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Multidisciplinary design analysis and optimization of floating offshore wind turbine substructures: A review

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ABSTRACT

The development of novel energy technologies to meet net zero carbon emission is essential in the provision of solutions to realize an increasing worldwide demand for renewable energy. Floating Offshore Wind Turbine (FOWT) is one of the emerging technologies to exploit the vast wind resources available in deep waters within the offshore wind sector. However, as a result of the complexity of a FOWT system, bringing FOWT technology up to speed requires a detailed understanding of the different disciplines within the system and the relationship between the FOWT system and the dynamics of the marine environment; hence, the need for Multidisciplinary Design Analysis and Optimization (MDAO) of the system.

This paper reviews the MDAO of FOWT substructures/platforms proposed in the literature. This review covers an overview of floating offshore wind turbine substructures' concepts, the design using geometric shape parameterization techniques and the analysis approaches (time and frequency domain) for response assessment of the FOWT system. It also provides a comprehensive review of MDAO frameworks for FOWT substructures. Regarding the optimization aspect, a review of some optimization algorithms used for floating offshore wind turbine substructure is provided, i.e., from the global search heuristic and meta-heuristics algorithms to the local search gradient-based optimization algorithms.

This work further identifies the research gaps in MDAO for FOWT substructures. The main proposed future research areas to address these gaps are: increasing design space richness by adopting more advanced parametrization techniques to represent the platform geometry (and other characteristics), utilize surrogate/meta models to replace the most computationally expensive high-fidelity models needed for quick sensitivity studies before detailed analyses on selected models are conducted, and exploring the upscaling of the geometric design parameters of an optimal shape parameterized FOWT platforms derived from existing designs which can be coupled with new generation highly rated and heavier turbines.

1. Introduction

The FOWT industry is not yet in the mature stage of development and currently, the fixed bottom foundation/platform is the dominant technology in the offshore wind turbine (OWT) sector (Zheng and Lei, 2018). However, the concept of floating offshore wind turbines was proposed by Heronemus (1972) as far back as 1972. In as much as Heronemus' vision was dated back to 1972, it was in the mid-1990s that FOWT started becoming a widespread concept after which several configurations of floating support platforms are being developed for OWTs and performance of the concepts tested by numerical and experimental methods (Wang et al., 2010; Zheng and Lei, 2018).

Three main floater concepts from the oil and gas industries have been adopted by the offshore wind sector: Spar, Semi-submersible, and Tension-Leg Platform (TLP). In 1998, the concept design for "FLOAT" – a Spar concept floating wind turbine - was presented in (Tong, 1998). The objective of the FLOAT concept is to allow the economical generation of electricity from wind power in offshore locations with water depth as deep as 100 m–300 m. For the semi-submersible concept, Henderson and Patel (1998) presented an analytical and numerical design tools for evaluating the performance of semi-submersible floating wind turbines. Their focus was on the determination of an optimum hull form for the floating structure and on developing analysis tools for the interaction of the motion in waves of the platform, with the turbine aerodynamic performance as well as the blade and hub loads. Development of the TLP

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Abbreviations

ABS	American Bureau of Shipping
AEP	Annual Energy Production
BA	Bat Algorithm
B-Spline	Basis Spline
BV	Bureau Veritas
CAD	Computer Aided Design
CAPEX	Capital Expenditure
CCD	Central Composite Design
DNV	Det Norske Veritas
DOE	Design of Experiment
DOF	Design of Freedom
EA	Evolutionary Algorithm
FBSM	Feature Based Solid Modelling
FEM	Finite Element Mesh
FFD	Free-Form Deposition
FOWT	Floating Offshore Wind Turbine
GA	Genetic Algorithm
GB	Gradient Based
GF	Gradient Free
HAWT	Horizontal Axis Wind Turbine
HF	High Fidelity
IDF	Individual Discipline Feasible
IEC	International Electrotechnical Commission
K-BA	Kriging BAT Optimization Algorithm
LCOE	Levelized Cost Of Energy
LF	Low Fidelity
LHS	Latin Hypercube Sampling
MDAO	Multidisciplinary Design Analysis and Optimization
MDF	Multidisciplinary Feasible
MO	Multi-Objective
NURBS	Non-Uniform Rational B-Spline
OWT	Offshore Wind Turbine
PSO	Particle Swarm Optimization
RAO	Response Amplitude Operator
RNA	Rotor Nacelle Assembly
SAND	Simultaneous Analysis and Design
SOA	Soft Object Animation
SQP	Sequential Quadratic Programming
TLP	Tension-Leg Platform
WADAM	Wave Analysis by Diffraction and Morison Theory
WAMIT	Wave Analysis at Massachusetts Institute of Technology

floaters came later, as reported in Withee (2004) and Wang et al. (2010). Withee (2004) performed a fully coupled time-domain simulations of the system responses for a 1.5 MW wind turbine mounted on a TLP floater, under wind and wave forces. They presented the simulation results for surge free decay tests carried out to estimate the damping arising from the turbine rotor, and the wave and viscous damping arising from the buoy. They found that the two damping mechanisms were comparable in magnitude.

Since the early days of OWT floaters highlighted above, extensive systems engineering analyses have been conducted in literature, and it was not until 2017 that the first commercial floating offshore wind farm went operational (WindEurope, 2019). However, with the world in urgent need to reduce the carbon emission footprint, to revert the existing trend of global warming and the need to reduce the levelized cost of electricity generated from wind, there have been increasing interest in the floating foundation/support for wind turbine system in recent years (Wang et al., 2010). Also, as offshore wind turbine installation frontiers gradually move into deeper waters with abundant and high-quality wind resources, the need for FOWT system has become imperative as the reliable fixed support/monopile foundation offshore wind turbines become very cost prohibitive in such environmental conditions (deep water >60m), as mentioned in Leimeister et al. (2018); Lefebvre and Collu (2012) and Dan Kyle Spearman (2020).

The substructure/platform for a FOWT system can account for circa 29.5% of the capital expenditure (CAPEX), while the corresponding substructure/foundation of a fixed bottom wind turbine accounts for 13.5% of CAPEX of the system (Ioannou et al., 2020); hence, the need for optimization or conducting a geometric shape parameterization technique with optimization on the substructure of the FOWT system to provide efficient means of reducing the costs is deemed more urgent than for offshore fixed bottom wind turbines. In addition, due to the complexity of the dynamic behaviour of a FOWT system, there is need to balance the design and optimization of the substructures and the computational cost (time) with adequate optimization framework using MDAO technique. Balancing the optimization process of the FOWT substructure with the computational cost is a very important trade-off, that should be considered in the MDAO of FOWT substructure. Ensuring the balance is to make use of the right model fidelity (high fidelity, multi-fidelity/surrogates, and low fidelity models) to explore the design space. Any selected model can subsequently be verified with a high-fidelity tool.

A FOWT is an engineering system with a multidisciplinary set of complex subsystems, as indicated in Fig. 1. These kinds of complex systems, in other industries, have successfully been optimized adopting

Fig. 1. Floating Offshore Wind Turbine System, adapted with permission from (Jonkman and Matha, 2011).

a MDAO approach. MDAO is a systems engineering methodology that uses numerical optimization techniques to design and analyse multidisciplinary engineering systems like a FOWT system (Perez-Moreno et al., 2016). This tool is perfect for both present and future design and analysis requirements for conducting or executing the optimization of various multidisciplinary systems.

MDAO is advantageous as it permits designers and engineers to incorporate all necessary disciplines simultaneously to explore the design and analysis space and select the optimal solution. This is a much superior approach to the sequential design and analyses process as it can exploit the integration and interface between disciplines. It is also a much quicker approach in comparison to when each discipline is treated as a standalone. However, simultaneous inclusion of multi-disciplines increases the complexity of the problem and poses some challenges. To execute an MDAO involves overcoming design and analysis challenges amongst which are design parameterization, computational time from modelling techniques and exploration of design space (Sclavounos et al., 2008). Overcoming the challenges requires an optimization framework that uses the right model fidelity within the MDAO framework (high fidelity, multi-fidelity, low fidelity) to solve the problem.

This review focuses on the FOWT substructure (the platform, anchors and mooring system) as defined in the International Electrotechnical Commission's technical specification (IEC-61400-3-2, 2019). Section 1 is an introduction to the early work done on FOWT system with a definition of MDAO. It also sets the scene for the scope of the paper. Section 2 details the design, parameterization and analysis approaches of FOWT substructures. Section 2.1 gives an overview of the FOWT substructures' classification, Section 2.2 details the design of a FOWT substructure in accordance to technical standards and guidelines, Section 2.3 discusses the parameterization of FOWT substructure with a focus on geometric shape parameterization techniques that have been successfully used in industries like aerospace, offshore oil and gas and automobile sectors, Section 2.4 provides an overview of the dynamic analysis approach for assessing the response of a FOWT substructure. Section 3 details the MDAO approach for assessing a FOWT system. Section 3.1 provides an overview of MDAO, its development in the aerospace industry, and its use in the offshore industry, Section 3.2 highlights the MDAO workflow, system scope, architecture/framework and model fidelities within the framework while Section 3.3 details MDAO work for FOWT substructures, detailing available optimizers and some of MDAO related work in the offshore wind turbine industry. Section 4 highlights the gaps in MDAO methodologies when applied to the offshore wind turbine sector, and Section 5 presents the main conclusions.

2. Design, parameterization and analysis approaches for floating offshore wind turbine substructures

2.1. Floating offshore wind turbine substructure overview

Different designs of FOWT platforms exist; however, based on the principle exploited to achieve static stability, FOWT substructures can be classified under three classes, detailed in Collu and Borg (2016) and Leimeister et al. (2018) while the advantages and disadvantages of the substructures classification are detailed in Bashetty and Ozcelik (2021) and highlighted below:

- The ballast stabilized platform (Spar) – This category of platform relies mainly on heavy ballast mass located at a deep draft, to ensure the platform's center of mass is well below the center of buoyancy, in order to produce a large restoring moment. Some advantages of a ballast stabilized spar are simple design geometry, higher stability and low wave induced motion on the structure while amongst its disadvantages are higher fatigue loads in tower and its deep-water requirements for installation.
- The buoyancy stabilized platform (semi-submersible/Barges) – This class of support structures uses the water plane area to ensure stability of the platform. A large second moment of water plane area is suitable to raise the metacenter of the platform above the center of mass to ensure platform stability. Advantages of a buoyancy stabilized semi-submersible includes low draft requirements, low mooring costs, transportation ease to installation site and adequate suitability for deep-water utilization. Some of it's disadvantages are its susceptibility to higher wave induced motions and the structural design are complex with several columns and braces.
- The mooring stabilized platform (TLP) – This category of FOWT platform uses taut vertical mooring lines to ensure the stability of the buoyant platform. Some advantages attributed to a TLP substructure includes low wave induced motion, simple structural design and low fatigue loads. Disadvantages associated to a TLP are mainly expensive mooring cost and difficulty in towing to install.

FOWT platforms are designed according to classification guidelines and standards and a fundamental design requirement to be satisfied in the design of FOWT platform is the stability. Different platform types have varying stability mechanisms or contributors as highlighted in (Collu and Borg, 2016). The contributors are waterplane area which results in the waterplane stabilized platform (semi-submersible), ballast which is the main contributor to a ballast stabilized platform (spar) and mooring which results in a mooring stabilized platform (TLP). The main parameters contributing to the roll/pitch restoring moment for the waterplane stabilized platform are the seawater density, acceleration due to gravity and the second moment of waterplane area. For the ballast stabilized platform, the main parameters contributing to the roll/pitch restoring moment are the buoyancy force, center of buoyancy, mass, acceleration due to gravity and center of gravity of the system. The main contributor to the roll/pitch restoring moment of a mooring stabilized platform is the mooring stiffness. While it is possible for the mooring contribution to be considered negligible for catenary mooring systems, it can be the main restoring mechanism for TLP systems (Collu and Borg, 2016).

