Orcelle Horizon

Wind as main propulsion

ORCELLE HORIZON

Deliverable D3.2 - Data-driven numerical framework for structural integrity assessment

Mekete Mulualem Mebratu, Kris Hectors and Wim De Waele (UGent)

Orcelle Horizon - Project: 101096673 — Orcelle — HORIZON-CL5-2022-D5-01
Start date: 2023-01-01
Duration: 60 months
Project coordinator: Wallenius Wilhelmsen Ocean AS
Coordinator contact: Vår Emilie Kjærnes, varemilie.kjaernes@walwil.com

This project has received funding from the European Union's Horizon Europe Research and Innovation program under grant no 101096673.

Funded by the European Union

Document information

Project Acronym	Orcelle
Project No.	101096673
Title	Orcelle Horizon_Del_3_2_UGent_M12/ Data-driven numerical framework for structural integrity assessment
Deliverable no.	D3.2
Draft delivery data	2023-12-18 - date for submission of draft version
Dissemination level	PU - Public
Deliverable type	Report
Authors	Mekete Mulualem Mebratu (UGent), Kris Hectors (UGent), Wim De Waele (UGent)

Document history:

Version	Date of issue	Content and changes	Edited by
1.0	18/12/2023	First draft	See authors

Abstract

Deliverable abstract	
One of the challenges regarding the development of a wing system for main vessel propulsion is to gain insight into its real-life structural integrity. This would allow early detection and identification of malfunction and degradation of its critical mechanical components. To address this challenge, the main objective of WP3.2 is to develop a data-driven numerical framework for structural integrity assessment of the wing system. The framework includes digital twinning of the wing system and will integrate real-time load monitoring sensors and numerical models of material and joint degradation that allow fatigue lifetime prediction. The prolonged exposure to wind and inertia loads and environmental conditions leads to structural degradation of the wing structure. This work focuses on fatigue, the progressive and localized structural damage occurring under cyclic loading. It is the primary degradation mechanism affecting the components and joints of the wing structure. To model the fatigue life of the wing sail, the stochastic nature of both the operational load and material strength degradation has to be considered. In this work, algorithms and reduced-order models will be developed aimed at simulating the degradation and fatigue life of critical mechanical components of the wing system subjected to uncertain operating conditions. Leveraging stochastic finite element simulation techniques and surrogate models, the study uses endurance based fatigue life prediction methods (also known as S-N approach). The stochastic finite element simulation enables the consideration of uncertainties in input parameters such as load and material properties. A Design of Experiment (DoE) framework is used to represent a spectrum of load and material input parameters. This approach allows for the systematic exploration of the parameter space, facilitating a deeper understanding of the impact of these factors on component degradation and lifetime. To mitigate the computational intensity of simulations, surrogate models are developed. Surrogate models serve as efficient approximations of the complex finite element simulations, allowing for faster evaluations across a range of input parameters while maintaining accuracy within acceptable margins. The fatigue life analysis is based on established S-N curves obtained from open-source literature, specifically tailored for steel components, welded joints, and (composite) sandwich structures. The integration of these curves into the predictive models forms a basis for assessing the fatigue life under varying load conditions. To qualify and quantify the effects of component failure on the structural integrity and safety of the entire wing system, the wing system is divided into three subsystems: foundation, main wing, and flap wing. To understand the interplay between fatigue reliability and structural integrity, a Fault Tree Diagram (FTD) is developed. This diagram illustrates the relationship between the overall integrity of the wing system and the fatigue failure of its individual, crucial components. Leveraging the design configuration of the wing system and drawing from fault tree diagrams developed for offshore wind turbine blades, an equivalent Bayesian network is created. Using the Continuous Time Bayesian Networks (CTBNs) method and the probability of failure (PoF) of the components, the system's fatigue reliability is estimated. This approach allows for detailed quantification of how component failures impact the overall structural integrity and safety of the entire wing system. In practical operational scenarios, (real-time) load data will be collected from field sensors. The developed surrogate models will allow to evaluate the structural response of components within the wing system using the sensors' data. The obtained structural response data will be integrated into the probabilistic fatigue lifetime and system reliability assessment models. The integration of these approaches aims to enhance the safety and reliability of the wing system by enabling early detection of issues and implementing proactive maintenance strategies.	

Contents

1 Introduction 5
1.1 Wing system for wind-assisted propulsion system 5
1.2 Main wing subsystem - fatigue reliability evaluation methodology 6
2 Data-driven numerical framework for the structural integrity assessment of the wing system: description of the main tools....8
2.1 Design of experiments (DoE): generation of representative samples 8
2.2 Finite element simulations 9
2.3 Surrogate model development....10
2.4 Components' fatigue lifetime prediction....12
2.4.1 Introduction 12
2.4.2 Fatigue life assessment 12
2.4.3 Welded steel joints 12
2.4.4 Sandwich panel fatigue failure 13
2.5 Components' fatigue reliability calculation....13
2.6 System reliability estimation 14
2.6.1 Wing system fault tree diagram....14
2.6.2 Reliability assessment methods 15
2.6.3 Wing system reliability analysis using CTBNs 16
3 Conclusions & further steps....17
References....18

1 Introduction

1.1 Wing system for wind-assisted propulsion system

The stresses experienced by any component of the wing system should not exceed the allowable stresses under either normal or extreme operating conditions. Given that the wing system will operate under highly stochastic, cyclic loading conditions, the fatigue limit state is most probably the critical limit state for design. This work aims to estimate the fatigue reliability and to assess the structural integrity of the wing system based on the failure contribution of the system components by considering load and material uncertainties.

This study considers the geometrical design configurations of “the two-wing element or Oceanbird’s wingsail design” designed by Alfa Wall. The wing system comprises three structural subsystems: (1) the foundation structure, (2) the main wing, and (3) the flap wing, shown in Figure 1. The fatigue reliability of the entire wing system is to be studied based on the failure contribution of its subsystems. The foundation structure and support structure of the wing system (i.e., the mast structure) are the two main load-bearing structures; hence a detailed fatigue lifetime analysis is required for these structures. The mast support structure of the wing system is being studied as one of the components within the main wing subsystem, whereas the foundation is studied as a separate subsystem.

The fatigue loading scenarios that are considered In the structural reliability analysis of this study, are based on DNV standards. The combination of wind and inertia loads are taken as the primary loads applied on the wing system, based on the DNV standard ST-0511 (DNV-ST-0511, 2022). The combination of the reaction forces and moments due to the overturning moment of the wing system and horizontal stress in the deck due to global wave bending of the hull girder will be considered in the fatigue life analysis of the foundation structure and its components.

Finite Element Analysis (FEA) will be used to model the structural response. Based on those results the fatigue performance of the system can be analyzed. Multi-scale Finite Element (FE) simulations for each subsystem will be applied to reduce the complexity and computational costs with the consideration of load and material uncertainties. The first stage of this study is the reliability estimation of the main wing subsystem. Next, a fatigue reliability study of the foundation structure will be performed using the aerodynamic and inertial loads at the interface between the main wing system and the foundation.

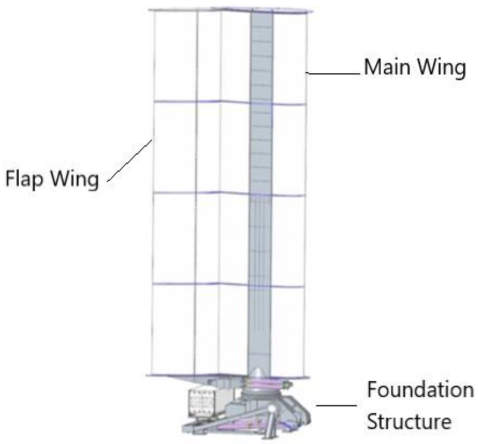

Figure 1 Oceanbird’s wing system

The geometrical configuration of the main wing subsystem structure shown in Figure 2 is taken from AlfaWall's “Oceanbird wing 560” general assembly drawing data. The figure shows the naming convention of the different components used for this study.

