Multidisciplinary design analysis and optimisation frameworks for floating offshore wind turbines
State of the art

Patryniak, Katarzyna; Collu, Maurizio; Coraddu, Andrea

DOI
10.1016/j.oceaneng.2022.111002

Publication date
2022

Document Version
Final published version

Published in
Ocean Engineering

Ocean Engineering 251 (2022) 111002

Contents lists available at ScienceDirect

Ocean Engineering

journal homepage: www.elsevier.com/locate/oceaneng

Review

Multidisciplinary design analysis and optimisation frameworks for floating offshore wind turbines: State of the art

Katarzyna Patryniak [a,*], Maurizio Collu [a], Andrea Coraddu [b]

[a] Department of Naval Architecture, Ocean & Marine Engineering, University of Strathclyde, Montrose St, Glasgow, G4 0LZ, United Kingdom
[b] Faculty of Mechanical, Maritime and Materials Engineering, Delft University of Technology, Mekelweg, Delft, 2628 CD, Netherlands

ARTICLE INFO

Keywords:
Floating offshore wind turbine
Multidisciplinary optimisation
MDAO
Coupled dynamics
Support structure
Offshore wind

ABSTRACT

Meeting climate and air quality targets, while preserving the focus on the reliability and cost-effectiveness of energy, became a central issue for offshore wind turbine engineers. Floating offshore wind turbines, which allow harnessing the large untapped wind resources in deep waters, are highly complex and coupled systems. Subsystem-level optimisations result in suboptimal designs, implying that an integrated design approach is important. Literature saw a few attempts on multidisciplinary design analysis and optimisation of floating wind turbines, with varying results, proving the need for an efficient, and sufficiently accurate, integrated approach. This paper reviews the state-of-the-art approaches to multidisciplinary design analysis and optimisation of floating support structures. The choice of the optimisation framework architecture, support platform design variables, constraints and objective functions are investigated. The techno-economic analysis models are closely examined, focusing on the approaches to achieving the optimum accuracy–efficiency balance. It is shown that the representation of the fully coupled system within the optimisation framework requires the introduction of a more complex multidisciplinary analysis workflow. Methods to increase the efficiency of such frameworks are indicated. Non-conventional support structure configurations can be conceived through the application of more advanced parametrisation schemes, which is feasible together with design space size reduction techniques. The set of design criteria should be extended by operation and maintenance cost, and power production metrics. The main technical limitations of the frameworks adopted so far include the inability to accurately analyse a diverse range of support structure topologies in multiple design load cases within a common framework. The cost approximation models should be extended by the chosen aspects of pre-operational phases, to better explore the benefits of the floating platforms.

1. Introduction

1.1. Context and problem statement

The global response to climate change requires a far-reaching transformation across the energy system. Wind is currently the fastest growing source of renewable energy, with year-over-year growth of 53% (Lee and Zhao, 2021). Even though land-based installations dominate, offshore wind capacity expands ten times as fast as its onshore counterpart (Lee and Zhao, 2021). Owing to ever-larger rotors and more consistent wind speeds, offshore wind also provides higher capacity potential, enough to cover the current total world's demand for electricity.

One of the main limitations of offshore wind farm development is water depth; when exceeding 50m, bottom-fixed foundations may no longer be economically viable (Myhr et al., 2014). With the development of floating offshore wind turbines (FOWTs), it is possible to remove the water depth constraint and harness large untapped wind resources far from shore, at higher operational efficiency and increased capacity factors (Johnston et al., 2020). Additionally, FOWTs have the potential to offer reduced installation cost, smaller seabed footprint, and less visual intrusiveness (Lee, 2005; IRENA, 2019). However, since the technology has not matured yet, the Levelised Cost of Energy (LCoE) related to these turbines remains high (Ghigo et al., 2020). A significant reduction of the cost cannot be achieved by a single innovation but requires a series of coordinated efforts in many disciplines (Evan et al., 2020; Barter et al., 2020). The success of FOWTs depends on advances at each stage of the turbine's life cycle, including installation, operation & maintenance, and decommissioning. However, continued improvement in design and manufacturing is a key cost-reduction driver (European Commission, 2021). Between 20–40% of

* Corresponding author.
E-mail addresses: katarzyna.patryniak@strath.ac.uk (K. Patryniak), maurizio.collu@strath.ac.uk (M. Collu), a.coraddu@tudelft.nl (A. Coraddu).

https://doi.org/10.1016/j.oceaneng.2022.111002
Received 10 November 2021; Received in revised form 14 February 2022; Accepted 27 February 2022
Available online 23 March 2022

Abbreviations

1P	Rotor frequency
3P	Blade passing frequency
BOBYQA	Bound Optimisation by Quadratic Approximation
CapEx	Capital Expenditure
DecEx	Decommissioning Expenditure
DLC	Design Load Case
DOF	Degrees of Freedom
FD	Frequency Domain
FOWT	Floating Offshore Wind Turbine
LCoE	Levelised Cost of Energy
MDAO	Multidisciplinary Design Analysis and Optimisation
MDA	Multidisciplinary Analysis
OC5	Offshore Code Comparison, Collaboration, continued, with Correlation
O&G	Oil and Gas
OpEx	Operating Expenditure
O&M	Operations and Maintenance
r	Discount rate
RAO	Response Amplitude Operator
RNA	Rotor-Nacelle Assembly
SQP	Sequential Quadratic Programming
t	Year
TD	Time Domain
TLP	Tension Leg Platform
TSR	Tip-speed ratio

Nomenclature

a_n	Projected area per unit length
c_d	Drag coefficient
D	Characteristic dimension
dL	Length of the thin horizontal slice
∇	Volume per unit length
v_c	Current velocity
ω	Wave frequency
ρ	Water density
SF	Safety factor
T	Static tension
T_{max}	Maximum tension allowed
u	Water particle velocity

the capital cost of a FOWT can be attributed to the support structure (Gentils et al., 2017; Mathern et al., 2021). Therefore, as noticed in multiple references including Myhr et al. (2014), Mathern et al. (2021), Tran and Kim (2017), Wang et al. (2022), the development of accurate simulation and optimisation tools is vital to the success of this technology.

1.2. Multidisciplinary design analysis and optimisation

Multidisciplinary Design Analysis and Optimisation (MDAO) is a field of engineering which focuses on the design of systems involving multiple disciplines and/or subsystems. Multidisciplinary optimisation is most useful in complex heterogeneous problems where the coupling between the multiple disciplines is too strong to be neglected, or where the synergy between subsystems can be exploited.

Such problems can be decomposed into a series of smaller blocks of computations, each with its own set of input and output variables (openmdao.org, 2021). The outputs of some of the blocks are passed as input to other components, creating either simple feed-forward connections or feed-back connections, which create a coupled model (Fig. 1).

A system containing feed-back connection(s), referred to as "Multidisciplinary Analysis", needs to be solved iteratively to obtain unique and valid outputs, and only after all cycles (i.e., groups of computations with feed-back connections) in the model are converged, the outputs can be used to compute the design objectives and constraints (as detailed in Section 1.3), which are then fed to the optimiser block driving the solution of the entire MDAO problem, as schematically presented in Fig. 2.

The way the particular disciplinary analysis components and cycles are grouped determines the hierarchy (or architecture) of the problem. A comprehensive review of many MDAO architectures developed was published by Lambe and Martins (2012), and the issues related to MDAO are extensively discussed in Agte et al. (2010) and Martins and Ning (2021).

Although applicable in all design stages, the MDAO of Floating Offshore Wind Turbines (FOWTs) is perhaps most effective at the conceptual design stage, when early decisions about the support platform topology are made. The knowledge gained in the concept phase is essential for the success of later phases, where any design changes can only be made at a relatively high cost (as illustrated in Fig. 14). As noticed in Safavi et al. (2016) and Barter et al. (2020), this is particularly true for complex, innovative structures with scarce prior empirical information. The physical environment and dynamics of FOWTs are very complex, with strong inter-dependencies between wind- and wave-driven responses (Bachynski and Moan, 2012).

The rotor nacelle assembly is primarily influenced by the aerodynamic loads, which in nature are nonlinear (the wind load varies with the square of the wind speed). The wind turbulence may excite low-frequency oscillations of the platform, blades and tower at multiples of the rotor rotational frequency (Lemmer et al., 2020). Additionally, the relatively low 1P frequency of the large 10-15MW rotors may overlap with the most energetic part of the sea spectrum, potentially magnifying the motion of the platform (Arany et al., 2016). The gyroscopic effect of the rotating rotor, which can be modelled as an additional damping term, affects the response of the entire system shifting the peak of the response spectrum to a higher frequency (Bahramiasl et al., 2018) and inducing a gyroscopic yaw moment (Jonkman, 2009). Inversely, the wave-induced rapid translational and rotational motion of the platform in the six degrees of freedom can substantially affect the tower-top motion, hence influencing the thrust and torque produced by the rotor (Karimirad et al., 2011) and the bending moments at the tower base and blade roots (Jonkman, 2007; Matha, 2010), subject to the action of the control system. Above the rated wind speed, the blade-pitch controller interacts with the platform pitch motion introducing the negative damping (Larsen and Hanson, 2007; Jonkman, 2008).

Traditionally, the floating support structures were designed to provide possibly the most stable, stiff platform for the tower and turbine adapted from bottom-fixed offshore wind turbines (Barter et al., 2020). The introduction of an integrated optimisation of the floating platform, mooring system, tower, rotor, and controllers allows to concurrently design the complete system, likely resulting in a less stiff and lighter substructure. To be able to study the cost advantages of the new configurations, economic modelling plays a crucial role. However, due to very limited experience with designing, manufacturing, installing, and operating these novel structures, cost components assumptions and models are subject to large uncertainties (Muskulus and Schafhirt, 2014). This indicates why the multidisciplinary approach to FOWT optimisation is not only justified, but necessary and challenging. Sufficiently advanced coupled models of economics, aerodynamics, hydrodynamics, structures, and control are necessary to capture all above-mentioned effects, while keeping the computational cost at reasonable levels (Bachynski and Moan, 2012; Jonkman, 2009).

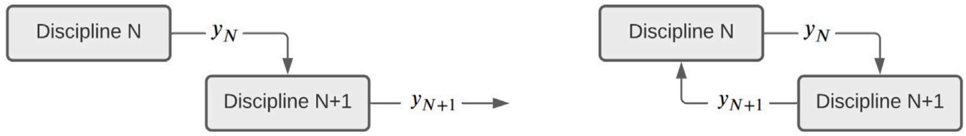

Fig. 1. An example of a feed-forward and feed-back schemes.

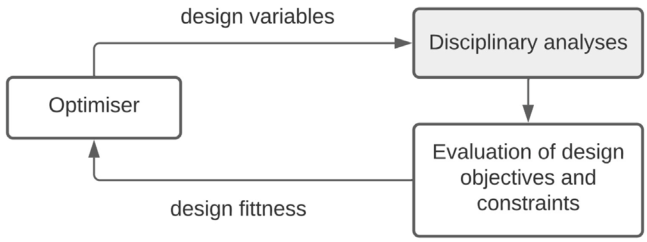

Fig. 2. General optimisation procedure.

1.3. Optimisation problem formulation

Many of the engineering design optimisation problems, including that of a FOWT system, can be classified as constrained multiobjective problems, with the following widely accepted mathematical formulation (Agte et al., 2010):

$$\begin{aligned} &min.\ f_1(\boldsymbol{x},\boldsymbol{p}),\dots,f_k(\boldsymbol{x},\boldsymbol{p}) \\ &w.r.t.\ \boldsymbol{x}=[x_1,\dots,x_n]^T,\ \boldsymbol{p}=[p_1,\dots,p_m]^T \\ &s.t.\ x_{i,LB}\le x_i\le x_{i,UB},\ i=1,2,\dots,n \\ &\boldsymbol{g}(\boldsymbol{x},\boldsymbol{p})\le 0,\ \boldsymbol{h}(\boldsymbol{x},\boldsymbol{p})=0 \end{aligned} \tag{1}$$

A multi-objective problem aims to optimise more than one design attribute. Several methods for combining the component attributes into one expression exist, one of the most often utilised being the Weighted Sum Method where the final cost function (f) is a weighted sum of the component functions (Zadeh, 1963). It is a matter of judgement to set these weights to reflect the importance of the chosen attributes (Arora, 2017). Other approaches to multi-objective optimisation exist, such as physical programming (Messac, 1996), or lexicographic method (Behringer, 1977). A comprehensive review of such methods is available, for example, in Arora (2017).

When considering a structural optimisation, the design vector ($\boldsymbol{x}$) contains the geometric/material features of a structure, which are varied to result in different candidate designs, with lower and upper bounds ($x_{i,LB}$, $x_{i,UB}$). The larger the vector of variables, the broader range of designs can be represented with a greater level of detail. However, an increasing number of variables leads to the so-called curse of dimensionality (Chen et al., 2015): as the number of variables ('dimensions') increases by n, the size of the search space increases by a factor of m^n, provided m is the number of values considered for each variable. Therefore, significant simplifications are often necessary. Parameters ($\boldsymbol{p}$) influence the behaviour of the system but are not controlled by the optimiser and cannot be freely chosen (material properties, operating conditions, etc.).

The collection of feasible designs is often referred to either as a feasible set or feasible design space. It is defined as a set of points that satisfy all inequality and/or equality constraints of the problem (Arora, 2017): $\boldsymbol{g}$ and $\boldsymbol{h}$ functions in Eq. (1), respectively. These constraints can be relative to the design variables (bounds) and/or performance of a system/subsystem (system constraints), and may vary in mathematical nature (linear/ nonlinear, explicit/implicit), which influences the choice of the optimisation algorithm and its performance.

In search of the best of all feasible solutions, two approaches can be distinguished: local and global (Arora, 2017). The most often followed practice, in the field of optimisation of floating structures, is to look for a local optimum, i.e., for a design that cannot be further improved by exploring its close neighbourhood (Arora, 2017). Unless one deals with a convex problem, the existence of a global optimum cannot be, in general, guaranteed (Arora, 2017). In an engineering approach, the goal is to find a much-improved design with the resources given, rather than looking for a globally-optimum design.

Article overview

The organisation of this article is as follows. Section 2 investigates the state-of-the-art implementations of MDAO frameworks in various engineering fields, including the design of FOWT support structures. Sections 3 through 5 review the existing approaches to the selection of the design variables, objectives, and constraints, respectively. Section 6 reviews the most often utilised optimisation algorithms. Sections 7 and 8 investigate the selection of approaches to dynamic and economic models in FOWT multidisciplinary optimisation studies. The article is concluded with a critical discussion and recommendations for further improvements (Sections 9 and 10).

2. Multidisciplinary design analysis and optimisation

2.1. Development drivers

The cornerstone of MDAO was laid by Schmit (1960), who performed a fully automated optimisation to minimise the weight of a three-bar truss system by varying cross-section areas subject to constraints on stress, deflections and size of the members. The system was described by five simultaneous equations, where the displacements of the bars were related to the stress and temperature rise in the member, hence marrying the two disciplines.

The importance of integrated numerical analysis demonstrated by Schmit was well understood in the aerospace industry, where the introduction of composite materials triggered changes to the design process. Grossman et al. (1988) showed that the integrated aerodynamic-structural optimisation of a wing is superior to the traditional iterative design techniques. To account for the coupling between the structure and aerodynamics, two matrices were introduced into the system of equations: one representing the change in lift coefficient due to a unit twist angle, and one representing the change in twist due to a unit aerodynamic load. These cross-sensitivity matrices were obtained through the method of small perturbations (for instance, by recording the change in lift due to a small increase in the twist of a section for a range of scenarios), at each step of the optimisation. Favourable interaction between the two disciplines was exploited through distributing the structural material such that large deformations did not reduce the aerodynamic performance (moving the centre of lift towards the root of

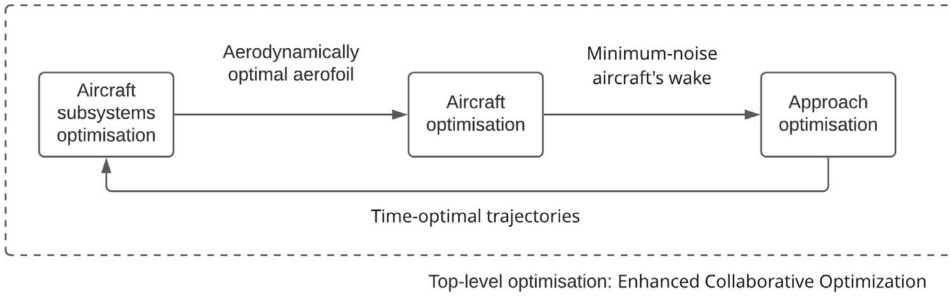

Fig. 3. Example of optimisation decomposition in aeroplane design, based on Subramanian and DeLaurentis (2016).

a wing), hence relaxing the need for keeping the deformations small. Reduced torsional stiffness allowed for reducing the structural mass, increasing the overall performance of the wing in a way not attainable through a sequential design.

Consideration of more complex cases required computational methods to become more efficient. Three different approaches to that task can be distinguished. Firstly, multiple disciplines can be merged to form hybrid disciplines (e.g., structural control (Haftka, 1990), hydroelasticity (Garg et al., 2017)). This way, simultaneous manipulation of design variables in several disciplines is possible by a single widely skilled analyst, reducing organisational difficulties. Another common approach is to lower the fidelity of the analysis at the conceptual level. For instance, Ripepi et al. (2018) developed a reduced order model to predict aero-elastic loads based on a linear aerodynamic model corrected with a small number of high-fidelity Computational Fluid Dynamics computations. This technique brought a massive reduction in optimisation time (Jayaram et al., 1992). The last approach focuses on decomposition and global sensitivity techniques. In that case, the problem is split into multiple subproblems (optimisation loops), each concerning small subsets of the variables and constraints, grouped at the global level (e.g., Concurrent Subspace Optimisation (Sobieszczanski-Sobieski, 1989)). This approach is particularly useful if the calculations can easily be run in parallel, provided parallel computing is available (Martins and Lambe, 2013). The workload can be distributed between specific analyst groups, which can be based in geographically distant locations. Finally, system-level optimisation can be performed with minimal changes to the disciplinary analysis codes, with efficient data exchange (Sobieszczanski-Sobieski, 1990). For instance, Subramanian and DeLaurentis (2016) decomposed their airport noise minimisation problem into three optimisations: that of aircraft subsystems, aircraft, and approach procedures, linking the three subproblems through their inputs and outputs into a hierarchical system design problem, as presented in Fig. 3.

2.2. MDAO applied to offshore oil and gas industry floating structures

While aerospace engineering can be dated back to 1910 (the beginning of the development of military aircraft), the first floating offshore structure, Ocean Driller, was deployed half a century later (1963). Around that time, Boeing 747 made its first transatlantic flight, and the first manned spacecraft landed on the Moon. With a less apparent need for multidisciplinary optimisation when considering offshore floating structures, the MDAO concept was not broadly applied in that field. Only a few studies employed formal optimisation algorithms for the hull design (e.g., Clauss and Birk, 1996; Jang et al., 2019).

Examples of multidisciplinary optimisation in this field are even more scarce. Perhaps the most advanced study of such type was conducted by Sugita and Suzuki (2016) who utilised the simulated annealing and genetic algorithm to minimise the weight of a TLP, subject to constraints stemming form different disciplines (mooring tension, platform offset and natural periods, structural stress). The analysis framework consisted of hydrodynamic analysis, structural analysis,

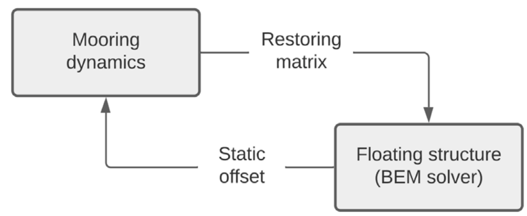

Fig. 4. Iterative approach to steady state offset and mooring restoring matrix.
Source: Adapted from Tracy (2007)

frequency-domain global performance analysis, and weight estimation modules. All modules were called in a sequential manner, once per each optimisation iteration, therefore, the responses were not converged at the system level before being passed to the objectives and constraints evaluation block. Regardless, this study was a great step in the transition from a traditional design approach to a fully automated approach.

2.3. MDAO applied to floating offshore wind turbines

The design of floating wind turbine support structures differs from the oil and gas platforms in many aspects. One of the most important distinctions is the fact that, while for O&G offshore structures the aerodynamic loads constitute a small fraction of the total load, FOWTs are designed to extract energy from the wind, and therefore both wind and wave loads are significant. Despite this, initially, FOWT platforms heavily relied on the oil and gas industry legacy, with conservative designs.

The first study on multidisciplinary design optimisation of FOWTs was published by Sclavounos et al. (2008), based on the thesis of Tracy (2007). The dynamic performance analysis was decomposed into three modules: mooring system, the floating structure, and the wind turbine, with the characteristics of each discipline assembled into one equation of motion based on a linear spring–mass–damper system in the frequency-domain (as presented in Section 7.1). Because the mooring loads may be nonlinear over large displacements, the platform steady state offset was computed by the hydrodynamic module and then used as a linearisation point by the mooring module, so that the offset and stiffness were computed iteratively, as per the simplified diagram in Fig. 4. The remaining inputs to the linear system were computed in sequence.

After the world's first FOWT, Hywind I (KARMØY), was deployed and proved to be a technically feasible concept, the research on support platforms gained more interest. Currently, the process of design and optimisation of these structures, and the urge to reflect the great complexity of the system within the optimisation process, better resemble the practices seen in aerospace engineering than the traditional offshore sector.

One of the most sophisticated approaches to integrated design optimisation has recently been demonstrated by Hegseth et al. (2020b). The

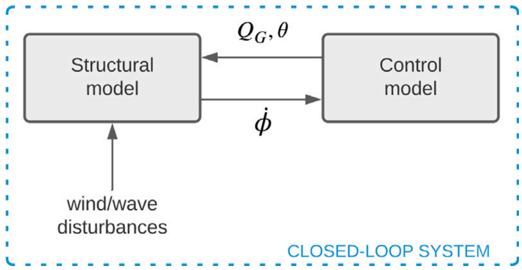

Fig. 5. Assembly of the structural and control models in one closed-loop state–space system through input/output pairs: generator torque Q_G, blade pitch θ and rotor speed $\dot{\phi}$.

authors optimised the Proportional Integral (PI) control system, tower, spar platform, and catenary mooring system in an integrated manner, by combining the structural and control state–space systems into a complete closed-loop aero-hydro-servo-elastic model, as per Fig. 5.

