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Quantifying uncertainties for Risk-Based Inspection planning using in-service Hull Structure Monitoring of FPSO hulls

R.B. Hageman [a,*], F.H. van der Meulen [b], A. Rouhan [c], M.L. Kaminski [b]

[a] MARIN, Haagsteeg 2, Wageningen, The Netherlands
[b] Delft University of Technology, Mekelweg 2, Delft, The Netherlands
[c] Bureau Veritas Marine & Offshore, 4 quai Duguay Trouin, 44800 Saint-Herblain, France

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ABSTRACT

In order to obtain valuable information from an Hull Structure Monitoring system, a large data set and consistent analysis of that data is required. The monitoring requires significant efforts over multiple years and as a result, uncertainties obtained from in-service measurements are rarely published. Instead, researchers have to rely on numerical simulations and conjecture to quantify certain parameters. In this article, two years of continuous monitoring data is used to quantify several sources of uncertainties of the hull structure of an FPSO. These sources include uncertainty related to the future extrapolation of loads and statistical uncertainty of the long-term sea states which is quantified using a Bayesian re-sampling scheme. Next, the uncertainty introduced through the use of analytical load distribution models is addressed. Finally, the uncertainty in the calculation method is quantified. These data are then used in a case study for the particular FPSO which has been monitored to demonstrate their practical application using a simple reliability model.

Multiple stochastic models for the long-term description of loads are examined. Besides the traditional Weibull model, the less frequently used Pareto, Lognormal and Gumbel model were tested and compared against an uncertainty modal based on a spectral fatigue assessment. The Pareto and Weibull models are considered appropriate models and were compared against design stage analyses. Good design procedures adopt conservative parameters to describe the uncertainties. In the presented example, this was found to be true and therefore the inclusion of measurement data in Risk Based Inspection analysis for the presented case results in prolongation of the inspection interval.

1. Introduction

Seagoing structures are subject to various degradation mechanisms and their structural integrity is ensured through inspections and maintenance. Historically, inspections for ships are performed in drydocks at regular intervals of typically five years. Usually, permanently moored offshore floating structures do not have drydockings maintenance scheduled. Hence, the inspection of these structures has to be performed on-site while in operation.

There are numerous challenges when performing on-site inspections while in operation. Inspections have a large impact on the operations on the floating unit. In addition, even though significant precautions are being taken, personnel involved in the

* Corresponding author.
E-mail addresses: r.hageman@marin.nl (R.B. Hageman), F.H.vanderMeulen@tudelft.nl (F.H. van der Meulen), antoine.rouhan@bureauveritas.com (A. Rouhan), M.L.Kaminski@tudelft.nl (M.L. Kaminski).

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inspection is exposed to risks due to working in confined spaces, working at heights and walking on slippery surfaces. Some of the safety precautions which can be taken during dry-docking might be impractical when performing on-site inspections, making these inspections more cumbersome and hazardous to those involved.

The first offshore floating units were conversions from existing tankers. The traditional survey regime for these vessels is guided by the SOLAS requirements [1]. Consequently, the same inspection regime has been initially applied to offshore floating units. The return of experience was that this regime was not well adapted from an operational point of view. To overcome this limitation, most classification societies now offer the possibility of classing such units under a Risk Based Inspection (RBI) regime, see e.g. [2–5]. RBI can be used in lieu of the traditional regular frequency inspection regime. In that case, the whole survey programme of the hull structure is based on risk evaluations. Alternatively, RBI can be used to complement the existing inspection plan with regular intervals. In that case, the quantitative RBI analysis provides insight and helps in establishing inspection frequency of the most critical components to be inspected.

One of the goals of RBI for the hull structure is to determine its inspection and maintenance scheme based on a defined level of risk which has to be kept acceptable. The risk evaluation considers both the condition of the structure, the operational practices and constraints onboard, as well as risk to personnel linked to inspection, maintenance and repair activities. On the practical side, when evaluating the structural risks for the entire hull of an FPSO, it is usually evaluated using first a qualitative approach and might be complemented in a second step using quantitative approaches for the most critical components for a more refined evaluation of the considered risks.

In order to use quantitative RBI, the different failure modes are described by limit state functions. These limit state functions are usually given as the difference between the load acting on the structure and the resistance of the structure against that load. Some of the parameters in the limit state function are not known from a deterministic point of view, and might be modelled as stochastic parameters which includes a degree of uncertainty. The limit state function can be analysed using reliability methods or probabilistic simulations and aims to calculate the probability of failure and hence the reliability level. The probability of failure is then coupled with the consequences of failure to evaluate the associated risk level. Such an analysis allows to plan the inspection at the time it is necessary to maintain the predefined risk level and to focus inspection efforts on the location where structural failures have the highest risk levels. In this paper, only the structural risk of fatigue failure of structural components is considered. In addition, the study will not address the low cycle fatigue due to loading/unloading. It will also concentrate on the probabilistic evaluation part within the risk evaluation, hence the consequences part is not addressed.

Initial fatigue calculations of structural details are conducted at design stage of the hull structure, with usually limited information regarding the environmental loads, such as wave, current and wind data, and uncertainties thereof. This limited knowledge by nature impacts the resulting inspection frequency of the quantitative RBI analysis. It is limited in the sense that the prior knowledge differs from the one that the real structure will actually face, the posterior knowledge. One way to increase the knowledge of the loads on the structure is, once the unit is on site, to use continuous Hull Structure Monitoring (HSM). By nature, the data from a HSM system increases the knowledge of the loads acting on the structure. Therefore, the uncertainty of the loads on a monitored structure can be reduced, as more information from the monitoring system is gained, and provides a better knowledge on the required inspection intervals of fatigue critical structural components.

In order to obtain valuable information from an HSM system, a large data set and consistent analysis of that data is required. The monitoring requires significant efforts over multiple years and as a result, uncertainties obtained from in-service measurements are rarely published. Instead, researchers have to rely on numerical simulations and conjecture to quantify certain parameters. In this article, several sources of uncertainty have been quantified. These sources include uncertainty related to the future extrapolation of loads and statistical uncertainty of the long-term sea states which is quantified using a Bayesian resampling scheme. Next, the uncertainty introduced through the use of analytical load distribution models is addressed. Finally, the uncertainty in the calculation method is quantified. These data are then used in a case study for the particular unit which has been monitored to demonstrate their practical application.

The paper is organized as follows. Section 2 provides a short introduction to quantitative RBI. Section 3 introduces the FPSO and the HSM system which have been used for this research. A discussion of fatigue assessment in the offshore industry is provided in Section 4. This section includes a discussion of the transition of the deterministic calculation to a stochastic calculation, which is required for RBI. A detailed discussion of the associated sources of uncertainty is detailed in Section 5. This section also covers the quantification of these uncertainties using the in-service measurements. In Section 6 these measurements are introduced into the fatigue and RBI calculations and the results of these analyses using measured uncertainties as input, are shown. Section 7 provides a discussion of the results and Section 8 presents the conclusions of this work.

2. Risk Based Inspection planning

Inspections, maintenance and repairs activities (IMR) aim at preserving the risk levels and limiting the risk of industrial operations. When applying quantitative Risk Based Inspection (RBI), the evolution of structural risk over time is quantified explicitly using probabilistic methods, see for example [6]. Such a strategy to determine inspection schedules has been extensively applied in mechanical, civil and structural systems.

For a redundant structure where a large number of components is considered, such as the hull of an FPSO, the failure of each individual component has generally a low impact on the function of the structure and immediate consequences of failure might be considered as low. However, a failure of a single component contributes in the reduction of the robustness of the structure. Apart from design, inspection and repair activities are the first preventive barrier against the robustness reduction [7,8] and can be scheduled in time before the robustness level becomes too low. For a low redundancy structure, a failure of one of its component might lead to loss of function of the structure, such an event can eventually be evaluated as very high with regards to loss of life, economic costs and/or environmental damage.

Inspections are used to verify the system condition and initiate action if needed. An example of this type of application is given by [9]. Procedures developed within other fields of engineering cannot be straightforwardly applied to ship and offshore floating structures, because of different requirements on risk level and service life of these structures [10]. A careful evaluation of the existing procedures and comparison with industry design procedures is required.

Classification societies provide guidelines for risk based inspection and reliability based analyses of structural integrity. Practical applications of reliability engineering within the offshore industry evolved following the issuing of design codes, such as [2–4,11]. A practical example of the application of the design code by BV is provided by [12]. The case study involved the integrity assessment of a jacket structure incorporating both strength and fatigue criteria.