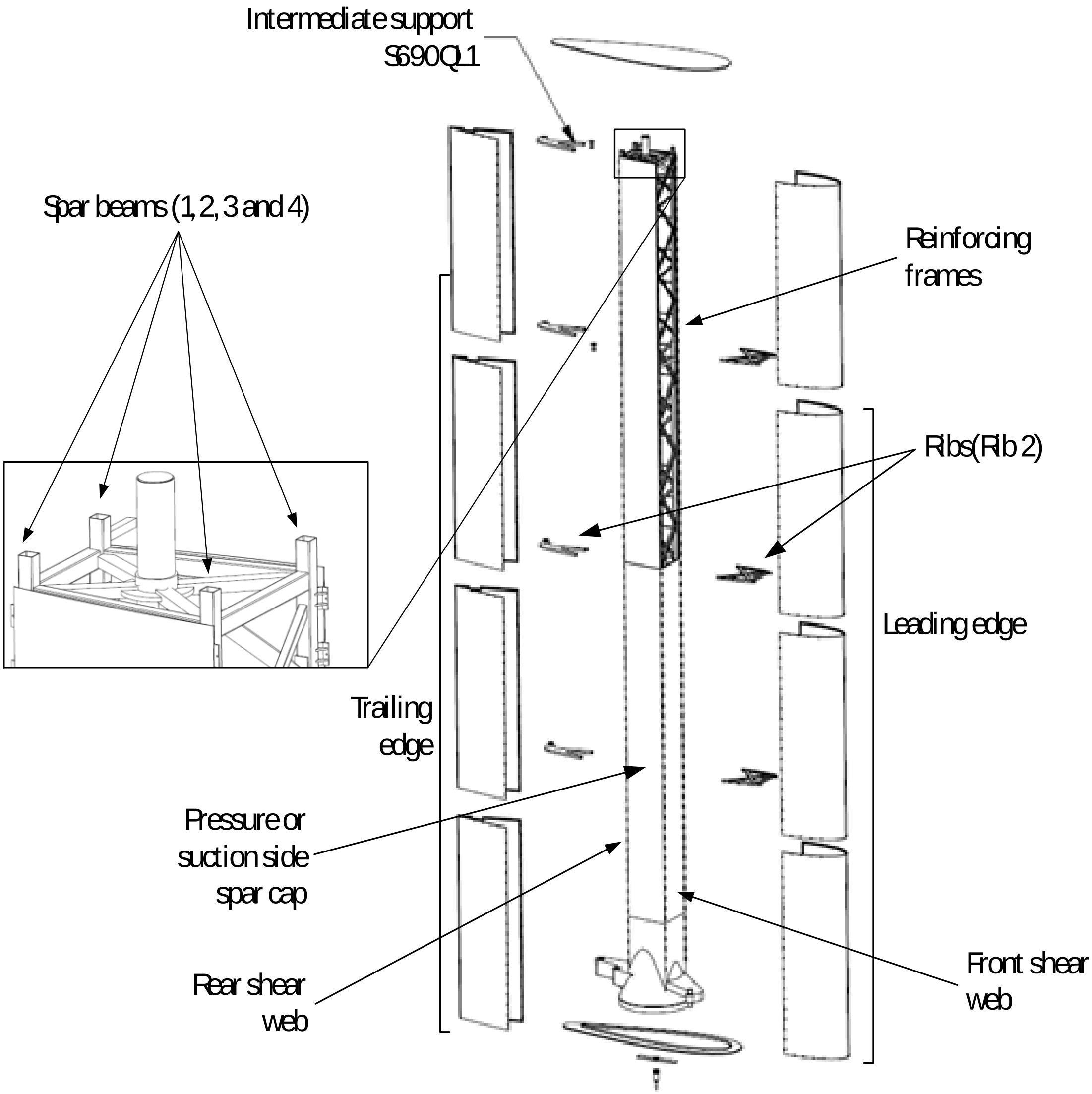

Figure 2 Components of the main wing subsystem from AlfaWall Oceanbird wing design

1.2 Main wing subsystem - fatigue reliability evaluation methodology

In actual engineering design, obtaining the exact solution for the failure probability of a system is impossible due to the stochastic nature of the input parameters. MC (Monte Carlo) simulations, First-Order Reliability Method (FORM), and Second-Order Reliability Method (SORM) are some of the common methods being used to obtain approximated solutions, especially for not too complex structures. Though it requires a large sample size, and each sample implies a deterministic structural response analysis, the MC simulation method is simple and widely applicable. However, the direct application of the FORM/SORM and MC simulation techniques becomes inefficient and impractical when the limit state function (LSF) is not explicitly available in a closed-form equation. In such cases, numerical calculation procedures are necessary such as FEA of the global system and/or subsystems (Shittu, Kolios, et al., 2021), (Chen et al., 2024). Finite Element Analysis (FEA), for instance, involves breaking down a structure into numerous small elements and performing calculations across these elements in a continuous manner to understand the behavior of the entire structure. Since the main wing system is composed of a variety of materials, has intricate geometries, and is subjected to multi-axial and non-linear loads, it is challenging to fully evaluate its structural reliability with simple numerical models. Therefore, the stochastic FEA technique is used to obtain the structural response and define the fatigue LSF of the system.

In the stochastic FEA, the uncertain nature of the input parameters can be represented by using representative samples generated using Quasi-Monte Carlo Sampling (QMCS). Considering the computational expense of the FE simulations, surrogate models will be developed based on the FE simulation results obtained for the representative samples. Next the surrogate models will be used to determine a sufficient amount of stress field data. This data is then used to determine the probability distribution function (PDF) of the fatigue stress amplitude at critical locations of each component. MC simulation will be applied to determine components' fatigue lifetime using the obtained stress amplitude data and fatigue deterioration models (S-N curves) of components based on open-access fatigue test data. This is motivated by the fact that, with an increasing number of samples, the MC simulation method can converge to the true and correct probabilistic results (Shittu et al., 2020). Based on the fatigue lifetime estimation of critical locations in each component obtained from the MC simulations, the corresponding components' fatigue lifetime probability distribution function will be obtained. A basic Fault Tree Diagram (FTD) is then constructed to illustrate the hierarchical relation between the fatigue failure of the wing system (top event) and the fatigue failure of its critical components (basic events). This FTD will be represented by equivalent Bayesian networks. Subsequently, the fatigue reliability of the wing system will be estimated through the utilization of the components' probability of failure (PoF) and the Continuous Time Bayesian Networks (CTBNs) method.

In practical operational scenarios, real-time load data (potentially supplemented with structural health data) will periodically or continuously stream from field sensors. Surrogate models will evaluate the structural response of components in the wing system using the monitored load data. The obtained structural response data will be integrated into the probabilistic fatigue lifetime assessment models. The integration of these approaches aims to enhance the safety and reliability of the wing system by enabling early detection of issues and implementing proactive maintenance strategies. The structural integrity assessment framework for the wing system is illustrated in Figure 3. More details of the phases involved in evaluating fatigue reliability within the framework are outlined in section 2 of the document.