A modular approach was applied, with discipline-specific calculations performed by individual units of code, connected in a multidisciplinary network by feed-forward connections (with one exception of a cycle for the calculation of viscous damping, as explained in Hegseth et al. (2020b)). By increasing the controller gains, a reduction in rotor speed variation was observed, however, this was achieved at the cost of increased fatigue damage. The cost and performance of the designs obtained thorough the integrated optimisation were also compared to those obtained without varying the controller gains, showing superiority of the coupled approach over the simpler structural optimisation.

When constructing an MDAO framework, numerous challenges must be overcome, including the choice of the order of execution of the disciplinary analyses, the management of the flow of information between the components, the choice of the system solver (linear/nonlinear, monolithic/recursive iterators), and the integration with an optimisation algorithm. Efficient implementation of these aspects requires a very specific set of skills and is time-consuming; the formalisation of system specification and workflow automation may take as much as 60–80% of project time, according to the survey in Ciampa and Nagel (2016). In that respect, the open-source and commercial tools developed by third parties are very powerful, taking a significant part of the coding burden off. A brief review of the three chosen non-proprietary tools is given in the next section.

2.4. An overview and comparison of available MDAO tools

OpenMDAO is an open-source framework for efficient multidisciplinary optimisation developed by the MDO Lab (Michigan University) in collaboration with NASA. One of its main advantages is the efficient data (input/output) passing between components through variables promotion or connect statements, and a choice of system iterative solvers (Gauss–Seidel, Newton, and more). Highly valued is also its ability to efficiently calculate the total derivatives, either numerically (finite-difference or complex-step), or through analytic partial derivatives followed by the computation of total derivatives (through a direct or adjoint method). Hence, gradient-based algorithms can be applied to optimisation problems with a large number of variables and constraints efficiently. Being open-source, the code can be fully customised. Additionally, an interactive model structure visualisation tool is provided. An example of the application of OpenMDAO to FOWT optimisation can be found in Hegseth et al. (2020b).

DAFoam, developed at the MDO Lab, models multidisciplinary physics with OpenFOAM – an open-source multiphysics software. The tool can deal with a large, constrained design space through the implementation of an efficient discrete adjoint method for total derivatives computation. The package also includes a geometry parametrisation module based on the Free-Form Deformation scheme (more details in Section 9), which makes DAFoam one of the most comprehensive tools available. However, the framework only supports optimisation algorithms available in the python library pyOptSparse, and the choice of physics solvers is limited to those implemented in OpenFOAM. An example of the application of DAFoam to engineering optimisation can be found in He et al. (2019).

DAKOTA is a multilevel parallel object-oriented framework for sensitivity and uncertainty analysis, design optimisation and calibration, developed by the Sandia National Laboratory with contributions from the community. This toolkit allows interfacing simulation codes with iterative mathematical and statistical methods through an interface developed by the user as a script in any language. This implies that DAKOTA can be connected to any simulation code, provided that the code can be executed from a command line and performs its I/O through data files. A wide range of optimisation algorithms is available, including both gradient-based and derivative-free methods. Additionally, nested models and parallel computing can be enabled and easily managed. An example of the application of DAKOTA to engineering optimisation can be found in Xia et al. (2018).

The main characteristics of these tools are reported and compared in Table 1.

3. Design variables

To be able to analyse the performance of a large number of designs in an optimisation environment efficiently, their characteristics must be represented with the smallest set of variables possible. At the same time, sufficient design flexibility (or detail) must be ensured to represent the topologies adequately. Hence, a trade-off between the richness of the design space and the cost of the optimisation process is observed.

An MDAO application requires a common set of variables that can be manipulated and exchanged among different disciplines. Ideally, the geometric model should also be smooth (shape modification should maintain a smooth geometry), provide local control, and short setup time. Unlike most of the geometric variables, the non-geometric features (such as material type, anchor type, etc.), and composition features (such as number of floaters, hull sections, mooring lines, etc.) often have discrete nature. Hence, the development of an efficient parametrisation scheme is a non-trivial task. See Samareh (1999, 2001) for an extensive review of formal parametrisation schemes.

The design optimisation of FOWTs followed a less strict methodology for shape parametrisation, with no record of any interest in efficient parametric modelling in the literature up to date. One of the most mature approaches was demonstrated in Hall et al. (2014), where the mooring configuration was defined in a formal mathematical way. The attachment of the lines to the hull was fixed, and the anchor positions were set to linearly vary with the parameter x_M ranging from 0 (i.e., anchor directly under the mooring attachment point) to 2 (i.e., the horizontal distance between the hull attachment and the anchor of twice the water depth). Taut configurations were represented by the negative values of the parameter x_M, as presented in Fig. 6. For a given platform design and water depth, this parametrisation scheme allowed to model a continuous range of mooring configurations with just one design variable.

Another detailed mooring system parametrisation was presented by Hegseth et al. (2020b) who included four variables: line diameter, depth of the fairleads below the water surface, the total length of the line, and the horizontal distance between the fairlead and anchor. The inclusion of the mooring attachment point location in the set of design variables allowed the observation of the important platform-mooring system couplings. The fairlead depth below the water surface was shown to strongly influence the surge-pitch coupled motion, therefore influencing the pitch response of the entire system.

A very common approach is to only include the mooring line length and its orientation defined by two additional continuous parameters:

Table 1
The MDAO tools reviewed in this study.

Code	OpenMDAO	DAKOTA	DAFoam
Reference	Gray et al. (2019)	Eldred et al. (2002)	He et al. (2020)
Language	Python	C++	C++, Python
Gradient-based algorithms	SNOPT, IPOPT, SLSQP, NLPQLP, FSQP, PSQP, ParOpt, CONMIN	Conjugate gradient methods, SQP methods, Newton methods, MFD, Augmented Lagrangian method	pyOptSparse compatible solvers including SNOPT
Derivative-free algorithms	NSGA2, ALPSO	PS, Simplex, Greedy Search Heuristic, NOWPAC, EA, DIRECT, EGO	–

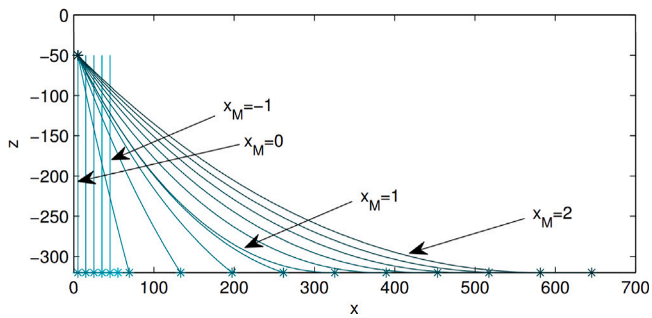

Fig. 6. Example of mooring line profiles for the line shape parameters $x_M \in [-1, 2]$.
Source: Reproduced from Hall et al. (2013).

the horizontal distance from the fairlead to anchor, and the angle of the lines with respect to a global coordinate system (Brommundt et al., 2012). Some complexity can be added by allowing the diameter of the lines to vary along the line length (Myhr and Nygaard, 2012) or by varying the material of each section of the line (Pillai et al., 2019).

Floating platform parametrisation is greatly based on the examples of structures from the oil and gas industry. A few classical concepts exist, with spars, TLPs, and semi-submersibles being the most popular (Leimeister et al., 2018). The geometry of each of the platform types can be uniquely defined by a different set of parameters. Therefore, the majority of the studies focuses on a chosen class, narrowing the range of free parameters down to a minimum.

The tower design is often represented as a truncated cone with variable base and top diameters and a linear distribution of diameters in between, keeping the hub height fixed (e.g., Hegseth et al., 2020a) or variable (e.g., Ashuri et al., 2016).

The hull is usually modelled as either a single axisymmetric body or an array of these. For instance, Hegseth et al. (2020b) modelled the spar platform with 10 sections, each having a variable height, top diameter, and wall thickness. The scantlings of the floating structures are usually considered only approximately by augmenting the wall thickness (for example in Hall et al. (2013)) or material density (for example in Jonkman (2010)) to account for the additional mass of the internal steel members. However, when structural dynamics are included in a multidisciplinary optimisation problem, it is necessary to model these structures more accurately.

This was achieved, for example, by Hegseth et al. (2020b), who proposed to model the T-ring stiffeners inside each of the 10 sections of the floater with 5 additional variables: the thickness and length of the webs and flanges, and the distance between the stiffeners. To reduce the number of variables and the computational effort, the authors adopted a B-spline approach. By using 4 control points, smooth distribution of these parameters along the depth of the floater was achieved, and the number of variables related to the stiffeners reduced from as many as 50 to just 20.

In their later study (Hegseth et al., 2020a), the authors noticed that the optimum wall thickness was mostly governed by the necessity to withstand the hydrostatic pressure. Hence, provided that the detailed scantlings design is not of interest, wall thickness can be expressed as a function of depth, with no need to be included in the set of variables.

To dampen the heave motion in near-resonance conditions, heave plates are often used, particularly in semi-submersible designs. Gilloteaux and Bozonnet (2014) allowed the use of multiple heave plates, with their spacing and radius as design variables. An interesting decision was to consider the ratio of the plate radius to the column radius, making this variable nondimensional. Lemmer et al. (2017) additionally considered the thickness of the plates, showing that with thick plates the wave cancellation effect can be achieved, significantly improving the platform response in waves.

A unique approach was followed by the researchers at the University of Victoria (Hall et al., 2013; Karimi et al., 2017), where the design space covered a wide range of designs moving beyond the standard classification of the foundations. The eight-parameter scheme consisted of a single central cylinder (characterised by a variable draft, radius and taper near the waterline), accompanied by a variable number of outer columns (each characterised by a draft, radius, heave plate radius and distance to the central cylinder). Such an approach brings along multiple additional challenges, not seen when parametrising a single-class platform. The scheme must be able to represent both the existing design topologies, as well as those not yet seen. The optimisation framework must be able to deal with the possible discontinuities in the complicated design space, where multiple local minima are possible. On top of that, the distant types of geometries generated by the parametrisation scheme must be evaluated with one common analysis model with comparable accuracy (these challenges are further discussed in Section 9.1).

Another approach to the task of covering all support structure configurations and beyond was presented by Hall et al. (2014). The basis function approach removes the consideration of the physical platform geometry and works with hydrodynamic coefficients instead. Hydrodynamic characteristics of each candidate design ($\boldsymbol{X}_0$) are represented as a linear combination of hydrodynamic characteristics of a set of basis platforms ($\boldsymbol{X}_n$), as given by Eq. (2):

$$\boldsymbol{X}_0(\omega) = c_1\boldsymbol{X}_1(\omega) + c_2\boldsymbol{X}_2(\omega) + \cdots + c_n\boldsymbol{X}_n(\omega) \tag{2}$$

where the hydrodynamic coefficients may or may not be functions of angular frequency, ω.

The optimisation problem is defined in such a way that the objectives are achieved by varying the coefficients of combination (or weights) c_i, which represent how much the final design resembles each of the basis designs. The final design is then reproduced by superposition of the basis geometries (no standard way of doing this exists). This approach avoids the requirement of expensive solution of the radiation and diffraction problems for every single design. Therefore, it offers a significant reduction in the optimisation time. However, ambiguity remains in the how these optimal combinations of basis functions should be translated to a physical geometry.

Note that the design of the fixed structural elements such as cross-bracings, tendon arms, ballast, fairleads, etc. was not discussed. Although essential for design integrity, such components are usually out of control of the optimisation algorithm and their parameters are chosen to fit the variable characteristics of each design. For an example of how these can be represented in a parametrisation scheme see Hall et al. (2013).

4. Design objective/s

Table 2 compares the design objectives, constraints, variables, and optimisation algorithms applied in the chosen 12 FOWT multidisciplinary optimisation studies. This section focuses on the review and assessment of design objectives.

4.1. Economic indicators

The economic viability of a given wind turbine design can be assessed based on the LCoE, defined as the ratio between the total life cycle cost (sum of discounted CapEx, OpEx and DecEx) and total energy production (AEP) (Castro-Santos et al., 2021).

$$LCoE = \frac{\sum_{t=1}^{n} \frac{CapEx_t + OpEx_t + DecEx_t}{(1+r)^t}}{\sum_{t=1}^{n} \frac{AEP_t}{(1+r)^t}} \tag{3}$$

Since this factor reflects the cost of a unit of energy produced, lowering its value is beneficial for electricity consumers and improves the competitiveness of wind energy in the energy market. Lower LCoE can be achieved by either increasing the energy production or reducing the costs of financing, manufacturing, installation, O&M, and decommissioning.

Most of the literature uses material weight and/or cost as a sole proxy for LCoE (Myhr and Nygaard, 2012; Karimi et al., 2017; Fylling and Berthelsen, 2011; USTUTT, 2016; Dou et al., 2020). Some positions also include the manufacturing costs (Hegseth et al., 2020b,a; Lemmer et al., 2017) and the cost of anchors (Hall et al., 2013; Karimi et al., 2017). The inclusion of the anchor cost is important when more than one class of support structures is considered, as the gravity and driven anchors for TLPs can be twice as expensive as the drag-embedded anchors used with semi-submersibles and spars (James and Ros, 2015). An interesting approach was adapted by Tracy (2007), who used the displacement volume as a cost driver, noticing that this single, easy to calculate factor accounts for both the mooring system static tension and the structural mass, which largely influences the capital cost. A similar approach is proposed in Bachynski (2018), with the structural mass approximated as the product of the displaced volume and an empirical factor.

It is noteworthy that in the case of objective functions describing either the capital cost (such as those outlined here), or full LCoE (such as that used in Ashuri et al. (2016) for optimisation of bottom-fixed offshore wind turbines), it is relatively straightforward to ensure that the function is continuous, smooth and differentiable, what makes the use of efficient gradient-based optimisation algorithms possible.

The details of the economic models applied in FOWT multidisciplinary optimisation studies are discussed in Section 8.

4.2. Performance indicators

Floating offshore wind turbines must be both cost-effective and achieve the required response to ensure an efficient and safe energy extraction. For that reason, along with the cost, a series of performance objectives are usually considered.

Sclavounos et al. (2008) claimed the nacelle motion to be a critical performance measure. In this work, the standard deviation of the nacelle acceleration was expressed as an integral of the response spectrum (Eq. (4)):

$$\sigma_{\ddot{\zeta}}^2 = \int_0^\infty (RAO_{\ddot{\zeta}}(\omega))^2 S(\omega) d\omega \tag{4}$$

The authors argued that an excessive nacelle acceleration causes degradation of turbine performance and damage to the equipment. This metric was also considered important in Hall et al. (2014, 2013), Karimi et al. (2017), for slightly different reasons: large platform motions were thought to reduce the turbine lifetime, induce higher flapwise bending moments, and reduce energy production. The popular belief that the nacelle acceleration is of uttermost importance in FOWT design was challenged by Nejad et al. (2019), who found there that there is no correlation between the tower-top acceleration and drivetrain responses. The study also concluded that the tower top acceleration does not affect the rotor torque (and so the power produced) in any significant way, as long as the pitch control system remains intact (similar conclusion can be seen for example in Pustina et al. (2020) - this is discussed further in Section 9.2.2). Finally, although the fatigue life was found to be the dominating parameter for the main bearings, it turned out not to be influenced by axial nacelle acceleration. These findings were recently applied by Hegseth et al. (2020b), who decided to discard this objective from their study.

Sclavounos et al. (2008) demonstrated a multi-objective approach in which they aimed to minimise the nacelle acceleration, simultaneously minimising the mooring lines tension. A trade-off between these two objectives was exposed, showing that the minimum-tension designs (i.e., designs with catenary lines) were characterised by an increased nacelle acceleration. Myhr and Nygaard (2012) aimed to minimise the force value in the mooring lines as well as their weight using a time-domain approach. Pillai et al. (2019) performed an optimisation to investigate the trade-offs between the mooring system cumulative lifetime fatigue damage and its cost. Since mooring lines tension significantly influences both the dynamic behaviour of a wind turbine and the capital cost, the attention it receives in support structure optimisation studies is justifiable.

A different objective was considered in the study of Hegseth et al. (2020b), where the rotor speed standard deviation ($\sigma_{\dot{\phi}}$) was used as a proxy for power quality. For a given blade pitch angle, there is one optimum tip-speed ratio at which a turbine extracts the power from the wind most efficiently, i.e., at the highest coefficient of power (this can be seen in Fig. 7). Therefore, for best performance, the ratio of the rotor speed to the wind speed should be kept at exactly this value (all else fixed). Large variations in the rotor speed at a constant wind speed result in suboptimal operation. Additionally, variations in the mechanical speed of the rotor (and hence the generator speed) necessitate the voltage and primary frequency control (to meet the grid connection requirements), which result in major power losses (Anaya-Lara et al., 2018). The need to minimise the rotor speed variation was emphasised by numerous studies on control strategies, including Namik and Stol (2010).

5. Design constraints

The classification of the criteria as objectives or constraints is not consistent in the literature, with the same criterion acting as an objective in one study and as a constraint in another.

For instance, the before-mentioned standard deviation of the nacelle acceleration, which was introduced as an objective in the previous subsection, was used as a constraint instead in Fylling and Berthelsen (2011), Dou et al. (2020), Gilloteaux and Bozonnet (2014). Rotor speed variation presented as an objective in Hegseth et al. (2020b) was instead used as a constraint in the later work of these authors (Hegseth et al., 2020a). It was observed that control systems can reduce these fluctuations, however, it is done at a cost of an increased blade pitch actuator use. Therefore, the control effort was included in the set of constraints as well. The threshold values for these two constraints were based on scaled values characteristic for bottom-fixed wind turbines (the matter of the use of various control systems to mitigate the consequences of the motion of a floating platform will be further discussed in Section 9).

Table 2
A comparison of the chosen elements of FOWT support structure MDAO frameworks.

Reference	Sclavounos et al. (2008)	Fylling and Berthelsen (2011)	Myhr and Nygaard (2012)	Hall et al. (2013)	Hall et al. (2014)	Karimi et al. (2017)	USTUTT (2016)	Lemmer et al. (2017)	Dou et al. (2020)	Hegseth et al. (2020b)	Hegseth et al. (2020a)	Lemmer et al. (2020)
Objectives and constraints												
Economic	o	o	o	o		o	o	o	o	o	o	o
Performance										o	x	
Hydrodynamic	o	x		o	o	o	x	o	x	x	x	x
Servo										x	x	
Elastic			x				o			x	x	
Mooring	o	x	o	x		x			x	x		
Modal		x	x						x	x	x	
Design variables												
Platform	x	x	x	x	x	x	x	x	x	x	x	x
Mooring	x	x	x	x		x			x	x		
Tower						x				x	x	
Cable		x										
Control								x	x	x	x	x
Optimisation algorithms												
Algorithm	BF	SQP	B-A	1	2	GA	PSr	PSr	SQP	S+S	S+S	BF
Search goal	Global	Local	Local	Global	Local	Global	Local	Local	Local	Local	Local	Global
Gradient-based		x							x	x	x	
Derivatives		FD							A	A	A	

x — criterion used as a constraint; o — criterion used as an objective; BF — brute force; PSr — Pattern search; S+S — SNOPT+SQP; B-A — BOBYQA; 1 — CMN GA; 2 — fminsearch; FD — finite-difference; A — analytic

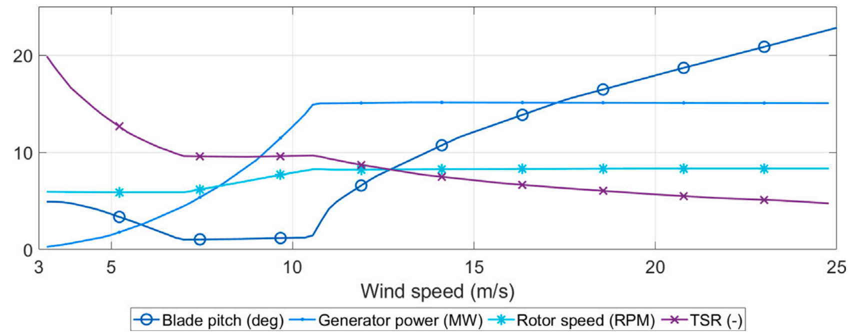

Fig. 7. IEA 15MW controller regulation trajectory — variable speed variable pitch strategy.
Source: Adapted from Evan et al. (2020).

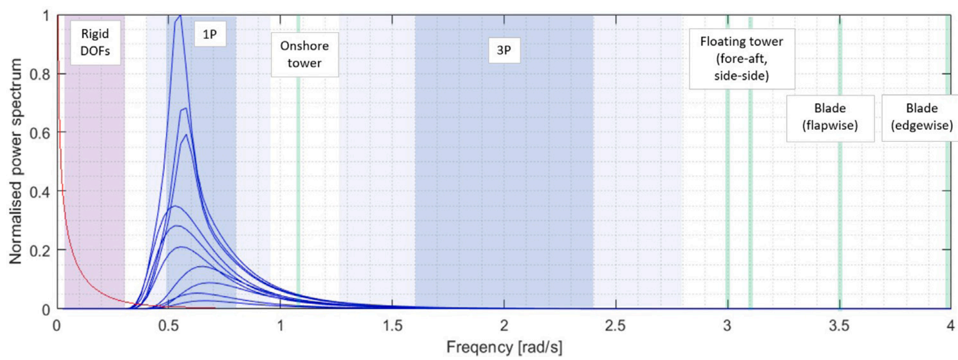

Fig. 8. Example frequency map for the IEA Wind 15MW reference rotor adapted from Allen et al. (2020). Red curve — Kaimal wind spectrum, blue curves — JONSWAP wave spectrum for a range of sea states. Dark shading for the main range, light shading for the safety margins of +/− 2 standard deviations. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Likewise, the mooring line tension is often treated as a constraint rather than an objective. Karimi et al. (2017) applied the minimum line tension constraint to avoid excessive slack in the taut mooring system, while Pillai et al. (2019), Hegseth et al. (2020b) and Brommundt et al. (2012) set a maximum tension of the catenary line tension to avoid exceeding the breaking strength of the chains. The last two studies also constrain the loading on the drag-embedded anchors to be purely horizontal. This is to ensure the anchors remain effective, not being designed to take any vertical loading. The same goal was achieved in a different way by Pillai et al. (2019), who set a limit on the number of line points in contact with the seabed, and Dou et al. (2020), who limited the length of the suspended line to be not more than 75% of the total line length.