The random behaviour of parameters which are associated with uncertainty requires the analysis to be conducted using probabilistic methods. One way of assessing the probability of failure is by using structural reliability methods. They have been in development for shipbuilding applications since the 1980s. The general theoretical frameworks have been established in this period. An early example of the application of reliability methods is provided by [13]. Overviews of the basic methodologies which still form the core of most modern day analysis are provided in [14,15]. These references cover the basic concepts which are used throughout the present paper including uncertainty models, First/Second Order Reliability Methods and Monte Carlo simulations. Further developments in the methodology of reliability engineering have been executed for specific challenges in this field. For example, e.g. [16] addressed the development of methods to efficiently solve systems with a large number of (parallel) limit states. Situations where limited data is available to describe the uncertainties can be addressed using Chebyshev's inequality [17].

Over the years many risk and reliability studies have been conducted. For example, the study by Akpan et al. [18] is a well described example of such a study. The number of examples is to large to discuss exhaustively here. However, when reviewing these studies, the quantitative values of the uncertainties have often been retrieved from a limited number of original literature sources. Frequently, the original sources of these uncertainties date back as far as the 1980s, such as the much cited work by Wirsching [19]. Obtaining data on uncertainties is very challenging as it requires extensive instrumentation and long-term systematic analysis of data [20]. It should therefore not be a surprise that very little actual data on these uncertainties during in-service operations is available. Fatigue resistance data, described by the S–N curves, can be considered as a notable exception, although this data is obtained in laboratory conditions and may be too optimistic [21].

Reliability analysis can be applied to various types of degradation in ship and offshore structures. Many researchers note the importance of an integrated reliability framework [22]. An early example considering ultimate strength, fatigue and corrosion of a double-hull tanker is provided by [23]. [24] compares fatigue degradation of a structure using both fracture mechanics and S–N curve approaches to describe fatigue resistance. Further work on integration of the fracture mechanics approach in an holistic framework for the assessment of fatigue integrity is provided by Zou [25]. Doshi [26] presents a combination of fracture mechanics analysis and Probability of Detection curves to model the ability of finding those cracks when performing NDT. [27] provides an example calculation for damaged and grounded ships. Reliability analyses are also executed to assess ultimate strength of ships and its structural components. [28] provides a good general discussion on this topic as well as an example of stiffened plating. The work by [29] shows an example in which the optimization challenge of the inspection procedures was defined. In this article, inspection using acoustic emission and ultrasonic inspection were considered.

RBI methods can be deployed at different stages of the lifetime of an offshore unit. [30] shows the development of inspection planning during the initial stages of the FPSO field development. [31] shows a similar analysis for a jackup structure and indicates when inspection should take place to maintain the pre-defined risk level.

There are additional challenges when considering the reliability of a whole system rather than a single component. [14] examines the reliability of systems under more or less correlation between the components of the system. A general framework for system reliability incorporating fatigue degradation in steel structures is provided by [32] using Bayesian decision theory to develop an inspection plan based on a system consisting of 20 structural components. The authors demonstrate the effect of different inspection outcomes on the structural reliability and maintenance requirements. Further development of this model with an application to a truss frame can be found in [33]. The Bayesian procedure was found to have superior computational efficiency when compared to a Markov Chain Monte Carlo method. Due to the vast amount of structural components on an offshore structure, it is unrealistic to inspect every welded joint [34]. [35] use structural similarities between different components to limit the required amount of inspections and to define expectations for non-inspected components. However, these methodologies require further validation before they can be applied to an actual floater.

The risk reduction remains an important driver for the development of risk based techniques. [36] uses a cost–benefit analysis to determine the optimal inspection interval for an arbitrary floating structure. [37] developed a model to assess the cost implications of inspections and related the model to different inspection outcomes. [38] introduces a cost–benefit analysis in addition to a combined fatigue and collapse system failure. [39] shows the potential of reliability methods for fleet monitoring using an imaginary example. Procedures to estimate the costs of structural repairs are discussed by [40]. These estimates are obtained for a ship in drydock and the actual in-situ repair costs for FPSOs will be significantly larger.

When dealing with risk analysis, one defines level of risks and associated acceptance criteria to determine actions to be undertaken given the risk level of a particular adverse event. The risk acceptance criteria define the maximum acceptable risks levels for such adverse events, which when exceeded requires a mitigation action. The risk acceptance criteria can be used to decide the time when an inspection is to be performed keeping the risks levels acceptable. For quantitative analysis, such criteria are derived

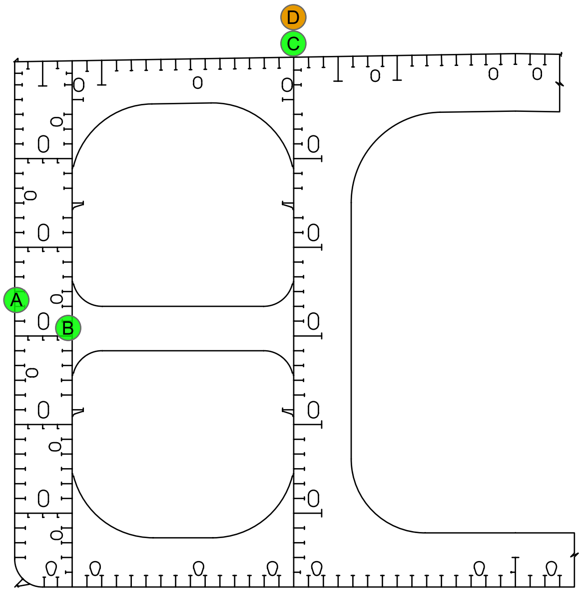

Fig. 1. An overview of the location of several strain gauges installed in a cross section of the hull from [45]. The figure indicates (A) a strain gauge on a side shell stiffener, (B) one on a stringer and (C) a normal and (D) long base strain gauge on top of the longitudinal bulkhead. For the analysis conducted in this article information from strain gauges installed symmetrically on port and starboard side near the midship area has been used.

under the form of the maximum annual probability of failure. For RBI of hull structure, one way to deal with risk acceptance criteria, is to define the risk level at a system level (i.e. the complete hull) and then to derive risk acceptance criteria for each components. Then for a given component, its risk is evaluated against the individual risk level. This strategy is presented in [41]. Such a strategy is a top-down approach for risk acceptance criteria. Another approach, which is out of the scope of the present paper, is the bottom-up approach as presented in [42], whereby the risk level of each component of the system is first evaluated and aggregated by means of, for example, a Probabilistic Bayesian Network. Then the global risk level of the system is evaluated and checked against the global risk acceptance criteria of the whole facility.

In the present article, the uncertainties on fatigue loads are examined in detail. To that aim, the overall uncertainty is considered to be an aggregation of several effects. The individual contributions of these different effects on the overall uncertainty are examined and an effort is made to quantify each contribution using operational data. Similar analyses quantifying the uncertainties in load effects have been executed on model scale by e.g. [43]. However, in the present article, extensive use is made of HSM using a systematic data gathering and analysis system for FPSOs [44,45].

3. RBI supported with hull structure monitoring

3.1. Application to structural fatigue detail

As an application case, we will consider a single component on an FPSO unit equipped with a hull structure monitoring system as previously described. The FPSO is a West-Africa spread-moored unit. The analysis will only consider the operation period of the unit and the towing phase will be excluded. Loading–offloading induced loads should be considered separately, but are not included in the analysis covered in this article. The design scatter diagram and the design operational profile consisting of different load cases and their occurrence are available. These consists in a total of around 18,000 conditions, each with its own probability of occurrence.

Let us consider a critical fatigue detail as a component to be studied. The hull structure under examination is designed for 20 years of operation and the component which will be studied is a joint of a bracket and under-deck longitudinal in the midship area, see Fig. 3. The primary loading at this location originates from vertical hull girder bending and is comparable to the loads observed on the bulkhead measurement locations. The joint has a Design Fatigue Factor (DFF) of 2. The DFF [46] being defined as the ratio between fatigue design lifetime of the component and the expected lifetime of the offshore unit at design stage and hence the component is designed for an expected lifetime of 40 years using the design S–N curve.

A quantitative RBI assessment is usually conducted using the design data available to examine future inspection campaigns, in particular with regard to the load data. In this paper we assess the impact on time to first inspection of the knowledge of the load applied to a fatigue structural detail. To do so, both the magnitude of the loads and the uncertainties in load predictions will be studied through the use of the HSM system.