Apart from the Spar, Semi-submersible, and the TLP platforms mentioned above, new and unique geometrically shaped platforms for the FOWT sector are being developed. Examples of these unique platform designs are the IDEOL "damping pool" barge platforms, the TetraSpar floating concept, and the Hexafloat (Ghigo et al., 2020). The Floatgen IDEOL barge concept is an altered barge design that uses a moonpool, also referred to as damping pool system, for motion reduction (Leimeister et al., 2018). The Hexafloat is a floating concept developed by Saipem. It is a pendulum lightweight structure composed of a submersible floater made of tubular elements, a counter weight connected to the floater with tendons, simple mooring lines with drag anchors, and a lazy wave dynamic cable (Ribuot, 2019). The TetraSpar floating concept was developed by Stiesdal Offshore Technologies A/S. This concept aims to provide a low-cost FOWT platform that can be easily installed in any condition; hence, contributing to low cost of electricity in comparison to bottom-fixed OWT (Stiesdal, 2021). Depending on the site conditions, the TetraSpar can be configured as a semi-submersible, as a Spar (pendulum configuration), or as a TLP.

The traditional platform concepts (Spar, Semisubmersible and TLP) and the different unique platform design concepts highlighted above are designed using optimization indicators/constraints. Common optimization objectives or problems in an optimization framework are minimizing the cost of the system and the LCOE, improving the performance of the system like the nacelle acceleration, system's dynamic response and fatigue. The objective functions/optimization problem are resolved by specifying constraints to the problem. These constraints are important for enriching the design space, improving computational time and optimization accuracy. Some of the constraints taken into consideration in the design and optimization of a FOWT substructure are: Costs, static pitch angle, dynamic pitch angle and slackness in mooring lines as detailed in Hall et al. (2013). In addition, section 3.3 highlights the definition of constraints in an optimization problem and it also highlights constraints of some works in literature on FOWT.

The three stability classifications described are illustrated in Fig. 2 a, b and c, represents the mooring line stiffness stabilized, the ballast stabilized and the buoyancy/waterplane stabilized platforms respectively. For a detailed mathematical model of the inclining and restoring moment physics, see Borg and Collu (2015).

2.2. *Design of a FOWT substructure*

The design procedure for a FOWT substructure follows the general engineering design process of preliminary/concept design followed by detailed design of the selected concept. Some of the requirements for a successful support structure design are well detailed in DNV-OS-J101 (2013), DNVGL-ST-0119 (2018) and highlighted below:

- Ensure design stability in intact conditions.
- Ensure range of eigenfrequencies of design avoid excitation of resonance by rotor frequencies, first-order wave forces and vortex shedding.
- Maximum offsets or displacements and limits on dynamic motions.
- Ensure safe operation of wind turbine during the design life of the turbine.
- Maintain acceptable safety for personnel and environment.
- Ensure adequate fatigue strength for 20–30 years operation of the system.

2.2.1. *Preliminary/concept design*

It is an iterative process which begins with concept selection or preliminary design. This is followed by a more detailed design and analysis of the loads and system's response to ensure the structural strength is sufficient to withstand the load effects (DNVGL-ST-0119, 2018).

As discussed in Borg and Collu (2015), Kolja Müller and Simon Tiedemann (2017) and Lefebvre and Collu (2012), the preliminary design of a floating substructure is divided into two stages, which are the preliminary sizing of the support structure's concept, and the design for further development and refinement. The main requirements to fulfil when sizing is the hydrostatic stability requirements which are:

- Support structure must ensure floatability
- A maximum pitch/roll angle of 5° for static equilibrium and 5° combined with ± 15 degrees of dynamic amplitude imposed in order not to substantially compromise the performance of the FOWT (Borg and Collu, 2015). As mentioned in Borg and Collu (2015), this is only a guideline.
- Maximum floater offset or floater excursion in surge including static, first and second order loads is less than 50% of the water depth (Kolja Müller and Simon Tiedemann, 2017).

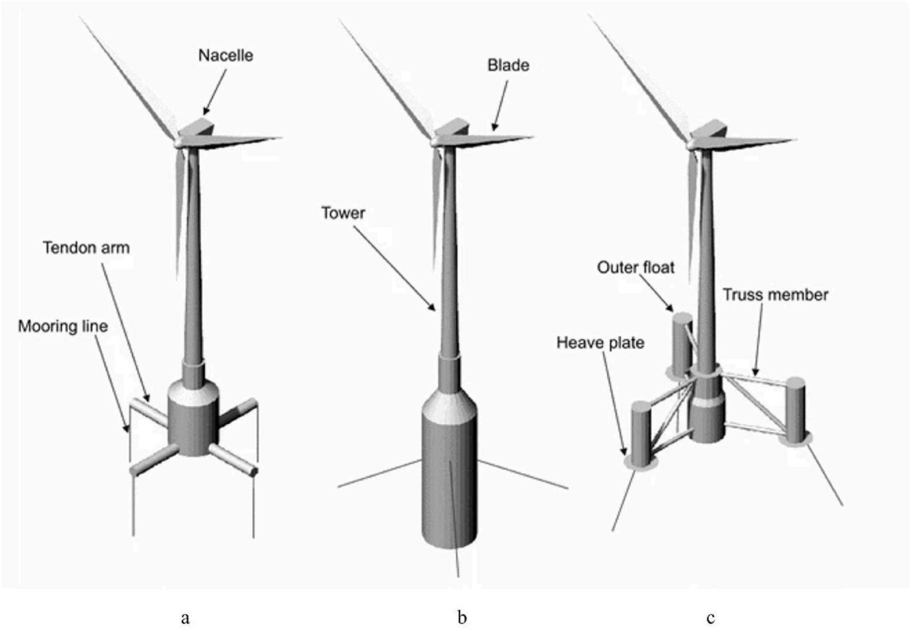
Other drivers to consider when sizing are the site conditions/metocean data designed for extreme driven ultimate limit state (ULS), turbine weight and inertias and the thrust force on the turbine (Friedemann Borisade et al., 2016).

The preliminary sizing is based on two equations which are the buoyancy force equation detailed in Lefebvre and Collu (2012) and the restoring moment equation detailed in Collu and Borg (2016). The buoyancy force acting on the FOWT system is equivalent to the weight of the turbine and weight of the support structures (tower, platform and mooring lines) while the restoring moment in roll/pitch is a summation of water plane stabilization parameters, ballast stabilization parameters and mooring stiffness discussed in Section 2.1.

An iterative method is used to solve the set of buoyancy force equation and restoring moment equation based on the substructure's geometry to select the concept for detailed design. The iterative method can also be in the form of optimizers to explore the design space based on design objectives like platform's motion response and platform's mass to select the optimal design concept.

2.2.2. *Detailed design*

For a detailed design assessment, the preliminary design is refined to ensure the structural strength has been improved in intact conditions (Lefebvre and Collu, 2012). Due to the complexity of FOWT as an engineering system, its design must be governed by adequate industry's technical standards and guidelines. The most widely used design standards for FOWTs are Det Norske Veritas (DNV) (DNV-OS-J101, 2013; DNVGL-RP-0286, 2019; DNVGL-SE-0422, 2018; DNVGL-ST-0119, 2018; DNVGL Oslo, 2018; DNVGLAS, 2016), American Bureau for Shipping



a b c

Fig. 2. Floating platform classification of OWT, left to right: TLP, Spar and Semi-submersible adapted with permission from (Karimi et al., 2017).

(ABS) (ABS, 2014, Updated July 2020.), Bureau Veritas (BV) (Veritas, 2010, 2015, Updated, 2019), Class NK (Kyokai, 2012) and the International Electrochemical Commission (IEC) (IEC-61400-1, 2014; IEC-61400-3-2, 2019; IEC-61400-3, 2009). The methodology used for most of the design standards highlighted is the "load and resistance factor design". The aim of this approach is to obtain design within the adequate safety level by considering safety factors to account for uncertainties in both structural load and structural resistance (Bachynski and Collu, 2019; DNV-OS-C105, 2008). In their work, Collu and Borg (2016) discussed the classifications criteria of the support structures based on existing codes and standards verification societies: BV (Veritas, 2010), ABS (ABS, 2015, Updated March 2018, 2020) and DNV (DNV-OS-J101, 2013).

BV (Veritas, 2010) adopts the classification criterion based on the floating platform's stability mechanisms i.e., ballast stabilized floating platforms (spar-buoy), buoyancy stabilized floating platforms (semi-submersibles and barges), and tensioned stabilized platform classes (TLP).

ABS (ABS, 2015; Updated March 2018; 2020) adopts the classification criterion based on the structural elements of the different floating substructure, without expressly defining the stabilizing mechanism.

For the DNV offshore standard, the criteria are based on whether a structure is restrained (displaced in the order of centimetres) or compliant (displaced in the order of meters or more).

Overview of the analysis approach for detailed design are discussed in Jonkman and Matha (2011) and highlighted below:

1. Develop a model of each complete system with a comprehensive simulation tool capable of modelling the coupled dynamic response of the system from combined wind and wave loading. This form of modelling requires the application of comprehensive aero-hydro-servo-elastic simulation tools that incorporate integrated models of the wind inflow, aerodynamics, hydrodynamics (offshore systems), control (servo) dynamics and structural (elastic) dynamics in the time domain in a coupled nonlinear simulation environment. Some of the available commercial simulation and modelling tools for FOWT system are: DNV suites (Genie, HydroD, Wadam, SIMA), Ansys Aqwa, Nastran, Orcaflex. An important open source simulation and analysis tool is OpenFAST code, developed by (Jonkman, 2007). It enables high fidelity model analysis and verification in the time domain.
2. Verify elements of each full system dynamics model from step 1 by checking its response predictions with responses predicted by a simpler model. When modelling a floating wind turbine, it is advantageous to check the sophisticated nonlinear time domain model against a much simpler linear frequency domain model. This kind of check can be made in terms of response amplitude operators of system motions and loads for excitation by regular waves or in terms of probability distributions of system motions and loads for excitation by irregular waves.
3. Using each full system dynamics model from step 1, a comprehensive loads analysis is performed to identify the ultimate loads and fatigue loads expected over the lifetime of the system. Loads analysis involves running a series of design load cases (DLCs) covering essential design-driving situations, with variations in external conditions and the operational status of the system.
4. Improve each floating system design through design iteration of the above steps, ensuring that each of the system components is suitably sized through limit-state analyses.

2.3. *Parameterization techniques in design*

The main objective of parametric modelling is to prescribe the properties of a structure (Birk, 2006). This process reverses the flow of traditional structural modelling with interactive CAD systems. Parametric modelling approach starts with specification of the desired form parameters and properties. This is passed to the parametric modelling system for the evaluation of unspecified properties and return of evaluated data to the user with little or no user interference (Birk, 2006). Some shape parameterization techniques from other industries and parameterization work in the offshore wind sector are highlighted below.

2.3.1. *Shape parameterization review*

Shape parameterization is an important concept in design. It facilitates the exploration of a conceptual design space and provides informed knowledge to make design decisions. Geometric shape parametric modelling cuts across all areas of design and has been widely researched in the aerospace, automotive, construction, architecture, manufacturing and civil engineering sectors.

Shape parameterization techniques review has been extensively done for aerospace geometric designs and are detailed in the works of Samareh (1999), Samareh (2001) and Kulfan and Bussoletti (2006). For offshore hydrodynamic models, the application of shape parameterization techniques for design, analysis and optimization can be seen in works done by (Birk and Clauss (2002), Birk et al. (2004) and Birk and Clauss (2008)). These techniques are the reviewed techniques from the aerospace sector and are highlighted in this section. Properties of a well conducted parameterization method as discussed in the works of Kulfan and Bussoletti (2006), Samareh (2001) and Zhu (2014) are:

1. Provide high flexibility to cover the potential solution in the design space;
2. Give as small number of design variable as possible;
3. Produce smoothness and reliability of geometric shapes;
4. Provide correct design parameters for geometric and physical understanding in design space exploration by the engineers.

An overview of some of the shape parameterization techniques are highlighted in Section 2.3.1.1 to 2.3.1.3.