When the mooring system is subject to optimisation and both the taut and slack lines are considered, both the minimum and maximum line tension constraints are necessary to eliminate unfeasible configurations. This approach was followed in Tracy (2007) and Fylling and Berthelsen (2011). It is worth noting that the sum of the static and dynamic line tension should be considered to account for the worst-case scenario. For instance, Tracy (2007) formulated the maximum tension constraint as $(T + 3\sigma_T)SF < T_{max}$ where $3\sigma_T$ – three times the standard deviation of the tension – represents the dynamic component of the tension. Similarly, the minimum line tension was formulated as $(T - 3\sigma_T)SF \geq 0$ — an approach easily applicable in frequency-domain frameworks.

A particularly useful constraint, which can be assessed early in the analysis process, is the avoidance of the resonance of the rigid body modes of oscillation with the environmental exciting loads. The full FOWT system must be designed in such a way that none of the important natural frequencies overlaps with the most energetic range of exciting frequencies. Here, the wind spectrum, wave spectrum, rotor and blade passing frequencies (1P and 3P) are to be considered, as illustrated in Fig. 8 for a 15MW reference turbine (Evan et al., 2020).

The intention behind this constraint is to avoid excessive motions. Often, this type of constraint is formulated more stringently by applying an additional 5–10% safety margin to account for the rotor speed variability and to ensure none of the system's important natural frequencies is near these ranges (as shown by the lightly-shaded regions in Fig. 8). For instance, Myhr and Nygaard (2012) only discouraged the frequencies in the 1P and 3P ranges, while Ashuri et al. (2016) considered wider near-resonant regions (i.e., 1.9P – 2.1P and 2.9P – 3.1P).

In addition to the rigid motion modes, the resonance of the flexible modes (e.g., tower fore-aft, blade flapwise and edgewise natural frequencies) with these exciting frequencies (wind, waves, 1P, 3P) could be considered, to avoid augmented structural loads. However, this has not been considered in FOWT optimisation frameworks up to date, up to the best knowledge of the authors.

In the case of spar platforms, it is useful also to consider the so-called Mathieu instability. When the heave natural period is $1/2, 1, 1\,1/2$ or 2 times the pitch natural period, the so-called internal resonance occurs, and the pitch motions become unstable (Rho et al., 2005). The constraint on the ratio between the two modes' natural frequencies was used in Hegseth et al. (2020b). Although this instability has a low probability of occurrence, it is an important design consideration since when it does occur, consequences may be severe (Haslum, 2000). This constraint may be design-driving but is often neglected. Because many of the optimisation frameworks utilise linear frequency-domain models, they are not able to directly account for this nonlinear effect. Therefore, a constraint on the simple ratio of natural frequencies is a very useful and inexpensive addition to those models, to avoid the above-mentioned instability.

Table 3
Constraint values used in FOWT optimisation studies.

Constraint	Units	Limit	Optimisation study	Reference
Max static pitch angle	deg	10	Hall et al. 2013	Hall et al. (2013)
		10	Karimi et al. 2017	Karimi et al. (2017)
Max static + dynamic pitch angle	deg	10	Tracy, 2007	Tracy (2007)
		10	Hall et al. 2013	Hall et al. (2013)
		10	Karimi et al. 2017	Karimi et al. (2017)
		9	Fylling et al. 2011	Fylling and Berthelsen (2011)
		15	Hegseth et al. 2021	Hegseth et al. (2021)
		10	Dou et al. 2020	Dou et al. (2020)
		10	Gilloteaux et al. 2014	Gilloteaux and Bozonnet (2014)
Max RNA acceleration	m/s^2	2.6	Fylling et al. 2011	Fylling and Berthelsen (2011)
		2.0	Dou et al. 2020	Dou et al. (2020)
		1.0	Karimi et al. 2017	Karimi et al. (2017)
		5.0	Gilloteaux et al. 2014	Gilloteaux and Bozonnet (2014)
Max horizontal offset	% of depth	15	Fylling et al. 2011	Fylling and Berthelsen (2011)
		10	Hegseth et al. 2020	Hegseth et al. (2020b)
		15	Dou et al. 2020	Dou et al. (2020)
Min line tension (TLP)	kN	0	Tracy, 2007	Tracy (2007)
		0	Hall et al. 2013	Hall et al. (2013)
		1000	Myhr et al. 2012	Myhr and Nygaard (2012)
		728	Fylling et al. 2011	Fylling and Berthelsen (2011)
		0	Karimi et al. 2017	Karimi et al. (2017)

Other constraints applied in FOWT support structure multidisciplinary optimisation studies include the fatigue stress in the steel structure (Hegseth et al., 2020b, 2021) and mooring lines (Fylling and Berthelsen, 2011), the sum of the static and dynamic pitch motion evaluated in the maximum thrust condition (Hall et al., 2013; Gilloteaux and Bozonnet, 2014; Karimi et al., 2017), the standard deviation of the free surface elevation to avoid slamming and green water (Tracy, 2007; Gilloteaux and Bozonnet, 2014), maximum platform motion to avoid breaking the power cable (Brommundt et al., 2012), or maximum cable tension (Fylling and Berthelsen, 2011).

Table 3 lists the constraint limiting values assumed in FOWT optimisation studies. It is noteworthy that some level of ambiguity is seen in setting these limits.

6. Optimisation algorithms

This section is not aimed at providing an exhaustive overview of all the optimisation algorithms available, but focuses on the algorithms that have been adopted in FOWT multidisciplinary optimisation studies.

The selection of an optimisation algorithm is governed by the consideration of the type of optimisation problem at hand, the search goal, and the search method. Like the majority of engineering problems, most, if not all, FOWT optimisation problems can be categorised as linearly or nonlinearly constrained problems. In some studies, the constraints are separated by introducing penalty functions, so that the use of unconstrained minimisation techniques can be made (e.g., Myhr and Nygaard, 2012).

The search goal defines the goal of the optimisation — whether the global or local optimum/optima are sought. Hall et al. (2013) studied a wide range of designs spanning diverse platform and mooring system topologies. Therefore, an insight into multiple local extrema (related to different classes of platforms) was essential (an algorithm that can converge to multiple locally optimal configurations simultaneously is very powerful at the initial design stages, where the general characteristics of the design space are studied). The robust Cumulative Multi-Niching Genetic Algorithm (CMN GA) (Hall, 2012) previously developed by the main author was utilised. Its distinctive feature is the ability to preserve the entire population during the entire optimisation process, adding new individuals to the population after each single objective evaluation, never discarding any information. An example of design space visualisation of the CMN GA is shown in Fig. 9.

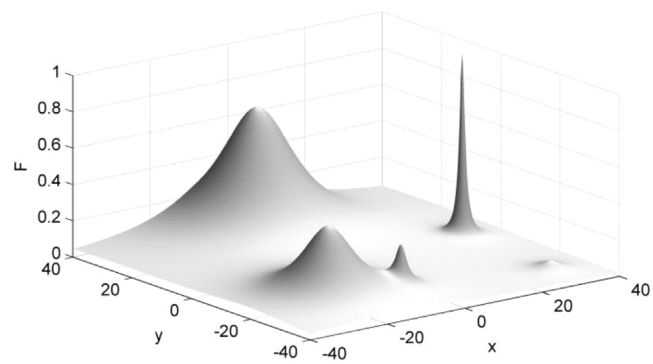

Fig. 9. Cumulative Multi-Niching Genetic Algorithm (CMN GA) 2D design space exploration — multiple local maxima can be seen.
Source: Retrieved from Hall (2012).

When working with FOWTs, even if a single class of platforms is considered (e.g., a spar), the design space is likely to be multimodal (i.e., contain multiple local optima). However, since global optimisation generally leads to a significantly increased computational effort, most studies conduct local search instead, leading to less expensive, but still useful, solutions. For instance, Myhr and Nygaard (2012) employed the Bound Optimisation by Quadratic Approximation (BOBYQA) algorithm to search for locally optimal taut mooring configurations. This trust-region method, partly depending on approximation of the objective function, was found to be particularly beneficial in nonlinear, nonconvex problems, with noisy objectives (Powell, 2009). Therefore, such algorithms can be successfully applied to a problem where the objectives depend on stochastic inputs.

Researchers at the USTUTT (2016) and Lemmer et al. (2017) used one of the Pattern Search methods. Like for all methods within the direct search optimisation family, the search is only performed in the close vicinity of a starting point, therefore, the results are strongly dependent on the choice of the initial set of variables (Eldred et al., 2002). For this reason, the local approaches are often complemented by the so-called 'multi-start' strategy, where the optimisation is repeated considering different initial design points (e.g., Hegseth et al., 2020b).

The last consideration is the search method, which refers to the way the optimiser 'moves' from one to the next improved design point. Up to 2020, the multidisciplinary FOWT optimisation studies almost exclusively used derivative-free algorithms. This was mainly driven by the fact that the sensitivity information is not always readily available, and the use of numerical approximation methods (e.g., finite difference) may significantly increase the computation time. The stochastic algorithms applied in FOWT optimisation projects include the previously mentioned BOBYQA, CMN GA and Pattern Search, as well as different versions of the Genetic Algorithm (GA) (e.g., Karimi et al., 2017). A comparison of a few derivative-free methods (Pattern Search, Particle Swarm, GA, and Simulated Annealing) in terms of their accuracy and efficiency was performed in USTUTT (2016), showing that the Pattern Search generally requires fewer function evaluations than the other methods considered.

In many other engineering fields, researchers often decide to employ one of the modern, highly efficient gradient-based algorithms. For smooth, unimodal and well-behaved problems, these methods outperform the derivative-free techniques in terms of convergence rates (Eldred et al., 2002). Within this group, in FOWT optimisation studies the methods using Sequential Quadratic Programming (SQP) are the most common. This family of methods can handle any degree of nonlinearity, however, since it requires computation of derivatives, it becomes cumbersome for large problems (i.e., problems with many variables or constraints).

If the optimisation problem is only composed of differentiable objectives and constraints, the partial derivatives with respect to the design variables can be obtained analytically. For instance, Dou et al. (2020) used the gradient-based SQP algorithm implemented in MATLAB Optimisation Toolbox, together with the analytical sensitivities of the mass, damping and stiffness matrices and the equation of motion.Hegseth et al. (2020a,b) used the SNOPT (Sparse Nonlinear OPTimizer) algorithm with analytical partial derivatives and total derivatives obtained by the adjoint method (Martins and Hwang, 2013). The advantage of this solution is that the cost of the evaluation of derivatives is independent of the number of design variables (Gill et al., 2005) – this method will be further discussed in Section 9.

However, many FOWT optimisation problems consist of objectives and/or constraints either given by functions which are difficult to differentiate analytically, or are evaluated by a 'black box' type of solver, whereby the analytic expressions are not available. In that case, numerical differentiation must be performed. For instance, the WINDOPT tool for optimisation of spar-type floating wind turbines (Fylling and Berthelsen, 2011) employs two-sided finite difference approximation. It is noteworthy that the gradient accuracy is critical for the success of these methods. Most often, if the derivatives cannot be evaluated analytically, one of the stochastic optimisation algorithms is preferred.

If precision is not of uttermost importance in an optimisation study, the brute force (or 'exhaustive search') method may be of use. Although it is not the most efficient search method, implemented in a correct way may aid concept-level studies. Brute force optimisation of FOWT support structure was first presented by Sclavounos et al. (2008), whose study of a wide range of cylindrical platforms paved the way for the subsequent increasingly complex studies. This optimisation approach has also been recently applied in Lemmer et al. (2020), following a careful selection of just two free variables, and defining their upper and lower bounds so as to ensure that the design space was Cartesian (i.e., the ranges of variables do not depend on the values of the other variables).

7. Dynamic modelling

This section investigates the fast linear frequency-domain (FD) models first, followed by the full time-domain (TD) models, the simplifications often applied in TD and extensions in FD frameworks.

7.1. Frequency-domain models

According to the traditional engineering design paradigm, the conceptual design is carried out using flexible, robust, low fidelity models. For floating wind turbines, typically, frequency-domain tools are used, being able to rapidly approximate the most important dynamics. In the simplest form, equations of rigid body motion in n degrees of freedom (DOFs) are derived by equating the inertial loads to the sum of the pressure and gravitational forces acting on the platform (Newman, 2018):

$$\sum_{j=1}^{n} \xi_j [-\omega^2 (M_{ij} + A_{ij}) + i\omega B_{ij} + C_{ij}] = aX_i \tag{5}$$

ξ_j relates to the complex amplitude of motion in the jth direction and a denotes the wave amplitude. M_{ij} and C_{ij} are the mass/inertia and stiffness matrices, respectively, usually evaluated analytically from the structural properties of the platform, tower, and rotor-nacelle assembly, and the linear properties of the mooring system (derived a priori).

The frequency-dependent matrices A_{ij}, B_{ij} (added mass and radiation damping), and the frequency- and direction-dependent wave excitation load matrix X_i can be approximated as solutions to the linear radiation–diffraction problem. This is often achieved using the Boundary Element Method (BEM), the numerical implementation of which can be found in open-source (e.g., NEMOH Babarit and Delhommeau, 2015) or commercial (e.g., WAMIT (Wamit Inc., 2002), WADAM (D.N.V. G.L. - Software, 2017)) codes (for a comprehensive review of these refer to McCabe (2004)).

Table 4 compares the different approaches to disciplinary analysis adopted in the 12 chosen FOWT support structure multidisciplinary optimisation studies. As indicated therein, the 1st order potential flow BEM method constitutes the basis for a large majority of frameworks. The hydrodynamic model applied in Tracy (2007) (one of the earliest studies on the subject) fully relies on the potential flow solution. This method remains the basis of many subsequent studies, however, it is always complemented by additional models accounting for viscous and, in some cases, 2nd-order effects.

The potential flow analysis of n degrees of freedom requires the solution of one diffraction and n radiation problems for each wave frequency. Alternatively, for some platform configurations (e.g., platforms with small waterplane areas), the added mass coefficients do not vary with frequency substantially, and the radiation damping force is significantly smaller than the added mass force (Rajabi et al., 1985). For these platform configurations, the added mass can be considered constant and calculated based on analytical 2D coefficients, and radiation damping can be neglected, as demonstrated in Hegseth et al. (2020b).

The solution of the diffraction problem is the most computationally expensive part of the FD solution. Therefore, alternative approaches are sought in cases where the impact of the platform on the incoming wave characteristics is negligible. Provided that the characteristic dimension of the platform is at least (approximately) five times smaller than the wavelength considered, the Morison approach in the frequency domain is often adopted, representing the wave load as a sum of inertial and viscous forces. In absence of diffraction, the inviscid load is equivalent to the inertial load, which can be calculated as a sum of the added mass force and the Froude–Krylov force. The viscous drag term, in general, depends on the relative velocity of water particles normal to the body surface, including the contributions of the water particles velocity, current velocity and platform motion velocity. Hence, an alternative equation of motion can be derived (Rajabi et al., 1985):

$$M\ddot{\xi} + B\dot{\xi} + C\xi = c_m \rho \nabla \dot{u} - (c_m - 1)\rho \nabla \ddot{\xi} + c_d \cdot \frac{1}{2}\rho a_n |v_c + u - \dot{\xi}|(v_c + u - \dot{\xi}) \tag{6}$$

The inertia coefficient (c_m) is taken so that the added mass matches that obtained by the potential approach. If viscous effects can be neglected, the last term on the right-hand side can be dropped, leaving a linear equation of motion suitable to be solved in the frequency domain. Alternatively, to preserve the viscous drag term, one of the drag linearisation techniques can be applied, as will be discussed later in this Section 9. Full Morison's approach (i.e., both inertial and viscous parts) was applied, for example in Myhr and Nygaard (2012), where

Table 4
A comparison of the design load cases, modelling approaches and systems optimised in various FOWT support structure multidisciplinary optimisation studies.

Reference	Sclavounos et al. (2008)	Fylling and Berthelsen (2011)	Myhr and Nygaard (2012)	Hall et al. (2013)	Hall et al. (2014)	Karimi et al. (2017)	USTUTT (2016)	Lemmer et al. (2017)	Dou et al. (2020)	Hegseth et al. (2020b)	Hegseth et al. (2020a)	Lemmer et al. (2020)
DLCs												
Directionality			x									
Wind speeds	1	2	2	2	3	3	7	7	12	3	15	22
Extreme		x	x								x	x
Modelling												
Domain	FD	FD	FD/TD	FD	FD	FD	FD	FD/TD	FD	FD	FD	FD
Aerodynamics	PTD	RV	UBEM	PTD	PTD	PTD	PBEM	PBEM	PBEM	PBEM	PBEM	PBEM
Wave excitation	PF	MCF +FK	M	PF	PF	PF	PF	PF	M	MCF	MCF	PF
Potential coeff.	PF	ST	M	PF	PF	PF	PF	PF	M	A	A	PF
Viscous drag	–	–	M	M	M	M	Emp	Emp	M	M	M	M
Mean drift	–	Maruo (1960)	–	–	–	–	–	–	–	–	–	PF
Slow-drift	–	–	–	–	–	–	–	–	–	–	–	Standing et al. (1987)
Elasticity	–	–	FEM	–	–	–	–	MB	–	Dirlik	Dirlik	MB
Mooring	QS	PTD	FEM	PTD	PTD	PTD	Jonkman and Buhl (2007)	PTD	Al-Solihat and Nahon (2016)	Lie and Sødahl (1993)	–	QS
Cost	Mat	Mat	–	M+A	–	Mat	Mat	Mat	Mat	Mat	Mat	Mat
System												
Platform	Range	Spar	TLP	Range	–	Range	SS	SS	Spar	Spar	Spar	SS
Rated MW	5	5	5	5	5	5	10	10	10	10	10	10
DOFs	1–6	1–6	1-6, 12 str	1–5	1–6	1–6	1,3,5 t, ω	1,3,5 t, ω	1,3,5 t	1,5 t, ω	1,5 t, ω	1,3,5 t, ω, θ

PTD — precomputed time-domain; RV — proportional to relative velocity; PBEM — precomputed BEM; UBEM — Unsteady BEM; PF — potential flow; MCF — McCamy Fuchs; FK — Froude–Krylov; ST — Strip Theory; M — Morison's equation; Emp — empirical; A — analytic; QS — quasi-static; MB — multibody; ω — rotor speed; θ — blade pitch; t — tower 1st mode; 1-6 — rigid body DOFs; 12 str — 12 structural DOFs, Mat — bill of material; M+A — material + anchors cost; SS — semi-submersible the bounds on the variable diameter were set ensuring validity of the approach (slender-body assumption).

Note that Morison's equation cannot be applied in heave DOF, where an alternative approach is necessary. For instance, Hegseth et al. (2020b) approximated the heave excitation as buoyancy forces integrated up to the instantaneous free surface. The same approach was deemed appropriate for deep-drafted platforms in Jonkman (2010).

An important observation is that all approaches described in this section have a great advantage of being defined as a set of explicit equations, which can be assembled into a single system and solved in a non-iterative manner.

7.2. Time-domain models

Traditionally, time-domain tools find their application in the preliminary and detailed design phases, used to answer more specific design questions, building upon the knowledge gained in the earlier design stages. Although a lot of insight into the initial design performance can be gained using the FD approach, it cannot always be justifiably applied. In operational conditions, especially close to the rated wind speed, the aerodynamic and mooring loads are known to be nonlinear (Jonkman and Buhl, 2007; Lupton, 2014). Likewise, to account for the realistic ultimate limit states over the lifetime of the structure, prediction of the extreme responses is required. When considering harsh environmental conditions, the hydrodynamic and aerodynamic loading, as well as the structural response, may be strongly nonlinear and should be solved in time-domain (Karimirad, 2011).

While frequency-domain codes are unable to account for these nonlinear loads and only useful in analysing the regime response, time-domain analysis enables insight into the transient phase response and impact of nonlinear loads. For instance, the nonlinear dynamics introduced through transient events and control system actions can be accounted for Cordle and Jonkman (2011).

Perhaps the best example of a state-of-the-art, open-source, and freely available time-domain analysis tool is OpenFAST (Jonkman, 2007). This code, developed at the National Renewable Energy Laboratory (NREL), encompasses aerodynamics, hydrodynamics, servodynamics, dynamics of mooring lines, and structural dynamics, numerically coupled to enable nonlinear aero-hydro-servo-elastic simulations of wind turbines (National Renewable Energy Laboratory (NREL), 2019). The internal coupling within the code means, from the MDAO framework development point of view, that no additional effort is required to converge the disciplines within an optimisation loop, therefore the implementation effort is much reduced compared to the use of individual solvers for each discipline.

For an extensive review of different TD tools, one can refer to the reports published within the Offshore Code Comparison Collaboration (OC3) project of the International Energy Agency (IEA), for instance (Robertson et al., 2014), and the more recent OC5 validation campaign (Robertson et al., 2020).

Despite their advantages, TD codes typically require a wall-clock time of the same order of magnitude (or one order of magnitude less) as the simulated time, i.e., for a 10^3 seconds simulation, around 10^2–10^3 seconds wall-clock time is required by an average desktop station. While this may not be a problem when analysing a single design, it becomes a significant obstacle when analysing thousands of candidate designs under a large number of load cases (and realisations), for optimisation purposes.

TD analysis was performed in very few FOWT optimisation studies, and solutions to reduce the computational costs had to be adopted. Myhr and Nygaard (2012) aimed to minimise the wave load on a TLP platform by introducing a space-frame section in the wave affected zone. Therefore, the level of accuracy and detail required from the structural analysis could only be achieved by applying Finite Element Analysis in the time domain.

