Addressing failure rate uncertainties of marine energy converters ☆

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Abstract

The interest in marine renewable energy is strong, but has not led to significant commercial scale investment and deployment, yet. To attract investors and promote the development of a marine renewable industry a clear concept of project risk is paramount, in particular issues relating to device reliability are critical. In the public domain, reliability information is often scarce or inappropriate at this early stage of development, as little operational experience has been gained. Thus, reliability estimates are fraught with large uncertainties. This paper explores sources and magnitudes of failure rate uncertainty and demonstrates the effect on reliability estimates for a notional marine energy converter. If generic failure rate data forms the basis of a reliability assessment, reliability estimates are not robust and may significantly over- or underestimate system reliability. The Bayesian statistical framework provides a method to overcome this issue. Generic data can be updated with more specific information that could not be statistically incorporated otherwise. It is proposed that adopting such an approach at an early stage in an iterative process will lead to an improved rate of certainty.

Keywords: Reliability, Wave energy, Bayesian updating

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1. Introduction

The interest in marine renewable energy is driven by issues of energy security, climate change and economic development. Wave and tidal energy is recognised to have a large potential with a worldwide technically exploitable resources between 140-750 TWh/year for presently available devices, and up to 2,000 TWh/year in the case of a mature industry [1, p.544]. In the UK as much as 17% of the electricity demand (58 TWh/year out of 340 TWh/year) could be provided by wave energy [2] contributing to security of supply and offseting an estimated $430g\, CO_2/kWh$ [3]. Another main driver in the UK is the opportunity to initiate economic growth with the creation of domestic and export markets. Market size estimations indicate worldwide investment volumes of up to £500 bn [4, p. 174] and annual electricity revenues in the range of £60 bn - £190 bn [3, p. 7].

At present, this potential is not tapped as marine energy only provides a diminutive share of 0.01% (0.54TWh) of renewable electricity worldwide in 2008 [5, p. 9]. Mueller and Wallace [6, p.4378] have reviewed the main obstacles that need to be overcome to establish marine renewable energy generation, key of which are:

- Creation of cost effective and reliable marine energy converters (MECs)
- Permit issues of commercial wave parks
- Grid integration

While the latter two items deal with aspects of regulation and integration into the existing electricity infrastructure, this paper focuses on the reliability of marine energy converters, which will have a severe economic impact on projects due to potential failures and resulting unavailability [3, p.25].

From an engineering point of view, marine energy is one of the least developed renewable energy technologies and is regarded as unproven [7]. The technological development phase has to be directly followed with reliability demonstration and cost reduction to successfully compete with with other means of conventional and renewable electricity generation [8, p.96].

Additionally, marine renewables are subject to significant uncertainties that hinder commercial development and are a barrier to the necessary investments. Mackay et al. [9] identify three main sources of uncertainty that influence the estimates of achievable annual electricity production:

- Uncertainty regarding energy resource conditions at the project site
- Conversion uncertainty, i.e. variations and unknowns along the conversion chain 'wave to wire'
- Uncertainty about the device availability

While the uncertainty of wave resource conditions can be estimated, the availability of devices is regarded as " (...) perhaps the most difficult to quantify" [9]. The main reasons are that i) it is difficult to predict failures for a new technology and ii) operational experience is scarce.

In particular, even the application of proven components and equipment in a harsh dynamic marine environment under significantly altered load conditions, implies large uncertainties regarding failure mechanisms and frequency. These uncertainties may lead to either costly design safety factors or field failures both of which would impede project viability.

A dilemma that is often faced when predicting the reliability of a new technology is that the sole use of specific- or generic data does not lead to appropriate reliability estimates. Shafaghi [10, p.87] emphasises that "(...) plant specific data is statistically invalid due to a short duration of data collection or limited population of equipment. Generic data, on the other hand, does not reflect the characteristics and conditions of the plant that the equipment is operated under." The Bayesian statistical framework provides a method to overcome this issue as the generic data can be updated with available plant specific information to give an improved reliability estimate. This is achieved through the utilisation of available additional information and data that could not be statistically incorporated otherwise.

The benefit of the Bayesian methodology is demonstrated by a number of different reliability applications.

- Updating of past field failure rates with specific Accelerated Life Tests (ALT) for new electronic products [11].
- Validation and updating of numerical fatigue life simulations with sparse full-scale tests for train wheel axles [12].

- Refinement of generic failure rate information through expert knowledge [10].
- Updating of past failure rate data with engineering knowledge and reliability demonstration test results for mechanical automotive components [13, 14].
- Updating of generic failure rate estimates with operational process plant data [15].

These examples illustrate the capacity of the Bayesian approach to incorporate a range of different data and information sources. In the examples above the uncertainty of reliability estimates was reduced with Bayesian techniques, i.e. a decrease of the predicted failure rates' standard deviations and confidence intervals was achieved.

When comparing these examples from other industries to the application for marine renewable components, a major difference is the quality of the prior information. The automotive industry for example can rely on decades of experience, development and mass production with established failure rate records. Guida [13] considers past data of 250,000 cars and applies the Bayesian approach to calibrate past data for a similar, redesigned component. Such a detailed and applicable pool of data is not available for the marine renewable case as operational experience is based on single prototypes.

Consequently, a Bayesian approach for marine renewable components cannot accurately determine reliability estimates, but strives to reduce the main uncertainties and indicate the correct order of magnitude of failure rates if generic and specific failure rate data are being combined. Furthermore, through incorporating best 'engineering knowledge' it will provide greater confidence in failure rate estimates for the purpose of reliability assessment.

The objective of this paper is to explore the sources and extent of component failure rate uncertainties for marine energy converters and to demonstrate the effect this has on overall system reliability estimates.

The paper is organised in four main parts. Section 2 takes a stakeholder perspective to highlight the need of addressing failure rate uncertainties. In section 3 and 4, the source and extent of failure rate uncertainties is described and the effect on system reliability is demonstrated for a generic marine energy converter. In section 5, a Bayesian updating procedure is being proposed to reduce the uncertainty of failure rate estimates. The method and its utility is illustrated with a case study on umbilical failure rate updates. The paper concludes with the main outcomes.

2. Stakeholder perspective and actuarial perception

Reliability information is required by a range of stakeholders in the marine renewable energy sector [16]:

- *Project developers*, i.e. companies developing commercial multi-device schemes that need *quantified* empirical evidence regarding device performance and survivability and associated technical risks to assess and ensure the project viability.

- *Manufacturing and service companies*, comprising materials- and component suppliers, contractors for installation, operation and maintenance, are expected to meet the required performance parameters.

- *Investors* require clear technology assessment based on performance criteria.

- *Insurance companies* require evidence of survivability, reliability and safety at all project stages (design, production, installation and operation) and suitable risk control.

