**Probabilistic Structural Integrity Assessment in Nuclear Sector**

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**Abstract**

There always exists uncertainty and variability in nuclear reactor design and subsequent structural integrity assessments arising from lack of knowledge, modelling approximations or differences between as-manufactured components and as-operated components, plausibly triggering uncertain or variable reactor lives. Such uncertainties and variabilities can be understood and quantified using probabilistic techniques together with reliability-based acceptance criteria so as to measure and balance risk. Over the past ten years, probabilistic design and assessment have become increasingly desirable in the nuclear sector to underwrite the lives of boiler and reactor internal components such as the through-life management strategies. This has led to providing probabilistic structural integrity assessment procedural guidance for the EDF Advanced Gas-cooled Reactors (AGRs) in the UK, which are also being used in developing the probabilistic aspects of new structural integrity design codes for application to high temperature Advanced Modular Reactor (AMR) designs. This review article provides a systematic appraisal of the latest literature and unpublished reports from the EDF UK nuclear plants, giving an overview of the existing knowledge of probabilistic/reliability structural integrity methodologies and tools from a multifaceted stance, including failure modes, problem types, material types, employed codes, correlations, probability distributions, etc. The concept of structural reliability analysis at different levels is discussed, particularly the recently developed Level 1 Reference Damage Model, approximate approaches and Monte Carlo analysis as well as sensitivity analysis.

**Keywords:** Probabilistic assessment, Structural integrity, Failure, Nuclear plant.

**Nomenclature**

|  |  |
| --- | --- |
|  | Pearson correlation coefficient |
|  | Damage based on everything best estimate |
|  | Damage values |
|  | Reference damage |
|  | Number of variables |
|  | Number of all combinations of three variables |
|  | Probability of failure |
|  | Probability of survival (Reliability) |
|  | Absolute sensitivity factor |
|  | Standard normal variate |
|  | Relative (Probabilistic) sensitivity factor |
|  | Safety index |
|  | Hasofer and Lind reliability index |
|  | Standard deviation |
|  | Failure region |
| AGR | Advanced Gas-cooled Reactor |
| AMR | Advanced Modular Reactor |
| AMV | Advanced Mean-Value |
| AMV+ | Advanced Mean-Value with iterations  |
| ANN | Artificial Neural Network |
| API | American Petroleum Institute |
| ARBIS | Adaptive Radial-Based Importance Sampling |
| ASME | American Society of Mechanical Engineers |
| ASTM | American Society for Testing and Materials |
| BS | British Standard |
| CoV | Coefficient of Variation |
| CDF | Cumulative Distribution Function |
| EASICS | Establishing Advanced Structural Integrity Codes and Standards (project for AMRs) |
| EDF | Électricité De France |
| FAVOR | Fracture Analysis of Vessels Oak Ridge |
| FEA | Finite Element Analysis |
| FEM | Finite Element Method |
| FESI | Forum for Engineering Structural Integrity |
| FORM | First Order Reliability Method |
| FOSM | First Order Second Moment |
| GDA | Generic Design Assessment |
| HC | High Cycle |
| HEA | High-Entropy Alloy |
| HL | Hasofer and Lind |
| HMV+ | enhanced Hybrid Mean-Value |
| IS | Importance Sampling |
| KS | Kriging Surrogate |
| LC | Low Cycle |
| LEFM | Linear Elastic Fracture Mechanics |
| LHS | Latin Hypercube Sampling |
| LSFM | Least Square Fitting Method |
| MC | Monte Carlo |
| MCMC | Markov Chain Monte Carlo |
| MCS | Monte Carlo Simulation  |
| ML | Machine Learning |
| MPP | Most Probable Point |
| MVM | Mean Value Method |
| ONR | Office for Nuclear Regulation (the UK nuclear regulator) |
| OPS | Orthogonal Plain Sampling |
| PDF | Probability Density Function |
| PDM | Probabilistic Distribution Method |
| PoF | Probability of Failure |
| PoI | Probability of Initiation |
| PSA | Probabilistic Safety Assessment |
| PSF | Partial Safety Factor |
| PWR | Pressurized Water Reactor |
| RCC-MR | French nuclear code: “Règles de Conception et de Construction des Matériels Mécaniques des Îlots Nucléaires RNR” (Design and Construction Rules for Mechanical Components of Nuclear Islands) |
| RPV | Reactor Pressure Vessel |
| RSM | Response Surface Model |
| SA | Sensitivity Analysis |
| SCF | Stress Concentration Factor |
| SMR | Small Modular Reactor |
| SORM | Second Order Reliability Method |
| SS | Subset Simulation |
| SVR | Support Vector Regression |
| VB | Visual Basic |
| 3T-RDM | Three-Term Reference Damage Model  |

1. **Introduction**

Probabilistic structural integrity assessments permit the uncertainties inherent in reactor design and operation to be considered and reflected in the quantification of reliability. Unlike deterministic assessments, where single point quantities are used for input parameters, parameters in a probabilistic assessment are assigned multiple possible magnitudes using either a distribution or, if adequate data is available, the data itself to represent the uncertainty. Accordingly, random combinations of input parameters, drawn from those distributions/data, are used in the calculations so as to obtain a set of quantities against probability for the output of interest. Such assessments allow the assessor to move away from pessimisms and bounding cases to a more risk-based approach to decision making. In addition, it provides an understanding of the most important parameters over the whole system which can aid understanding the plant and to provide evidence, for or against, any current assumptions made in assessments [1].

In the UK, where EDF Advanced Gas-cooled Reactors (AGRs), the only commercially operated fleet of high temperature reactors in the world, dominate nuclear power generation [2], increased efforts have recently been focussed on plant life extension to help manage future energy generation. This has driven the use of probabilistic approaches in order to increase the confidence in structural integrity assessments through the effective management of uncertainties, compared to the more traditional deterministic and potentially conservative approaches, which still dominate design codes. However, EDF’s goal for an R5V2/3 Appendix (A15) [3] to provide advice on probabilistic approaches to structural integrity assessments is gathering momentum. Currently, there is a great deal of interest in the nuclear sector concerning probabilistic approaches, and recently a guidance document for probabilistic structural integrity published by the Nuclear Structural Integrity Probabilistics Working Group was published on-line hosted by the Forum for Engineering Structural Integrity (FESI) [4].

On the other hand, the UK, as well as many other countries, are putting funding in place for potential vendors and researchers to demonstrate the technical and economic viability of high temperature Advanced Modular Reactors (AMRs) [5]. AMRs are expected to be more cost effective and faster to build than larger, more conventional nuclear power stations and are therefore seen by many as the future solution for the nuclear power sector to deal with capacity increases against a legacy of aged nuclear fleet Worldwide [6]. It was estimated in 2018 that there were 50 AMR or Small Modular Reactor (SMR) designs in various stages of development in over 10 different countries [5], with some potentially being operational by 2020-21. In the UK, Rolls-Royce has almost completed the feasibility stage in the development of its SMR and the Generic Design Assessment (GDA) will be completed in about 2024, and will be ready for grid use in 2030 [7]. Although some generic details are known about the designs of new AMRs and SMRs, different designs will demand different operating temperatures [2]. Temperatures for certain plant components above 450 °C are high for traditional ferrous-based alloys (low alloy, stainless etc) used in plant, causing susceptibility to creep rupture. Nickel based alloy development in the future could see creep-free operational temperatures to about 750 °C [8]. High-temperature variant designs of gas cooled reactors could push operating temperatures to between 800 and 1,000 °C [4] for some plant components. However, together with thermal cycling over many years of likely operation, including transient as well as steady state conditions, suggests the highly complex phenomenon of creep-fatigue will be an important failure mode to address.