Lemmer et al. (2017) performed an optimisation using a reduced-order TD model, to be able to study the dynamic behaviour of the turbine coupled with of a control system. In their later study (Lemmer et al., 2020), the same authors compared the experimental, TD, and FD approaches, and found that the TLP's response can be predicted with the linearised model sufficiently well for preliminary sizing purposes.

It should be noticed that even the state-of-the-art time-domain analysis tools (such as those mentioned in this section) still suffer from an inability to accurately predict the response of the floating platforms in some of the environmental conditions. For instance, these mid-fidelity solvers were found to underpredict the nonlinear responses of semi-submersibles in the low frequency wave range (Robertson et al., 2017). Development and validation of high-fidelity tools for that purpose, such as Computational Fluid Dynamics (CFD) routines, are currently subject to intense research, with some of the early results being published, for example, in Wang et al. (2021), where a range of CFD tools have been successfully validated against experimental results for the prediction of the nonlinear difference-frequency wave excitation in surge and pitch.

Challenging the traditional design paradigm, Safavi et al. (2016) argues that to be able to make more accurate design decisions at the conceptual design stage (and so to lower the cost incurred in later stages), it is necessary to increase the fidelity of the analysis at the very onset of a project. The adoption of an MDAO approach may address this specific requirement. Being able to search through extensive design spaces more efficiently, the use of increased fidelity tools in conceptual design can be afforded, potentially resulting in a reduced overall development cost. This same consideration was presented in Barter et al. (2020), where it was observed that the traditional design paradigm is currently being replaced by modern, multi-fidelity standard (i.e., the low, medium, and high-fidelity tools are used concurrently when evaluating the concept - more details in Section 9.4.5).

In the FOWT multidisciplinary optimisation context, up to date, rather than relying on the highest fidelity tools in the conceptual design space exploration, compromises are being sought by developing either simplified time-domain or augmented frequency-domain analysis tools. The examples of the application of the two alternative approaches in FOWT optimisation studies will be reviewed in the subsequent sections.

7.3. Simplified time-domain models

The first simplification, which can reduce the solution time significantly, is a careful selection of the rigid body degrees of freedom. The majority of FOWT optimisation studies ignore the yaw motion (Table 4), many of them being limited to surge, heave and pitch only, taking advantage of the axisymmetry of the platforms analysed.

Time-domain codes can, in general, model the load distributions along the chosen elastic members such as the blades or the tower (Finite Element Method - FEM). Significant improvement in solution time can be achieved if the structural loads and deflections are calculated at single nodes instead (e.g., blade root, tower base). This is often achieved by a coupled multibody approach (e.g., Lemmer et al., 2017). In that case, the higher frequency modes are not modelled, and the number of degrees of freedom is much reduced.

Major benefits in terms of reduced simulation time can be achieved by avoiding unnecessary iterations, recursions, integrations, TD to FD conversions, and excessive memory use (Sandner et al., 2012). Some of these points can be achieved by precomputation of the aerodynamic coefficients and mooring lines forces. Instead of using the iterative Blade Element Momentum (BEM) method during the analysis, look-up tables of torque and thrust coefficients can be assembled by running a TD simulation for various tip-speed ratios and blade pitch angles a priori (Schlipf et al., 2013). The quasi-static fairlead forces can be obtained by interpolating the look-up data with the horizontal and vertical displacements as inputs (Jonkman, 2010). These simplifications were included in the SLOW code used in the FOWT optimisation study by Lemmer et al. (2020), resulting in a high simulated time/ wall-clock time ratio of 160 (for comparison, this ratio can be of the order of 0.5 for a full nonlinear time-domain simulation).

7.4. Extended frequency-domain models

FOWT support structure multidisciplinary optimisation frameworks most often rely on the extended frequency-domain or hybrid frequency–time-domain analysis models. In that case, the main challenge lies in finding, and assessing, accurate linearised approximations of the chosen nonlinear effects not accounted for in the simplest frequency-domain model. The remainder of the section deals with the chosen extensions of the hydrodynamic, aerodynamic, elastic, and control submodels.

7.4.1. Hydrodynamic forces

As outlined before, the simplest approach to hydrodynamic modelling in FD frameworks only includes the first-order potential loads, which are often a lot larger than the higher-order loads. The loads at the difference of these two frequencies excite slow-drift motions, may resonate with low natural frequency modes of FOWT (such as surge motion), and can increase dynamic tension in the catenary mooring lines (Coulling et al., 2013). The loads at the sum of the frequencies may potentially excite the first tower bending mode (Duarte et al., 2014), and have a significant effect on fatigue and ultimate loads on TLPs (Bachynski and Moan, 2014).

The statistics of the combined first and second-order wave loads are, in general, non-Gaussian. Therefore, analysis of the response of the platform to these loads in FD is not straightforward, and is very rarely performed in FOWT optimisation studies. An exception is the work by Lemmer et al. (2020), where the second-order slow-drift forces were shown to be significant for the platform analysed (Triple Spar), especially for the low-drafted candidate designs. The approximated model applied in the study uses the first-order potential flow problem solution to derive the second-order wave excitation quadratic transfer functions (QTFs). To speed up the calculations, Standing's version of Newman approximation is applied, whereby the off-diagonal terms of the QTFs are estimated from the diagonal terms (Newman, 1975; Standing et al., 1987). This approximation is considered sufficiently accurate for conceptual design purposes and is computationally less expensive that the full QTF approach ($2N$ functions evaluations instead of N^2 in original approach, with N being the number of wave frequencies) (Lemmer, 2018).

The second possible extension, which allows to cover a much wider range of platform geometries and environmental conditions, is the addition of a linearised viscous drag model. While for many platform geometries, and many load cases, the response may be dominated by inertial loads (e.g., large volume floaters, short waves), the exploration of large design spaces requires a common approach valid for all distinct designs, also including those for which flow separation effects are not negligible. For this reason, amongst others, from 2012 onwards, most of the FOWT optimisation studies consider viscous loads in their models of dynamics (see Table 4). Two different approaches were presented in FOWT literature up to date: the use of the drag term from Morison's equation (e.g., Hall et al., 2013), and a simpler empirical approach (e.g., USTUTT, 2016).

As can be seen in Eq. (6), the drag modelled by Morison's equation is quadratic with respect to the water particle velocity relative to the body. To be able to apply it in the FD model of dynamics, it must be linearised. Different methods were presented in the literature, however, FOWT multidisciplinary optimisation studies are largely dominated by the stochastic linearisation method proposed by Borgman (1967) and more recently reintroduced in the context of FOWTs optimisation in Hall et al. (2013). Provided that the wave surface elevation is a Gaussian random process with zero-mean, and the linear wave theory is applicable, then the fluid velocity is also a Gaussian process, and the following expression can be derived for the drag load acting on a thin slice:

$$\frac{df_d}{dL} = \frac{1}{2} c_d \rho D \sqrt{\frac{8}{\pi}} \sigma_u u \tag{7}$$

The drag load given by this approximate expression depends on the statistics of the normal velocity (standard deviation σ_u), which in turn depend on both the platform response and the water particle velocity due to the waves. Because the platform response statistics are necessary to calculate the viscous loads, and the calculation of the response requires the viscous drag as an input, an iterative approach is necessary.

Note that, in general, the relative normal velocity depends both on the platform velocity, and the fluid velocity due to the wave and the current. Therefore, Morison's drag term can be split into two parts, the first of which acts as a damping contribution, and the second contributes to the wave excitation force. Often, the velocity due to water particle motion is considered small in comparison to that resulting from the platform motion (as a consequence of the linear wave kinematics assumption). Hence, the exciting load part is often disregarded (e.g., Karimi et al., 2017). In some references, both parts are preserved, split between two sides of the equation of motion (e.g., Lemmer et al., 2020; Myhr and Nygaard, 2012). The guidance regarding the applicability of the relative velocity in the Morison equation is available in DNV's Recommended Practice DNV-RP-C205 (Det Norske Veritas, 2010), based on the consideration of the motion amplitude compared to the size of the structure.

7.4.2. Mooring forces

In FOWT multidisciplinary optimisation studies, a range of different approaches to mooring load modelling exist. Myhr and Nygaard (2012), who utilised a time-domain approach, applied the most accurate nonlinear Finite Element Model with cable elements of reduced bending stiffness. More frequently, however, precomputation of the mooring stiffness in time-domain is performed, as presented for example in Karimi et al. (2017), Fylling and Berthelsen (2011), Dou et al. (2020) - see Table 4. A linearisation subroutine of a state-of-the-art TD code FAST is often utilised at the preprocessing stage of the optimisation (Jonkman et al., 2018). The series of steps includes the identification of the steady state (or operational) point, translational displacements of the floating structure about this point, and numerical computation of the restoring matrix (i.e., force–displacement relationships) through a central-difference perturbation technique. Since mooring loads can be highly nonlinear over large displacements (Tracy, 2007), it is recommended to perform this linearisation around each operational point individually. The steady state position of the platform depends on the mooring properties, and the mooring stiffness depends on the position of the platform, therefore, this approach requires an iterative procedure. However, if the load on the mooring line itself is of no interest, and the focus is on the platform response, some studies (e.g., Hall et al., 2014) perform a simpler single linearisation about the zero-offset (or, no wind) point, and use the results for all environmental conditions considered, hence eliminating the requirement of iterative solution.

Alternatively, analytical formulations can be applied, such as the method of Al-Solihat and Nahon (2016) used in the recent FOWT optimisation by Dou et al. (2020). In this approach, the mooring stiffness matrix is derived as an implicit function of the horizontal and vertical projection of the mooring line, vertical position and radius of the fairleads, as well as the horizontal and vertical force at the fairlead obtained through a catenary equation. A unique solution was applied in Hegseth et al. (2020b) whereby the inertia and damping of the mooring lines, modelled as a 1 degree of freedom spring–damper system, were also computed in addition to the stiffness.

7.4.3. Aerodynamic forces

Due to the specifics of the industry, the designs of the rotor and the support structure are very rarely integrated (Hassan, 2017). However, when optimising the platform and mooring system, it is necessary to account for the aerodynamic loads, at least in a simplified way. The aero-elastic loads on the rotor may result in nonlinear, time–history dependent forces and moments on the foundation (Burton et al., 2011). Nonetheless, the aerodynamic loading is strictly related to the design of the rotor, not the platform, so the precomputation in the time-domain is possible (i.e., the results of the TD simulations performed outside the optimisation routine can be re-used inside the optimisation loop with any platform design).

Most of the published literature on FOWT optimisation relies on a steady-state solution of the standard BEM approach at different tip-speed ratios and blade pitch angles. Two-dimensional look-up tables for power coefficient and thrust coefficients are assembled. Since the aerodynamic torque and thrust are additionally dependent on the square of the rotor effective relative wind speed, linearisation is necessary before the results can be used in an FD framework. Most often this is achieved by expanding the standard thrust and torque formulations as a Taylor series up to the first order (tangent linearisation) (Sandner et al., 2014). Additionally, a range of semiempirical correction can be used, such as that for unsteady inflow applied for example in Myhr and Nygaard (2012).

A slightly different approach was followed by Hegseth et al. (2020b), who applied a linearised BEM theory with semiempirical corrections as well, but instead of precomputing the thrust and torque coefficients, the normal and tangential induction factors for the different blade elements were found in advance. Additionally, the blade root loads (flapwise shear, flapwise bending moment, and edgewise bending moment) were calculated through the integration of the normal and tangential forces over the length of the blade. These were then linearised using Taylor expansion. To obtain the resultant aerodynamic forces on the rotor (thrust and torque), the Taylor series was used as well. The required partial derivatives of the resulting loads with respect to wind speed, blade pitch angle and rotor speed (the so-called 'gain factors' in the prime (Halfpenny, 1998)) were obtained based on the corresponding derivatives of the normal and tangential blade element loads. These were found numerically by perturbing the inputs and observing how the forces change. The linearisation was performed for each blade element, therefore the information about the distribution of the loads along the blade was readily available.

The method applied in Tracy (2007), Hall et al. (2013), Karimi et al. (2017) relies on the precalculation of the aerodynamic matrices (added mass, damping, and stiffness) using the linearisation functionality of TD software. The added mass matrix reflects the additional inertia introduced to the full system by the acceleration of the air around the moving rotor-nacelle assembly. The aerodynamic stiffness effect is due to the fact that, when the platform inclines in pitch, the rotor plane changes its orientation relative to the average wind direction, resulting in a change of induction factors and, as a result, a change in aerodynamics loads. Aerodynamic damping, by definition, is linked to a change of aerodynamic loads due to a change of the relative wind speed. As the platform moves in waves, the rotor inflow speed changes, hence influencing the generated thrust. In the studies considered, the added mass, stiffness and damping coefficients were linearised at each wind speed condition at the static equilibrium pitch angle, assuming that the platform pitch motion is generally small, and keeping the blade pitch angle fixed at the value required for that specific undisturbed wind speed.

7.4.4. Structural dynamics and fatigue

Most of the FD models reviewed assumed that the entire WT structure is rigid (e.g., Karimi et al., 2017); structural dynamics were very rarely included in the FOWT optimisation frameworks. One example is a rigid multibody system approach applied in USTUTT (2016), where an additional degree of freedom (tower-top fore-aft displacement due to deformation) was added to the set of rigid motion DOFs, to enable the consideration of tower flexibility in a very simplified way. The nonlinear equations of motions were transformed into state–space form and then linearised about the steady operating point. The elasticity of the blades was not considered. A similar approach was applied by Hegseth et al. (2020b), who also pointed out that this method was too simplistic to be able to model the blade deflections accurately.

Fatigue damage is very rarely included as a design criterion, and only one approach to evaluate the hull and tower fatigue, and one to evaluate mooring line fatigue, were presented in FOWT multidisciplinary optimisation studies, to the best knowledge of the authors. Hegseth et al. (2020b, 2021) computed the fatigue resistance using a SN curve approach in accordance with the recommendations of the DNV RP-C203 code (Det Norske Veritas (DNV), 2014a), whereby the predicted number of cycles to failure (N) is found from the following relationship:

$$N = K S^{-m} \tag{8}$$

with K and m obtained from SN plots, and S being the stress range. The cumulative lifetime fatigue damage (D_{tot}) was calculated based on the Palmgren–Miner hypothesis about linear accumulation of damage with the probability density function of the stress ranges obtained by the empirical method of Dirlik (1985). The total fatigue damage was calculated by summing the products of damage and the frequency of occurrence of a number of short-term conditions.

Mooring line fatigue was accounted for in the FOWT optimisation study by Fylling and Berthelsen (2011) using an analogous TN curve approach, as proposed by Hasan in Hasan (2017).

7.4.5. Control system dynamics

Modern horizontal axis wind turbines usually adopt a variable-speed, variable-pitch control strategy. At low wind speeds, the rotor speed is adjusted to the changing wind speed, while in above-rated conditions the rotor blades are pitched to maintain the maximum power produced and avoid any damage. Therefore, an implementation of this control strategy within an analysis tool requires two additional degrees of freedom, namely, the rotor speed and the blade pitch angle. Modelling of the behaviour of a multidisciplinary system coupled with a control system can be computationally expensive and requires significant implementation effort (including linearisation). Therefore, initially, it received very little attention in FOWT optimisation literature.

The idea of incorporating the action of the control system into the FOWT optimisation studies gained some appreciation in the work of Lemmer et al. (2017), where it was noticed that it may influence the power production performance considerably. In this work, time-domain reduced-order nonlinear simulations were initially performed to determine the steady state of the system. Based on this, a linearised model was derived and employed to design an optimal model-based the Proportional–Integral (PI) controller for each design. The study adapted the controller of the NREL 5MW reference wind turbine (Jonkman et al., 2009) below rated wind speeds, and a Linear Quadratic Regulator with a state-feedback controller above rated wind speeds. The control outputs included the blade pitch angle and the generator torque, while the inputs were all states of the linearised model (i.e., platform surge, heave and pitch displacements, tower-top fore-aft displacement, and the rotor speed, and their derivatives). At the end of each optimisation iteration, a nonlinear time-domain code was used to simulate the system response and evaluate the design objectives (note that this is a sequential approach whereby the control system is being tuned in isolation from the remaining design variables).

In a recent optimisation study performed by Hegseth et al. (2020b), the control system was described as a 1st order state–space system with the rotor speed as the only input, and the generator torque and blade pitch angle as outputs. A low-pass filter was applied to avoid the high-frequency excitation of the controller. For low wind speeds, generator torque was set to be proportional to the rotor speed squared, while

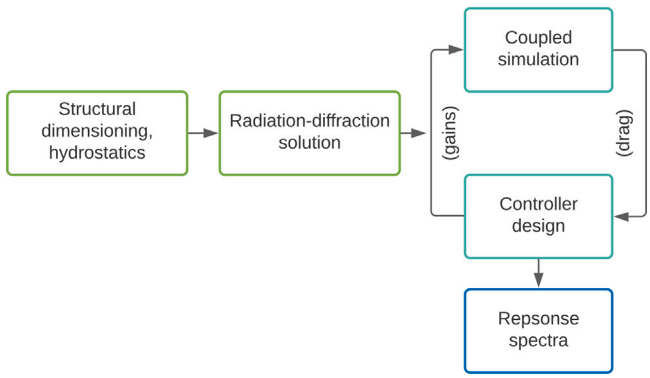

Fig. 10. FOWT system-level design optimisation scheme including drag-control loop.
Source: Reproduced from Lemmer et al. (2020).

for high wind speeds, the blade pitch angle was adjusted according to the proportional–integral control strategy. The structural and control models were assembled forming a single closed-loop system, which was then transformed to the frequency domain for calculation of the response spectra and statistics. This enabled a simplified, but sufficiently accurate, coupled (or integrated) analysis of the entire system.

A similar exercise was repeated for different, more advanced, types of controllers in the later work of Hegseth et al. (2020a). Four control strategies were compared, including a basic gain-scheduled Proportional–Integral (PI) controller, as well as its three variations incorporating additional platform pitch/nacelle velocity feedback and a low-pass filter. Through introduction of the velocity feedback, the platform pitch motion and fatigue loads in the tower were reduced, while the low-pass filter improved the power output quality.

Lastly, in Lemmer et al. (2020), a Single-Input-Single-Output (SISO) Proportional–Integral (PI) controller was applied, with the generator torque and blade pitch as outputs to the plant, and rotor speed and tower top displacement as inputs, with wind and wave disturbances. Both the system and disturbance transfer functions were obtained from a linear model of dynamics, similar to the previously mentioned references. Additionally, it has been noticed that the viscous drag coefficient, dependent on the KC number, and hence dependent on the relative flow velocity and the response of the platform, influences the process of controller gains tuning. Therefore, the viscous drag and the controller gains were computed iteratively, as per Fig. 10. The details about the controller design procedure can be found in a companion paper of the authors (Lemmer et al., 2019).

8. Cost modelling

The Levelised Cost of Energy (LCoE) consists of both the total life cycle cost (i.e., sum of discounted annual capital and annual operation & maintenance expenditures) and the energy yield part (i.e., sum of discounted annual energy yields). To avoid the inherent difficulties of the power output modelling, it is a popular approach to focus on the cost part of this metric, carefully selecting the most noticeable components of LCoE. As shown in Section 9.2, the FOWT support structure optimisation studies usually aimed to minimise the capital cost.

Hegseth et al. (2020b) modelled the total cost as a sum of the costs of the floater, tower, and mooring system. The cost of the floater and the tower were composed of material and manufacturing costs, both based on the approach proposed by Farkas and Jármai (2013) for unstiffened conical shells. Additionally, the cost model for the floater was enriched by factors related to ring stiffeners. The full fabrication sequence was considered, including the processes of forming, welding and painting. On top of the structural mass and surface area, the details such as the complexity of assembly, number of structural parts, welding type and technology were factored in. Good use of this comprehensive model was made by applying it to a flexible and detailed parametric scheme, which consisted of both the external shape of the tower and the floater, as well as the variables controlling the internal scantlings.

In the studies where the parametric model was less detailed (e.g., considering the external shape of the hull only), adequately simpler cost models were applied. As can be seen in Table 4, the vast majority of studies followed the bill of material approach whereby the cost was modelled as a product of the steel material mass and a cost per unit mass. This cost may include material cost only, or a sum of material, manufacturing, and installation costs, which are all assumed to be proportional to the total weight of the structure.

Hall et al. (2013) assumed the material, fabrication and installation costs to be linearly proportional to the total mass. This assumption was based on the study of van Hees Bulder et al. (2002), who showed that the specific costs of different steel structural elements do not vary significantly. Similarly, Fylling and Berthelsen (2011) assumed that the total cost of one representative design is available and can be scaled proportionally to the structural mass. Rather than calculating the mass of each new design directly, scaling laws were applied relative to this representative design. For instance, the structural mass per unit length of the underwater part of the floater subjected to hydrostatic loading was assumed to vary with the section's depth and diameter. While the cost of the ballast was usually assumed to be negligible, some studies included the mass-proportional ballast cost as well (e.g., Dou et al., 2020).

The cost of mooring lines was usually modelled as a function of the total line length (e.g., Dou et al., 2020) and the maximum tension the lines must withstand (e.g., Hall et al., 2013). Some studies also included the cost of the anchors installed, depending on their type and size. For instance, in Hall et al. (2013) and Karimi et al. (2017) the cost of the anchors was modelled as a function of the maximum steady-state load experienced (which dictates the size of the anchor) and the line angle at the anchor (which dictates the anchor type).

9. Discussion

This section critically discusses the applied parametrisation schemes, followed by the discussion on the choice of economic and performance criteria, the framework architecture, and optimisation algorithms applied. Improvements are proposed based on the experience matured in other engineering fields. The section finishes with a discussion on the dynamic and economic models.

9.1. Design space

The parametrisation schemes presented in the literature related to multidisciplinary optimisation of FOWT support structures are mostly limited to the consideration of the physical characteristics of the designs, such as the draft and radius of the sections of the floater, column spacing, anchor radius, and similar, as outlined in Section 3. This approach has the advantage of design variables having a direct engineering meaning. However, the resultant designs are limited to familiar configurations, potentially concealing novel topologies.