The common theme of these stakeholder views is that commercial development is driven by traditional plant-performance indicators (reliability, availability and maintainability) as it is these that impact heavily on project cost and revenue. While prototype development is mainly focused on the demonstration of working principles, conversion efficiency and the survivability of devices, addressing these commercial drivers is imperative for the successful transition to commercial deployment.

In particular, the actuarial perception of marine renewables is reserved due to the associated risks and uncertainties. An extensive study on financial risk management instruments for renewable energy projects [17] carried out a risk assessment for the different technologies covering resource -, technical - and operational risk. For each type the probability of the risk affecting a project and the impact of the risk are evaluated. In the case of marine renewable technology it was found that there is "(...) insufficient operating experience, and schemes need to demonstrate long-term performance and reliability" [17, p.10].

The results of an associated survey [18] provide a more detailed appraisal of the main underwriting concerns and specific risks. The responding insurance companies pointed to i) the risk of new, prototypical and scale-up technologies; ii) inherent technical perils associated with offshore installation, operation and maintenance of projects; and iii) the risk of faulty design, material and workmanship.

More than 50% of respondents did not see future business potential in wave and tidal energy, reflecting the concerns over an inmature technology which is located offshore.

The insurance industry will typically only insure those project risks that can be classified and priced, i.e. have the following attributes:

- Quantifiable losses
- Reliable estimates concerning claim frequency and severity
- Small potential for catastrophic loss
- Feasible premium levels
- Large pool of potential insured projects to distribute risk

The prevalent risks of marine energy devices coupled with the lack of appropriate reliability information and associated uncertainties [19, 20] make it challenging to estimate the failure frequency and consequence and deter insurers and investors alike. The sources, potential magnitude and effect of failure rate uncertainties are described and demonstrated in the following.

3. Failure rate characteristics

3.1. Uncertainty of failure rates

The term *uncertainty* can be pragmatically defined as a situation where the available quantitative and qualitative information does not suffice to predict the behaviour and characteristics of a system at a particular required level [21].

The type of uncertainty can be classified as either aleatory or epistemic uncertainty [22]. *Aleatory uncertainty* describes random, irreducible or stochastic uncertainty that characterises the inherent variation of physical systems or the environment under consideration. *Epistemic* uncertainty refers to reducible, subjective, state of knowledge or model uncertainty describing a lack of knowledge, data or information. The categorisation in either of the above groups defines if the uncertainty can be decreased through additional tests or knowledge (epistemic) or if it is irreducible (aleatory).

Whenever the reliability of a system is predicted, it is essential to identify and account for the uncertainty inherit to these predictions. This is particularly the case if new components, new materials and different operating environments increase the prediction uncertainty [23, p. 1356].

The main source of failure rate uncertainty for MECs is the lack of knowledge with regard to inadequate or missing experimental and operational data. This manifests itself in the use of generic, rather than device/operation specific reliability failure rate data, which can often not be directly applied. Furthermore the detailed specification of components and sub-systems is generally not publicly available [20].

Two aspects of epistemic failure rate uncertainty are explored in the following:

- The variation of the mean failure rate.
- The uncertainty about the failure probability distribution and parameters, which describes the variation of failure rate with time and depends on the knowledge of failure types and mechanisms.

3.2. Mean failure rate variation

There are few studies that compare predicted failure rates against actual field failure rates to give an indication of prediction uncertainties. Cox and Tait [24, p. 193ff.] report two cases where detailed surveys have been conducted.

In the first study operational failure rates for a ten year period in a processing plant are compared with previously predicted mean failure rates. The ratio r_F of actual rate to predicted rate is reported to stay largely within $0 < r_F < 4$. The most extreme case of divergence exhibited a factor of $r_F > 1000$. Such large deviations were reasoned to be due to unexpected failure modes that were not considered during the analysis. Other discrepancies were mainly caused by maintenance shortfalls (e.g. erroneous replacement, calibration and undetected degradation) and imprecise failure definition for deteriorating components.

The second comparative study [24] considered failure records for mechanical, electrical and electronic equipment. About 2/3 of the investigated cases did not exceed a factor $r_F = 2$ and almost all cases (93%) did not exceed $r_F = 4$.

An incomplete analysis where potential failure modes are overlooked can have serious impact, as this source of uncertainty is not considered in probabilistic risk assessments [25]. This risk can only be reduced through quality control of the analysis together with dedicated research and testing programs.

In most engineering disciplines (in)accuracies of a factor of 10 are not acceptable. However, it may be deemed as a reasonable accuracy in the realm of probabilistic reliability assessments. As an example, a failure rate data bank, set up by the International Energy Agency [26], compares equipment and instrumentation failure rates between different fusion test reactors. It classifies values that agree within a factor of 3 as "good", within a factor of 10 as "fair" and values that differ by more than an a factor of 10 as "poor" comparison. Similarly, Zio [27, p.314] applies variations up to a factor of 10 in a failure rate uncertainty analysis.

Two implications may be drawn from the above cases:

1. One of the main objectives during the development phase should be to reveal all likely, and possibly unknown failure modes. This is particularly the case for components that are established in other industries/environments but may be subject to new failure modes if deployed in a MEC.
2. When the critical failure modes are established and quantified, the two described studies show failure rate variability factors of up to four, while failure rate data that agrees within a factor of 10 might be considered as sufficient for probabilistic calculations.

3.3. Failure rate distribution

To quantify and to model failure rates a variety of statistical probability distributions is available. The exponential distribution is commonly applied and implies that the failure rate is constant with time whereas the log normal- and Weibull distribution allow the description of time dependant failure rates, i.e. early failures and ageing effects (a more detailed list of distributions can be found in [28, 29]).

The two-parameter Weibull distribution is a flexible distribution that allows to model different types of failure rate behaviour (Equation 1).

1. Early failures with decreasing failure rate over time ($\alpha < 1$)
2. Random failures during the useful life of the system, showing constant failure rates ($\alpha = 1$)
3. Wear-out failures or ageing failures exhibiting increasing failure rates over time ($\alpha > 1$)

An ubiquitous reliability concept is the bathtub curve [30, 31] that is qualitatively shown in Figure 1. It describes the failure rate over time and considers all three types of failure rate behaviour.

$$R(t) = e^{-(\lambda t)^{\alpha}} \tag{1}$$

Where λ is the scale parameter and α is the shape parameter of the distribution.

The reciprocal value of the scale parameter $\frac{1}{\lambda}$ is also called the characteristic life. In the case where $\alpha = 1$ this corresponds to the commonly used mean time to failure (MTTF).

The initial assumption in most reliability assessments is a constant failure rate, modelled by an exponential distribution, which only covers the 'bottom-part' of the bathtub curve (see Figure 1). A constant failure rate implies that the failure mechanism is time-independent. This is arguably not the case for failure mechanisms like fatigue, wear and corrosion. Wolfram [19, p.62] advocates the use of log normal probability distributions for component reliability.

4. Modelling failure rate uncertainty for MECs

One method to account for the inherit variability of component failure rates is to model the uncertainty by failure rate probability distribution functions. Compared to simple point estimates, the degree of uncertainty is reflected in the system reliability calculations [32].