2.3.1.1. Free form deformation (FFD). FFD dates back to the mid nineteen eighties. Algorithms for morphing images and deforming objects are quite common in the field of soft object animation (SOA) in computer graphics (Jamshid, 1999; Sederberg and Parry, 1986). SOA algorithm can serve as the basis for an efficient FFD shape parameterization technique. These algorithms (SOA) are powerful tools for modifying shapes as they use high-level shape deformation rather than manipulating lower geometric entities (Jamshid, 1999). The SOA algorithms treat the model as rubber that can be twisted, bent, tapered, compressed, or expanded, while retaining its topology (Samareh, 2001). The SOA algorithms relate the grid-point coordinates of an analysis model to a number of design variables (Jamshid, 1999; Samareh, 2001). Coppedé et al. (2018) proposed a new approach for hull shape modification. Their proposal is based on a combination of the Subdivision Surface technique for hull surface modelling and FFD algorithm for shape variation. In their work, a transformation made of two FFDs on a fast ferry was analysed with respect to both local and global relevant geometric parameters. The results and the quality of the modified surfaces prove that the proposed combined SS-FFD approach can be applied for further specific design and variation studies like an automatic ship design by optimization process, where reduction of number of parameters is a key feature for faster convergence.

2.3.1.2. CAD-based approach. The use of commercial CAD systems for geometry modelling can potentially save development time for a multidisciplinary design optimization application; however, parameterizing an existing CAD model is still a challenging task as the models created can be deficient for automatic grid generation tools (Townsend et al., 1998). The use of feature-based solid modelling (FBSM) capable of creating dimension-driven objects in today's CAD system coupled with the geometry modelling allows designers to work in three-dimensional space while using topologically complete geometry that can be modified from the dimensions of the features from which it was created (Jamshid, 1999; Samareh, 2001).

Although the use of parametric modeling in design would make the FBSM tools ideal for optimization, existing FBSM tools are not capable of calculating sensitivity derivatives analytically (Samareh, 2001). Issues involved with the use of a CAD system for an MDO application are discussed in Townsend et al. (1998) (Townsend et al., 1998). Some of the issues identified are: allowing for replacement of the CAD system when required, and determining the analytical sensitivity derivatives required by a gradient-based optimizer.

Due to the large computer codes for commercial CAD systems, to differentiate the entire system with automatic differentiation tools may be very challenging, hence, the calculation of the analytical sensitivity derivatives of geometry with respect to the design variables could prove to be challenging within a commercial CAD environment (Townsend et al., 1998). For some limited cases, the analytical shape sensitivity derivatives can be calculated based on a CAD model (Jamshid, 1999; Samareh, 2001); however, this method will not work under all circumstances. One difficulty is that, for some perturbation of some dimensions, the topology of the CAD part may be changed. To control the dimension and topology effectively requires the use of polynomials and splines.

2.3.1.3. Polynomials and spline techniques. Polynomial and splines have been vastly used in engineering design, from the aerospace and automobile sectors to naval architecture, as most CAD modelling are based on splines. The number of variables needed to generate a smooth shape can be greatly reduced by using a polynomial or spline representation (Samareh, 2001). Polynomials also have the capability of describing a curve in a compact form with a reduced set of design variables. It can be expressed in its standard power basis form shown in Eq. (1).

$$\overline{R}_{(U)} = \sum_{i=0}^{n-1} \overline{C}_i u^i \tag{1}$$

Where $\overline{C}_i$ is the coefficient vectors corresponding to three-dimensional coordinates in which their vector components can serve as design variables; $\overline{R}$ is geometry sensitivity derivative with respect to $\overline{C}_i$ and u^i. In this representation, the coefficient of vectors provides little geometric information about the shape of the curve. This polynomial representation in the power basis form is prone to round-off error when there is a large variation in the magnitude of coefficients (Straathof, 2012). It is difficult to predict how a change in the coefficient vector $\overline{C}_i$ will influence the overall shape of the polynomial curve.

An improved representation of a polynomial curve is done through the Bezier representation highlighted in Eq. (2).

$$\overline{R}_{(U)} = \sum_{i=1}^{n} \overline{P}_i B_{i,p}(u) \tag{2}$$

Where n is the number of control points, $B_{i,p}(u)$ is the degree p Bernstein polynomials, the coefficients $\overline{P}_i$ are control points also utilized as design variables. The Bezier form is a much improved representation of curves than the power basis (Farin, 1993b). Although, the Bezier form and the power basis are mathematically equivalent, the computation of Bernstein polynomials which is a recursive algorithm (de Casteljau algorithm) minimizes the round off error in the Bezier curve (Farin, 1993a; Samareh, 2001). In a Bezier curve, the control points approximate the curve as the convex hull of the Bezier control polygon contains the curve. The first and last control points in a Bezier curve are located at the beginning and the end of the curve respectively. The Bezier curve is a suitable representation for shape optimization and parameterization of simple curves.

Complex curves however, requires a high degree Bezier form and as the degree of a Bezier curve increases, so does the roundoff error (Samareh, 2001). In addition, computing a high degree Bezier curve is computationally expensive and inefficient. As described in Samareh (2001), several low-degree Bezier segments can be used to represent a complex curve rather than using a high degree Bezier curve. The resulting composite curve is a spline more accurately referred to as B-spline. A multisegmented B-spline is described in Eq. (3).

$$\overline{R}_{(U)} = \sum_{i=1}^{n} \overline{\boldsymbol{P}}_i N_{i,p}(u) \tag{3}$$

Where $\overline{P}_i$ are the B-spline control points, p is the degree, $N_{i,p}(u)$ is the *I th* B-spline basis function of degree p. In comparison to the Bezier representation, the low degree B-spline form can represent complex curves more efficiently and accurately. In Eq. (2), the Bernstein polynomials $B_{i,p}$ is replaced by a set of B-spline basis functions $N_{i,p}$ and the Bernstein coefficient vector $\overline{P}_i$ replaced by a B-spline control polygon $\overline{\boldsymbol{P}}_i$. A disadvantage of a regular B-spline representation is that it doesn't have the capability to represent implicit conic sections accurately. A different type of B-spline with the capability of rectifying this deficiency is Non Uniform Rational B-spline (NURBS) (Farin, 1990). NURBS can represent most parametric implicit curves without loss of accuracy (Farin, 1990; Samareh, 2001). A NURBS curve is defined as highlighted in Eq. (4).

$$\overline{R}_{(U)} = \frac{\sum_{i=1}^{n} \overline{\boldsymbol{P}}_i W_i N_{i,p}(u)}{\sum_{i=1}^{n} W_i N_{i,p}(u)} \tag{4}$$

Where $\overline{\boldsymbol{P}}_i$ are the control points, W_i are the weights and $N_{i,p}(u)$ is the ith B-spline basis function of degree p. A similarity between Basis, Bezier, regular B-spline and NURBS representation of curves is that the sensitivity derivatives with respect to the control points are fixed during optimization cycles. However, in a NURBS scenario, if the weights are selected as design variables, the sensitivity derivatives will be functions of the weight design variables (Samareh, 2001).

2.3.2. Parameterization work on FOWT

Efficient evaluation of a large number of FOWT designs require adequate parameterization, which can enable the exploration of a rich design space limiting the number of design variables. The design parameterization should ideally cut across more floating platform classes and different geometrical variables for optimization purposes. A detailed parametric study of a FOWT system is presented in (Tracy, 2007), where the optimization leads to the definition of the Pareto fronts for mean square acceleration of the turbine against multiple cost drivers of the offshore structure (simply put – a trade-off between performance and cost). The cost drivers include displacement of the structure and total mooring line tension.

Another work on FOWT parameterization and optimization can be traced to Sclavounos et al. (2008). In this work, they presented a coupled dynamic analysis of floating wind turbines incorporating a parametric design study of floating wind turbine concepts and mooring system. They presented a Pareto optimal design that has a favourable combination of nacelle acceleration, mooring system tension, and displacement of the floating substructure supporting a 5 MW wind turbine. Their results show that, for a fully coupled dynamic analysis conducted for the wind turbine, the floating substructure and the mooring system, considering both wind and sea state environmental conditions, the Pareto optimal structures are generally either a narrow deep drafted spar or a shallow barge ballasted with concrete. The varying parameters for this work are the draft and the diameter of the platform.

It can be observed from the examples provided that the parametric approach is mainly varying platform diameter and draft. To apply geometric shape parameterization technique, there is need to look at other offshore sectors like the oil and gas and maritime sectors. In their study, Zhang et al. (2008), noted that a successful hydrodynamic optimization of ship hull depends on the geometric variation of hull planer forms. The parametric design of hull forms involves; specifying form parameters, design of a set of longitudinal curves, parametric modelling of sections which forms the body parts and generating hull forms (Zhang et al., 2008). This curve parameterization technique has been successfully used in the design of ship hulls, and can be implemented in the design of FOWT platforms. Another parameterization and optimization work, carried out for oil & gas offshore structures, with an optimization methodology based on linear analysis of wave-body interaction, has been done by Birk and Clauss (2008). This work was started over a decade earlier as hydrodynamic shape optimization of large offshore structures by the same authors (Clauss and Birk, 1996). In Birk and Clauss (2008), a reliable hydrodynamic analysis, using the WAMIT program, has been integrated with a newly developed parametric hull design methodology, which enables the automated generation of hull shapes, without the need for user interaction. The optimization algorithm is used to optimize the shapes with the hull responses. The shape parameterization technique discussed in Section 2.3.1 can be employed in the design, analysis, and optimization of FOWT platforms.

2.4. Dynamic analysis techniques

Two ways for analysing a FOWT model is to conduct the analysis in the frequency or the time domain, to access the dynamic response of the structure. These approaches help estimate the response to wind and wave forces which impose oscillatory motions on the FOWT system.

2.4.1. Frequency domain approach

The frequency domain approach has been extensively used in the oil and gas industry, as it enables the assessment of the system's wave response spectrum given the wave spectrum of the site and the response amplitude operator (RAO) of the given system (Journée and Massie, 2001; Patel, 2013). For a FOWT system in regular wave, the resultant system of equations of motion, in the frequency domain is highlighted in Coraddu et al. (2020) and Newman (2018).

The formulation for the radiation and diffraction boundary value problem and the resulting hydrodynamic added mass, damping matrices and wave-excitation force depend on frequency, water depth, and sea current, as well as on the geometric shape of the support platform, its proximity to the free surface, and its forward speed. Additionally, the wave-excitation force depends on the heading direction of the incident waves (Jonkman, 2007). The frequency dependence of the hydrodynamic added mass and damping matrices is of a different nature to that of the wave-excitation force. In the frequency dependence of the hydrodynamic added mass and damping matrices, the matrices depend on the oscillation frequency of the particular mode of support platform motion. However, the frequency dependence of the wave-excitation force means that the force depends on the frequency of the incident wave. Both set of frequencies (added mass and damping frequency and wave excitation frequency) are identical because the platform is assumed to oscillate at the same frequency as the incident wave.

By definition, the frequency-domain model assumes that the platform motions are at the same frequency as the incident waves and that the incident waves are regular. While this means that the transient response of the system cannot be modelled, the assumption of linearity implies that the responses at different wave frequencies can be superimposed according to a wave spectrum to predict the system behaviour in irregular sea states (Hall et al., 2013). Extensive discussion of these hydrodynamic coefficients can be found in Anaya-Lara et al. (2018) and Journée and Massie (2001). The hydrodynamic coefficients (added mass. radiation damping and first order wave excitation) can be approximated as solution to the linear radiation-diffraction problem using the boundary element method. This is implemented in softwares like WAMIT, detailed in WAMIT-Inc (2020) and WADAM in DNVGL Høvik (2019).

The complex magnitude of the response transfer function between the amplitude of the wave and the amplitude of oscillation in the oscillatory degree of freedom is the RAO highlighted in Eq. (5).

$$RAO_j = \left| \sum_{k=1}^{6} \frac{X_k}{-\omega^2 \left(M_{kj} + a_{kj}\right) + i\omega b_{kj} + c_{kj}} \right| \tag{5}$$

Where ω is the frequency of oscillation of the platform, M_{kj} is the total system mass matrix, a_{kj} is the hydrodynamic added mass coefficient, b_{kj} is the radiation damping coefficient without the consideration of viscous forces and c_{kj} is the sum of the hydrostatic and mooring stiffness coefficients. and X_k is the first order wave excitation load transfer function (Coraddu et al., 2020; Newman, 2018).