To eliminate this limitation, the practice prevalent in the aerospace field could be adopted, whereby formal differential geometry techniques are utilised to model various shapes. This family of methods is very broad and well covered in the literature. For instance, comprehensive information about differential geometry and Computer Aided Geometric Design concepts can be found in Farin (2002). This section only provides a brief presentation of two groups of methods (grid deformation and polynomial/spline functions), aiming to give a general idea of what can be achieved. Note that this does not exhaust the range of methods available.

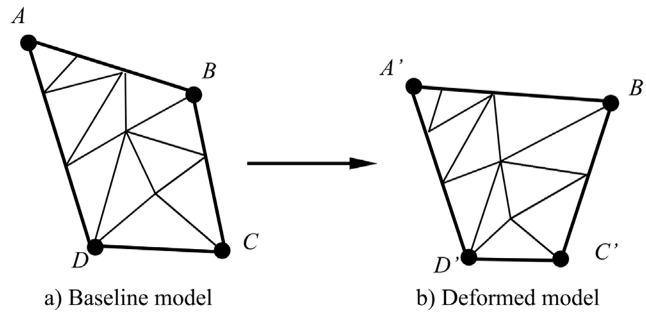

Fig. 11. Domain element method — macro element shape transformation.
Source: Reproduced from Samareh (1999).

Grid deformation techniques are based on the translations of the chosen geometry points. For instance, the domain element approach divides a structure into a number of macroelements, described by a set of key nodes (A, B, C and D in Fig. 11). A set of design variables describes the location of the nodes, and the geometry can be controlled by translating these nodes within the prescribed boundaries. Each macro element consists of a few microelements which move together with the key nodes, preserving their position relative to the main nodes. This scheme ensures the smoothness of the geometry and adequate local control, however, on its own, it can only be applied for relatively simple geometries (Imam, 1982).

A different group of methods uses the polynomial or spline functions (e.g., Bezier curves, B-splines, NURBS). In that case, the design variables are associated with the coordinates of the control points which approximate a curve. This method offers a significant reduction in the number of design variables (Samareh, 1999), and allows to automatically account for some of the geometric constraints needed to prevent unrealistic designs. The geometry of the axisymmetric structures such as spar platforms can be mathematically defined with just one curve in a compact form, with a small set of variables. Most importantly, however, the analytical derivatives can be computed efficiently (Farin, 2002), which is useful in evaluating the geometric continuity constraint (minimum level of geometric continuity must be ensured for the shape to be physical and easy to manufacture).

So far, the geometric variables were discussed. Even though most of the parametrisation schemes developed in the literature hugely focus on the external and, less often, the internal shape of the support structure, the use of different structural and ballast materials could be explored. Since FOWT designs are very much based on the legacy of the oil and gas industry, standard materials such as offshore steel and/or concrete are most often used. It seems worthwhile to investigate whether alternative modern materials would be feasible and beneficial. Although steel (mainly S355 steel) is the default structural material of choice (Igwemezie et al., 2018), the classification societies allow different materials, considering their applicability on a case-by-case basis (American Bureau of Shipping, 2015). Research on the usefulness of unconventional materials, such as sandwich panels with E-glass/epoxy skins and polyester core for the construction of towers, has been done (Lim et al., 2012). However, despite multiple potential benefits (e.g., reduced weight, higher specific strength, ease of fabrication, corrosion resistance), examples of similar studies with respect to the floating support structures design are scarce. Once exception is the work of Young et al. (2017), who developed a methodology to optimise a composite tower for the use with a 6MW floating wind turbine under strict strength and serviceability criteria.

When considering the use of a more detailed parametrisation scheme spanning all classes of support structures, an additional issue must be considered. The hydrodynamic approaches applied in various studies were developed specifically for a given group of structures. For instance, a Morison-only approach is only strictly valid for small volume members, for wave load conditions such as their characteristic length is less than about 20% of the wavelength considered (Det Norske Veritas (DNV), 2014a). Many hydrodynamic models are only valid for vertical-walled structures; in that case, the maximum taper angle or ratio of hull sections is imposed (for instance, an angle of 10 degrees in Hegseth et al. (2020b) or ratio of 2 in Karimi et al. (2017)). Introduction of a more flexible framework with a more comprehensive parametric model requires concurrent refinement of disciplinary analysis tools to ensure validity across the entire design space. The use of the simplest models may no longer be possible, and alternative, possibly higher-fidelity, approaches may have to be developed (Hegseth et al., 2020b; Lupton and Langley, 2020).

For maximum flexibility in structural optimisation, it is desirable to have as many design variables as possible. However, since an increased dimensionality of the design space tends to increase its modality (Chernukhin and Zingg, 2013) (i.e., number of local extrema), this may negatively affect the performance of some of the optimisation algorithms. More importantly, with the size of the design space increasing, the computational cost of optimisation becomes prohibitive. To address this issue, one of the methods to reduce the number of design variables could be applied. The simplest solution is the screening analysis, whereby lower-fidelity or data-driven methods are employed to select a reduced set of design variables with maximum likely impact on design objectives (e.g., fuzzy rough set based screening in Zheng et al. (2015)). However, this approach leads to the reduction of the design space, and may prevent the optimiser from finding an optimum solution only existent in the original design space, but not represented in the reduced design space. The quality of the screening depends on multiple factors such as the choice of the screening method (Design of Experiments), and the choice of the regression model. Alternatively, more strict data dimensionality reduction techniques could be applied, where the set of design variables is reduced under the condition that the generality of the design space is preserved (this is achieved through creating a smaller set of new variables, each being a combination of the original variables). This group of methods includes Principal Components Analysis (PCA), Proper Orthogonal Decomposition (POD), Generative Topographic Mapping (GTM), Active Subspace Method (ASM), to name but a few (Qiu et al., 2018).

9.2. Design criteria

As can be seen in Table 2, no two FOWT optimisation studies define the optimisation problem the same way. The spread of the choice of objectives and constraints is substantial, with no consensus on the most reasonable setup. For an unbiased multidisciplinary optimisation, the consideration of a broad range of criteria is crucial. This can be best seen by comparing different studies which look for optimum support structure topology utilising different sets of objectives. The work of Leimeister et al. (2018), largely relying on expert surveys, considered ten different criteria of diverse nature including LCoE, mooring system requirements, suitability for volume production, and ease of handling. It was concluded that spar designs, in general, overperform TLPs. On the other hand, the study by Karimi et al. (2017), which aimed at the minimum platform cost and standard deviation of nacelle acceleration, found TLP better than the spar concept. Clearly, the results of the optimisation studies can only be analysed and interpreted within the context of the optimisation problem definition, and cannot be generalised. To be able to compare the different studies, their methodologies and results, it would be beneficial to establish a common set of design objectives and constraints. The lack of this is a major shortfall, impairing the process of converging at the best optimisation approach.

For the most realistic design, the set of design constraints should include those stemming from the need to satisfy the design regulations for certification purposes. To ensure the integrity of floating offshore wind turbines, designs should comply with a range of codes, including the IEC 61400 3 2:2019 technical specification (International Electrotechnical Commission (IEC), 2019), which specifically concerns FOWTs. Some of the guidelines include the requirement of sufficient stability, maximum dynamic motion, mean static inclination, and the requirements for safe operation and serviceability of FOWTs. However, the regulations (or specifications) are often non-prescriptive, requiring a designer to prove that a certain standard of safety is achieved (for instance through Formal Safety Assessment approaches), rather than prescribing the exact limiting values (this is particularly true when novel structures are concerned). Therefore, it may be a challenging task to formulate these considerations in a mathematical manner. This, and the fact that many of the regulations concern the detailed design (as opposed to the concept design), limit the usefulness of these criteria for optimisation frameworks.

A broad range of objectives should be explored, ideally covering all of the four goals: reliability, resilience, affordability, and safety (IEA, IRENA, UNSD, World Bank and WHO, 2020; DOE, 2017). However, any multi-objective optimisation has a certain level of bias built-in, since, for instance, it may require the user to specify the weights associated with each objective (as in the weighted approach (Zadeh, 1963)) or rank the objectives in a specific order of preference (as in the lexicographic approach (Emelicheva et al., 1997)). Additionally, the computational burden and the requirement of deep understanding and accurate modelling of the physics of multiple subsystems are usually heavy barriers for this ideal situation to occur.

The challenges and possible improvements in terms of cost and performance objectives and constraints will now be discussed in more detail.

9.2.1. Economic metrics

According to the study performed at NREL (Stehly et al., 2018), Capital Expenditure (CapEx) is the most significant parameter affecting the LCoE of the floating wind farms. Assuming a 30-year project life, CapEx can be more than twice as high as the Operating Expenditure (OpEx) (Stehly et al., 2018). Unlike the bottom-fixed turbines, FOWT's foundation constitutes a significant portion of the capital cost, at about 30% (Stehly et al., 2018). This finding is consistent with other references, including (James and Ros, 2015) and Katsouris and Marina (2016a), which estimate that the floater and mooring system contribute to 33–37% and 24–38% of the life cycle cost, respectively, and slightly lower than reported more recently in Rinaldi et al. (2021): 33.6–39.2% (based on the North Sea location). Therefore, any reduction in the substructure capital cost has a tangible impact on LCoE reduction, and so the use of the capital cost of the support structure as a design objective seems appropriate.

The most recent studies such as that of Rinaldi et al. (2021) suggest that OpEx provides a substantial contribution to LCoE of floating wind turbines as well. As part of a detailed LCoE model, the authors applied an accurate and specific operation and maintenance model (developed in Rinaldi et al. (2017) and validated in Rinaldi et al. (2018)), including the aspects such as downtime, availability, and costs related to the repair or replacement of individual WT components, as well as the effect of inherent uncertainties. Based on two case studies, it has been shown that O&M cost of floating projects can constitute as much as 13.9–19.6 % of LCoE. Although the floater has been shown not to contribute to the downtime and number of failures much in itself, the global dynamic response to waves is mainly determined by the floater design, and this dynamic response may heavily impact on the performance of the mooring system and hydraulic blade pitch control system. These two subsystems were found to cause most of the failures and contribute to over 60% of wind turbine downtime, leading to the most frequent corrective interventions and profit losses. Again, while the cost of the repairs of the floating structure is negligible, the costs of repair or replacement of mooring system and pitch system lead to the highest maintenance expenditures, whose fatigue life is strongly influenced by the design of the floating support structure, and therefore O&M cost should be included in FOWT support structure optimisation studies.

An interesting perspective was presented in the recent work of Hegseth et al. (2021), where the trade-off between CapEx and OpEx was studied, seen as a trade-off between the current and future costs. The authors investigated the effect of fatigue crack inspections on the reliability of the structure. Having set a target accumulated reliability after 20 years of operation, a probabilistic fracture mechanics model was applied to estimate the required inspection intervals with two different lower safety factors resulting in appropriately increased O&M costs and decreased capital costs. Although in this study the reliability assessment was performed after the optimisation process (i.e., at the postprocessing stage), the authors emphasised that inclusion of reliability model in the optimisation would allow to achieve the lifetime cost reduction (albeit significantly increasing the complexity of the frameworks). As the knowledge about the importance of various design criteria and modelling techniques mature, co-optimisation of FOWT support structure and O&M strategy, never considered before, seems to be a natural next development, just like the co-optimisation of the controllers has been.

9.2.2. Performance metrics

Except for the low cost, a superior design must also show good performance in terms of the quantity and quality of energy production, as well as reliability and safety. Table 2 makes it clear that the FOWT optimisation studies very rarely include any performance metrics (other than the power quality criterion considered in Hegseth et al. (2020b), as indicated in Section 4). One of the most profound consequences of this is the fact that the power production efficiency is not represented in the optimisation problems in any way, which may lead to suboptimal designs.

Ideally, the Annual Energy Production (AEP) should be modelled, being the energy output of the turbine based on a given annual average wind speed (Fingersh et al., 2006), as indicated in . However, simplified metrics can be derived by considering the chosen factors affecting AEP:

- Rotor power coefficient
- Mechanical and electrical losses
- Blade soiling losses
- Wind farm losses
- Turbine availability.

While most of these items are independent of the support structure design, the power coefficient and turbine availability are affected by the dynamic response of the system to the environmental loads, and consequently by the floating substructure, and therefore could be modelled as functions of the floating platform variables.

The power coefficient is a function of the tip-speed ratio, which in turn is a function of the rotor speed and inflow velocity. Wen et al. (2018) showed that the rigid motion of the platform, as well as the resulting elastic deformations of the blades and the tower, change both the speed and direction of the incoming flow, hence influencing the time history of the instantaneous power coefficient. Lee and Lee (2019) showed that platform motions strongly affect the wake evolution, introducing a significant variation of the torque and thrust loads (in particular, the study showed up to 58.64% and 28.46% variation in the relative percentage difference in the peak magnitudes of the power output and thrust forces, respectively, due to the periodic surge oscillation of the floating platform). Hence, the aerodynamic performance of a floating wind turbine vastly depends on the design of the support structure.

The above-mentioned studies did not consider the action of any control system, which, to some extent, could compensate for the platform motions. Pustina et al. (2020) applied a variable pitch variable torque control system to prove that the power fluctuations can be effectively reduced by using an optimised controller. Lemmer et al. (2016), and Fontanella et al. (2021), among others, developed model-based controllers to reject wave excitation.[1] A very comprehensive study was also performed by Aliabadi and Rasekh (2020). Using a similar controller, the authors studied power variation in various wind speed regimes as a response to the pitch motions of different amplitudes and frequencies. It was concluded that the pitch motion decreases the average power coefficient in above-rated conditions (i.e., at high wind speeds and TSR below 7), partly due to the time delay in blades pitching. But, in below-rated conditions (low wind speed, TSR above 7), the platform pitching motion increases the average power coefficient. However, this is at a cost of significantly increased power fluctuations, structural loads, and control effort (and so increased frequency of preventive and reactive maintenance and downtime). Since the pitch actuation system is one of the least reliable assemblies of an offshore wind turbine (Tavner, 2012), it seems worthwhile to represent the trade-off between the power quantity/quality and the control effort in FOWT optimisation studies (as also recently noticed in Lemmer et al. (2020), Hegseth et al. (2020a)).

The later factor affecting AEP, availability, defined as the proportion of time a wind turbine can produce energy, strongly depends not only on the wind conditions but also on the seakeeping characteristics of a given design, as well as the frequency and duration of the planned and corrective maintenance (Hassan, 2017). The link between the availability and the design characteristics can be modelled through techniques focused on wind turbines' reliability, such as those developed for bottom-fixed offshore structures in Karadeniz et al. (2009). In that case, the trade-offs between the design sturdiness (and so the weight and the cost) and failure rates could be investigated.

9.3. MDAO frameworks and optimisation algorithms

Introduction of MDAO strategies at the onset of the design process brings multiple advantages, including the ability to accurately represent the tight inter-dependencies between the subsystems, readily evaluate the system-level implications of technical decisions at the subsystem-level, and to encompass the stakeholders' requirements and lifetime considerations within a common design framework (Barter et al., 2020). Through MDAO, the contributions of structural, hydrodynamic, aerodynamic, control, electrical, and power engineers, made concurrently, can be balanced to yield a truly optimal, safe system, not dominated by a single design consideration (Hirshorn, 2007). Parallel computing and multi-fidelity approaches can be exploited (Barter et al., 2020), largely influencing the time of the solution.

To achieve the common objective of maximum lifetime cost of energy reduction, the specialists of all subsystems should work together. According to the findings of project FORCE (Dobbin et al., 2014), integrated design of wind turbines and their support structures is one of the most potent ways to save cost in offshore wind, capable of reducing the cost of electricity by at least 10%. However, currently, the rotor-nacelle assembly and the floating support structures are developed under separate contracts, with wind turbines identical to those used with bottom-fixed structures (Barter et al., 2020; Dobbin et al., 2014; Perez-Moreno et al., 2016). Before these commercial barriers are overcome, the focus is on the multidisciplinary design optimisation of the particular assemblies: support structure (discussed by this article) and RNA (for example Bottasso et al., 2012; Bortolotti et al., 2016), as a necessary step towards system-level, and eventually wind-farm-level, integrated design.

To realise the fully coupled floating system, the disciplinary analysis tools within an MDAO framework must be appropriately interconnected. An exemplary way of interfacing the modules was demonstrated within the state-of-the-art dynamic analysis tool OpenFAST, as illustrated in Fig. 12, where all disciplines including the mooring, platform, tower, and RNA dynamics, as well as environmental forcing, form two-way connections (dependencies).

Although many of the optimisation frameworks analysed in this paper successfully reflected the most critical coupling effects in FOWT systems (e.g., control system — RNA dynamics, waves — platform dynamics), some important interactions were not considered (e.g., waves — mooring dynamics, drivetrain dynamics — nacelle dynamics), and some were modelled as one-way relationships (e.g., mooring dynamics — platform dynamics), often only approximately (aerodynamics — nacelle dynamics). The application of a fully coupled aero-hydro-servo-elastic simulation within an optimisation framework may require a much more complex MDAO architecture than those applied in the context of floating wind turbine design up to date.

This was well demonstrated by Ashuri et al. (2014) in their multidisciplinary design optimisation of the blades and tower of a bottom-fixed offshore wind turbine. The main challenge of the study lied in the fact that the analysis was performed in time-domain, multiple load cases, constraints, and variables were considered, and, on top of that, a gradient-based optimisation algorithm with finite-difference derivatives was utilised. To make the process attainable, a multilevel optimisation was utilised, where the design variables and constraints were decomposed into two levels (bi-level optimisation (Sinha and Deb, 2013)). As illustrated in Fig. 13, each global optimisation iteration consisted of two optimisation processes at the lower levels, and the global iterations were repeated until convergence on the common objective was achieved. To further speed up the computation, 12 different design load cases were computed in parallel, each on a separate CPU.

Generally, the high computational effort required to complete a multidisciplinary optimisation of the FOWT foundation is dictated by several factors. The design space may be high-dimensional, the modelling of the dynamic behaviour of the coupled system may be time-expensive, especially if low-fidelity FD tools cannot be used, and multiple load cases need to be considered (fatigue assessment of FOWTs requires at least about 30 load cases to keep the error at acceptable levels (Stieng and Muskulus, 2018)). Taking into account the stochastic nature of the excitation loads (wind and waves), a considerable number of realisations of each load case are additionally required.

To overcome these obstacles, surrogate modelling proves to be highly effective, being a well-established method in other fields. The advantages of using the surrogate models prior to FOWT optimisation were explored in USTUTT (2016). It was noticed that to be able to properly interpret the optimisation results, it is important to understand the overall system behaviour. The surrogate served that purpose and was then used to test and evaluate the optimisation algorithm, before running it with the actual simulation tools. They can also be used for design space screening purposes (i.e., selection of the most critical design variables), and uncertainty assessment.

Alternatively, the surrogate models can act as inexpensive stand-ins for optimisation studies (surrogate-based optimisation (Queipo et al., 2005)), shifting the computational effort from the optimisation to the preprocessing stage. In that case, instead of performing time-consuming simulations during the optimisation, approximate models are being evaluated at each iteration, in a small fraction of time. The applicability of this approach was demonstrated in two frameworks for optimisation of TLP (Zhang et al., 2018) and semi-submersible (Qiu et al., 2019) O&G floating structures. In both cases, the most probable maximum heave motion was modelled as a response to five hull shape variables.

[1] Note that such controllers have to be tailored to each FOWT design individually, therefore they must be tuned, or optimised, at each step of the support structure optimisation; this raises the question of the most efficient MDAO architecture.

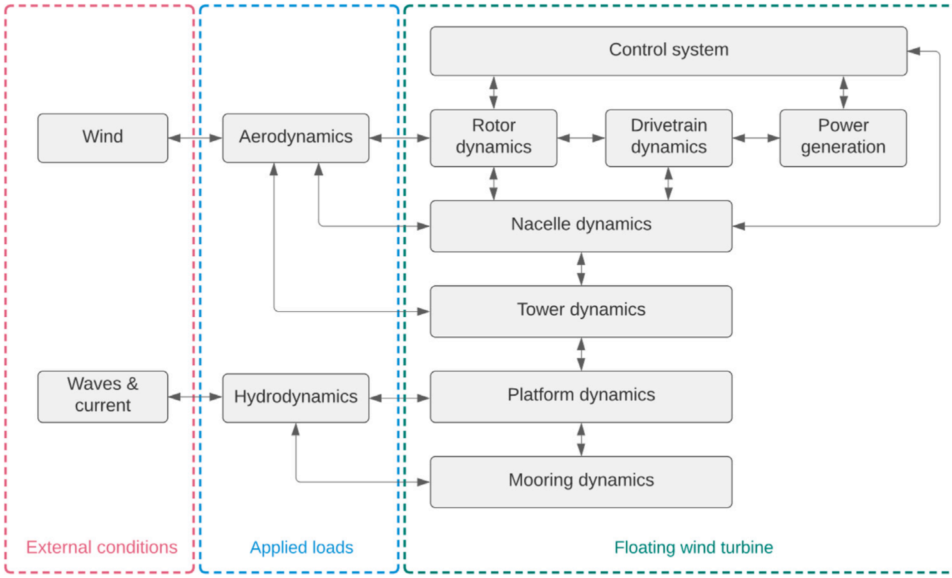

Fig. 12. Modules interface in a fully coupled aero-hydro-servo-elastic model within OpenFAST.
Source: Reproduced from Jonkman (2007).