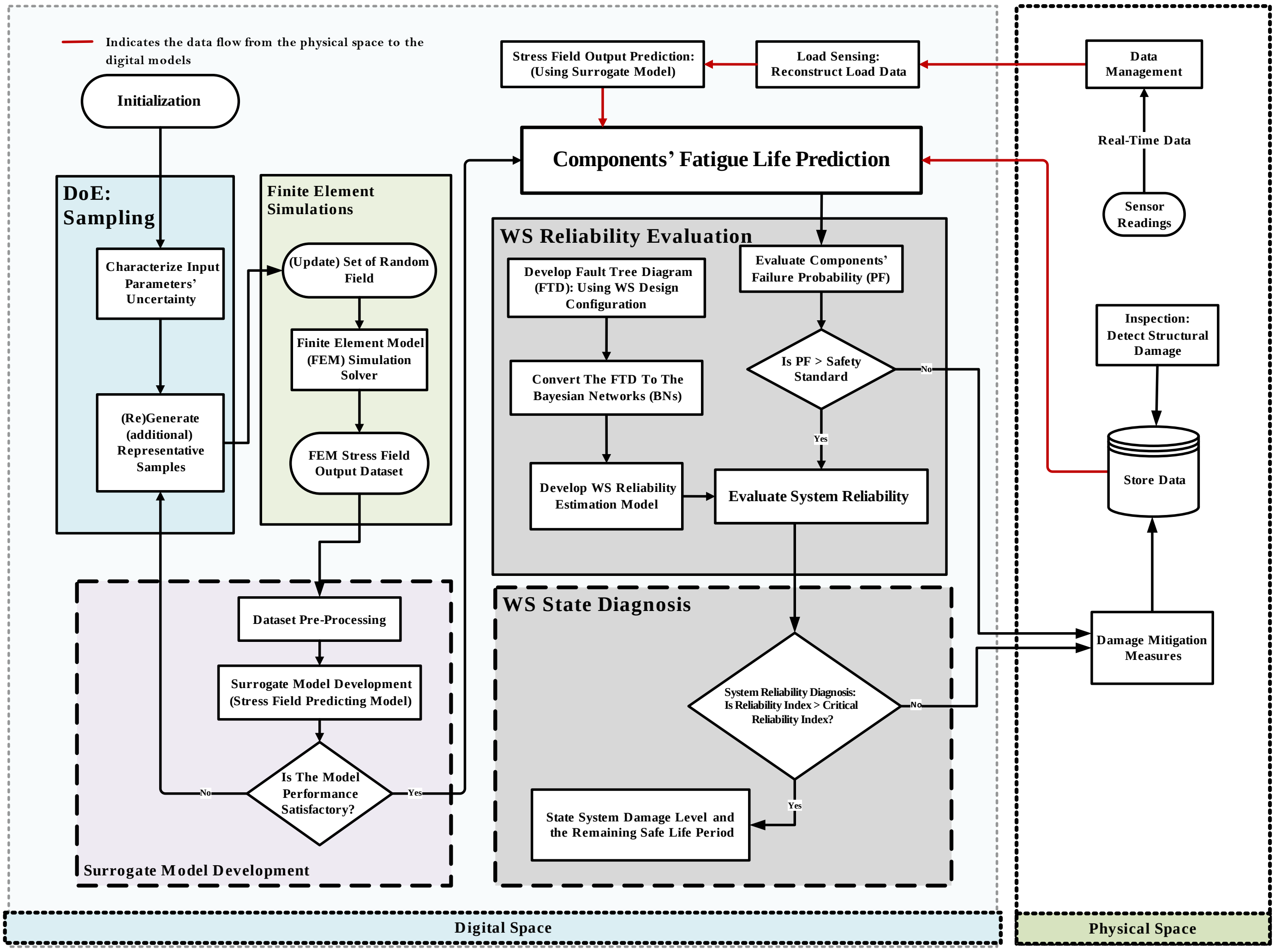

Figure 3 Data-driven numerical framework for the structural integrity assessment of the wing system

2 Data-driven numerical framework for the structural integrity assessment of the wing system: description of the main tools

2.1 Design of experiments (DoE): generation of representative samples

The incorporation of parameter uncertainties and methods to describe and address these uncertainties in structural analysis have been a prominent research focus over the past 30 years (Y. Liu et al., 2019). Studies indicate that one of the most significant concerns of stochastic simulations is efficiently and accurately generating suitable random fields to represent the uncertainties. Balancing the accuracy and the computational costs, an appropriate number of random fields need to be generated in any stochastic simulation.

In this work, material and load uncertainties are represented by independent random variables as input parameters for FE simulations. Table 1 provides an overview of the considered random variables, their mean values and coefficients of variation (CoV). Deterministic FE simulations are performed with representative samples from these variables. A large number of possible combinations of values is expected; it is computationally too expensive to consider all combinations in the FEA. Therefore, a multidimensional random sampling technique is applied to generate representative combinations of values that cover the design space more uniformly ensuring that each interval contains a maximum of one sample. This can be achieved with Quasi Monte Carlo (QMC) sampling.

Table 1 Input parameters and their uncertainties

Input Parameters	Units	Distributions	Mean	CoV %	References
True wind speed	m/s	Gaussian	6.84	43.3	IMO MEPC.1/Circ.896
Critical angle of attack	degrees	Gaussian	16	18.75	(C. Li et al., 2023)
Vessel speed	m/s	Uniform: ranges	5.15	7.2	Orcelle GA Document
Density of air	kg/mm^3	Gaussian	1.23	5.61	-
Steel S690QL elastic modulus	GPa	Gaussian	210	15	(Kolios et al., 2018)
PET foam shear modulus	MPa	Gaussian	[1]28.75	[2]10	[1](Xie et al., 2022),
GFRP elastic modulus	GPa	Gaussian	[1]15.75	[2]10	[2](Kim & Hwang, 2004)

2.2 Finite element simulations

FEA is a suitable tool for fatigue performance simulations of structures where the full-scale testing is overly complex and costly. In a wing-assisted propulsion system, the wing system should resist combined environmental phenomena of uncertain magnitude (e.g. wind, wave, operational loads, etc). Since full-scale testing is challenging, the stochastic response of a structure under specific loading conditions is determined through FEA.

Each of the wing system's three subsystems (the foundation, main wing, and flap wing) contains structural components and joints. To effectively analyse the entire wing system, a multi-scale finite element modeling approach is used. This method is particularly advantageous for large and complex structures. In this work, the focus is on the analysis of the main wing subsystem. Deterministic FE simulations are performed for each combination of the considered representative samples of combinations of input parameters. The details of the FE model are described in Table 2.

The fatigue loads acting on the wing system and foundation structure included in the structural design load calculations are based on DNV's standard on wind-assisted propulsion systems (WAPS) (DNV-ST-0511, 2022). Wind and inertial loads are the two fundamental loads to be considered in the fatigue analysis of the wing system. Inertia loads are loads excited by the motion of the vessel and the self-weight of the WAPS.

Table 2 FE model information

CAD model of the main wing system	Using AlfaWall Oceanbird wing design general assembly drawing The airfoil shape of the main wing (NACA0025) is taken from an open-access airfoil design website.
Software	Abaqus v2023, Python, X-foil 6.99
External load and boundary conditions	Fatigue loads: wind and inertia loads are considered based on DNV-ST-0511 (2022).
	The mean wind speed data at 10m above the sea surface with probability for different 'wind states' characterized by true wind speed and true heading relative to the ship is taken from the Global Wind Probability Matrix data IMO MEPC.1/Circ.896 appendix 2 of the IMO circular.
Aerodynamic pressure load model	Data regarding the distribution of pressure over the suction and pressure sides of the airfoil across its chord length is taken from X-foil 6.99 open-source software.
	Data regarding the variation of lift and drag coefficients of NACA 0025 airfoil to the angle of attack is taken from the work of Klemperer et al. (Klemperer et al., 2023).

Inertia load	DNV inertia load modeling procedures are applied for a Ro-Ro ship having the main dimensions of the ship reported in the work of Nielsen et al. (Nielsen et al., 2019).