In the context of a future nuclear capability in the UK, the technical and economic viability of AMRs will not happen through collaboration of government and industry alone, but also requires commitment from regulators, e.g., the Office for Nuclear Regulation (ONR) in the UK [9]. It is also timely to promote the use of probabilistic approaches as mandatory for future nuclear design, analysis and assessment of AMR plant, including high or very high temperature AMR designs. For example, current Probabilistic Safety Assessment (PSA) guidance from the ONR states in Section 4.6.3.3 [10, 11]:

*“The methodology used for the calculation of probabilities of structural failures should be justified and the details of the analysis should be transparent…If use is made of probabilistic fracture mechanics codes, the codes should be state of the art and should have been validated against operational experience and/or experiments….”*

From this statement, the mandatory use of probabilistic approaches is not guaranteed but suggested, yet no guidance on what approaches to use or what constitutes a methodology for probabilistic structural integrity exists. It is also important that whatever approach is used, it should be validated in some way, rather than just being verified or checked.

The current paper is a contribution to the Establishing Advanced modular reactor Structural Integrity Codes and Standards (EASICS) project [12] aiming to establish guidance on the structural integrity codes and standards that are required to support GDA of AMR designs in the UK through technology innovation and transfer. The specific focus of this paper is on providing a state-of-the-art-review of existing probabilistic guidance in current structural design codes and wider literature that explore the application of probabilistic techniques at different stages of the product lifecycle for various nuclear reactor geometries and materials. This provides advice on what would be suitable for inclusion within codes and standards. The findings of this work should be of interest to key stakeholders, including, (i) the regulator (ONR), (ii) high temperature nuclear design code developers, i.e., EDF R5 and R6 procedures, RCC-MR and ASME III division 5, (iii) AMR vendors and the wider industry. The context is to seek acceptance of a quite fundamental shift in design code approach and seek changes in international design codes.

The remainder of this paper is organized as follows. In Section 2, the concept of structural reliability at three levels is introduced. Specific attention is given to introducing a newly proposed Level 1 structural reliability analysis, called Three-Term Reference Damage Model (3T-RDM) [13], which establishes a simplified means of estimating the failure probability. Also discussed in Section 2 are approximate approaches used in Level 2, and Monte Carlo (MC) analysis and sampling strategies employed in Level 3. In Section 3, sensitivity analysis (SA) and most commonly used SA approaches together with their pros/cons are explained. The current status of probabilistic assessment in the nuclear sector is reviewed and analysed in Section 4. Section 5 summarizes the conclusions and presents some potential future directions in the field.

1. **Probabilistic Structural Analysis**

The purpose of structural assessment procedures is to understand the margin to failure by comparing the output of a model of the structural degradation behaviour or performance with a measure of the withstand capacity, or resistance, of the structure. When there are uncertainties in the inputs to the structural degradation model, the structural reliability approach can be used to understand margin to failure using probability. Basically, structural reliability aims at quantifying the failure probability caused by uncertainties in design, manufacturing, and environmental conditions. In the wider literature, this is commonly visualised using **Figure 1** where the combined effects of uncertainties in the various loading and resistance terms result in PDFs of load and resistance [14]. Note that uncertainties are classified as epistemic or aleatory; epistemic uncertainties can be divided into measurement, statistical, and model uncertainties whilst aleatory uncertainty is represented by the physical uncertainty linked to the natural randomness of a quantity. More details about uncertainties can be found in Ref. [15].

In probabilistic analyses, to take into account uncertainties, variables are represented as distributions, where common types are Normal, Lognormal and Weibull. The probability density function (PDF) is essentially a continuous histogram; the area under the curve for some interval gives the probability that the performance metric will lie in that interval. The cumulative distribution function (CDF) is the integral of the PDF and specifies the probability of the response occurring at or below a specified value. The CDF always ranges in value from 0 to 1, representing a 0% probability at the lower bound and a 100% probability at the upper bound.



**Figure 1. Structural reliability load and resistance concept.**

Probabilistic methods predict a distribution of the performance metric, from which the likelihood of a specific level of performance can be determined. In structural reliability applications, the linear performance function or linear limit state function, , is typically defined as

 (1)

 (2)

where is the strength or resistance, is the applied stress or stress intensity factor or J-integral, and are random variables. As an example, when applied to the Linear Elastic Fracture Mechanics (LEFM) conditions, a convenient limit state equation is given by: .

The failure probability () is the likelihood that the stress exceeds the strength or that the limit state equation . So, the is

 (3)

An exact solution of requires the integration of a multiple integral denoted as

 (4)

where is the joint PDF of , and is the failure region. Analytic solution of this multiple integral is, in general, not possible, and direct numerical evaluation is impractical when the dimensionality of is large. Alternatively, MC or efficient approximation methods are used [16], see Sections 2.2 and 2.3.

The reliability or probability of survival, , is the converse; . The can be a function of the material’s resistance to failure and may depend on basic variables such as flow stress and fracture toughness. Likewise, the can be a function of the geometry, size of defects in the structure and the applied forces and moments. The and variables are each described by their own PDFs.

The potential modes of failure can be divided into those which cause failure on the net cross section such as plastic collapse, bending, buckling, torsion, and shear as well as those which cause failure by progressive growth of a crack i.e., creep, fatigue, corrosion and fracture [17].

Probabilistic structural analysis, also referred to as structural reliability analysis, can be categorized into three levels [18], as shown in **Table 1**. These levels may be used in general cases where the limit state function is more complex than the simple linear form in Eq. (1).

**Table 1. Levels of structural reliability analysis.**

|  |  |  |
| --- | --- | --- |
| **Level 1** | **Level 2** | **Level 3** |
| * Failure probability is not calculated explicitly.
* A set of partial safety factors is used, which are determined with reference to the failure probability calculations made using Level 2 or Level 3 reliability analysis methods.
* PSFs and 3T-RDM are examples of Level 1 reliability analysis.
 | * Failure probability is calculated explicitly.
* An approximation of the exact value of failure probability is obtained.
* MPP methods combined with FORM/SORM, AMV or HMV are examples of Level 2 reliability analysis.
* The degree of accuracy should be determined using conducting a Level 3 reliability analysis.
 | * Failure probability is exactly calculated explicitly.
* Sampling techniques, e.g., MC, LHS and MCMC, are normally used.
* There is generally no restriction on the form of the constituent distributions.
* A large number of individual trials is required for accuracy.
 |

There is a hierarchy of probabilistic techniques available for application to structural integrity assessment as shown in **Figure 2**. The most appropriate technique for a particular case depends on the maturity of design and level of data available. For example, for early design sensitivity, scoping studies or rapid assessment of service data, an inferred calculation of probability may be acceptable. For structural justification purposes, explicit calculation of probability is likely to be required using a MC approach or a suitably calibrated partial safety factor (PSF) approach [4].



**Figure 2. Hierarchy of assessment tools.**

* 1. **Level 1: 3T-RDM**

3T-RDM was recently proposed as a novel Level 1 approach [13]. The method provides a Design Chart that can be used to determine failure probability from a set of stochastic inputs and a deterministic analysis of the structural degradation mechanism of interest. The approach is not restricted to a particular failure mechanism. Potentially, fracture, creep rupture, creep-fatigue crack initiation and creep-fatigue crack growth are all within its scope, and non-metallic materials (e.g., graphite) may also be addressed.