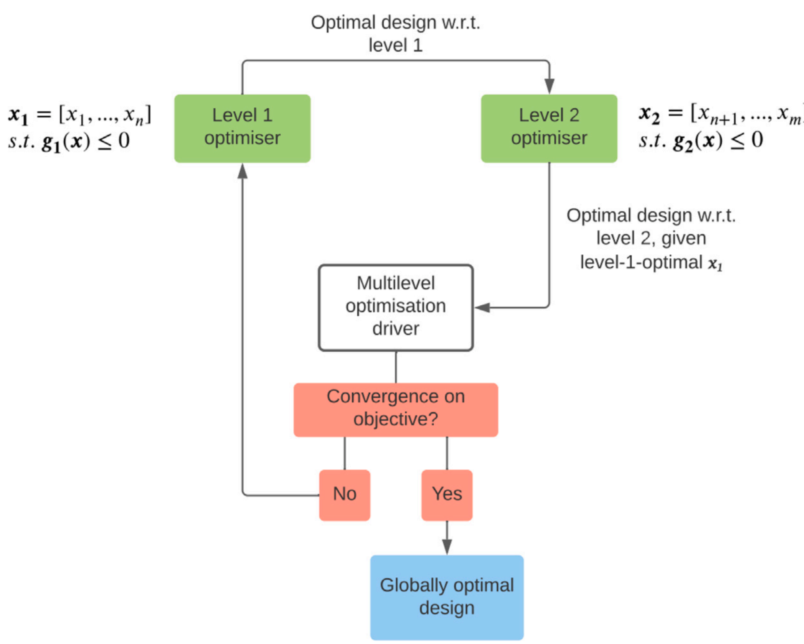

Fig. 13. Multilevel optimisation approach with decomposition of the design space into two disjoint sets x_1 and x_2.
Source: Reproduced from Ashuri et al. (2014).

Artificial Neural Network (ANN) as well as Radial Basis function (RBF) models were trained based on about 700 samples obtained through a frequency-domain analysis. In the context of FOWTs, the use of surrogate modelling was recently demonstrated in Coraddu et al. (2020) where the Response Amplitude Operators (RAOs) of spar-type FOWT were approximated with the Extreme Learning Machines (ELMs).

In the recent literature, there is also a significant focus on applying the adjoint methods for computing total derivatives in gradient-based optimisation problems. These methods can compute the derivatives efficiently (at the cost linearly proportional to the number of design objectives and constraints, but irrespective of the number of variables), and with high accuracy (i.e., with accuracy higher than through numerical approximations), improving the optimisation convergence rates (Martins and Hwang, 2013). Hence, the adjoint methods outperform other methods such as direct design sensitivity (utilised in Dou et al. 2020) or finite difference (utilised in Fylling and Berthelsen 2011), with the total time of gradient computation approximately equal to the time of computation of the objective/constraint function itself (Giannakoglou and Papadimitriou, 2008). The advantages of this group of methods were appreciated in many other fields such as aero-structural optimisation (e.g., Kenway and Martins, 2014). However, they remain unpopular in FOWT optimisation studies, with only a few examples of application (e.g., Hegseth et al., 2020b). The adjoint method functionality has been implemented in OpenMDAO and it also available in MATLAB Optimisation Toolbox (the so-called 'reverse mode automatic differentiation'). Other optimisation tools such as DAKOTA (Eldred et al., 2002) support analytic derivatives as well, but require these to be provided by an external solver.

On a final note, the review of 17 FOWT multidisciplinary optimisation studies showed that the selection of the most efficient optimisation

Table 5
Potential areas for improvement in MDAO approaches — recommendations.

Subject	Recommendation
MDAO	• Implement a fully coupled aero-hydro-servo-elastic FOWT system through a more advanced MDAO architecture with two-way connections between the relevant modules
Design variables	• Increase the flexibility of the design space based on the formal geometry parametrisation schemes to allow novel configurations free from O&G structures bias • Apply screening and dimensionality reduction techniques • Study the feasibility and usefulness of introducing additional non-geometric discrete design variables such as structural materials
Economic criteria	• focusing on the CapEx as a proxy for LCoE, and introduce OpEx as a secondary factor
Performance criteria	• Include possibly largest range of design criteria for unbiased design • Introduce new design criteria as a proxy for the power production part of LCoE, e.g., coefficient of power • Study the trade-offs between the power quality and control effort (or actuator fatigue life) • Investigate possible implementation of reliability and availability models
Optimisation algorithms	• Explore the use of data-driven methods to approximate the physical models at different stages of optimisation (including surrogate-based optimisation) • Make use of adjoint methods to efficiently compute total derivatives, enabling the use of efficient gradient-based algorithms

algorithm for a given problem receives very little attention. As outlined in Section 6, the choice of optimisation problem should be based on the consideration of the mathematical nature of the optimisation problem, as well as the search goal and search method. As indicated in Table 2, many studies apply local optimisation algorithms without the due consideration of this fact when interpreting the results. Significantly more attention is given to the consideration of the type of design objectives and constraints (whether continuous, differentiable, smooth), and design variables (design space dimensionality, and whether continuous or discrete). However, the choice of these is often dictated by the requirements of the optimisation algorithm selected *a priori*. Most studies omit any justification of this selection; some (e.g., USTUTT, 2016) follow a trial-and-error process. It is important to notice that the selection of the optimisation algorithm is strongly constrained by practical considerations such as the availability in the package/environment used by the researchers, or ease of coupling with the multidisciplinary analysis framework. It seems worthwhile to investigate whether a more rigorous and systematic approach to selection of algorithms would result in significant efficiency gains.

A summary of potential areas for improvement and recommendations for MDAO approaches is given in Table 5.

9.4. Techno-economic models

This paper highlighted the fact that, currently, there is a substantial emphasis on reducing the time and cost of the disciplinary analysis for FOWT optimisation frameworks. A massive effort is devoted to making the methods more efficient, often at the cost of accuracy and level of detail. However, considering the big picture and seeing the total cost as a sum of the costs related to all design phases, a question must be asked whether increasing the fidelity, and so the cost, of the analysis during the structural optimisation phase could result in money savings at later stages (the cost of change generally increases as the project progresses, as shown in Fig. 14). Hence, this section identifies the possible extensions to the models of dynamics, focusing on the phenomena which are usually neglected but may significantly affect the design and global response of FOWTs.

9.4.1. Design load cases

The IEC TS 61400-3 specification provides a list of 42 DLCs that should (as a minimum) be analysed in the process of design of an offshore wind turbine. Due to the prohibitively long simulation time required to complete the optimisation of FOWT considering all DLCs, a compromise must be made selecting only a few load cases. Most of the literature focused on two or three DLCs representative of typical operating conditions (Table 2). However, there seems to be an emerging trend towards increasing the number of load cases, supported by the use of more sophisticated models of dynamics capable of considering the extreme conditions (e.g., second-order hydrodynamics for more accurate representation of low-frequency dynamics in long waves), more efficient optimisation algorithms (searching design space with fewer iterations/simulations), as well as increasing computational speed and power mainly through increased availability of multi-core architectures and parallel computing (this can be seen for example in Hegseth et al. 2020b, Ashuri et al. 2014).

Matha et al. (2014) proposed a systematic method for an efficient critical design load case identification, in which a computationally efficient reduced nonlinear model was used to select the most important subset of DLCs which should be taken forward to optimisation. Since this method relies on running reduced model simulations to identify the critical load cases, it would be most advantageous in those FOWT optimisation frameworks that utilise high-fidelity analysis tools.

An alternative approach was more recently proposed by Stieng and Muskulus (2018), whereby the analysis over a full set of DLCs was performed once, and then the different cases were sorted by their severity (measured as the product of a particular response, e.g., fatigue damage, and probability of occurrence). The most severe cases were selected, and the relative error resulting from using only these cases was estimated. This error was then assumed constant for a range of similar designs. Although it is not clear for how broad design spaces this method remains accurate, it presents a very pronounced benefit of simplicity.

The vast majority of FOWT support structure optimisation studies only investigated codirectional wind and waves. However, the fact that FOWTs support structures are in constant motion, and lack aerodynamic damping in the side-to-side direction, may cause environmental loads directionality to have a more pronounced effect on their response. While for the axisymmetric floating structures such as a spar this is the most critical condition, wind-wave misalignment may result in larger structural loads in semi-submersible platforms (Bachynski et al., 2014; Li et al., 2020). Equally important is the consideration of misaligned environmental loads in the case of a TLP design, where the minimum mooring tension must be modelled accurately to avoid slack lines (offset of the wave direction with respect to the main wind direction may ease the tension in the mooring lines). This was appreciated by Myhr et al. in their optimisation study devoted specifically to TLPs (Myhr and Nygaard, 2012). The study performed at NREL (Barj et al., 2014) showed that in normal power production conditions, the neglect of the misalignment may result in as much as 50% underestimation of the tower side-side bending moment, and 5% overestimation in fore-aft tower loads. Even though the side-to-side moment is generally a lot less significant than the fore-aft moment, the authors recommended to consider at least two wave directions: aligned with the wind and 90 degrees misaligned. Lastly, misalignment consideration is required by the IEC TS 61400-3-2 technical specification (International Electrotechnical Commission (IEC), 2019). The justification of this requirement lies in the fact that FOWT systems lack aerodynamic damping in the side-to-side direction, hence being more prone to the impact of wind, waves, and current directionality. The ultimate and fatigue loads in the base of the tower are of particular concern.

9.4.2. Control system

Many of the multidisciplinary optimisation frameworks for FOWT support structures did not consider the use of a controller. This was

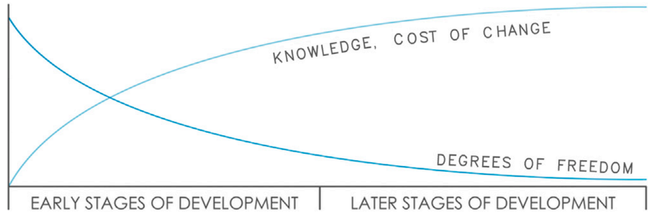

Fig. 14. Evolution of the knowledge, costs of change, and degrees of freedom during the design process.
Source: Reproduced from de Koeijer et al. (2017).

partly justified by the fact that these studies only considered the rated (or near-rated) conditions, where the control action is rather limited. The most recent FOWT optimisation studies such as Hegseth et al. (2020a), Lemmer et al. (2020) investigated a wide spectrum of distinct wind speeds. In these cases, the importance of integration of the aero-hydro-elastic model with the model of a controller was well understood.

A recent study by Aliabadi and Rasekh (2020) demonstrated that even at the rated wind speed, the incorporation of a power control system is still important to minimise the variation of aerodynamic loads and prevent the occurrence of negative power coefficient. As shown in Sandner et al. (2014), damping of the platform significantly influences the design of the optimal controller, and conversely, the torque varied by the controller influences the aerodynamic thrust, significantly affecting the support structure motions. Additionally, an introduction of the controller in the optimisation loop allows for the power production to be considered alongside the cost of the FOWT (Hegseth et al., 2020b). Therefore, an integrated optimisation of the floating structure and the controller may result in better performing and cheaper designs, missed by sequential optimisation studies (Hegseth et al., 2020b). It is worth noting that an efficient implementation of a control strategy is possible in frequency-domain frameworks, as demonstrated for example by Lupton (2014).

9.4.3. Viscous wave loads

Almost all studies reviewed employed a linearised Morison equation approach to model either the total wave load, or the viscous contribution to the wave excitation force and damping. Although this method is only strictly valid for hydrodynamically slender floating structures, defined as those elements with a characteristic length to wave length ratio D/λ below 0.2, in which case diffraction is negligible (Det Norske Veritas (DNV), 2014b), it is not uncommon to see the Morison equation applied to floaters and sea conditions resulting in D/λ ratios as large as 0.4 or more.

For the viscous drag and diffraction effects to be simultaneously significant, the wave height must be large ($H/D > 1.5$), and, at the same time, the wave length must be small ($D/\lambda > 0.2$), as compared to the significant dimension of the structure (Patel, 1989). Imposing the deep water breaking condition ($H/\lambda < 1/7$), it can be demonstrated that this is practically unrealisable for a single member. Violation of the $D/\lambda < 0.2$ limit is therefore a concern only in those studies which apply the full Morison approach (i.e., for calculation of both the drag and inertia components of load), or which are applied to a structure consisting of both large and small volume members. In optimisation studies, where a range of floaters of different topologies and sizes are analysed over a wide range of wave frequencies (or lengths), the need to rank the designs requires that the dynamic approach applied remains valid for all designs in all significant environmental conditions.

This can be accomplished through the implementation of an alternative hydrodynamic model such the combined potential flow — Morison approach. Alternatively, if such an approach cannot be afforded (due to increased computational effort), the design space must be narrowed to exclude large structures.

9.4.4. Flexible structure

Compared to bottom-fixed wind turbines, the rotors supported by floating platforms are subjected to larger cyclic gravitational, inertial, and aerodynamic loads (Lupton, 2014). With the size and weight of the rotors increasing, it becomes increasingly important to consider the flexibility of the long aerodynamically shaped blades and the tower. At specific combinations of platform motion frequency and rotor speed, the structural response of the blades is known to be nonlinear with respect to the amplitude of the platform motion. However, in many practical cases, such as those analysed in Lupton (2014), where the rotor speed and platform motion frequencies are small (lower than 20 rpm and 0.2 Hz, respectively), this nonlinearity is insignificant. In that instance, a simplified, linearised model of structural dynamics can improve the overall accuracy of the frequency-domain frameworks.

Accounting for the flexibility of the floating structure may be particularly important for extreme design load cases. The IEC 61400-3-2 specification provides the guidance as for when a structure can be considered rigid, based on the natural frequency of the structure (f_n) and the frequency of external excitation (f_{in}):

- If $f_{in} \ll f_n$, a structure can be assumed a rigid body
- If $f_{in} \approx f_n$, resonance is possible and flexibility must be modelled
- If $f_{in} \gg f_n$, the influence of the structure flexibility on the total response may be significant and the flexibility must be modelled.

If the structural frequency of some of the candidate designs is expected to be close to or below the frequency of excitation loads (wind, waves, vortices shed), it is important to introduce flexibility into the model. This was so far only achieved in a few FOWT optimisation studies, in a simplified way, as already mentioned in Section 7.4. Only the flexibility of the tower was included.

In the case of large-volume floaters, a one-way feed-forward connection between the hydrodynamic loads and structural response can be applied, as recommended in D.N.V. G.L. (2018). Although this approach neglects the effect of structural deformation on hydrodynamic loads, it can be useful in approximating the internal loads in floating structures, if these are within the set of optimisation criteria. The so called "dry" approach, on the other hand, ignores the effect of the surrounding fluid on the structural response. For instance, Mantadakis et al. (2019) developed a linear hydroelastic analysis in the frequency domain for analysis of the coupled behaviour of a spar floating structure. The structural responses were computed based on a "dry" modes superposition principle, with modal parameters obtained from a FEM code, while the hydrodynamic loads were computed through a Boundary Element Method solving the diffraction/radiation problem. The floater elastic modes were included in the vector of degrees of freedom alongside the six rigid motion modes.

Two-way coupled hydro-elastic solvers ("wet" approach) are very rarely applied to floating support structures. Due to the dependence of added mass on frequency, this problem is nonlinear and cannot be solved in the frequency domain. Recently, Leroy et al. (2021) studied hydro-elastic response of a bottom-fixed monopile by coupling a non-linear potential flow solver with a modal approach (FEM), achieving the tight coupling through an explicit coupled equation system. Although in many cases this fully coupled approach yields more accurate results (Loukogeorgaki et al., 2014), its applicability to the analysis of floating structures within multidisciplinary optimisation frameworks may be limited due to the need to account for rigid body motions and high computational effort related to high-fidelity time-domain FEM computations. Regardless, the authors provided a valuable early insight into the importance of fully coupled hydroelastic analysis for the ever-larger submerged structures.

A comprehensive review of different approaches to FOWT structural flexibility modelling is available, for instance, in Chen et al. (2017), where the trade-offs between the ease of implementation, accuracy and computational effort of four different models (single-rigid-body, corrected single-rigid-body, multi-rigid-body, and multi-rigid–flexible-body) are explored.

9.4.5. Mixed-fidelity analysis

The ability to model the system as an interconnected network of disciplinary solvers allows a range of processes which make the multidisciplinary optimisation more efficient. For instance, multi-fidelity dynamic models can be utilised, whereby different disciplines are modelled with just a sufficient level of detail, specific for each discipline. For instance, Lemmer et al. (2017) used a fast frequency-domain model to design the controller at each optimisation iteration, and a nonlinear time-domain model to compute the evaluate the design response and criteria. The use of tools of different fidelity can also be made at different stages of the optimisation. For instance, Sandner et al. (2014) performed a spar wind turbine optimisation study using a linearised simplified nonlinear simulation model to find a theoretically suitable range of controller gains (i.e., narrow the design space), and then applied a nonlinear model to further tune the controller gains for each candidate platform. Effective reduced-order models can also be used for the purpose of screening the design space before attempting optimisation (fast parametric analyses) (Berci and Cavallaro, 2018), or for uncertainty propagation approximation (Martins and Hwang, 2013; Moore, 2012). In that respect, data-driven models offer potential advantages, not yet explored in floating wind field. Lastly, low-fidelity tools can be used for sensitivity computation within a gradient-based optimisation, while employing medium or high-fidelity methods for functional evaluation of the objectives and constraints (Berci and Torrigiani, 2020).

9.4.6. Economic models

Economic modelling is, in general, challenging, mainly due to the scarcity of information available at the initial design stages, when the optimisation often takes place. The vast majority of FOWT optimisation studies published up to date employ simplistic metrics to reflect the profitability aspect of the design. While these simple models have the advantage of being easy and cheap to implement within an optimisation loop, the use of more detailed models may improve the cost-competitiveness of the designs.

Most, if not all, frameworks only considered the cost of material and manufacturing of the support structure components. Progress can already be made by focusing on just these two cost components and improving their respective models. For instance, more detailed scantlings of the platform, and the inclusion of the internal structural members in the material-bill and manufacturing cost calculations, could potentially result in lower overall mass and cost (so far, the main emphasis has been on the optimisation of the external shape, somewhat neglecting the internal structure). This, of course, would require an appropriate model of structural dynamics. A step towards that goal has recently been made by Hegseth et al. (2020b).

To further extend the capabilities of CapEx modelling, the cost-benefit of the modularity of design and suitability for mass production should be explored. As shown in van Hees Bulder et al. (2002), the simultaneous production of a large number of floating wind turbines for installation in multi-hundred-megawatt wind farms has the potential to lower the price significantly. This reduction can be mainly attributed to a decreased design effort and manufacturing benefits of scale, both contributing 10%–20% of the total cost reduction.

A step forward can also be made by including the costs incurred in the other life cycle phases (i.e., related to installation, maintenance, operation and decommissioning). Although the relationship between the design characteristics usually controlled by the optimiser and the costs related to the post-development phases is less clear, some aspects of the structural design can be accounted for in the OpEx model. This has not been achieved in the support structure optimisation studies so far, to the best knowledge of the authors. While the fabrication of the floating platforms is considered to be more expensive than that for bottom-fixed structures (Katsouris and Marina, 2016b), the major cost advantages are seen in the post-manufacturing phases. Therefore, FOWT optimisation frameworks should be able to explore these benefits.

For instance, the ability of the complete system to float in an upright position without being attached to the moorings determines whether the use of an expensive heavy-lift jack-up and dynamic positioning vessels at the installation site can be avoided, saving some costs (James and Ros, 2015). The low draft and good initial stability of the semi-submersible platforms makes them suitable for being fully assembled onshore and then towed by small tugboats to their final destination. They can also be safely tugged back to shore for major repairs, further reducing the lifetime costs (Lerch, 2020). TLP platforms are not stable without the mooring system in place, therefore, in general, they need more expensive special purpose-built vessels for transportation and installation. Likewise, spars often require a barge and a heavy-lift vessel for assembly (Lerch, 2020). The need to consider towability as a design criterion was also emphasised by Barter et al. (2020).

Aspects of maintenance cost could be included in LCOE models as well. For instance, in Lerch (2020) it was noticed that concrete substructures require fewer on-site inspections than steel structures. Therefore, the influence of the type of substructure material on the frequency of preventive maintenance, and so the lifetime cost, could be modelled. Likewise, the effect of the support structure response characteristics on the fatigue loads of the WT components and the lifetime cost of inspections, repairs and replacements can be accounted for.

Another consideration that requires increased attention is the issue of power cable damage and the associated costs. Being installed in a dynamic environment influenced by the platform motions, dynamic cables are expected to suffer greater levels of mechanical stress and failure rates (Young et al., 2019), requiring more frequent inspections and replacements. This largely influences both the maintenance and insurance costs. Therefore, respecting the requirement of cable integrity through appropriate modelling of both the fatigue and extreme loads due to platform motions can potentially lead to a lower life cycle cost.

The recommendations for the techno-economic modelling made throughout the article are summarised in Table 6.

10. Conclusions

The growth of offshore wind utilisation as a means to achieve the required CO2 reductions can be accelerated by installation of wind turbines far from shore where the wind is stronger and more consistent. Floating offshore wind turbines (FOWT) offer a feasible solution in these conditions. However, a range of efforts in multiple disciplines at all stages of the turbine's life cycle is essential for the economic viability of this technology.

Since FOWTs are strongly coupled systems with complex physics, large gains are expected through the adoption of Multidisciplinary Design Analysis and Optimisation (MDAO) approaches. This article reviewed the state-of-the-art in MDAO of FOWT support structures,

Table 6
Potential areas for improvement in techno-economic modelling — recommendations.

Subject	Recommendation
General	• Study the project life cycle benefits of increased fidelity analysis at the early stages of a project • Study the benefits of the multi-fidelity approaches to FOWT dynamic modelling for optimisation • Depending on computational power available, consider easing some of the system couplings to make the application of nonlinear TD analysis feasible within optimisation
DLCs	• Continue the trend of an increasing number of design load cases considered, based on the critical design load cases identification techniques • Include at least one misaligned wind-waves load case
Control system	• Continue the trend of incorporating the controllers in optimisation studies, possibly co-designing (optimising) the power control system in an integrated manner • Explore the benefits of the control strategies in line with the particular choice of design objectives
Hydrodynamics	• Perform a formal study of the necessity to model the slamming and slapping load • Develop a dynamic analysis tool capable of analysing a wider range of support structure topologies in a larger range of environmental conditions • Improve the model of viscous damping through alternative linearisation method (FD) • Ensure validity of the hydrodynamic model applied
Structural dynamics	• Compare the natural frequency of the structure with the most energetic range of frequencies of external excitation to determine correct approach to flexibility modelling • Ensure the validity of the rigid body assumption whenever such assumption is made; constrain the natural frequencies of the structures accordingly
Cost modelling	• Expand the capital cots model by more detailed consideration of material and manufacturing costs • Expand the capital cots model by consideration of the benefits of scale and the modularity of design • Include the assembly, installation, maintenance and operation phases in the cost model

critically discussing the details of the optimisation problem formulation and its implementation.