The primary output of the FEA is the nominal stress field of critical components within the main wing subsystem. These stress field outputs serve as input for training a surrogate model. The stress fields determined with the surrogate model will enable the determination of the fatigue lifetime for these specific components.

2.3 Surrogate model development

In the past 20 years, the application of surrogate models for structural reliability analysis has grown (Chen et al., 2024). The two primary objectives of surrogate models in this study are (1) to generate larger datasets of components' stress fields to obtain more representative probability distribution functions, and (2) to enable real-time evaluation of the structural response of the wing system given real-time or periodically assessed data from load sensors.

Why is the generation of larger stress field datasets needed? Although the QMC sampling used in the DoE stage is one of the best methods for multivariable sampling and has superior performance on the uniformly covering of the probability space, it cannot consider all the possible combinations of input variables. In addition, the FE model of the main wing system is computationally expensive, so it is not feasible to conduct deterministic FE simulations for many representative samples. The latter is required to determine representative stress field probability density functions. Therefore, surrogate models will be developed using a learning dataset of the limited numbers of samples of the combinations of input parameters and their corresponding FE simulations stress field outputs. The surrogate models will give the possibility of determining stress field outputs for a larger number of input variable combinations for critical components of the main wing system than what is possible with the FE simulations.

In FEA-assisted reliability analysis, various surrogate modeling techniques such as Artificial Neural Network (ANN) (Shittu, Mehmanparast, et al., 2021), Support Vector Machine (SVM) (Z. Liu et al., 2023), and Kriging model (Chen et al., 2024) are applicable for deriving the performance functions expressed in terms of stochastic variables. In this study, fatigue load parameters and material data serve as the inputs, and the stress fields in critical regions of the components as outputs for the surrogate model.

Though the surrogate model type to be used is not yet decided, one of the most popular applicable models is the Feed-forward Neural Network (FNN). Figure 4 shows the architecture of the FNN in which the samples representing load and material properties are the input variables and the corresponding stress field outputs resulting from the FE simulations are output variables. The FNN models will establish an implicit function relationship of load, material parameters, etc., with the nominal stress of critical regions in each component.

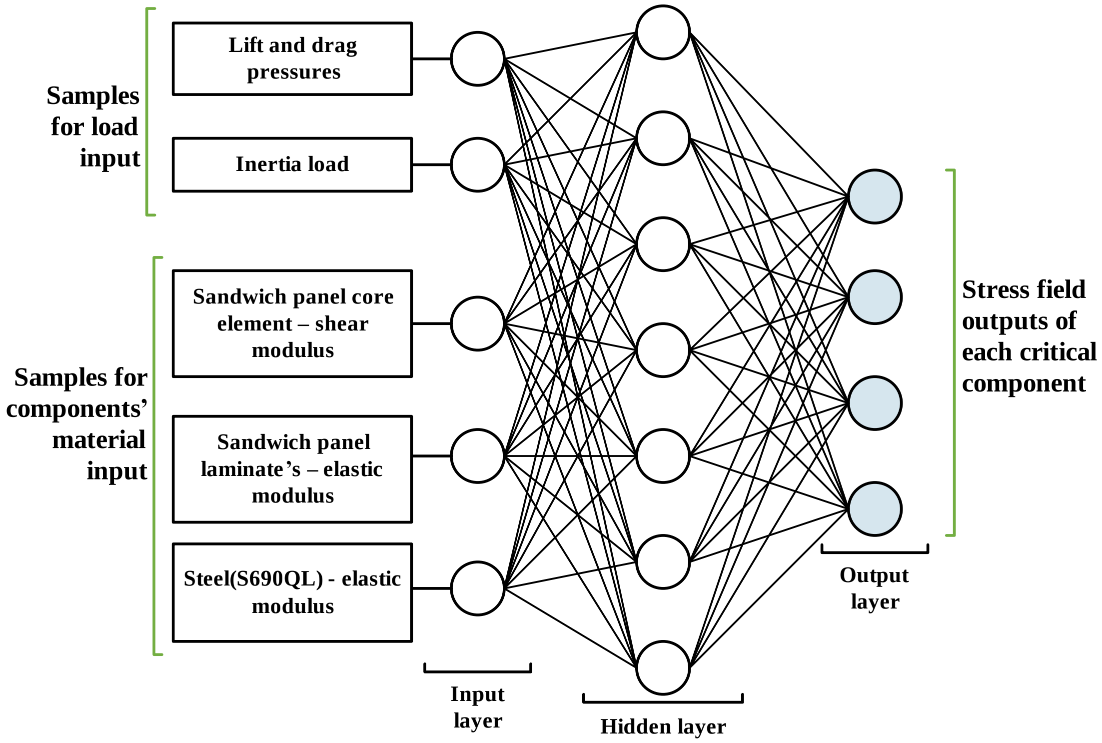

Figure 4 Single hidden layer Feed-forward Neural Network (FNN)

If the predictive performance of the models falls below satisfactory levels, additional representative samples of a combination of input parameters can be generated using the same sampling technique, and FE simulations will be conducted using these new samples. This step would be continued until the performance of the surrogate model reaches the desired level. The stress field outputs obtained from these simulations will then enhance the knowledge of the model. Subsequently, validated surrogate models will be acquired and utilized to generate stress field data for larger sets of combined input parameters, thereby expanding the nominal stress field dataset for each component.

To quantify the uncertainty in the nominal stress range affected by random loads and uncertain material parameters, various probability distributions, such as lognormal, Weibull, Gamma distributions, etc., will be employed to fit the regenerated data. The most suitable probability distribution function will be selected for further analysis of the probabilistic fatigue lifetime of components.

The generation of additional samples will be done with sampling techniques that improve the performance of the surrogate model. This is most commonly done through adaptive sampling (Hu & Mahadevan, 2018). An adaptive sampling strategy or learning function guides the selection of candidate samples to update the sample set during the analysis process (Chen et al., 2024). Exploitation-based and exploration-based sequential design methods are the two most common adaptive sampling methods. In exploration-based ones, new sample points will be searched from the dense region in the sample space and taken from the dense sample space and filled up evenly (Zhang et al., 2023). This method will be applied in this study.

In addition to generating larger datasets, the developed surrogate models will be used to predict the stress field at critical regions of the components from the real-time load monitoring sensors. In this case, the pre-processed load data from the load monitoring sensors will be fed into the models, and the models will predict the stress field output corresponding to each input value. Then, the same procedure will be applied to calculate the probability of failure of that component using the stress amplitude data obtained from the real-time load sensors.

2.4 Components' fatigue lifetime prediction

2.4.1 Introduction

The wing system is composed of different components mainly made up of high-strength steel (S690QL) and composite-based sandwich panels (glass fiber reinforced polymer (GFRP) face sheets and PET foam core). The fatigue deterioration modes of these components depend on the constituent materials. In this work, the focus is on macroscopic/component level fatigue failure. For sandwich composite panel components, the fatigue strength estimation method is based on the shear failure of the core element/region and the tensile/compressive failure of the face sheet laminates. For the steel components and their welds, fatigue strength is dominated by principal stresses that can be determined using either the nominal stress approach and known stress concentration factors, or either the structural stress approach that accounts for stress concentration resulting from the weld joint. Fatigue strength data (i.e. S-N curves) of components are taken from open-source literature.

Lifetime probability distribution data of the components is a prerequisite to perform the structural reliability analysis of systems by using Bayesian Networks (BNs). For most marine systems, there is a scarcity of lifetime distributions and likelihood data for the characterization of component lifetime. Most system reliability analysis studies express the probabilities of failure, commonly using exponential equations, with a constant failure rate parameter. The failure rate parameter is usually taken from reports, manuals, and expert opinion (H. Li et al., 2020). Besides the lack of failure rate data for structures similar to the studied wing sail, the fatigue failure rate of a component cannot be accurately represented by a constant parameter. In this study, the lifetime distributions of the main wing system components will be obtained using probabilistic finite element and fatigue strength analyses.