Following steps should be taken in order to calculate 3T-RDM:

* **Without Correlation**
1. Calculate damage based on everything best estimate ().
2. If variables are distributed, consider all combinations of three variables, of which there are .
3. For each combination of three variables, carry out a deterministic assessment setting the three variables to their level (plus or minus depending which increases damage; is standard deviation), whilst keeping all other variables best estimate, thus giving damage values where . Care must be taken with the signs of the changes from best estimate to ensure that each one increases damage. For example, creep deformation should be increased whereas creep ductility should be decreased. The magnitude of a compressive stress is greater if the error is negative.
4. Define the Three-Term Reference Damage as where, .
* **With Correlation**

When considering correlation between input parameters, the definition of the three-term reference damage must be modified to accommodate this correlation, as specified below. Note that the definition below is restricted to a single pair of correlated variables. Other pairs of correlated variables could be included in the same way.

Suppose variables and are correlated, with Pearson correlation coefficient , which must lie between -1 and +1. In general, the sign is crucial.

**Step (a)**

In the uncorrelated procedure, above, the variable contributes through each damage term in which is one of the three varied parameters. The variable may or may not also be one of the varied parameters. There will also be involving variation of but not of . The three possibilities are,

1. is one of the three terms, is not: is calculated by setting at its level and also setting at its level.
2. is one of the three terms, is not: is calculated by setting at its best estimate value and also setting at its level.
3. and are both in the three terms: is calculated by setting at its level and also setting at its level.

This provides the first estimate of .

**Step (b)**

This is identical to step (a) but with and reversed in the above procedure. This results in a second estimate of . The larger should be used [13].

**Figure 3** illustrates a Design Chart, i.e., a plot of probability of creep-fatigue crack initiation in 316H stainless steel versus 3T-RDM, obtained based on a benchmark problem and validated by three EDF case-studies [13]

**Figure 3. Design Chart obtained using Level 1 3T-RDM for creep-fatigue crack initiation in 316H stainless steel [13].**

* 1. **Level 2: MPP**

The most probable point (MPP) methods are based on mapping of the original random variables into independent standard Normal variables and determining the most probable point using optimization [19]. Reliability can be computed based on the location of the MPP by a variety of methods including first or second order reliability methods (FORM or SORM) or a higher-order method such as advanced mean-value with iterations (AMV+) or enhanced hybrid mean-value (HMV+) methods. The MV method constructs a mean-based response function and computes the MPP for the specified probability levels. As a first-order method, it provides a good approximation of the solution near the mean, but can deviate significantly toward the tails for non-linear problems. The MV method requires n + 1 trials, where n is the number of random variables. The advanced mean-value (AMV) method utilizes higher-order terms to achieve a better representation of the response and requires n+1+m trials, where m is the number of specified probability levels. The advanced mean-value with iterations (AMV+) method involves the implementation of AMV but also includes iterations on the MPP to ensure that convergence to a specified level is reached. AMV+ has been shown to be very accurate even for non-linear problems, though the number of trials varies with the problem [16, 20]. The hybrid mean-value (HMV) method works well for convex or concave performance functions, however, it could fail to converge for highly nonlinear output performance functions. Enhanced HMV (HMV+) method offers improved numerical stability and efficiency for such highly nonlinear output performance functions [21]. It is worth noting that while the MPP methods are approximate, they are accurate in comparisons with MC simulation results, while requiring a small fraction of the number of computations.

FORM/SORM, as two standard structural reliability methods, have been applied to nuclear structural integrity analysis more than other methods. They are analytical approximations in which the Hasofer and Lind (HL) reliability index () is interpreted as the minimum distance from the origin to the limit state surface in standardized normal space (**u**-space),, tangent to the MPP. The most likely failure point (design point) is searched using an appropriate non-linear optimisation algorithm to calculate the MMP of failure. Using FORM, the surface is approximated to a hyperplane, , (a first order/linear approximation) whilst SORM employs a second order/quadratic approximation to a hyperparaboloid, . **Figure 4** illustrates a schematic representation of the FORM/SORM in a two-dimensional standard normal space. The accuracy of FORM/SORM is generally dependent on three parameters, i.e., the curvature radius at the design point, the number of random variables and the first-order reliability index [22]. A disadvantage of this method is that the random parameters must be continuous, and every limit state function must also be continuous.



**Figure 4. Basic principle of FORM/SORM.**

* 1. **Level 3: MC**

The essence of a MC probabilistic assessment is simply to carry out a deterministic assessment many times with different combinations of the distributed parameters, each combination having the same probability of occurrence. Basically, a MC probabilistic assessment approximates the probability distribution of an output parameter based on the repeated computations of the performance function using randomly generated combinations of the input variables, with the samples going into these randomly generated combinations being sampled from the associated PDFs or possibly discreet data. The performance function is defined by the underlying deterministic procedure.

MC provides the most effective approach to the propagation and analysis of uncertainty in many situations for various combinations of the following reasons: (i) large uncertainties are often present and a sampling-based approach provides a full coverage of the range of each uncertain variable, (ii) modification of the model is not required, (iii) direct estimates of distribution functions are provided, (iv) analyses are conceptually simple and logistically easy to implement, (v) analysis procedures can be developed that allow the propagation of results through systems of linked models, and (vi) a variety of sensitivity analysis procedures are available [23].

To produce accurate representations of the failure distribution, a suitably large number of MC trials must be computed. The total number of MC trials should be at least an order of magnitude greater than the reciprocal of the failure probability requirement for the result to be statistically significant. This puts a limitation on the applicability of MC when searching for an occurrence which has very low failure probability thus MC can be prohibitive in the time needed to achieve results. For such cases a sampling strategy such as Latin-Hypercube Sampling (LHS) [24] can aide in reducing the number of trials needed to produce a representative output PDF. LHS is based on the principle that for each input parameter the samples supplied to MC modelling must have equal probability. In other words, a Latin hypercube is a hypercube in which exactly variables cells are “occupied” and such that no two occupied cells share a bin in any variable. If an input parameter distribution is known then samples are determined by dividing the area under the PDF into portions of equal area, which in fact represent equal probabilities of occurrence.

In cases where the CDF may be intractable to evaluate yet the PDF may be tractable, Markov Chain Monte Carlo (MCMC) techniques can provide a means to produce a sample using a ‘random walk’ through the solution space. A particular strength of MCMC is that it can be used to draw samples from distributions even when all that is known about the distribution is how to calculate the density for different samples. Unlike MC sampling methods which draw independent samples from the distribution, in MCMC methods, while each new sample depends on the one before it, new samples do not depend on any samples before the previous one (this is the “Markov” property) [25]. These techniques are frequently required when conducting Bayesian updating using operating data.

Efficient MC-based methods such as advanced variance-reduction techniques, e.g., importance sampling (IS), adaptive radial-based importance sampling (ARBIS) [26], subset simulation (SS), and orthogonal plain sampling (OPS), metamodels, i.e., Kriging and polynomial expansions, or adaptive combinations of the two can be very powerful and computationally efficient techniques for propagating uncertainties in the complex models for reliability and risk assessment purposes, hence, pose promising future efforts in the field of nuclear probabilistic structural integrity.

**Figure 5** provides an example of a possible flow diagram of the overall MC probabilistic approach. Details may vary according to the application.