The model that is proposed here aims to use a conventional Reliability Block Diagram and to explicitly consider the uncertainties of the input values

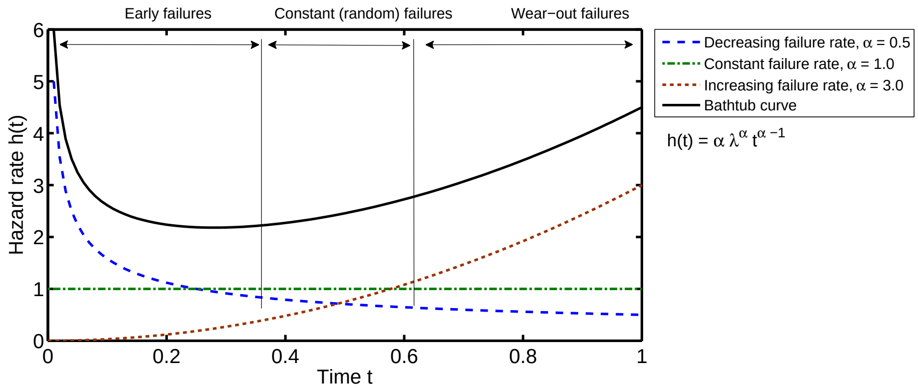

Figure 1: Bathtub curve failure rate behaviour, modelled with Weibull distribution $\lambda = 1$

(i.e. failure rates) with regard to i) mean failure rate variation and ii) failure rate behaviour.

4.1. Model structure

A generic MEC is modelled as series of four sub-systems (Figure 2) and is assumed to be non-repairable for the period of one year, which is commonly regarded as a sensible maintenance interval [19]. Further assuming that the series structure consists of independent components, the system reliability $R_S(t)$ can be calculated as the product of the component reliability functions $R_i(t)$ for the number of components/sub-systems in series $i = 1 \dots n$ [28, p.153]:

$$R_S(t) = \prod_{i=1}^{n} R_i(t) \tag{2}$$

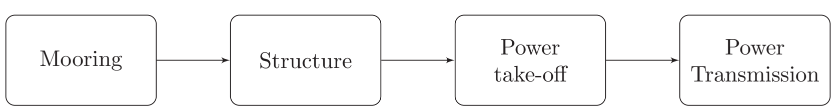

Figure 2: Block diagram of generic floating marine energy converter

The sub-system reliabilities are assumed to follow a two-parameter Weibull distribution (Equation 1). The mean failure rates λ_{Mean} have been estimated for generic sub-systems of a notional hydraulic wave energy converter in [20].

In order to estimate the effect that a lack of knowledge regarding the exact mean failure rates has, the analysis was also undertaken for higher and lower bounds of the mean failure rate; based on the indicative ranges given in [24]. A lower bound is defined as $\lambda_{Lower} = \lambda_{Mean} \cdot 0.5$ and an upper bound is calculated as $\lambda_{Upper} = \lambda_{Mean} \cdot 2$.

The effect of different failure rate *behaviours* is modelled with the Weibull shape parameters α. The values are based on experience with wind turbine failures [33] where early failures are modelled by $\alpha_1 = 0.5$; the useful life (constant failure rate) is modelled with $\alpha_2 = 1$ and wear-out failures use $\alpha_3 = 3$. The failure rate parameters are summarised in Table 1.

Table 1: Failure rate parameters

Mean Failure rate [20]

Sub-system	Mooring	Structure	Power take-off	Transmission
$\lambda_{Mean}\,[1/year]$	0.56	1.19	2.42	0.47

Failure behaviour [33]

Type	Early	Constant	Wear-out
$\alpha\,[-]$	0.5	1.0	3.0

A basic reliability system has been modelled to demonstrate the effect of the stated uncertainties on system reliability for three cases:

- Case 1 - *To determine the effect of uncertainty in the mean failure rate.* A low, medium and high mean failure rate are applied to each system while the failure rate distribution is assumed to be constant with time, i.e. $\alpha = 1$.

- Case 2 - *To determine the effect of uncertainty in the failure rate model.* In this case the system reliability for each sub-system is computed for different shape parameters α , corresponding to the "early", "constant" and "wear-out" regions, while the failure rate is assumed as the medium mean failure rate.

- Case 3 - *To determine the effect of uncertainty in both the mean failure rate λ and the failure rate model.* The sub-system reliability is computed with varying values for shape parameter α and mean failure rate λ.

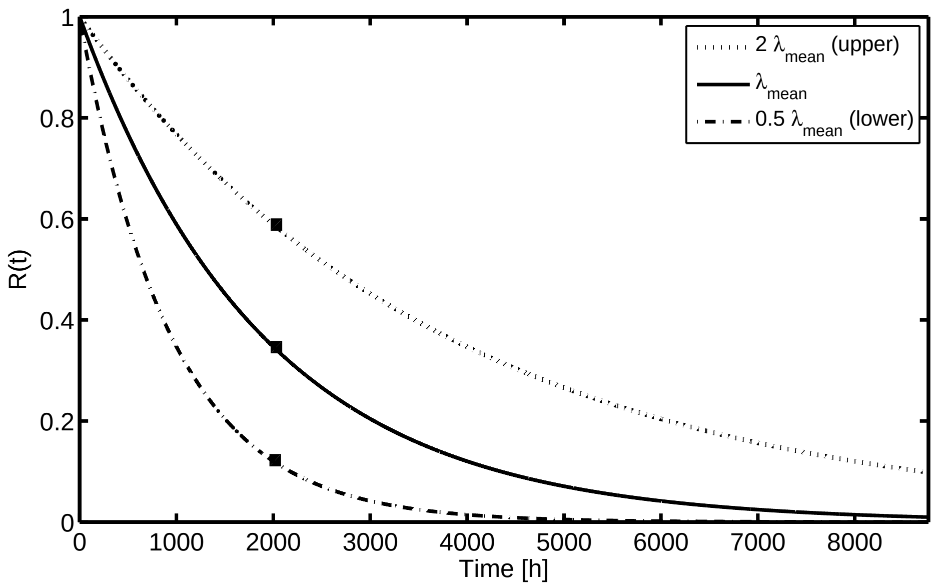

Figure 3: Case 1 - System reliability of in-series subsystems for different mean failure rates (λ)

4.2. Model results

The system reliabilities for the variation of the mean failure rate (case 1) are shown in Figure 3. The reliability (survivor) function R(t) describes the probability that the system does not fail in the given time interval (here 1 year=8,760 hours). The uncertainty that is introduced through the application of three different mean failure rates leads to a considerable range of possible system reliability. To illustrate this we define $\Delta R(t) = \lambda_{upper}(t) - \lambda_{lower}(t)$.

For example at $Time = 2,000h$ a spread of $\Delta R(2,000h) = 0.5$ is present. The spread decreases with time to $\Delta R(4,000h) = 0.35$ and to $\Delta R(6,000h) = 0.2$.