2.4.2 Fatigue life assessment

The most common fatigue life evaluation method for structural components is a fatigue damage accumulation analysis based on Miner's rule and the well-known S-N curves. In this study, the S-N approach will be the primary method to be applied for all components of the main wing subsystem. A fatigue damage accumulation model predicts the fatigue life of a structure subjected to a certain stress spectrum by combining the stress history with the S-N curve data. In this case, the stress-based S-N curve (including stress correction factors) is the data source for fatigue life calculation, and the load sequence effect is usually neglected. For stress levels lower than the fatigue limit, the number of cycles to failure N_f is assumed to be infinity, which means the stress fluctuations below the fatigue limit are non-damaging, according to the Miner rule. However, it has generally been accepted that there is no fatigue limit in variable amplitude loading conditions. Therefore, modification of the S-N curves for stress ranges lower than the fatigue limit will be considered in this study.

By using the surrogate model described higher (trained based on the stress field output results obtained from FEA), a large amount of stochastic stress amplitude data will be generated for critical regions of each component. The obtained stochastic stress amplitude data will be fitted with probability distributions which can represent the stress range parameter. The fatigue lifetime of components will be determined by combining the obtained stress range distribution and nominal stress-based S-N curve constants using the MC simulation method. Then, the calculated components' fatigue lifetime data will be fitted with a best-fit probability distribution model. The result will enable us to estimate reliability indices such as the probability of failure or reliability of each component within the subsystem.

2.4.3 Welded steel joints

Welds in steel structures are typical fatigue critical details. When using finite element analysis to assess welds, stress results will be non-converging due to the geometric discontinuity. In other words, the stresses tend to go to infinity as the mesh is further refined. Consequently, the stress values calculated by the finite element software exactly at the weld toe cannot be used for fatigue calculations directly. Generally, fatigue assessment of structural details requires determination of a nominal stress that can be used together with a stress concentration factor or an S-N curve of a certain joint configuration (also called detail category) that is reported in a structural design code. For complex parts, such information might not be available and determination of the nominal stress is difficult or even impossible. Therefore, the structural stress approach (also called hot spot stress approach) has been developed. In its most simple form it is based on the extrapolation of surface stresses calculated at two points located at different distances from the weld toe. The structural stress approach is well established at this point and has been adopted by design codes for both onshore and offshore applications. UGent has implemented this approach in a numerical framework that will be used in this project.

2.4.4 Sandwich panel fatigue failure

Sandwich composites can fail in several ways, including tension or compression failure of the facings, shear failure of the core, wrinkling failure of the compression facing, local indentation, debonding of the core/facing interface, and global buckling. The initiation, propagation, and interaction of failure modes depend on the type of loading, constituent material properties, and geometrical dimensions (Sharma et al., 2006). Fatigue damage models are widely adopted for fatigue life analysis of the sandwich components. The above-mentioned failure modes and the fatigue data (S-N curves, residual strength, or stiffness degradation rules) are the basis for life analysis. There are two approaches to analyse the life of sandwich composites based on the dominant failure mode of the component.

The first approach assumes that, under cyclic loading conditions, the main failure mode of the sandwich panel is the shear failure of the core. This is because cyclic loading reduces the residual shear strength of the foam core. The subsequent face sheet fracture and face sheet/core delamination are caused by the core failure (Zaharia et al., 2020)., and the life of sandwich panels can be predicted by using the stress in the core and this can simplify the life prediction process of sandwich panels (Bednarcyk et al., 2013), (Ma et al., 2020).

The second approach considers both main failure modes; face sheet tension/compression fracture and core shear failure (Zenkert & Burman, 2011a), (Ma et al., 2021), (Suzuki & Mahfuz, 2018). These researchers stated that for high load amplitude and a small number of cycles to failure, the beams fail by core shear fracture, while for lower loads and many cycles to failure the beams fail by face sheet tensile failure (Zenkert & Burman, 2011b). This is due to the difference in slopes of the S-N curves, especially the small slope of the core, resulting in an inflection point where the failure mode changed from core shear to skin tensile failure mode (Zenkert & Burman, 2011b), (Suzuki & Mahfuz, 2018). In this study the second approach will be followed.

2.5 Components' fatigue reliability calculation

Reliability analysis is performed to determine the probability that the structure or system satisfies its specified design function under a given service condition. This response is defined by a limit state function $g(x)$, and failure is defined as the point that the response function exceeds some threshold value $g^{\max}$. For a system with m failure modes, the reliability R_m is defined as:

$$R_m = P[g_1(\mathrm{x}) - g_1^{max} \leq 0 \cap g_2(\mathrm{x}) - g_2^{max} \leq 0 \cap \cdots \cap g_m(\mathrm{x}) - g_m^{max} \leq 0] \tag{1}$$

$$R_m = 1 - P_{mf} \cong 1 - P\big[min\big(g_1(\mathrm{x}), g_2(\mathrm{x}), \cdots, g_m(\mathrm{x})\big) > 0\big] \tag{2}$$

It is complex to calculate the reliability if there is interaction between the m failure modes. A simplification can be made by only considering the most probable or a certain failure mode. The reliability can then be calculated with the equation below. This work focuses on the reliability of the system under fatigue loading, therefore component's reliability under fatigue failure mode could be expressed as.

$$R = 1 - P[g(x) > 0] \tag{3}$$

where $g(x)$ is the fatigue limit state function. The most simple case assumes the structure is subjected to constant amplitude stress for an infinite number of cycles and local fatigue strength is described by Gaussian distribution. The fatigue failure probability can be calculated as:

$$P_f = \emptyset(-\beta) \tag{4}$$

Where β is the fatigue strength reliability index or safety margin for failure probability, and $\emptyset$ is a normal standard cumulative distribution function operator.

In most real cases the stress amplitude is highly variable, therefore the fatigue assessment shall consider the dispersion of fatigue lives and uncertainty/scatter of the local stress spectrum. The stochastic assessment of fatigue life could be obtained by utilizing the concept of load spectrum and damage accumulation. The S-N curve could be expressed as follows, in Basquin's equation:

$$N = \frac{C}{S^k} \tag{5}$$

Fatigue life data could be evaluated for each stress block. Due to inherent variation in fatigue lives, C is a random variable, $C = N.S^k$. The dispersion of C would be related to the dispersion of fatigue lives that could be estimated with an appropriate interpolation of fatigue data. The cumulative fatigue damage of a stress spectrum consisting of L load bins, could be calculated as:

$$D = \frac{1}{C}.\sum_{i=1}^{L} n_i S_i^k \tag{6}$$

$$\log(D) = -\log(C) + \log\left(\sum_{i=1}^{L} n_i S_i^k\right) \tag{7}$$

The above equation shows that damage D is a random variable with the same scatter as the fatigue life. The mean and dispersion values of the damage value D can be calculated from its probability distribution. Then, with a given Miner index at failure, D_{cr}, the probability of failure would be calculated by using the inverse of the cumulative distribution function as follows:

$$P_f = P(D > D_{cr}) = \emptyset(-\beta) \tag{8}$$

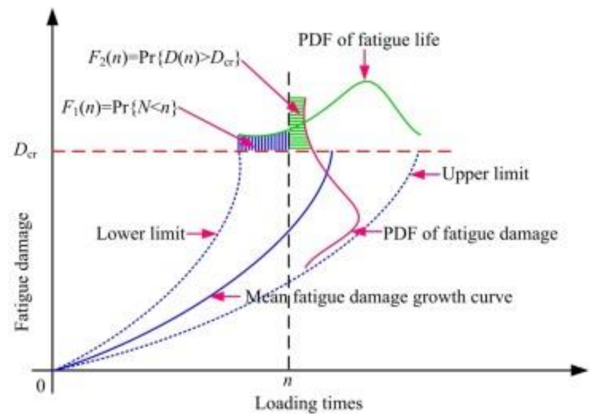

Figure 5 Schematic diagram of failure probability equivalence (Gao & Yuan, 2020)

The fatigue damage generally exhibits a certain dispersion due to the randomness of the material properties and fatigue loads. This probabilistic formulation for damage calculations has the advantage of being easily applicable in a MC simulation method since the realizations of the damage can be obtained by simply calculating D onto different realizations of the S–N diagram (Beretta & Regazzi, 2018).

