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LES-based investigation of wake dynamics: from single wind turbine to wind farm flow interaction

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Original Citation:

LES-based investigation of wake dynamics: from single wind turbine to wind farm flow interaction / Manganelli, F.. - ELETTRONICO. - (2026).

Availability:

This version is available at <http://hdl.handle.net/11589/304300> since: 2026-06-28

Published version

DOI:

Publisher: Politecnico di Bari

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15 July 2026



**Politecnico
di Bari**

DEPARTMENT OF MECHANICS, MATHEMATICS AND MANAGEMENT

MECHANICAL ENGINEERING

PH.D. PROGRAM

SSD: IIND-06/A - FLUID MACHINERY

Final dissertation

**LES-based investigation of wake dynamics: from
single wind turbine to wind farm flow interaction**

by

FELICE MANGANELLI

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Coordinator of the Ph.D. Program:

Prof. Giuseppe Casalino

Course XXXVIII, 01/01/2023 - 31/12/2025



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Al Magnifico Rettore
del Politecnico di Bari

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Abstract

Predictive modelling of utility-scale wind turbines demands numerical frameworks capable of resolving coupled physical processes across a wide range of scales, from blade-level aeroelastic deformations to farm-wide wake evolution within a turbulent Atmospheric Boundary Layer (ABL). This thesis develops and applies a Computational Fluid Dynamics - Computational Structural Dynamics (CFD-CSD) framework in which the fluid domain is resolved through Large Eddy Simulation (LES), rotor aerodynamics is represented via Actuator Line and Disc Models (ALM/ADM), and complex solid boundaries are handled through an Immersed Boundary Method (IBM). Structural dynamics is evaluated with a modal beam solver, yielding fully coupled aeroelastic simulations at tractable computational cost.

The framework underpins five distinct but interconnected investigations. The first examines wake coherent structures of the NREL 5MW turbine under two distinct inflow regimes: an idealised pressure-driven boundary layer and a fully developed, Coriolis-driven Ekman layer. Proper Orthogonal Decomposition (POD), Dynamic Mode Decomposition (DMD), and Sparsity-Promoting DMD (SPDMD) are applied to the LES flow fields to extract spatially and dynamically dominant modes. The analysis quantifies the role of atmospheric wind veer in wake skewing, lateral recovery asymmetry, providing the modal basis for physics-informed Reduced-Order Models (ROMs).

The second study performs a fully coupled aeroelastic comparison between the NREL 5MW and IEA 15MW reference turbines under identical sheared inflow conditions, isolating the effect of rotor scaling on torsional deformation, blade load distribution, and wake-tower interaction. The results show that torsion-bending coupling becomes increasingly pronounced at larger rotor diameters, introducing non-negligible feedback on sectional aerodynamic loading that linearised structural models fail to capture.

In the third study, these atmospheric and structural insights are extended to a two-turbine in-line array of IEA 15MW machines under Coriolis-driven inflow. Yaw misalignment is imposed for active wake steering, and its interaction with wind veer is systematically characterised in terms of farm power output, wake deflection morphology, and downstream blade fatigue loading, which is evaluated through the Rainflow cycle counting method.

The fourth study investigates Diffuser-Augmented Wind Turbines (DAWTs) using LES coupled with IBM. Multiple duct geometries are assessed under partial-load Maximum Power Point Tracking (MPPT) operation, quantifying the effect of area

ratio and diffuser half-angle on rotor torque augmentation, internal adverse pressure gradient, tip-vortex suppression, and near-wake recovery length.

Finally, a Multi-Agent Reinforcement Learning (MARL) framework is developed for farm-level yaw control, benchmarking nine algorithms across three families — PPO, SAC, and TD3 — under independent, CTDE, and fully centralised coordination paradigms, on a canonical three-turbine array and the irregular Ablaincourt Energies farm. Training is conducted in the FLORIS engineering surrogate and policies are transferred to LES to assess the sim-to-real fidelity gap. PPO and entropy-regularised SAC achieve 100% convergence reliability and power gains of approximately 25% on the three-turbine array and 10% on the seven-turbine Ablaincourt farm over the uncontrolled baseline, while deterministic TD3 policies exhibit severe convergence degradation and persistent yaw oscillations — a structural limitation traced to the absence of a stable fixed point in the deterministic policy map.

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List of Acronyms

ABL	Atmospheric Boundary Layer
ADM	Actuator Disc Model
ADMM	Alternating Direction Method of Multipliers
AI	Artificial Intelligence
ALM	Actuator Line Model
BEM	Blade Element Momentum (theory)
CFD	Computational Fluid Dynamics
CFL	Courant–Friedrichs–Lewy (condition)
CPPO	Centralized Proximal Policy Optimisation
CSAC	Centralized Soft Actor-Critic
CSD	Computational Structural Dynamics
CTD3	Centralized Twin Delayed Deep Deterministic Policy Gradient
CTDE	Centralized Training, Decentralized Execution
DAWT	Diffuser-Augmented Wind Turbine
DEL	Damage Equivalent Load
DMD	Dynamic Mode Decomposition
DNS	Direct Numerical Simulation
DWT	Ducted Wind Turbine
FEM	Finite Element Method
FSI	Fluid–Structure Interaction
GAE	Generalized Advantage Estimation
HPC	High-Performance Computing
IBM	Immersed Boundary Method
IPPO	Independent Proximal Policy Optimisation
ISAC	Independent Soft Actor-Critic

ITD3	Independent Twin Delayed Deep Deterministic Policy Gradient
LCOE	Levelised Cost of Energy
LES	Large Eddy Simulation
MAPPO	Multi-Agent Proximal Policy Optimisation
MARL	Multi-Agent Reinforcement Learning
MASAC	Multi-Agent Soft Actor-Critic
MATD3	Multi-Agent Twin Delayed Deep Deterministic Policy Gradient
MKE	Mean Kinetic Energy
MPPT	Maximum Power Point Tracking
NREL	National Renewable Energy Laboratory
OWT	Open Wind Turbine
PI	Proportional–Integral (controller)
POD	Proper Orthogonal Decomposition
PPO	Proximal Policy Optimisation
PSD	Power Spectral Density
RADM	Rotating Actuator Disc Model
RANS	Reynolds-Averaged Navier–Stokes
RL	Reinforcement Learning
ROM	Reduced-Order Model
SAC	Soft Actor-Critic
SGS	Subgrid-Scale
SP-DMD	Sparsity-Promoting Dynamic Mode Decomposition
SVD	Singular Value Decomposition
TD3	Twin Delayed Deep Deterministic Policy Gradient
TI	Turbulence Intensity
TSR	Tip Speed Ratio
UTD-WF	University of Texas at Dallas Wind-Farm (LES solver)

Chapter 1

Introduction

To meet global energy demand while adhering to decarbonisation targets [1], wind energy has become a scalable component of the modern electrical grid. The pursuit of lower Levelised Cost of Energy (LCOE) has driven a systematic upscaling of turbines, particularly offshore, resulting in rotor dimensions at scales that introduce complex aeroelastic phenomena and fundamentally alter the interaction between turbines and the surrounding atmosphere.

These challenges cannot be fully addressed by conventional engineering tools alone. As conventional horizontal-axis turbines approach their structural and logistical limits, alternative designs such as Diffuser-Augmented Wind Turbines (DAWTs) are emerging as promising solutions for confined spaces. Meanwhile, dense wind farms face severe aerodynamic wake interactions that reduce efficiency and increase structural fatigue. Resolving the underlying physics of these phenomena requires physics-resolving computational tools — specifically Large Eddy Simulation (LES) coupled with a modal beam structural solver (CSD), which in turn generate the data necessary to train next-generation Artificial Intelligence (AI) controllers and build predictive Digital Twins (DT).

This research employs fluid-structure interaction modelling within an advanced LES framework to study the aeroelastic behaviour and wake dynamics of modern wind turbines, alongside the development of data-driven methodologies for wind farm optimisation.

1.1 The Energy Context and Industrial Drive

The transition to clean energy is accelerating, driven by climate change and initiatives such as the Paris Agreement [1]. To align with global climate goals, the 2023 IRENA report underlines the necessity of the renewable power capacity being tripled by 2030, with wind energy being projected to account for almost a third of this substantial expansion [2]. Wind power is now a core utility-scale technology, representing 25% of global renewable capacity [3].

This is primarily attributable to its scalability and declining LCOE [4].

As reported in [5], the sector recently exceeded the 1 Terawatt (TW) threshold for cumulative installed capacity. Presently, the Asia-Pacific region dominates both onshore and offshore markets, driven by China’s integrated supply chain. Concurrently, the United States is witnessing an augmentation in the implementation of utility-scale deployment, a development that has occurred in the wake of the Inflation Reduction Act (IRA). Latin American markets are also expanding by taking advantage of high capacity factors to meet domestic energy demand. Offshore wind energy is expanding rapidly across all these regions. In 2023, over 35.5 GW of offshore capacity was under construction [6], driven by high energy density and fewer land use constraints.

However, meeting 2050 net-zero targets requires faster deployment. The European market is indicative of the practical difficulties experienced in this regard. The European Union (EU) aims for a 40% renewable energy share by 2030 [7]. While EU wind generation reached a record 475 TWh in 2024, it dropped slightly to 465 TWh in 2025 because of lighter wind conditions. Wind still provided 19% of the EU-27 electricity demand that year (16% onshore, 3% offshore [8], see Tab. 1.1). Yet, the 19.1 GW of new European capacity added in 2025 fell short of industry forecasts by 15%, primarily due to supply chain bottlenecks and offshore logistical delays.

Table 1.1: Wind power contribution to total electricity consumption in the EU-27 and EU+UK (2025) [8].

	EU-27	EU+UK
Electricity consumption [TWh]	2,500	2,783
Onshore wind energy production [TWh]	402	437
Offshore wind energy production [TWh]	63	115
Total wind energy production [TWh]	465	552
Share of consumption met by wind energy	19%	20%

In response to these logistical and economic pressures, and to maximise energy yield within increasingly constrained spatial envelopes, the global industry is pursuing a sustained technological push toward turbine upscaling. Onshore platforms are transitioning from an average 2.6 MW capacity (in 2018) to near-term developments of 5–6 MW units featuring rotors of 160–170 m in diameter. Capitalising on stronger marine winds, next-generation offshore turbines push these boundaries even further, projected to reach diameters of 250 m and produce 15–20 MW per unit over the next decade [9]. Early commercial wind turbines in the 1980s typically featured rotor diameters

of around 15 m and capacities of just 100 kW; in contrast, cutting-edge reference models such as the DTU 10MW [10] and the IEA 15MW [11] feature rotor diameters of 178 m and 240 m, respectively, enabling modern turbines to generate over 80 times more power than their early counterparts. To illustrate the magnitude of this shift, a single 15 MW turbine can generate enough electricity to power approximately 20,000 European households annually. Figure 1.1 illustrates this upscaling trend from 1980 to the present day.

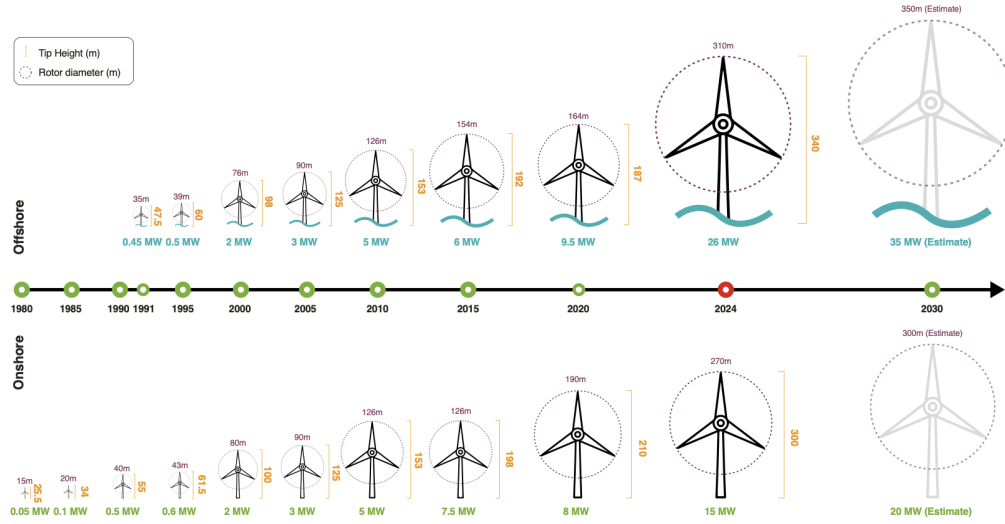


Figure 1.1: Trend of onshore and offshore turbine size between 1980 and 2030. Data reported in the Global Wind Report 2025 [12].

While this upscaling optimises energy capture and reduces the LCOE, it introduces engineering complexities that must be resolved for the sector to continue growing sustainably.

Outlook 2026–2030: Bridging the Target Gap

Looking ahead to the rest of the decade, the wind energy sector is poised for massive, yet highly scrutinised, expansion. Globally, the GWEC projects that cumulative installed capacity will double, surpassing the 2 TW threshold by 2030 [5]. While the Chinese market continues its intense centralisation, the broader Asia-Pacific (APAC) region—excluding China—is rapidly emerging as a critical growth vector, expected to account for 12% of global wind energy installations by the end of the decade.

Within Europe, these global trends translate into ambitious but difficult regional targets. According to WindEurope’s baseline estimations [8], the European continent is projected to install 151 GW of new capacity between 2026 and 2030, representing an average installation rate of 30 GW per year. When accounting for the decommissioning of ageing fleets, Europe’s total

installed wind capacity is projected to reach 439 GW by 2030. Crucially, within the EU-27 specifically, this falls well short of the official 2030 target of 425 GW (see Figure 1.2), highlighting that meeting energy goals relies not only on technological scaling but also on navigating the complex socio-technical landscape that governs wind energy deployment.

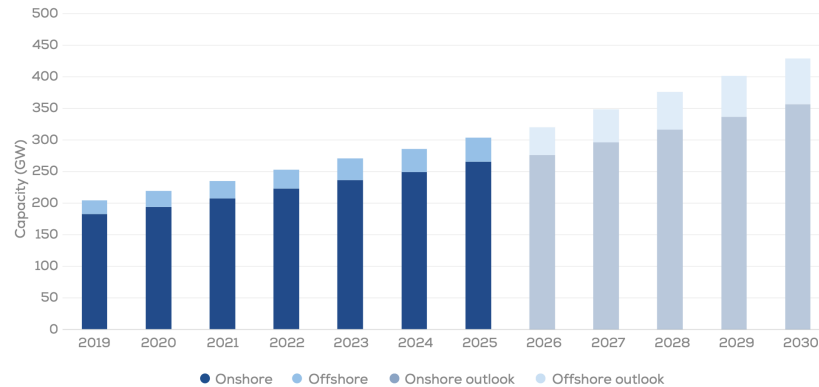


Figure 1.2: Projected wind capacity in Europe through 2030, illustrating the gap between baseline scenarios and official EU targets. Data from [8].

Social Impact of Wind Energy

Although wind energy is central to the energy transition, its deployment frequently clashes with local socio-territorial realities. This dynamic creates a distinct “social gap” [13]: while aggregate public support for renewables often exceeds 80% in European surveys, the success rate of local wind farm applications remains significantly lower. Historically, this local resistance was dismissively labelled as the “NIMBY” (Not In My Back Yard) syndrome. However, Wolsink [14] critically deconstructed this myth within the wind sector, demonstrating that public opposition is rarely driven by mere selfishness; instead, it is deeply influenced by the perceived fairness of the planning process and strong psychological attachments to local landscapes.

Beyond planning policies, the tangible physical and aerodynamic footprint of modern turbines plays a dominant role in shaping public perception. As rotors grow to maximise energy capture, their acoustic and visual impacts become increasingly polarising. A study by Pedersen and Waye [15] revealed that the highly modulated aerodynamic noise of wind turbines—the rhythmic “swishing” caused by blades interacting with atmospheric turbulence—triggers considerably higher public annoyance than road or industrial noise at equivalent decibel levels. Compounded by the visual “shadow flicker” effect, these factors heavily fuel local scepticism. Furthermore, even offshore wind farms face social friction due to the visual impact on the landscape from the shoreline

[16], proving that moving turbines out to sea does not entirely erase their socio-environmental footprint.

1.2 Challenges in Modern Wind Energy

The rapid upscaling of wind turbines, while a remarkable engineering achievement, introduces compounding physical challenges that span multiple disciplines. One of the most significant consequences of scaling rotors to the 200 m class is that turbines can no longer be treated as small aerodynamic perturbations within the atmospheric boundary layer (ABL). This directly challenges the assumptions underlying classical fluid-dynamic models, which treat turbine arrays as isolated objects embedded in an otherwise undisturbed flow. Instead, as first conceptualised by Calaf et al. [17], large wind farms must be regarded as rough-wall boundary layer flows, where turbines collectively act as an additional source of drag and turbulent mixing, giving rise to the notion of a *fully developed wind turbine array boundary layer*. Beyond these macroscopic aerodynamic effects, van Kuik et al. [18] identified three overarching challenges that define this era: the physics of the heterogeneous atmospheric wind source and its interaction with turbine arrays, the response of structurally enlarged turbines under unsteady and nonlinear fluid-structure-control coupling, and the integrated optimisation of entire wind plant fleets within the broader electrical grid. The following subsections address each of these dimensions in turn.

Aeroelastic Complexity of Large Rotors

As blade lengths increasingly exceed 100 m—weighing upwards of 60 tons—they experience intense aerodynamic, inertial, and gravitational forces that cannot be managed by simply scaling up existing structural designs. Maintaining structural stiffness constant as dimensions grow would result in massive, impractical blades; consequently, modern rotors are designed to be not only longer and more slender, but also far more flexible [18]. This intentional compliance makes blades highly susceptible to large deformations, elevating the prediction of aeroelastic instabilities—such as flutter, blade-tower collision, and high-cycle fatigue—to a central engineering challenge [19, 20, 21, 22, 23]. To mitigate these risks, the industry relies on advanced materials like carbon fibre-reinforced polymers [24] and specialised aerodynamic tip shapes designed to alleviate extreme transient loads [25]. Nevertheless, as rotor scales continue to increase, the accurate prediction of aeroelastic response under realistic, turbulent inflow conditions remains one of the most critical and least resolved problems in the field.

Aerodynamic Wake Interactions and Farm-Level Penalties

Beyond the single-turbine scale, dense wind farm arrays introduce a further layer of complexity through turbine–turbine aerodynamic interactions. Turbines operating in the wake of upstream machines experience significantly reduced wind speeds and elevated turbulence levels, with efficiency reductions reaching up to 40% in offshore applications [26, 27]. These wake interactions simultaneously reduce energy yield and amplify structural fatigue loads on downstream rotors, motivating the development of farm-layout optimisation strategies and cooperative, farm-level control approaches.

Offshore environments compound this challenge, offering superior wind resources while imposing severe environmental constraints such as extreme weather events and high ambient turbulence [28, 29]. While bottom-fixed substructures (monopiles, jackets) are standard in shallow waters, the industry is actively transitioning toward Floating Offshore Wind Turbines (FOWT) to unlock deep-water potential, introducing a further coupling between aerodynamic rotor loads, hydrodynamic forces, and platform kinematics [30]. In all these contexts, a physically accurate representation of wake evolution and recovery within the ABL is a prerequisite for reliable performance prediction and load assessment.

Emerging Turbine Configurations: Diffuser-Augmented Wind Turbines

While utility-scale upscaling dominates the mainstream, a parallel research thread addresses scenarios where massive rotor growth is unviable—urban and constrained environments, distributed generation, or sites with strict height limitations. In these contexts, Diffuser-Augmented Wind Turbines (DAWTs), also referred to as ducted wind turbines (DWTs), have attracted growing attention. By surrounding the rotor with an aerodynamic diffuser, DAWTs accelerate the incoming flow through the rotor disk, potentially increasing power output beyond the Betz limit applicable to open-rotor machines [31, 32]. However, the aerodynamic interaction between the diffuser and the enclosed rotor is inherently three-dimensional and unsteady, involving boundary layer separation, recirculation, and tip-vortex dynamics that semi-empirical models struggle to capture reliably [33, 32]. High-fidelity simulation is therefore essential to characterise the governing flow physics and translate theoretical performance gains into practical design guidance.

From Single-Turbine to Farm-Level Control

To safely manage intense structural loads and optimise power extraction at the individual machine level, modern turbines rely on sophisticated, multi-degree-

of-freedom control systems. Active pitch control continuously adjusts blade angle of attack to regulate power output and shed excessive aerodynamic loads during above-rated wind speeds, while yaw control aligns the nacelle with the prevailing wind direction to maximise energy capture.

At the farm level, the control paradigm has shifted from single-turbine “greedy” optimisation toward cooperative strategies that explicitly account for turbine–turbine interactions. Among these, active wake steering via intentional yaw misalignment has emerged as a particularly promising method: by deflecting the upstream rotor wake away from downstream machines, farm-level energy yield can be markedly enhanced [34, 35, 36]. However, intentional yaw misalignment introduces highly asymmetric loads on the deflecting turbine itself, necessitating robust aeroelastic assessment of the yawed rotor response. Furthermore, the time-varying, partially observable nature of real wind farm environments—where wind speed, direction, and turbulence intensity fluctuate continuously—demands control strategies capable of real-time adaptation, a requirement that classical model-based approaches struggle to satisfy.

1.3 High-Fidelity Simulation in Context

Addressing the challenges outlined above requires a level of physical fidelity that conventional engineering tools cannot fully provide. High-fidelity LES, coupled with structural solvers and data-driven methods, constitutes the shared computational foundation of the work presented in the following subsections.

CFD-CSD Coupling for Aeroelastic Analysis

Traditional engineering modelling approaches, such as Blade Element Momentum (BEM) theory, are computationally efficient and widespread, but rely on strong assumptions regarding the impinging flow and require extensive empirical corrections for dynamic stall, 3D tip losses, and skewed inflows [37, 38]. The current industry standard—lifting-line codes like OpenFAST [39], which couples BEM with structural solvers such as ElastoDyn [40] or BeamDyn [41]—is increasingly inadequate for multi-megawatt turbines. Recent comparative studies show that these codes largely underestimate the massive structural deformations that occur when flexible blades pass through the tower shadow [42], and that neglecting blade flexibility leads to substantial thrust underestimation for the IEA 15MW rotor [43].

LES-based FSI models coupling CFD with CSD have therefore become indispensable [44, 45, 46]. Early contributions by Bazilevs et al. [47] demonstrated full-scale rotor simulations using isogeometric shell formulations coupled with incompressible Navier–Stokes solvers, establishing that three-dimensional FSI is computationally achievable at the cost of bespoke discretisation strategies. Subsequent work by Heinz et al. [48] introduced partitioned URANS-CSD

coupling using the FLOWer solver and Carat++ beam elements for the DTU 10-MW rotor, finding that rotor elasticity increases power and thrust by approximately 1% through edgewise deformation contributions to torque. Trigaux et al. [49] extended these investigations to the IEA 15MW turbine using a flexible actuator line method, confirming that high-fidelity aerodynamic modelling is crucial to predict the aeroelastic response of large rotors and that blade flexibility significantly modifies the near-wake structure by suppressing the high-frequency velocity fluctuations observed with rigid blades. Zhang et al. [50] similarly showed, using a two-way LES-CSD model, that tip-vortex dynamics and wake turbulence intensities differ substantially between rigid and flexible blade representations, with consequences for downstream turbine loading. Most recently, Leng et al. [51] proposed an FSI model based on flexible multi-body dynamics coupled with LES and demonstrated that flexible blades eliminate the spurious high-frequency velocity spike at the blade tip that rigid-blade models inevitably predict.

In this thesis, LES serves as the fluid modelling backbone. Coupled with the Actuator Line Model (ALM), LES accurately resolves the interactions between turbulent atmospheric flows and flexible turbine structures [52, 53, 54], capturing the continuous feedback loop between aerodynamic forces and structural deflections that determines both performance and durability. As turbines continue to scale up, this class of simulation is increasingly essential to optimise structural designs, accurately quantify fatigue margins, and support wind energy's role as a reliable power source.