The wave response spectrum should be minimized in order to minimize the displacements and accelerations of the FOWT system. It is important that the natural frequencies (periods) of the FOWT system should be outside the most energetic frequency (period) range of the wave spectrum (Collu and Borg, 2016). This depends on the location, but in general wave spectra are most energetic between the 5s and 25s period (1.25–0.25 rad/s), and therefore the structure should aim at having natural periods above 25s or below 5s in all the DOFs (Collu and Borg, 2016).

The frequency domain analysis approach is mostly used for preliminary design of FOWTs as the RAO concept is strictly valid to estimate the regime response to waves and by definition is a linear approach (Collu and Borg, 2016). To capture the transient behaviour of a FOWT due to non-linear loading from wind and irregular seastate, a more detailed approach is required as in the time domain approach.

2.4.2. Time domain approach

A time-domain approach adopts a time-domain coupled model of dynamics with the capability to take into account nonlinear forces and also estimate the transient regimes. With this approach, it is possible to estimate the loads acting on the structure and the displacements, velocities, accelerations, and time responses of the system in all DOFs (Collu and Borg, 2016; Journée and Massie, 2001). Adopting the use of statistical analysis, the maximum, minimum, mean, variance, standard deviation, and significant values of each of the displacements, velocities and acceleration can be determined in order to have a more realistic estimate of these values. However, it is more difficult to understand in depth how to modify the design in order to obtain a more suitable response to wind and wave forces (Collu and Borg, 2016).

A major contribution to time domain integrated dynamics design codes is discussed in Jonkman (2007). In his work, Jonkman developed a robust simulation tool for the coupled dynamic response of a horizontal axis wind turbine (HAWT) and performed integrated dynamic analysis on a HAWT mounted on a barge-type platform according to the IEC 61400-3 design standard. This tool is integrated into OpenFAST which is one of the most widely used open-access FOWT design and simulation codes.

Just like in the frequency domain, Newton's second law yields the linear equation of motion in time domain (Journée and Massie, 2001). This is known as the Cummings equation and represented in Eq. (6). Cummings equation does not consider the structural flexibility degrees of freedom; hence, it is the time domain equation of a rigid body.

$$X(t) = (\mathrm{M} + \mathrm{A}) \bullet \ddot{x}(t) + \int_0^\infty B(\tau) \bullet \dot{x}(t-\tau) \bullet d\tau + C \bullet x(t) \tag{6}$$

Where $\ddot{x}(t)$ is the translational or rotational acceleration at time (t), $\dot{x}$ is the translational or rotational velocity at time (t), $x(t)$ is the translational or rotational displacement at time (t), M is the solid mass or mass moment of inertia, A is the hydrodynamic (or added) mass coefficient, $B(\tau)$ is the retardation functions, C is the spring coefficient from ship geometry and t, τ is time. Details of how to determine coefficients A and B are discussed in Journée and Massie (2001).

2.4.3. Review of analysis domain for FOWT system design

Table 1 shows a list of design analysis and optimization work done on FOWT system and the analysis domain adapted in each case. The majority of the works shown in Table 1 adopt a frequency domain approach.

For optimization purposes that entails large design space exploration, time domain dynamics evaluation becomes computationally expensive and time consuming. The way around the computationally expensive time domain dynamics evaluation issue is to conduct the dynamic analysis in the frequency domain. In spite of the frequency domain analysis advantage of being computationally less expensive, it has its own limitations amongst which are:

1. Frequency domain analysis is not suitable for non-linear dynamic systems. It only applies to linear systems such that the system's behaviour is linearly related to its displacement, velocity and acceleration (Journée and Massie, 2001).
2. Frequency domain analysis does not take into consideration the impulse response function – irradiated waves that keep exciting the body due to memory of past motion of the body even when the body has suddenly stopped (Journée and Massie, 2001). This memory effect is effectively covered in the time domain analyses using the Cummings equation (Journée and Massie, 2001).

These limitations are not deterrent to the use of frequency domain analysis technique to solve optimization problems in comparison to computationally expensive time domain techniques. As highlighted in Section 3.3.2, which reviews the multidisciplinary design analysis and optimization of a floating offshore wind turbine system, most of the analysis conducted for the research work reviewed are conducted using the frequency domain analysis technique. However, verification of the optimal design can be done with the more accurate non-linear time domain analysis technique, for a reduced design space.

3. Multidisciplinary design analysis and optimization approaches for floating offshore wind turbine system

3.1. MDAO overview

MDAO is an engineering/research field that studies the use of numerical optimization techniques to design engineering systems that involves multiple disciplines/subsystems or components (Martins and Lambe, 2013). It is a systematic design and analysis process that deals with the interfacing between different components and disciplines within a system. This review will look at how MDAO is applied to the FOWT substructure system (platform and mooring/station keeping).

Table 1
Analysis domain overview for optimization of FOWT system.

Work	Analysis Domain	Reference
Practical application of global optimization to the design of offshore structures	Frequency domain	Birk et al. (2004)
WINDOPT - An optimization tool for floating support structures for deep water wind turbines	Frequency domain	Fylling and Berthelsen (2011)
Evolving Offshore Wind: A genetic algorithm-based support structure optimization framework for floating wind turbines	Frequency domain	Hall et al. (2013)
A multi-objective design optimization for floating offshore wind turbine support structures	Frequency domain	Karimi et al. (2017)
Integrated design optimization of spar floating wind turbines	Frequency domain	Hegseth et al. (2020)
Platform Optimization and Cost Analysis in a Floating Offshore Wind Farm	Frequency domain	Ghigo et al. (2020)
Optimization of floating wind turbine support structures using frequency domain analysis and analytical gradients	Reduced order time domain and Frequency domain	Dou et al. (2020)
Development of a framework for wind turbine design and optimization	Frequency domain	Leimeister et al. (2021)

MDAO was initially developed in the aerospace industry as a result of strong influences between different disciplines (aerodynamics and structural dynamics) that affect the performance of the aircraft (Dykes et al., 2011). MDAO went to be further successfully applied in other industries amongst which are automotive, civil and naval engineering (Perez-Moreno et al., 2016).

Gray et al. (2019) and Agte et al. (2009) highlighted the aerospace and the automotive sectors as the early adopters in the use of MDAO framework and it's applications to the industry. Some of the MDAO application and gains from using MDAO within the aerospace and automotive sectors are highlighted in Table 2. A very detailed review of the application of MDAO in the aerospace industry highlighting the problem, model structure, design variables, objective functions and constraints are presented in Gray et al. (2019).

The IEA (International Energy Agency) Wind Task 37 identified three important dimensions of an MDAO simulation set-up or workflow amongst which are: model fidelity, size and scope of simulation, and MDAO architecture (Bortolotti et al., 2019).

Earlier examples of applications of MDAO to wind energy systems are conducted by Crawford and Haimes (2004); Bottasso et al. (2010) and He et al. (2011). Each of these optimization studies result shows a system-wide reduction in the cost of energy from 2% to 15%, based on the sub-system optimization (Dykes et al., 2011).

Crawford and Haimes (2004) incorporated the National Renewable Energy Laboratory (NREL) aeroelastic design codes with a cost-scaling model based on linear, quadratic, and cubic function of the rotor diameter from the CAD geometry to influence the cost changes in the respective subsystems. The MDAO approach is the sequential optimization of the turbine using the NREL aeroelastic codes, CAD software interface and the custom cost of energy algorithm.

The MDAO approach for Bottasso et al. (2010) is for the design of a wind turbine blade focusing on the structural and aerodynamic trade-offs in blade design taking into consideration, the total aero-servo-elastic effects on the blade structure and the noise constraints. This study was conducted using a sequential MDAO approach that involves a comprehensive aero-servo-elastic, non-linear, finite-element-method-based, multibody dynamics solver at a first level, and a second level using a finite-element, cross-sectional model of the blade to perform a section-wise load calculations to determine the blade weight, and a third level using macro parameters to optimize the overall objective of the annual energy production (AEP) to weight ratio minimization.

He et al. (2011) applied a multi-level MDAO approach to the system design utilizing two disciplines (maximizing annual energy production

Table 2
Examples of gains from application of MDAO in aerospace and automotive sectors(Agte et al., 2009).

Industry/ Sector	Component/Activity	Advantages/Gains from MDAO
Aerospace	Nacelle Configuration	Noise reduction and 15% reduction in weight
Aerospace	Vertical fin major aircraft	Significant increase in effectiveness of the fin
Automotive	Optimized structural design for crash worthiness.	Significant reduction in time to achieve acceptable level of impact performance from 1.5 years to 1.5 days
Aerospace	Flight test program	Reduced from 2 to 3 years to less than 1 year.

and minimizing blade root moment) under a system level analysis and optimization. Their work borrowed the NREL aeroelastic design codes and cost models, and in addition to the distinct multi-level approach, their work incorporated the use of the Kriging-based metamodels to replace higher fidelity models in order to save computation time required for the optimization process.

An extensive review of approaches in the design optimization of wind turbine support structures and the challenges associated with it is presented in Muskulus et al. (2014). In this work, the authors reviewed the different techniques of optimizing wind turbine structures amongst which are optimization of wind turbine structures using static analysis, optimization of wind turbine structures using frequency domain, and time domain analyses. Further to this, they reviewed Windopt - a well-known optimization tool used with the spar-type FOWTs. Windopt allows for the design of the spar buoy, mooring system and the power cable, using sequential quadratic programming and a combination of commercial analysis tools. However, its limitation is that the wind turbine rotor is only represented as a state-dependent drag coefficient/force acting in a single node at the top of the tower. Also in their work, Muskulus et al. (2014) made recommendations to the field of structural optimization and amongst their recommendations are the use of gradient-based and gradient-free optimization which are largely in use today. Other structural optimization recommendations made in Muskulus et al. (2014) are: modelling with a hierarchy of fidelities, reduction of load cases and interfaces for efficient integrated design and exploration of probabilistic design.

Dykes et al. (2011) researched MDAO works relevant to both wind turbines and wind farms. From this work, they laid the foundation for MDAO workflow WISDEM (Wind Plant Integrated System Design and Engineering Model). They observed that most researches are conducted on singular components or disciplines and concluded there are large opportunities for MDAO research and development in the wind energy sector (offshore/onshore).

Ashuri et al. (2014)., conducted research on design optimization, capable of simultaneous designs of wind turbine blade and tower subject to constraints on fatigue, stresses, deflections and frequencies with the Levelized Cost of Energy (LCOE) as the objective function. From their experiment, the results show an improvement in the quality of the design process with a realistic assessment of the LCOE and constraints, while preserving the coupling of the components and disciplines by using the power of numerical optimization. Since then, researchers like Hall et al. (2013), Karimi (2018) and Hegseth et al. (2020) have been able to demonstrate the effectiveness of using numerical optimization algorithms in MDAO for the design of FOWT substructures, and these research works are highlighted with more details in section 3.3.2.

3.2. MDAO workflow

MDAO comprises of a workflow with a set of computational tools (analysis block) that represents different components and disciplines coupled together to simulate an entire system (Moreno, 2019). With this technique, drivers can be included to control how and when each tool can be executed. The functionality of the workflow is defined as a use case which describes any domain problem that can be solved by MDAO i.e., optimization of the objective function. A simplified diagram of an MDAO workflow is shown in Fig. 3.

The driver (numerical method governing the use case) integrating the modules in an MDAO workflow can have different uses amongst which are, performing uncertainty quantification (UQ), running design of experiments (DOE) or implementing optimization algorithms (Moreno, 2019). Optimization algorithms helps in finding the optimal system design that maximizes system's performance by exploring the design space smartly. More on optimization algorithm is discussed in Section 3.3.