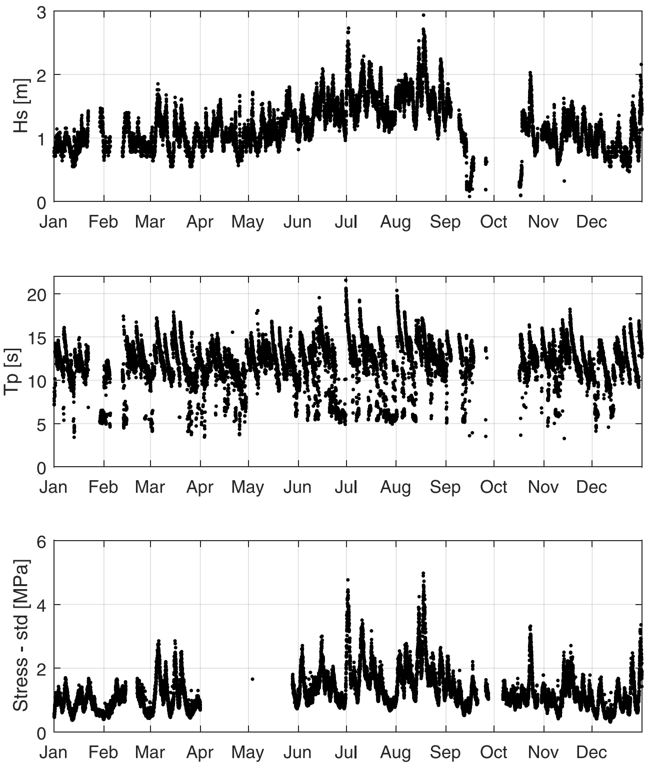

Fig. 2. A subset of the measurements analysed in this work. The presented data include statistical data from the wave buoy and stresses observed at one of the measurement locations.

3.2. Hull structure monitoring system and data

The measurement system captures global loading information such as the sea states and wind loads with the help of a weather monitoring buoy located nearby the offshore unit. It also registers operating conditions by recording the ullage inside all tanks in the cargo region, providing data on the loading–unloading patterns. At the same time, global hull structure responses are measured by using both local strain sensors and long-base strain sensors attached to the hull structure at various locations. On top of that, motions of the hull are being recorded.

Stresses are monitored at a selected number of locations on the hull structure with a unidirectional stress condition. The location of the sensors in the cross section of the hull is shown in Fig. 1. Data is retrieved at two cross sections of which both the port and starboard sides have been instrumented in a similar fashion. Use has been made of strains obtained from the upper deck mounted long-base sensors. The monitored locations are not fatigue critical locations, but so-called cold spot locations. The strategy being that the sensors are placed at locations where a single global load effect is dominating the structural response. By using monitoring at cold spot locations, a durable monitoring system can be achieved. Furthermore, the well-defined stress field at such monitoring locations results in minimal uncertainties on the measurement data as a result of sensor placement etc. This setup therefore allows for rational qualification of design tools and methods. The uncertainties obtained for the cold spot locations can then be transferred to the critical details taking into account a multiplication of the load level.

For this unit, two years of continuous monitoring data has been used for the analyses conducted herein. For the wave buoy, a subset of the statistical data registered during this period is shown in Fig. 2. The measured waves indicate a clear seasonal trend over the year. The measurements show a dominating swell with a period roughly between 10 and 16 s. However, in some conditions a wind driven sea provides a more pronounced peak in the wave spectrum leading to a sudden shift in the observed wave period to 5 s. The reader should note that not only statistical data, but the full time series data of the two year period has been used in further analyses.

4. Fatigue assessment

In this section, deterministic fatigue computations are presented first. Then, the calculation model which is used to assess fatigue within the RBI framework is presented and discussed. It introduces the basic calculation model used in this article. The uncertainty sources used in this analysis are also presented.

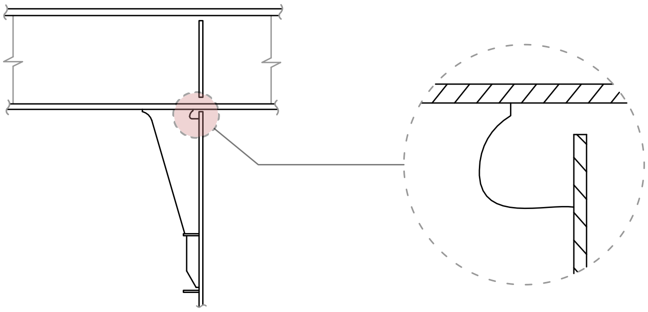

Fig. 3. Fatigue detail location and type.

4.1. Deterministic fatigue assessment at design stage

The current state of the art approach for conducting fatigue assessments wave induced loads of offshore structures is based on the spectral fatigue assessment. In such an approach the stress response spectrum at a selected component in a sea state is obtained from a spectral multiplication of the wave spectrum and the RAO of stress at this component. The RAO is obtained from a numerical hydrodynamic and structural model taking into account the appropriate loading condition. The analysis is repeated for the possible combinations of loading conditions and environmental conditions taking into account their probability of occurrence. The spectral fatigue assessment adopts the Palmgren–Miner linear damage hypothesis.

4.2. Deterministic fatigue assessment during operations

During operations, the hull structure monitoring system provides information which can be used to obtain more accurate estimates of the fatigue consumption. The fatigue assessment can be improved in two ways over the original design calculations as follows:

- **in-service spectral fatigue**: the spectral fatigue assessment can be repeated using the actual encountered environmental and operational conditions. This calculation will result in an improved estimate of the fatigue accumulation up to that moment, but it should be realized that operational and environmental conditions can change in the future.
- **time-domain fatigue**: the fatigue can be assessed by analysis of the actual measured strains at the respective components. Such an analysis does not rely on numerical models and calculation assumption which will introduce uncertainties or inaccuracies into the spectral fatigue calculation. At the same time, the stresses depend on the encountered conditions and require knowledge of those to interpret the results.

Both analyses provide valuable information on the true fatigue accumulation during operations. The first type of analysis yields information regarding the accuracy and uncertainty introduced by the design assumptions on environmental and operational conditions. The second analysis adds to that insight in the uncertainties introduced through design models and simplifications.

4.3. Stochastic fatigue model

In this section the typical calculation which is used to assess fatigue within the context of an RBI analysis is presented. In the spectral fatigue approach, the long-term design loads are obtained from the combination of short-term expectations during a large number of conditions each described by different environmental and operational parameters. The distribution obtained in this way is quite accurate, but becomes more challenging to analyse and interpret. A simplified model later referred as the *stochastic fatigue model* will be adopted to facilitate interpretation of the long-term wave-induced loads on a floating structure and uncertainties thereof. Historically, a Weibull distribution has often been used for this aim. In the present article, the fatigue resistance is described by a single slope S–N curve $S^m N = a$ with intercept a, slope m and N is the number of cycles to fatigue failure at stress level S. Under these assumptions, the fatigue damage in each condition can be evaluated analytically [47]. The long-term fatigue damage which is accumulated for a single structural component at time t, denoted by $D_{\mathrm{LT}}(t)$, is given by:

$$D_{\mathrm{LT}}(t) = \nu_0 t \frac{B^m}{a} \Gamma\left(1 + \frac{m}{\lambda}\right) \tag{1}$$

where (B, λ) are the scale and the shape parameters of the Weibull distribution, $\Gamma(.)$ denotes the Gamma function and ν_0 is the mean frequency of stress cycles. The moment at which fatigue accumulation starts is denoted $t = 0$.

In this paper, the parameters a, B and λ are considered as stochastic parameters and are therefore endowed with a probability distribution that reflects the current state of knowledge and/or inherent randomness. Other parameters are considered as deterministic parameters. The associated sources of uncertainty of these variables are discussed in the next section.

4.4. Probabilistic fatigue design assessment

In this section, the probability of fatigue failure for the considered structural detail at design stage is presented.

The probability of fatigue failure is evaluated using First Order Reliability Methods (FORM). The implementation of FORM from [48] has been used to evaluate the reliability index.

In the study, the risk acceptance criteria for the considered detail and facility has been defined at component level and for the specific detail under consideration, the maximum acceptable annual probability of failure is set to 3.4×10^{-4}. Similar values have been proposed as criteria in commercial ships and naval vessels [49]. Inspection is required when the reliability level falls below this threshold value.