The system reliability for different failure rate behaviours (case 2) is shown in Figure 4 and exhibits a larger divergence at the beginning with $\Delta R(2,000h) = 0.7$ and decreases soon with $\Delta R(4,000h) = 0.15$. In both cases the system reliability probabilities R(t) show a considerable extent of uncertainty for the separate variation of mean failure rate and behaviour.

The different mean failure rates and behaviours have been further combined to an optimistic and pessimistic scenario (case 3). The optimistic

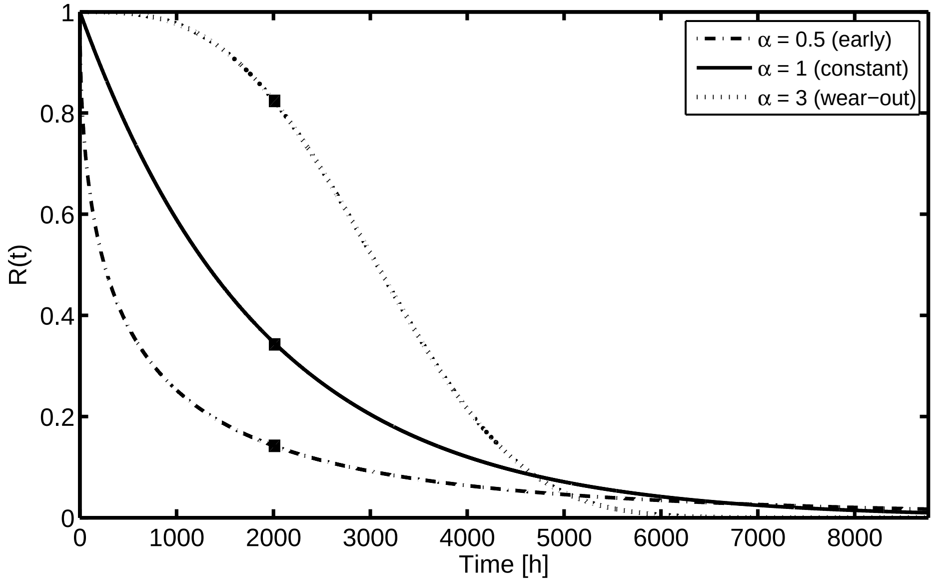

Figure 4: Case 2 - System reliability of in-series subsystems for different failure rate behaviour parameters (α)

setting assumes the lower bound of the mean failure rate in conjunction with wear-out failures. The pessimistic setting assumes the higher mean failure rate and early failure behaviour as input. The resulting system reliabilities are shown in Figure 5. Considering the variation across the full time range, it is not easy to make a statement about the realistic reliability of the system. As a consequence of these variations, a simple constant failure rate assumption may significantly over- or underestimate the system reliability. Therefore, a reliability assessment that is based on generic data with a constant failure rate assumption clearly is not robust, as it does not include considerations of existing variations in the mean failure rate and behaviour.

5. Reduction of failure rate uncertainty

The Bayesian updating methodology is a promising approach to reduce the uncertainty of failure rates. In this section the mathematical theorem is briefly described and the updating procedure is subsequently demonstrated for the failure rate of a dynamic marine power cable.

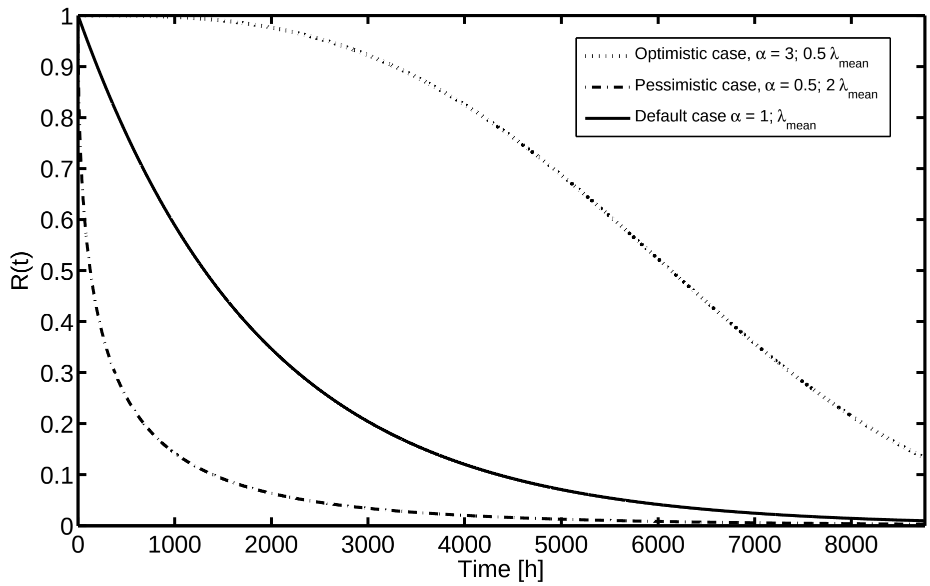

Figure 5: Case 3 - System reliability of in-series subsystems for optimistic, constant mean failure rate and pessimistic case

5.1. Bayes' theorem

The statistical Bayesian model consists of two parts [34, p.15]:

1. The ***prior*** probability distribution expresses the knowledge of the parameters of interest before any additional data has been obtained/analysed.
2. The ***likelihood*** probability function describes the data that has been obtained from a test/experiment.

Both elements, prior distribution and likelihood function are then combined to compute the ***posterior* probability** distribution. This resulting distribution describes the uncertainty (degree of belief) of the parameter after the additional information has been considered.

Bayes' theorem relates the probability that the event or hypothesis (H_k) is true given the data/events (D) to the probability of the data, if the hypothesis was true ($Pr(D \mid H_k)$). Mathematically this is generally stated as:

$$\Pr(H_k|D) = \frac{\Pr(D \mid H_k)\Pr(H_k)}{\sum_{i=1}^{\infty}\Pr(D \mid H_i)\Pr(H_i)} \tag{3}$$

With $H_1, H_2, ..., H_n$ as mutually exclusive and exhaustive events, stemming from a sample space S with $Pr\left(\cup_{i=1}^{\infty} H_i\right) = 1(exhaustive)$; $H_i \cap H_j = \varnothing(independent)$ for i $\neq$ j; $\Pr(H_i) > 0$ for each i; and D as an event in S with $\Pr(D) > 0$.

Or if the theorem is expressed in the form of probability density functions with regard to the failure rate λ it can be rewritten as:

$$g(\lambda \,|\, x) = \frac{f(x \,|\, \lambda)\; g(\lambda)}{\int_0^\infty f(x \,|\, \lambda)\; g(\lambda)\mathrm{d}\lambda} \tag{4}$$

Where $g(\lambda \,|\, x)$ is the posterior distribution for λ given the recorded data x, $g(\lambda)$ is the prior distribution of the failure rate λ and $f(x \,|\, \lambda)$ is the likelihood function for the observed data x given the unknown failure rate λ.