MDAO workflow consists of system scope, model fidelity, and architecture/framework. The system scope and model fidelity are highlighted in Section 3.2.1, and the MDAO architecture discussed in Section 3.2.2.

3.2.1. System scope and model fidelity

The scope of the system is clearly defined before instantiating the MDAO workflow because, not all components or disciplines influence one another with the same intensity. Moreno highlighted two examples of use cases with different system scope in the field of wind energy (Moreno, 2019). The examples are the optimization of the layout of an offshore wind farm and the sensitivity analysis of LCOE with respect to foundation type. For the optimization of the layout of an offshore wind farm, the workflow will have to include the calculation of wake losses and cable lengths; however, for the latter, there is no need to re-analyse the performance or cost of the electrical connection system as the interaction between them are negligible. The scope of an MDAO example is shown in Fig. 4.

Model fidelity is very important in MDAO as it represents the degree to which a model or simulation reproduces the state and behaviour of a real-world object which helps to define the objective function within the optimization problem. Different model fidelities or level of accuracy and sophistication of the integrated models are available for the different disciplines in a FOWT system. Examples are: spreadsheet model, a simple beam model, or a full finite element mesh (FEM) model with a higher precision, or a computationally expensive computational fluid dynamics (CFD) model.

In System engineering, model fidelity ranges from low fidelity (LF) model to the high-fidelity (HF) model while the middle model between

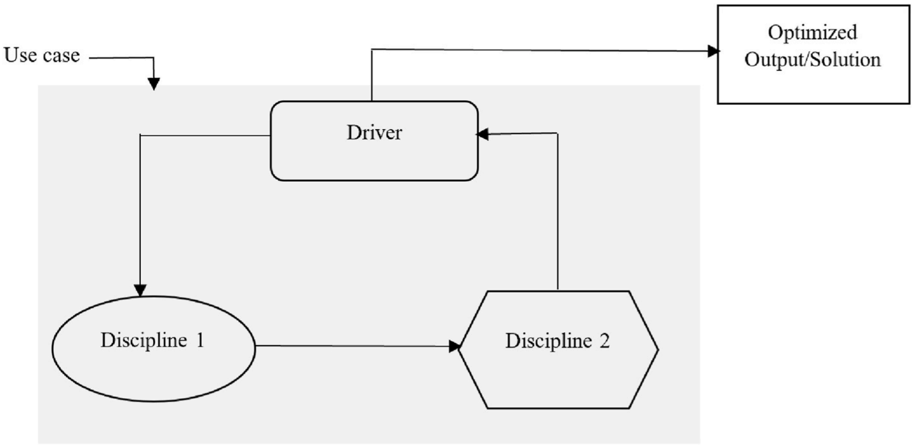


Fig. 3. Simplified diagram of an MDAO workflow comprising an analysis block of two modules and a driver.

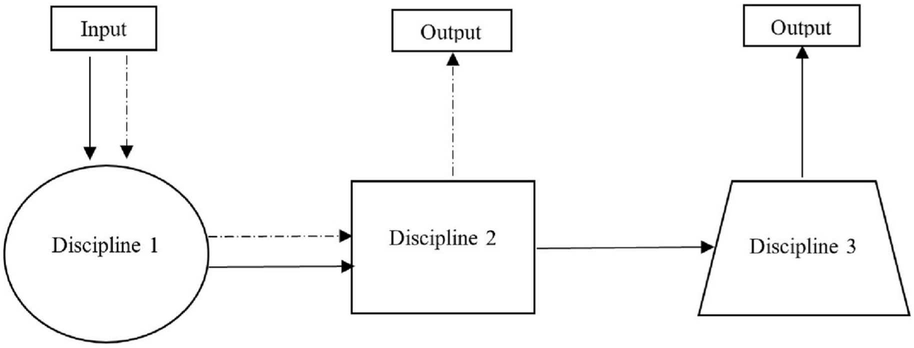


Fig. 4. Two workflows with different system scope. Dashed arrows include components/disciplines 1 and 2 while straight arrows include 1, 2 and 3.

the low and high-fidelity models can be classed as a multi-fidelity surrogate model. Shi et al. (2020) demonstrated that to take advantage of HF and LF models, multi-fidelity surrogate models integrating information from both HF and LF models can be used, and are increasingly gaining popularity.

Examples of multi-fidelity surrogate models are Kriging based, radial basis function (RBF) and support vector regression CO_SVR surrogate models (Shi et al., 2020). These surrogate models used with optimization algorithms provides competitive accuracy as HF models. Example of the multi-fidelity surrogate model where the Kriging based example has been employed is highlighted in (Karimi et al., 2017) and discussed in Section 3.3.2.

3.2.2. MDAO architecture/framework

MDAO architecture/framework defines how the different models are coupled and how the overall optimization problem is solved. Martins et al., highlights MDAO architecture as either monolithic or distributed (Martins and Lambe, 2013). In a monolithic architecture approach, the MDAO problem is solved as a single optimization problem. A distributed approach solves the MDAO problem using a set of optimization problems or subproblems. MDAO architectures from the Monolithic approach are the simultaneous analysis and design (SAND), multidisciplinary feasible (MDF) and individual discipline feasible (IDF) architectures. The differences between these three architectures depends on the equality constraint group eliminated from the optimization problem. In the SAND approach, the consistency constraint is eliminated from the optimization problem while for the IDF approach, the disciplinary analysis constraint is eliminated from the optimization problem. MDF approach is the most used of the monolithic approaches and both disciplinary analysis constraint and consistency constraint are eliminated from the optimization problem. For further reading, a comprehensive detail of other monolithic and distributed MDAO architectures is presented in Martins and Lambe (2013).

To develop MDAO architecture will require an automated framework. Example of an automated framework developed for wind turbine design optimization is highlighted in Leimeister et al. (2021). There are two parts to the framework which are automation and automation plus optimization. The first part of the framework (automated simulation) comprises of the modelling environment, simulation tool and the programming framework. The holistic framework integrates a driver/-optimizer to the automated simulation framework (automation plus optimization). An example of a holistic architecture/framework with optimization functionalities that can be used with a FOWT system is highlighted in Fig. 5.

3.2.3. MDAO tools

MDAO architecture can be executed by developing powerful scripts to execute design and optimize a problem of interest or use commercial MDAO packaged to provide solution to the problem of interest. The development of commercial MDAO frameworks dates back to the late 1990s with iSIGHT (Gray et al., 2019). Since the development of iSIGHT. Several other commercial frameworks have been developed amongst which are: Phoenix Integration's Model Center/CenterLink, Esteco's model FRONTIER, TechnoSoft's AML suite, Noesis Solutions' Optimus and Vanderplaats' VisualDOC (Gray et al., 2019). Since the development of the highlighted frame works, MDAO framework has evolved. One of

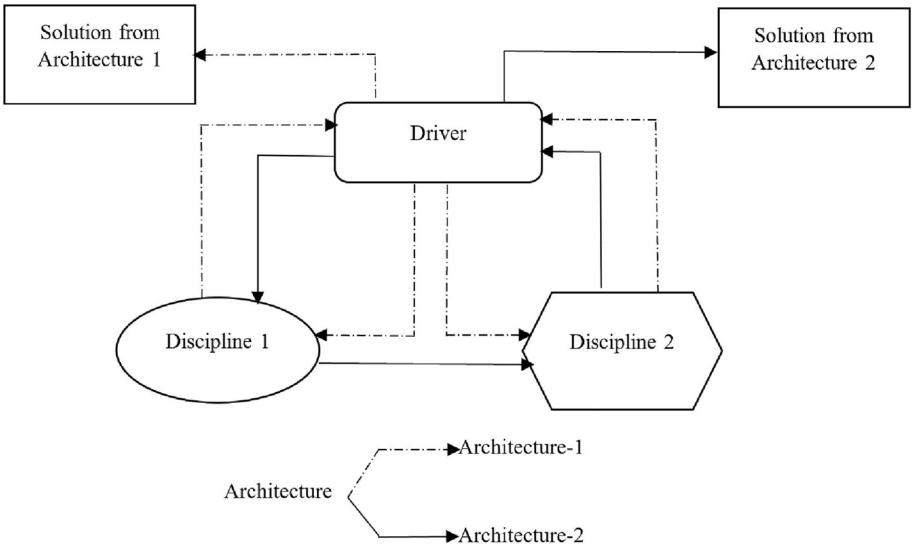


Fig. 5. Architecture/Framework with Optimization functionalities for FOWT.

the recent evolutions of optimization framework is the open-source, freely available OpenMDAO (openmdao.org., 2016), with the capability of gradient-based and metaheuristic optimization algorithm., Pymdo and Dakota. These open-source MDAO tools are discussed below and summarized in Table 3.

3.2.3.1. OpenMDAO. Its origin dates back to 2008 when researchers from NASA highlighted the need for a new MDO framework to deal with the challenges of aircraft design. It was developed by collaboration between researchers from MDO lab in Michigan university and NASA (Gray et al., 2019). OpenMDAO is an open-source multidisciplinary design, analysis and optimization tool for the exploration and exploitation of coupled multidisciplinary system to determine the system's global optimum design. OpenMDAO work done related to FOWT design and optimization is detailed in Hegseth et al. (2020). It also facilitates the solution of an MDO problem utilizing distributed memory parallelism and high-performance computing resources with leverage on message passing interface (MPI) and Portable, Extensible Toolkit for Scientific Computation (PETSc) library.

3.2.3.2. PyMDO. PyMDO was developed in the early 2000's and it was the first object-oriented framework that focused on automating the implementation of different MDO architectures (Martins et al., 2009). In pyMDO, the general MDO problem once by the user and the framework would reformulate the problem in any architecture with no further user effort. Its ability to introduce parallel computing codes into the MDO framework is essential to realize the vision of a high-fidelity, integrated design environment.

3.2.3.3. DAKOTA. DAKOTA was developed in the mid-nineties at the Sandia National Laboratories. It is a Multilevel Parallel Object-Oriented Framework for Design Optimization, Uncertainty Quantification, Parameter Estimation, and Sensitivity Analysis. Dakota toolkit permits connection between analysis codes and iteration methods. This provides a robust, open-source interface to many different systems analyses methods that can be used alone or integral to more advanced optimization strategy. Dakota contains algorithms for optimization with gradient and non-gradient-based methods. An example of design, analysis and optimization study of ducted wind turbines using DAKOTA is detailed in Khamlaj and Rumpfkeil (2018).

3.3. MDAO for FOWT substructures

A FOWT substructure consists of the platform, the mooring, and the anchors, and a comprehensive assessment of the system involves the structural, hydrostatic and hydrodynamic disciplines. Multidisciplinary design and analysis (MDA) assessment from the model design to the analyses technique that can be applied to a FOWT substructure is discussed in Section 2. Exploring a large design space requires the use of optimization algorithms to select the optimal design within the MDA framework giving rise to the much efficient MDAO approach.

Table 3
Open-source MDAO tools.

Tool	Language	GB Algorithm	GF Algorithm	Reference
OpenMDAO	Python	SNOPT, SLSQP, CONMIN	NSGA2, ALPSO	Gray et al. (2019)
PyMDO	Python, C, C++	SNOPT		(Gray et al., 2019; Martins et al., 2009)
DAKOTA	C++	SQP method, CONMIN, Newton method	EA, PS, Simplex, MOGA	Khamlaj and Rumpfkeil (2018)

3.3.1. Review of MDAO optimizers for FOWT substructures

The main objective of FOWT stakeholders is to minimize the cost of energy of wind turbines and increase its reliability to compete and surpass fossil-fuel sources of energy. Presently, the floating platform accounts for about 29.5% of the total CAPEX of a FOWT system and the fixed bottom platform accounts for 13.5% of the total CAPEX for a fixed offshore wind turbine system (Ioannou et al., 2020); hence, a clever way of designing a floating substructure to minimize the cost will contribute to the reduction of CAPEX for a FOWT system and subsequently, a reduction in the LCOE of the FOWT system. This clever approach to design requires the need of optimization algorithms for selecting optimal solutions.