**Figure 5. Possible flow diagram for the Level 3 MC probabilistic procedure.**

1. **Sensitivity Analysis**

Sensitivity analysis (SA) methods apportion the variability in the probabilistic output of an analysis process (e.g., accumulated damage) to the variability in specific input parameters. This permits a ‘ranking’ of input parameters with respect to their relative contribution to the reliability function. SA results can be utilized to identify design drivers which have the greatest impact on the variability observed in outputs thus future work can then be focused on the design drivers. In addition, SA results can be fed-back into the probabilistic analysis method and surrogate modelling methods in a process known as parameter ‘screening’. Parameter screening identifies the input parameters that do not provide a significant contribution to the output variability and fixes such parameters to nominal deterministic values when conducting the probabilistic analysis and training of the surrogate model. The use of parameter screening can reduce the amount of training data required for surrogate models and potentially increase the rate of convergence for a probabilistic analysis method. The combination of both of these factors could result in a reduction in the computational resource required to implement a probabilistic analysis methodology [27].

There are relative and absolute sensitivities, each with unique advantages. Relative sensitivities are commonly referred to as probabilistic sensitivity factors, , and give the change in safety index, , with respect to the standard normal variate,. The probabilistic sensitivity factor is defined as

 (5)

for each variable with equal to a specific probability level. The safety index, , is represented in standard normal variate space, where, for example, probabilities of 0.01 to 0.99 are represented by standard normal variates of −3 to +3.

On the other hand, absolute sensitivities, and , provide the change in probability with respect to the mean and standard deviation, respectively. In this case, sensitivities are non-dimensional, allowing comparisons to be made between all of the variables. These sensitivities indicate how much the mean and standard deviation of each random variable contribute to the variability in the response [20].

, (6)

There are various approaches for SA; four commonly employed ones along with their pros/cons are summarised in **Table 2** [28].

**Table 2. Comparison of commonly used SA approaches; *R*, *I* and *N* are the number of runs required, the number of input parameters and the number of trials, respectively, in the probabilistic assessment [28].**

|  |  |  |  |
| --- | --- | --- | --- |
| Approach | R | Pros | Cons |
| Finite-difference approach |  | Simple and quick to implement. | Inputs are assumed to be normally distributed and have no interactions. Hence, it examines local sensitivity only. |
| Variance-basedapproach |  | Conceptually simple toimplement. | Not suitable for highly skewed distributions (i.e. lognormal) as it assumes normal distributions. |
| Correlation-basedapproach |  | Requires the same number of runs as the probabilistic assessment. | As the effect of each parameter is not isolated, it can overestimate theimportance of the least influential parameters. |
| -sensitivity |  | Measures global sensitivities. | Computationally taxing as it requires large numbers of runs. |

1. **Current Status of Probabilistic Assessment in Nuclear Sector**

To assist in the process of identifying current practice in the use of probabilistic approaches in the nuclear sector (2000-2020), the following were collated:

* 12 reports from EASICS Project Team, not in the public domain (See Section 4.1).
* 25 publications from the general literature, published in the public domain (See Section 4.2).
* 10 publications from EASICS Project Team in the public domain (References [28-37]).

Note, the latter set of publications have been omitted from all data sets and charts except where making a comparison at a high level between UK and international publications over the last 20 years. In terms of using these papers for further analysis on the use of probabilistic approaches, this was considered to be in some cases ‘double counting’ as many of the publications by the EASICS Project Team are based on a non-published EASICS Project Cases, desensitised appropriately due to commercial issues.

Each case study was summarised using a proforma, a form-based template with distinct fields of categorised information to be completed. It was originally developed at the University of Bristol for another project [38], but adapted for the case studies involved in this project. An example of a proforma can be found in **Figure 6**, completed for EASICS Project case-study #3.



**Figure 6. Example proforma (EASICS project case-study #3).**

The different classifications and category headings in the proforma have been adapted and refined to make them generally applicable to many types of probabilistic problem. The intention of the proforma is to capture the key information contained, often within lengthy industrial reports and journal papers, and reduce it to a point where quantitative assessment of the information can be made and compared under common headings. The proforma can be used in a proactive way to help define a probabilistic approach to a problem, guiding the practitioner from important problem formulation issues to the consideration of uncertainty in the models and parameters, and finally how this might impact on the reliability prediction. It could also be used to summarise future case studies for dissemination in reports and papers. **Table 3** is used to summarise the information from the proformas under similar classification headings, with the addition of further categories. A tally is kept of the applicability of each case study and its relevance to each category.

**Table 3. Proforma data summary table.**



* 1. **Overview of EASICS project case-studies and literature**
		1. **EASICS Project Case-Studies**

Overview:

* Published between 2009 and 2020.
* Citations and original reference documents not available due to commercial sensitivity.
* 12 publications in total relate to probabilistic creep-fatigue or probabilistic assessments of nuclear plant.

**Table 4. Summary of case-studies from EASICS project stakeholders.**

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| ID | Case Title | Failure Mode/ Degradation Mechanism | Material | Feature | Failure Characteristic | Probabilistic Technique(s) Used | Stage | Implications/Outcome |
| 1 | Boiler Spines | Creep-Fatigue | Esshete 1250 | Weldment | Crack Growth | MCS (analytical function) | In-service Assessment | Downgrade Plant |
| 2 | Bifurcations | Creep-Fatigue | SS316 | Weldment | Rupture | MCS (FEA + analytical function) | In-service Assessment | Monitoring compliance with service envelope |
| 3 | Bifurcations | Creep-Fatigue | SS316 | Weldment | Crack Initiation | MCS (FEA + analytical function) | In-service Assessment | Monitoring compliance with service envelope |
| 4 | Bifurcations | Creep-Fatigue | SS316 | Weldment | Crack Growth | MCS (FEA) | In-service Assessment | Health Monitoring  |
| 5 | Bifurcations | Creep-Fatigue + Carburisation | SS316 | Weldment | Crack Initiation | MCS (FEA) | In-service Assessment | Identification of new failure contributing cause (carburisation) |
| 6 | Fuel Plug Units | Static  | SS321 (irradiated) | Weldment | Fracture | MCS (analytical function) | In-service Assessment | Confidence in PoF against code |
| 7 | Gas Circulator Impellers | HC Fatigue | 2¼ Cr/Mo | Parent | Crack Growth | MCS (analytical function) | In-service Assessment | Inform Inspection Interval |
| 8 | Tube Plate Ligament | Creep-Fatigue | SS316 | Constrain-ed Plate with Holes | Crack Initiation | MCS (analytical function + FEA) | Method Development | Improve Confidence over Deterministic Approach/PoI Prediction |
| 9 | Boiler Spaces | Creep-Fatigue + Carburisation(interaction of cycles) | SS316 | Weldment | Crack Initiation | MCS (analytical function + FEA)/LHS | In-service Assessment | Identification of new failure contributing cause (carburisation) |
| 10 | Gas Turbine Blade | Creep Fatigue | Ni Alloy | Parent | Crack Initiation | MCS (analytical function + FEA)/Surrogate Modelling | In-service Assessment | Life Extension |
| 11 | Graphite Moderator | Displacement | Graphite (irradiated) | Parent | N/A | MCS (analytical function)/Bayes Theorem/Markov Chains | In-service Assessment | Probabilistic Framework Development |
| 12 | Core Constraints | Fracture  | 2¼ Cr/Mo + C/Mn Steels (irradiated) | Weldment | Fracture | MCS (analytical function)/LHS | In-service Assessment | Model Definition |

* + 1. **Literature**

Overview:

* Published between 2000 and 2019 in the public domain.
* 25 publications in total relate to probabilistic creep, fatigue, thermal shock, etc., applied to the nuclear sector.
* Mix of both journal (majority) and conference proceeding papers.
* Not confident all conference proceedings have been peer reviewed.
* Does not include publications by EASICS project stakeholders or papers relating to EASICS project cases.