The considered limit state function $G(.)$ for fatigue, see e.g. [50], is given by:

$$G(t) = D_{\mathrm{al}} - D_{\mathrm{LT}}(t) \quad (2)$$

where D_{al} is the fatigue damage representing the fatigue failure limit and $D_{\mathrm{LT}}(t)$ the fatigue damage accumulation at the given point in time t. The fatigue limit D_{al} is considered a stochastic parameter [51]. [49] provides an overview of different fatigue limit models. In this article, the model from [19] is used, which suggests to model D_{al} using a Lognormal distribution with median equal to 1.0 and Coefficient of Variation of 0.3.

The parameters describing fatigue resistance have been determined from the fatigue endurance tests which were used to develop the S–N curves. In the model data provided by [52], the parameter a is considered stochastic, while m is considered deterministic. The parameter a is described using the mean S–N curves with an associated standard deviation of 0.2.

For the unit under consideration, no dedicated reliability analysis have been executed at design stage. To define the parameters describing the design loads use has been made from general descriptions, in particular:

- The load frequency ν_0 is considered as a deterministic parameter at design stage and has been obtained using the definition from [53]. This resulted in a value of $\nu_0 = 0.14$ Hz.
- The Weibull shape parameter λ is defined as a stochastic parameter. The reciprocal parameter is given by a Normal distribution with a mean of 1.18, as per [54], and a coefficient of variation of 0.1 [55].
- The Weibull scale parameter B is obtained through reverse engineering of the expected lifetime of the structural component under investigation and Eq. (2). Using the mean value of λ and ν_0 and the design values of a and m and the 40 years design fatigue life, the mean value of B has been calculated using Eq. (1) [56]. A value of 8.43 was obtained. The uncertainty on this parameter is modelled using a normal distribution with coefficient of variation of 0.1, as per [55].

The uncertainties B and λ represents the uncertainties relating to the fatigue loads which originate from the following effects:

- **Fatigue Load Model uncertainty.** The fatigue loads are modelled using the Weibull distribution. However, this distribution does not exactly represent the true loading distribution. The associated epistemic uncertainty is modelled and further referred as fatigue load model uncertainty.
- **Statistical variability of loads.** Distributions of the wave and operational loads on the structure are obtained from assumptions or measurements with finite duration. Statistical variation in the actual conditions leads to an aleatoric uncertainty that needs to be accounted for.
- **Extrapolation uncertainty of loads**. While in service, at a given point in time, the HSM data covers a limited period of time of the service life (except at the end of live). Use of such data over the whole service life of the unit requires an extrapolation of the HSM data. The aleatoric uncertainty related to the use of environmental or operational data with a limited acquisition time, is quantified.
- **Condition of the structure.** An offshore unit is subject to corrosion, deformations and other degradation mechanisms. During construction, plate misalignments, weld defects etc. may occur. Therefore, the true condition of the structure is not equal to the idealized condition as used in the structural model. Moreover, the structural model contains some conservatism in the fact that the thickness of different plates in this model is reduced compared to the as-built structure. Some of these effects, such as weld defects and plate thickness, have very localized influence. The condition of the structure can therefore be considered an epistemic uncertainty in the stochastic analysis.
- **Calculation simplifications.** The calculation method used to assess the fatigue damage features some epistemic uncertainties, such as the linearization of the relation between waves and stress and discretization of the operational conditions.

The list above does not encompass the uncertainty related to the Palmgren–Miner summation and the fatigue criterion or the fatigue resistance. These uncertainties are covered by the parameters D_{al} and a respectively in Eq. (2) and will not be investigated in this article.

In this analysis, the parameters are considered to be independent and are summarized in Table 1. Fig. 4 shows the gradually decreasing reliability index of the detail over the entire 20 year design life in this example. After 3 years of operation, the reliability drops below the required reliability level and intervention through physical inspection is needed.

Importance factors are indicators of the contribution of each variable to the total variance of the linearized limit state and well adapted in the case where the random variables are independent. Importance factors are retrieved directly from a FORM analysis. The importance factors of this calculation are shown in Fig. 5. The graphs on this figure indicates that uncertainty in the fatigue loads, B and λ combined, is around 55% of the total uncertainty. This result is in line with earlier findings from [57].

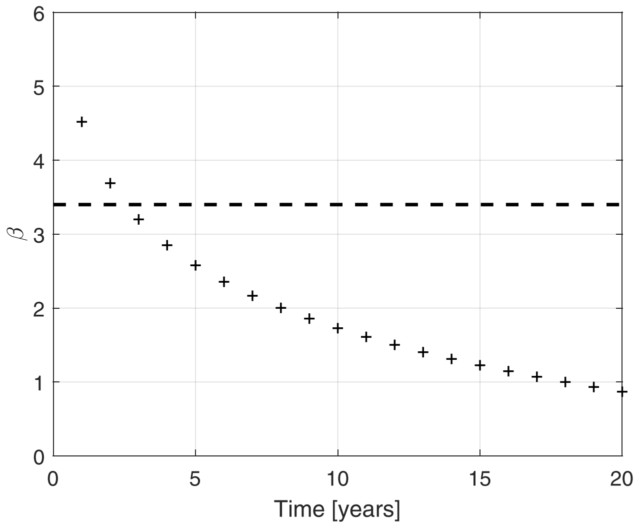

Fig. 4. Reference RBI analysis for a hot-spot of 20 year design life with Design Fatigue Factor of 2 using First Order Reliability Method. The dashed line indicates the target reliability level of $PoF = 3.4 \times 10^{-4}$.

Table 1
Parameters used in the reference calculation described by Eq. (2). S–N curve C for free corrosion was selected.

Parameter	Unit	Distribution	Mean	Standard deviation
D_{al}	–	Lognormal	1.04	0.313
ν_0	Hz	Deterministic	0.14	–
B	MPa	Normal	8.43	0.843
λ^{-1}	–	Normal	1.18	0.118
$\log(a)$	$\log(\mathrm{MPa}^m)$	Normal	12.115	0.2
m	–	Deterministic	3	–

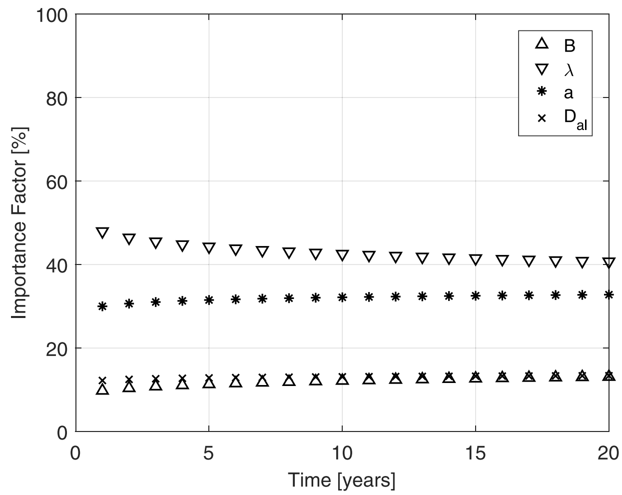

Fig. 5. Importance factors of different parameters in reference RBI analysis as function of time. These factors denote how much the different sources of uncertainty contribute to the overall uncertainty of the calculation.

5. Uncertainties model

In this section the uncertainties model used is presented. It accounts for various sources which are highlighted. The sustained hydrodynamic loads and its associated uncertainties are obtained from the Hull Structure Monitoring system described in Section 3.2.

Table 2
Comparison between values of Weibull distribution used in design phase and measured during operation.

Parameter	Unit	Mean design value	Mean measured value
ν_0	Hz	0.14	0.084
B	MPa	8.43	3.66
λ^{-1}	–	1.18	1.08

5.1. Extrapolation uncertainty — Uncertainties of environmental and operational conditions

During design phase, the stresses which are calculated for the different structural components are based on assumed environmental and operating conditions. Environmental conditions are based on historical measurements while operating conditions are based on experience from other production units and assumed performance of the field and unit. These conditions are not necessarily what the structure will encounter in reality.

During operational phase, environmental and operating loads are available through HSM. On the unit under consideration, the actual fatigue loads, expressed as a summation of the cubed stress range, $\Delta\sigma^m$, is only 30 to 50% of the design value. Example values of the loading parameters from in-service measurements on this FPSO are shown in Table 2. However, this data is based on a limited time-frame only, and hence cannot be considered representative for the entire lifetime.

General values related to uncertainty of environmental and operational conditions are not available in the literature. The authors reckon that the total of this uncertainty in the design approach is mainly the result of uncertainty in the future operations and environment, uncertainty which can be greatly reduced through monitoring of these conditions in the field. It should be noted that any uncertainty resulting from the accuracy of the measurement system itself is much smaller than the uncertainty experienced when relying on design assumptions.