The formulation of a general design optimization problem is defined in the context of minimizing or in some cases maximizing an objective function subject to constraints. This statement can be represented as expressed in Eqs. (7)–(11).

Find:

$$\widehat{x} = [x_1, x_2, \ldots, x_k] \tag{7}$$

That minimizes

$$\widehat{J}(x) = [J_1(x), J_2(x), \ldots, J_k(x)] \tag{8}$$

4. Subject to

$$\widehat{x}_{lower} \le \widehat{x} \le \widehat{x}_{upper} \tag{9}$$

$$h_i(x) = 0; i = 1 \ to \ m \tag{10}$$

$$g_i(x) \le 0; j = 1 \ to \ p \tag{11}$$

Where $\widehat{x}$ is a k-dimensional vector of design variables with lower and upper bounds, $\widehat{J}(x)$ is an n dimensional vector of objective functions, m is the number of equality constraints and p is the number of inequality constraints.

With multidisciplinary optimization algorithms, designers can identify the Pareto front/trade-off curve that reveals the weaknesses, anomalies and rewards of a certain target like minimizing the LCOE or improving the performance metrics, such as the root mean square (RMS) of the nacelle acceleration (Chehouri et al., 2016). Optimization algorithms are mainly categorized into two groups: Gradient Based (GB) optimization algorithm and Gradient Free (GF) optimization algorithm.

GB methods are iterative methods that use gradient information of the objective function during iterations (Yang, 2019). They are efficient for finding local minima for high dimensional, non-linearly constrained convex problems.

GF, also called Metaheuristic optimization algorithms, are usually characterized by a superior search efficiency and robustness unlike GB that has the tendency of being stuck in local minima for optimization problem with a multimodal objective function (Hegseth et al., 2020). GF have been introduced to solve complex nonlinear optimization problems that GB optimization methods cannot deal with (Saad et al., 2017). Once the optimization problem has been defined, optimizers to execute the optimization algorithms must be selected to solve the optimization task. A table of available optimizers is highlighted in Table 4.

Table 4 The optimizers are classed into Quasi-Newton method, Sequential Quadratic Programming (SQP), Evolutionary Algorithm (EA), Particle Swarm Optimization (PSO) and other types and grouped into the GB and GF optimization algorithms. Also highlighted in Table 4 are optimizers with the capability of handling Multi-Objective (MO) functions.

4.1. Review of MDAO work for FOWT system

Modelling FOWT systems involves complex integration/coupling of

Table 4
Overview of applicable optimizers.

Class	Optimizer	GB	GF	MO	Reference
Quasi-Newton	Newton Conjugate Gradient (Newton-CG)	✓			Buckley (1978)
	Powell	✓			Xian et al. (2006)
	Truncated Newton (TNC)	✓			(Izzo, 2015; Leimeister et al., 2021)
	Broyden-Fletcher-Goldfarb-Shanno (BFGS)	✓			(Izzo, 2015; Leimeister et al., 2021)
	Limited-memory BFGS with Box constraints (L-BFGS-B)	✓			(Izzo, 2015; Leimeister et al., 2021)
SQP	Feasible SQP (FSQP)	✓			(Izzo, 2015; Leimeister et al., 2021; openmdao.org., 2016)
	Preconditioned SQP (PSQP)	✓			(Izzo, 2015; Leimeister et al., 2021; openmdao.org., 2016)
	Sequential Least Squares Quadratic Programming (SLSQP)	✓			(Izzo, 2015; Leimeister et al., 2021)
EA	Genetic Algorithm (GA)		✓	✓	(Izzo, 2015; Siarry, 2016)
	Non-dominated Sorting GA II (NSGAII)		✓	✓	(Hadka, 2015; Izzo, 2015; Leimeister et al., 2021; openmdao.org., 2016)
	Non-dominated Sorting GA III (NSGAIII)		✓	✓	(Hadka, 2015; Izzo, 2015; Leimeister et al., 2021; openmdao.org., 2016)
	Steady-state Epsilon-MO EA (EpsMOEA)		✓	✓	(Hadka, 2015; Leimeister et al., 2021; openmdao.org., 2016)
	MO EA based on Decomposition (MOEAD)		✓	✓	(Hadka, 2015; Leimeister et al., 2021; openmdao.org., 2016)
	Generalized Differential Evolution 3 (GDE3)		✓	✓	(Hadka, 2015; Leimeister et al., 2021; openmdao.org., 2016)
	Strength Pareto EA 2 (SPEA2)		✓	✓	(Hadka, 2015; Leimeister et al., 2021; openmdao.org., 2016)
	Indicator-Based EA (IBEA)		✓	✓	(Hadka, 2015; Leimeister et al., 2021; openmdao.org., 2016)
	Parallel Eas (PEAS)		✓	✓	(Hadka, 2015; Leimeister et al., 2021; openmdao.org., 2016)
	Pareto Envelope-based Selection Algorithm (PESA2)		✓	✓	(Hadka, 2015; Leimeister et al., 2021; openmdao.org., 2016)
	Covariance Matrix Adaptation Evolution Strategy (CMAES)		✓	✓	(Hadka, 2015; Izzo, 2015; Leimeister et al., 2021; openmdao.org., 2016; Siarry, 2016)
PSO	Augmented Lagrangian PSO (ALPSO)		✓		(Izzo, 2015; Leimeister et al., 2021)
	Our multi-objective PSO (OMOPSO)		✓	✓	(Hadka, 2015; openmdao.org., 2016)
	Speed-constrained multi-objective PSO (SMPSO)		✓	✓	(Hadka, 2015; openmdao.org., 2016)
Others	Non-linear Optimization Mesh Adaptive Direct (NOMAD)		✓	✓	Le Digabel (2011)
	Sparse Nonlinear OPTimizer (SNOPT)	✓			(Izzo, 2015; Leimeister et al., 2021)
	CONstrained function Minimization (CONMIN)	✓			(Izzo, 2015; Leimeister et al., 2021)
	Interior Point OPTimizer (IPOPT)	✓			(Izzo, 2015; Leimeister et al., 2021)
	Nelder-Mead		✓		(Izzo, 2015; Leimeister et al., 2021)
	Constrained Optimization BY Linear Approximation (COBYLA)		✓		(Izzo, 2015; Leimeister et al., 2021)
	Simulated Annealing (SA)		✓		(Izzo, 2015; Janga Reddy and Kumar, 2020; Siarry, 2016)

multidisciplinary systems together. The coupling of the FOWT system can be done using the monolithic or distributed architecture described in section 3.2.2 with the monolithic architecture the most commonly used in the field of FOWT. The MDF architecture which is one of the monolithic approaches and most dominant approach for coupling FOWT system is well defined in Ashuri et al. (2014).

As illustrated in Fig. 5 of Section 3.2.2 and highlighted in Leimeister et al. (2021), with the MDF architecture, the multidisciplinary analysis model simulation with the design variables are passed to an optimizer. Fig. 5 can also be illustrated with the use of the extended design structure matrix (XDSM) standard detailed in Martins and Lambe (2013).The hydrodynamic, mooring, aerodynamic and structural design variables are passed to the multidisciplinary framework for analysis simulation from which the objective functions are computed. Then, the computed objectives and specified constraints are passed back to be assessed by the optimizer and the iterative approach continues until the convergence is reached.

MDAO tools like OpenMDAO allows data transfer/coupling design variables between disciplines using variations of system iterative solvers like Gauss-Seidel, Jacobi and Newton's method to achieve solution's convergence. The convergence of the solution is dependent on the nature of the optimization problem specified in the objective function. If the objective function is a convex function, the solution will converge to a global minimum or maximum. A nonconvex function will have multiple locally optimal solutions.

4.1.1. *MDAO and design parameterization offshore substructures*

MDAO and parameterization of a system go hand in hand as the parametric scheme describes the design space of the system for exploration. Some examples of parametric studies conducted on floaters are reviewed here. A precursor to the parametrization of floating offshore wind turbine substructure is the parametric design model of oil and gas substructures, optimized to reduce the downtime through improved seakeeping by Birk et al. (2004). In this work, they automated the hull design stage by introducing parametric shape generation, numeric hydrodynamics analysis assessment tools and non-linear programming algorithms for process control. Their investigation compares the performance of three different optimization algorithms (SQP, GA and SA) within a shape optimization framework and found that the GF optimizers (SA and GA) require more computation time and do not always produce better results than the classical deterministic SQP method. However, both sets of algorithms show significant improvement of seakeeping qualities. A parametric optimization of a semi-submersible platform with heave plates was conducted by Aubault et al. (2007). Their work was conducted on Minifloat, a novel concept of semi-submersible platform developed to enable hydrocarbon production from marginal fields in deep and ultra-deep water. In their work, they developed a simplified hydrodynamic model to capture the parametric sensitivity of the platform responses to primary design parameters as the hydrodynamic responses of the platform are driven by its mass properties and geometric parameters, including that of the heave plates. Also, the use of GA to optimize the responses of the platform was discussed in this work, and an optimized design solution was found for the simple Minifloat platform with no substructure accessories. Results with static constraints show a linear relationship between the payload and the platform displacement. However, the need of a sizeable draft is determined by hydrodynamic considerations, the GA optimization process for the Minifloat resulted in a shallow operating draft.

For FOWT, Bachynski conducted a parametric work related to TLP as part of her thesis in Bachynski (2014). Here, hydrodynamic loading of first, second and third order is considered with the combination of the controller and controller faults in extreme sea states.

4.1.1.1. *MDAO of FOWT substructures.*

A couple of MDAO studies in the offshore wind turbine industry are detailed in this section. In the work of Fylling and Berthelsen (2011), a GB optimization approach (SLSQP) for a spar floater, including the mooring lines and the power cables, was presented. The objective function modelled the cost of the system, and the design variables represented the geometric properties of the spar and mooring system. The constraints considered are the nacelle acceleration, tower inclination and maximum tensions in mooring lines. The results indicate that response can be optimized by modifying the cylindrical shape of the spar.

In Hall et al. (2013), the authors conducted a study on the hull shape and mooring line optimization of FOWT across different substructure categories using a GA and a frequency domain model derived from FAST software with a linear representation of the hydrodynamic viscous damping and no representation of the wind turbine control. The GA is applied for single and multi-objective optimization, and the results indicate an un-conventional design that shows the necessity for cost function refinement.

Karimi et al. (2017) improved the work of Hall et al. (2013) by using a new optimization algorithm and a linearized dynamic model, which improved the optimal solutions. Karimi et al. (2017) incorporated a fully coupled frequency domain dynamic model and a design parameterization scheme to evaluate the system motions and forces in turbulent winds and irregular wave scenarios. They also selected the Kriging-Bat optimization algorithm (a surrogate-based evolutionary algorithm) to represent the design exploration and exploitation of optimal designs across three stability classes of platform (MIT/NREL TLP, OC3-Hywind Spar, and OC4-DeepCwind semi-submersible platform). This optimization aimed to explore the cost implications of platform stability, expressed through the nacelle acceleration objective function, across the three FOWT platform stability classes. An improved correlation between cost and substructure design was obtained in this study in comparison to the work of Hall et al. (2013).

Hegseth et al. (2020) developed a linearized aero-hydro-servo-elastic model to optimize the platform, tower, mooring, and blade-pitch controller of a 10 MW spar floating wind turbine. In this work, optimal design solutions are found using GB optimization algorithm, considering fatigue and extreme response constraints, taken into account as objective function – a weighted combination of system cost and power quality. The geometric shape of the platform below the waterline is an hourglass shape that maximizes the distance between the center of buoyancy and center of gravity, to increase the restoring moment and natural frequency in pitch. The large bottom diameter of the platform increases the added mass in heave, which helps to place the natural frequency outside the wave frequency to avoid resonance. The optimization results show that local minima occur in both the soft-stiff and stiff-stiff range of the first tower bending mode.