**Table 5. Summary of case-studies from literature.**

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| ID | Author(s) | Failure Mode/Degradation Mechanism | Material | Feature | Failure Characteristic | Probabilistic Technique(s) Used | Stage | Implications/Outcome |
| 13 | (Kim, Park et al. 2011) [39] | Creep | Gr. 91 steel | Parent (test specimen) | Crack Growth | LSFM, MVM, PDM, MCS | Method Development | PDM and the MCS are useful to assess creep crack growth |
| 14 | (Zhu, Foletti et al. 2017) [40] | Multiaxial LC Fatigue  | Gr. 91 steel | Notched Component (test specimen) | Rupture | LHS/FEA | Design | Probabilistic Framework Development |
| 15 | (Ishikura, Xu et al. 2014) [41] | HC Fatigue Due to flow-Induced Vibration | Mod.9Cr-1 Mo Steel | Hot-Leg Piping | Damage Evolution | Various distributions (Rice, Gaussian, Rayleigh), Rain-flow cycle counting | In-service Assessment | Probabilistic Framework Development/Verification |
| 16 | (Qian and Niffenegger 2014) [42] | Pressurised Thermal Shock | Base: Ferritic low alloy steelClad:AISI 304 | RPV beltline regionconsidering parent and clad | Crack Initiation and Rupture | FAVOR code (MCS) | Method Development | Master Curve method is more realistic than the FAVOR model |
| 17 | (Beaufils, Meister et al. 2011) [43] | Pressurised Thermal Shock | Base: Ferritic low alloy steelClad:AISI 304 | RPV considering parent and clad | Rupture | Subset simulations method, analytical | In-service Assessment | Life extension |
| 18 | (Chou and Huang 2016) [44] | Pressurised Thermal Shock | Ferritic steel with SS cladding | RPV beltline region considering parent and clad | Crack Initiation and Rupture | FAVOR code (MCS) | In-service Assessment | Health Monitoring |
| 19 | (Appalanaidu and Gupta 2014) [45] | Thermal Creep-Fatigue  | HK-40 stainless steel | Pipeline (test specimen) | Damage Evolution and Rupture | MCS + Rain-flow cycle counting | In-service Assessment | Model Definition /Showing the effect of epistemic uncertainties in the reliability calculations |
| 20 | (Ibisoglu and Modarres 2015) [46] | Creep-fatigue  | SS316FR | Parent (test specimen) | Rupture | WinBUGS code (Bayesian analysis and Markov Chain) | In-service Assessment | Verification |
| 21 | (Tian, Zhang et al. 2017) [47] | Quasi-Static (Internal Pressure + Axial Tension) | Austenite-ferrite duplexstainless steel (Z3CN20-09M) | Pipe+weldment containing internal circumferential surface crack | Rupture | FEA/MCS | In-service Assessment | Health Monitoring |
| 22 | (Li et al. 2013) [48] | Thermal Aging (Tensile+Bending Stresses) | Z3CN20-09M steel | Pipe containing circumferential crack on the inner surface | Rupture | MCS | In-service Assessment | Health Monitoring |
| 23 | (Chen et al. 2015) [49] | Pressurised Thermal Shock | Base: SA508 Class 3 steelClad:austenitic stainless steel | RPV beltline region considering parent and clad | Crack Initiation and Failure | FAVOR code (MCS) | In-service Assessment | Health Monitoring |
| 24 | (Qian, Niffenegger et al. 2013) [50] | Internal pressure loading | Steel | RPV | Crack Growth/Leak-to-Break | MCS and Nataf transformation  | Method Development | Model Definition/Verification |
| 25 | (Sudret and Guédé 2005) [51] | Thermal Fatigue | SS304 and SS3016 | Pipe | Rupture | Lognormal/Normal/Beta/LHS  | In-service Assessment | Probabilistic Framework Development |
| 26 | (Nagai, Miura et al. 2018) [52] | LC Fatigue | SS316 | Pipe containing circumferential crack on the inner surface | Crack Growth/Rupture | MCS (PDF/Lognormal/Normal) | Method Development | Probabilistic Framework Development/PEDESTRIAN code |
| 27 | (Hu, Liu et al. 2011) [53] | Stress Corrosion Cracking | Alloy 600 Inconel Nickel Alloy | Steam generator tube | Rupture/Leak | MCS | Life-cycle management | Health Monitoring/ Verification |
| 28 | (Maeda and Shoji 2011) [54] | Stress Corrosion Cracking | SS304 | Weldment in piping | Crack Growth | FEA+MCS | In-service Assessment | Risk-informed In-service Inspection Period |
| 29 | (Chatterjee and Modarres 2012) [55] | Fretting Fatigue | Alloy 690 Inconel Nickel Alloy | Steam generator helical tube | Crack Growth/Rupture | Bayesian (WinBUGS code), Gamma, Poisson distribution | In-service Assessment | ProbabilisticFramework Development |
| 30 | (Hojo, Hayashi et al. 2016) [56] | LC Fatigue | Cast stainless steelSCS14A | PWR coolant system pipe containing circumferential flaw on the inner surface | Crack Growth/Leak/Failure | MCS (Lognormal/Normal) | Method Development | ProbabilisticFramework Development |
| 31 | (Javonavic et al, 2004) [57] | Creep-fatigue | Not stated | Pipe/components with defects/cracks | Crack initiation and growth | MCS/SA | Method Development | ProbabilisticFramework Development under KBS  |
| 32 | (Deschanels et al 2006) [58] | Creep-fatigue | SS316L | Pipe/component with cracks | Crack growth | MCS (most PDFs) | In-service Assessment | ProbabilisticFramework Development |
| 33 | (Dogan et al, 2007) [59] | Creep-fatigue | P22 Low Alloy Steel | Components with defects/cracks (pipes, tubes) | Crack initiation and growth | MCS | Method Development | ProbabilisticFramework Development |
| 34 | (Vojdani et al, 2018) [60] | Creep-fatigue | SS316L(N) | Plate with surface defect | Crack growth | MCS/FORM/SA | In-service Assessment | ProbabilisticFramework Development |
| 35 | (Mao et al, 2000) [61] | Creep-fatigue | 9Cr-1Mo Steel | Not stated | Life | MCS/FORM/SA | Method Development | ProbabilisticFramework Development |
| 36 | (Bielak et al, 2003) [62] | Creep-fatigue | 0.5Cr-0.5Mo-0.3V Steel | Pipes and piping systems | Crack initiation | FORM | In-service Assessment | Risk-informed In-service Inspection Period |
| 37 | (Vojdani et al, 2019) [63] | Creep-fatigue | SS316L (N) | Pipe with surface defect | Crack growth | MCS/FORM/SA | In-service Assessment | ProbabilisticFramework Development |

* 1. **Results**

In the following, the reports and publications by EASICS Team as well as those available in the literature are analysed using different criteria and subsequently discussed in Section 4.3.