5.2. Statistical variability of loads in a sea state

When designing an offshore structure, a scatter diagram describing long term wave data and operational profile is used to represent the conditions in which the unit may be operating throughout its lifetime. The scatter diagram contains all possible combinations of significant wave height and period of the sea states at the deployment location. The operational profile contains the planned loading and offloading sequences and resulting draft and trim.

On site measurements provided by the HSM are available during a finite sampling period of time. As a consequence, only a subset of the metocean conditions that the unit will experiment during its life time is recorded. Extending the knowledge from a limited period of measurements to larger period for computations, leads to an uncertainty in the data referred to as statistical variability of loads.

The effect of statistical variability of the data can be assessed through a Bootstrap analysis [58], if the complete set of environmental and operational conditions is known. The design scatter diagram and the operational profile consisting of different load cases and their occurrence are available. To estimate the uncertainty due to statistical variability of loads in the load models, the following procedure is applied:

1. Select a number of random environmental and operating conditions. Conditions are assumed stationary during three hour periods. For example, to assess variability for a ten year period, $10 \times 365.25 \times 8$ random conditions are selected.
2. Define the Rayleigh load distribution for all separate conditions.
3. Obtain the joint distribution through weighted summation of all Rayleigh distributions.
4. Obtain the best fit load parameters for the different models.
5. Repeat steps 1 to 4, 10^4 times
6. Derive mean and standard deviation of different load parameters.

The resampling scheme based on Bayesian statistics is described in more detail in [59]. This procedure also allows the calculation of the load frequency ν_0.

The variation in the results from the Monte-Carlo simulation have been examined and is shown in Fig. 6. As can be expected, the coefficient of variation is approximately inversely proportional with the square root of sampling period. The statistical variability of loads is a time-dependent parameter and hence the uncertainty to be used depends on the time frame for which the RBI assessment is to be executed.

In the design assessment, the different load parameters have been considered as independent variables. However, the simulation allows to assess the dependency between the variables for this source of uncertainty. The correlation matrix of the parameters, resulting from a Bootstrap analysis, is shown in Table 3. An inverse correlation between the scale parameter B and shape parameter λ can be seen. The correlation of the period ν_0 with the other two parameters is so small that it will be considered an independent variable.

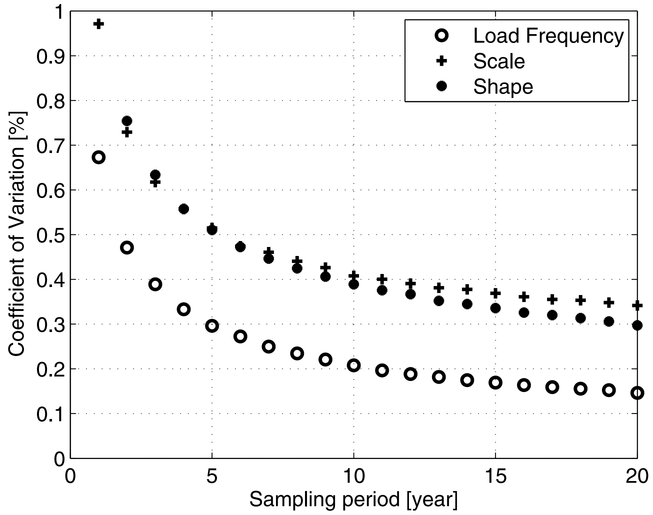

Fig. 6. Statistical variability of the load parameters in the Weibull model with sampling period. As expected, the uncertainty reduces with approximately $\sqrt{t}$ for increasing intervals.

Table 3
The correlation matrix of the parameters describing the long-term distribution of wave-induced stresses obtained using Monte Carlo simulations.

	Weibull Scale — B	Weibull Scale — λ	ν_0
Weibull Scale — B	1	−0.58	0.01
Weibull Scale — λ	−0.58	1	−0.16
ν_0	0.01	−0.16	1

Table 4
The fatigue bias for the best fit of different families of distributions. The fit has been obtained using Maximum Likelihood Estimators. All results are smaller than 1 indicating conservatism in the models.

Distribution	Bias			
	Location 1	Location 2	Location 3	Location 4
Gumbel	0.70	0.69	0.42	0.31
Weibull	0.86	0.85	0.61	0.51
Pareto	0.88	1.00	0.80	0.82
Lognormal	0.88	0.87	0.60	0.46

5.3. Fatigue load model uncertainty

As was discussed in Section 4 the Weibull distribution has historically been used to model the long-term loads. A more modern approach to assess the fatigue accumulation is through a Spectral Fatigue Assessment (SFA). In such calculation, the loads in individual sea states are modelled using a Rayleigh distribution. The total fatigue accumulation is obtained by combining the fatigue assessments from the individual conditions taking into account the relative occurrences. However, it is not straightforward to quantify and interpret uncertainties in the loads of numerous individual sea states. Parametric distributions to quantify the loads are more convenient for that purpose. Besides the Weibull distribution, other distributions have been used to model long-term load expectations as well [60,61]. These proposed models include the families of Gumbel, Lognormal and Pareto distributions and have, in the past, mainly been applied to assess extreme load events. Note that both the Gumbel and the Weibull distribution are special cases of the Generalized Extreme Value distribution. The load distribution obtained using the SFA calculation will be used as reference when comparing the various distributions.

5.3.1. Load distribution model

The applicability of the parametric long-term models of stresses for fatigue assessment has been examined using a subset of the HSM measurements. The probability density function of the stress at the examined measurement location can be found in Fig. 7. This figure shows both the measurements as assessed during design and obtained from in-service measurements in the 24 month period. It can be seen that the in-service measurements show smaller stresses than were assumed in the design stage. Table 2 provides the Weibull parameters describing both distributions.

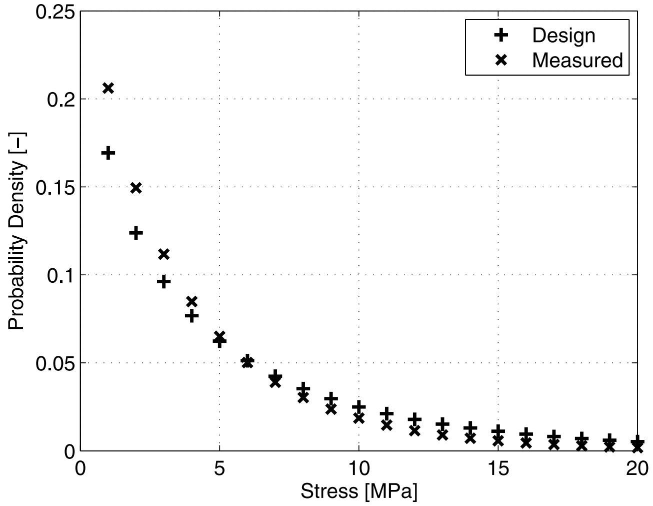

Fig. 7. Distributions of design and measured stress distribution for a single location, see also Table 2.

QQ-plots have been used to compare the various long-term load models. Maximum likelihood estimation has been used for parameter estimation within the selected families of distributions. In order to remove non-physical stress cycles, a threshold of 1 [MPa] was applied during processing of the measurements. The QQ-plots of different families of probability density functions are displayed in Fig. 8. The left hand tail of these distributions is shown in Fig. 9. In addition to QQ-plots, the bias in fatigue damage is calculated as the ratio of fatigue damage resulting from the fitted (F) distribution of stress ranges, $p_F(\Delta\sigma)$ and that of the reference distribution, $p_{\mathrm{SFA}}(\Delta\sigma)$ according to Eq. (3), assuming a single-slope S–N curve without cut-off and inverse slope m:

$$\mathrm{Bias} = \frac{\sum_{i=1}^{k} p_F(\Delta\sigma_i)\Delta\sigma_i^m}{\sum_{i=1}^{k} p_{\mathrm{SFA}}(\Delta\sigma_i)\Delta\sigma_i^m} \tag{3}$$

where k is a number of bins in the histogram of measured stress ranges up to twice the yield stress, i.e. $\Delta\sigma = 2\sigma_y$. This upper boundary of the summation is a somewhat arbitrary choice. Alternative choices may be the expected maximum stress range during operations or the stress ranges at 10^4 cycles to failures. However, it is the authors' opinion that any stresses leading to plastic deformations cause violation of the linear damage hypothesis and therefore the boundary on stress range of twice the yield stress should be regarded as an absolute upper bound. Note that in the Weibull closed form expression, there is no upper bound on the maximal stress range.