The work of Ghigo et al. (2020) is based on the use of an in-house hydrostatic tool used to estimate the main hydrostatic parameters of five different floating substructures. Some of the hydrostatic parameters estimated by the in-house tools are the metacentric height and hydrostatic stiffness in heave, roll and pitch. Furthermore, by application of a generic thrust force at the center of the rotor, the maximum inclination angle in pitch can be estimated. Ghigo et al. (2020) verified the validity of results from their in-house tools by comparing with results obtained from Ansys Aqwa. The inhouse tool was further enhanced introducing a GA-based optimization framework order to identify the best concept in terms of reducing the LCOE while satisfying all design requirements and the constraints imposed by the standards. This work yielded a new floating platform concept, a derivative of the Hexafloat with all lateral brackets removed from the Hexafloat in order to reduce weight and cost of the new substructure.

The authors of Dou et al. (2020) developed an optimization framework for floating wind turbine support structure (spar-buoy floater), including the mooring system. The framework builds on frequency domain modelling, and the analysis capabilities are extended to provide analytical design sensitivities for the design requirements. This capability allows quick optimization using SQP optimization algorithm (Dou et al., 2020).

Recently, Leimeister et al. (2021) developed a holistic and highly flexible framework for automated simulation and optimization of wind turbine systems, including all components within the system and their fully coupled aero-hydro-servo-elastic behaviour. The framework consists of a modelling environment using the MoWiT software, the simulation engine (Dymola) and a gradient free multi-objective (GF MO) genetic optimization algorithm. This holistic framework provides suitable applications in the areas of design optimization of floating wind turbine support structures, optimization of wind turbine performance (power output) and loading (thrust force), tuning of wind turbine controller for load reduction and other optimization tasks within a wind farm.

A recent investigation of estimating a platform's hydrodynamic response by surrogacy approach is conducted by Coraddu et al. (2020). Their work demonstrates the feasibility and performance of a surrogate model to determine the hydrodynamic response of an axis-symmetric spar-buoy type of platform. To conduct their analyses, Coraddu et al. (2020) used a family of meta-model choice listed in Fig. 6 (ANN) and the sub family of the ANN meta-model choice used is the Extreme Learning Machines (ELMs), developed with dataset of simulations from state-of-the art potential flow based computational code. The authors found that based on the result of a state-of-the- art potential flow code on a limited set of geometries, the ELM based surrogate model developed to approximate the RAO of the axis-symmetric spar-buoy type of FOWT can predict the RAO of any FOWT geometry to an average Mean Absolute Percentage Error (MAPE) OF 2% across all DOFs. This demonstrates the feasibility of replacing computationally expensive and accurate time domain solvers with fast and reasonably accurate surrogate model. The categorization of MDAO work done from literature on FOWT platform is presented in Table 5.

5. Research gaps and proposed future areas of research

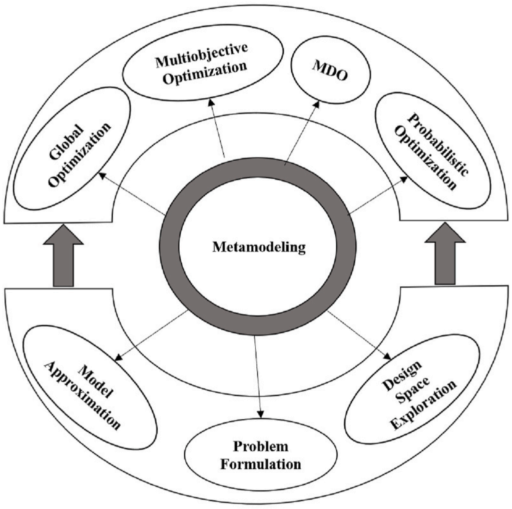
As highlighted in the introductory section of this review, the offshore wind turbine sector is still at an infancy stage, with most of the design and optimization methodologies transferred from the oil & gas sector (fixed and floating structure). The reliance on these prompts the need to identify gaps needed for development within the FOWT sector, as the design requirements for an oil and gas structure is different from a FOWT structure. From the review conducted on MDAO, several gaps in the FOWT sector craving for more research are detailed below.

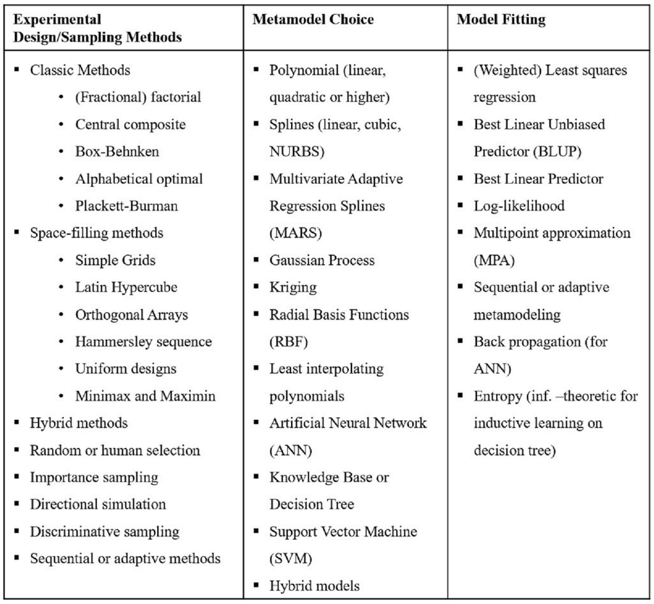
5.1. *Surrogacy and MDAO*

A surrogate is a mathematical approximation method used to predict the behaviour of a system using a set of sampling points, generally acquired from numerical simulations (Saad et al., 2019). Surrogate models/metamodels are models that mimic or clone the behaviour of the engineering system or the asset under investigation as closely as possible while being computationally less expensive to evaluate in comparison to the simulation model. The concept of surrogacy in any multidisciplinary system is fundamental. The surrogate model provides a more realistic representative model of the system than a low fidelity model while also avoiding the high computational expense associated with high fidelity models, as discussed in section 3.2.1. Different surrogate/meta modelling techniques of choice for multidisciplinary design analysis and optimization study are presented in Fig. 6. Detailed review of these surrogate modelling techniques are provided in Younis and Dong (2010) and Jin (2011).

Optimization technique within an MDAO framework can have a combination of metamodel choices and optimization algorithms for effective system optimization. In the study conducted by Karimi (2018) on multidisciplinary design optimization of floating offshore wind turbine support structures for levelized cost of energy, the Kriging BAT (K-BA) optimization algorithm was used to increase the efficiency of the BA algorithm to find the global optimal solutions. Just like the K-BA, these surrogate modelling techniques highlighted in Fig. 6 can be combined with optimization algorithms for FOWT substructure optimization.

As highlighted in the works of Karimi (2018) and (Karimi, 2018);





Experimental Design/Sampling Methods	Metamodel Choice	Model Fitting
▪ Classic Methods • (Fractional) factorial • Central composite • Box-Behnken • Alphabetical optimal • Plackett-Burman ▪ Space-filling methods • Simple Grids • Latin Hypercube • Orthogonal Arrays • Hammersley sequence • Uniform designs • Minimax and Maximin ▪ Hybrid methods ▪ Random or human selection ▪ Importance sampling ▪ Directional simulation ▪ Discriminative sampling ▪ Sequential or adaptive methods	▪ Polynomial (linear, quadratic or higher) ▪ Splines (linear, cubic, NURBS) ▪ Multivariate Adaptive Regression Splines (MARS) ▪ Gaussian Process ▪ Kriging ▪ Radial Basis Functions (RBF) ▪ Least interpolating polynomials ▪ Artificial Neural Network (ANN) ▪ Knowledge Base or Decision Tree ▪ Support Vector Machine (SVM) ▪ Hybrid models	▪ (Weighted) Least squares regression ▪ Best Linear Unbiased Predictor (BLUP) ▪ Best Linear Predictor ▪ Log-likelihood ▪ Multipoint approximation (MPA) ▪ Sequential or adaptive metamodeling ▪ Back propagation (for ANN) ▪ Entropy (inf. –theoretic for inductive learning on decision tree)

Fig. 6. Surrogate/Meta Modelling as part of system optimization (left), Surrogate/Meta modelling techniques (right). (*Frank Lemmer et al., 2016*)

Table 5
MDAO work on FOWT substructures.

Architecture	Type	Algorithm	Platform	Reference
MDF	Gradient Based	SNOPT using SQP	Spar	Hegseth et al. (2020)
MDF		SQP	Spar	Dou et al. (2020)
MDF		SQP	Spar	Fylling and Berthelsen (2011)
MDF	Gradient Free	GA	Spar; Semi-submersible; TLP	Hall et al. (2013)
MDF		Bat (BA)	Spar; Semi-submersible; TLP	Karimi et al. (2017)
MDF		GA	Spar	Leimeister et al. (2021)
MDF		GA	New concept	Ghigo et al. (2020)

Saad et al. (2019), surrogacy (in this case Kriging-Surrogate model) helps to increase the efficiency of the BA algorithm to find global optimal solutions. Results of the work done by Saad et al. (2019)shows that in terms of search capability, efficiency and robustness, the new K-BA could demonstrate superior capability and suitability to other well-known global optimization (GO) algorithms. This is an area of research to be explored as it has the potential to make feasibility studies of projects to be conducted faster. Fig. 6 also mentions the design of experiments (DOE), a technique for the optimal placing of test points within the design space to estimate the actual system model using one of the surrogate techniques (Saad et al., 2019). Some of the widely used DOE techniques shown in Fig. 6 are Fractional Factorial, Central Composite Design (CCD), Box-Behnken, and Latin Hypercube Sampling (LHS).

5.2. Larger design space exploration

Design space exploration provides the ability to explore design alternatives prior to implementation (Kang et al., 2011). Design space exploration is important to perform optimization, eliminate inferior designs and select a set of final design candidates for further study or validation. Large design space exploration and exploitation can be tailored to optimize the FOWT support structures.

In the works of Karimi et al. (2017) and Hall et al. (2013), the design space explored for optimization purposes spans across three stability classes of platforms with the main parameterization variables of diameter and draft. This design space can be made more expansive by including the mooring line design variables and constraints to increase the design space. A more expansive design space exploration and exploitation has the capability of providing more information with regards to the understanding and optimization of FOWT systems. At the moment, design space exploration of FOWT substructural system is mainly confined to the stability of the FOWT substructure. In simpler cases, the design space may be characterized as single body substructure (Spar) or multi-body substructure (Semi-submersible, TLP).

To expand the scope of study conducted in Karimi et al. (2017) and Hall et al. (2013) for offshore wind turbine platform is to perturb/alter the shape/geometry of the platform. Instead of focusing on the diameter and draft variables for characterizing the design space as highlighted in Karimi et al. (2017) and Hall et al. (2013); (Karimi et al., 2017), perturbation of the geometry can expand the design space and enhances the selection of optimal and richer designs. Expanding a design space is achievable by increasing the variables in the parameterization scheme. Increasing the number of combinations of substructural parameters or the use of robust parametric schemes to describe the design space increases the chances of identifying an optimally designed system. The search for the optimal system is conducted using an optimization search algorithm and in cases where the search is exhaustive, surrogate-based optimization algorithms as discussed in section 4.1 - Surrogacy and MDAO can be used to identify the optimal design.

Another way of creating a large design space is to deviate from the traditional design in terms of geometric shapes and size as highlighted in Section 4.2.1.

5.2.1. Deviation from the traditional geometric shapes of FOWT substructure

The floating substructure configurations adopted by the FOWT industry have been based on the stability classes highlighted in Section 2.1. In this infancy stage of FOWT systems, there is a need for deviation from the traditional shapes of floating substructure/platforms for design and optimization purposes. From this review, a research gap in platform's geometric shapes design for optimization purpose is identified with a need to develop a novel design framework that allows the exploration and analysis of unconventional floating support structural geometries optimized for FOWT requirements i.e., minimal requirements of effective hydrodynamic stability in deep waters coupled with the provision of a low levelized cost of energy (LCOE) from the FOWT system.

A design and optimization framework developed in the work of Leimeister et al. (2021) shows that the OC3 floating spar-buoy wind turbine system is heavily over-dimensioned as unnecessarily high safety factors are applied which inherently makes the design more costly (but should be noticed that this OC3 spar design has been developed more as a concept for numerical verification and comparison than a reference of an optimized spar). Leimeister et al. (2021) designed a FOWT system which is still safely operating but close to the operational limits while constraining the outer floater dimensions to less than what obtains in the OC3 floater design; hence, a potential cost reduction.