In fatigue reliability analysis, determining the likelihood of material failure under cyclic loading involves two approaches: one based on fatigue life distribution and another on fatigue damage distribution (Gao & Yuan, 2020). In Figure 5, the blue lines illustrate fatigue damage values as loading instances increase, while the green line represents the Probability Distribution Function (PDF) of fatigue life. The red curve represents the PDF of fatigue damage when loading instances reach 'n.' When considering a specific loading level and instances of loading, the failure probability computed through fatigue life distribution matches that calculated through fatigue damage distribution. The area shaded by the blue lines equals that shaded by the green lines, clarifying the principle of failure probability equivalence (Gao & Yuan, 2020).

2.6 System reliability estimation

2.6.1 Wing system fault tree diagram

One of the three subsystems of the wing system is the main wing sail subsystem which is assembled of many components. Though each component within the subsystem has a contribution to the system failure, it is computationally expensive to consider the failure contribution of all the components. Hence, this study focuses on the failure probability of components that have the most influence on the fatigue reliability of the main wing subsystem.

A Bayesian Network (BN) model will be constructed based on the propagation of failure through the wing system which is represented by a Fault Tree Diagram (FTD) of the wing system. A FTD is a hierarchical diagram that demonstrates how failures propagate through systems. For the sake of this study, the failure propagation of the wing system is represented by the FTD shown in Figure 6. This FTD is constructed based on the wing system design configuration and by applying analogical relation with the FTD of offshore wind turbine blades (Z. Liu et al., 2023). The FTD specific to the main wing subsystem is described by the shaded nodes in Figure 6.

In principle, the failure of the wing system is caused by a certain subsystem or component failures, which results from a combination of failure causes. The failure at any stage of the FTD represents an event with a certain probability. The failure of the wing system is the top event, failures of subsystems or components are intermediate events, and failure causes are basic events. The hierarchical relationships among events can be represented by logic gates e.g. AND and OR gates. The events of the main wing subsystem FTD, shown Figure 6, are Leading Edge Failure (LEF), Trailing Edge Failure (TEF), Rear Shear Web Failure (RSWF), Front Shear Web Failure (FSWF), Spar Caps Failure (suction-side Spar Cap Failure (SSCF) and Pressure-Side Spar Cap Failure (PSCF)), Spar Beams Failure (SB1F, SB2F, SB3F and SB4F), Reinforcing Frames Failure (RFF) and Rib Failure(R1F, R2F, R3F, and R4F). The FTD shown in Figure 6 is used to construct the continuous time BN model used for system reliability estimation (section 2.6.3).

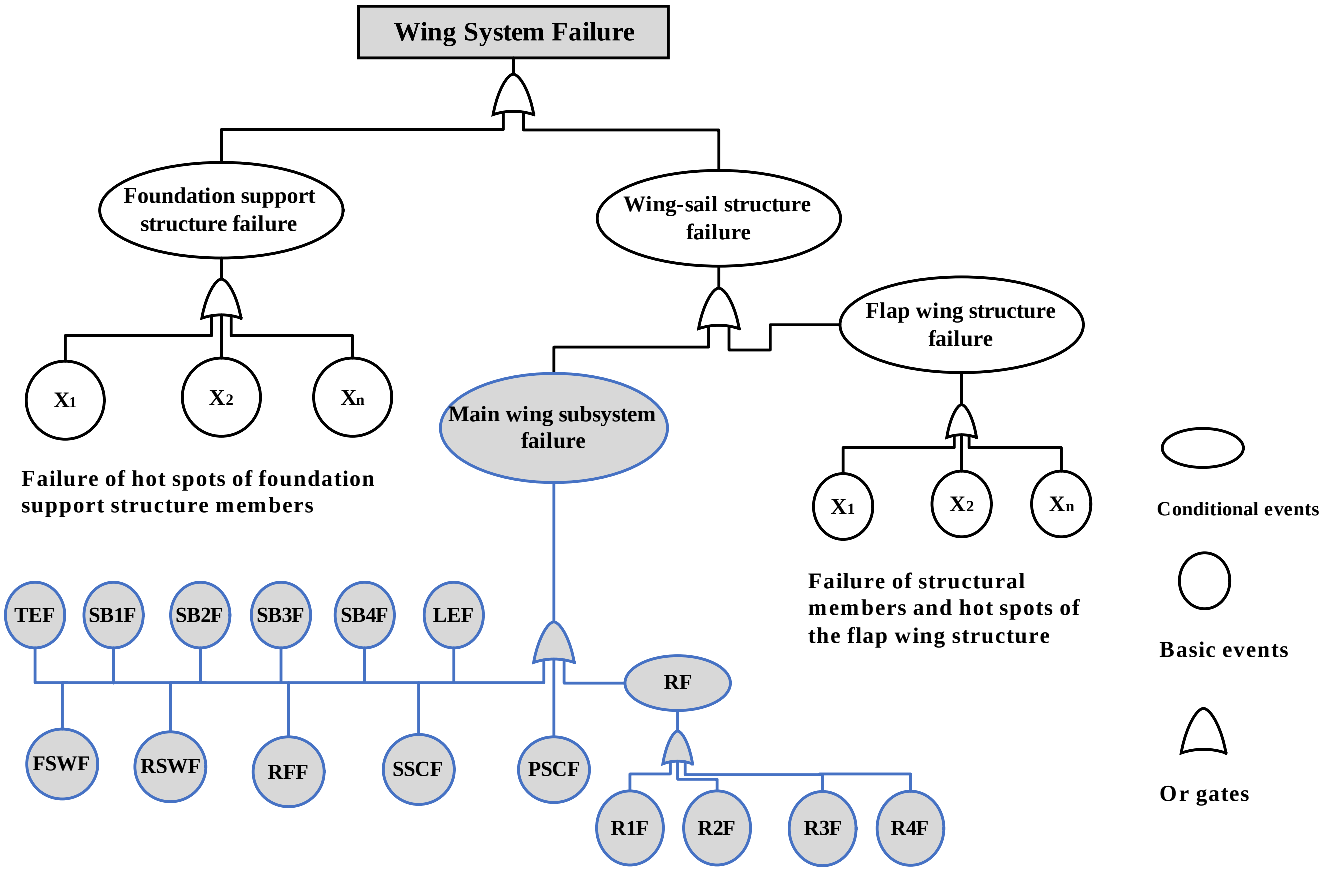

Figure 6 Fatigue failure fault tree diagram of the wing system

2.6.2 Reliability assessment methods

Reliability Assessment (RA) plays a crucial role in minimizing potential downtime and the risk of system failures by identifying and addressing the weakest areas of the system. It is extensively utilized to quantify the Mean Time To Failure (MTTF) of a structure and to recommend proactive maintenance measures to prevent malfunctions before they occur. RA of offshore structural systems such as floating offshore wind turbines (H. Li et al., 2020), (Du et al., 2019) has three basic targets: (a) calculating the system reliability indices (failure probability, failure rate metering index, and mean time to failure of the system); (b) determining the critical component(s) that can result in the failure of the system; and (c) suggest failure mitigation measures to reduce the probability of failure of the system. To achieve these targets, there are two common approaches: field data collection and model-based RA methods.