The Atmospheric Boundary Layer and Wake Physics

The accurate prediction of wake evolution within the ABL is paramount [55]. Large-scale turbines operate deeply embedded within the lower atmosphere, where the incoming flow is far from uniform, and the interplay between atmospheric dynamics, rotor aerodynamics, and downstream wake evolution governs both the energy yield and the structural integrity of wind energy systems.

The macroscopic dynamics of the ABL are primarily governed by atmospheric stability—ranging from unstable (convective) to neutral and stable conditions. This thermal stratification shapes the vertical wind shear profile and the intensity of the ambient incoming turbulence, establishing the background environment that dictates the turbine's aerodynamic response. The role of atmospheric stability on wake recovery has been quantified in a series of LES studies: Abkar and Porté-Agel [56] showed that stable stratification delays wake recovery by suppressing turbulent mixing, while Churchfield et al. [57] demonstrated that unstable conditions sharply accelerate it. Wu and Porté-Agel [58] further established that even under nominally neutral conditions, the vertical wind shear characteristic of the surface layer introduces pronounced asymmetry in wake turbulence intensity above and below hub height.

Beyond thermal stratification, the Earth’s rotation introduces further kinematic complexity through the Coriolis force, which drives the formation of the Ekman spiral [59]: a continuous rotation of the wind velocity vector with height, commonly referred to as wind veer, whose relative importance can be quantified through the Rossby number [60]. As this veer interacts with the rotor disk, it severely distorts the downstream flow, generating skewed and asymmetric wake structures that have been documented both experimentally [61, 62] and numerically [63, 64]. Abkar et al. [65] established that Coriolis forcing enhances ambient turbulent kinetic energy production, accelerating wake recovery relative to pressure-gradient-driven reference cases. The interaction between wake rotation and the Ekman spiral has been further characterised by Englberger et al. [66], who showed through LES that the rotational direction of the turbine determines the sense of the lateral wake deflection induced by background wind veer: a counter-clockwise rotor in a northern-hemisphere veering inflow produces a wider and more strongly deflected wake than its clockwise counterpart. Narasimhan et al. [63] systematically quantified these effects using LES for both yawed and un-yawed turbines in a Truly Neutral Boundary Layer and a Coriolis-driven boundary layer, showing that existing wake models designed for the former cannot reproduce the lateral asymmetry induced by veer without explicit generalisation to include Coriolis and stratification effects. This motivated the development of extended analytical wake models by Narasimhan et al. [67] that couple the vortex-sheet-based yawed-wake formulation with coupled Ekman–surface-layer descriptions of the ABL vertical structure.

In the immediate rotor near-wake, the flow is dominated by a pronounced velocity deficit and highly organised tip and root vortices. As these vortices become unstable and break down, the wake transitions to a fully turbulent state. In the far wake, velocity deficit recovery relies on the *entrainment* of kinetic energy from the surrounding undisturbed flow, driven by atmospheric turbulence and large-scale coherent structures that mix high-momentum fluid from above into the energy-depleted wake [68].

Wake Dynamics: A Modal Perspective

To systematically characterise how the structural features of the incoming ABL govern wake dynamics, modal decomposition techniques have proven highly effective. Proper Orthogonal Decomposition (POD) extracts the most energetically dominant coherent structures [69, 70, 71], providing a low-rank representation of the dominant kinetic energy content. The application of POD to wind turbine wakes dates back to the work of Iungo et al. [72], and has been progressively refined: Lignarolo et al. [73] used PIV-based POD to characterise tip-vortex instability in the near wake of a model turbine, identifying the leapfrogging mechanism that triggers wake breakdown. More recently, Hamilton et al. [74] applied POD to velocity measurements in wind

turbine array configurations under varying stability conditions, finding that the dominant POD modes shift from tip-vortex-dominated structures in near-neutral conditions to large-scale meander modes under stable stratification, and that the energy content of the dominant modes is strongly sensitive to the background turbulence structure of the incoming flow. Beyond the identification of coherent structures, the POD energy budget provides direct access to the Mean Kinetic Energy (MKE) distribution within the wake, enabling a rigorous characterisation of the spatial regions where kinetic energy is produced, transported, and dissipated—a perspective that is central to understanding how wakes recover and how upstream turbine operations affect the energy available to downstream machines [75, 76].

Dynamic Mode Decomposition (DMD) complements POD by isolating dynamically relevant frequencies and their spatial distributions [77, 78], revealing that inflow turbulence radically alters the wake’s coherent structure—suggesting that wake dynamics are largely driven exogenously by the specific wavelengths and frequencies of the incoming ABL [79, 80]. The application of DMD to wind turbine wakes was pioneered by Schmid [77] and subsequently extended to wind energy problems by De Cillis et al. [71], who compared the POD and sparsity-promoting DMD representations of the NREL 5MW wake under laminar uniform inflow, finding that DMD recovers a minimal set of physically interpretable modes at specific frequencies associated with blade-passing, tip-vortex shedding, and large-scale meander, while POD distributes the same energy content across a broader, less interpretable modal basis. Building upon standard DMD, the Sparsity-Promoting DMD (SPDMD) variant [81] offers a further layer of interpretability by identifying the minimal set of dynamically dominant modes that best reconstruct the observed flow field. This approach makes SPDMD particularly suited to isolating the physical mechanisms that distinguish competing inflow regimes—such as Coriolis-driven versus pressure-gradient-driven ABLs—and to quantifying the role of specific coherent structures in governing wake deflection and recovery.

A key property of both POD and DMD is that they naturally lend themselves to the construction of Reduced-Order Models (ROMs): by retaining only the most energetically or dynamically dominant modes, the full LES flow field can be reconstructed at a fraction of the original computational cost. While a ROM built on a small number of DMD modes necessarily introduces a reconstruction error relative to the full LES field—whose magnitude depends on the truncation rank and the complexity of the inflow—this trade-off between accuracy and efficiency is well-characterised and controllable [82]. More importantly, the global modes extracted from a given simulation retain, in principle, a degree of generalisability: by identifying the dominant spatio-temporal structures common across different operating conditions, it becomes possible to construct generalised ROM bases that extrapolate beyond the specific simulation from which they were derived, providing a pathway toward fast, physics-informed surrogate models for wake prediction and control [83].

Reinforcement Learning for Wind Farm Optimisation

Generating high-fidelity LES data is not merely an academic exercise: it provides the foundational dataset for training next-generation, data-driven control strategies. Historically, integrating LES directly into control optimisation has been a major challenge. A decade ago, Goit et al. [84] formulated a conjugate-gradient optimisation method in combination with LES for the optimisation of wind turbine controls. Since then, computational capabilities and reduced order models have evolved considerably. Early approaches often relied on open-loop control, where strategies follow a predetermined dynamic behaviour without feedback. However, studies by Howland et al. [85] and Munters et al. [86] found that open-loop dynamic forcing provides limited or no improvement compared to quasi-static or static control strategies. Consequently, the field has decisively shifted towards closed-loop control architectures, where the controller senses and actively responds to the continuously changing atmospheric flow conditions [87].

At the farm level, the challenge of coordinating dozens of interacting turbines in a time-varying, partially observable environment has positioned Reinforcement Learning (RL) as a uniquely powerful framework for closed-loop management. RL is a machine learning paradigm in which a controller (or agent) learns to make sequential decisions by interacting with the environment and receiving rewards based on its actions [88, 89] (see Figure 1.3). Given the decentralised nature of wind arrays [90], this paradigm naturally extends to Multi-Agent Reinforcement Learning (MARL). As shown by Bui et al. [91], distributed operation using multi-agent approaches can effectively optimise wake steering and power setpoint management to maximise the overall output power of the wind farm.

Recent work in this domain has focused heavily on advanced algorithms suited to the continuous action spaces inherent to turbine control. Proximal Policy Optimisation (PPO) [92] provides a robust on-policy baseline via clipped surrogate objectives, and has been applied to yaw control in both single-turbine and farm-level settings [93]. Soft Actor-Critic (SAC) [94] further improves sample efficiency through entropy maximisation, encouraging exploration in environments where rewards are delayed and noisy; a load-constrained MARL variant based on Independent SAC was recently applied by Astrand et al. [95] to simultaneously optimise power and fatigue damage equivalent loads, confirming that the two objectives can be balanced through reward shaping without additional computational overhead. Twin Delayed Deep Deterministic Policy Gradient (TD3) [96] addresses value-function overestimation in continuous control settings, achieving strong performance in yaw optimisation tasks [97, 98]. Kadoche et al. [99] proposed MARLYC, a centralised-training decentralised-execution MARL yaw controller verified on 15 real-world farm layouts ranging from 4 to 151 turbines, achieving consistent power improvements across all configurations and establishing the scalability of MARL to

operationally relevant farm sizes.

A critical bottleneck, however, is that training RL agents directly within high-fidelity LES environments is computationally prohibitive. A practical approach to this bottleneck is multi-fidelity transfer learning. Policies are often first trained on fast, control-oriented surrogate models such as FLORIS [100]—a steady-state engineering wake model. To bridge the reality gap without incurring the extreme computational costs of full-domain LES, researchers increasingly employ mid-fidelity dynamic models like FAST.Farm [101]. These mid-fidelity tools capture essential transient aerodynamic phenomena, such as wake meandering and dynamic inflow, making them an ideal intermediate environment for policy refinement. Finally, the pre-trained agents can be fine-tuned or validated against high-fidelity LES environments. This hierarchical pipeline drastically reduces computational cost while preserving policy quality, crucially allowing the agent to exploit the rich physical information (e.g., tip vortex dynamics, turbulent wake structures, instantaneous velocity fields) that simplified engineering models fundamentally cannot represent [102, 93].

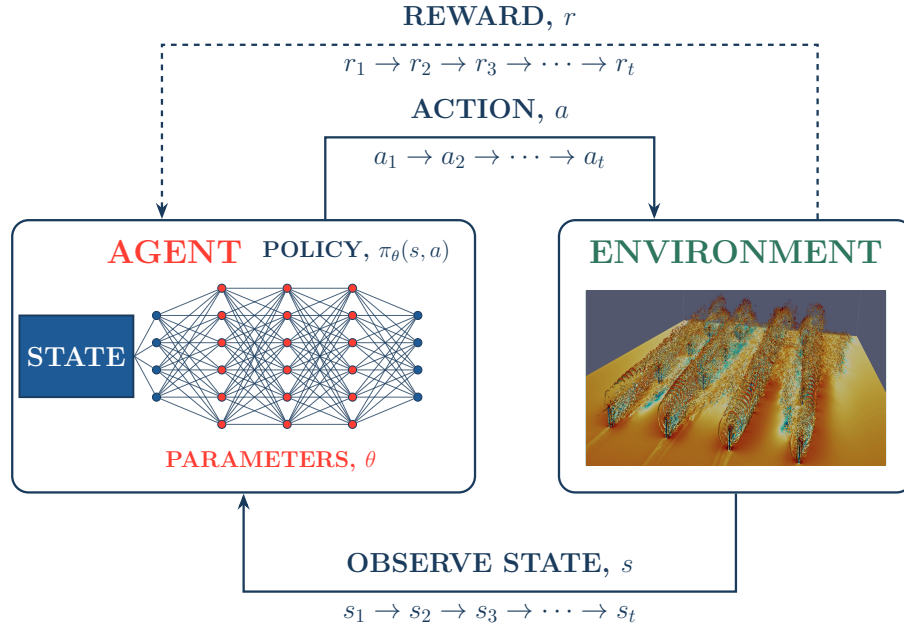


Figure 1.3: Detailed schematic of the Reinforcement Learning loop.

Digital Twins

Digital twins may be defined, following K. E. Willcox, as “a set of virtual information constructs that mimics the structure, context, and behaviour of a natural, engineered, or social system, is dynamically updated with data from its physical twin, has a predictive capability, and informs decisions that realize value” [103]. The bidirectional interaction between the virtual and the physical

system is central to this paradigm: unlike a static simulation, a digital twin is a living model that continuously assimilates operational data to refine its predictions and close the loop with real-world behaviour.

The concept has gained substantial traction in the wind energy community over the past decade. Stadtmann et al. [104] provided a comprehensive review of predictive digital twin technology for wind energy systems, mapping the spectrum from purely data-driven surrogate models to physics-based replicas and identifying the main open challenges in real-time model updating and uncertainty propagation. Zhang and Zhao [105] reported what they term the first digital twin for a wind farm flow system, integrating LiDAR measurements with the Navier–Stokes equations and an actuator disk model through physics-informed neural networks (PINNs) [106]. Their framework achieves real-time spatiotemporal prediction of the wind field across the entire farm, including wake interaction and meandering, by fusing observational data with the governing equations as soft constraints during training—directly addressing the generalisation limitation of purely data-driven surrogates. Fahim et al. [107] similarly combined sensor data streams with machine learning models to construct a predictive digital twin for individual turbine performance monitoring, achieving accurate fault detection under realistic sensor noise conditions. For floating offshore turbines, NREL and academic partners have proposed digital twin architectures that integrate structural health monitoring and virtual sensing to infer unmeasured loads from a limited sensor array [108], enabling condition-based maintenance strategies that drastically reduce reliance on costly vessel inspections.

The practical realisation of a wind energy digital twin depends on three interconnected technological components. First, modern wind farms—equipped with Supervisory Control And Data Acquisition (SCADA) systems, distributed sensors, LiDAR, and structural health monitoring instrumentation—are capable of generating massive streams of operational data. This abundance of *big data* provides the continuous observational input that drives model updates and anomaly detection [104]. Second, Artificial Intelligence (AI) plays a dual role in managing this data: black-box models such as neural networks and Gaussian processes can identify fitting functions between inputs and outputs without requiring explicit physical knowledge of the system, enabling fast surrogate predictions of turbine performance, structural loads, and wake behaviour. However, purely data-driven approaches are inherently limited by the coverage of their training data and can fail to generalise to unseen conditions. For this reason, the field is increasingly converging toward physics-informed, integrated approaches that embed the governing equations of fluid mechanics and structural dynamics as constraints within the learning process [106], combining the generalisation capacity of physics with the adaptability of machine learning. Third, the development of High-Performance Computing (HPC) and its integration with Reduced-Order Models (ROMs) has made it computationally feasible to maintain an accurate, continuously updated

virtual replica of a complex system in near real-time. This HPC-ROM synergy directly enables three critical capabilities: the construction of high-fidelity digital twins of both individual turbines and entire farm processes, Uncertainty Quantification (UQ) to bound prediction errors and propagate operational uncertainties through the model, and systematic data analytics pipelines for fleet-level performance monitoring and degradation tracking.

Applied to wind energy, this paradigm opens several concrete operational opportunities. By replacing expensive physical inspections with continuous virtual diagnostics, digital twins enable condition-based maintenance that drastically reduces unplanned downtime—a critical concern in remote offshore environments where vessel access is costly and weather-constrained [109]. At the farm level, digital twins trained on high-fidelity LES data can predict wake interaction losses under varying atmospheric conditions in a fraction of the time required for a full simulation, making them indispensable for real-time control and long-term energy yield assessment [104]. In this perspective, the continuous assimilation of operational data into aerodynamic and structural models—carried out within a sustainable computational budget that favours the reuse of prior simulation work—represents a key requirement for managing ageing turbine fleets whose operating conditions progressively diverge from original design assumptions.

1.4 Problem Definition and Thesis Objectives

State of the Art and Research Gaps

The wind energy research community has made substantial progress across all the disciplines discussed above. Engineering aeroelastic solvers have been systematically validated against experimental campaigns and can predict turbine loads with reasonable accuracy under idealised, uniform inflow conditions. Wake models ranging from the Jensen top-hat formulation [110] to the Gaussian-based extensions of Bastankhah and Porté-Agel [111] have provided fast, tractable tools for farm-layout optimisation. High-fidelity LES frameworks have matured to the point where they can simulate turbulent ABL flows over realistic terrain and through multi-row turbine arrays [112], and modal decomposition methods have been applied with success to extract coherent structures from both numerical and experimental datasets [83]. In parallel, Reinforcement Learning controllers have achieved measurable gains in idealised wind farm simulations, and the concept of the digital twin has transitioned from a theoretical construct to a commercially pursued objective.

Yet this progress has largely advanced within separate disciplinary communities, and the boundaries between them are precisely where current tools are most severely tested. The highest demands on predictive accuracy arise in the regimes that are furthest from the assumptions underlying current methods:

fully turbulent, Coriolis-affected atmospheric inflows interacting with rotors of unprecedented flexibility, operating within arrays where wake turbulence is both a structural hazard and an aerodynamic resource. The gap between what engineering models can reliably predict and what high-fidelity physics can reveal is widest here. Similarly, the gap between the low-fidelity environments in which RL agents are trained and the complex, unsteady physics of real wakes represents a central unresolved challenge for data-driven control. Several specific research gaps motivate the contributions of this thesis:

- **Structural scaling and torsion-bending coupling.** While aeroelastic solvers are routinely used for MW-class turbines, the leap to 15MW architectures introduces severe nonlinearities. Specifically, the role of the torsional degree of freedom and its dynamic feedback on blade aerodynamic loading remains under-characterised in fully coupled LES-CSD environments when scaling from standard models (e.g., NREL 5MW) to ultra-large flexible rotors (e.g., IEA 15MW).
- **Coriolis effects and realistic ABL representation.** The vast majority of numerical wake studies adopt pressure-gradient-driven ABL setups in which the Coriolis force is neglected. This simplification overlooks the wind veer produced by the Ekman spiral, generating symmetric wakes that differ fundamentally from reality. A systematic characterisation of the coherent structures arising from this atmospheric forcing—and their contrast with idealised reference cases—using advanced modal tools (POD, DMD, SPDMD) is strictly required to derive physics-informed Reduced-Order Models (ROMs).
- **Aeroelastic behaviour of ultra-large arrays under active control.** The coupled aeroelastic response of the IEA 15MW rotor subjected to the highly sheared, Coriolis-driven wake of an upstream turbine remains an open question. In particular, the degree to which active wake steering (yaw misalignment) amplifies downstream blade fatigue and alters structural deflections has not been comprehensively quantified in LES-based aeroelastic environments.
- **Diffuser-Augmented Wind Turbines (DAWTs).** Despite their theoretical promise, DAWTs remain poorly understood from a fully resolved fluid-dynamic perspective. Existing analyses largely rely on RANS simulations, which struggle to capture three-dimensional unsteady separation inside the diffuser. A rigorous LES investigation evaluating torque augmentation and wake recovery across different duct geometries under Maximum Power Point Tracking (MPPT) conditions is needed to assess their viability.
- **Reinforcement learning for wind farm control: bridging fidelity levels.** While RL-based controllers have shown farm-level gains, a

persistent sim-to-real gap remains. Policies trained exclusively on steady-state engineering tools like FLORIS are exposed to a systematic bias in wake shape and turbulence. A principled transfer learning pipeline that pre-trains RL agents (e.g., via Proximal Policy optimisation) in fast surrogate environments and fine-tunes them against transient LES data has yet to be fully established.

Original Contributions of This Thesis

The research presented in this thesis advances the state of the art across five interconnected areas of wind energy science. The original contributions, which directly address the research gaps identified above, are the following:

1. **Modal characterisation of wind turbine wake dynamics under Coriolis forcing.** Using LES combined with POD, DMD, and Sparsity-Promoting DMD, the coherent structures of the NREL 5MW wake are systematically contrasted between an idealised pressure-gradient-driven ABL and a fully developed, neutrally-stratified Ekman layer. The analysis establishes that Coriolis-induced wind veer inverts the energetic hierarchy of the dominant POD modes, compresses the MKE entrainment zone radially, and generates oblique wake structures absent from axisymmetric models. A physics-informed DMD-based ROM is derived, achieving a reconstruction error below 7% with 75 mode pairs.
2. **Aeroelastic scaling and the torsion-bending coupling from 5 MW to 15 MW.** A fully coupled CFD-CSD comparison of the NREL 5MW and IEA 15MW reference turbines under identical inflow isolates the effect of rotor scale on structural response. The results demonstrate that torsion-bending coupling, negligible at 5 MW, becomes a primary driver of blade loading at 15 MW: including the torsional degree of freedom reduces mean out-of-plane deflection but simultaneously increases the Damage Equivalent Load by up to 20%, a counter-intuitive trade-off with direct implications for next-generation blade certification.
3. **Yaw-asymmetric aeroelastic response under atmospheric wind veer.** A two-turbine in-line array of IEA 15MW machines is simulated under Coriolis-driven inflow with upstream yaw misalignment swept from -30° to $+30^\circ$. The study establishes that the Ekman-layer wind veer breaks the lateral symmetry of wake steering: positive misalignment ($+30^\circ$) simultaneously maximises array power gain (+15%) and nearly minimises downstream blade fatigue ($DEL_{OoP} = 177 \text{ kN}$), while negative misalignment produces a curled, elliptical wake that imposes structural penalties exceeding 200 kN. This directional preference constitutes a design guideline absent from axisymmetric wake models.

4. **LES-IBM evaluation of Diffuser-Augmented Wind Turbines under MPPT control.** Three DAWT geometries of progressively increasing exit area are assessed for the first time under partial-load Maximum Power Point Tracking conditions using LES coupled with the Immersed Boundary Method. The simulations reveal the tip-vortex suppression mechanism responsible for the load redistribution toward the outer blade span, and establish a monotonic relationship between exit area and torque augmentation, reaching +78.6% for the largest diffuser. The LES-resolved near-wake topology provides a physically consistent baseline that one-dimensional actuator-disc analyses cannot reproduce.
5. **Multi-Agent Reinforcement Learning benchmark for wind farm yaw control with sim-to-real transfer.** A comprehensive benchmark of nine MARL algorithms — spanning the PPO, SAC, and TD3 families under independent, CTDE, and fully centralised coordination paradigms — is conducted on a three-turbine in-line array and the irregular Ablaincourt farm. PPO and entropy-regularised SAC achieve 100% convergence reliability with power gains of $\approx 25\%$ (three turbines) and $\approx 10\%$ (seven turbines). The subsequent transfer to a turbulence-resolving LES environment with blade root bending moment monitoring reveals a $\approx 5\%$ power surplus relative to the FLORIS surrogate and exposes a structural fixed-point instability in deterministic TD3 policies — a deployment-critical failure mode previously uncharacterised in the literature.

Software Contributions of This Thesis

The numerical framework employed throughout this work builds upon the UTD-WF LES solver [113, 114, 115], originally developed at the University of Texas at Dallas. The following components were implemented by the author as original contributions of this thesis within the existing codebase:

- **Coriolis forcing and Ekman-layer ABL:** implementation of the geostrophic wind forcing term and the PI yaw-alignment controller of Sescu and Meneveau [116], enabling the generation of fully developed Ekman-spiral inflows (Chapter 5).
- **Aeroelastic extension to the IEA 15MW turbine:** adaptation of the modal beam structural solver [46] to the IEA 15MW blade geometry, including the torsional degree of freedom and the torsion-bending feedback coupling (Chapters 6 and 7).
- **MARL framework via SmartRedis:** design and implementation of the Multi-Agent Reinforcement Learning environment, including the SmartRedis middleware layer for runtime coupling between the Fortran/C++ LES solver and the Python-based RL agents (Chapter 9, Appendix B).

- **GPU acceleration:** porting of the LES solver to GPU-accelerated architectures via CUDA/OpenACC, and performance benchmarking on international HPC systems (Appendix A).

The structural FEM solver used to compute the blade natural frequencies and mode shapes is based on the formulation of Della Posta et al. [46] and was extended and integrated by the author for the turbine models considered here.