* + 1. **Publications Data**



**(a)**



**(b)**

**Figure 7. Frequency of publications versus (a) Year of publication, (b)Publication county of origin (first author).**

* + 1. **Problem Type**



**(a)**



**(b)**



**(c)**



**(d)**

**Figure 8. Frequency of publications versus (a) Objective of case study or publication, (b)** **Case study type, (c) Failure mode or degradation mechanism, (d) Feature type.**

* + 1. **Modelling**



**(a)**



**(b)**



**(c)**

****

**(d)**

**Figure 9. Frequency of publications versus (a) Code used, (b) Probabilistic methods used, (c) Sensitivity analysis used, (d) Software platform.**

* + 1. **Inputs**



**(a)**



**(b)**

****

**(c)**



**(d)**



**(e)**

**Figure 10. Frequency of publications versus (a) Number of statistical parameters, (b) Material type, (c) Data sources, (d) Distribution type, (e) Correlations.**

* + 1. **Outputs**



**(a)**

 ****

**(b)**



**(c)**

**Figure 11. Frequency of publications versus (a) Metric/Measure calculated, (b) Risk/Uncertainties, (c) Verification/Validation.**

* 1. **Discussion**

There are a number of points revealed by the charts shown in Section 4.2 and worth expanding on next:

* Over 80% of all public domain publications are from the last 10 years, and approximately 30% of publications are from UK authors. This is perhaps an indication of several different contributory factors:
	+ The maturity of probabilistic approaches at this time.
	+ Higher accessibility and lower cost of high-performance computing, software and source code.
	+ Plant life extension objectives (particularly in UK).
	+ Wider dissemination in order to change culture from determinism to probabilism in the sector. It is interesting to note that a survey of practitioners in 2006 associated with fatigue analysis concluded that a probabilistic approach to fatigue was not a high priority [64].
	+ Regulatory bodies promoting the determination of probability of failures for structural integrity assessments in satisfaction of PSAs.
* Half of the publications are associated with probabilistic methodology development, with the remainder shared almost equally between health monitoring (inspection interval) and life prediction objectives. This is a reinforcement of the point that probabilistic methods are mature, but not probabilistic methodologies, which tend to be failure mode specific.
* Just over 50% of publications are associated with actual in-service components, compared to theoretical or experimental (test) based problems. There is always a difficulty associated with the publication of nuclear plant related research, and so theoretical, benchmark or purely experimental (test) cases are all useful to disseminate methodologies in a desensitised manner.
* There is an even distribution of problems with a focus on crack initiation, growth and rupture.
* Tubes and pipes are a common feature for probabilistic assessment; probably due to the volume of such plant components, and susceptibility to loading uncertainties (mechanical and thermal).
* The R5 code is not commonly used outside of the EDF related EASICS case studies analysed. In fact, few publications reference any of the other codes either. There is large category of ‘Other’ which refer to multiple mentions of several standards, empirical rules and models, e.g., FAVOR, R66 and ASTM. Though not codes, it appears many publications use a composition reference sources to facilitate the modelling of creep-fatigue in particular.
* On average in a third of cases, more than one probabilistic method was used, and overall, MC simulation is by far the most popular method, followed by LHS and then direct statistical treatment of experimental data. FORM/FOSM are not popular, possibly due to their unsuitability and inaccuracy when incorporating non-Normal input distributions.
* Around only 30% of cases use a SA approach, which is surprising for the following reasons. SA is used to prioritise the importance of statistical input parameters from measures which reflect he uncertainty contribution of each parameter compared to the output. In this way, it helps direct further data collection exercises, focusses design effort and helps allocate resources to control certain parameters. Once the probabilistic routine has been developed for a problem, it is also not a great deal of additional effort to derive sensitivity measures, and many different types of approach are available for the practitioner, even allowing intervals to be used to determine sensitivity measures.
* Software platforms used to conduct probabilistic routines are not stated in the majority of publications or state the use of commercial packages such as MATLAB and FAVOR. The high use of spreadsheets (MS Excel with VB Macros) within the EASICS case studies is attributed to a select number of individuals conducting the assessments.
* About two thirds of all cases use fewer than 10 statistically characterised parameters. The complexity of creep-fatigue analysis may demand more, but the obvious inhibitor is available data at statistically relevant sample sizes. Different models also dictate the inclusion of a different number of parameters. The use of SA could be helpful in this respect, and determine which parameters require further data collection, and which parameters have negligible contribution with respect to their variability.
* For high-temperature applications, stainless steels are showing to be the dominant material type concerning probabilistic structural integrity assessments of components in service or as part of the theoretical case study. Stainless steel clad with low alloy steel is also popular, though low alloy steels are mostly associated with reactor pressure vessel plate.
* Data, assumed statistical, were mostly for material properties and loads, and collated from a variety of sources. Standards and codes were the most popular followed by measurements, and historical plant data. A moderate number of publications failed to provide a source for data at all.
* As expected, the use of Normal and Lognormal distributions to characterise input parameters dominates with two thirds usage across all cases (multiple responses used). A select number of other distributions types are also used, e.g., Uniform, Exponential, Beta, Gamma, Rice etc. The use of Weibull distributions is limited, and possibly reserved for fracture related data.
* In over 40% of cases, some type of correlation analysis between key parameters was used, and although only stated a few times, the strength of correlation was usually high, justifying its inclusion.
* The probability of failure (and frequency of failure if plant number known), is the primary (decision making) output from two thirds of cases, commensurate with conducting a probabilistic approach. Other measures may well have been determined for these cases too of course.
* Risk and uncertainties (assumptions being valid etc) is a judgement made from any comments provided by the author(s) in the reports and papers and is subjective rating. However, there is a pattern where papers in the public domain do not comment often on this, whereas reports not in the public domain often do. Any assumptions questioned in light of reflections of the risks and uncertainty would be interesting to gauge, but not evident in any case study.
* The majority of papers do not state any verification or validation of the work presented. However, the ONR specify that structural integrity assessments should be validated against plant data information. This was observed in only 11% of cases.
1. **Summary and Outlook**

The nuclear industry has traditionally favoured deterministic design code use over probabilistic techniques for structural integrity assessments. However, deterministic design codes require large factors of safety to account for variability in stochastic design parameters. Furthermore, in some cases it has been shown that even large factors of safety may be insufficient when the combined effects of multiple stochastic design variables are considered. Probabilistic design and assessment of reactors allows a more thorough understanding of the effects of uncertainty and variability on reactor performance and enables a more accurate assessment of reliability and risk.

From the perspective of probabilistic structural integrity, procedural guidance for Level 3 and Level 2 approaches is mature, however, there is no generally accepted practice for implementing the Level 1 methods, thus, they are less mature. Of particular interest is the Level 1 Reference Damage Model [13] which could readily be incorporated into existing deterministic design codes as a “design engineer friendly”, especially with a view to future nuclear technologies. The approach forms a lookup curve (a Design Chart) that can be used to determine failure probabilities, as a function of Reference Damage, from a set of stochastic inputs and a deterministic analysis method. It is envisioned that such simple Level 1 procedures will be further developed and included in design codes and assessment procedures, e.g., EDF R5 and R6, RCC-MR, ASME III, BS 7910 and API 579 in the near future for rapid and accurate estimation of the failure probability linked to a deterministic analysis.

In this review, in total, 37 reports and papers were analysed using a systematic approach to gauge recent and current practice in probabilistic approaches in the nuclear sector. The focus was on creep-fatigue failure, mostly in anticipation of high temperature operating characteristics of many AMR designs. In addition to the analysed documents in this study, there is a body of probabilistic work in the public domain which sits outside of applications in the nuclear sector, which could also be useful in defining current trends and practice. It is worth noting that the extraction of information and data from the reports and papers used in the study is not an exact science, and very much open to interpretation in several cases due to the poor quality of reporting, in particular, in peer reviewed papers. Another point is that the development of a probabilistic approach to any problem will be more complex and time consuming than a deterministic approach, particularly in the areas of data collation and statistical characterisation for inputs, and the development of efficient probabilistic routines for different types of models and objectives. No assessment of this was made in this study due to the lack of author reflections in this area in both the reports and papers. Also, the popularity of certain ‘qualities’ seen across the range of probabilistic case studies collated could validate their inclusion when composing a general probabilistic methodology. It could also be argued that just because it is popular or typical, this does not mean that it is optimum or best practice; and what constitutes best practice is difficult to define.