The formulation of the optimisation problem comprises the definition of design variables, objectives, and constraints. The choices of these three elements observed in the 12 chosen FOWT optimisation studies were collated in Table 2 and systematically examined.

The parametrisation methods presented in FOWT-related literature are mostly limited to very simple schemes, whereby the design variables represent the physical characteristics of the structure. Although most of the studies only consider a single class of support structures (TLPs, semi-submersibles, or spars), the trend is to include a wider design space spanning all types of configurations. In that respect, the use of formal parametrisation schemes prevalent in other fields was proposed. Methods to select the critical subset of design variables prior to optimisation were indicated.

In literature, there is no consensus on what the Floating Offshore Wind Turbine (FOWT) support structure optimisation should aim for. Although consideration of the levelised cost of energy (LCoE) as a design objective would best reflect the industry's goals, the economic metrics are most often limited to the bill of material as a proxy for the capital cost. However, since the major cost-advantages of floating systems are seen in the later development/operation stages, it is proposed to extend the models by some aspects of the assembly, installation, operation and maintenance phases. Operation and Maintenance (O&M) costs constitute a significant contribution to the total cost of FOWT, and are significantly influenced by the design of the support structure. The article stressed that along the affordability aspect, the reliability, resilience, and safety of the overall system should be considered.

The performance criteria applied in the literature included the nacelle fore-aft acceleration, mooring line tension, fatigue life, and rotor speed standard deviation. These were critically assessed, and additional factors were proposed, including the coefficient of power, turbine's availability (for the highest power production with the least output fluctuations), and control effort (for lower fatigue damage of the blade actuator and less downtime), among other criteria. A systematic and in-depth review of all objectives and constraints has been carried out, highlighting the fact that there is no agreement on the number and type of criteria to be considered.

The field of FOWT multidisciplinary optimisation is dominated by monolithic MDAO architectures with one-way couplings between disciplinary solvers. However, to represent the fully coupled system, an introduction of a more advanced distributed network with two-way connections is a feasible solution. The reduction of the optimisation time can be achieved using carefully selected more efficient optimisation algorithms. Although derivative-free approaches dominate, the advantages of the derivative-based alternatives have recently gained more appreciation, together with a rising interest in efficient total derivative computation methods. Significant gains in terms of optimisation time and accuracy are expected by the application of the multi-level optimisation and/or mixed-fidelity approaches, potentially involving data-driven methods.

It has been shown that quick and robust frequency-domain (FD) tools are most often utilised within such frameworks. The article argued that increasing the fidelity of the analysis tools in early design stages may lower the costs incurred in later stages. With this in view, possible extensions to the FD models were proposed. These included the integration with a control system, improved hydrodynamic modelling (for instance through improvements to common approaches such as the linearised viscous drag model), as well as the introduction of structural flexibility. Time-domain approaches were reviewed for completeness.

The focus of the most recent research in the field of FOWT optimisation is on increasing the complexity and accuracy of the frequency-domain models. However, due to the inevitable limitations of this approach (e.g., inability to model the nonlinear effects and realistic ultimate limit states), multi-fidelity approaches are gaining momentum. This trend is supported by an increasing appreciation of the MDAO concept and the modular capabilities that it offers.

The comprehensive review of the optimisation approaches and techno-economic models commonly considered in FOWT support structure optimisation studies are summarised in Tables 2 and 4.

CRediT authorship contribution statement

Katarzyna Patryniak: Conceptualization, Investigation, Writing – original draft. **Maurizio Collu:** Conceptualization, Writing – review & editing, Supervision. **Andrea Coraddu:** Conceptualization, Writing – review & editing, Supervision.

Declaration of competing interest

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

Acknowledgements

This work was supported by the University of Strathclyde REA 2022, United Kingdom. The discussions with Matthew Hall (NREL) and John Marius Hegseth (Olav Olsen) are greatly appreciated.

References

Agte, J., Weck, O.D., Sobieszczanski-Sobieski, J., Arendsen, P., Morris, A., Spieck, M., 2010. MDO: Assessment and direction for advancement-an opinion of one international group. Struct. Multidiscip. Optim. 40 (1–6), http://dx.doi.org/10.1007/s00158-009-0381-5.

Al-Solihat, M.K., Nahon, M., 2016. Stiffness of slack and taut moorings. Ships and Offshore Struct. 11, 890–904.

Aliabadi, S.K., Rasekh, S., 2020. Effect of platform disturbance on the performance of offshore wind turbine under pitch control. Wind Energy 23 (5).

Allen, C., Viselli, A., Dagher, H., Goupee, A., Gaertner, E., Abbas, N., Hall, M., Barter, G., 2020. Definition of the UMaine VolturnUS-S Reference Platform Developed for the IEA Wind 15- Megawatt Offshore Reference Wind Turbine. IEA Wind TCP Task 37. Tech. rep..

American Bureau of Shipping, 2015. Guide for building and classing floating offshore wind turbine installations.

Anaya-Lara, O., Tande, J.O., Uhlen, K., Merz, K., 2018. Offshore wind energy technology.

Arany, L., Bhattacharya, S., Macdonald, J.H.G., Hogan, S.J., 2016. Closed form solution of Eigen frequency of monopile supported offshore wind turbines in deeper waters incorporating stiffness of substructure and SSI. Soil Dyn. Earthq. Eng. 83, http://dx.doi.org/10.1016/j.soildyn.2015.12.011.

Arora, J.S., 2017. Optimum design concepts: Optimality conditions. In: Introduction to Optimum Design. http://dx.doi.org/10.1016/b978-0-12-800806-5.00004-4.

Ashuri, T., Martins, J.R.R.A., Zaaijer, M.B., van Kuik, G.A.M., van Bussel, G.J.W., 2016. Aeroservoelastic design definition of a 20 MW common research wind turbine model. Wind Energy 19 (11), http://dx.doi.org/10.1002/we.1970.

Ashuri, T., Zaaijer, M.B., Martins, J.R.R.A., van Bussel, G.J.W., van Kuik, G.A.M., 2014. Multidisciplinary design optimization of offshore wind turbines for minimum levelized cost of energy. Renew. Energy 68, http://dx.doi.org/10.1016/j.renene.2014.02.045.

Babarit, A., Delhommeau, G., 2015. Theoretical and numerical aspects of the open source BEM solver NEMOH. In: 11th European wave and tidal energy conference (EWTEC2015).

Bachynski, E.E., 2018. Fixed and floating offshore wind turbine support structures. pp. 115–116,

Bachynski, E.E., Kvittem, M.I., Luan, C., Moan, T., 2014. Wind-wave misalignment effects on floating wind turbines: Motions and tower load effects. J. Offshore Mech. Arct. Eng. 136 (4), http://dx.doi.org/10.1115/1.4028028.

Bachynski, E.E., Moan, T., 2012. Design considerations for tension leg platform wind turbines. Mar. Struct. 29 (1), http://dx.doi.org/10.1016/j.marstruc.2012.09.001.

Bachynski, E.E., Moan, T., 2014. Ringing loads on tension leg platform wind turbines. Ocean Eng. 84, http://dx.doi.org/10.1016/j.oceaneng.2014.04.007.

Bahramiasl, S., Abbaspour, M., Karimirad, M., 2018. Experimental study on gyroscopic effect of rotating rotor and wind heading angle on floating wind turbine responses. Int. J. Environ. Sci. Technol. 15 (12), http://dx.doi.org/10.1007/s13762-017-1519-4.

Barj, L., Stewart, S., Stewart, G., Lackner, M., Jonkman, J., Robertson, A., Matha, D., 2014. Wind/wave misalignment in the loads analysis of a floating offshore wind turbine. In: 32nd ASME Wind Energy Symp.. http://dx.doi.org/10.2514/6.2014-0363.

Barter, G.E., Robertson, A., Musial, W., 2020. A systems engineering vision for floating offshore wind cost optimization. Renew. Energy Focus 34 (6), 1143–1148. http://dx.doi.org/10.1016/j.ref.2020.03.002.

Behringer, F.A., 1977. Lexicographic quasiconcave multiobjective programming. Zeitschrift für Oper. Res. 21 (3), http://dx.doi.org/10.1007/BF01919766.

Berci, M., Cavallaro, R., 2018. A hybrid reduced-order model for the aeroelastic analysis of flexible subsonic wings-A parametric assessment. Aerospace 5 (3), http://dx.doi.org/10.3390/aerospace5030076.

Berci, M., Torrigiani, F., 2020. Multifidelity sensitivity study of subsonic wing flutter for hybrid approaches in aircraft multidisciplinary design and optimisation. Aerospace 7 (11), http://dx.doi.org/10.3390/aerospace7110161.

Borgman, L.E., 1967. The spectral density for ocean wave forces.

Bortolotti, P., Bottasso, C.L., Croce, A., 2016. Combined preliminary–detailed design of wind turbines. Wind Energ. Sci. 1, 71–88.

Bottasso, C.L., Campagnolo, F., Croce, A., 2012. Multi-disciplinary constrained optimization of wind turbines. Multibody Syst. Dyn. 27, 21–53.

Brommundt, M., Krause, L., Merz, K., Muskulus, M., 2012. Mooring system optimization for floating wind turbines using frequency domain analysis. In: Energy Proc.. 24, http://dx.doi.org/10.1016/j.egypro.2012.06.111.

Burton, T., Jenkins, N., Sharpe, D., Bossanyi, E., 2011. Wind Energy Handbook, Second Edition http://dx.doi.org/10.1002/9781119992714.

Castro-Santos, L., deCastro, M., Costoya, X., Filgueira-Vizoso, A., Lamas-Galdo, I., Ribeiro, A., Dias, J., Gómez-Gesteira, M., 2021. Economic feasibility of floating offshore wind farms considering near future wind resources: Case study of Iberian Coast and Bay of Biscay. Int. J. Environ. Res. Public Health 18.

Chen, J., Hu, Z., Liu, G., Tang, Y., 2017. Comparison of different dynamic models for floating wind turbines. J. Renew. Sustain. Energy 9 (6), http://dx.doi.org/10.1063/1.5002750.

Chen, S., Montgomery, J., Bolufé-Röhler, A., 2015. Measuring the curse of dimensionality and its effects on particle swarm optimization and differential evolution. Appl. Intell. 42 (3), http://dx.doi.org/10.1007/s10489-014-0613-2.

Chernukhin, O., Zingg, D.W., 2013. Multimodality and global optimization in aerodynamic design. Am. Inst. Aeronaut. Astronaut. J. 51.

Ciampa, P.D., Nagel, B., 2016. Towards the 3rd generation MDO collaboration environment. In: 30th Congr. Int. Counc. Aeronaut. Sci.. ICAS.

Clauss, G.F., Birk, L., 1996. Hydrodynamic shape optimization of large offshore structures. Appl. Ocean Res. 18 (4), http://dx.doi.org/10.1016/S0141-1187(96)00028-4.

Coraddu, A., Oneto, L., Kalikatzarakis, M., Ilardi, D., Collu, M., 2020. Floating spar-type offshore wind turbine hydrodynamic response characterisation: a computational cost aware approach. In: Glob. Ocean. 2020 Singapore – U.S. Gulf Coast. pp. 1–8. http://dx.doi.org/10.1109/IEEECONF38699.2020.9389074.

Cordle, A., Jonkman, J., 2011. State of the art in floating wind turbine design tools. In: Proc. Int. Offshore Polar Eng. Conf..

Coulling, A.J., Goupee, A.J., Robertson, A.N., Jonkman, J.M., 2013. Importance of second-order difference-Frequency wave-Diffraction forces in the validation of a fast semi-submersible floating wind turbine model. In: Proc. Int. Conf. Offshore Mech. Arct. Eng. - OMAE. vol. 8, http://dx.doi.org/10.1115/OMAE2013-10308.

de Koeijer, B., Wever, R., Henseler, J., 2017. Realizing product-packaging combinations in circular systems: Shaping the research agenda. Packag. Technol. Sci. 30 (8), http://dx.doi.org/10.1002/pts.2219.

Det Norske Veritas, 2010. Environmental conditions and environmental loads, recommended practice DNV-RP-C205.

Det Norske Veritas (DNV), 2014a. Recommended Practice DNV-RP-C205.

Det Norske Veritas (DNV), 2014b. Recommended Practice DNV-RP-C205.

Dirlik, T., 1985. Application of computer in fatigue analysis.

D.N.V. G.L., 2018. DNVGL-ST-0126 Support structures for wind turbines.

D.N.V. G.L. - Software, 2017. Sesam user manual. wadam. wave analysis by diffraction and morison theory. valid from program version 9.3.

Dobbin, J., Quarton, D., Phillips, J., Reynolds, P., 2014. Project FORCE: Offshore wind cost reduction through integrated design, DNV GL.

DOE, 2017. Staff Report on Electricity Markets and Reliability Staff Report to the Secretary on Electricity Markets and Reliability Staff Report on Electricity Markets and Reliability, U.S. Department of Energy. https://www.energy.gov/staff-report-secretary-electricity-markets-and-reliability.

Dou, S., Pegalajar-Jurado, A., Wang, S., Bredmose, H., Stolpe, M., 2020. Optimization of floating wind turbine support structures using frequency-domain analysis and analytical gradients. In: J. Phys. Conf. Ser.. 1618, (4), http://dx.doi.org/10.1088/1742-6596/1618/4/042028.

Duarte, T.M., Sarmento, A.J., Jonkman, J., 2014. Effects of second-order hydrodynamic forces on floating offshore wind turbines. In: 32nd ASME Wind Energy Symp.. http://dx.doi.org/10.2514/6.2014-0361.

Eldred, M.S., Report, S., Giunta, A.A., Waanders, B.G.V.B., Wojtkiewicz, S.F., Hart, W.E., Alleva, M.P., 2002. DAKOTA, A Multilevel parallel object-oriented framework for design optimization, parameter estimation, uncertainty quantification, and sensitivity analysis (SAND 2001-3514). Analysis (April).

Emelicheva, V.A., Girlikhb, E., Yanushkevich, O.A., 1997. Lexicographic optima of a multicriterial problem. Diskretnyi Analiz i Issledovanie Operatsii 4.

European Commission, 2021. Onshore and offshore wind. https://ec.europa.eu/energy/topics/renewable-energy/onshore-and-offshore-wind_en. (Accessed 15 February 2021).

Evan, G., Rinker, J., Sethuraman, L., Zahle, F., Shields, M., Feil, R., Dykes, K., Bredmose, H., Allen, C., Viselli, A., Bortolotti, P., Anderson, B., Skrzypinski, W., Barter, G., Scott, G., Abbas, N., Meng, F., 2020. IEA Wind TCP Task 37 Definition of the IEA Wind 15-Megawatt Offshore Reference Wind Turbine Technical Report. National Renewable Energy Laboratory, Technical University of Denmark, Technical University of Denmark.

Farin, G., 2002. Curves and surfaces for computer aided design, A Practical Guide. In: Morgdan Kaufmann Publ..

Farkas, J., Jármai, K., 2013. Optimum design of steel structures. In: Optim. Des. Steel Struct.. http://dx.doi.org/10.1007/978-3-642-36868-4.

Fingersh, L., Hand, M., Laxson, A., 2006. Wind turbine design cost and scaling model. NREL 29 (December).

Fontanella, A., Al, M., van Wingerden, J.-W., Belloli, M., 2021. Model-based design of a wave-feedforward control strategy in floating wind turbines. Wind Energ. Sci. 6, 885–901.

Fylling, I., Berthelsen, P.A., 2011. WINDOPT - An optimization tool for floating support structures for deep water wind turbines. In: Proc. Int. Conf. Offshore Mech. Arct. Eng. - OMAE. vol. 5, http://dx.doi.org/10.1115/OMAE2011-49985.

Garg, N., Kenway, G.K.W., Martins, J.R.R.A., Young, Y.L., 2017. High-fidelity multipoint hydrostructural optimization of a 3-D hydrofoil. J. Fluid. Struct. 71, 15–39.

Gentils, T., Wang, L., Kolios, A., 2017. Integrated structural optimisation of offshore wind turbine support structures based on finite element analysis and genetic algorithm. Appl. Energy 199, http://dx.doi.org/10.1016/j.apenergy.2017.05.009.

Ghigo, A., Cottura, L., Caradonna, R., Bracco, G., Mattiazzo, G., 2020. Platform optimization and cost analysis in a floating offshore wind farm. J. Mar. Sci. Eng. 8 (11), http://dx.doi.org/10.3390/jmse8110835.

Giannakoglou, K.C., Papadimitriou, D.I., 2008. Adjoint methods for shape optimization. In: Optim. Comput. Fluid Dyn.. pp. 79–108.

Gill, P.E., Murray, W., Saunders, M.A., 2005. SNOPT: An SQP algorithm for large-scale constrained optimization. SIAM Rev. 47 (1), http://dx.doi.org/10.1137/S0036144504446096.

Gilloteaux, J.C., Bozonnet, P., 2014. Parametric analysis of a cylinder-like shape floating platform dedicated to multi-megawatt wind turbine. In: Proc. Int. Offshore Polar Eng. Conf..

Gray, J.S., Hwang, J.T., Martins, J.R.R.A., Moore, K.T., Naylor, B.A., 2019. OpenMDAO: an open-source framework for multidisciplinary design, analysis, and optimization. Struct. Multidiscip. Optim. 59 (4), http://dx.doi.org/10.1007/s00158-019-02211-z.

Grossman, B., Gurdal, Z., Haftka, R.T., Strauch, G.J., Eppard, W.M., 1988. Integrated aerodynamic/structural design of a sailplane wing. J. Aircr. 25 (9), http://dx.doi.org/10.2514/3.45670.

Haftka, R.T., 1990. Integrated structure-control optimization of space structures. http://dx.doi.org/10.2514/5.9781600866029.0055.0069.

Halfpenny, A., 1998. Dynamic analysis of both on and offshore wind turbines in the frequency domain. Tech. rep..

Hall, M., 2012. A cumulative multi-niching genetic algorithm for multimodal function optimization. Int. J. Adv. Res. Artif. Intell. 1 (9), http://dx.doi.org/10.14569/ijarai.2012.010902.

Hall, M., Buckham, B., Crawford, C., 2013. Evolving offshore wind: A genetic algorithm-based support structure optimization framework for floating wind turbines. In: Ocean. 2013 MTS/IEEE Bergen Challenges North. Dimens.. http://dx.doi.org/10.1109/OCEANS-Bergen.2013.6608173.

Hall, M., Buckham, B., Crawford, C., 2014. Hydrodynamics-based floating wind turbine support platform optimization: A basis function approach. Renew. Energy 66, http://dx.doi.org/10.1016/j.renene.2013.12.035.

Hasan, M.S., 2017. A simplified method for analyzing the fatigue life of a fpso mooring system. Proc. Eng. 194, 502–508.

Haslum, H.A., 2000. Simplified methods applied to nonlinear motion of spar platforms. In: NTNU, Dr. thesis.

Hassan, G., 2017. DNV GL White Paper on Definitions of Availability Terms for the Wind Industry. Document No.: EAA-WP-15, DNV GL.

He, P., Filip, G., Martins, J.R.R.A., Maki, K.J., 2019. Design optimization for self-propulsion of a bulk carrier hull using a discrete adjoint method. Comput. Fluid. 192.

He, P., Mader, C.A., Martins, J.R.R.A., Maki, K.J., 2020. DAFoam: An open-source adjoint framework for multidisciplinary design optimization with openFOAM. AIAA J. 58 (3), http://dx.doi.org/10.2514/1.J058853.

Hegseth, J.M., Bachynski, E.E., Leira, B.J., 2021. Effect of environmental modelling and inspection strategy on the optimal design of floating wind turbines. Reliability Engineering and System Safety 214.

Hegseth, J.M., Bachynski, E.E., Martins, J.R.R.A., 2020a. Design optimization of spar floating wind turbines considering different control strategies. In: J. Phys. Conf. Ser.. vol. 1669, (1), http://dx.doi.org/10.1088/1742-6596/1669/1/012010.

Hegseth, J.M., Bachynski, E.E., Martins, J.R.R.A., 2020b. Integrated design optimization of spar floating wind turbines. Mar. Struct. 72, http://dx.doi.org/10.1016/j.marstruc.2020.102771.

Hirshorn, S.R., 2007. NASA Systems Eengineering Handbook, 2nd edition, Washington, DC.

IEA, IRENA, UNSD, World Bank and WHO, 2020. Tracking SDG 7: The Energy Progress Report 2020.

Igwemezie, V., Mehmanparast, A., Kolios, A., 2018. Materials selection for XL wind turbine support structures: A corrosion-fatigue perspective. Mar. Struct. 61, http://dx.doi.org/10.1016/j.marstruc.2018.06.008.

Imam, M.H., 1982. Three-dimensional shape optimization. Int. J. Numer. Methods Eng. 18 (5), http://dx.doi.org/10.1002/nme.1620180504.

International Electrotechnical Commission (IEC), 2019. Technical Specification IEC 61400-3-2. Wind energy generation systems - Part 3-2: Design requirements for floating offshore wind turbines.

IRENA, 2019. Future of wind: Deployment, investment, technology, grid integration and socio-economic aspects (A Global Energy Transformation paper), International Renewable Energy Agency, Abu Dhabi, IRENA.

James, R., Ros, M.C., 2015. Floating Offshore Wind : Market and Technology Review. Tech. rep., Carbon Trust.

Jang, B.S., Kim, J.D., Park, T.Y., Jeon, S.B., 2019. FEA based optimization of semi-submersible floater considering buckling and yield strength. Int. J. Nav. Archit. Ocean Eng. 11 (1), http://dx.doi.org/10.1016/j.ijnaoe.2018.02.010.

Jayaram, S., Mykiebust, A., Gelhausen, P., 1992. ACSYNT - A standards-based system for parametric, computer aided conceptual design of aircraft. In: Aerosp. Des. Conf. 1992. http://dx.doi.org/10.2514/6.1992-1268.

Johnston, B., Foley, A., Doran, J., Littler, T., 2020. Levelised cost of energy, A challenge for offshore wind. Renew. Energy 160, 876–885. http://dx.doi.org/10.1016/j.renene.2020.06.030.