5.2. Failure rate refinement for marine power cable under dynamic loading

The application of the Bayesian updating methodology to reduce failure rate uncertainty is in this paper demonstrated for a dynamic marine power cable, also termed as umbilical. The process comprises three consecutive steps:

- Establishing the prior distribution
- Deriving the likelihood distribution
- Computing the posterior distribution

5.2.1. Establishing the Prior Distribution

As prior information a failure rate estimate for an umbilical given in the OREDA handbook [35, p.811] is used. There are considerable differences between the cases reported in OREDA and the marine energy application. Oil and gas production umbilicals often comprise not only electrical but also multiple hydraulic supplies. Also the power cables used for floating marine energy applications will be exposed to more energetic sea conditions and possibly higher dynamic load mechanisms. Despite these differences, the OREDA data can be considered to be a 'good starting point' as prior reliability information. The handbook summarises the data from 9 umbilical units with 2 reported failures, external leakage and transmission failure.

The handbook generally assumes an exponential failure rate distribution with time. The probability density function $f(t)$ is thus defined as:

$$f(t|\lambda) = \lambda e^{-\lambda t} \text{ with } t > 0 \tag{5}$$

where λ is the component failure rate, where the possibility of choosing a different λ from the distribution in Equation 6 is acknowledged.

The mean failure rate is given as $\lambda = 4.2669/10^6 h$ with a standard deviation $\sigma = 4.8281/10^6 h$. The number of hours denote the time aggregated in service. This corresponds to a $MTTF = \frac{1}{\lambda} = 26.7$ years with $\sigma = 23.6$ years.

The handbook further suggests to model the sampling variability of the recorded failures as a Gamma distribution with the parameters k and Θ, $\Gamma(k, \Theta)$ (see Equation 6). The properties of the Γpdf are: Mean $\mu = \frac{k}{\Theta}$ and variance $\sigma^2 = \frac{k}{\Theta^2}$. Hence the distribution parameters can be calculated as: $\Theta = \frac{\mu}{\sigma^2}$ and $k = \mu\theta$.

Computing the Γ parameters accordingly for the dynamic umbilical with $\sigma^2 = 23.31$ and $\mu = 4.27$ yields: $k = 0.78$ and $\Theta = 5.46$.

$$\pi(\lambda|k, \Theta) = \frac{\Theta^k}{\Gamma(k)} \lambda^{k-1} e^{-\Theta\lambda} \tag{6}$$

Where $\Theta = \frac{\mu}{\sigma^2}$ and $k = \mu\theta$; with $\Gamma(k) = \int_0^\infty t^{k-1} e^{-t} dt$ for $\Theta > 0$.

In the following the Γ distribution $\pi(\lambda|k,\, \Theta)$ with the parameters computed for the given umbilical failure rate information will be used as prior information (see Figure 6).

5.2.2. Likelihood Distribution

As a second step the likelihood distribution must be established. Failure rate data obtained during field trials, prototype or component testing of the actual component could be used as an information basis. In this example the likelihood distributions are chosen as illustration fro two important failure scenarios. The aim is to examine how new information may be modelled through likelihood functions and how this will result in an updated posterior distribution. The likelihood distribution for both cases is modelled with a two-parameter Weibull distribution (see Equation 7 and Figure 7). The mean μ and variance σ^2 of the failure rate are computed using Equations 8 and 9.

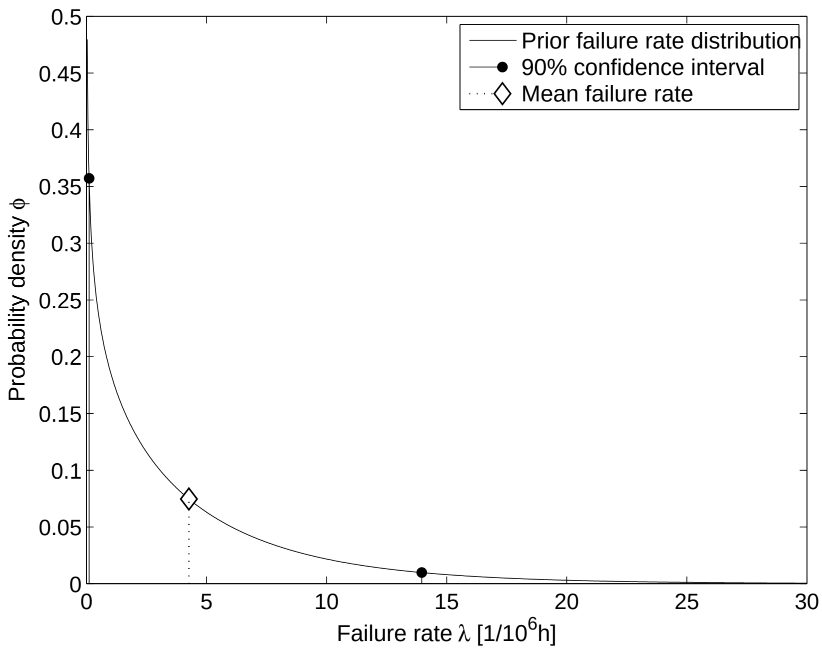

Figure 6: Prior distribution of umbilical failure rate, 90% confidence interval ranges from 0.2-14 failures $/10^6h$; see also Equation 6

1. *Modelling the effect of fatigue type failures.* Physical component tests may provide an indicative component failure rate. Accelerated fatigue tests subject the component to a certain number of load cycles that can be related to a distinct operational time. Through repeated tests a mean failure rate may be established. To illustrate how such information may be incorporated with existing knowledge a mean failure rate $\mu_{fatigue} = 10/10^6 h$ with $\sigma^2_{fatigue} = 26/10^6 h$ shall be assumed. The likelihood function can thus be modelled as a Weibull pdf with $a = 11$ and $b = 2$. These values are chosen so that $\mu_{fatigue}$ coincides with the upper confidence limit of the prior distribution and $\sigma^2_{fatigue} < \sigma^2_{prior}$. Thus the assumed MTTF for the likelihood distribution is about 11 years and one has a somewhat stronger confidence in the test results as opposed to the prior information.
2. *Modelling the effect of unknown failure modes.* The application of components in new environments bears the risk that additional failure modes (FM) arise which have not been considered in the design phase. Such an unknown, overlooked failure mode may typically lead to a failure rate increase by an order of magnitude. Such information may become available from initial field installations, but may also be modelled as 'engineering knowledge' to explore the effect of a potentially unknown failure mode. For the case illustrated here, it is assumed that the upper confidence limit of the prior distribution is exceeded by an order of magnitude, and fraught with a large degree of uncertainty. Thus, the likelihood function is modelled as Weibull pdf with the parameters $a = 105$ and $b = 5$. This yields $\mu_{FM} = 96/10^6 h$ and $\sigma^2_{FM} = 487/10^6 h$.