With regard to multi-failure probabilistic design and assessment considering multi-source uncertainties, it is desirable to develop unified probabilistic frameworks. Data-driven surrogate models can be valuable alternatives to direct MC simulation which avoid a large number of FEA simulations thus improving computational efficiency with an acceptable accuracy. For this purpose, classical surrogate models such as response surface model (RSM), artificial neural network (ANN), support vector regression (SVR) and Kriging surrogate (KS) can be incorporated into the unified probabilistic frameworks [65-67]. In addition, advanced variance-reduction techniques, e.g., IS and ARBIS, are powerful and computationally efficient methods for propagating uncertainties. Moreover, data-driven machine learning (ML) techniques have gained great popularity in various areas of science, primarily owing to their flexibility, computational efficiency and capability to uncover complex nonlinear relationships. Accordingly, it is anticipated that surrogate modelling, advanced variance-reduction techniques and ML methodologies as well as their combination will be further adopted in the field of probabilistic structural integrity and life prediction of nuclear components.

It is hoped that a ten-year follow-up to this review will see more detailed publications on nuclear structural integrity assessments dealing with novel, simple yet accurate unified probabilistic frameworks and data-driven approaches applied to new materials, i.e., high-entropy alloys (HEAs) [68] and Ni-base superalloys [69], considering SA. The immediate objective must be to gain acceptance of probabilistic techniques within structural design codes; the methodologies are now sufficiently mature for this to be done.

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**References**

1. Tuck, O.G., C.K. Pyke, and N.J. Underwood, *A review of probabilistic creep assessment reporting relating to volume 2/3 of the R5 procedure.* International Journal of Pressure Vessels and Piping, 2021: p. 104295.

2. World Nuclear Association (WNA), *Nuclear Power Reactors.* https://world-nuclear.org/information-library/nuclear-fuel-cycle/nuclear-power-reactors/nuclear-power-reactors.aspx, 2020.

3. EDF Energy, *Assessment Procedure R5, Volume 2/3, Appendix A15: Advice on Probabilistic Assessments, Draft 2.* 2018.

4. Martin, M. and R. Marshall, *Nuclear structural integrity probabilistic working principles*, N.S.I.P.W. Group, Editor. 2019.

5. IAEA, *Advances in Small Modular Reactor Technology Developments - a Supplement to: IAEA Advanced Reactors Information System (ARIS)*. 2018.

6. Mearns, E. *The Age and Future Size of the Global Nuclear Fleet*. 2016.

7. World Nuclear News, *Rolls-Royce on track for 2030 delivery of UK SMR.* https://www.world-nuclear-news.org/Articles/Rolls-Royce-on-track-for-2030-delivery-of-UK-SMR, 2021.

8. Tancret, F., H. Bhadeshia, and D. MacKay, *Design of a creep resistant nickel base superalloy for power plant applications: Part 1-Mechanical properties modelling.* Materials Science and Technology, 2003. **19**(3): p. 283-290.

9. Steedman, S., *Small but powerful*, in *Ingenia*. 2015.

10. *Probabilistic Safety Analysis - NS-TAST-GD-030 Revision 7*, R. Exley, Editor. 2019, ONR.

11. Booker, J., et al., *A proposal and methodology for the accelerated implementation of probabilistic approaches in the nuclear sector*, in *Proc. 5th International Creep & Fracture Conference (ECCC2021)*. 18-20 October, 2021: Edinburgh.

12. EDF Energy, *Establishing AMR Structural Integrity Code and Standards for UK GDA (EASICS)*. 2019-2021, Department of Business, Energy and Industrial Strategy (BEIS): United Kingdom.

13. Zare Chavoshi, S., R. Bradford, and J. Booker, *A Validated Approach to Simplify the Estimation of the Probability of Creep-Fatigue Crack Initiation for Potential Design Code Implementation.* Submitted to *Eng.Frac.Mech.*, 2021.

14. Martin, M., *Probabilistic Structural Integrity Assessment Guidance for AMR Codes and Standards.* EASICS Work Package 1, Version 3.0, 2021.

15. Melchers, R.E. and A.T. Beck, *Structural reliability analysis and prediction*. 2018: John wiley & sons.

16. Wu, Y.-T., H. Millwater, and T. Cruse, *Advanced probabilistic structural analysis method for implicit performance functions.* AIAA journal, 1990. **28**(9): p. 1663-1669.

17. Burdekin, F., *General principles of the use of safety factors in design and assessment.* Engineering Failure Analysis, 2007. **14**(3): p. 420-433.

18. Bullough, R., et al., *A review of methods and applications of reliability analysis for structural integrity assessment of UK nuclear plant.* International Journal of Pressure Vessels and Piping, 1999. **76**(13): p. 909-919.

19. Melchers, R.E. and A. Beck, *Structural Reliability Analysis and Prediction–John Wiley & Sons.* New York, NY, 1999.

20. Easley, S.K., et al., *Finite element-based probabilistic analysis tool for orthopaedic applications.* Computer methods and programs in biomedicine, 2007. **85**(1): p. 32-40.

21. Youn, B.D., K. Choi, and L. Du, *Adaptive probability analysis using an enhanced hybrid mean value method.* Structural and Multidisciplinary Optimization, 2005. **29**(2): p. 134-148.

22. Zhao, Y.-G. and T. Ono, *A general procedure for first/second-order reliabilitymethod (FORM/SORM).* Structural safety, 1999. **21**(2): p. 95-112.

23. Helton, J.C. and F.J. Davis, *Latin hypercube sampling and the propagation of uncertainty in analyses of complex systems.* Reliability Engineering & System Safety, 2003. **81**(1): p. 23-69.

24. McKay, M.D., R.J. Beckman, and W.J. Conover, *A comparison of three methods for selecting values of input variables in the analysis of output from a computer code.* Technometrics, 2000. **42**(1): p. 55-61.

25. Van Ravenzwaaij, D., P. Cassey, and S.D. Brown, *A simple introduction to Markov Chain Monte–Carlo sampling.* Psychonomic bulletin & review, 2018. **25**(1): p. 143-154.

26. Grooteman, F., *Adaptive radial-based importance sampling method for structural reliability.* Structural Safety, 2008. **30**(6): p. 533-542.

27. Hoole, J., *Probabilistic fatigue methodology for aircraft landing gear*. 2020, University of Bristol.

28. Zentuti, N., et al., *A review of probabilistic techniques: towards developing a probabilistic lifetime methodology in the creep regime.* Materials at High Temperatures, 2017. **34**(5-6): p. 333-341.

29. Bradford, R. and P. Holt, *Application of probabilistic modelling to the lifetime management of nuclear boilers in the creep regime: Part 2.* International Journal of Pressure Vessels and Piping, 2013. **111**: p. 232-245.

30. Holt, P. and R. Bradford, *Application of probabilistic modelling to the lifetime management of nuclear boilers in the creep regime: Part 1.* International journal of pressure vessels and piping, 2012. **95**: p. 48-55.

31. Bradford, R., *Application of probabilistic assessments to the lifetime management of nuclear boilers in the creep regime.* 2015.

32. Zentuti, N., et al. *Management of complex loading histories for use in probabilistic creep-fatigue damage assessments*. in *Pressure Vessels and Piping Conference*. 2018. American Society of Mechanical Engineers.

33. Zentuti, N., et al., *Correlations between creep parameters and application to probabilistic damage assessments.* International Journal of Pressure Vessels and Piping, 2018. **165**: p. 295-305.