Table 4 provides the values of the biases on fatigue accumulation for multiple distributions. The results are presented for four measurement locations, which are all sensors at various locations on top of longitudinal bulkheads. The Pareto distribution appears to be superior in modelling the long-term distribution of the mid-range stress ranges. The bias for this distributions varies between 0.80 and 1.00. This means that the fatigue calculated using fitted distributions functions is 0 to 20% lower than the fatigue accumulation calculated using the spectral method, hence in all cases the fitting is not conservative. This is the result of an under-prediction of the tail of the distributions which hold few stress cycles, but which have a large amplitude and are therefore important in the fatigue accumulation, see also Fig. 8. The Pareto distribution is the most representative for modelling fatigue loads experienced by this unit. It should be noted that the performance of the Weibull distribution varies between different locations. The accuracy of the Lognormal and Weibull models are comparable. The Gumbel distribution performs worse than the other models and will be discarded from here on.

5.3.2. Fatigue model

There is no closed formula expression for the assessment of fatigue using the Pareto or Lognormal distributions to describe the long-term loads. Therefore, a numerical evaluation has been used. The fatigue from the measured load histogram can be assessed in the same way. The fatigue damage definitions for the Pareto, Lognormal and measured load distributions are given in Eqs. (4)–(6), respectively.

$$D_{\mathrm{LT}}^{\mathrm{Par}}(t) = \frac{\nu_0 t}{a} \sum_{i=1}^{k} p_{\mathrm{Pareto}}(\Delta\sigma_i|\xi,\kappa) \cdot \Delta\sigma_i^m \tag{4}$$

$$D_{\mathrm{LT}}^{\mathrm{LogN}}(t) = \frac{\nu_0 t}{a} \sum_{i=1}^{k} p_{\mathrm{LogN}}(\Delta\sigma_i|\mu_{\mathrm{LogN}},\sigma_{\mathrm{LogN}}) \cdot \Delta\sigma_i^m \tag{5}$$

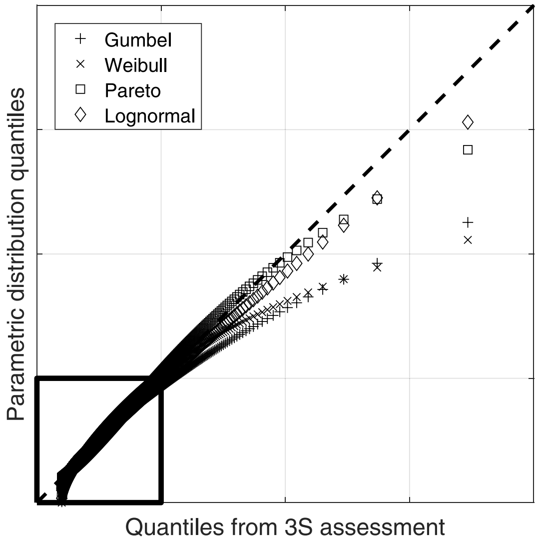

Fig. 8. QQ-plot of the empirical distribution against the different families of parametric distributions for location 2. The parametric distributions have been obtained using Maximum Likelihood Estimators. The part of the distribution in the square is shown in more detail in Fig. 9.

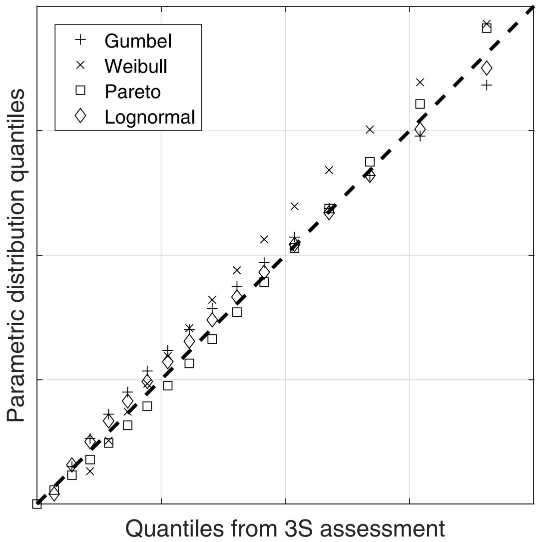

Fig. 9. QQ-plot of the left tail of the empirical distribution against the different families of parametric distributions for location 2 focussing on the left corner of the graph. The parametric distributions have been obtained using Maximum Likelihood Estimators.

Table 5
Full set of parameters used in the reliability analysis using different equivalent load models.

Loading model	Parameter	Unit	Distribution	Mean	Standard deviation
	$\log(a)$	$\log(\mathrm{MPa}^m)$	Normal	12.115	0.2
	m	–	Deterministic	3	–
	D_{al}	–	Lognormal	1.04	0.313
	ν_0	Hz	Deterministic	0.14	–
Pareto	κ	MPa	Lognormal	2.11	1.71
	ξ	–	Deterministic	0.0673	–
Lognormal	μ_{LN}	log(MPa)	Deterministic	0.988	–
	σ_{LN}	log(MPa)	Lognormal	0.600	0.082
SFA	ζ_{SFA}	–	Lognormal	1	0.34

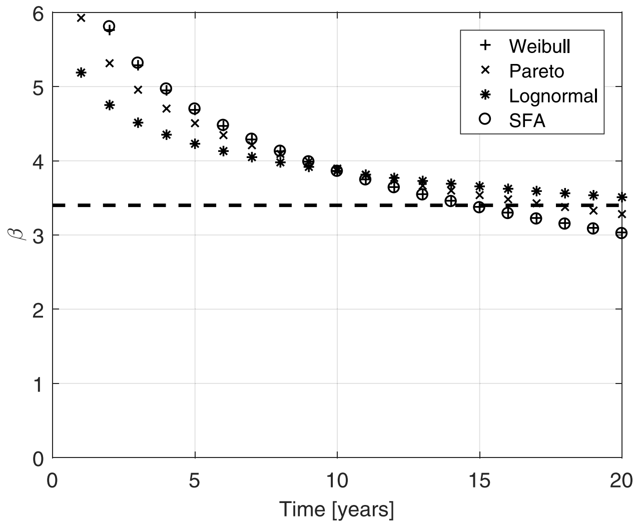

Fig. 10. Reliability index of monitored location using four different load models. Note that the uncertainties in the Pareto, Lognormal and summation models have been determined from fitting these functions to the Weibull model with design assumptions regarding uncertainty. The curves show a clear difference in time dependency.

$$D_{\mathrm{LT}}^{\mathrm{SFA}}(t) = \frac{\nu_0 t}{a} \sum_{i=1}^{k} p_{\mathrm{SFA}}(\Delta\sigma_i) \cdot \Delta\sigma_i^m \tag{6}$$

κ and ξ are the shape and scale parameter of the Pareto distribution respectively and the parameters μ_{LogN} and σ_{LogN} are the mean and standard deviation of the natural logarithm of $\Delta\sigma$. The limit state functions can be found by substituting these equations in Eq. (2).

Uncertainty in the fatigue loads is represented in the Weibull distribution using stochastic parameters for both B and λ. To obtain equivalent load models, uncertainty in the other models needs to be included. To do so, a single parameter in each of the load models will be considered as a stochastic variable. In the Pareto model, the scale parameter, κ, was selected, while in the Lognormal model, the parameter σ_{LogN} is considered stochastic. The SFA model does not feature a variable which can be considered stochastic. Hence, the SFA model was extended to include a global uncertainty parameter ζ_{SFA}, which was used to obtain the required stochastic model, see Eq. (7).

$$D_{\mathrm{LT}}^{\mathrm{SFA},\zeta_{\mathrm{SFA}}}(t) = \zeta_{\mathrm{SFA}} \frac{\nu_0 t}{a} \sum_{i=1}^{k} p_{\mathrm{SFA}}(\Delta\sigma_i) \Delta\sigma_i^m \tag{7}$$

The mean value of the stochastic parameters are set equal to their maximum likelihood estimates. The different load parameters are modelled using a Lognormal distribution. The uncertainty of these parameters is estimated using a numerical optimization by fitting the curve obtained using the other distributions to the reliability curve of the Weibull model in Fig. 4 over the entire lifetime of the unit.