As highlighted in section 2.3.2, design curve parameterization technique used for the design of ship hulls in Birk et al. (2004), Zhang et al. (2008) and Birk and Clauss (2008) can methodically be applied to the design of FOWT system to optimize floater design and generate design with optimal shapes satisfying the design requirements. A good representation of the different optimal shape is shown in Fig. 7 and Fig. 8. Fig. 7 shows early shape design of semi-submersible and a new optimized semi-submersible shape in comparison to older generations of semi-submersibles – GVA 4000 (1983) and Transdetter (1987) while Fig. 8 shows different design shape configuration for spar platform. This process of parameterization of the polynomial curves to automatically generate shapes for platform is discussed in the work of Birk et al. (2004) and Clauss and Birk (1996) although this is for platforms used in the oil and gas sector. This concept of shape generation and subsequent optimization can be used to increase the design space and design, analyse, and select optimal platforms in for a floating wind turbine.

5.3. Upscaling of the platform design geometric variables

The concept of upscaling is a common tool employed in engineering design. An increase in turbine size contributes to the reduction in the levelized cost of energy. However, the substructure (Fixed bottom or floating) on which the turbine and tower is mounted must get larger. Instead of redesigning the support structure, the concept of upscaling the baseline substructure to the target substructure can be employed.

As detailed in the Light Rotor project (Bak et al., 2012), there has been a continuous upscaling of wind turbines since the early 70's. The Light Rotor project showed the design of a rotor and a wind turbine for a 10 MW wind turbine from a 5 MW wind turbine. The main objective is the use of a systems' approach to change the design of the blades to increase the stiffness and overall performance of the rotor taking into account aero-servo-elastic dynamics consideration. This kind of upscaling can be challenging because the mass of the turbine increases with the cube of the rotor radius with linear upscaling. It's concluded that upscaling laws tend to overestimate the mass of the nacelle and drivetrain. Thus, the mass of the nacelle and drivetrain was reduced relative to the 5 MW wind turbine.

Few studies have been done on upscaling a FOWT system with a focus on the platform as FOWT technology is a relatively new technology in the pre-commercial stage of development. However, some of the work done in upscaling FOWT system are highlighted in this section.

FOWT substructures, being a complex multidisciplinary structure can be optimized with regards to key performance metrics such as costs, structural integrity, reliability, nacelle acceleration subject to various constraints. Another means of optimizing a FOWT substructure is by upscaling the optimal shape parameterized floaters to highly rated and larger turbines. Just like a baseline design, the main criteria for upscaling a geometrically parameterized and optimized substructure for a FOWT system are stability, eigen frequencies, dynamic behaviour and response in accordance to recommended design requirements guidelines.

An example of linear or rational upscaling process of a FOWT substructure is discussed in the work of Leimeister et al. (2016b) in which they upscaled a 5 MW OC4 semi-submersible (baseline model) to 7.5 MW semi-submersible (target model). Upscaling of the semi-submersible FOWT substructure was based on the simple upscaling procedure in which the geometrical scaling factor is determined by the power rating of the wind turbines. The scaling factor of the platform is the square root of the ratio between the targeted power rating and the baseline power rating. They observed that the upscaled FOWT system had excess pitch stability and higher natural period than the baseline design. Building on this methodology, Ferri et al. (2020) Ferri proposed an optimization procedure that is able to reduce the peak response amplitude operator (RAO) in pitch up to 50% with respect to a traditional scaling factor based on the square root of the ratio of turbine power ratings.

Another example of rational upscaling is reported in Kikuchi and Ishihara (2019) in which the authors upscaled a 2 MW floating wind turbine used in the Fukushima FORWARD project to 5 MW and 10 MW by scaling the floater column radius with the cubic root of the mass ratio between turbines, and then scaling the column distance to preserve the static balance in pitch between overturning moment and pitch restoring moment. They found the overturning moment to scale roughly proportional to the power rating between turbines, or with the square of the turbine scale factor rather than the cubed scaling that would be expected in linear upscaling. Furthermore, Kikuchi and Ishihara (2019) estimated that capital costs per kW can be reduced by up to 57% when upscaling a 2 MW FOWT to 10 MW.

Further example of FOWT upscaling is detailed in Leimeister et al. (2016a). In this work, 7.5 MW and 10 MW semi-submersibles were developed based on the 5 MW OC4 semi-submersible platform. This work is based on an assumption made for scaling the overturning

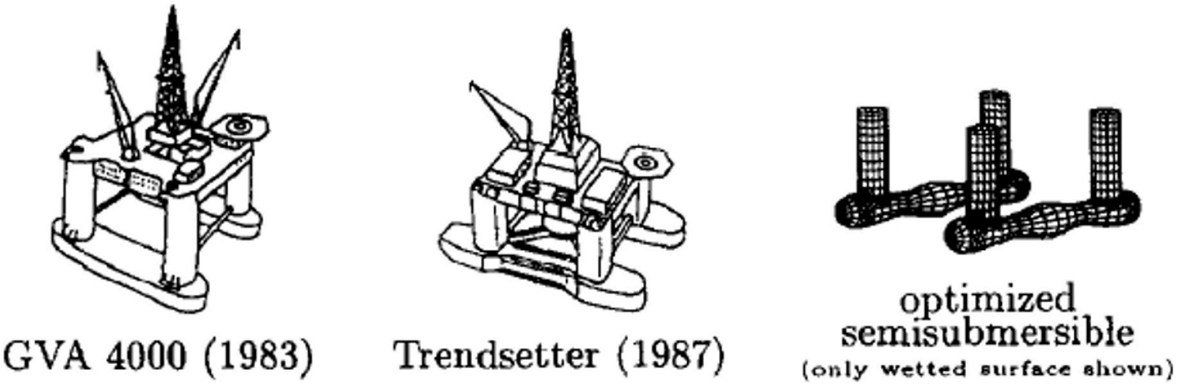


Fig. 7. Deviation model from conventional semi-submersible design (Optimized model vs earlier generation models), adapted with permission from (Clauss and Birk, 1996).

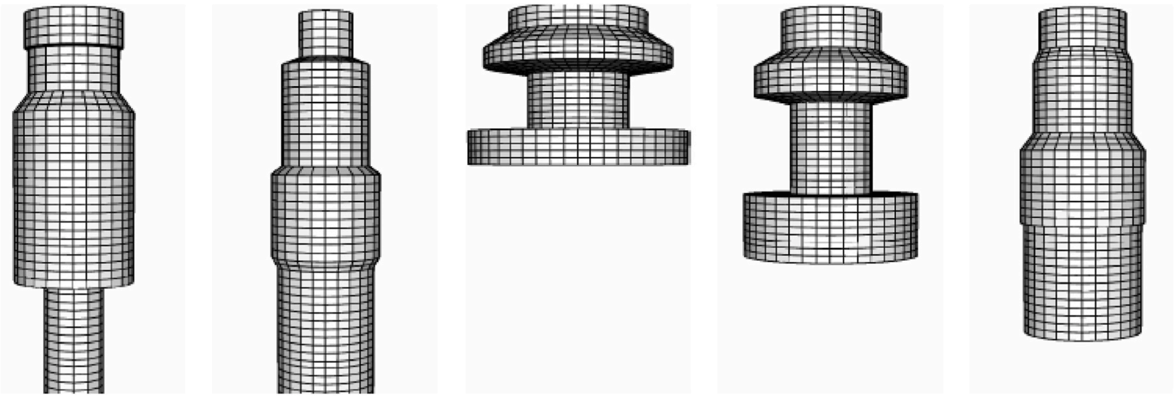


Fig. 8. Deviation from conventional spar design with automated shape generation using polynomial curves, adapted with permission from (Birk and Clauss, 2008).

moment and this involves scaling the pitch restoring stiffness proportionally between the base design and the target design to preserve the maximum target pitch angle.Wu and Kim (2021) took this further by upscaling a 5 MW OC4 semi-submersible to a 15 MW semi-submersible. They developed two different scaling approaches: one that scales column radius and distance together with the same scale factor (referred to as Distance and Radius Scaling), and one that only scales the distance between columns (referred to as Distance Scaling) (Wu and Kim, 2021). They found that scaling column radius was found to increase the metal mass and ballast mass of the platform, slowing the elevation of the center of gravity, and raising the heave natural period. Also, scaling column distance only was found to slightly reduce the heave natural period, which may pose issues related to resonant effects during storm conditions with long wave periods.

A comprehensive upscaling study was recently conducted by Papi and Bianchini (2022). The goal of their study is to define a set of metrics easily replicable by researchers that could enable a sufficiently fair comparison of turbines having different sizes. The two turbines compared in their study are the NREL 5 MW DeepCWind semi-submersible and the UMaine IEA 15 MW semi-submersible. The actual scale factors for the components within the FOWT system was presented in their study and the platform scale factor is lower than the values obtained using rational upscaling. With the use of a high-fidelity tool 'OpenFAST ', both sets of FOWT systems were analysed. Papi and Bianchini (2022) showed from their study that although platform RAOs decrease, tower loads are influenced by wave loading to a greater extent in the larger FOWT system. This is due to the increase in weight of the RNA, despite the fact that due to technological advancements RNA weight has increased far less than what would be expected from looking at turbines of a decade ago (Papi and Bianchini, 2022). Tower weight also contributes to increasing gravitational loading, especially in the IEA 15 MW, where the tower's design required stiffening to support the additional loads.

For this review, the novelty of upscaling is its use on the geometrical shape parameterized and optimized floater scaled up to larger sizes based on the power rating of the new FOWT system. This approach is anticipated to reduce the cost of material expended on the system and also save a lot of computational time required for MDAO of a bigger turbine.

6. Conclusion

Presently, the concept of parameterization and multidisciplinary design analysis and optimization is mostly used in the aerospace and automotive sector. The use of MDAO is at its infancy stage with regards to the FOWT sector. This paper discusses the multidisciplinary design analysis and optimization of FOWT systems, with a focus on the substructure/platform. The aim of this paper is to review the available MDAO and parameterization work on FOWT substructures in literature and identify research gaps to improve the optimization framework.

Firstly, the review of the available MDAO works for FOWT substructure looks at the design with a focus on geometric shape parameterization, analysis, and optimization approaches for FOWT substructures. This starts with an overview of FOWT substructures, parameterization technique for design to recommended standard and guidelines, design and analysis of the model, MDAO approaches for FOWT system, optimization algorithms, and a critical review of MDAO on FOWT substructures. The review also highlights the available optimizers and their classification and groups as highlighted in Table 4. This review shows that the use of MDAO framework can yield an efficient approach to design, analyse, and select the optimal design of a FOWT substructure which can substantially contribute to the reduction of the CAPEX for a FOWT system.

Secondly, the review identifies gaps in multidisciplinary design analysis and optimization of FOWT substructure, amongst which are: increasing the design space of the substructure by deviating from traditional geometric shapes and utilizing curve parameterization techniques like B-spline and Free-form deformation used in the design and optimization of ship hulls to create richer design space with fewer parameters in comparison to standard CAD design. More recently, the development of a surrogate model coupled with meta-heuristic optimization algorithms is finding its way to the FOWT sector from other industries like the aerospace and automotive sectors. This process can be further developed to suit the design and optimization of FOWT substructures. A final gap identified is upscaling the design variables of an optimal geometric shape parameterized platform with a highly rated and more efficient new generation turbines. This will further the objective to effectively reduce the CAPEX on a FOWT system.

This review concludes that if the gaps highlighted are applied to the design of a FOWT substructure/platform to meet all standard design requirements, there will be significant reduction in the capital and computational cost required for design and build of the FOWT system. It can also facilitate the futuristics platform design that meets the fundamental stability design requirements with a reduced CAPEX at the front-end engineering design stage of a project prior to conducting a detailed engineering design at a later stage of the project.

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.

Data availability

No data was used for the research described in the article.

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