Outline of the Thesis

In addition to this introductory chapter, the present thesis is organised to address the aforementioned research gaps through a progressive methodological and analytical framework, structured as follows:

- **Chapter 2 – Methodology:** this chapter details the comprehensive computational framework. It presents the governing equations of the LES fluid solver, the numerical discretisation methods, and the Immersed Boundary Method (IBM). It further introduces the turbine parameterizations (Actuator Line and Disc Models), the structural solver, and the Fluid-Structure Interaction (FSI) coupling scheme. Finally, it outlines the mathematical formulations for data-driven modal decompositions (POD, DMD, SPDMD) and the Reinforcement Learning framework.
- **Chapter 3 – Reference Wind Turbines:** this chapter introduces the main specifications, scaling parameters, and aerodynamic characteristics of the turbine models employed in the computational campaigns, specifically the NREL 5MW, the IEA 15MW, and the 3-Bladed NREL Phase VI.
- **Chapter 4 – Validation and Verification of the Numerical Code:** this chapter presents a systematic verification of the in-house CFD-CSD framework against the OpenFAST engineering reference (ElastoDyn and BeamDyn) for both the NREL 5MW and IEA 15MW turbines. Eigenfrequency benchmarks, spanwise aerodynamic load distributions, structural deformations, and integral performance coefficients are compared across multiple solver configurations.
- **Chapter 5 – Effects of Atmospheric Wind Veer on Wake Dynamics:** this chapter investigates the fluid dynamics of wake evolution, comparing an idealised pressure-driven boundary layer with a fully developed Coriolis-driven Ekman layer. Advanced modal decomposition techniques are applied to the LES flow fields to isolate the effects of atmospheric wind veer on wake skewing, coherent structures, and mean kinetic energy entrainment.

- **Chapter 6 – Effects of Flexibility:** this chapter provides a fully coupled aeroelastic assessment, evaluating the complex fluid-structure interactions on the turbine blades. It focuses on the impact of structural flexibility on aerodynamic load distribution, power and thrust generation, dynamic structural deformations, and blade root fatigue reactions.
- **Chapter 7 – Aeroelastic Response of Wind Turbine Arrays:** extending the framework to multi-turbine configurations, this chapter analyses a two-turbine in-line array of IEA 15MW machines under Coriolis-driven inflow. It systematically quantifies the asymmetric impact of active wake steering (yaw misalignment) on array power performance, wake morphology, and downstream fatigue loading (Damage Equivalent Loads).
- **Chapter 8 – Diffuser-Augmented Wind Turbines:** moving beyond conventional open rotors, this investigation employs LES coupled with IBM to assess flow augmentation techniques. It evaluates the impact of static diffusers of increasing exit area on rotor torque augmentation, tip-vortex dynamics, and near-wake recovery.
- **Chapter 9 – Reinforcement Learning for Wind Farm Control:** this final chapter bridges LES physics and data-driven control by developing a Multi-Agent Reinforcement Learning framework for wind farm yaw optimisation. Nine algorithms spanning the PPO, SAC, and TD3 families are benchmarked under independent, CTDE, and fully centralised coordination paradigms. Policies trained in the FLORIS surrogate are transferred to the LES environment to quantify the sim-to-real fidelity gap.
- **Appendix A – CPU/GPU Scalability:** details the porting of the LES solver to GPU-accelerated architectures using CUDA and OpenACC, and presents strong- and weak-scaling benchmarks on international HPC systems (CINECA Leonardo, TACC Lonestar6). GPU acceleration yields an approximately tenfold reduction in wall-clock time relative to the CPU baseline.
- **Appendix B – SmartRedis Ecosystem:** describes the in-memory database middleware used to couple the Fortran/C++ LES solver with the Python-based MARL agents at runtime, detailing the client API, tensor-exchange primitives, and on-database model inference that enable the control campaigns of Chapter 9.
- **Appendix C – FLORIS and the Gaussian Wake Model:** outlines the engineering wake model used as the training surrogate for the MARL controllers, presenting the Gaussian velocity-deficit formulation, the yaw

deflection model, and the main modelling assumptions that motivate the sim-to-real transfer study.

- **Appendix D – OpenFAST Framework:** summarises the two OpenFAST structural modules (ElastoDyn and BeamDyn) and the AeroDyn aerodynamic module used as reference solvers in the aeroelastic verification of Chapter 4, highlighting the key formulation differences that motivate the comparison.

Chapter 2

Methodology

This chapter details the numerical and theoretical foundations of the methodology employed in this study. It begins with a description of the physical governing equations and the Large Eddy Simulation (LES) approach used to resolve the turbulent flow field, followed by an outline of the numerical methods employed for their discretisation. Subsequently, the theoretical framework for Atmospheric Boundary Layer (ABL) modelling is introduced, alongside the numerical strategies adopted to represent solid bodies and wind turbines within the computational domain. Building upon these physical and aerodynamic elements, the comprehensive Fluid–Structure Interaction (FSI) framework is then delineated. The discussion subsequently shifts to advanced post-processing and flow analysis techniques, presenting the core principles of Proper Orthogonal Decomposition (POD) and Dynamic Mode Decomposition (DMD). The chapter closes with an outline of the Reinforcement Learning (RL) methodology developed for wind farm control.

2.1 The Fluid Model

Governing Equations

In the study of wind farm aerodynamics, the flow can be reasonably approximated as incompressible. Under typical operating conditions, the Mach number remains low ($Ma \leq 0.25$), allowing compressibility effects to be neglected. Accordingly, an incompressible flow model is adopted in this work.

The governing equations for the fluid model are the *incompressible Navier–Stokes equations*, which consist of the continuity and momentum conservation equations:

$$\nabla \cdot \mathbf{u} = 0, \quad (2.1)$$

$$\frac{\partial \mathbf{u}}{\partial t} + \mathbf{u} \cdot \nabla \mathbf{u} = -\frac{1}{\rho} \nabla p + \nu \nabla^2 \mathbf{u} + \mathbf{f} + \mathbf{f}_{ABL}, \quad (2.2)$$

where $\mathbf{u}$ denotes the velocity vector, p the pressure, $\mathbf{f}$ a generic body force acting on the fluid, and $\mathbf{f}_{ABL}$ the forcing associated with the ABL (see Section 2.6). The fluid density ρ and kinematic viscosity ν are assumed constant, and t denotes time. To express the governing equations in non-dimensional form, characteristic reference scales for length and velocity are introduced:

$$\mathbf{u}^* = \frac{\mathbf{u}}{U_0} \quad x^* = \frac{x}{L_0} \quad t^* = \frac{tU_0}{L_0} \quad p^* = \frac{p}{\rho_0 U_0^2} \quad \mathbf{f}^* = \frac{\mathbf{f} L_0}{U_0^2}, \quad (2.3)$$

Substituting these definitions into the governing equations yields:

$$\nabla^* \cdot \mathbf{u}^* = 0, \quad (2.4)$$

$$\frac{\partial \mathbf{u}^*}{\partial t^*} + \mathbf{u}^* \cdot \nabla^* \mathbf{u}^* = -\nabla^* p^* + \frac{1}{Re} \nabla^{*2} \mathbf{u}^* + \mathbf{f}^* + \mathbf{f}_{ABL}^*, \quad (2.5)$$

where $[\nabla^*]_i = \partial/\partial x_i^*$ and $Re = U_0 L_0 / \nu$ is the Reynolds number. For notational simplicity, the non-dimensional form of the equations will be used hereafter, and the superscript $*$ will be omitted.

According to the principle of dynamic similarity, two geometrically similar flow configurations sharing the same Reynolds number are dynamically similar—a principle extensively leveraged in both experimental and computational fluid dynamics.

Large Eddy Simulation Approach

Since the pioneering experiments of Osborne Reynolds, it is well established that flows transition to turbulence when the Reynolds number exceeds a critical value dependent on the flow configuration. Turbulent flows are three-dimensional, unsteady, and characterised by chaotic velocity fields $\mathbf{u}(x, t)$.

A direct approach to solving the Navier–Stokes equations is Direct Numerical Simulation (DNS), in which all relevant spatial and temporal scales are fully resolved. While DNS provides the highest level of accuracy, its computational cost is prohibitive for most practical applications. For the Reynolds numbers typical of engineering flows, the required computational resources exceed current capabilities.

According to Kolmogorov’s theory of homogeneous isotropic turbulence [117], the ratio between the largest and smallest turbulent scales is given by:

$$\frac{L}{\eta} = \mathcal{O}\left(Re^{3/4}\right), \quad (2.6)$$

where L is the integral scale of the flow and η is the Kolmogorov scale, which is the smallest scale not directly dissipated by viscosity. The theory also presents a similar estimation for the characteristic time scales:

$$\frac{T}{t_\eta} = \mathcal{O}\left(Re^{1/2}\right), \quad (2.7)$$

where T is the integral time scale and t_η is the Kolmogorov time scale. To accurately simulate turbulent flows and capture the full energy cascade, DNS requires both fine grid resolution and a sufficiently large computational domain. The grid spacing δ in each direction must be at most equal to the Kolmogorov scale η to resolve the smallest eddies, while the domain size Δ must be at least equal to the integral scale L . The ratio of the domain size to the grid spacing N_{s-1D} , which provides an estimate of the number of grid points in one direction, scales as $Re^{3/4}$. The total number of grid points for a three-dimensional DNS therefore grows as $N_s \sim Re^{9/4}$. Since the time step δT , dictated by the Courant-Friedrichs-Lewy (CFL) condition, must be smaller than or equal to the Kolmogorov time scale t_η , and the total simulation time must span at least the integral time T , the number of time steps scales as $N_T \sim Re^{1/2}$. The computational cost of DNS is therefore proportional to $N_s \cdot N_T \sim Re^{11/4}$. For modern utility-scale wind turbines, with typical diameters $D \approx 100$ m and freestream velocities $U_\infty \approx 10$ m/s, the Reynolds number $Re = \frac{U_\infty D}{\nu}$ is on the order of 10^8 . At such high Reynolds numbers, DNS requires a total number of unknowns proportional to $Re^{11/4}$, necessitating alternative modelling approaches. As a result, DNS is strictly limited to flows with low or moderate Reynolds numbers, necessitating alternative approaches for practical engineering problems.

As a conceptually opposite approach to DNS, the Reynolds-Averaged Navier-Stokes (RANS) approach relies on statistical modelling rather than the explicit resolution of all the scales. This technique involves *Reynolds decomposition* to separate the velocity field into its mean and fluctuating components. By applying an ensemble average to the Navier-Stokes equations, the RANS equations are derived. An additional term—the Reynolds stress tensor—, accounting for the effects of fluctuating turbulent scales on the resolved ones, is introduced to the RANS framework. Because this tensor cannot be explicitly formulated from the mean flow variables, thereby posing the well-known closure problem, auxiliary turbulence models are required to approximate these stresses. By modelling rather than resolving the smaller turbulent scales, the computational expense is substantially mitigated. This reduction in computational burden enables the investigation of high-Reynolds-number flows of practical engineering interest, an approach that has proven highly effective in various domains, notably within the field of wind energy [118]. In this context, two-equation formulations, such as the k - ε and k - ω models are frequently employed. However, extending this framework to transient phenomena through Unsteady RANS (URANS) introduces notable drawbacks. Compared to steady-state simulations, URANS often exhibits reduced accuracy, an increased sensitivity to the choice of turbulence closure, and substantially higher computational demands [119].

The Large Eddy Simulation (LES) approach represents an optimal compromise between the computational efficiency of RANS methods and the high fidelity of DNS. The LES framework explicitly resolves only the most energetic,

large-scale turbulent motions—termed *large eddies*—which are intrinsically tied to the specific boundary conditions and geometry of the flow under investigation. Relying on Kolmogorov’s theory of local isotropy [120], it is postulated that at sufficiently high Reynolds numbers, the small-scale turbulent motions (specifically, those smaller than a characteristic length scale l_0) behave in a statistically isotropic manner. Kolmogorov’s hypothesis also asserts that the statistical properties of these small scales ($l \ll l_0$) are universal, governed exclusively by the turbulent dissipation rate ϵ and the kinematic viscosity ν . This inherent universality provides the theoretical foundation for LES: it suggests that unresolved small scales can be effectively modelled rather than explicitly resolved, thereby substantially reducing computational overhead. In a turbulent flow, the distribution of kinetic energy across different length scales (or wavenumbers k) defines the turbulence energy cascade. This spectrum is classically partitioned into three distinct regimes: the energy-containing range, the inertial subrange, and the dissipation range. The *energy-containing range* is located at low wavenumbers and encompasses the largest turbulent structures. These eddies extract energy directly from the mean flow and are heavily influenced by the domain geometry and external forcing mechanisms, such as wind shear or the atmospheric boundary layer (ABL). The energy spectrum in this region is therefore relatively broad, housing the bulk of the turbulent kinetic energy. As energy cascades down to smaller scales, it traverses the *inertial subrange*. Governed by Kolmogorov’s hypothesis of local isotropy, turbulence statistics in this intermediate regime become independent of the macroscopic flow configuration. Here, energy is transferred purely via inertial forces, with viscous effects remaining negligible. Finally, at the highest wavenumbers, the flow transitions into the *dissipation range*. In this regime, viscous forces dominate, and turbulent kinetic energy is irreversibly dissipated into internal energy in the form of heat. The extent and separation of these three regions are highly dependent on the Reynolds number. As illustrated in Fig. 2.1, an increase in the Reynolds number leads to a more pronounced scale separation between the energy-containing and dissipation ranges, widening the inertial subrange. At low Reynolds numbers, however, this subrange shrinks and can even vanish completely. This enhanced separation at high Reynolds numbers is precisely what ensures the validity and effectiveness of subgrid-scale (SGS) modelling. By explicitly resolving the large, geometry-dependent structures and modelling the universal small-scale behavior, LES accommodates much coarser grid resolutions (δ) compared to DNS, thus optimising computational expenditure.

In the present work, LES is employed to investigate the wake dynamics of wind turbines. This methodology accurately resolves the large-scale turbulent structures—whose shape, trajectory, and dominant wavenumbers are strictly dictated by the turbine geometry—while the more universal, small-scale fluctuations are parameterized via SGS models. Ultimately, this approach ensures a faithful representation of the dominant aerodynamic processes while preserving

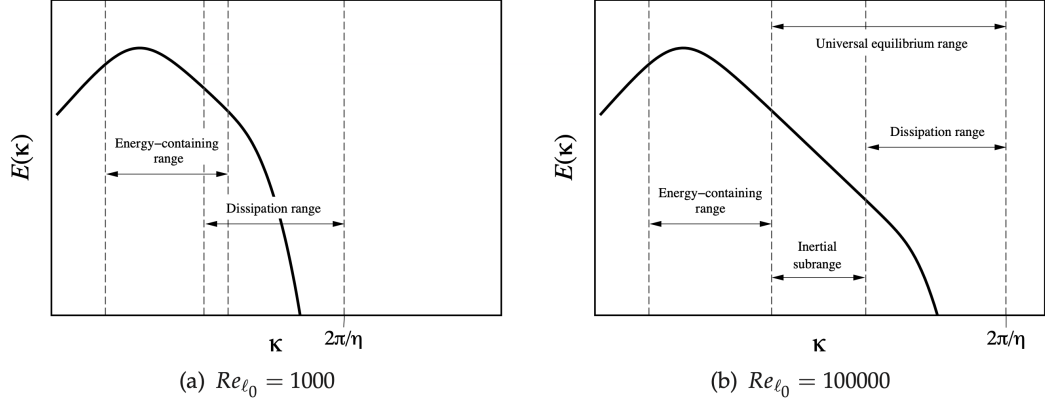


Figure 2.1: Turbulence kinetic energy spectrum $E(k)$ and corresponding regions of the energy cascade, expressed as a function of the wavenumber $k = 2\pi/l$, for two distinct Reynolds numbers: a) $Re_{l_0} = 10^3$, b), $Re_{l_0} = 10^5$. As illustrated, at lower Reynolds numbers, the inertial subrange shrinks considerably and may ultimately vanish [121].

computational efficiency. Indeed, recent literature [122] has extensively validated the application of LES in wind turbine fluid dynamics, demonstrating that this methodology provides unparalleled accuracy and deeper physical insights when compared to traditional modelling paradigms.

Filtered Navier-Stokes Equations

Mathematically, the LES framework is founded upon the application of a low-pass spatial filtering operation to the Navier-Stokes equations. This mathematical procedure effectively decouples the energy-containing, large-scale motions from the unresolved, subgrid-scale fluctuations. By eliminating turbulent structures smaller than a prescribed cutoff length, the continuous flow variables are smoothed, allowing them to be discretised and solved on a comparatively coarse computational mesh.

Formally, the filtering of an arbitrary flow variable $\phi(x, t)$ is defined as a convolution integral with a filter kernel $G(x - \xi, t - t')$. This kernel is characterised by specific spatial and temporal cutoffs scales, associated with spatial and temporal cutoff scales Δ and τ_c , respectively:

$$\phi(x, t) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \phi(\xi, t') G(x - \xi, t - t') dt' d^3\xi. \quad (2.8)$$

The resulting filtered variable, denoted by $\tilde{\phi}(x, t)$, represents resolved, macroscopic component of the flow field. The unresolved fraction—referred to as the residual or subgrid-scale component—is defined as the difference between the exact and the filtered field, $\phi'(x, t) = \phi(x, t) - \tilde{\phi}(x, t)$. The instantaneous flow

variable therefore undergoes the following decomposition:

$$\phi(x, t) = \tilde{\phi}(x, t) + \phi'(x, t). \quad (2.9)$$

To ensure the mathematical consistency required to manipulate the Navier-Stokes equations post-filtering, the convolution operation must satisfy several key properties [123]:

- **Conservation of constants:** $\tilde{a} = a$,
- **Linearity:** $\widetilde{\phi + \psi} = \tilde{\phi} + \tilde{\psi}$,
- **Commutation with derivatives** (spatially and temporally uniform filters): $\nabla \tilde{\phi} = \widetilde{\nabla \phi}$, $\frac{\partial \tilde{\phi}}{\partial t} = \widetilde{\frac{\partial \phi}{\partial t}}$.

Applying this filtering procedure to the continuity and Navier-Stokes equations for an incompressible fluid yields the filtered governing equations:

$$\frac{\partial \tilde{\mathbf{u}}}{\partial t} + \tilde{\mathbf{u}} \cdot \nabla \tilde{\mathbf{u}} = -\nabla \tilde{p} - \nabla \cdot \boldsymbol{\tau}_R + \frac{1}{Re} \nabla^2 \tilde{\mathbf{u}} + \tilde{\mathbf{f}}, \quad (2.10)$$

$$\nabla \cdot \tilde{\mathbf{u}} = 0. \quad (2.11)$$

While the filtered continuity equation preserves its original structure, the momentum equations are modified by the appearance of a new term, $-\nabla \cdot \boldsymbol{\tau}_R$. Here, $\boldsymbol{\tau}_R$ denotes the subgrid-scale or residual stress tensor, mathematically defined as:

$$\boldsymbol{\tau}_R := \widetilde{\mathbf{u} \otimes \mathbf{u}} - \tilde{\mathbf{u}} \otimes \tilde{\mathbf{u}}. \quad (2.12)$$

This residual tensor encapsulates the dynamic interactions between the resolved eddies and the unresolved subgrid scales, introducing a closure problem that necessitates the formulation of an appropriate SGS model. It is crucial to highlight a key distinction between LES and RANS approaches: unlike the time-averaged fields in RANS, the filtered variables in LES retain their unsteady, three-dimensional, and chaotic nature, even under statistically stationary or homogeneous conditions. The explicit formulation of the SGS stress tensor is tied to the chosen filter type and its associated cutoff width.

By resolving the energetic large-scale structures while modelling the dissipative small scales, LES enables the investigation of high-Reynolds-number flows at a fraction of the cost of DNS.

Subgrid-Scale Stress Tensor

The subgrid-scale (SGS) stress tensor, $\boldsymbol{\tau}_R$, emerges from the non-linear convective term in Equation 2.5, encapsulating the complex dynamic interactions between the explicitly resolved eddies and the unresolved subgrid scales. To systematically dissect these interactions, Leonard [124] proposed a widely adopted

mathematical decomposition of $\boldsymbol{\tau}_R$. By applying the filtering operation to the non-linear tensor product $\mathbf{u} \otimes \mathbf{u}$ and using the velocity decomposition from Equation 2.9, the SGS stress tensor can be expanded as:

$$\boldsymbol{\tau}_R = \mathcal{L} + \mathcal{C} + \mathcal{R}, \quad (2.13)$$

where the *Leonard stresses* $\mathcal{L}$ are defined as:

$$\mathcal{L} := \widetilde{\tilde{\mathbf{u}} \otimes \tilde{\mathbf{u}}} - \tilde{\mathbf{u}} \otimes \tilde{\mathbf{u}} \quad (2.14)$$

The *cross stresses* $\mathcal{C}$ are formulated as:

$$\mathcal{C} := \widetilde{\tilde{\mathbf{u}} \otimes \mathbf{u}'} + \widetilde{\mathbf{u}' \otimes \tilde{\mathbf{u}}}, \quad (2.15)$$

and the *SGS Reynolds stresses* $\mathcal{R}$ are given by:

$$\mathcal{R} := \widetilde{\mathbf{u}' \otimes \mathbf{u}'}. \quad (2.16)$$

Physically, the Leonard stresses represent the kinematic interactions among the resolved scales that produce unresolved fluctuations. The cross stresses denote the direct dynamic coupling between the macroscopic and subgrid scales, while the SGS Reynolds stresses account for the energy transfer occurring purely within the unresolved residual field. Although highly insightful, Leonard's original decomposition lacks Galilean invariance in some of its constituent terms. This central limitation subsequently motivated the development of alternative formulations, most notably Germano's triple decomposition [125]. To achieve mathematical closure for the filtered Navier-Stokes equations, $\boldsymbol{\tau}_R$ must be parameterized as a function of the resolved velocity field. Standard practice dictates modelling only the anisotropic (deviatoric) fraction of the stress tensor. The isotropic component is therefore absorbed into a modified pressure field, defined as:

$$\tilde{p}^\dagger := \tilde{p} + \frac{1}{3} \text{tr}(\boldsymbol{\tau}_R), \quad (2.17)$$

where $\text{tr}(\boldsymbol{\tau}_R)$ denotes the trace of the SGS stress tensor. If this isotropic contribution becomes dynamically relevant, an explicit transport equation for the residual kinetic energy, $k_r = \frac{1}{2} \text{tr}(\boldsymbol{\tau}_R)$, may also be required. Eddy viscosity models constitute the most widely adopted family of SGS closures. This modelling paradigm posits that the dynamic effect of unresolved turbulent scales is phenomenologically analogous to molecular transport mechanisms, such as the diffusion of momentum or heat. A key distinction therefore arises: whereas molecular viscosity (ν) is an intrinsic thermodynamic property of the fluid responsible for microscopic dissipation, the *eddy viscosity* (ν_r) is exclusively a macroscopic property of the flow, dictated by the local kinematics of the explicitly resolved features. Building upon this analogy and invoking

the Boussinesq hypothesis [126], the deviatoric component of the SGS stress tensor can be formulated as:

$$\boldsymbol{\tau}_R^d = \boldsymbol{\tau}_R - \frac{1}{3}\text{tr}(\boldsymbol{\tau}_R)\mathbf{I} = -2\nu_r\tilde{\mathbf{S}} = -\nu_r(\nabla\tilde{\mathbf{u}} + \nabla^T\tilde{\mathbf{u}}), \quad (2.18)$$

where $\tilde{\mathbf{S}}$ denotes the resolved strain-rate tensor—defined as the symmetric part of the filtered velocity gradient—and the superscript T indicates the transpose operator. By employing this parameterization, the additional divergence term introduced in Equation 2.10 can be recast as:

$$-\nabla \cdot \boldsymbol{\tau}_R^d = \nabla \cdot [\nu_r(\nabla\tilde{\mathbf{u}} + \nabla^T\tilde{\mathbf{u}})] = \nu_r\nabla^2\tilde{\mathbf{u}} \quad (2.19)$$

where only the deviatoric part of the residual stress tensor is considered. The linear proportionality enforced by the Boussinesq hypothesis dictates a strict local alignment between the principal axes of $\boldsymbol{\tau}_R^d$ and $\tilde{\mathbf{S}}$. While this assumption holds true for many engineering applications, it is notoriously invalid for certain complex flow regimes. Among the various SGS models, the *Smagorinsky model* [127] is one of the most widely used. The eddy viscosity of Equation 2.18 can be assumed as:

$$\nu_r = (C_s\tilde{\Delta})^2\tilde{\mathbf{S}} = (C_s\tilde{\Delta})^2\sqrt{2\tilde{\mathbf{S}}:\tilde{\mathbf{S}}}, \quad (2.20)$$

with $\tilde{\Delta}$ as the filter width, C_s as the Smagorinsky constant, $\tilde{\mathbf{S}}$ is the characteristic filtered stress tensor and the symbol $:$ indicates the Frobenius inner product ($A:B = \sum_{i,j} A_{ij}B_{ij}$). The Smagorinsky constant is flow-dependent, typically ranging from 0.1 to 0.2, though in this study, $C_s = 0.09$ was used based on previous research [114, 128].