The parameters appearing in Eqs. (4), (5) and (7), including their uncertainties, are given in Table 5. Probabilistic calculation using the different load models have been executed. Due to the fact that the stresses at the measurement locations are cold spots, these measured stresses have been scaled using a constant factor obtained from the design assessment, to reflect the stresses at the hotspot location. The resulting reliability of the fatigue detail are given in Fig. 10. It can be seen that the reliability curves feature different time dependence. The trend provided by the measured SFA model and the Weibull fit are very similar. The Pareto distributed loads and especially the Lognormal distributed loads show a slower decline of the reliability over time. In the final calculations, the Pareto and Weibull model have been included.

5.4. Calculation assumptions uncertainty

In this section, we will evaluate the statistical distribution reflecting the difference between measured stress and stress evaluated at design stage. This difference is considered as an uncertainty from the design calculation assumptions point of view. Let us introduce the parameter δ to quantify this uncertainty.

The spectral fatigue assessment is a simplified method to assess fatigue accumulation. The difference between the predicted stress at design stage and the measured stress with the HSM can be quantified by comparing the measured stress histogram and the stress distribution predicted using the spectral method from design. Note that this can only be done during operations for locations for which stress measurements are available. The stress histogram is obtained from the time series using rainflow counting. By

Table 6
Parameters used in the reliability calculation using uncertainties obtained through in-service measurements. The standard deviation of the loading variables v_0, B and λ varies in time according to the results shown in Fig. 6. Note that for some parameters, normal distributions have been selected although the parameters cannot physically be negative. Considering the relatively small standard deviation compared to the mean, the negative values is not of any practical importance.

Parameter	Unit	Distribution	Mean	Standard deviation
D_{al}	–	Lognormal	1.04	0.313
δ	–	Lognormal	0.50	0.16
v_0	Hz	Normal	0.14	Variable
B	MPa	Normal	8.43	Variable
λ^{-1}	–	Normal	1.18	Variable
$\log(a)$	$\log(\mathrm{MPa}^m)$	Normal	12.115	0.2
m	–	Deterministic	3	–

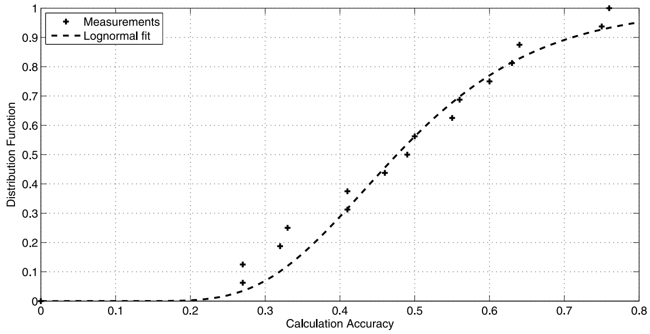

Fig. 11. Cumulative distribution function of $p_\delta(.)$ representing the accuracy of the spectral fatigue calculation method and based on the analysis of 16 measurement locations on two different FPSOs.

comparing the measured stress histogram against the results obtained from the spectral analysis for a number of locations, a global overview of the performance of the spectral assessment can be obtained.

For each measurement location using the HSM data, the parameter δ is calculated from the ratio between the fatigue damage obtained from the strain gauges and that of the spectral calculations. A total of 16 measurement locations are available for which the parameter δ can be calculated and hence, a distribution for this parameter can be derived. Only structural details which are mainly subjected to hull girder loads have been considered.

The cumulative distribution function of δ using the 16 measured numbers is displayed in Fig. 11. The parameter varies between 0.26 and 0.76, meaning that the design method is conservative, up to a factor of four on fatigue life. This is partially the result of conservatism in the design model. The design model uses plate thicknesses which are smaller than the actual as-built thickness. This will lower the measured stresses and hence result in a conservative method.

Several parametric distributions have been tested to model δ. The Lognormal model provided the best fit using the Maximum Likelihood value as a criterion. Moreover, δ, being the ratio of two positive numbers, is strictly positive. The Lognormal distribution ensures that the parameter has a lower bound at zero and thereby enforces this strict bound. The fitted Lognormal distribution is included in Fig. 11. Its mean and standard deviation are 0.50 and 0.16 respectively.

6. Reliability assessment of fatigue failure using HSM data

6.1. Combined uncertainty

Section 4.4 provided an overview of various sources of uncertainty which contribute to the overall uncertainty on stress fluctuations. The previous sections have shown how the individual sources of uncertainty have been assessed using the two years measurements from the HSM. In this section, the results of these individual analyses are integrated into a single assessment which can replace the original design assessment which was presented in Section 4.3. The probabilistic analysis follows the same approach as was used in Section 4.4.

The different sources of uncertainty will be included in the analysis as follows:

- **Model misspecification.** The Weibull distribution has historically often been used to model the long-term loads. It has been found that the Pareto distribution is also a suitable model for this purpose.
- **Statistical variability of loads** is defined as the uncertainty on the Weibull parameters B and λ, or alternatively on the Pareto parameters κ and ξ, and v_0 as was discussed in Section 5.2. The statistical variability of these parameters reduces with time.

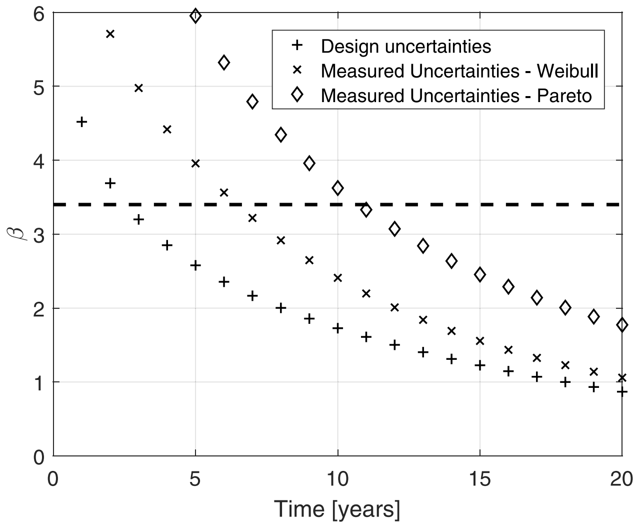

Fig. 12. Comparison of the RBI analysis using uncertainties used in design phase and uncertainties on the fatigue loads which have been obtained from in-service measurements. The uncertainties have been determined for both the Weibull distributed stresses as well as the Pareto distributed stresses.

- **Extrapolation uncertainty of loads** is included as uncertainty on the Weibull parameters B and λ according to Section 5.1 or in the same manner for the Pareto model.
- **Calculation assumptions** is defined as an overall uncertainty on fatigue given by δ as discussed in Section 5.4.
- **Condition of structure** is not incorporated explicitly, but is implicitly included in the bias of the calculation uncertainty.

In this section, only the influence of uncertainties in the fatigue calculation are addressed and compared against the design assessment. Therefore, the same mean load parameters as used in the design have been used here. The details of the measured uncertainties are given in Table 6. The limit state function incorporating all uncertainties using Weibull distributed stresses is given by:

$$G^{\mathrm{Wb}}(t) = D_{\mathrm{al}} - \frac{\delta \nu_0 t}{a} B^m \Gamma\left(1 + \frac{m}{\lambda}\right). \tag{8}$$

The equivalent limit state function using Pareto distributed stresses is:

$$G^{\mathrm{Par}}(t) = D_{\mathrm{al}} - \frac{\delta \nu_0 t}{a\kappa} \sum_{\Delta\sigma=0}^{2\sigma_Y} \Delta\sigma^m \left[1 + \frac{\xi \Delta\sigma}{\kappa}\right]^{-1-\frac{1}{\xi}} \tag{9}$$

6.2. Probabilistic fatigue in-service assessment

The probabilistic assessment incorporating the measured uncertainties is shown in Fig. 12. This figure shows a considerable higher reliability using the measured uncertainties, meaning that in the design procedure conservative assumptions have been made. With respect to inspection planning, the predefined threshold is reached after 7 or 11 years, depending on whether one is using the Weibull or Pareto distribution to model the long-term loads. This is considerably later than the initial planned inspection after 3 years. Note that this analysis can be repeated at regular intervals to further update the inspection schedule. The inspection time ensuring the required reliability can move backward due to lower loads and reduced uncertainties, or forward due to higher than predicted loads.

The importance factors of this calculation are shown in Figs. 13 and 14 for the calculations using the Weibull and Pareto models respectively. Recall that the initial importance factors in the design assessment, shown in Fig. 5, denoted that the uncertainty in the fatigue loads was dominant. However, having substituted these assumed uncertainties with values from the fatigue load monitoring efforts, the uncertainties on fatigue load have greatly reduced and instead, the uncertainties regarding fatigue resistance are now dominating the overall reliability in the first years of the extrapolation. Logically, when looking further into the future, the uncertainty on the loads becomes more important again. For the Weibull model, the joint uncertainties of all loading parameters, which are B, λ, ν_0 and δ, are responsible for 50% of the total uncertainty. For the Pareto model, this point is already reached after 4 years. It should be noted that any uncertainty on the load frequency has a negligible effect on the final reliability when using either of the load models.

