tank; ST=soft tank; GR=gas riser; OR=oil riser; X=S-N curve X'; and TDP=touch down point). For some structural locations considered, failure probabilities were too low, that is, essentially zero. Only those locations exhibiting a failure probability $P_f \geq 1 \times 10^{-5}$ are presented in the table below.

The deterministic results (i.e., cumulative damage) and the reliability results (i.e., failure probabilities and reliability indices) are presented in Table 4. These results suggest that the hang-off region is consistently the most critical in terms of fatigue. The deterministic fatigue life was predicted using Flexcom-3D/LifeTime software, while the general-purpose reliability analysis tool COMPASS (Orisamolu et al., 1992) was used for the prediction of reliability. A review of the parametric importance factors predicted by the probabilistic analysis suggests that the fatigue strength exponent (i.e., slope of the S-N curve) '*m*' and stress range 'S_i', respectively, are the two parameters whose uncertainty (indicated by their respective COVs) most affects riser reliability, followed by the modeling uncertainty parameter B_R and Miner's index Δ (which generally exhibit an equal importance) and finally the bias factor B_S. It should be noted that in reality, it is expected that '*K*' and '*m*' will be correlated random variables, and should therefore exhibit a comparable level of importance. The pie chart in Figure 2 depicts typical results for the distribution of parametric uncertainty importance at two locations (HT/OR/X-E632-SP7 and HT/OR/X-E632-SP1 (see Table 4).

It is interesting to note that reliability and the relative importance of the basic random variables (B_R, Δ, B_S, m, K, and S_i) is strongly a function of the randomness of the fatigue strength exponent '*m*'. For example, when only '*m*' is considered deterministic, structural reliability increases dramatically, with B_R and Δ becoming the most important parameters. Therefore, efforts should be directed toward adequate calibration of 'm' for the various materials at the locations of interest. Since stress range S_i is a function of sea state statistics, close attention should also be paid to the calibration of this variable. Uncertainties in both '*m*' and 'S_i' will impact on the accuracy of both deterministic and probabilistic results.

To illustrate the parametric importance of the fatigue strength exponent '*m*', a sensitivity study was conducted, in which its original probabilistic characteristics were modified and the resulting impact on reliability noted. The results are summarized in Figure 3, Figure 4 and Figure 5. One of the most critical hot-spot locations (Hard Tank – Oil Riser – E632-SP7, (see highlighted location in Table 4) was selected for this demonstration.

SUMMARY AND CONCLUSIONS

The study developed and demonstrated a practical methodology and procedures for probabilistic reliability of SCRs. A procedure was formulated and implemented for reliability assessment of SCRs, which uses deterministic fatigue results as the starting point, in conjunction with reliability solution strategies such as first order reliability methods. A case study involving a SPAR SCR host structure was presented. The following conclusions can be drawn based on this study:

1. The methodology was constructed with careful consideration of the needs and practices followed in offshore design. It builds on deterministic results and should be seen as a complementary strategy to existing deterministic procedure for fatigue analysis.
2. This methodology realistically accounts for the various types/sources of uncertainties involved in the fatigue analysis of SCR, including uncertainties in fatigue strength parameters, material types, and fatigue loads.
3. The fatigue reliability methodology was applied to three case studies presented in INTEC Engineering (2006), in which the SCR was attached to either a SPAR or semi-submersible platform. For the sake of brevity, only one case is presented here. The lowest reliability index for the selected critical locations was approximately 3.2. In general, the fatigue reliability estimates followed closely the trends of the deterministic results, suggesting that the reliability strategy can complement existing deterministic efforts.

4. Results from the case study show that uncertainty in fatigue strength exponent (*m*) has the highest impact on the fatigue reliability of SCRs. It should be noted here that while the probabilistic importance factor of the fatigue strength coefficient (*K*) was low, in practice, *K* and m are correlated random variables. This correlation was not considered in the analysis presented here.
5. Parametric sensitivity studies of the fatigue strength parameters indicate that the reliability is sensitive to both their standard deviation and probabilistic distribution, thus highlighting the need for accurate probabilistic calibration of these random variables.