Despite its computational efficiency and its capability to accurately capture the globally dissipative character of turbulence, the standard Smagorinsky model suffers from several well-documented limitations:

- the Smagorinsky coefficient (C_s) is strongly flow-dependent, necessitating ad hoc empirical tuning for distinct applications;
- the formulation tends to introduce excessive, spurious subgrid-scale dissipation within attached boundary layers;
- the strictly positive nature of the modelled eddy viscosity solely permits a forward energy cascade, thereby precluding the physical representation of kinetic energy backscatter;
- it enforces a restrictive, and often physically invalid, alignment between the principal axes of the SGS stress tensor and the resolved strain-rate tensor.

A critical manifestation of these shortcomings occurs in the vicinity of solid boundaries. The standard formulation is unable to naturally reduce the eddy

viscosity (Equation 2.20) as the wall is approached. To address this issue, as proposed by Moin and Kim [129] van Driest damping is routinely incorporated to impose the correct asymptotic scaling, forcing the eddy viscosity to vanish at the wall via the following modifying function:

$$(C_s \tilde{\Delta})_{\text{damped}} = C_s \tilde{\Delta} \left[1 - \exp \left(-\frac{y^+}{A} \right) \right], \quad (2.21)$$

In this formulation $y^+ = u_\tau y / \nu$ is the dimensionless wall normal distance, where $u_\tau = \sqrt{\tau_w / \rho}$ represents the friction velocity and τ_w is the local wall shear stress. The parameter A is an empirical damping constant, classically assigned a value of 25. In the broader context of LES, the selection of the filter and the grid resolution is of paramount importance. Implicit filtering is the most widely adopted approach due to its efficiency, as the computational grid itself performs the filtering operation. In accordance with the Nyquist theorem, the mesh acts as a top-hat filter with a cutoff wavenumber $k_c = \pi / \Delta x$, effectively removing all turbulent eddies smaller than the grid spacing. To avoid unphysical results, grid sensitivity studies are essential to verify that the cutoff wavenumber falls safely within the inertial subrange of the energy spectrum, thus guaranteeing that the subgrid-scale model operates within its theoretical limits.

2.2 Numerical Method

This section details the numerical discretisation strategy implemented to solve the governing physical and mathematical models introduced in Section 2.1. The numerical simulations are performed using the UTD-WF code [115], which relies on a second-order, central finite-difference scheme to evaluate spatial derivatives across a Cartesian orthogonal grid. For temporal advancement, the solver employs a fractional-step methodology. Specifically, a low-storage, third-order Runge-Kutta scheme is utilized for the explicit integration of the non-linear convective terms, whereas the linear viscous terms are treated implicitly via a Crank-Nicolson scheme.

To efficiently invert the large, sparse algebraic systems arising from the implicit discretisation of the linear terms, the solver incorporates an approximate factorization technique, thereby drastically reducing the overall computational burden. A projection method is additionally applied to enforce the solenoidal constraint on the velocity field, as dictated by Equation 2.11, simultaneously yielding the updated pressure field. For an exhaustive derivation and discussion of this numerical framework, the reader is directed to the foundational work by Orlandi [130].

A defining feature of the spatial discretisation is the adoption of a staggered grid arrangement, wherein different flow variables are stored at topologically distinct locations within the computational domain. As is well documented [131,

[132], this staggered layout naturally suppresses spurious pressure oscillations—commonly referred to as the “checkerboard” effect—that often plague collocated grid formulations. Moreover, staggering facilitates the use of highly compact stencils for computing spatial derivatives, thereby preserving the formal accuracy of the numerical scheme. As depicted in Figure 2.2, the pressure field is evaluated at the volumetric center of the computational cell. Each velocity component, by contrast, is defined precisely at the centroid of the cell face whose normal vector aligns with the respective velocity direction.

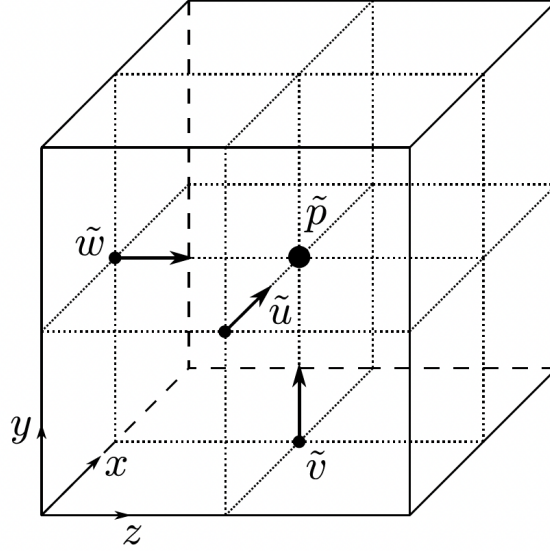


Figure 2.2: Computational grid cell illustrating the spatial arrangement of the flow variables on a staggered mesh. The pressure node (p) is located at the cell center, whereas the velocity components (u, v, w) are defined at the centers of their respective orthogonal faces.

Discretisation scheme

To clearly isolate the distinct numerical treatments applied to the filtered Navier-Stokes equations, the momentum equation (Equation 2.10) can be conveniently recast into an operator framework:

$$\frac{\partial \tilde{\mathbf{u}}}{\partial t} = \mathbf{N}(\tilde{\mathbf{u}}) + \mathbf{L}(\tilde{\mathbf{u}}) + \tilde{\mathbf{f}}(\tilde{\mathbf{u}}) \quad (2.22)$$

Here, the operator $\mathbf{N}(\tilde{\mathbf{u}})$ encapsulates the non-linear convective contributions:

$$\mathbf{N}(\tilde{\mathbf{u}}) = \tilde{\mathbf{u}} \cdot \nabla \tilde{\mathbf{u}} \quad (2.23)$$

Meanwhile, $\mathbf{L}(\tilde{\mathbf{u}})$ aggregates the linear viscous and pressure gradient terms:

$$\mathbf{L}(\tilde{\mathbf{u}}) = \left(\frac{1}{Re} + \frac{1}{Re_r} \right) \nabla^2 \tilde{\mathbf{u}} - \nabla \tilde{p} \quad (2.24)$$

where Re_r denotes the turbulent Reynolds number, defined on the basis of the subgrid-scale eddy viscosity. As previously stated, the external forcing term $\tilde{\mathbf{f}}(\tilde{\mathbf{u}})$ is temporarily neglected in the present numerical discussion; its formal definition and discretisation will be thoroughly detailed in Section 2.4.

Non-linear terms

Temporal advancement of the governing equations is achieved through a hybrid, low-storage, third-order Runge-Kutta (RK3) scheme, originally proposed by Wray [133]. Within this framework, the non-linear convective terms are integrated explicitly, whereas the linear diffusive terms are treated implicitly. This semi-implicit strategy ensures an optimal balance between temporal accuracy and computational efficiency. The "low-storage" designation highlights the scheme's ability to achieve third-order temporal accuracy while allocating only two memory locations per flow variable—equivalent to the memory footprint of a standard second-order scheme. The numerical solution is advanced from the current time level t^n to the subsequent level t^{n+1} via three intermediate substeps. Following this methodology, the solution for a generic velocity component $\tilde{u}$ at the spatial grid node i is updated during the intermediate substep l according to:

$$\tilde{u}_i^{l+1} = \tilde{u}_i^l + \rho_l \Delta t N_i(\tilde{\mathbf{u}}^l) + \gamma_l \Delta t N_i(\tilde{\mathbf{u}}^{l-1}), \quad l = 0, \dots, 2 \quad (2.25)$$

where $\tilde{u}_i^0 = \tilde{u}_i^n$ denotes the solution at the current time step t^n , and $\tilde{u}_i^3 = \tilde{u}_i^{n+1}$ represents the fully updated solution at the new time step t^{n+1} . The operator N_i defines the spatially discretised non-linear convective term, evaluated using the velocity field at the intermediate substep l . The integration coefficients ρ_l and γ_l are derived to satisfy a specific set of constraints inherent to the method [130], namely:

- the method should use no more than two memory locations;
- the new approximation must be consistent with a Taylor series expansion;
- the operations must be cyclic, ensuring that all quantities needed for the next time step are available by the end of the current step.

To ensure the scheme is self-starting—meaning it does not require flow field information from time levels prior to t^n —the initial coefficient ρ_0 is strictly constrained to zero. By recursively summing Equation 2.25 across all substeps l and matching the resulting terms with the third-order Taylor series expansion, a system governing the unknown coefficients is established. The specific set of coefficients adopted in this study is defined as follows:

$$\rho_0 = 0, \quad \rho_1 = -\frac{17}{60}, \quad \rho_2 = -\frac{5}{12}, \quad (2.26a)$$

$$\gamma_0 = +\frac{8}{15}, \quad \gamma_1 = +\frac{5}{12}, \quad \gamma_2 = +\frac{3}{4}. \quad (2.26b)$$

Linear terms

The implicit temporal integration of the linear terms is executed via a Crank-Nicolson scheme, which is formally centered at the midpoint of each Runge-Kutta substep, $t^{l+1/2}$. To guarantee strict temporal synchronization between the explicit advancement of the non-linear convective terms and the implicit treatment of the diffusive terms, the fractional time-step increments α_l , defined such that $\alpha_l \Delta t = t^{l+1} - t^l$, must satisfy the following algebraic constraint:

$$\alpha_l = \rho_l + \gamma_l \quad (2.27)$$

The fully discretised formulation of the filtered Navier-Stokes equations for the i -th velocity component is expressed as:

$$\begin{aligned} \frac{\tilde{u}_i^{l+1} - \tilde{u}_i^l}{\Delta t} + \rho_l N_i(\tilde{\mathbf{u}}^l) + \gamma_l N_i(\tilde{\mathbf{u}}^{l-1}) = \\ = -\alpha_l \left. \frac{\delta \tilde{p}}{\delta x_i} \right|^{l+1/2} + \alpha_l \left(\frac{1}{Re} + \frac{1}{Re_r} \right) L_{jj} \left(\frac{\tilde{u}_i^{l+1} + \tilde{u}_i^l}{2} \right) \end{aligned} \quad (2.28)$$

where the operator $\frac{\delta}{\delta x_i}$ designates the discrete spatial gradient, Re_r corresponds to the subgrid-scale turbulent Reynolds number based on the local eddy viscosity, and L_{jj} denotes the discrete Laplacian operator. Both spatial differential operators are evaluated utilizing a strictly second-order, central finite-difference scheme.

Approximate factorization and pressure correction

Direct temporal integration of Equation 2.28 is computationally impractical due to the inherent difficulty in evaluating the pressure gradient at the intermediate time $t^{l+1/2}$. At this stage, the pressure field is known only at the preceding time step t^l . Evaluating the momentum equations using solely p^l would yield an intermediate velocity field $\hat{\mathbf{u}}$ that directly violates the solenoidal constraint. To circumvent this issue, the *fractional-step method*, popularized by Moin and Kim [129], is employed. This paradigm first computes a predictor, non-solenoidal velocity field utilizing the pressure from the current time step. Subsequently, a scalar pseudo-pressure field is introduced to enforce continuity, effectively projecting the predicted velocity field onto a divergence-free subspace, after which the actual pressure field is updated.

By substituting the intermediate velocity $\hat{\mathbf{u}}$ for $\tilde{\mathbf{u}}^{l+1}$ and defining the velocity increment $\Delta \tilde{u}_i := \hat{u}_i - \tilde{u}_i^l$, Equation 2.28 is reformulated as:

$$\begin{aligned} \Delta \tilde{u}_i + \alpha_l \Delta t \left(\frac{1}{Re} + \frac{1}{Re_r} \right) L_{jj} \left(\frac{\Delta \tilde{u}_i}{2} \right) = -\alpha_l \Delta t \left. \frac{\delta \tilde{p}}{\delta x_i} \right|_l \\ - \rho_l \Delta t N_i(\tilde{\mathbf{u}}^l) - \gamma_l \Delta t N_i(\tilde{\mathbf{u}}^{l-1}) + \alpha_l \Delta t \left(\frac{1}{Re} + \frac{1}{Re_r} \right) L_{jj}(\tilde{u}_i^l) \end{aligned} \quad (2.29)$$

which can be compactly expressed in operator form as:

$$\left[\delta_{jj} + \frac{\alpha_l \Delta t}{2} \left(\frac{1}{Re} + \frac{1}{Re_r} \right) L_{jj} \right] \Delta \tilde{u}_i = RHS_i \quad (2.30)$$

where RHS_i aggregates all the explicit terms on the right-hand side of Equation 2.29, and δ_{jj} denotes the Kronecker delta.

Due to the second-order central difference stencil employed for the spatial derivatives within the Laplace operator, the implicit matrix arising from Equation 2.30 is a large, sparse banded matrix. Direct inversion of this matrix for a computational domain comprising N grid points would necessitate $\mathcal{O}(N^3)$ floating-point operations, imposing a prohibitive computational burden even on relatively coarse grids. To efficiently circumvent this bottleneck, the solver implements an approximate factorization technique, splitting the three-dimensional implicit operator into three sequential one-dimensional inversions:

$$\left[\delta_{jj} + \frac{\alpha_l \Delta t}{2} \left(\frac{1}{Re} + \frac{1}{Re_r} \right) L_{11} \right] \underline{\underline{\Delta \tilde{u}}}_i = RHS_i, \quad (2.31a)$$

$$\left[\delta_{jj} + \frac{\alpha_l \Delta t}{2} \left(\frac{1}{Re} + \frac{1}{Re_r} \right) L_{22} \right] \underline{\underline{\Delta \tilde{u}}}_i = \underline{\underline{\Delta \tilde{u}}}_i, \quad (2.31b)$$

$$\left[\delta_{jj} + \frac{\alpha_l \Delta t}{2} \left(\frac{1}{Re} + \frac{1}{Re_r} \right) L_{33} \right] \Delta \tilde{u}_i = \underline{\underline{\Delta \tilde{u}}}_i. \quad (2.31c)$$

Here, L_{11} , L_{22} , and L_{33} denote the one-dimensional discrete Laplace operators along the respective Cartesian coordinate directions, while $\underline{\underline{\Delta \tilde{u}}}_i$ and $\underline{\underline{\Delta \tilde{u}}}_i$ represent intermediate auxiliary velocity increments. This algebraic splitting reduces the complex three-dimensional inversion to the sequential solution of three strictly tridiagonal matrices per grid point. These can be solved highly efficiently via the Thomas algorithm, substantially reducing the operation count to $3N$. It is important to acknowledge, however, that this approximate factorization introduces a splitting error that formally degrades the temporal accuracy of the implicit viscous integration to second order.

Following the predictor step, the intermediate, non-solenoidal velocity field $\hat{u}_i = \Delta \tilde{u}_i - \tilde{u}_i^l$ is fully determined. To satisfy the continuity constraint, a scalar pseudo-pressure ϕ is introduced to project $\hat{\mathbf{u}}$ onto a divergence-free space:

$$\tilde{\mathbf{u}}^{l+1} = \hat{\mathbf{u}} - \Delta t \nabla \phi \quad (2.32)$$

By taking the divergence of Equation 2.32 and enforcing the solenoidal condition $\nabla \cdot \tilde{\mathbf{u}}^{l+1} = 0$, the classical Poisson equation for the pseudo-pressure is recovered:

$$\nabla^2 \phi = \frac{1}{\Delta t} \nabla \cdot \hat{\mathbf{u}} \quad (2.33)$$

Given the assumption of periodicity in the spanwise direction and inflow-outflow boundary conditions in the streamwise direction, Equation 2.33 can

be efficiently inverted using a Fourier decomposition approach in the x and z directions.

The kinematic boundary conditions naturally enforce homogeneous Neumann boundary conditions on the Poisson equation. The pseudo-pressure field is thus determined only up to an arbitrary additive constant. Because the flow dynamics are driven solely by pressure gradients rather than absolute pressure levels, this mathematical indeterminacy is physically inconsequential. Numerically, it is resolved by subtracting the spatial mean of the pseudo-pressure from the entire field at each computational time step.

Once the pseudo-pressure at the cell centers is computed, the pressure field at the new time step t^{l+1} must be updated for thermodynamic and dynamic consistency. By substituting Equation 2.32 back into the original momentum formulation (Equation 2.28), the consistent pressure update is given by:

$$p^{l+1} = p^l + \phi - \frac{\alpha_l \Delta t}{2} \left(\frac{1}{Re} + \frac{1}{Re_r} \right) L_{jj} \phi \quad (2.34)$$

Ultimately, this pressure-correction architecture underscores the central role of pressure in incompressible flows: it acts as a kinematic Lagrange multiplier that instantaneously guarantees mass conservation, ensuring that the discrete numerical framework remains a faithful representation of the continuous physical model.

Stability and accuracy of the numerical scheme

This hybrid third-order Runge-Kutta/Crank-Nicolson scheme formally yields second-order accuracy in both time and space, primarily due to splitting errors inherent to the fractional-step method and the underlying spatial discretisation. However, this theoretical reduction is offset by the scheme's minimal memory footprint and robust stability properties. Because the convective terms are integrated explicitly, the allowable time step is strictly governed by the Courant-Friedrichs-Lewy (CFL) stability criterion [134]. Physically, this constraint ensures that a fluid particle cannot traverse a distance greater than the local computational cell within a single time step:

$$CFL = \max_{i=1,2,3} \left| \frac{\tilde{u}_i \Delta t}{\Delta x_i} \right| \leq CFL_{max} \quad (2.35)$$

The maximum allowable Courant number, CFL_{max} , is an intrinsic property of the chosen explicit numerical scheme and imposes a strict upper bound on the allowable time step Δt . In this context, the multi-stage architecture of the RK3 method affords a considerably expanded stability region. Whereas standard explicit methods are typically constrained by a theoretical limit of $CFL_{max} \leq 1$, the three-stage Runge-Kutta scheme systematically relaxes this restriction. Specifically, for a linear advection problem, the maximum permissible Courant number is extended to:

$$CFL_{max} = \sqrt{3}. \quad (2.36)$$

In the present work, however, the primary restriction on the allowable time step stems from the turbine modelling approach detailed in Section 2.4. As highlighted in the literature [135, 136], it is widely recommended to constrain the time step such that the turbine blade tip traverses no more than one computational grid cell per time increment. This kinematic condition, dictated by the rotor's angular velocity, is particularly stringent and formally imposes:

$$CFL \leq \frac{U\Delta t}{\Delta x} = \frac{U(\Delta x/\Omega R)}{\Delta x} = \frac{1}{TSR} \quad (2.37)$$

where $TSR = \Omega R/U$ denotes the *tip speed ratio*, Ω is the rotor's angular velocity, R is the turbine radius, and U is the characteristic inflow velocity. Nevertheless, the robust stability properties of the overall numerical scheme permit the use of slightly larger time steps, although the operating Courant number in the present simulations rarely exceeds $2/TSR$.

The implicit integration of the viscous and subgrid-scale diffusive terms also alleviates additional stability restrictions that become particularly prohibitive at low Reynolds numbers. For instance, the classical explicit viscous stability limit [137] dictates that:

$$\frac{\Delta t}{\Delta x^2 Re} \leq \frac{1}{2n} \quad (2.38)$$

where n represents the spatial dimensionality of the problem. Physically, this condition ensures that viscous diffusion does not propagate information beyond a single grid cell Δx within a given time step Δt . By treating these diffusive terms implicitly, this severe time-step restriction is effectively bypassed, further enhancing the computational efficiency of the solver.

2.3 Immersed Boundary Method

To represent solid interfaces within the computational domain—specifically, the wind turbine tower and nacelle—the present numerical framework employs the Immersed Boundary Method (IBM) [138]. This approach effectively circumvents the need for computationally expensive and complex body-fitted curvilinear meshes. Specifically, a formulation analogous to the one proposed by Orlandi and Leonardi [139] has been adopted.

The implementation of the IBM entails enforcing a zero-velocity condition at all grid nodes located strictly within the solid boundaries. Concurrently, the discretisation of the spatial derivatives is suitably modified for the fluid nodes immediately adjacent to the solid interface (as illustrated in Figure 2.3). Rather than relying on the uniform grid spacing between interior and exterior nodes, this method explicitly incorporates the exact geometric distance between the actual surface of the immersed body and the first active fluid node outside it. This precise spatial treatment prevents the numerical degradation and unphysical flow features typically associated with representing a solid boundary via

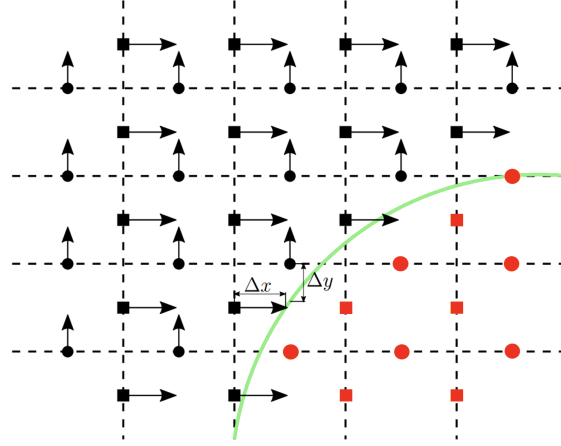


Figure 2.3: Two-dimensional schematic of the staggered grid layout in the vicinity of an immersed solid boundary. The horizontal and vertical velocity components (represented by arrows) are evaluated at the active fluid nodes (**black** markers). Conversely, velocity is strictly set to zero at nodes enclosed within the solid body (**red** markers). For fluid nodes immediately adjacent to the boundary, spatial derivatives are corrected using the exact local distances, Δx and Δy , to the actual solid interface (**green** line).

a fictitious, step-like approximation. This IBM formulation has been verified across a range of fluid dynamic configurations, and has demonstrated accurate representation of wind turbine structural components in previous studies [114].

While the IBM effectively models macroscopic bluff bodies like the tower and nacelle, applying it directly to the rotating blades is computationally prohibitive. Explicitly resolving streamlined lifting surfaces at high Reynolds numbers would necessitate an impractically fine mesh to capture boundary layer dynamics, a challenge further compounded by the severe computational cost of a moving-boundary formulation to track the unsteady solid-fluid interface [140]. To achieve an optimal balance between computational efficiency and aerodynamic fidelity, the physical rotor must be replaced by dedicated parameterization techniques, which will be the focus of the following section.

2.4 Turbine Model

The necessity for such parameterization stems from the inability of current computational resources to simultaneously resolve microscopic blade boundary layers and macroscopic wake structures. To make LES tractable, the turbine's aerodynamic impact is instead represented through equivalent body forces projected onto the fluid domain. The two most established methodologies for this task are the Actuator Disc Model (ADM) and the Actuator Line Model

(ALM). The ADM smears forces over the entire swept rotor area, offering computational efficiency ideal for large wind farms [17, 141, 142]. The ALM, by contrast, concentrates forces along discrete, rotating lines, yielding superior accuracy for near-wake vortex dynamics at a higher computational cost [136, 143].

The following subsections detail the ADM and ALM, establishing the framework for a novel methodology developed in this thesis: the Rotating Actuator Disc Model (RADM). By explicitly incorporating blade rotation into the classic ADM, the RADM aims to deliver a more realistic wake description without the heavy computational burden of the ALM.