RA based on field data collection requires actual system failure data recorded in real operating conditions of the system, which is quite expensive and rare for emerging technologies such as wingsail systems. The model-based RA approach theoretically calculates the reliability of systems according to structural relationships and failure data of their components (H. Li et al., 2020). Among the model-based RA methods, failure mode and defect analysis (FMDA) (Kang et al., 2017), fault tree analysis (FTA) (Kang et al., 2019), and Bayesian networks (BNs) methods are widely applied to the wind turbine systems failure analysis, such as the whole wind turbine system, the gearbox, the wind turbine blade and so on.

Research findings suggested that the conventional FTA and its derived methods are naturally unprecise methodologies since they can be used to calculate either the upper bound or the lower bound of reliability of structural systems (H. Li et al., 2020). A combination of FTA-based methods has the potential to improve the accuracy of the analysis of reliability indices. However, this kind of approach is computationally expensive. BN methods are more computationally precise than the FTA method, as they can better deal with correlated data. Additionally, the predictive and diagnostic information propagation capabilities enable BNs to accomplish reliability estimation and critical components identification of the system within one model (H. Li et al., 2020).

Discrete-time Bayesian networks (DTBNs) have been applied for system reliability analysis of different structures such as floating offshore wind turbines (H. Li et al., 2020), (H. Li & Guedes Soares, 2022). Liu et al. (Z. Liu et al., 2023) performed a system reliability analysis of a composite wind turbine blade structure by using FEA and a continuous time BN-based fatigue reliability analysis method. The continuous-time BN method has an exact closed-form analytical expression, thus it is more suitable for reliability modeling and analysis when the states of the root nodes are continuous (Z. Liu et al., 2023).

2.6.3 Wing system reliability analysis using CTBNs

In the wing system, fatigue deterioration in various parts and subsystems of the wing structure is interconnected. Therefore, the fatigue failure probability of the entire wing system will be evaluated based on the failure contribution of each subsystem. The failure probability of the subsystem within the system is also based on the failure contribution of its components. Hence, the estimated fatigue reliability of each component is a building block for estimating the fatigue reliability and assessing the structural integrity of the entire wing system.

The structural reliability assessment of the entire wing system will be done based on the generalized stochastic responses to be obtained from the stochastic FE simulation results. The FE simulation results (stress field outputs) are to be combined with the numerical reliability analysis procedures to calculate the reliability of the components. The failure mechanisms of structural systems and components are expressed through limit state functions (in this case fatigue), which distinguish a failure and a safe region of operation. For any structural system, the fatigue limit state function should link the loads acting on it locally to the response of each structural member.

The CTBNs method will be utilized to calculate the entire wing system fatigue reliability. Reliability characteristics such as failure probability, failure rate, and mean time to failure of the system will be determined according to the Bayesian Network top-down reasoning pattern or predictive analysis.

Initially, the FTD of the main wing subsystem needs to be translated into an equivalent BN as shown in Figure 7. Each basic event of the FTD is represented as a root node. All gates (including the top gate system failure) in the FTD are intermediate nodes in the BN and possess a Conditional Probability Table (CPT) associated with each one of them. CPTs and prior probability tables are defined according to the failure probability distributions of the basic components and the types of gates tying them together.

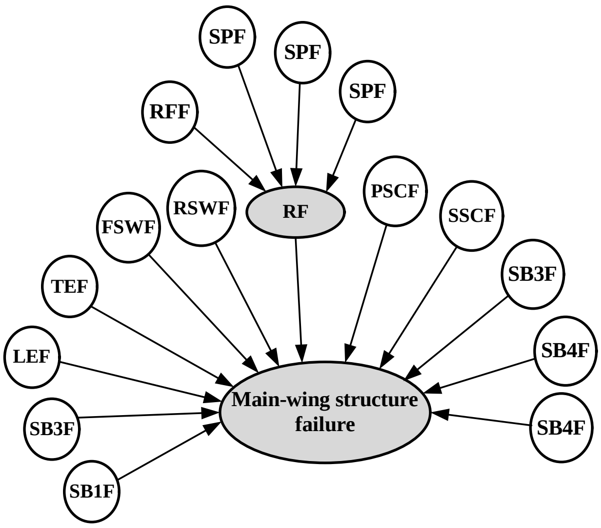

Figure 7 Main wing structure failure fault tree diagram to Bayesian Networks (BNs) conversion

Each node (or random variable) in the BN model represents a system component or the output of a gate. A system component can be either a basic component or a subsystem describing the interaction between a collection of components. The states of a variable (or component) are interpreted as the failure of the component at a point in time. Root nodes have marginal prior probability tables associated with them, and all other nodes have CPTs associated with them. The CPT of a Random Variable (RV) specifies the probability of each of the variable's states conditioned on the value of each of its parent nodes.

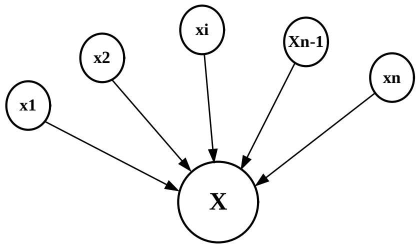

Figure 8 Typical example of BNs

There are two typical information propagation processes in BNs. Top-down (predictive-support reasoning) and bottom-top (diagnostic-support reasoning) patterns. The bottom-up reasoning pattern propagates information by conditional probability function or Bayesian inference. The predictive-support reasoning pattern propagates information by joint probability function determined using the chain rule, given as (H. Li et al., 2020):

$$\begin{aligned} P(X_1, X_2, \cdots, X_n) &= P(X_n \mid X_{n-1}, X_{n-2}, \cdots, X_1) P(X_{n-1} \mid X_{n-2}, X_{n-3}, \cdots, X_1) \cdots P(X_2 \mid X_1) P(X_1) \\ &= \prod_{i=1}^{n} P(X_i \mid X_{i-1}, X_{i-2}, \cdots, X_1) \end{aligned} \tag{8}$$

To specify the probability distribution of a Bayesian network, one must give the prior probabilities of all root nodes (nodes with no predecessors) and the conditional probabilities of all non-root nodes, given all possible combinations of their direct predecessors. Bayesian networks allow one to calculate the conditional probabilities of the nodes in the network given that the values of some of the nodes have been observed (Charniak, 1991). However, the conditional independence assumption of BNs defines the state of a node only depending on the state(s) of its parent(s), i.e. parents (X_i). The joint probability function of a set of independent variables $\{X_1, X_2, \dots, X_n\}$ is given as:

$$P(X_1, X_2, \cdots, X_n) = \prod_{i=1}^{n} P\left(X_i \mid \text{parents } (X_i)\right) \tag{9}$$

where $\mathrm{pa}(X_i)$ are the parent nodes set of node X_i, and if $\mathrm{pa}(X_i) = 0, \Pr\{X_i \mid \mathrm{pa}\ (X_i)\}$ is the marginal distribution $\Pr\ (X_i)$ (Z. Liu et al., 2023).

3 Conclusions & further steps

This report outlines the proposed data-driven numerical framework designed to evaluate the structural integrity of the wing system. It emphasizes the steps involved in a probabilistic system reliability estimation considering uncertainties in material properties and wind loads using stochastic FE simulations. The stochastic FE simulation is used to derive the fatigue performance response of components, and the estimation of fatigue lifetime relies on S-N curves. Furthermore, the report highlights the application of a Continuous Time Bayesian Networks (CTBNs) approach to incorporate the impact of component failures in predicting the overall reliability of the wing system.