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Table 1: Generic SPAR Hull Data (INTEC Engineering (2006a))

Item	Value	Unit
Hull Geometry		
Displacement	53550	Te
Draft	152.5	m
Hard tank diameter	35	m
Hard tank height	71	m
Free board	15.5	m
Truss height	91.5	m
Soft tank height	5.5	m
Soft tank width/breadth	24.8	m
Center-well width/breadth	15	m
Truss Configuration		
Truss column diameter	2.5	m
Number of heave plates	3	-
Heave plate OD	35	m
Mooring Configuration		
Number of mooring line groups	4	-
Number of mooring lines	16	-
Fairlead hang-off elevation	97	m (above keel)
Riser configuration		
Number of SCRs	2	-
SCR hang-off elevation (Option 1 – soft tank)	5.5	m (above keel)
SCR hang-off elevation (Option 2 – hard tank)	97	m (above keel)
Topside Weights		
Max. topside weight in extreme condition	13690	Te
Deck VCG in extreme condition (from keel)	188	m
Max. topside weight in operating condition	13910	Te
Deck VCG in operation condition (from keel)	189	m

Table 2: SCR Hang-Off Details (INTEC Engineering, 2006a)

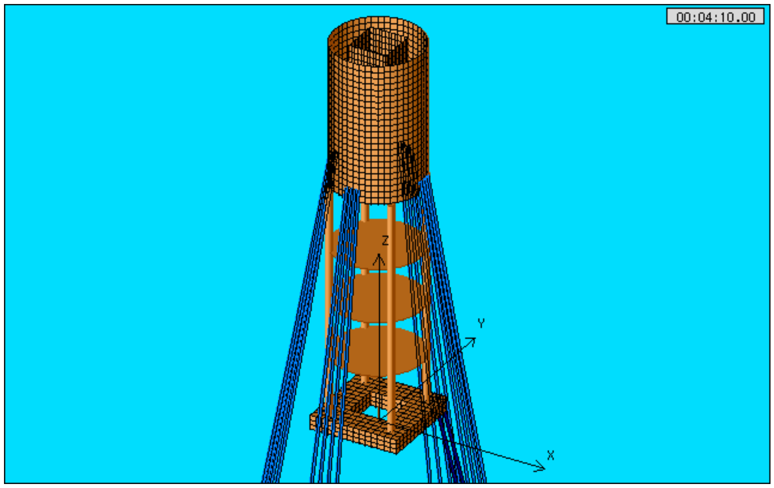
Hang-Off Option	X (m)	Y (m)	Z(m)	Azimuth Angle wrt X-axis (degree)
Option 1 – Soft Tank				
Gas riser	11.5	18.0	5.5	50
Oil riser	14.5	18.0	5.5	45
Option 2 – Hard Tank				
Gas riser	11.5	18.0	97	50
Oil riser	14.5	18.0	97	45

Table 3: Random Variables Used in the Reliability Analysis (Hang-Off Strategies)

Variable Name	Mean Value	Coeff. of Variation	Probabilistic Distribution
DELTA	1.000	0.25	Weibull
BR	1.000	0.25	Weibull
BS	1.000	0.25	Lognormal
S-N_m	3.740	0.10	Lognormal
S-N_K	2.50E+13	0.10	Lognormal
Fatigue Stress Levels (MPa)	0.250-575	0.40	Gumbel

Table 4: Probabilistic Reliability Analysis Results (Hang-off Strategies)

Load Case Description	Location	Element / Stress Point	Cumulative Damage	Reliability Index	Failure Probability
HT/GR/X	G1610 Hangoff	E632-SP1	2.279E-04	3.302	4.803E-04
HT/GR/X	G1610 Hangoff	E632-SP7	6.810E-05	3.996	3.220E-05
HT/GR/X	G1610 Hangoff	E631-SP7	5.626E-05	4.223	1.204E-05
HT/GR/X	G1610 Hangoff	E630-SP7	4.637E-05	4.258	1.028E-05
HT/OR/X	O1610 Hangoff	E632-SP1	2.930E-04	3.177	7.439E-04
HT/OR/X	O1610 Hangoff	E632-SP7	7.445E-05	3.997	3.200E-05
HT/OR/X	O1610 Hangoff	E631-SP7	6.071E-05	4.121	1.885E-05
ST/GR/X	G1610 Hangoff	E632-SP1	2.054E-04	3.308	4.707E-04
ST/GR/X	G1610 Hangoff	E632-SP3	1.002E-04	3.739	9.222E-05
ST/GR/X	G1610 Hangoff	E631-SP3	8.323E-05	3.782	7.790E-05
ST/GR/X	G1610 Hangoff	E630-SP3	6.907E-05	3.870	5.433E-05
ST/GR/X	G1610 Hangoff	E629-SP3	5.741E-05	4.180	1.456E-05
ST/GR/X	G1610 Hangoff	E628-SP3	4.585E-05	4.200	1.331E-05
ST/OR/X	O1610 Hangoff	E632-SP1	2.103E-04	3.314	4.606E-04
ST/OR/X	O1610 Hangoff	E632-SP3	8.459E-05	3.838	6.199E-05
ST/OR/X	O1610 Hangoff	E631-SP3	6.810E-05	3.985	3.373E-05
ST/OR/X	O1610 Hangoff	E630-SP3	5.456E-05	4.119	1.900E-05
ST/OR/X	O1610 Hangoff	E629-SP3	4.350E-05	4.205	1.304E-05