$$f(\lambda|a, b) = ba^{-b}\lambda^{b-1}e^{-\left(\frac{\lambda}{a}\right)^b} \tag{7}$$

$$\mu(f) = a\left(\Gamma(1 + \frac{1}{b})\right) \tag{8}$$

$$\sigma^2(f) = a^2\left(\Gamma(1 + \frac{2}{b}) - \Gamma(1 + \frac{1}{b})^2\right) \tag{9}$$

Beyond this application of 'engineering knowledge' one must resort to component testing, where the distribution of failure rates is likely to be derived from a limited number of test points. To illustrate this the assumed

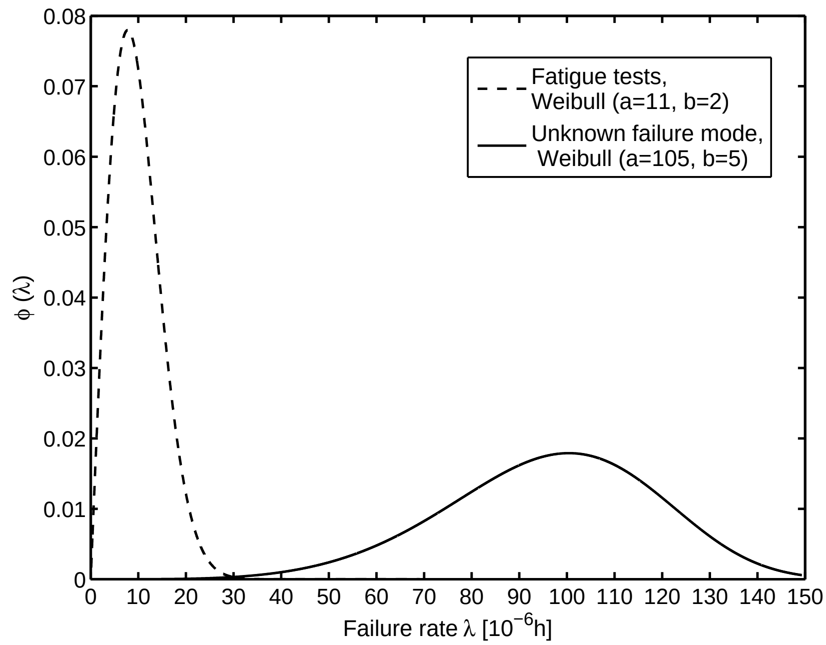

Figure 7: Likelihood distribution for two illustrative cases. Mean failure rates λ and associated variance σ^2 are given in Table 2.

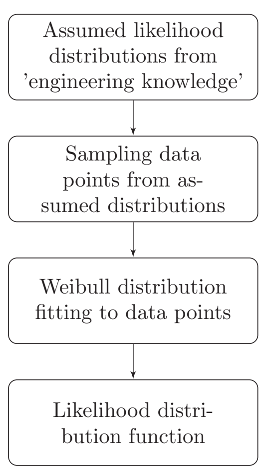

Figure 8: Block diagram of modelling procedure to establish the likelihood distribution function

Table 2: Weibull distribution parameters modelling the assumed failure rate likelihood distribution

Description	Weibull pdf		Measures $[\frac{1}{10^6 hours}]$	
Case 1: Fatigue tests	$a = 11$	$b = 2$	$\mu = 10$	$\sigma^2 = 26$
Case 2: Unknown failure mode	$a = 105$	$b = 5$	$\mu = 96$	$\sigma^2 = 487$

likelihood distributions were used to generate 5 sample points for each case from which the likelihood distribution is subsequently evaluated. The modelling procedure is illustrated in Figure 8. The two main steps comprise:

1. Drawing a random sample from the distribution specified for the two cases (defined in Table 2) to reflect the fact that any additional information will have a limited number of data from which the likelihood distribution can be estimated. For the cases considered here, a sample size of $n = 5$ was chosen, the question what sample size is required to satisfy a given reliability target is discussed in detail in [29, chap. 10].
2. The likelihood distribution is established by fitting a two-parameter Weibull distribution to the simulated data. This is somewhat trivial for the case study, as the data was generated from a Weibull distribution. However, fitting a distribution to measured test results is a crucial step in the application of real experimental data. In this case there is no physical reason to choose the Weibull distribution but it is employed because it provides a reasonable fit to a range of observed data and is thus widely used for reliability applications. Figure 9 shows an example of the sampled failure rates and the fitted Weibull distribution; as expected the fit indicates good agreement. To establish an adequate statistical fit to the data is likely to be not as straight forward for an actual data set, but usually the Weibull distribution proves to be flexible enough.

5.2.3. Posterior Distribution

Once the prior and likelihood distribution are established, the posterior distribution can be computed via Bayes' theorem (Equation 3 and 4).

Figure 10 shows the updating process and posterior distribution result for case 1 and 2. Each plot shows the prior distribution (dashed line), the fitted likelihood distribution (dotted line) and the updated posterior distribution (solid line, with 90% confidence interval). The plot shows how the initial

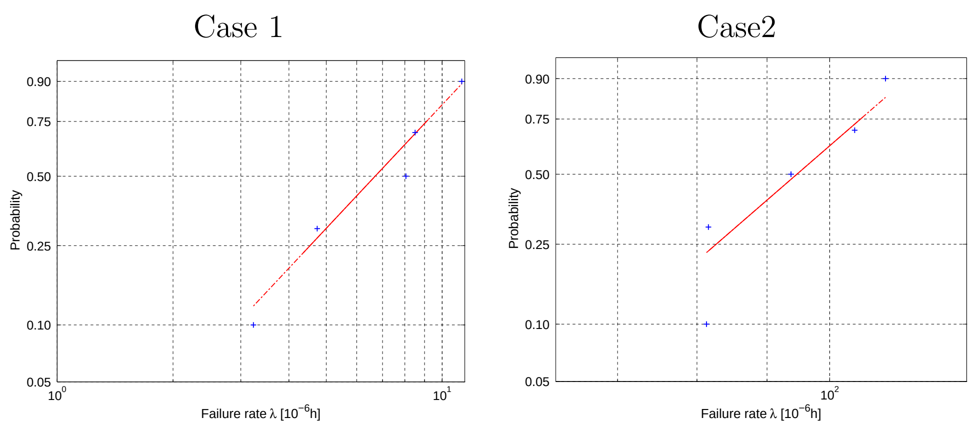

Figure 9: Weibull Probability plot, showing the sampled data points and the fitted distribution

prior distribution is updated with the likelihood function, which yields the posterior probability distribution.

For case 1 the posterior distribution yields a 90% confidence interval $CI_{posterior,1} = [1, 11]$. This is a reduction compared to the confidence interval of the prior distribution $CI_{prior} = [0.2, 14]$. The initial Γ distribution is amended to a distribution with similar shape to a Weibull distribution. This illustrates, how the failure rate uncertainty may be reduced when applicable data with a limited variance, i.e. a reasonably strong belief in the data, is available to update generic failure rate information.