References

Bednarcyk, B. A., Yarrington, P. W., & Arnold, S. M. (2013). Multiscale fatigue life prediction for composite panels. *Computers, Materials and Continua*, *35*(3), 229–254. https://doi.org/10.2514/6.2012-1546

Beretta, S., & Regazzi, D. (2018). Probabilistic fatigue assessment for railway axles and derivation of a simple format for damage calculations. *International Journal of Fatigue*, *86*(August 2015), 13–23. https://doi.org/10.1016/j.ijfatigue.2015.08.010

Charniak, E. (1991). *Probabilistic reasoning in intelligent systems: Networks of Plausible Inference*.

Chen, Z., He, J., Li, G., Yang, Z., Wang, T., & Du, X. (2024). Fast convergence strategy for adaptive structural reliability analysis based on kriging believer criterion and importance sampling. *Reliability Engineering and System Safety*, *242*(October 2023), 109730. https://doi.org/10.1016/j.ress.2023.109730

DNV-ST-0511. (2022). *Wind assisted propulsion systems*. *October*.

Du, J., Chang, A., Wang, S., Sun, M., Wang, J., & Li, H. (2019). Multi-mode reliability analysis of mooring system of deep-water floating structures. *Ocean Engineering*, *192*(September), 106517. https://doi.org/10.1016/j.oceaneng.2019.106517

Gao, J., & Yuan, Y. (2020). Probabilistic model of fatigue damage accumulation of materials based on. *Structures*, *28*(September), 659–667. https://doi.org/10.1016/j.istruc.2020.09.023

Hu, Z., & Mahadevan, S. (2018). Adaptive surrogate modeling for time-dependent multidisciplinary reliability analysis. *Journal of Mechanical Design, Transactions of the ASME*, *140*(2). https://doi.org/10.1115/1.4038333

Kang, J., Sun, L., & Guedes Soares, C. (2019). Fault tree analysis of floating offshore wind turbines. *Renewable Energy*, *133*, 1455–1467. https://doi.org/10.1016/j.renene.2018.08.097

Kang, J., Sun, L., Sun, H., & Wu, C. (2017). Risk assessment of floating off shore wind turbine based on correlation-FEMEA. *Ocean Engineering*, *129*(154), 382–388. https://doi.org/10.1016/j.oceaneng.2016.11.048

Kim, T.-U., & Hwang, I. H. (2004). Reliability analysis of composite wing subjected to gust loads. *Composite Structures*, *66*(2004), 527–531. https://doi.org/10.1016/j.compstruct.2004.04.072

Klemperer, C. J. Von, Horwitz, R. A. D., & Malan, A. G. (2023). An articulating wingsail design for Wind Assisted Ship Propulsion (WASP) applications. *Scientific African*, *20*, e01699. https://doi.org/10.1016/j.sciaf.2023.e01699

Kolios, A., Di Maio, L. F., Wang, L., Cui, L., & Sheng, Q. (2018). Reliability assessment of point-absorber wave energy converters. *Ocean Engineering*, *163*(April), 40–50. https://doi.org/10.1016/j.oceaneng.2018.05.048

Li, C., Wang, H., & Sun, P. (2023). Study on the influence of gradient wind on the aerodynamic characteristics of a two - element wingsail for ship - assisted propulsion. *J. Mar. Sci. Eng.* https://doi.org/10.3390/jmse11010134

Li, H., & Guedes Soares, C. (2022). Assessment of failure rates and reliability of floating offshore wind turbines. *Reliability Engineering and System Safety*, *228*(December 2021). https://doi.org/10.1016/j.ress.2022.108777

Li, H., Guedes Soares, C., & Huang, H. Z. (2020). Reliability analysis of a floating offshore wind turbine using Bayesian Networks. *Ocean Engineering*, *217*(October 2019). https://doi.org/10.1016/j.oceaneng.2020.107827

Liu, Y., Li, J., Sun, S., & Yu, B. (2019). Advances in Gaussian random field generation: a review. *Computational Geosciences*, 1011–1047.

Liu, Z., He, Z., Tu, L., Liu, X., Liu, H., & Liang, J. (2023). A fatigue reliability assessment approach for wind turbine blades based on continuous time Bayesian network and FEA. *Quality and Reliability Engineering International*, *November 2022*, 1–19. https://doi.org/10.1002/qre.3262

Ma, M., Yao, W., Jiang, W., Jin, W., Chen, Y., & Li, P. (2020). Fatigue behavior of composite sandwich panels under three point bending load. *Polymer Testing*, *91*(July), 106795. https://doi.org/10.1016/j.polymertesting.2020.106795

Ma, M., Yao, W., Jiang, W., Jin, W., Chen, Y., & Li, P. (2021). A multi-area fatigue damage model of composite honeycomb sandwich panels under three-point bending load. *Composite Structures*, *261*(September 2020), 113603. https://doi.org/10.1016/j.compstruct.2021.113603

Nielsen, U. D., Brodtkorb, A. H., & Sørensen, A. J. (2019). Sea state estimation using multiple ships simultaneously as sailing wave buoys. *Applied Ocean Research*, *83*(February), 65–76. https://doi.org/10.1016/j.apor.2018.12.004

Sharma, N., Gibson, R. F., & Ayorinde, E. O. (2006). Fatigue of foam and honeycomb core composite sandwich structures: A tutorial. *Journal of Sandwich Structures and Materials*, *8*(4), 263–319. https://doi.org/10.1177/1099636206063337

Shittu, A. A., Kolios, A., & Mehmanparast, A. (2021). *A Systematic Review of Structural Reliability Methods for*

Deformation and Fatigue Analysis of Offshore Jacket Structures. 1–37.
Shittu, A. A., Mehmanparast, A., Hart, P., & Kolios, A. (2021). Comparative study between S-N and fracture mechanics approach on reliability assessment of offshore wind turbine jacket foundations. *Reliability Engineering and System Safety*, *215*(August 2020), 107838. https://doi.org/10.1016/j.ress.2021.107838
Shittu, A. A., Mehmanparast, A., Wang, L., Salonitis, K., & Kolios, A. (2020). Comparative study of structural reliability assessment methods for offshore wind turbine jacket support structures. *Applied Sciences (Switzerland)*, *10*(3). https://doi.org/10.3390/app10030860
Suzuki, T., & Mahfuz, H. (2018). Fatigue characterization of GFRP and composite sandwich panels under random ocean current loadings. *International Journal of Fatigue*, *111*(February), 124–133. https://doi.org/10.1016/j.ijfatigue.2018.02.004
Xie, H., Shen, C., Fang, H., Han, J., & Cai, W. (2022). Flexural property evaluation of web reinforced GFRP-PET foam sandwich panel : Experimental study and numerical simulation. *Composites Part B*, *234*(February), 109725. https://doi.org/10.1016/j.compositesb.2022.109725
Zaharia, S. M., Pop, M. A., & Udroiu, R. (2020). Advances in Gaussian random field generation : a review. *Materials*. https://doi.org/10.3390/ma13102310
Zenkert, D., & Burman, M. (2011a). Failure mode shifts during constant amplitude fatigue loading of GFRP/foam core sandwich beams. *International Journal of Fatigue*, *33*(2), 217–222. https://doi.org/10.1016/j.ijfatigue.2010.08.005
Zenkert, D., & Burman, M. (2011b). Failure mode shifts during constant amplitude fatigue loading of GFRP / foam core sandwich beams. *International Journal of Fatigue*, *33*(2), 217–222. https://doi.org/10.1016/j.ijfatigue.2010.08.005
Zhang, X., Zhang, K., Yang, X., Fazeres-Ferradosa, T., & Zhu, S. P. (2023). Transfer learning and direct probability intergral method based reliability analysis for offshore wind turbine blades under multi-physics coupling. *Renewable Energy*, *206*(January), 552–565. https://doi.org/10.1016/j.renene.2023.02.026