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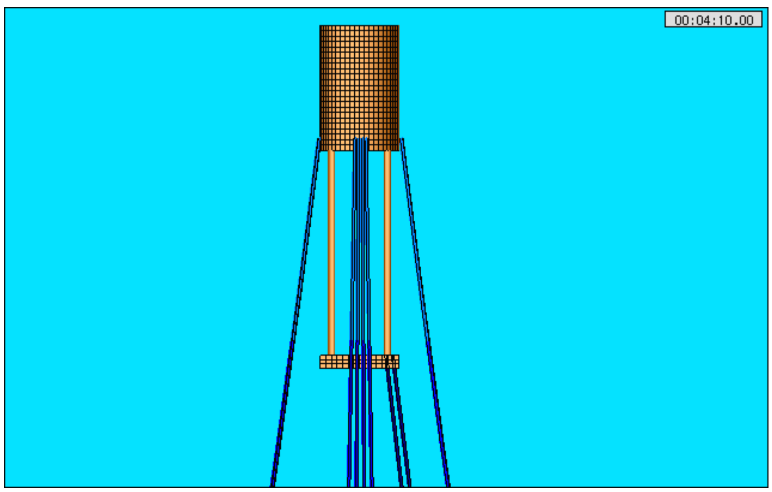

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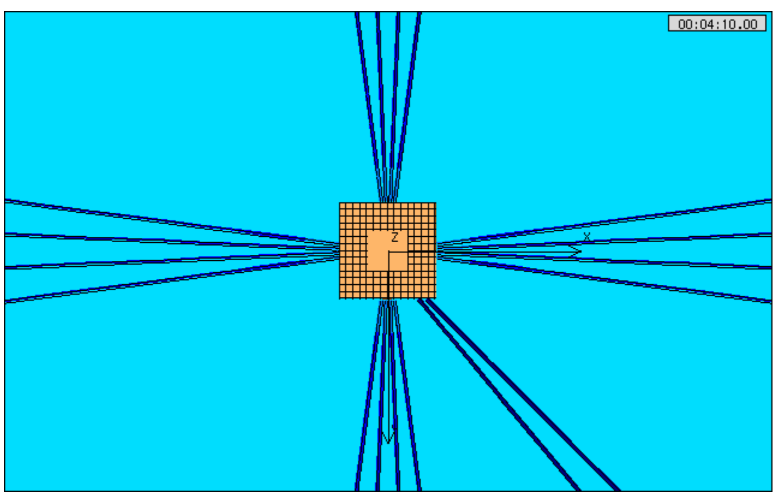
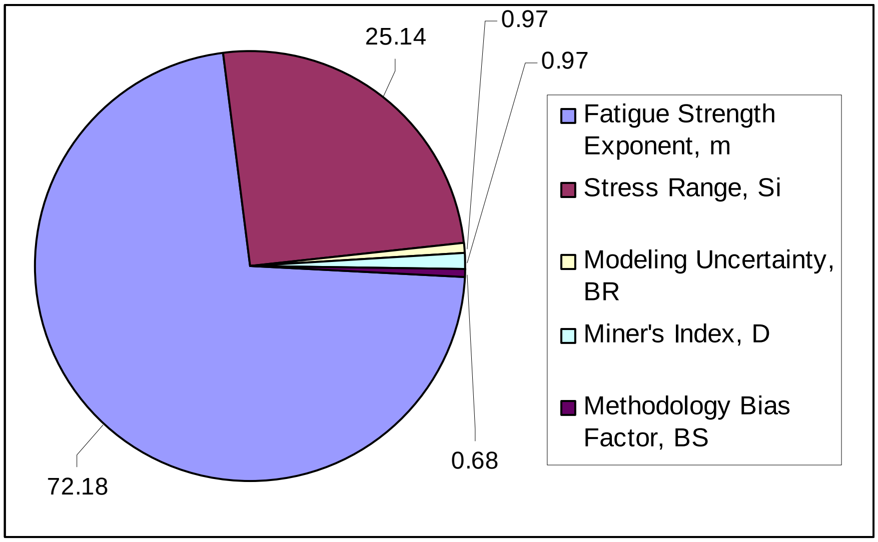