Actuator Line Model

To represent the rotor blades within the fluid domain, the code utilizes the widely adopted Actuator Line Model (ALM) introduced by Sørensen and Shen [144]. This approach evaluates the aerodynamic forces exerted by the blades on the flow using blade element theory. These forces are subsequently distributed as body forces along rotating lines that trace the exact kinematic positions of the blades.

Based on blade element analysis, for a 2D airfoil section positioned at a radial distance r from the hub center, the lift force F_l and drag force F_d per unit length are formulated as:

$$F_l = \frac{1}{2} \rho u_{rel}^2 C_l(\alpha) c F, \quad (2.39)$$

$$F_d = \frac{1}{2} \rho u_{rel}^2 C_d(\alpha) c F, \quad (2.40)$$

where ρ is the fluid density, c is the local chord length, u_{rel} is the relative incoming velocity, α is the local angle of attack, and F represents the Prandtl tip loss correction factor. For each blade segment, the relative inflow velocity u_{rel} and the angle of attack α are dynamically computed, as illustrated in Figure 2.4. The pre-computed aerodynamic lookup tables for 2D airfoils cannot intrinsically account for the three-dimensional effects of circulation distribution along a finite blade. To mitigate the typical overprediction of loads at the blade tip and root, the model incorporates a modified Prandtl tip correction factor [145] into Equation 2.39 and Equation 2.40, defined as:

$$F = \frac{4}{\pi^2} \cos^{-1} \left[\exp \left(\frac{gB(r-R)}{2r \sin(\alpha + \phi)} \right) \right] \cos^{-1} \left[\exp \left(\frac{gB(R_h - r)}{2r \sin(\alpha + \phi)} \right) \right], \quad (2.41)$$

with the function g given by:

$$g = \exp(-0.125(B \cdot \lambda - 21.0)) + 0.1, \quad (2.42)$$

where B is the number of blades, R is the rotor radius, and R_h is the hub radius, and $\lambda = \omega R / U_\infty$ is the tip speed ratio (TSR), with ω being the angular

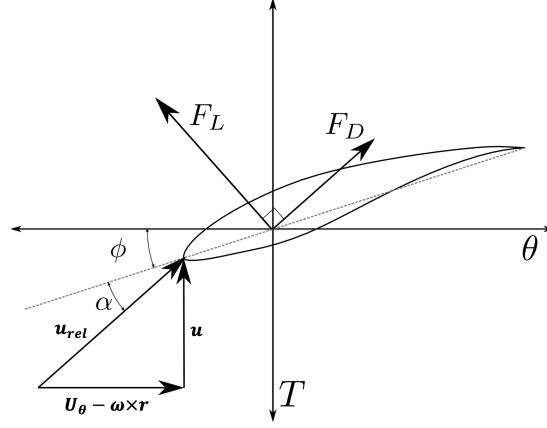


Figure 2.4: Cross-sectional schematic of the rotor blade, where the vector θ represents the azimuthal direction and T indicates the thrust force. The parameters ω and r denote the angular velocity and local radial position, respectively, while ϕ defines the local twist angle.

velocity of the rotor and U_{∞} the undisturbed free-stream velocity. The local aerodynamic force vector, $\mathbf{f}^{aero}$, is then projected onto the surrounding flow field. To prevent numerical instabilities associated with the application of singular, concentrated forces on a discrete grid, a 2D Gaussian regularization kernel, η , is employed to smoothly smear these forces within a cylindrical volume surrounding each actuator line (see Figure 2.5). Thus, the body force vector $\tilde{\mathbf{f}}$ acting on the fluid nodes is expressed as:

$$\tilde{\mathbf{f}} = -\mathbf{f}^{aero}\eta = -\mathbf{f}^{aero}\frac{1}{\epsilon^2\pi}\exp\left[-\left(\frac{r_{\eta}}{\epsilon}\right)^2\right], \quad (2.43)$$

where r_{η} is the local radial distance of a computational grid point from the actuator line, and ϵ represents the spreading parameter.

Extensive literature demonstrates that the spreading parameter ϵ critically influences both the resolved flow field and the resulting aerodynamic loads. Troldborg [146] established a direct dependency between ϵ and the local mesh spacing, suggesting a lower bound of $\epsilon/\Delta \geq 2$ to suppress unphysical numerical oscillations. More recent studies, [147, 148], however, advocate linking ϵ to the local chord length c . Specifically, Martínez-Tossas et al. [148] concluded that while ϵ should scale with Δ for grid resolutions coarser than the chord, it should scale with c when the grid spacing is smaller than the chord. In the present simulations, even for the finest meshes where $\Delta/c < 1$, the spreading parameter is scaled proportionally to the grid spacing, strictly adhering to the classical constraint $\epsilon/\Delta = 2$. This conservative choice was mandated by the onset of severe numerical instabilities observed when further reducing the spreading radius.

Finally, to estimate the aerodynamic pitching moment acting on the blades—which is essential for evaluating the structural dynamics—a similar blade element



Figure 2.5: Scheme of the Actuator Line Model, where the Gaussian kernel η distributes the aerodynamic forces around the actuator lines.

approach is employed. The pitching moment per unit length, referenced to the airfoil's quarter-chord point, is calculated as:

$$M^{aero} = \frac{1}{2} \rho u_{rel}^2 c^2 C_m(\alpha) F \quad (2.44)$$

where C_m denotes the local pitching moment coefficient.

Actuator Disc Model

Within the ADM framework, the aerodynamic forces are computed exactly as in Equations 2.39 and 2.40. However, rather than being concentrated along discrete lines, these forces are spread across the rotor area using a two-dimensional Gaussian kernel:

$$\eta = \exp \left[- \left(\frac{x - x_c}{\epsilon} \right)^2 \right] \exp \left[- \left(\frac{\phi - \theta}{2\pi} \right)^2 \right], \quad (2.45)$$

$$\tilde{\mathbf{f}} = -\mathbf{f}^{aero} \eta^* = -\mathbf{f}^{aero} \frac{\eta}{\iint_A \eta \, dA}, \quad (2.46)$$

where $x - x_c$ denotes the streamwise distance of a given grid point from the rotor plane location x_c , and ϵ is a spreading parameter that dictates the axial thickness of the actuator disc. The term $\phi - \theta$ represents the azimuthal distance from the current angular position of the blade θ . The force distribution over the annular swept area is therefore not uniform; instead, it depends explicitly on both the radial and azimuthal coordinates of each grid point. As the blade advances in time, the aerodynamic force evaluation follows its exact kinematic position, effectively generating a rotating force distribution over the disc.

By distributing the forces over a broader spatial region, the ADM substantially mitigates the numerical stability issues often associated with the

concentrated singular forces of the ALM. The enhanced spreading also yields a globally smoother force field within the rotor area. This increased smoothness relaxes the numerical stability constraints, allowing for the use of larger time steps and substantially reducing the overall computational cost—which remains the primary drawback of the standard ALM approach. However, this gain in computational efficiency inevitably comes at the expense of localized aerodynamic fidelity, resulting in a reduced capability to resolve fine near-wake details, such as discrete tip vortices.

Rotor dynamics

The low-speed shaft angular velocity ω evolves over time according to a single-degree-of-freedom rotational dynamic equation:

$$I_d \cdot \dot{\omega} = T_{aero} - T_{gen}, \quad (2.47)$$

where I_d represents the total rotational inertia of the drivetrain, encompassing the combined inertia of the rotor and the generator, T_{aero} is the driving aerodynamic torque generated by the blades, and T_{gen} is the resistive torque exerted by the generator.

In this study, the analysis focuses on a variable-speed wind turbine operating in Region II (see Figure 2.6). In this operational regime, a standard quadratic control law is applied to maximise power extraction, as detailed by Njiri et al. [149]. This control law is expressed as:

$$T_{gen} = k_{gen}\omega^2, \quad (2.48)$$

where the torque gain k_{gen} is a function of the optimal conditions of the wind turbine.

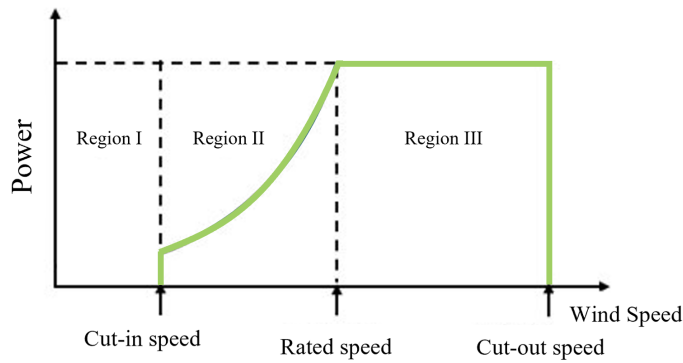


Figure 2.6: Generalised power curve of a wind turbine. Region I: cut-in phase (zero power output). Region II: variable-speed optimisation. Region III: rated power, limited by mechanical and electrical constraints.

2.5 Structural Model and FSI Coupling

This section outlines the structural model and the Fluid–Structure Interaction (FSI) methodology developed to evaluate the aeroelastic response of the wind turbine. The framework is designed to capture the essential fluid-solid coupling mechanisms without appreciably increasing the computational cost of the underlying fluid solver.

The discussion is divided into two primary components. The first subsection presents the structural model, focusing exclusively on the dynamics of the highly flexible rotor blades. It introduces the modal representation of the blades as rotating Euler-Bernoulli cantilevered beams and defines the governing structural dynamic equations, explicitly incorporating the apparent inertial contributions induced by the moving frame of reference. The second subsection details the FSI coupling strategy. It describes the parallel staggered, two-way partitioned algorithm implemented to interface the LES and the structural solver, outlining the precise velocity kinematics and the formulation of the effective angle of attack modified by the instantaneous structural deformations.

Structural model

From an aerodynamic perspective, the rotor blades are the most flexible components of a wind turbine. Previous studies have demonstrated that their modal properties overwhelmingly dictate the aeroelastic dynamics of the entire system [150, 151]. Analysing the isolated blades provides sufficient accuracy to estimate critical aeroelastic phenomena, such as the flutter velocity, for the complete structure [152]. Given that the tower and shaft exhibit comparatively negligible deflections due to their high structural stiffness, the aeroelastic model formulated in this study focuses exclusively on the blade dynamics.

The structural framework adopted herein builds upon the methodology presented by Della Posta et al. [46, 153]. To simulate operational conditions, the blades are modelled as rotating Euler-Bernoulli cantilever beams rigidly clamped at the hub. The formulation assumes small deformations relative to a local moving frame of reference (FOR). The blade's neutral axis, defined to pass through the quarter-chord point, corresponds to the pitch axis direction X_1 . The out-of-plane flapwise motion aligns with the X_2 axis, oriented in the positive streamwise direction, while the in-plane edgewise direction X_3 is defined to complete a right-handed Cartesian coordinate system, as illustrated in Figure 2.7. Under the assumption of linear structural behavior, the generalized elastic displacement vector $\mathbf{d}$, encompassing both translational (d_i) and rotational (θ_i) degrees of freedom (DoFs), is projected onto a reduced modal basis along the neutral axis X_1 :

$$\mathbf{d}(X_1, t) = \sum_{m=1}^M q_m(t) \boldsymbol{\psi}^m(X_1), \quad (2.49)$$

where $\psi^m(X_1)$ denotes the m -th elastic mode shape extracted from the structural modal analysis, $q_m(t)$ is the corresponding time-dependent modal coordinate, and M is the total number of retained modes.

The generalized inertial coupling in the modal space incorporates the methodology developed by Reschke [154] and adapted for wind turbine applications by Della Posta et al. [46]. The two-way coupling algorithm assumes that the overall rotor inertia remains unaffected by the instantaneous blade deformations. The governing equation for the structural dynamics evaluates to:

$$\begin{aligned} \mathbf{M}\ddot{\mathbf{q}} + [\mathbf{D} + \mathbf{D}^{Co}(\Omega)]\dot{\mathbf{q}} + [\mathbf{K} + \mathbf{K}^c(\Omega) + \mathbf{K}^{Eu}(\dot{\Omega})]\mathbf{q} \\ = \mathbf{e} + \mathbf{e}^c(\Omega) + \mathbf{e}^{Eu}(\dot{\Omega}), \end{aligned} \quad (2.50)$$

where $\mathbf{M}$, $\mathbf{D}$, and $\mathbf{K}$ denote the purely structural modal mass, damping, and stiffness matrices, respectively, and $\mathbf{e}$ represents the external aerodynamic loads projected onto the modal basis. The additional matrices and forcing vectors arise from the non-inertial moving FOR: the superscripts *Co*, *c*, and *Eu* correspond to the Coriolis, centrifugal, and Euler inertial contributions, respectively. These apparent inertial terms are evaluated discretely using only the mode shapes and structural properties derived from the Finite Element Method (FEM) model, following the approach of Saltari et al. [155].

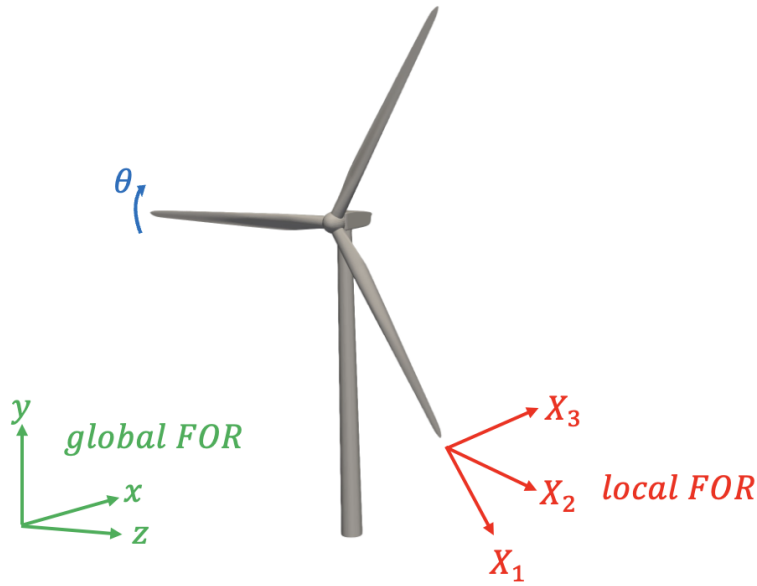


Figure 2.7: Schematic representation of the frames of reference utilized for the CFD and CSD simulations.

The underlying modal analysis utilizes a 6-DoFs beam FEM model, assuming Euler-Bernoulli behavior for the X_2 and X_3 bending directions, alongside

linear shape functions for axial and torsional deformations. The structural matrices are assembled incorporating the local pre-twist, and a lumped-mass representation is adopted to accurately account for the local center-of-mass offsets relative to the neutral axis X_1 . Finally, the temporal integration of Equation 2.50 is performed using the generalized- α method [156], providing a second-order accurate and unconditionally stable solution for linear dynamics.

Fluid-Structure Interaction model

The proposed aeroelastic model relies on a two-way, loose partitioned coupling strategy based on a parallel staggered algorithm. It employs the ALM sectional approach, dynamically coupling two independent solvers (fluid and structural) that exchange information once at the beginning of each RK time substep. This restriction ensures optimal computational efficiency by avoiding consecutive fluid-solid re-evaluations. Because the stringent time step required by the LES fluid solver (e.g., $\Delta t_F \approx \mathcal{O}(10^{-3})$ s) yields a sampling frequency that far exceeds the highest relevant natural frequencies of the structural blade modes (typically $f < 20$ Hz), the method remains stable and accurate without the need for subcycling.

At each RK substep, the local angle of attack (AoA) and relative velocity are modified according to the instantaneous blade motion provided by the structural dynamics. Specifically, the relative fluid velocity for a rotating blade section is defined as:

$$\mathbf{u}_{rel} = \mathbf{u}_{abs} - \boldsymbol{\Omega} \times \mathbf{r}_{OP} - \mathbf{u}_{def}, \quad (2.51)$$

where $\mathbf{u}_{abs}$ is the filtered fluid velocity sampled from the LES solver at the actuator line, $\mathbf{r}_{OP}$ is the general radial vector pointing to the considered section, $\boldsymbol{\Omega}$ is the rotor rotational velocity, and $\mathbf{u}_{def} = \dot{\mathbf{d}}$ is the local translational deformation velocity of the structure.

To accurately evaluate the aeroelastic response, the complete elastic state of the blade is fed back to the fluid solver. This encompasses not only the translational deformation velocities but also the local angular deformations. In particular, the torsional dynamics must be explicitly considered, as the instantaneous torsional deformation angle directly alters the local incidence of the blade, directly impacting the generated aerodynamic forces.

The effective AoA α used to determine the aerodynamic load coefficients via lookup tables is then computed as:

$$\alpha = \text{atan} \left(-\frac{\mathbf{u}_{rel} \cdot \mathbf{X}_2}{\mathbf{u}_{rel} \cdot \mathbf{X}_3} \right) - \phi = \text{atan} \left[\frac{(\mathbf{u}_{abs} - \mathbf{u}_{def}) \cdot \mathbf{X}_2}{\Omega r - (\mathbf{u}_{abs} - \mathbf{u}_{def}) \cdot \mathbf{X}_3} \right] - \phi, \quad (2.52)$$

where ϕ is the local structural pre-twist angle of the blade, θ_t represents the instantaneous torsional deformation angle, and $\mathbf{X}_i$ are the unit vectors of the relative FOR rotating with the structure. In this formulation, $v_2 = \mathbf{u}_{def} \cdot \mathbf{X}_2$

represents the flapwise deformation velocity component, and $v_3 = \mathbf{u}_{def} \cdot \mathbf{X}_3$ represents the edgewise component. The updated aerodynamic forces are then passed back to both the ALM source terms and the structural solver to advance the system to the next time step.

A key advantage of this coupling procedure is the one-dimensional sectional formulation of the ALM. Interpolating structural motions and aerodynamic forces along 1D lines avoids the remeshing and interface-tracking costs that body-conformal approaches necessarily incur.

2.6 Atmospheric Boundary Layer

To accurately reproduce the realistic operational environment of the wind turbine, the incoming flow is modelled as an Atmospheric Boundary Layer. The inclusion of a realistic ABL is of paramount importance; extensive literature demonstrates that atmospheric features such as the Coriolis-induced wind veer and ambient turbulence intensity profoundly influence both the aerodynamic performance of the rotor and the morphological evolution of its wake [55, 65, 63, 64].

From a thermodynamic perspective, the present study considers a neutrally stratified ABL. Under neutral stability conditions, the vertical gradient of potential temperature is zero. Thermal stratification and buoyancy effects are therefore entirely neglected. This underlying assumption allows the energy equation to be decoupled from the momentum equations, thereby omitting any thermal source terms from the fluid solver.

Within the fluid solver, the macroscopic atmospheric forcing is introduced as an additional momentum source term, $\mathbf{f}_{ABL}$, explicitly added to the filtered Navier-Stokes equations. This term accounts for both the geostrophic pressure gradient and the Coriolis force, alongside a volume-averaged flow controller, and is formulated as:

$$\mathbf{f}_{ABL} = \frac{1}{Ro} [\mathbf{e}_2 \times (\mathbf{u} - \mathbf{u}_G)] + \mathbf{f}_{PI}, \quad (2.53)$$

where $\mathbf{u}$ is the resolved fluid velocity vector and $\mathbf{u}_G$ represents the geostrophic velocity vector driven by the synoptic-scale pressure gradient. The parameter $Ro = \frac{u_G}{f_c D}$ is the Rossby number, formulated using the geostrophic wind magnitude $u_G = \|\mathbf{u}_G\|$, the Coriolis frequency f_c , and a reference length scale D . The unit vector $\mathbf{e}_2$ denotes the vertical direction in the computational domain (aligned with the y -axis). Finally, $\mathbf{f}_{PI}$ is a Proportional-Integral (PI) forcing term, dynamically adjusted during the simulation to drive the planar-averaged wind velocity to a desired target value at a specific reference height. The first term on the right-hand side of Equation 2.53 intrinsically balances the Coriolis acceleration and the geostrophic forcing. This three-way force balance drives the formation of the atmospheric Ekman layer [59], characterised by the classic

Ekman spiral, wherein the mean wind magnitude decreases and its direction progressively rotates as it approaches the ground. Because fully developed, quasi-steady atmospheric turbulence cannot be generated instantaneously, a precursor simulation technique is employed. A concurrent, standalone LES domain with periodic boundary conditions is driven by $\mathbf{f}_{ABL}$ to establish a statistically stationary Ekman layer.

While the Ekman spiral is physically accurate, the unconstrained natural wind veer poses a numerical challenge: it would result in an unpredictable misalignment between the incoming flow at the turbine hub height and the streamwise axis of the main computational domain. To circumvent this issue and enforce a zero spanwise velocity component at hub height, a dynamic controller approach originally introduced by Sescu and Meneveau [116] is implemented. This method introduces the dynamic forcing term $\mathbf{f}_{PI}$ in the precursor simulation, which acts as an artificial body force that induces a counterclockwise rotation of the velocity field in the horizontal plane, imposing the following source terms:

$$\mathbf{f}_{PI} = \begin{cases} f_{PI,1} = +\omega_{PI}u_3 \\ f_{PI,2} = 0 \\ f_{PI,3} = -\omega_{PI}u_1 \end{cases} \quad (2.54)$$

where $\omega_{PI}(t)$ denotes the time-dependent control action. The instantaneous mean flow rotation is quantified by the horizontal flow angle:

$$\theta(t) = \tan^{-1} \left(\frac{\langle u_3 \rangle}{\langle u_1 \rangle} \right), \quad (2.55)$$

with $\langle u_1 \rangle$ and $\langle u_3 \rangle$ denoting the horizontally-averaged streamwise and spanwise velocities at hub height, respectively. The Proportional-Integral (PI) control law regulating the rotation is expressed as:

$$\omega_{PI}(t) = K_P e(t) + K_I \int e(t) dt, \quad (2.56)$$

where K_P and K_I are empirically determined tuning coefficients corresponding to the proportional and integral gains of the controller, respectively, and $e(t) = \theta_{desired} - \theta(t)$ is the flow angle error, with $\theta_{desired} = 0$ to achieve perfect streamwise alignment. The complete architecture of this feedback loop is illustrated in Figure 2.8. During the active control phase, the magnitude of the geostrophic wind $u_G = \sqrt{u_{g1}^2 + u_{g3}^2}$ is held strictly constant. Once the error $e(t)$ falls below a prescribed strict threshold ($\theta_{threshold}$), the PI controller is deactivated. The resulting fully developed, yaw-aligned Ekman layer is then extracted to provide the unsteady inflow boundary conditions for the main wind turbine domain.

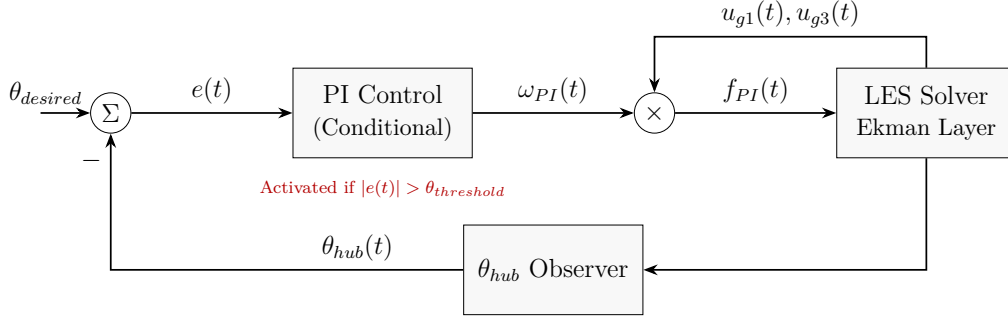


Figure 2.8: Control loop for yaw alignment in an LES-resolved Ekman layer.

2.7 Data-Driven Decompositions and Energy Budgets

Proper Orthogonal Decomposition

Turbulent flows are characterised by coherent spatio-temporal structures. The Proper Orthogonal Decomposition (POD) is a powerful, statistically-based technique designed to extract these dominant organised features from time-resolved datasets, such as those generated by LES.