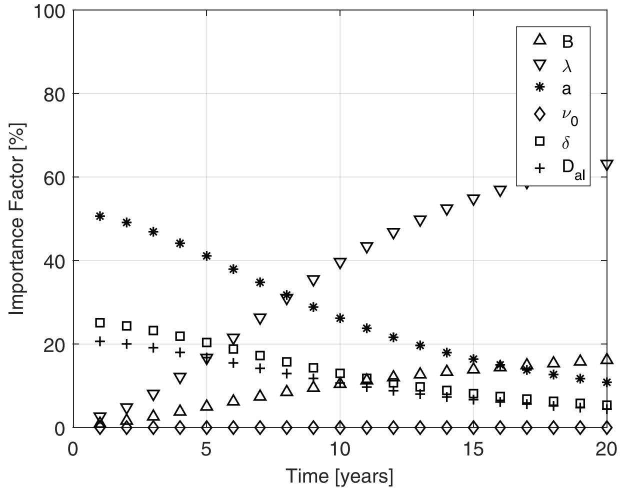

Fig. 13. Importance factors of different parameters in RBI analysis using measured uncertainties for fatigue loads using the Weibull load model. The importance of the uncertainties related to structural loads increases as the period for the calculation increases reflecting the larger uncertainty when making predictions further in the future.

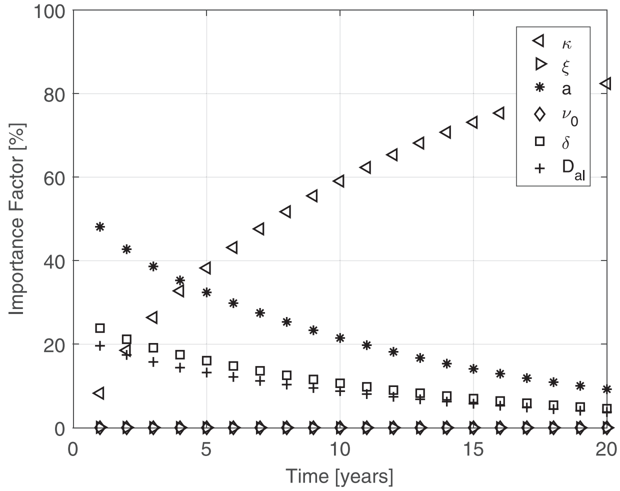

Fig. 14. Importance factors of different parameters in RBI analysis using measured uncertainties for fatigue loads using the Pareto load model. The importance of the uncertainties related to structural loads increases as the period for the calculation increases reflecting the larger uncertainty when making predictions further in the future.

7. Discussion and recommendations

When using HSM, epistemic uncertainties on the knowledge of the structural response can be reduced because of the better knowledge on loads acting on the structure. However, there remain uncertainties on the knowledge of localized effects, such as plate misalignment, thickness reduction due to wear/corrosion and welding defects for example. The uncertainties of these effect cannot be captured for all individual details using strain gauges. On top of that, aleatoric uncertainties can be quantified, but will also need to be incorporated. Therefore, some degree of uncertainty on the structural response needs to be included in the updated reliability analysis.

Using HSM allows to better capture the actual loads that applies to the structure and hence refine with better confidence the evaluation of fatigue of structural details. As a consequence, it can be used to target inspections on critical details given the data measurement. As such it can been seen as a pro-active means to get enhanced information and forecast on the condition of the structure. On the other side, surveys performed on-board allows to look for and find various types of defects, including those that are not predicted by computations by lack of knowledge. Both approaches are complementary and mutually supportive for better structural integrity management [62].

The future developments of digital twins offer good possibilities for further integration of structural management tools. A digital twin can be considered a container which allows for storage and retrieval of data related to the real structure. The power of a digital twin lies within the integrity tools that can be used in association with such a model. This can include FE calculations, uncertainty analysis as presented herein and inspection reports. An example of incorporating corrosion and inspection data explicitly in a reliability calculation is provided by [63]. As an example of a full digital twin development, the paper by Baht et al. [64] provides insight in the development for a unit such as the one considered in this research.

When doing load forecast for the purpose of fatigue evaluation, the uncertainties on the load knowledge are increasing with the time of the forecast. The use of information gathered from HSM data can be used to regularly update in time the load knowledge and consequently reduce the related uncertainties. By updating the load knowledge using the HSM updated data, new inspection times can be determined. Insight in the uncertainty of extrapolations for certain specific sites can be obtained using climate models [65], but has up to this date received limited attention in design methods.

Uncertainty regarding fatigue resistance is incorporated through the S–N curve used. The Palmgren–Miner hypothesis is assumed to be valid. Considerable uncertainties in the calculation of fatigue resistance still exist. Examples of research regarding fatigue resistance models under different loading configurations include [21] and [66]. As an alternative to the use of S–N curves, crack growth analysis can be used. The findings from this paper on fatigue loads are equally valid for such models since these are based on the same assumptions regarding the fatigue loads. The uncertainty related to the fatigue damage criterion is not addressed. A monitoring system using e.g. an acoustic emission method will be able to track initiation and propagation of cracks and can be used to address or most of the uncertainty related to the fatigue damage criterion.

During our investigations, we have noted that in the design assessment, uncertainties on the fatigue loads accounted for around 60% of the total uncertainty in the fatigue assessment. However, after determining the aforementioned uncertainties, the component reliability improved and uncertainties in fatigue resistance dominated the reliability for short-term predictions. For long-term predictions these uncertainties become more important. This stresses the importance of frequently revisiting the calculations, for example on an annual or bi-annual basis. In the framework of RBI evaluation, this ensures that the inspection plan for the evaluated fatigue details remain up-to-date and the target structural reliability can be maintained.

It is recommended to revise RBI procedures for structures which are equipped with a fully functioning HSM system. These systems provide essential information on the particular structure which can be used in the RBI assessment. Using HSM can significantly improve risk levels for the structure as well as reduce costs of in-service inspections. An interactive and partially automated RBI assessment for monitored structures is recommended to ensure the analyses are performed consistently and are up-to-date. This is acknowledged by classification societies, although no approach or method to do so is defined, see e.g. [3,4].

8. Conclusions

The FPSO considered in this study is a new-built unit which has been designed according to standard for operation in the West-Africa area. Several years of measurements on this unit are available. Uncertainties in the lifetime assessment of the unit have been quantified using in-service measurements. The results presented in this study are therefore considered indicative of modern design practices for similar units.

The Gumbel, Pareto and Lognormal distribution have been compared against the traditional Weibull model to describe long-term fatigue loads on a two year set of HSM data. All models underestimated the tail of the true stress distribution when compared to a Spectral Fatigue Assessment. The Gumbel model resulted in a significant underestimation of the fatigue accumulation. Full stochastic fatigue assessments using measured load uncertainties have been executed using the Pareto and Weibull models. The probabilistic calculation conducted during the early design stage incorporates several sources of uncertainty and should yield a conservative assessment. Based on the in-service measurements, it was found that the uncertainties used in the design stage are indeed conservative. Hence, when using uncertainties obtained from the HSM system, the structural reliability is higher than when using design values.

The unit under consideration is operating in a relatively mild environment. A structural detail subject to hull girder bending was examined and measurements at a nearby location were compared to structural calculations to quantify the uncertainties. The parameters and load models thus obtained can be considered representative of modern design approaches for this type of structure. In particular, it should be noted that the spectral fatigue calculation method introduced an safety factor of two, on average, over the monitored locations of this unit. It should be noted that the variation between the individual measurement locations was significant. However, in all cases, the spectral fatigue assessment provided a larger fatigue accumulation compared to the strain measurement, and hence, the spectral assessment effectively introduces an additional safety margin.

In the example reliability assessment carried out for a detail on an FPSO hull, the initial assessment using design methods yielded that a first inspection is to be executed after 3 years to maintain the defined safety level. The analysis was repeated using improved estimates on the loading uncertainties from the in-service measurements. In that case, the recommended period for the first inspection became 7 or 11 years, depending on the load model. A repetition of the analysis at regular intervals is recommended to further improve the inspection scheduling and maintain the target structural reliability.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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