For case 2 the posterior distribution does not clearly resemble either distribution. The reason for this is the relatively large variance σ^2 for both the prior and the likelihood distribution. Due to the significantly larger mean failure rate modelled for the unknown failure mode likelihood distribution, the posterior distribution is shifted to the right of the prior, yielding a 90% confidence interval $CI_{posterior,2} = [9, 46]$. Thus, in the light of the additional information the failure rate uncertainty would increase.

Both examples indicate the updating procedure when an initial distribution with large uncertainties is updated with additional information. Depending on the 'belief' in the additional information, which is expressed by the variance σ^2 of the likelihood distribution the uncertainty in the failure rate distribution is decreased when $\sigma^2_{prior} > \sigma^2_{likelihood}$ and increased if $\sigma^2_{prior} < \sigma^2_{likelihood}$.

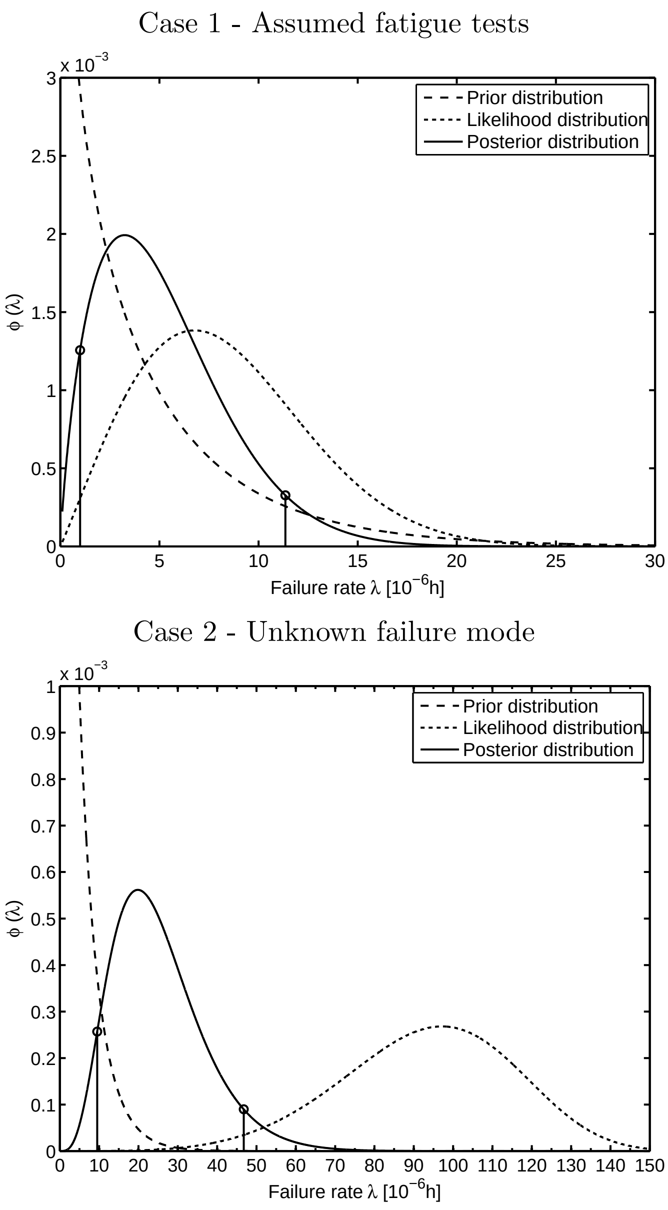

Figure 10: Prior, likelihood and posterior distribution for umbilical failure rate update. 90% confidence interval indicated for posterior distribution.

5.3. *Specific reliability information for marine renewables*

The uncertainty of failure rates will be reduced if generic data is updated by specific failure rate information obtained in a marine environment. This could either be the simulation of field conditions in purpose-built test rigs or the deployment of devices in the field.

An initiative to test the reliability of MEC components on a dedicated test rig is described in [36]. It proposes the application of service simulation testing where field loads are replicated in accelerated reliability tests. Such testing will provide specific reliability information that can be used to reduce the uncertainty of generic failure rates. Additionally, such testing would potentially reveal unexpected failure modes and design weaknesses ahead of field deployments.

By its very nature, dealing as it does with an investigation of the problems associated with sparse data and operational experience, the paper should be seen as illustrative, although the results from this study have inspired and guided the development of specific component testing equipment and methods. Specific component test facilities for dynamic marine applications are implemented at the University of Exeter as part of the Peninsula Research Institute of Marine Renewable Energy (PRIMaRE) [37].

6. Conclusions

The paper has explored two sources of failure rate uncertainty, estimated their extent and shown the effect on the system reliability for a notional generic MEC. The following conclusions are drawn.

Major sources of failure rate uncertainties are unknown failure modes which typically lead to a substantial underestimate of the field failure rate. Thus it is desirable to identify all failure modes, to be confident that the estimated failure rate ranges in the same order of magnitude as the actual field failure rate. It was also shown that a potential misrepresentation of the component failure behaviour leads to uncertainties in the overall system reliability. If a simple constant failure rate is assumed both early failures and wear-out failures are typically not considered which leads to an overestimation of the system reliability.

These considerable uncertainties are a risk for project developers and investors. In the case of marine renewable energy the required technology investment is inhibited and the envisaged commercial-scale deployment is deferred.

In order to address failure rate uncertainties, reliability assessments should consider the source and extent of uncertainties to identify components where the uncertainty needs to be reduced. The outlined Bayesian updating provides a promising approach to reduce the uncertainty of failure rates. The modelled examples show how failure rate distributions are influenced through the incorporation of 'engineering knowledge' and test data. In this way, uncertainties can be reduced through specific component reliability testing and the potential effect of unknown failure modes can be quantified at an early design stage to ensure an acceptable mean failure rate. Hence the application of the Bayesian method helps to reduce the uncertainty of component failure rates and to improve the confidence in system reliability estimates for emerging technologies.

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References

[1] World Energy Council [WEC], Survey of energy resources 2007, Tech. rep. (2007).

[2] Department for Business, Enterprise & Regulatory Reform [BERR], Energy statistics: electricity. annual tables: Digest of uk energy statistics (dukes), Tech. rep. (2008).

[3] J. Callaghan, R. Boud, Future marine energy - results of the marine energy challenge: Cost competitiveness and growth of wave and tidal stream energy, Tech. rep., The Carbon Trust (2006).

[4] T. W. Thorpe, A brief review of wave energy, Tech. Rep. ETSU-R120, The UK Department of Trade and Industry (1999).

[5] Observatoire des énergies renouvelables [ObservER], Worldwide electricity production from renewable energy sources. 11th Inventory, Tech. rep. (2009).