(c)

Figure 1: SPAR Model (a) Isometric View; (b) Elevation View; (c) Bottom View



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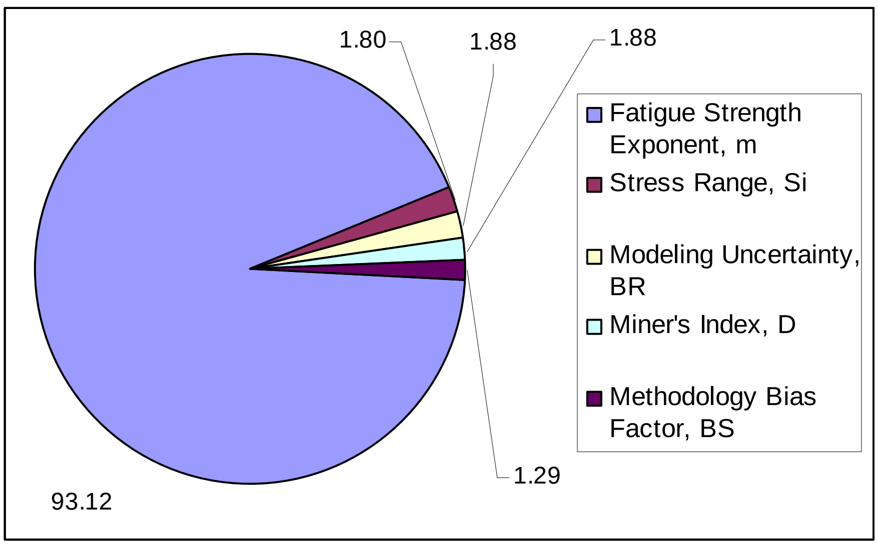

(b)

Figure 2: Distribution of Importance Factors for the Random Variables (a) HT/OR/X – E632-SP7; (b) HT/OR/X – E632-SP1

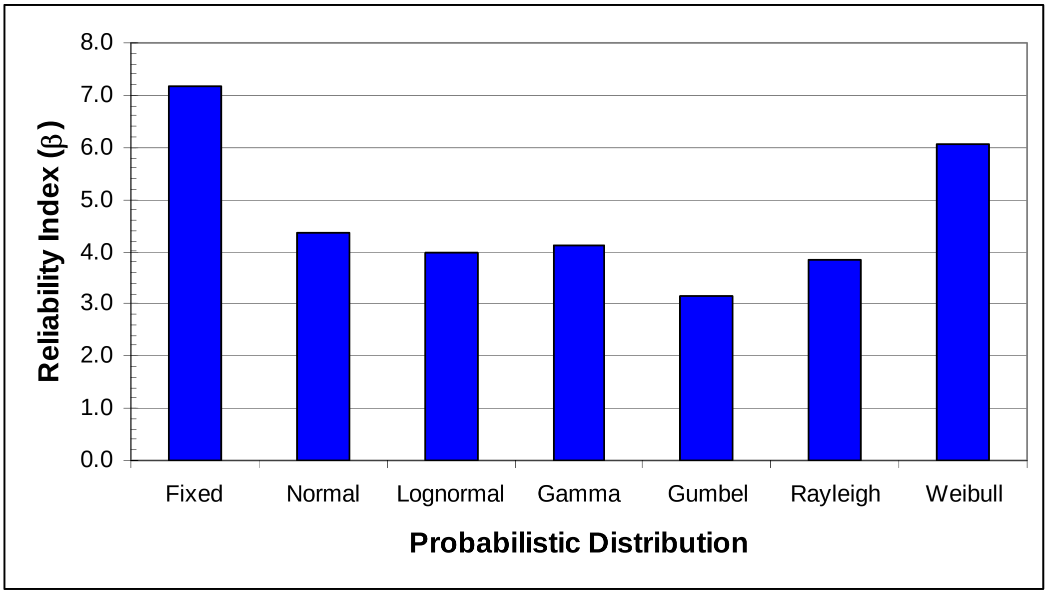

Figure 3: Reliability Index as a Function of Probabilistic Distribution of Fatigue Strength Exponent '*m*' (HT/OR/X – O1610 Hang-Off)