Jonkman, J.M., 2007. Dynamics modeling and loads analysis of an offshore floating wind turbine. Tech. rep. NREL/TP-500-41958, NREL.

Jonkman, J.M., 2008. Influence of control on the pitch damping of a floating wind turbine. In: 46th AIAA Aerosp. Sci. Meet. Exhib.. http://dx.doi.org/10.2514/6.2008-1306.

Jonkman, J.M., 2009. Dynamics of offshore floating wind turbines-model development and verification. Wind Energy 12 (5), http://dx.doi.org/10.1002/we.347.

Jonkman, J., 2010. Definition of the Floating System for Phase IV of OC3. Tech. rep. NREL/TP-500-47535, NREL.

Jonkman, J.M., Buhl, M.L., 2007. Loads Analysis of a Floating Offshore Wind Turbine Using Fully Coupled Simulation. Tech. rep. NREL/CP-500-41714, NREL.

Jonkman, J., Butterfield, S., Musial, W., Scott, G., 2009. Definition of a 5-MW reference wind turbine for offshore system development.

Jonkman, J.M., Wright, A.D., Hayman, G.J., Robertson, A.N., 2018. Full-system linearization for floating offshore wind turbines in OpenFAST. In: 1st International Offshore Wind Technical Conference, San Francisco, California.

Karadeniz, H., Toğan, V., Vrouwenvelder, T., 2009. An integrated reliability-based design optimization of offshore towers. Reliab. Eng. Syst. Saf. 94 (10), http://dx.doi.org/10.1016/j.ress.2009.02.008.

Karimi, M., Hall, M., Buckham, B., Crawford, C., 2017. A multi-objective design optimization approach for floating offshore wind turbine support structures. J. Ocean Eng. Mar. Energy 3 (1), http://dx.doi.org/10.1007/s40722-016-0072-4.

Karimirad, M., 2011. Stochastic dynamic response analysis of spar-type wind turbines with catenary or taut mooring systems.

Karimirad, M., Meissonnier, Q., Gao, Z., Moan, T., 2011. Hydroelastic code-to-code comparison for a tension leg spar-type floating wind turbine. Mar. Struct. 24 (4), http://dx.doi.org/10.1016/j.marstruc.2011.05.006.

Katsouris, G., Marina, A., 2016a. Cost Modelling of Floating Wind Farms. ECN-E–15-078, ECN.

Katsouris, G., Marina, A., 2016b. Cost modelling of floating wind farms.

Kenway, G.K.W., Martins, J.R.R.A., 2014. Multipoint high-fidelity aerostructural optimization of a transport aircraft configuration. J. Aircr. 51 (1), http://dx.doi.org/10.2514/1.C032150.

Lambe, A.B., Martins, J.R.R.A., 2012. Extensions to the design structure matrix for the description of multidisciplinary design, analysis, and optimization processes. Struct. Multidiscip. Optim. 46 (2), http://dx.doi.org/10.1007/s00158-012-0763-y.

Larsen, T.J., Hanson, T.D., 2007. A method to avoid negative damped low frequent tower vibrations for a floating, pitch controlled wind turbine. In: J. Phys. Conf. Ser.. 75, (1), http://dx.doi.org/10.1088/1742-6596/75/1/012073.

Lee, K.H., 2005. Responses of floating wind turbines to wind and wave excitation, mit.

Lee, H., Lee, D.J., 2019. Effects of platform motions on aerodynamic performance and unsteady wake evolution of a floating offshore wind turbine. Renew. Energy 143, http://dx.doi.org/10.1016/j.renene.2019.04.134.

Lee, J., Zhao, F., 2021. Global Wind Report 2021. Tech. rep., Global Wind Energy Council (GWEC), Brussels, Belgium.

Leimeister, M., Kolios, A., Collu, M., 2018. Critical review of floating support structures for offshore wind farm deployment. In: J. Phys. Conf. Ser.. 1104, (1), http://dx.doi.org/10.1088/1742-6596/1104/1/012007.

Lemmer, F., 2018. Low-order modeling, controller design and optimization of floating O shore wind turbines.

Lemmer, F., Müller, K., Yu, W., Schlipf, D., Cheng, P.W., 2017. Optimization of floating offshore wind turbine platforms with a self-tuning controller. In: Proc. Int. Conf. Offshore Mech. Arct. Eng. - OMAE. vol. 10, http://dx.doi.org/10.1115/OMAE2017-62038.

Lemmer, F., Schlipf, D., Cheng, P.W., 2016. Control design methods for floating wind turbines for optimal disturbance rejection. In: The Science of Making Torque from Wind (TORQUE 2016).

Lemmer, F., Yu, W., Müller, K., Cheng, P.W., 2020. Semi-submersible wind turbine hull shape design for a favorable system response behavior. Mar. Struct. 71, http://dx.doi.org/10.1016/j.marstruc.2020.102725.

Lemmer, F., Yu, W., Schlipf, D., Cheng, P.W., 2019. Robust gain scheduling baseline controller for floating offshorewind turbines. Wind Energy 23, 17–30.

Lerch, M., 2020. Technical-economic analysis, modeling and optimization of floating offshore wind farms.

Leroy, V., Bachynski-Polić, E., Babarit, A., Ferrant, P., Gilloteaux, J.C., 2021. A weak-scatterer potential flow theory-based model for the hydroelastic analysis of offshore wind turbine substructures. Ocean Eng. 238.

Li, X., Zhu, C., Fan, Z., Chen, X., Tan, J., 2020. Effects of the yaw error and the wind-wave misalignment on the dynamic characteristics of the floating offshore wind turbine. Ocean Eng. 199.

Lie, H., Sødahl, N., 1993. Simplified dynamic model for estimation of extreme anchorline tension.

Lim, S.-J., Kong, C.-D., Park, H.-B., 2012. A study on optimmal design of filament winding composite tower for 2 MW class horizontal axis wind turbine systems. J. Korean Soc. Compos. Mater. 25 (2), http://dx.doi.org/10.7234/kscm.2012.25.2.054.

Loukogeorgaki, E., Michailides, C., Angelides, D.C., 2014. "Dry" and "wet" mode superposition approaches for the hydroelastic analysis of floating structures. In: 9th International Conference on Structural Dynamics, EURODYN 2014, Porto, Portugal.

Lupton, R., 2014. Frequency-domain modelling of floating wind turbines.

Lupton, R.C., Langley, R.S., 2020. Harmonic linearisation of aerodynamic loads in a frequency-domain model of a floating wind turbine. Wind Energy 24, 833–856.

Mantadakis, N., Loukogeorgaki, E., Karimirad, M., 2019. Accounting for hydroelasticity in the analysis of offshore wind turbine spar-type platforms. In: The 29th International Ocean and Polar Engineering Conference, Honolulu, Hawaii.

Martins, J.R.R.A., Hwang, J.T., 2013. Review and unification of methods for computing derivatives of multidisciplinary computational models. In: AIAA J.. 51, (11), http://dx.doi.org/10.2514/1.J052184.

Martins, J.R.R.A., Lambe, A.B., 2013. Multidisciplinary design optimization: A survey of architectures. AIAA J. 51 (9), http://dx.doi.org/10.2514/1.J051895.

Martins, J.R.R.A., Ning, A., 2021. Multidisciplinary design optimization. Eng. Des. Optim. 469–531.

Maruo, H., 1960. The drift of a body floating on waves. J. Ship Res..

Matha, D., 2010. Model Development and Loads Analysis of a Wind Turbine on a Floating Offshore Tension Leg Platform. Tech. rep. NREL/SR-500-45891, NREL.

Matha, D., Sandner, F., Schlipf, D., 2014. Efficient critical design load case identification for floating offshore wind turbines with a reduced nonlinear model. In: J. Phys. Conf. Ser.. 555, (1), http://dx.doi.org/10.1088/1742-6596/555/1/012069.

Mathern, A., von der Haar, C., Marx, S., 2021. Concrete support structures for offshore wind turbines: Current status, challenges, and future trends. Energies 14.

McCabe, A.P., 2004. SuperGen Marine Workpackage 2 (T2.3.4). An Appraisal of a Range of Fluid Modelling Software.

Messac, A., 1996. Physical programming: Effective optimization for computational design. AIAA J. 34 (1), http://dx.doi.org/10.2514/3.13035.

Moore, K.T., 2012. Calculation of sensitivity derivatives in an MDAO framework. In: 12th AIAA Aviat. Technol. Integr. Oper. Conf. 14th AIAA/ISSMO Multidiscip. Anal. Optim. Conf.. http://dx.doi.org/10.2514/6.2012-5481.

Muskulus, M., Schafhirt, S., 2014. Design optimization of wind turbine support structures- a review. J. Ocean Wind Energy.

Myhr, A., Bjerkseter, C., Ågotnes, A., Nygaard, T.A., 2014. Levelised cost of energy for offshore floating wind turbines in a lifecycle perspective. Renew. Energy 66, http://dx.doi.org/10.1016/j.renene.2014.01.017.

Myhr, A., Nygaard, T.A., 2012. Load reductions and optimizations on tension-leg-buoy offshore wind turbine platforms. In: Proc. Int. Offshore Polar Eng. Conf..

Namik, H., Stol, K., 2010. Individual blade pitch control of floating offshore wind turbines. Wind Energy 13 (1), http://dx.doi.org/10.1002/we.332.

National Renewable Energy Laboratory (NREL), 2019. OpenFAST Documentation. Release 1.0. Tech. rep..

Nejad, A.R., Bachynski, E.E., Moan, T., 2019. Effect of axial acceleration on drivetrain responses in a spar-type floating wind turbine. J. Offshore Mech. Arct. Eng. 141 (3), http://dx.doi.org/10.1115/1.4041996.

Newman, J.N., 1975. Second-order, slowly-varying forces on vessels in irregular waves. Tech. rep. MIT Paper 19, Massachusetts Institute of Technology.

Newman, J.N., 2018. Marine Hydrodynamics, 40th Anniversary Edition, 2nd edition The MIT Press Cambridge, Massachusetts.

openmdao.org, 2021. OpenMDAO Theory manual. https://openmdao.org/newdocs/versions/latest/theory_manual/theory_manual.html. (Accessed 10 September 2021).

Patel, M.H., 1989. Dynamics of Offshore Structures. Butterworths.

Perez-Moreno, S.S., Zaaijer, M.B., Bottasso, C.L., Dykes, K., Merz, K.O., Rethore, P.-E., Zahle, F., 2016. Roadmap to the multidisciplinary design analysis and optimisation of wind energy systems. In: The Science of Making Torque from Wind (TORQUE 2016).

Pillai, A.C., Thies, P.R., Johanning, L., 2019. Mooring system design optimization using a surrogate assisted multi-objective genetic algorithm. Eng. Optim. 51 (8), http://dx.doi.org/10.1080/0305215X.2018.1519559.

Powell, M.J.D., 2009. The bobyqa algorithm for bound constrained optimization without derivatives.

Pustina, L., Lugni, C., Bernardini, G., Serafini, J., Gennaretti, M., 2020. Control of power generated by a floating offshore wind turbine perturbed by sea waves. Renew. Sustain. Energy Rev. 132, http://dx.doi.org/10.1016/j.rser.2020.109984.

Qiu, Y., Bai, J., Liu, N., Wang, C., 2018. Global aerodynamic design optimization based on data dimensionality reduction. Chinese J. Aeronaut. 31 (4), http://dx.doi.org/10.1016/j.cja.2018.02.005.

Qiu, W., Song, X., Shi, K., Zhang, X., Yuan, Z., You, Y., 2019. Multi-objective optimization of semi-submersible platforms using particle swam optimization algorithm based on surrogate model. Ocean Eng. 178.

Queipo, N.V., Haftka, R.T., Shyy, W., Goel, T., Vaidyanathan, R., Tucker, K., 2005. Surrogate-based analysis and optimization. Progr. in Aerosp. Sci. 41, 1–28.

Rajabi, F., Ghosh, S., Oran, C., Shield, D.R., 1985. Review of Semisubmersible and Tension Leg Platform Analysis Techniques, Volume 1 - Literature Survey. TM No.: 44-85-02CR.

Rho, J.B., Choi, H.S., Shin, H.S., Park, I.K., 2005. A study on mathieu-type instability of conventional spar platform in regular waves. Int. J. Offshore Polar Eng. 15 (2).

Rinaldi, G., Garcia-Teruel, A., Jeffrey, H., Thies, P.R., Johanning, L., 2021. Incorporating stochastic operation and maintenance models into the techno-economic analysis of floating offshore wind farms. Appl. Energy 301.

Rinaldi, G., Pillai, A.C., Thies, P.R., Johanning, L., 2018. Verification and Benchmarking Methodology for O&M Planning and Optimization Tools in the Offshore Renewable Energy Sector. In: Conference: 37th International conference on ocean, offshore and arctic engineering (OMAE 2018), Madrid, Spain.

Rinaldi, G., Thies, P.R., Walker, R., Johanning, L., 2017. A decision support model to optimise the operation and maintenance strategies of an offshore renewable energy farm. Ocean Eng. 145.

Ripepi, M., Verveld, M.J., Karcher, N.W., Franz, T., Abu-Zurayk, M., Görtz, S., Kier, T.M., 2018. Reduced-order models for aerodynamic applications, loads and MDO. CEAS Aeronaut. J. 9, 171–193.

Robertson, A.N., Gueydon, S., Bachynski, E., Wang, L., Jonkman, J., 2020. OC6 Phase I: Investigating the underprediction of low-frequency hydrodynamic loads and responses of a floating wind turbine. J. Phys. Conf. Ser. 1618, The Science of Making Torque from Wind (TORQUE 2020).

Robertson, A., Jonkman, J., Vorpahl, F., Popko, W., Qvist, J., Frøyd, L., Chen, X., Azcona, J., Uzunoglu, E., Soares, C.G., Luan, C., Yutong, H., Pengcheng, F., Yde, A., Larsen, T., Nichols, J., Buils, R., Lei, L., Nygaard, T.A., Manolas, D., Heege, A., Vatne, S.R., Ormberg, H., Duarte, T., Godreau, C., Hansen, H.F., Nielsen, A.W., Riber, H., Cunff, C.L., Beyer, F., Yamaguchi, A., Jung, K.J., Shin, H., Shi, W., Park, H., Alves, M., Guérinel, M., 2014. Offshore code comparison collaboration continuation within IEA wind task 30: Phase II results regarding a floating semisubmersible wind system. In: Proc. Int. Conf. Offshore Mech. Arct. Eng. - OMAE. vol. 9B, http://dx.doi.org/10.1115/OMAE2014-24040.

Robertson, A.N., Wendt, F., Jonkman, J.M., Popko, W., Dagher, H., Gueydon, S., Qvist, J., Vittori, F., Azcona, J., Uzunoglu, E., Soares, C.G., Harries, R., Yde, A., Galinos, C., Hermans, K., Vaal, J.B.D., Bozonnet, P., Bouy, L., Bayati, I., Bergua, R., Galvan, J., Mendikoa, I., Sanchez, C.B., Shin, H., Oh, S., Molins, C., Debruyne, Y., 2017. OC5 Project Phase II: Validation of Global Loads of the DeepCwind Floating Semisubmersible Wind Turbine. Energy Proc. 137, http://dx.doi.org/10.1016/j.egypro.2017.10.333.

Safavi, E., Tarkian, M., Ölvander, J., Najafabadi, H.N., Munjulury, R.C., 2016. Implementation of collaborative multidisciplinary design optimization for conceptual design of a complex engineering product. Concurr. Eng. Res. Appl. 24 (3), http://dx.doi.org/10.1177/1063293X16661224.

Samareh, J.A., 1999. A survey of shape parametrization techniques. In: CEAS/AIAA/ICASE/NASA Langley Int. Forum Aeroelasticity Struct. Dyn.. NASA Langley Research Center, pp. 333–343.

Samareh, J.A., 2001. Survey of shape parameterization techniques for high-fidelity multidisciplinary shape optimization. Am. Inst. Aeronaut. Astronaut. J. 39.

Sandner, F., Schlipf, D., Matha, D., Cheng, P.W., 2014. Integrated optimization of floating wind turbine systems. In: Proc. Int. Conf. Offshore Mech. Arct. Eng. - OMAE. vol. 9B, http://dx.doi.org/10.1115/OMAE2014-24244.

Sandner, F., Schlipf, D., Matha, D., Seifried, R., Cheng, P.W., 2012. Reduced nonlinear model of a spar-mounted floating wind turbine.

Schlipf, D., Schlipf, D.J., Kühn, M., 2013. Nonlinear model predictive control of wind turbines using LIDAR. In: Wind Energy. 16, (7), http://dx.doi.org/10.1002/we.1533.

Schmit, L.A., 1960. Structural design by systematic synthesis. In: Proceedings, 2nd Conf. Electron. Comput. ASCE.

Sclavounos, P., Tracy, C., Lee, S., 2008. Floating offshore wind turbines: responses in a seastate pareto optimal designs and economic assessment. In: Proc. Int. Conf. Offshore Mech. Arct. Eng. - OMAE. vol. 6, http://dx.doi.org/10.1115/OMAE2008-57056.

Sinha, A., Deb, K., 2013. Bilevel multi-objective optimization and decision making. Stud. Comput. Intell. 482, http://dx.doi.org/10.1007/978-3-642-37838-6_9.

Sobieszczanski-Sobieski, J., 1989. Optimization by decomposition: A step from hierarchic to non-hierarchic systems, NASA.

Sobieszczanski-Sobieski, J., 1990. Sensitivity of complex, internally coupled systems. AIAA J. 28 (1), http://dx.doi.org/10.2514/3.10366.

Standing, R.G., Brendling, W.J., Wilson, D., 1987. Recent developments in the analysis of wave drift forces, low-frequency damping and response. In: Proc. Annu. Offshore Technol. Conf.. 1987-April.

Stehly, T., Beiter, P., Heimiller, D., Scott, G., 2018. 2017 Cost of Wind Energy Review. TP-6A20-72167, Natl. Renew. Energy Lab. NREL.

Stieng, L.E.S., Muskulus, M., 2018. Reducing the number of load cases for fatigue damage assessment of offshore wind turbine support structures using a simple severity-based sampling method. Wind Energy Sci. 3, 805–818.

Subramanian, S.V., DeLaurentis, D.A., 2016. Application of multidisciplinary systems-of-systems optimization to an aircraft design problem. Syst. Eng. 19.

Sugita, T., Suzuki, H., 2016. A study on TLP hull sizing by utilizing optimization algorithm. J. Mar. Sci. Technol. 21 (4), http://dx.doi.org/10.1007/s00773-016-0377-y.

Tavner, P., 2012. Offshore wind turbines: reliability, availability and maintenance. In: Offshore Wind Turbines Reliab. Availab. Maint.. http://dx.doi.org/10.1049/pbrn013e.

Tracy, C., 2007. Parametric Design of Floating Wind Turbines. (Master's thesis). Massachusetts Institute of Technology.

Tran, T.T., Kim, D.-H., 2017. A CFD study of coupled aerodynamic-hydrodynamic loads on a semisubmersible floating offshore wind turbine. Wind Energy 21, 70–85.

USTUTT, 2016. Qualification of innovative floating substructures for 10MW wind turbines and water depths greater than 50 m. optimisation framework and methodology for optimized floater design, LIFES50+.

van Hees Bulder, Henderson, H., Pierik, S., Wijnants, W., 2002. Study of feasibility and of boundary conditions for floating offshore wind turbines.

Wamit Inc., 2002. Wamit user manual, version 6.1 (available for download from the website www.wamit.com).

Wang, L., Robertson, A., Jonkman, J., Kim, J., Shen, Z.-R., Koop, A., Nadal, A.B., Shi, W., Zeng, X., Ransley, E., Brown, S., Hann, M., Chandramouli, P., Viré, A., Reddy, L.R., Li, X., Xiao, Q., López, B.M., Alonso, G.C., Oh, S., Sarlak, H., Netzband, S., Jang, H., Yu, K., 2022. OC6 Phase Ia: CFD Simulations of the Free-Decay Motion of the DeepCwind Semisubmersible. Energies 15.

Wang, L., Robertson, A., Jonkman, J., Yu, Y.-H., Koop, A., Nadal, A.B., Li, H., Bachynski-Polić, E., Pinguete, R., Shi, W., Zeng, X., Zhou, Y., Xiao, Q., Kumar, R., Sarlak, H., Ransley, E., Brown, S., Hann, M., Netzband, S., Wermbter, M., Lópezm, B.M., 2021. OC6 Phase Ib: Validation of the CFD predictions of difference-frequency wave excitation on a FOWT semisubmersible. Ocean Eng. 241.

Wen, B., Tian, X., Dong, X., Peng, Z., Zhang, W., 2018. On the power coefficient overshoot of an offshore floating wind turbine in surge oscillations. Wind Energy 21 (11), http://dx.doi.org/10.1002/we.2215.

Xia, C.C., Gou, Y.J., Li, S.H., Chen, W.F., Shao, C., 2018. An automatic aerodynamic shape optimisation framework based on DAKOTA.

Young, A.C., Goupee, A., Dagher, H.J., Viselli, A.M., 2017. Methodology for optimizing composite towers for use on floating wind turbines. J. Renew. Sustain. Energy 9.

Young, D.G., Ng, C., Oterkus, S., Li, Q., Johanning, L., 2019. Predicting failure of dynamic cables for floating offshore wind. In: Adv. Renew. Energies Offshore - Proc. 3rd Int. Conf. Renew. Energies Offshore, RENEW 2018.

Zadeh, L.A., 1963. Optimality and non-scalar-valued performance criteria. IEEE Trans. Automat. Contr. 8 (1), http://dx.doi.org/10.1109/TAC.1963.1105511.

Zhang, X., Song, X., Qiu, W., Yuan, Z., You, Y., Deng, N., 2018. Multi-objective optimization of Tension Leg Platform using evolutionary algorithm based on surrogate model. Ocean Eng. 148.

Zheng, K., Yang, R.-J., Hu, J., 2015. A new variable screening method for design optimization of large-scale problems. SAE Int. J. Mater. Manufact. 8.