34. Cathcart, H., et al. *Probabilistic Methods: Risk Based Design and Assessment*. in *ASME 2019 Pressure Vessels & Piping Conference*. 2019. American Society of Mechanical Engineers Digital Collection.

35. Zentuti, N., et al., *Probabilistic structural integrity: methodology and case-study in the creep regime.* Materials at High Temperatures, 2020. **37**(2): p. 101-113.

36. Zentuti, N., et al., *Plant loading uncertainties and their incorporation in probabilistic creep damage assessments.* International Journal of Pressure Vessels and Piping, 2020. **187**: p. 104134.

37. Cathcart, H., et al. *Probabilistic Lifing Methods for Digital Assets*. in *ASME Turbo Expo 2020: Turbomachinery Technical Conference and Exposition*. 2020. American Society of Mechanical Engineers Digital Collection.

38. Goh, Y.M., C. McMahon, and J. Booker, *Improved utility and application of probabilistic methods for reliable mechanical design.* Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability, 2009. **223**(3): p. 199-214.

39. Kim, W.-G., et al., *Probabilistic assessment of creep crack growth rate for Gr. 91 steel.* Nuclear engineering and design, 2011. **241**(9): p. 3580-3586.

40. Zhu, S., S. Foletti, and S. Beretta, *Probabilistic framework for multiaxial LCF assessment under material variability.* International Journal of Fatigue, 2017. **103**: p. 371-385.

41. Ishikura, S., Y. Xu, and K. Satoh, *Application of the Probabilistic Fatigue Evaluation of Flow-Induced Vibration for Hot-Leg Piping in Japan Sodium-Cooled Fast Reactor.* Nuclear Science and Engineering, 2014. **178**(1): p. 76-85.

42. Qian, G. and M. Niffenegger, *Deterministic and probabilistic analysis of a reactor pressure vessel subjected to pressurized thermal shocks.* Nuclear Engineering and Design, 2014. **273**: p. 381-395.

43. Beaufils, R., E. Meister, and E. Ardillon. *Using a probabilistic approach in the brittle fracture deterministic integrity assessment of a nuclear reactor pressure vessel*. in *ASME 2011 Pressure Vessels and Piping Conference*. 2011. American Society of Mechanical Engineers Digital Collection.

44. Chou, H.-W. and C.-C. Huang, *Fracture risk assessment for the pressurized water reactor pressure vessel under pressurized thermal shock events.* Nuclear Engineering and Design, 2016. **300**: p. 412-421.

45. Appalanaidu, Y. and S. Gupta, *Probabilistic damage estimation in piping components against thermal creep and fatigue.* Nuclear Engineering and Design, 2014. **273**: p. 202-214.

46. Ibisoglu, F. and M. Modarres, *Probabilistic life models for steel structures subject to creep fatigue damage.* Int J Prognost Health Manage, 2015.

47. Tian, Y., et al., *Probabilistic and non-probabilistic failure assessment curves of primary coolant pipe contained internal circumferential surface crack in pressurized water reactor nuclear power plant.* Nuclear Engineering and Design, 2017. **322**: p. 313-323.

48. Li, S., et al., *Probabilistic fracture mechanics analysis of thermally aged nuclear piping in a pressurized water reactor.* Nuclear Engineering and Design, 2013. **265**: p. 611-618.

49. Chen, M., et al., *The probabilistic structural integrity assessment of reactor pressure vessels under pressurized thermal shock loading.* Nuclear Engineering and Design, 2015. **294**: p. 93-102.

50. Qian, G., et al., *Probabilistic leak-before-break analysis with correlated input parameters.* Nuclear engineering and design, 2013. **254**: p. 266-271.

51. Sudret, B. and Z. Guédé, *Probabilistic assessment of thermal fatigue in nuclear components.* Nuclear engineering and design, 2005. **235**(17-19): p. 1819-1835.

52. Nagai, M., N. Miura, and M. Yamamoto, *Pedestrian: Probabilistic fracture mechanics analysis code based on direct sampling with replacement.* International Journal of Pressure Vessels and Piping, 2018. **167**: p. 52-58.

53. Hu, J., et al., *Life prediction of steam generator tubing due to stress corrosion crack using Monte Carlo Simulation.* Nuclear engineering and design, 2011. **241**(10): p. 4289-4298.

54. Maeda, N. and T. Shoji. *Failure Probability Analysis Based on FRI Model for Stress Corrosion Cracking Growth Introducing Residual Stress Distribution by Weld*. in *ASME 2012 Pressure Vessels and Piping Conference*. 2012. American Society of Mechanical Engineers Digital Collection.

55. Chatterjee, K. and M. Modarres, *A probabilistic physics-of-failure approach to prediction of steam generator tube rupture frequency.* Nuclear science and engineering, 2012. **170**(2): p. 136-150.

56. Hojo, K., et al., *Benchmark analyses of probabilistic fracture mechanics for cast stainless steel pipe.* Mechanical Engineering Journal, 2016. **3**(4): p. 16-00083-16-00083.

57. A Jovanovic, et al., *ALIAS-HIDA, a Knowledge-based System for Probabilistic & Sensitivity Analysis of Creep & Fatigue Crack Growth in High Temperature Components.* OMMI, 2004. **3**(3).

58. Deschanels, H., et al., *Assessment of industrial components in high temperature plant using the “ALIAS-HIDA”–A case study.* Engineering Failure Analysis, 2006. **13**(5): p. 767-779.

59. Dogan, B., et al., *Sources of scatter in creep/fatigue crack growth testing and their impact on plant assessment.* Welding in the World, 2007. **51**(7): p. 35-46.

60. Vojdani, A., et al., *Probabilistic assessment of creep-fatigue crack propagation in austenitic stainless steel cracked plates.* Engineering Fracture Mechanics, 2018. **200**: p. 50-63.

61. Mao, H. and S. Mahadevan, *Reliability analysis of creep–fatigue failure.* International journal of fatigue, 2000. **22**(9): p. 789-797.

62. Bielak, O., V. Bína, and J. Korou, *Risk Based Lifetime Assessment of Piping under Creep-Fatigue Conditions (M495).* 2003.

63. Vojdani, A. and G. Farrahi, *Reliability assessment of cracked pipes subjected to creep-fatigue loading.* Theoretical and Applied Fracture Mechanics, 2019. **104**: p. 102333.

64. Darlington, J. and J. Booker, *Development of a design technique for the identification of fatigue initiating features.* Engineering failure analysis, 2006. **13**(7): p. 1134-1152.

65. Song, L.-K., G.-C. Bai, and C.-W. Fei, *Multi-failure probabilistic design for turbine bladed disks using neural network regression with distributed collaborative strategy.* Aerospace Science and Technology, 2019. **92**: p. 464-477.

66. Song, L.-K., G.-C. Bai, and C.-W. Fei, *Dynamic surrogate modeling approach for probabilistic creep-fatigue life evaluation of turbine disks.* Aerospace Science and Technology, 2019. **95**: p. 105439.

67. Yang, H., et al., *Dynamic reliability based design optimization of the tripod sub-structure of offshore wind turbines.* Renewable Energy, 2015. **78**: p. 16-25.

68. Rozman, K.A., et al., *Long-Term Creep Behavior of a CoCrFeNiMn High-Entropy Alloy.* Journal of Materials Engineering and Performance, 2020. **29**(9): p. 5822-5839.

69. Hardy, M., et al., *Solving recent challenges for wrought Ni-base superalloys.* Metallurgical and Materials Transactions A, 2020. **51**(6): p. 2626-2650.