Mathematically, the space-only variant of the POD [157] treats the unsteady flow field $\mathbf{q}(\mathbf{x}, t)$ as a realization of a stochastic process. The objective is to identify a deterministic spatial basis function, or mode, $\phi(\mathbf{x})$ that provides an optimal approximation of the flow field by maximising its projection onto the dataset. Using standard variational calculus, this maximisation problem can be recast as a Fredholm eigenvalue problem:

$$\int_{\Omega} \mathbf{C}(\mathbf{x}, \mathbf{x}') \mathbf{W}(\mathbf{x}') \phi(\mathbf{x}') d\mathbf{x}' = \lambda \phi(\mathbf{x}), \quad (2.57)$$

where Ω is the spatial domain, $\mathbf{W}(\mathbf{x})$ is a positive-definite Hermitian weight tensor, and $\mathbf{C}(\mathbf{x}, \mathbf{x}') = E\{\mathbf{q}(\mathbf{x}, t) \mathbf{q}^*(\mathbf{x}', t)\}$ is the two-point spatial correlation tensor, with $E\{\cdot\}$ denoting the expectation (time-average) operator.

According to Hilbert-Schmidt theory, Equation 2.57 yields a countably infinite set of orthogonal eigenfunctions $\phi_j(\mathbf{x})$ and corresponding real, non-negative eigenvalues λ_j . These eigenvalues are intrinsically ordered such that $\lambda_1 \geq \lambda_2 \geq \dots \geq 0$, meaning that the first mode captures the maximum possible turbulent kinetic energy of the flow. The unsteady flow field can thus be decomposed into a linear combination of these spatial modes and time-dependent amplitude coefficients $a_j(t)$:

$$\mathbf{q}(\mathbf{x}, t) = \sum_{j=1}^{\infty} a_j(t) \phi_j(\mathbf{x}). \quad (2.58)$$

In practical CFD applications, the flow field is discrete in both space and time. To perform the POD, the dataset is reorganised into a snapshot matrix

$\mathbf{Q} \in \mathbf{R}^{N \times M}$, where M is the number of instantaneous snapshots and N represents the spatial degrees of freedom (e.g., the three velocity components evaluated at every grid point). Each column of $\mathbf{Q}$ represents a single flow realization $\mathbf{q}^i$:

$$\mathbf{Q} = \begin{bmatrix} | & | & & | \\ \mathbf{q}_1 & \mathbf{q}_2 & \dots & \mathbf{q}_M \\ | & | & & | \end{bmatrix}. \quad (2.59)$$

Solving the eigenvalue problem explicitly for the spatial correlation matrix $\mathbf{C} \in \mathbf{R}^{N \times N}$ is computationally prohibitive due to the massive spatial resolution of LES grids. To circumvent this, the present work computes the POD via the Singular Value Decomposition (SVD) of the snapshot matrix [158]. Assuming a uniform spatial discretisation, the weight matrix $\mathbf{W}$ reduces to the identity matrix. The scaled snapshot matrix is thus decomposed as:

$$\frac{\mathbf{Q}}{\sqrt{M}} = \mathbf{U} \mathbf{\Sigma} \mathbf{V}^T, \quad (2.60)$$

where the columns of the orthogonal matrix $\mathbf{U}$ contain the spatial POD modes (ϕ_j), and $\mathbf{\Sigma}$ is a diagonal matrix containing the singular values, which are related to the eigenvalues by $\mathbf{\Sigma} \mathbf{\Sigma}^T = \mathbf{\Lambda}$. Finally, the temporal coefficients $a_j(t)$, which dictate the dynamic evolution of each spatial mode, are efficiently extracted from the rows of the matrix $\sqrt{M} \mathbf{\Sigma} \mathbf{V}^T$.

Dynamic Mode Decomposition

Dynamic Mode Decomposition (DMD) [159, 77] is a data-driven mathematical technique designed to extract dynamically relevant flow features from time-resolved datasets. In the field of fluid dynamics, this approach states that the temporal evolution of a system can be closely approximated by a linear operator mapping between successive snapshots of the flow field, whether obtained from experiments or numerical simulations. Consistent with the POD framework established in Section 2.7, the dataset consists of sequential flow field snapshots uniformly sampled in time. Each snapshot is organised as a column vector $\mathbf{q}_i \in \mathbf{R}^N$, where the dimension N corresponds to the total spatial degrees of freedom (i.e., the three velocity components evaluated at S selected grid points, such that $N = 3 \times S$). Assuming a linear, time-invariant mapping operator $\mathbf{A}$, the relationship between two consecutive snapshots can be expressed as:

$$\mathbf{q}_{i+1} = \mathbf{A} \mathbf{q}_i, \quad i = 0, \dots, M-2, \quad (2.61)$$

where M represents the total number of available snapshots. To analyse the dynamics, the dataset is partitioned into two time-shifted data matrices, $\mathbf{Q}_0$

and $\mathbf{Q}_1$, representing the current and the subsequent states of the system:

$$\mathbf{Q}_0 = [\mathbf{q}_0, \mathbf{q}_1, \dots, \mathbf{q}_{M-2}], \quad (2.62)$$

$$\mathbf{Q}_1 = [\mathbf{q}_1, \mathbf{q}_2, \dots, \mathbf{q}_{M-1}]. \quad (2.63)$$

Combining Equation 2.61 with the matrix definitions yields the core DMD relationship:

$$\mathbf{Q}_1 = \mathbf{A}\mathbf{Q}_0. \quad (2.64)$$

Because explicitly computing the high-dimensional matrix $\mathbf{A} \in \mathbf{R}^{N \times N}$ is computationally intractable for typical CFD grids, a robust and economical low-dimensional approximation is required. This is achieved by projecting the initial dataset $\mathbf{Q}_0$ onto a reduced POD subspace. Performing a SVD on $\mathbf{Q}_0$ and selecting a truncation rank r retains only the most energetic spatial structures, providing the optimal rank- r approximation:

$$\mathbf{Q}_0 \approx \widetilde{\mathbf{Q}}_0 = \widetilde{\mathbf{U}}\widetilde{\mathbf{\Sigma}}\widetilde{\mathbf{V}}^T, \quad (2.65)$$

where $\widetilde{\mathbf{U}} \in \mathbf{R}^{N \times r}$ contains the first r POD modes, $\widetilde{\mathbf{V}} \in \mathbf{R}^{(M-1) \times r}$ contains the corresponding right singular vectors, and $\widetilde{\mathbf{\Sigma}} \in \mathbf{R}^{r \times r}$ is the diagonal matrix of the leading r singular values.

The high-dimensional operator $\mathbf{A}$ is then projected onto the r -dimensional basis $\widetilde{\mathbf{U}}$ to formulate a reduced-order matrix $\widetilde{\mathbf{A}} \in \mathbf{R}^{r \times r}$. Minimising the Frobenius norm of the residual error $\|\mathbf{Q}_1 - \mathbf{A}\mathbf{Q}_0\|_F$ in this reduced space yields the exact expression for the similar matrix $\widetilde{\mathbf{A}}$:

$$\widetilde{\mathbf{A}} = \widetilde{\mathbf{U}}^T \mathbf{Q}_1 \widetilde{\mathbf{V}} \widetilde{\mathbf{\Sigma}}^{-1}. \quad (2.66)$$

To extract the underlying dynamic modes, the eigendecomposition of the reduced matrix $\widetilde{\mathbf{A}}$ is computed:

$$\widetilde{\mathbf{A}} = \mathbf{Y} \mathbf{D}_\mu \mathbf{Z}^* = \begin{bmatrix} \mathbf{y}_1 & \dots & \mathbf{y}_r \end{bmatrix} \begin{bmatrix} \mu_1 & \dots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \dots & \mu_r \end{bmatrix} \begin{bmatrix} \mathbf{z}_1^* \\ \vdots \\ \mathbf{z}_r^* \end{bmatrix}, \quad (2.67)$$

where $\mathbf{y}_k$ and $\mathbf{z}_k^*$ denote the right and left eigenvectors of $\widetilde{\mathbf{A}}$, respectively, mutually normalized such that $\mathbf{z}_j^* \mathbf{y}_k = \delta_{jk}$. The diagonal entries μ_k represent the discrete-time eigenvalues of the mapped system. The full-dimensional spatial DMD modes, ϕ_k , are finally reconstructed by projecting the eigenvectors back into the physical space:

$$\phi_k = \widetilde{\mathbf{U}} \mathbf{y}_k. \quad (2.68)$$

The complex frequencies and growth rates associated with each spatial mode ϕ_k are directly recovered from their respective eigenvalues μ_k . For a complete

reconstruction of the transient flow field, each DMD mode must be weighted by an initial amplitude α_k . Denoting by $\mathbf{x}_i \in \mathbb{R}^r$ the reduced-order state vector at time step i , with initial condition $\mathbf{x}_0$ whose k -th component equals α_k , the dynamics in the POD subspace are governed by the propagator $\mathbf{x}_i = \tilde{\mathbf{A}}^i \mathbf{x}_0$. Projecting this back to the high-dimensional space allows the i -th snapshot to be approximated as a linear superposition of the dynamic modes:

$$\mathbf{q}_i \approx \tilde{\mathbf{U}} \mathbf{x}_i = \sum_{k=1}^r \tilde{\mathbf{U}} \mathbf{y}_k \mu_k^i \alpha_k = \sum_{k=1}^r \phi_k \mu_k^i \alpha_k. \quad (2.69)$$

While Equation 2.69 provides the flow field reconstruction at discrete sampling intervals, the temporal evolution can also be expressed continuously for any generic time t . By mapping the discrete-time eigenvalues μ_k to their continuous-time counterparts, the flow field is reconstructed as:

$$\mathbf{q}(t) \approx \sum_{k=1}^r \phi_k \exp(\omega_k t) \alpha_k, \quad (2.70)$$

where $\omega_k = \ln(\mu_k)/\Delta t$ represents the complex continuous-time eigenvalue associated with the k -th dynamic mode, and Δt is the uniform time step between consecutive snapshots. In this formulation, the real part of ω_k dictates the exponential growth or decay rate of the mode, while its imaginary part strictly defines the oscillation frequency.

The entire snapshot matrix $\mathbf{Q}_0$ can thus be expressed in a compact matrix form:

$$\mathbf{Q}_0 \approx \Phi \mathbf{D}_\alpha \mathbf{V}_{and}, \quad (2.71)$$

where $\Phi = [\phi_1, \dots, \phi_r]$ contains the spatial DMD modes, $\mathbf{D}_\alpha = \text{diag}(\alpha_1, \dots, \alpha_r)$ is the diagonal matrix of mode amplitudes, and $\mathbf{V}_{and}$ is a Vandermonde matrix containing the temporal evolution dictated by the eigenvalues μ_k :

$$\mathbf{V}_{and} = \begin{bmatrix} 1 & \mu_1 & \dots & \mu_1^{M-2} \\ 1 & \mu_2 & \dots & \mu_2^{M-2} \\ \vdots & \vdots & \ddots & \vdots \\ 1 & \mu_r & \dots & \mu_r^{M-2} \end{bmatrix}. \quad (2.72)$$

The optimal modal amplitudes $\boldsymbol{\alpha} = [\alpha_1, \dots, \alpha_r]^T$ are typically determined by minimising the reconstruction error over the entire temporal sequence, formulated as a Frobenius norm minimisation problem:

$$\min_{\boldsymbol{\alpha}} J(\boldsymbol{\alpha}) = \|\mathbf{Q}_0 - \Phi \mathbf{D}_\alpha \mathbf{V}_{and}\|_F^2, \quad (2.73)$$

or through more elaborate minimisation strategies, as discussed in the following.

Sparsity Promoting Dynamic Mode Decomposition

Reduced Order Models (ROMs) generally seek to reconstruct the temporal evolution of a flow field using a minimal subset of dynamically relevant structures. In standard DMD, the exact superposition of all extracted modes—weighted by their amplitudes and evolving according to their respective frequencies and growth rates—optimally approximates the data sequence. However, the standard Frobenius norm minimisation formulated in Equation 2.73 solely prioritizes reconstruction accuracy and does not explicitly penalise the cardinality of the modal basis and tends to yield representations containing a large number of redundant modes or dynamically insignificant modes.

To achieve a concise and parsimonious representation of the system's behavior, this study employs the Sparsity-Promoting Dynamic Mode Decomposition (SP-DMD) algorithm introduced by Jovanović et al. [81]. Following recent literature [79, 160], this goal is achieved through a systematic two-step procedure: (i) identifying a sparsity structure that balances the number of retained modes against the approximation error, and (ii) fixing this sparsity structure to optimally recalculate the exact amplitudes of the retained modes.

In the first step, the standard DMD objective function $J(\boldsymbol{\alpha})$ is augmented with an ℓ_1 -norm regularization term applied to the amplitude vector $\boldsymbol{\alpha}$. This convex optimisation problem is formulated as:

$$\min_{\boldsymbol{\alpha}} J(\boldsymbol{\alpha}) + \gamma \|\boldsymbol{\alpha}\|_1 = \min_{\boldsymbol{\alpha}} \left(\|\mathbf{Q}_0 - \boldsymbol{\Phi} \mathbf{D}_{\boldsymbol{\alpha}} \mathbf{V}_{and}\|_F^2 + \gamma \sum_{i=1}^r |\alpha_i| \right), \quad (2.74)$$

where $\gamma > 0$ is a user-defined regularization parameter that dictates the optimal trade-off between the exactness of the flow reconstruction and the sparsity of the resulting modal basis. Higher values of γ enforce stronger penalisation on non-zero elements, driving the amplitudes of less relevant modes exactly to zero and yielding sparser solutions. This convex optimisation problem is robustly solved utilizing the Alternating Direction Method of Multipliers (ADMM) [81].

While the ℓ_1 -norm penalty successfully identifies the optimal sparse subset of modes (the so-called *sparsity structure*), it introduces a bias by construction that suppresses the magnitude of the surviving non-zero amplitudes. Therefore, in the second step (often referred to as the polishing step), the sparsity structure is frozen, and the optimal values of the non-zero amplitudes are strictly re-computed to eliminate this bias. This constrained optimisation is expressed as:

$$\min_{\boldsymbol{\alpha}} J(\boldsymbol{\alpha}) \quad \text{subject to} \quad \mathbf{E}^T \boldsymbol{\alpha} = \mathbf{0}, \quad (2.75)$$

where $\mathbf{E} \in \mathbf{R}^{r \times N_z}$ is a structural matrix encoding the sparsity structure of $\boldsymbol{\alpha}$. Its columns are unitary basis vectors whose non-zero elements correspond to the N_z zeroed components of $\boldsymbol{\alpha}$ determined during the first step. The numerical methodology used to solve Equation 2.75 follows the exact formulation proposed in [81]. Finally, to quantitatively evaluate the trade-off between the degree

of sparsity (i.e., the number of retained modes) and the accuracy of the flow reconstruction, it is highly useful to define the relative performance loss:

$$\Pi_{\text{loss}}(\%) = 100 \sqrt{\frac{J(\boldsymbol{\alpha})}{J(\mathbf{0})}} = 100 \frac{\|\mathbf{Q}_0 - \boldsymbol{\Phi} \mathbf{D}_{\alpha} \mathbf{V}_{\text{and}}\|_F}{\|\mathbf{Q}_0\|_F}. \quad (2.76)$$

This metric quantifies the percentage of energy lost in the SP-DMD temporal reconstruction relative to the optimal, full-rank low-dimensional POD subspace. By parametrically varying γ , a Pareto front can be generated, allowing the user to select the optimal compromise between dynamical accuracy and modal sparsity. As previously noted, the regularization parameter γ strictly dictates the selectivity of the algorithm. When $\gamma = 0$, the optimisation is unconstrained by the cardinality of the modal basis, thus reverting exactly to the classical DMD algorithm and retaining all r modes. Conversely, higher values of γ yield increasingly sparse representations.

While this selection process is computationally and analytically beneficial, it introduces an inherent trade-off: the reduced-order model cannot capture the full complexity of the original turbulent flow, leading to the aforementioned performance loss. In the context of the SP-DMD pipeline, this deviation from the true behavior stems from three distinct mathematical sources:

- **Sparsity (Truncation) Error:** this is the direct consequence of the SP-DMD selection process. By forcing the amplitudes of less relevant modes to zero, some dynamic scales and flow features are permanently discarded. If γ is set too high, dynamically important modes may be entirely excluded, causing the reconstruction to deviate appreciably from the original dataset.
- **Projection Error:** before the DMD algorithm is even applied, the original high-dimensional snapshot matrix is projected onto a lower-dimensional subspace via the initial POD truncation (rank r). Any spatial structure or turbulent fluctuation orthogonal to this subspace is inevitably lost at the very beginning of the procedure.
- **Linear Approximation Error:** the underlying assumption of DMD is that the complex, non-linear Navier-Stokes dynamics can be approximated by a linear, time-invariant mapping operator $\tilde{\mathbf{A}}$ acting on consecutive snapshots. For highly chaotic and non-linear turbulent flows, this linear approximation naturally introduces discrepancies over time.

Mean Kinetic Energy equation

To investigate the turbulent energy fluxes in the wind turbine wake, we analyse the transport equation for the Mean Kinetic Energy (MKE). Higher turbulence intensity is known to accelerate wake recovery [161, 58, 162]. This phenomenon

is driven by the enhanced diffusion generated by turbulent fluctuations, which facilitates the transport of kinetic energy from the outer unperturbed flow into the wake region.

To isolate the effect of coherent structures on wake recovery, we evaluate the individual contribution of each POD mode. In this analysis, POD is preferred over DMD for two primary reasons. First, POD modes are, by construction, the most energetic structures within the flow, making them ideally suited for characterising energy exchanges among the modes, the mean flow, and the turbulent fluctuations. Second, the POD modes constitute an orthonormal basis. This mathematical property permits the exact reconstruction of the Reynolds stress tensor via a direct summation of the modes weighted by their respective time-dependent amplitude coefficients—a procedure that would not be possible using the non-orthogonal DMD modes. Focusing on the MKE transport equation, the balance is expressed as:

$$0 = -\bar{u}_j \frac{\partial}{\partial x_j} \left(\frac{1}{2} \bar{u}_i \bar{u}_i \right) - \frac{\partial}{\partial x_i} (\bar{u}_i p) + \bar{u}_i \bar{F}_i + \frac{1}{Re} \nabla^2 \left(\frac{1}{2} \bar{u}_i \bar{u}_i \right) - \frac{1}{Re} \frac{\partial \bar{u}_i}{\partial x_j} \frac{\partial \bar{u}_i}{\partial x_j} + \underbrace{-\frac{\partial}{\partial x_j} (\bar{u}_i \bar{u}'_i \bar{u}'_j) - \frac{\partial}{\partial x_j} (\bar{u}_i \bar{\tau}_{ij}^r) + \bar{u}'_i \bar{u}'_j \frac{\partial \bar{u}_i}{\partial x_j} + \bar{\tau}_{ij}^r \frac{\partial \bar{u}_i}{\partial x_j}}_{\text{Turbulent M.K.E. flux}}, \quad (2.77)$$

where $\bar{(\cdot)}$ denotes the time average and the prime symbol $(\cdot)'$ indicates turbulent fluctuations. Within the wake, subgrid-scale stresses $(\bar{\tau}_{ij}^r)$ are generally negligible; instead, the Turbulent MKE flux represents the dominant mechanism governing wake recovery [114, 163, 164]. The total turbulent MKE flux per unit area entering a generic closed surface S is quantified as:

$$\mathcal{F}_T = \frac{1}{S} \int_V -\frac{\partial}{\partial x_j} (\bar{u}_i \bar{u}'_i \bar{u}'_j) dV, \quad (2.78)$$

where V is the volume enclosed by S . Leveraging the orthonormality of the POD modes, the Reynolds stress tensor can be expanded and simplified as:

$$\overline{u'_i u'_j} = \overline{\sum_{k=1}^N (a_k \phi_i^k) \sum_{l=1}^N (a_l \phi_j^l)} = \sum_{k=1}^N \sum_{l=1}^N \overline{a_k a_l} \phi_i^k \phi_j^l = \sum_{k=1}^N \lambda_k \phi_i^k \phi_j^k, \quad (2.79)$$

allowing the specific contribution of the k -th POD mode to the turbulent MKE flux to be expressed as:

$$\mathcal{F}_T^k = \frac{1}{S} \int_V -\frac{\partial}{\partial x_j} (\bar{u}_i \lambda_k \phi_i^k \phi_j^k) dV. \quad (2.80)$$

By applying the Divergence Theorem, Equation 2.80 can be recast as a surface integral:

$$\mathcal{F}_T^k = \frac{1}{S} \int_S -\bar{u}_i \lambda_k \phi_i^k \phi_j^k dS_j. \quad (2.81)$$

To evaluate the turbulent MKE flux radially entrained into the wake, a cylindrical control volume of radius R_c and length L_c , aligned with the rotor axis, is considered. The infinitesimal surface vector $d\mathbf{S}$ on the lateral boundary is strictly normal to the streamwise direction and is defined as:

$$d\mathbf{S} = (0, dc_2, dc_3) dx, \quad (2.82)$$

where dc_2 and dc_3 are the vertical and transverse components of the normal vector $d\mathbf{c}$ corresponding to the infinitesimal arc of the circumference C . The total turbulent MKE flux per unit area across the lateral surface for each POD mode is therefore computed as:

$$\mathcal{F}_T^k = \int_{L_c} f_T^k(x) dx, \quad (2.83)$$

$$f_T^k(x) = -\frac{1}{2\pi R_c L_c} \int_C \bar{u}_i(x) \lambda_k \phi_i^k(x) \phi_j^k(x) dc_j. \quad (2.84)$$

The local fluxes $f_T^k(x)$ are computed along a representative circumference, while the total flux $\mathcal{F}_T^k$ is analysed over a parametrically varied range of radii R_c to comprehensively characterise the radial extent of the energy entrainment. To circumvent the complexities of direct numerical integration over cylindrical surfaces on a Cartesian grid, the surface integral in Equation 2.84 is mathematically transformed back into a volume integral. This volume integral is subsequently discretised and evaluated numerically using the midpoint rule across spatial subintervals consistent with the local grid resolution.

2.8 Reinforcement Learning Framework

This section outlines the Reinforcement Learning (RL) methodology developed for the coordinated control optimisation of the wind farm. Training a Deep Reinforcement Learning (DRL) agent directly within the LES environment is computationally prohibitive due to the massive number of interactions required for convergence. Therefore, the core of the proposed control strategy relies on a multi-fidelity transfer learning framework. An intensive training phase is first conducted using a steady-state, computationally efficient surrogate wake model. Once the optimal policy is learned, it is transferred and evaluated within the LES environment to assess its robustness under fully resolved, dynamic turbulent flow conditions.

2.8.1 The MARL Framework for Wind Farm Control

The wind farm yaw control problem is formalized as a Decentralized Partially Observable Markov Decision Process (Dec-POMDP) featuring M interacting agents (wind turbines). A Dec-POMDP is defined by the tuple

$\langle M, S, O, A, P, o^1, \dots, o^M, r \rangle$, where S is the global state space, O is the joint observation space, A is the joint action space, P is the stochastic transition kernel, o^i is the local observation of agent i , and r is the shared scalar reward signal. For any agent $i \in \{1, \dots, M\}$, O_i is the local observation space and A_i is the continuous local action space. The global observation and action spaces are the Cartesian products $O = \times_{i=1}^M O_i$ and $A = \times_{i=1}^M A_i$, respectively. At each step, agents execute a joint action $\mathbf{a} \in A$, and the system transitions to a new state $s' \in S$ sampled from the kernel $P : S \times A \times S \rightarrow [0, 1]$.

State and Observations

A true Markovian description of the system's full state S would require the complete, instantaneous wind velocity field of the entire wind farm, which is impossible to measure in practice. Therefore, the framework assumes partial observability, distinguishing between local observations o_i and a global observation o_g :

- **Local Observation** (o_i): exclusively available to the individual agent, it contains the local wind velocity u_i , local wind direction ϕ_i , and the last target yaw value sent to the actuator θ_i . Thus, $o_i = (u_i, \phi_i, \theta_i)$.
- **Global Observation** (o_g): the concatenation of all local observations together with the free-stream conditions: $o_g = (o_1, \dots, o_M, u_\infty, \phi_\infty)$.