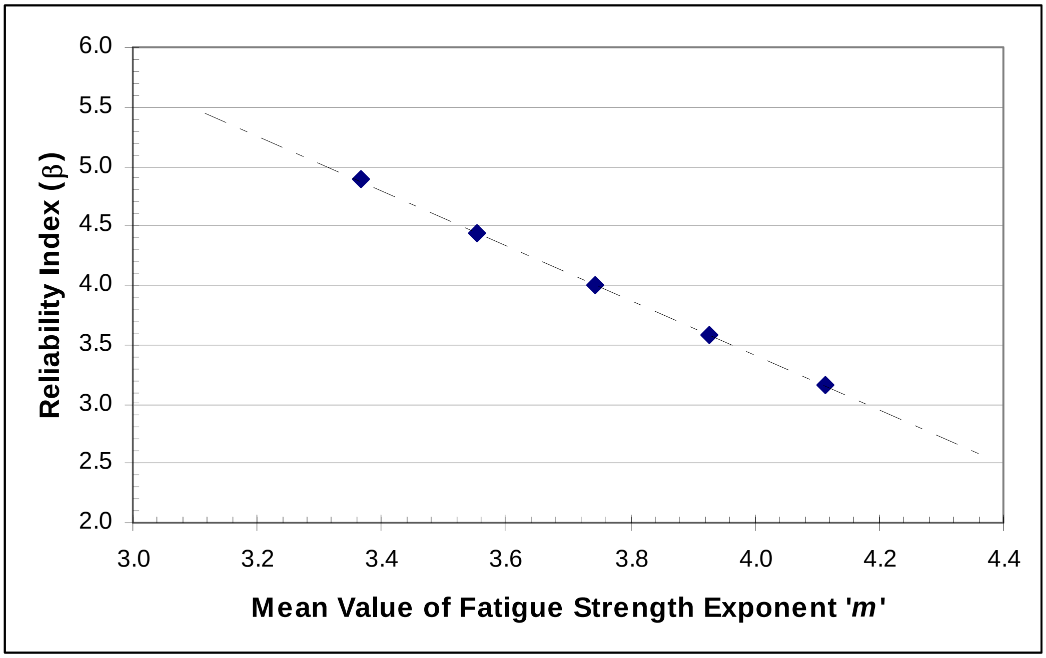

Figure 4: Reliability Index as a Function of Mean Value of Fatigue Strength Exponent '*m*' (HT/OR/X – O1610 Hang-Off)

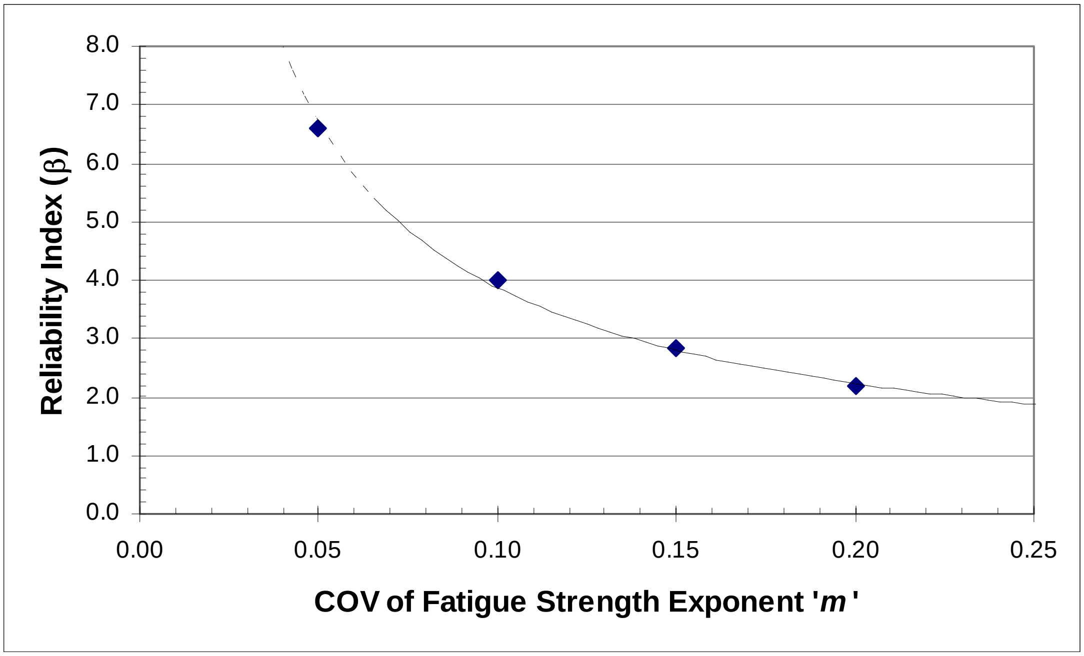

Figure 5: Reliability Index as a Function of COV of Fatigue Strength Exponent '*m*' (HT/OR/X – O1610 Hang-Off)