[6] M. Mueller, R. Wallace, Enabling science and technology for marine renewable energy, Energy Policy 36 (2008) 4376–4382. doi:10.1016/j.enpol.2008.09.035.

[7] DECC, Marine Energy Action Plan 2010 - Executive Summary & Recommendations, Tech. rep., HM Government (2010).

[8] L. Béchou, Y. Dantoa, J.-Y. Deletagea, F. Verdiera, Y. Deshayesa, S. Fregonsea, C. Maneuxa, T. Zimmera, D. Laffitte, Challenges and potential of new approaches for reliability assessment of nanotechnologies, Comptes Rendus Physique 9 (2008) 95–109. doi:10.1016/j.crhy.2007.12.001.

[9] E. B. Mackay, A. S. Bahaj, P. G. Challenor, Uncertainty in wave energy resource assessment. part 1: Historic data, Renewable Energy 35 (8) (2010) 1792 – 1808. doi:10.1016/j.renene.2009.10.026.

[10] A. Shafaghi, Equipment failure rate updating - Bayesian estimation, Journal of Hazardous Materials 159 (2008) 87–91. doi:10.1016/j.jhazmat.2008.01.042.

[11] R. Pan, A Bayes approach to reliability prediction utilizing data from Accelerated Life Tests and field failure observations, Quality and Reliability Engineering International 25 (2009) 229 – 240. doi:10.1002/qre.964.

[12] M. Akama, Bayesian analysis for the results of fatigue test using full-scale models to obtain the accurate failure probabilities of the Shinkansen vehicle axle, Reliability Engineering & System Safety 75 (3) (2002) 321–332. doi:10.1016/S0951-8320(01)00129-6.

[13] M. Guida, G. Pulcini, Automotive reliability inference based on past data and technical knowledge, Reliability Engineering & System Safety 76 (2) (2002) 129 – 137. doi:10.1016/S0951-8320(01)00132-6.

[14] M. Guida, G. Pulcini, M. Vianello, Early inference on reliability of upgraded automotive components by using past data and technical information, Journal of Statistical Planning and Inference 139 (5) (2009) 1604 – 1618, special Issue on Degradation, Damage, Fatigue and Accelerated Life Models in Reliability Testing. doi:10.1016/j.jspi.2007.08.008.

[15] X. Yang, W. J. Rogers, M. S. Mannan, Uncertainty reduction for improved mishap probability prediction: Application to level control of distillation unit, Journal of Loss Prevention in the Process Industries 23, 1 (2010) 149–156. doi:10.1016/j.jlp.2009.07.006.

[16] A. Mill, Engineering testing of marine energy devices - an introduction to engineering testing of marine renewables devices, Tech. rep., Carbon Trust (2009).

[17] Marsh, Scoping study on financial risk management instruments for renewable energy projects, Reference document, Sustainable Energy Finance Initiative (SEFI) of the United Nations Environment Programme (UNEP), in association with: Ted Olivier, Andlug Consulting, Rdl & Partner, Supported by: Climate Change Capital, Det Norske Veritas, Global Sustainable Development Project (2005).

[18] Marsh, Survey of insurance availability for renewable energy projects, Tech. rep., United Nations Environment Programme (March 2006).

[19] J. Wolfram, On assessing the reliability and availability of marine energy converters: The problems of a new technology, Proc. of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability 220 (1) (2006) 55–68. doi:10.1243/1748006XJRR7.

[20] P. R. Thies, J. Flinn, G. H. Smith, Is it a showstopper? Reliability assessment and criticality analysis for wave energy converters, in: 8th European Wave and Tidal Energy Conference (EWTEC), 7-10 September, Uppsala, Sweden, 2009.

[21] H.-J. Zimmermann, An application-oriented view of modeling uncertainty, European Journal of Operational Research 122 (2000) 190–198. doi:10.1016/S0377-2217(99)00228-3.

[22] W. L. Oberkampf, J. C. Helton, C. A. Joslyn, S. F. Wojtkiewicz, S. Ferson, Challenge problems: uncertainty in system response given uncertain

parameters, Reliability Engineering and System Safety 85 (2004) 11–19. doi:10.1016/j.ress.2004.03.002.

[23] P. D. O'Connor, Quantifying uncertainty in reliability and safety studies, Microelectron. Reliab. 35 (1995) 1347–1356. doi:10.1016/0026-2714(95)99382-S.

[24] S. Cox, R. Tait, Safety, reliability, and risk management : an integrated approach, 2nd Edition, Butterworth-Heinemann, Oxford, 1998.

[25] D. C. Cox, P. Baybutt, Methods for Uncertainty Analysis: A Comparative Survey, Risk Analysis 1 (1981) 251–258. doi:10.1111/j.1539-6924.1981.tb01425.x.

[26] L. C. Cadwallader, Comparisons of facility-specific and generic component failure rates for tritium-bearing components used in fusion research, Fusion Engineering and Design 54 (2001) 353–359. doi:10.1016/S0920-3796(00)00554-8.

[27] E. Zio, Computational methods for reliability and risk analysis, Vol. 14 of Series on Quality, Reliability and Engineering Statistics, World Scientific Publishing, 2009.

[28] M. Rausand, A. Høyland, System reliability theory. Models statistical methods and applications., second revised Edition, Series in probability and statistics, Wiley, 2004.

[29] W. Q. Meeker, L. A. Escobar, Statistical Methods for Reliability Data, Wiley Series in Probability and Statistics, Wiley, 1998.

[30] P. D. T. O'Connor, Practical reliability engineering, 4th Edition, Wiley, 2008.

[31] E. E. Lewis, Introduction to reliability engineering, Wiley, London, 1994.

[32] E. Zafiropoulos, E. Dialynas, Reliability and cost optimization of electronic devices considering the component failure rate uncertainty, Reliability Engineering and System Safety 84 (2004) 271284. doi:10.1016/j.ress.2003.11.012.

[33] H. Stiesdal, P. H. Madsen, Design for reliability, in: Copenhagen Offshore Wind Conference, 26 - 28 Oct., Copenhagen, Denmark, 2005.

[34] M. Hamada, A. Wilson, C. Reese, H. Martz, Bayesian Reliability, no. ISBN: 978-0-387-77948-5 in Springer Series in Statistics, Springer, 2008.

[35] DNV, OREDA - Offshore Reliability Data Handbook, DNV - Det Norske Veritas, 2002.

[36] P. R. Thies, L. Johanning, G. H. Smith, Towards component reliability testing for marine energy converters, Ocean Engineering 38 (23) (2011) 360 – 370. doi:10.1016/j.oceaneng.2010.11.011.

[37] L. Johanning, P. R. Thies, D. Parish, G. H. Smith, Offshore reliability approach for floating renewable energy devices, in: Proceedings of the ASME 30th International Conference on Offshore Mechanics and Arctic Engineering OMAE, no. OMAE2011-49844, 2011, 19 - 24 June, Rotterdam, Netherlands. doi:10.1115/OMAE2011-49844.