Actions

The primary control mechanism is active wake steering via yaw control. To reflect the physical constraints and response times of mechanical actuators, actions a_i are defined as *incremental variations* (increases or decreases) to the current actuator target value, rather than absolute setpoints. The continuous action space is bounded by strict upper and lower mechanical limits.

Objective and Reward Shaping

The objective of the MARL problem is to find a global policy $\pi^* = (\pi_1^*, \dots, \pi_M^*)$ that maximises the expected discounted sum of rewards J collected over an episode of length T :

$$\max_{\pi} \mathbb{E}_{s_0, a_0, s_1, \dots} [J], \quad J := \sum_{k=0}^T \gamma^k r_k, \quad (2.85)$$

where $0 < \gamma < 1$ is the discount factor. The reward function r_k is multi-objective, designed to balance maximising total array power production against minimising structural fatigue loads:

$$r_k = r_k^P - \alpha r_k^L, \quad (2.86)$$

where α is a tunable weighting parameter prioritizing turbine safety. The power production component r_k^P is normalized with respect to the number of agents M and the free-stream wind velocity $u_{\infty,k}$ cubed:

$$r_k^P = \frac{1}{M} \sum_{i=1}^M \frac{\hat{P}_k^i}{(u_{\infty,k})^3}, \quad (2.87)$$

where $\hat{P}_k^i$ is the measured power production of turbine i .

The formulation of the load penalty term r_k^L depends on the fidelity of the underlying simulated environment. In the computationally efficient FLORIS framework, a kinematic proxy evaluating local turbulence intensity (TI) and velocity gradients over the rotor planes is employed:

$$r_{k,\text{FLORIS}}^L = \frac{1}{M} \sum_{i=1}^M \left(\sum_{j=1}^9 TI_k[x_{i,j}, y_{i,j}] + \sigma(u_k) + \sigma(v_k) + \sigma(w_k) \right), \quad (2.88)$$

where TI_k is evaluated at 9 grid points and σ denotes the standard deviation of the velocity components. Conversely, within the LES environment, where aeroelastic interactions are fully resolved, the load penalty is evaluated using the blade root bending moments:

$$r_{k,\text{LES}}^L = \frac{1}{m} \sum_{i=1}^m \left(\sum_{j=1}^3 |M_{op_t}[i, j]| + \sum_{j=1}^3 |M_{ip_t}[i, j]| \right), \quad (2.89)$$

where M_{op_t} and M_{ip_t} are the $m \times 3$ matrices of out-of-plane and in-plane bending moments for the 3 blades of each turbine at time-step t .

2.8.2 Multi-Agent Control Paradigms

A key design choice in any MARL system concerns how much information agents share during training and execution. Three distinct paradigms are evaluated in this work, each representing a different point in the centralisation–decentralisation spectrum. These paradigms are *algorithm-agnostic*: they are applied uniformly to all three optimisation engines (PPO, SAC, TD3), producing nine distinct benchmark configurations.

Independent (I) — Fully Decentralized

In the Independent paradigm, each turbine i is treated as a fully autonomous agent. Both the actor and the critic operate exclusively on the local observation o_i :

- Each agent i maintains its own actor π_{θ^i} (or μ_{θ^i} for deterministic policies) and its own local critic $V_{\phi^i}(o_i)$ (or $Q_{\phi^i}(o_i, a_i)$ for Q-critics).
- Off-policy variants maintain a separate per-agent replay buffer $\mathcal{D}^i$.

- No information is shared across agents at any stage.

This approach is maximally scalable and privacy-preserving, but it does not address the non-stationarity of the environment induced by the simultaneous learning of other agents, potentially slowing or destabilizing convergence.

Multi-Agent CTDE (MA) — Centralized Training, Decentralized Execution

The Multi-Agent paradigm follows the Centralized Training with Decentralized Execution (CTDE) principle [165]. Actors remain *local* — each agent i executes its policy using only o_i — but during *training*, a shared global critic is conditioned on richer information:

- All agents share a single centralized critic $V_\phi(o_g)$ (for on-policy methods) or twin critics $Q_{\phi_k}(o_g, \mathbf{a})$, $k = 1, 2$ (for off-policy methods), where o_g is the global observation and $\mathbf{a} = (a^1, \dots, a^M)$ is the concatenated joint action vector.
- Off-policy variants maintain a joint replay buffer $\mathcal{D}$ that stores full farm transitions $(o_{g,t}, \mathbf{o}_t, \mathbf{a}_t, r_t, o_{g,t+1}, \mathbf{o}_{t+1})$.
- The global critic provides a stationary, farm-wide value signal during training, mitigating non-stationarity without compromising runtime decentralisation.

Centralized (C) — Fully Centralized

The Centralized paradigm is the theoretical upper bound on information sharing. Both training and execution are fully centralized:

- A single joint actor π_Θ (or μ_Θ) receives the global observation o_g and outputs the entire joint action vector $\mathbf{a} \in A$ simultaneously, where the output dimensionality is $M \times |\mathcal{A}_i|$.
- A single centralized critic $V_\Phi(o_g)$ or twin critics $Q_{\Phi_k}(o_g, \mathbf{a})$ are used.
- All turbine decisions are computed by a single controller with full farm-state visibility at runtime. This paradigm is not deployable in distributed hardware architectures, but serves as an important performance benchmark.

The key structural distinction from the MA paradigm is that in MA the actors remain local and are trained from individual advantage/Q-value signals, whereas in C a single monolithic policy is responsible for coordinating all turbines simultaneously.

Table 2.1 summarises the nine benchmark configurations arising from the combination of the three paradigms with the three optimisation algorithms.

Table 2.1: Overview of the nine benchmark configurations. “Actor input” refers to the observation seen at execution time; “Critic input” refers to what the critic processes during training.

Paradigm	Algorithm	Label	Actor input	Critic input
Independent	PPO	IPPO	o_i	o_i
Independent	SAC	ISAC	o_i	(o_i, a_i)
Independent	TD3	ITD3	o_i	(o_i, a_i)
Multi-Agent	PPO	MAPPO	o_i	o_g
Multi-Agent	SAC	MASAC	o_i	$(o_g, \mathbf{a})$
Multi-Agent	TD3	MATD3	o_i	$(o_g, \mathbf{a})$
Centralized	PPO	CPPO	o_g	o_g
Centralized	SAC	CSAC	o_g	$(o_g, \mathbf{a})$
Centralized	TD3	CTD3	o_g	$(o_g, \mathbf{a})$

2.8.3 Proximal Policy Optimisation (PPO)

The control policy is optimised using the PPO algorithm [92]. PPO is an on-policy policy gradient method renowned for its stability and sample efficiency in continuous action spaces. Unlike the off-policy methods presented in the following subsections, PPO collects rollout trajectories directly from the current policy before performing gradient updates, discarding all data afterward.

Let $r_t(\theta)$ denote the probability ratio between the current policy π_θ and the old policy $\pi_{\theta_{\text{old}}}$ at discrete time step $t \in \{0, 1, \dots, T\}$:

$$r_t(\theta) = \frac{\pi_\theta(a_t | s_t)}{\pi_{\theta_{\text{old}}}(a_t | s_t)}. \quad (2.90)$$

The advantage function $\hat{A}_t$ quantifies how much better action a_t is relative to the baseline of the current policy at state s_t . It is estimated via Generalized Advantage Estimation (GAE) [166]:

$$\hat{A}_t = \sum_{l=0}^{T-t} (\gamma\lambda)^l \delta_{t+l}, \quad \delta_t = r_t + \gamma V_\phi(s_{t+1}) - V_\phi(s_t), \quad (2.91)$$

where δ_t is the one-step temporal difference (TD) residual, $\lambda \in (0, 1)$ is the GAE trace-decay parameter controlling the bias–variance trade-off, and $V_\phi(s_t)$ is the value function approximated by the Critic network. The clipped surrogate objective for the Actor is:

$$L^{\text{CLIP}}(\theta) = \hat{\mathbb{E}}_t \left[\min \left(r_t(\theta) \hat{A}_t, \text{clip}(r_t(\theta), 1 - \epsilon, 1 + \epsilon) \hat{A}_t \right) \right], \quad (2.92)$$

where ϵ is the clipping hyperparameter bounding the ratio $r_t(\theta)$ to $[1 - \epsilon, 1 + \epsilon]$. The Critic network is updated by minimising the value function loss:

$$L^{\text{VF}}(\phi) = \hat{\mathbb{E}}_t \left[(V_\phi(s_t) - V_t^{\text{target}})^2 \right], \quad V_t^{\text{target}} = \hat{A}_t + V_\phi(s_t). \quad (2.93)$$

An entropy bonus $S[\pi_\theta](s_t)$ penalises excessively peaked action distributions, encouraging exploration. The total composite loss is:

$$L^{\text{PPO}}(\theta, \phi) = \hat{\mathbb{E}}_t [L^{\text{CLIP}}(\theta) - c_1 L^{\text{VF}}(\phi) + c_2 S[\pi_\theta](s_t)], \quad (2.94)$$

where c_1 and c_2 are scalar weighting coefficients.

In the Centralized variant (CPPO), the single joint actor π_Θ outputs all $M \times |\mathcal{A}_i|$ action dimensions simultaneously from the global observation o_g . The probability ratio $r_t(\Theta)$ is then the ratio of joint Gaussian densities, which accumulates contributions from all turbine actions. To prevent instability caused by the amplification of the joint log-probability ratio, early stopping of the PPO update epochs is applied when the approximate KL divergence exceeds a threshold δ_{KL} .

Algorithm 1: Integrated PPO Training Framework (IPPO / MAPPO / CPPO)

```

1 Initialization:
2 Configure Wind Farm Layout ( $M$  turbines);
3 if CPPO then Initialize one joint Actor  $\pi_\Theta(o_g)$  with output dim
    $M \times |\mathcal{A}_i|$  else Initialize local Actors  $\{\pi_{\theta^i}(o_i)\}_{i=1}^M$ ;
4 if IPPO then Initialize Local Critics  $\{V_{\phi^i}(o_i)\}_{i=1}^M$  else Initialize Shared
   Critic  $V_\Phi(o_g)$ ;
5 for  $ep = 1$  to  $N_{\text{episodes}}$  do
6   Sample Wind Conditions; reset environment;
7   for  $t = 1$  to  $T_{\text{train}}$  do
8     if CPPO then sample joint action  $\mathbf{a}_t \sim \pi_\Theta(\cdot \mid o_{g,t})$  else each
       agent  $i$  samples  $a_t^i \sim \pi_{\theta^i}(\cdot \mid o_t^i)$ ;
9     Execute  $\mathbf{a}_t$ ; observe reward  $r_t$  and next states;
10    Store  $(o_t, \mathbf{a}_t, r_t)$  in rollout buffer;
11  end
12  Compute advantages  $\hat{A}_t$  via GAE;
13  for  $epoch = 1$  to  $K_{\text{epochs}}$  do
14    Update Actor(s) via  $L^{\text{CLIP}}$ ; update Critic(s) via  $L^{\text{VF}}$ ;
15    if CPPO: break early if approx KL  $> \delta_{\text{KL}}$ ;
16  end
17 end

```

2.8.4 Soft Actor-Critic (SAC)

Soft Actor-Critic [94] is an off-policy, model-free algorithm grounded in the *maximum entropy* RL framework. Unlike PPO, SAC maintains a **replay buffer** $\mathcal{D}$ from which past transitions are uniformly sampled for gradient updates, decoupling data collection from parameter optimisation and enabling high sample efficiency.

Maximum Entropy Objective

The core innovation of SAC is the augmentation of the standard RL objective with an entropy bonus:

$$J_{\text{SAC}}(\pi) = \mathbb{E}_{\pi} \left[\sum_{t=0}^T \gamma^t (r_t + \alpha \mathcal{H}(\pi(\cdot | o_t))) \right], \quad (2.95)$$

where $\mathcal{H}(\pi(\cdot | o_t)) = -\mathbb{E}_{a \sim \pi} [\log \pi(a | o_t)]$ is the differential entropy of the policy and $\alpha > 0$ is a temperature parameter governing the relative importance of entropy versus return. Higher values of α encourage broader exploration of the yaw configuration space.

Stochastic Actor with Reparameterisation

The SAC actor is a *stochastic* policy whose network outputs a mean $\mu_{\theta}(o)$ and a log-standard deviation $\log \sigma_{\theta}(o)$, clamped to $[\log \sigma_{\min}, \log \sigma_{\max}]$ for numerical stability. Actions are sampled via the reparameterisation trick and squashed through a tanh nonlinearity to enforce actuator bounds:

$$\tilde{a} = \mu_{\theta}(o) + \sigma_{\theta}(o) \odot \varepsilon, \quad \varepsilon \sim \mathcal{N}(0, I), \quad a = \tanh(\tilde{a}) \cdot \sigma_{\text{scale}} + b_{\text{scale}}, \quad (2.96)$$

where $\sigma_{\text{scale}} = (a_{\max} - a_{\min})/2$ and $b_{\text{scale}} = (a_{\max} + a_{\min})/2$. The log-probability is corrected for the tanh transformation via the change-of-variables formula:

$$\log \pi_{\theta}(a | o) = \sum_j [\log \mathcal{N}(\tilde{a}_j; \mu_j, \sigma_j^2) - \log(\sigma_{\text{scale},j} (1 - \tanh^2(\tilde{a}_j)) + \epsilon)]. \quad (2.97)$$

Twin Critics and Soft Bellman Target

To mitigate overestimation bias, SAC employs *twin critics* Q_{ϕ_1} and Q_{ϕ_2} updated by minimising the Bellman residual against a shared soft target:

$$y_t = r_t + \gamma(1 - d_t) \left[\min_{k=1,2} Q_{\bar{\phi}_k}(o_{t+1}, \tilde{a}_{t+1}) - \alpha \log \pi_{\theta}(\tilde{a}_{t+1} | o_{t+1}) \right], \quad (2.98)$$

where $\tilde{a}_{t+1} \sim \pi_{\theta}(\cdot | o_{t+1})$ and $Q_{\bar{\phi}_k}$ are exponentially moving target networks updated via soft Polyak averaging with coefficient τ :

$$\bar{\phi}_k \leftarrow \tau \phi_k + (1 - \tau) \bar{\phi}_k, \quad k = 1, 2. \quad (2.99)$$

The critic loss is the sum of mean squared Bellman errors:

$$L^Q(\phi_1, \phi_2) = \hat{\mathbb{E}}_{\mathcal{D}} \left[(Q_{\phi_1}(o_t, a_t) - y_t)^2 + (Q_{\phi_2}(o_t, a_t) - y_t)^2 \right]. \quad (2.100)$$

Actor and Temperature Update

The actor is updated every f_{actor} critic gradient steps by minimising the expected soft value:

$$L^\pi(\theta) = \hat{\mathbb{E}}_{\mathcal{D}} \left[\alpha \log \pi_\theta(\tilde{a} \mid o_t) - \min_{k=1,2} Q_{\phi_k}(o_t, \tilde{a}) \right]. \quad (2.101)$$

When entropy autotuning is enabled, the temperature α is itself a learnable parameter adjusted to enforce a target entropy $\bar{\mathcal{H}}$. For local actors, $\bar{\mathcal{H}} = -|\mathcal{A}_i|$;

Algorithm 2: Integrated SAC Training Framework (ISAC / MASAC / CSAC)

```

1 Initialization:
2 if CSAC then Initialize joint Actor  $\pi_\Theta(o_g)$  with output dim  $M \times |\mathcal{A}_i|$ 
   else Initialize local Actors  $\{\pi_{\theta^i}(o_i)\}_{i=1}^M$ ;
3 if ISAC then Initialize local Twin Critics  $\{Q_{\phi_1}^i, Q_{\phi_2}^i\}$  and per-agent
   buffers  $\{\mathcal{D}^i\}$  else Initialize shared Twin Critics  $Q_{\phi_1}(o_g, \mathbf{a}), Q_{\phi_2}(o_g, \mathbf{a})$ 
   and joint buffer  $\mathcal{D}$ ;
4 Copy parameters to target critics:  $\bar{\phi}_k \leftarrow \phi_k$ ;
5 Initialize temperature  $\alpha$  (fixed or autotuned);
6 for  $t = 1$  to  $N_{\text{steps}}$  do
7   if  $t < N_{\text{warm-up}}$  then
8     | Sample random actions  $\mathbf{a}_t \sim \mathcal{U}(\mathcal{A})$ ;
9   else
10    | if CSAC then  $\mathbf{a}_t \sim \pi_\Theta(\cdot \mid o_{g,t})$  else each agent  $i$ :
      |    $a_t^i \sim \pi_{\theta^i}(\cdot \mid o_t^i)$ ;
11    end
12    Execute  $\mathbf{a}_t$ ; observe  $r_t, o_{t+1}$ ; store in  $\mathcal{D}$ ;
13    if  $t \geq N_{\text{warm-up}}$  then
14      | Sample mini-batch; normalise rewards:  $r \leftarrow (r - \bar{r})/(\hat{\sigma}_r + \epsilon)$ ;
15      | Compute soft Bellman target  $y$  using twin target critics;
16      | Minimise  $L^Q(\phi_1, \phi_2)$ ; soft-update  $\bar{\phi}_k$ ;
17      | if  $t \bmod f_{\text{actor}} = 0$  then
18        | | Minimise  $L^\pi(\theta)$  for each actor;
19        | | if autotune: minimise  $L^\alpha$ ; clamp  $\log \alpha \geq \log \alpha_{\min}$ ;
20      | end
21    end
22 end

```

for the joint Centralized actor, $\bar{\mathcal{H}} = -M \times |\mathcal{A}_i|$, scaled by the number of agents:

$$L^\alpha = \hat{\mathbb{E}}_{\mathcal{D}} \left[-e^{\log \alpha} (\log \pi_\theta(\tilde{a} | o_t) + \bar{\mathcal{H}}) \right], \quad (2.102)$$

with $\log \alpha$ clamped from below to prevent entropy collapse.

2.8.5 Twin Delayed Deep Deterministic Policy Gradient (TD3)

Twin Delayed Deep Deterministic Policy Gradient [96] addresses two principal failure modes of its predecessor DDPG [167]: overestimation bias and sensitivity to hyperparameters. Like SAC, TD3 is off-policy and employs a replay buffer, but it uses a *deterministic* policy rather than a stochastic one, relying on extrinsic noise for exploration.

Deterministic Actor

The TD3 actor maps observations directly to deterministic actions, squashed to actuator bounds:

$$a = \tanh(\mu_\theta(o)) \cdot \sigma_{\text{scale}} + b_{\text{scale}}. \quad (2.103)$$

In the Centralized variant (CTD3), a single joint actor $\mu_\Theta(o_g)$ outputs all $M \times |\mathcal{A}_i|$ actions simultaneously.

Twin Critics and Clipped Double Q-Learning

TD3 maintains twin critics Q_{ϕ_1}, Q_{ϕ_2} and their respective target networks. The Bellman target is constructed using the *minimum* of the two target critics evaluated on smoothed target actions, suppressing overestimation bias:

$$y_t = r_t + \gamma(1 - d_t) \min_{k=1,2} Q_{\bar{\phi}_k}(o_{t+1}, \tilde{a}_{t+1}). \quad (2.104)$$

The critic loss is:

$$L^Q(\phi_1, \phi_2) = \hat{\mathbb{E}}_{\mathcal{D}} \left[(Q_{\phi_1}(o_t, a_t) - y_t)^2 + (Q_{\phi_2}(o_t, a_t) - y_t)^2 \right]. \quad (2.105)$$

Target Policy Smoothing

To prevent the actor from exploiting sharp peaks in the critic landscape, clipped Gaussian noise is added to the target actor's output:

$$\epsilon = \text{clip}(\mathcal{N}(0, \sigma_p^2), -c, c), \quad (2.106)$$

$$\tilde{a}_{t+1} = \text{clip}(\mu_{\bar{\theta}}(o_{t+1}) + \epsilon, a_{\min}, a_{\max}), \quad (2.107)$$

where σ_p is the target policy noise and c is its clipping bound, both expressed as fractions of the action half-range.

Algorithm 3: Integrated TD3 Training Framework (ITD3 / MATD3 / CTD3)

```

1 Initialization:
2 if CTD3 then Initialize joint Actor  $\mu_{\Theta}(o_g)$  with output dim  $M \times |\mathcal{A}_i|$ 
   and joint Target Actor  $\mu_{\bar{\Theta}}$  else Initialize local Actors  $\{\mu_{\theta^i}(o_i)\}$  and
   Target Actors  $\{\mu_{\bar{\theta}^i}\}$ ;
3 if ITD3 then Initialize local Twin Critics  $\{Q_{\phi_1}^i, Q_{\phi_2}^i\}$  and per-agent
   buffers  $\{\mathcal{D}^i\}$  else Initialize shared Twin Critics  $Q_{\phi_1}(o_g, \mathbf{a}), Q_{\phi_2}(o_g, \mathbf{a})$ 
   and joint buffer  $\mathcal{D}$ ;
4 Copy parameters:  $\bar{\phi}_k \leftarrow \phi_k, \bar{\theta} \leftarrow \theta$ ;
5 for  $t = 1$  to  $N_{steps}$  do
6   Compute  $\sigma_e(t)$  via linear decay schedule;
7   if  $t < N_{warm-up}$  then
8     Sample random actions  $\mathbf{a}_t \sim \mathcal{U}(\mathcal{A})$ ;
9   else
10    if CTD3 then  $\mathbf{a}_t = \text{clip}(\mu_{\Theta}(o_{g,t}) + \xi_t, \mathbf{a}_{\min}, \mathbf{a}_{\max})$  else each
       agent  $i$ :  $a_t^i = \text{clip}(\mu_{\theta^i}(o_t^i) + \xi_t^i, a_{\min}, a_{\max}),$ 
        $\xi \sim \mathcal{N}(0, \sigma_e(t)^2 \sigma_{\text{scale}}^2)$ ;
11    end
12    Execute  $\mathbf{a}_t$ ; observe  $r_t, o_{t+1}$ ; store in  $\mathcal{D}$ ;
13    if  $t \geq N_{warm-up}$  then
14      Sample mini-batch; normalise rewards:  $r \leftarrow (r - \bar{r})/(\hat{\sigma}_r + \epsilon)$ ;
15      Compute smoothed target actions  $\tilde{\mathbf{a}}$ ;
16      Compute Bellman target  $y$  using clipped double Q-learning;
17      Minimise  $L^Q(\phi_1, \phi_2)$ ; soft-update  $\bar{\phi}_k$ ;
18      if  $t \bmod f_{actor} = 0$  then
19        Ascend  $Q_{\phi_1}$ -gradient w.r.t. actor(s); soft-update target
        actor(s)  $\bar{\theta}$ ;
20      end
21    end
22 end

```

Delayed Policy and Target Updates

To reduce harmful variance in the actor gradient caused by a rapidly changing critic, the actor and all target networks are updated less frequently than the critics, every f_{actor} critic gradient steps:

$$\theta \leftarrow \theta - \eta \nabla_{\theta} \hat{\mathbb{E}}_{\mathcal{D}}[-Q_{\phi_1}(o_t, \mu_{\theta}(o_t))], \quad (2.108)$$

$$\bar{\phi}_k \leftarrow \tau \phi_k + (1 - \tau) \bar{\phi}_k, \quad k = 1, 2, \quad (2.109)$$

$$\bar{\theta} \leftarrow \tau \theta + (1 - \tau) \bar{\theta}. \quad (2.110)$$

Note that unlike SAC, the target *actor* also receives a soft update, since TD3 uses a separate target actor copy to compute the smoothed target actions.

Exploration Strategy

Since the actor is deterministic, online exploration is achieved by injecting Gaussian noise into the executed action at each step:

$$a_t^{\text{exec}} = \text{clip}(\mu_\theta(o_t) + \xi_t, a_{\min}, a_{\max}), \quad \xi_t \sim \mathcal{N}(0, \sigma_e(t)^2 \cdot \sigma_{\text{scale}}^2), \quad (2.111)$$

where the exploration magnitude $\sigma_e(t)$ is linearly annealed from an initial value $\sigma_{e,0}$ to a final value $\sigma_{e,T}$ over training, encouraging broad exploration early and refined exploitation later.

2.8.6 Environments and the Transfer Task

Since direct exploration on operational wind farms carries significant economic and safety risks, training policies offline on surrogate models before deployment is a practical necessity.

Training in FLORIS and Transfer to LES

The training phase relies on FLORIS [100], a static engineering wake model that provides computationally cheap evaluations of the farm's aerodynamic interactions. To evaluate the robustness of the policies learned on the static model, we define a Transfer Task. In this task, the dynamic UTD-WF LES solver is utilized as a proxy for the real wind farm. Unlike FLORIS, the LES environment captures transient aerodynamic phenomena such as wake meandering and dynamic inflow, providing a rigorous testbed for the transferability of the DRL policies.

Wind Condition Scenarios

To ensure generalization, the environments are subjected to different meteorological conditions:

- **Wind Scenario I:** all trajectories are run under a constant, prevailing free-stream wind velocity and direction.
- **Wind Scenario II:** the wind farm is subjected to dynamic variations. New free-stream conditions (u_∞, ϕ_∞) are sampled at the beginning of each episode according to $u_\infty \sim \mathcal{W}(\bar{u}, \lambda)$ and $\phi_\infty \sim \mathcal{N}(\bar{\phi}, \sigma_\phi)$, where $\mathcal{W}$ is a Weibull distribution and $\mathcal{N}$ is a Normal distribution.

Online Learning and Scoring Metric

The final evaluation score is defined as the weighted average of the cumulative episodic rewards across a predefined set of n_w distinct wind conditions:

$$\text{score}(\pi_1, \dots, \pi_M) = \sum_{j=1}^{n_w} \rho_j \sum_{t=0}^T r_{jt}, \quad (2.112)$$

where ρ_j is the weighting factor associated with the probability of occurrence of each atmospheric scenario, such that $\sum_{j=1}^{n_w} \rho_j = 1$.

2.8.7 Integrated Training and Evaluation Framework

The full multi-fidelity workflow is common to all nine benchmark configurations. Phase 1 trains the policy (using one of the algorithms described above in one of the three paradigms) entirely within the FLORIS surrogate environment. Phase 2 loads the trained weights and evaluates them in the LES environment without further learning, producing the final performance metrics.

Algorithm 4: Multi-Fidelity Training and LES Transfer Evaluation

- 1 **Phase 1: Training (Surrogate FLORIS Environment)**
 - 2 Select algorithm $\in \{\text{PPO, SAC, TD3}\}$ and paradigm $\in \{\text{I, MA, C}\}$;
 - 3 Initialize networks and buffers according to Table 2.1;
 - 4 Run the corresponding training loop (Algorithms 1–3);
 - 5 Save optimal weights $\theta^* = \{\theta^{1*}, \dots, \theta^{M*}\}$ (or Θ^* for C);
 - 6 **Phase 2: Evaluation (LES Transfer Task)**
 - 7 Initialize LES domain matching the FLORIS wind farm layout;
 - 8 **for** *each evaluation scenario* $w = 1$ **to** N_{wind} **do**
 - 9 $s_0 \leftarrow \text{les.reset}(\text{scenario } w)$;
 - 10 **for** $t = 1$ **to** T_{eval} **do**
 - 11 | Run LES with deterministic actions from π^* (or μ^*);
 - 12 **end**
 - 13 **end**
 - 14 Compute final score: power gain and fatigue load mitigation;
-

Chapter 3

Reference Wind Turbines

The aerodynamic and aeroelastic analyses presented in this work rely on standardized, publicly available turbine models, which allow for consistent benchmarking and direct comparison with the existing literature.

This chapter details the specific properties of the three reference wind turbine models employed throughout this research: the NREL 5MW, the IEA 15MW, and the NREL Phase VI. These models cover a wide range of scales and technological generations (see Figure 3.1). For each model, the main macroscopic parameters, aerodynamic polars, distributed structural properties, and geometric blade definitions are presented and analysed.

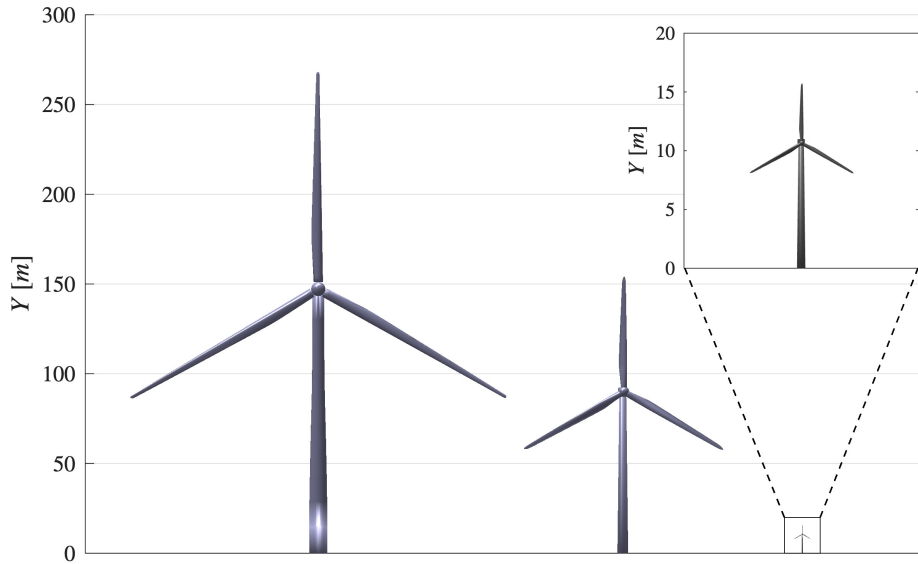


Figure 3.1: Schematic representation of the three wind turbine models employed in the simulations, illustrating their relative scale and dimensions. From left to right: IEA 15MW, NREL 5MW, and NREL Phase VI.

3.1 NREL 5MW

The 5 MW baseline wind turbine developed by the National Renewable Energy Laboratory (NREL) [168] is a conceptual model—meaning no physical prototype was ever constructed—whose essential features are representative of a typical utility-scale machine. Because of the availability and representativeness of its aerodynamic, structural, and control properties, it is arguably the most widely used benchmark in the wind energy community for evaluating aeroelastic codes and fluid-dynamic solvers.

The rotor is a conventional three-bladed, upwind design, equipped with variable-speed and variable-blade-pitch-to-feather mechanisms. The macroscopic specifications of the turbine are summarised in Table 3.1. For the specific purpose of the numerical simulations carried out in this work, the blade precone angle is neglected to simplify the geometrical representation of the rotor. Furthermore, the nacelle is modelled as a simple parallelepiped, with dimensions inferred from the early reference studies defining the DOWEC project [169], which served as the foundational basis for the NREL 5MW blade design.

Table 3.1: Macroscopic properties of the NREL 5MW reference wind turbine.

NREL 5MW	
Rating	5 MW
Rotor Orientation	Upwind
Number of Blades	3
Control	Variable Speed
Rotor Diameter	126 m
Hub Height	90 m
Hub Diameter	3 m
Cut-In Wind Speed	3.0 m/s
Rated Wind Speed	11.4 m/s
Rated Rotor Speed	12.1 RPM
Design Tip-Speed Ratio	7.5
Cut-Out Wind Speed	25.0 m/s

The turbine’s control system relies on a generator-torque controller to maximise power production below rated conditions, while a blade-pitch controller regulates the generator speed to preserve structural safety above rated

wind speeds. As all simulations in this work are carried out under Region-II conditions, the blade-pitch controller is inactive, and the generator-torque controller maintains the optimal Tip-Speed Ratio (TSR). Using a standard BEM algorithm, the global aerodynamic performance can be evaluated. As illustrated in Figure 3.2, the peak power extraction is achieved at $TSR_{opt} \approx 7.5$, yielding a maximum power coefficient of $C_{P,max} = 0.486$ and a corresponding thrust coefficient of $C_T = 0.786$.

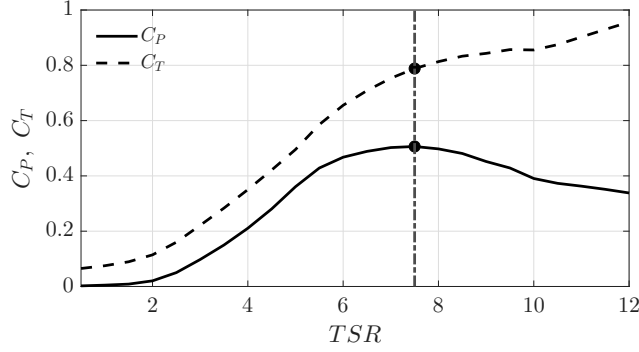


Figure 3.2: Power and thrust coefficients of the NREL 5MW turbine versus tip speed ratio. The dotted line marks the optimal tip speed ratio.

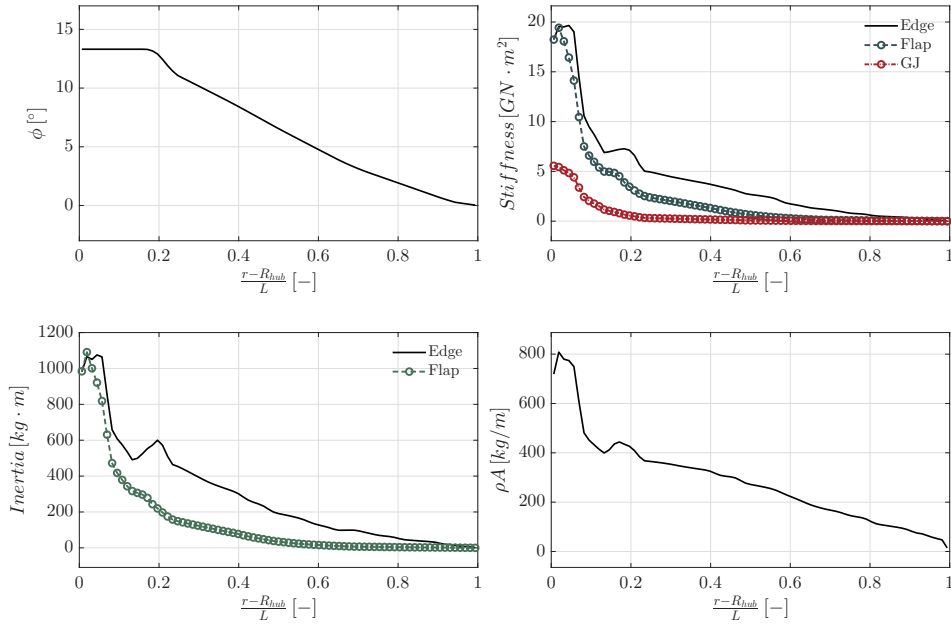


Figure 3.3: Blade structural properties along the span: twist angle (top-left), stiffness (top-right), inertia (bottom-left), and density (bottom-right).

Beyond global aerodynamic metrics, an accurate aeroelastic description requires the distributed structural properties along the 61.5 m blade span (total mass: 17,740 kg per blade). Figure 3.3 shows the spanwise distribution of

six cross-sectional properties along the nondimensional radial axis: structural twist angle, mass per unit length, flapwise and edgewise stiffnesses (EI_{flap} , EI_{edge}), torsional stiffness (GJ), and extensional stiffness (EA).

Aerodynamically, the blade shape is defined by 8 unique airfoils. After 2 cylindrical sections near the root (necessary for structural integrity), 6 wind energy airfoils of the DU (Delft University) and NACA families define the active aerodynamic response. The tabulated aerodynamic data for these profiles, originally corrected to account for 3D rotational augmentation, define the static lift, drag, and moment coefficients (see Figure 3.4).

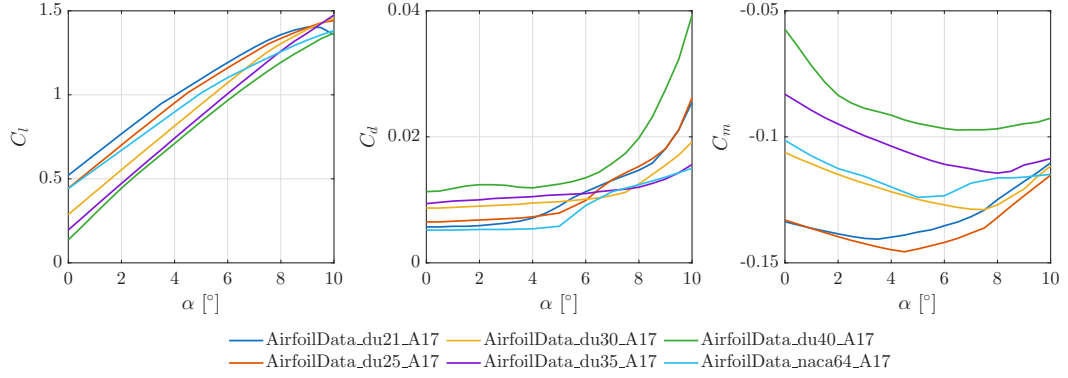


Figure 3.4: Aerodynamic coefficients of the six airfoils of the NREL 5MW wind turbine.

The precise geometric layout of these 2D cross-sections shapes the 3D blade. The pitch axis is assumed to pass through each airfoil exactly at the quarter-chord point. Figure 3.5 illustrates the alignment of the blade sections, explicitly denoting the spatial offsets of the aerodynamic center and the center of mass relative to this quarter-chord axis. This relative offset is a critical driver of torsional-bending coupling during aeroelastic deformations.

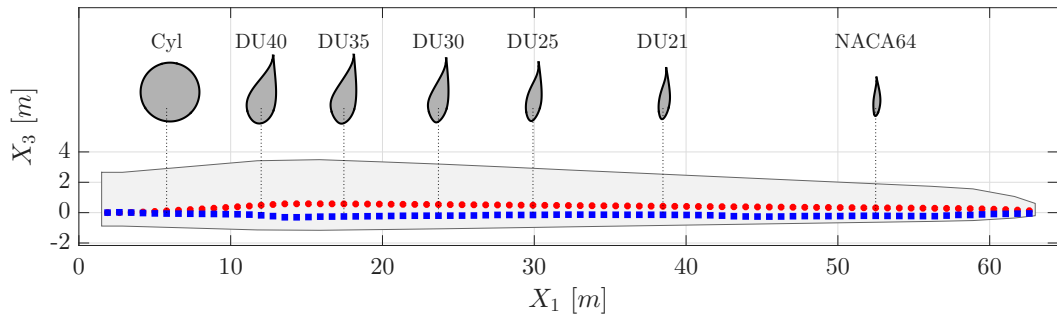


Figure 3.5: Aerodynamic centre (red), centre of mass (blue) and airfoils of the NREL 5MW wind turbine blade.

It should be noted that in the original NREL model [168] adopted in this work, the spanwise transition from one airfoil family to another is strictly

abrupt. Consequently, there is no mathematical guarantee of continuity in the aerodynamic forces along the span. This discontinuity is particularly evident in the pitching moment coefficient, which can exhibit sudden jumps at a given angle of attack when transitioning between adjacent airfoils. The resulting fully lofted 3D blade geometry, which interacts with the turbulent flow field in the simulations, is visualized in Figure 3.6.

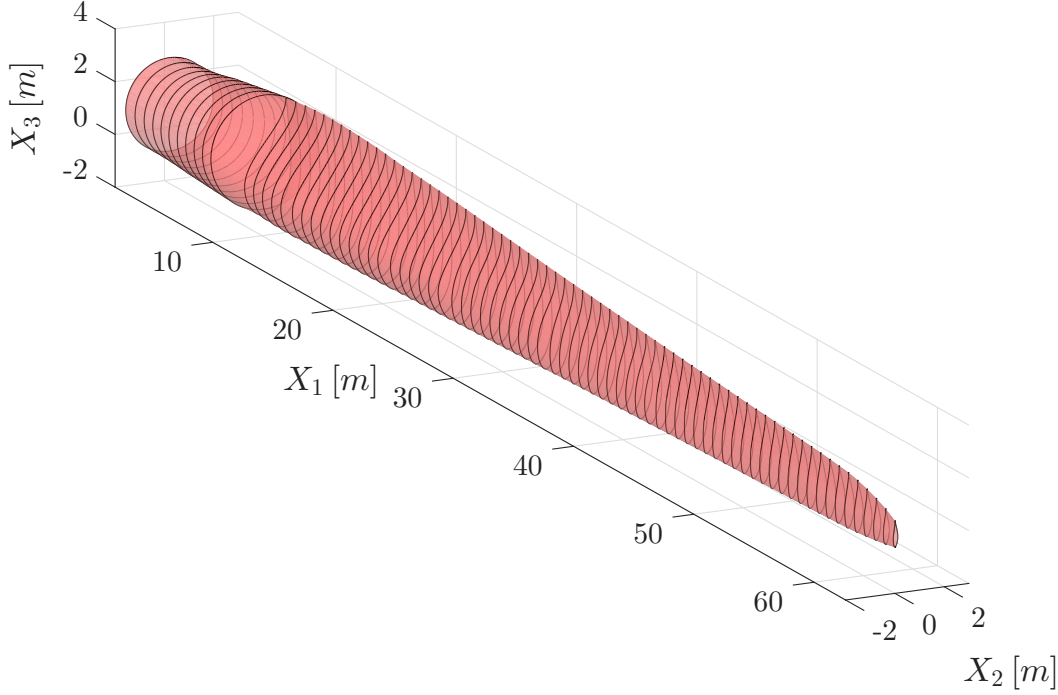


Figure 3.6: 3D-model of the NREL 5MW blade.

3.2 IEA 15MW

To address the rapid upscaling of the offshore wind sector and the need for updated public benchmarks, the IEA Wind Technology Collaboration Programme developed the IEA 15MW reference wind turbine [11]. Unlike the NREL 5MW, which represents a typical utility-scale onshore/shallow-offshore turbine from the late 2000s, the IEA 15MW embodies the next generation of ultra-large, highly flexible offshore architectures. The primary macroscopic specifications of this turbine are provided in Table 3.2.

Due to the large-scale 240 m rotor diameter, the rated rotor speed is significantly lower (7.56 RPM) compared to the 5 MW model. This reduction is an engineering necessity to maintain structural integrity, limit blade tip speeds, and mitigate severe aerodynamic noise and leading-edge erosion in offshore environments. Consequently, the rotor is designed to operate at a

Table 3.2: Macroscopic properties of the IEA 15MW reference wind turbine.

IEA 15MW	
Rating	15 MW
Rotor Orientation	Upwind
Number of Blades	3
Control	Variable Speed
Rotor Diameter	240 m
Hub Height	150 m
Hub Diameter	5.2 m
Cut-In Wind Speed	3.0 m/s
Rated Wind Speed	10.59 m/s
Rated Rotor Speed	7.56 RPM
Design Tip-Speed Ratio	9.0
Cut-Out Wind Speed	25.0 m/s

higher optimal Tip-Speed Ratio ($TSR_{opt} = 9.0$). Figure 3.7 displays the global power and thrust coefficients (C_P and C_T) as a function of the TSR, highlighting the aerodynamic operational peak of the machine.

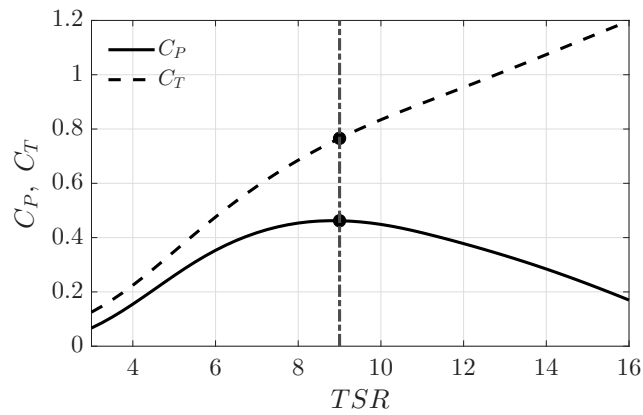


Figure 3.7: Power and thrust coefficients of the IEA 15MW wind turbine as a function of the tip speed ratio. The dotted vertical line indicates the optimal tip speed ratio.

Scaling the rotor to these dimensions introduces significant aeroelastic challenges. The blades span 117 m in length and feature a highly optimised structural layout to balance weight and rigidity. Figure 3.8 illustrates the

distributed structural properties along the nondimensional blade span, including the structural twist, cross-sectional stiffness (EI_{flap} , EI_{edge}), mass inertia, and linear density. Given the extreme slenderness of these blades, accurately modelling these spanwise structural properties is necessary to capture large deflections and fluid-structure interactions, particularly during blade passage through the tower shadow.

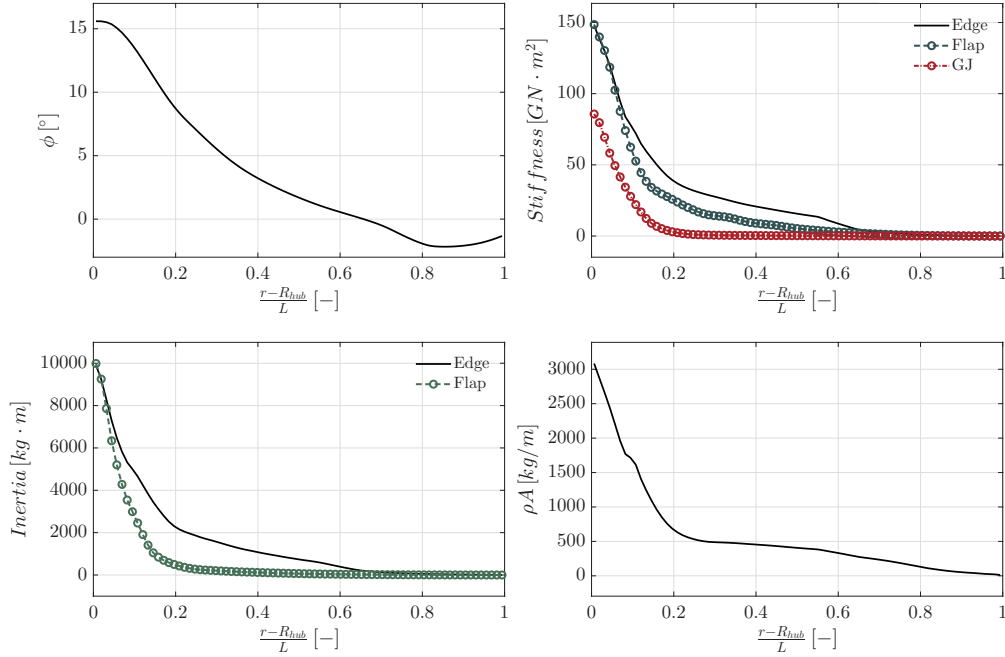


Figure 3.8: Structural properties of the blade along the span: local twist angle (top-left), stiffness (top-right), inertia (bottom-left), and density (bottom-right).

From an aerodynamic perspective, the IEA 15MW turbine abandons the DU and NACA profiles used in older generation models, employing instead the FFA-W3 airfoil series. These airfoils, designed specifically for large wind turbine rotors, offer high aerodynamic efficiency and favorable structural thickness ratios, which are essential for accommodating the internal spar caps. The static lift, drag, and pitching moment coefficients for these specific FFA airfoils are plotted in Figure 3.9.

Finally, the 2D cross-sectional layout and the fully reconstructed 3D geometry are presented. Figure 3.10 details the alignment of the 2D aerodynamic sections along the pitch axis, emphasizing the spatial offset between the aerodynamic center and the center of mass. For a blade of this length and flexibility, this offset significantly amplifies torsional-bending coupling under unsteady aerodynamic loading. The final 3D surface of the blade, used as the physical boundary in the LES simulations, is shown in Figure 3.11.

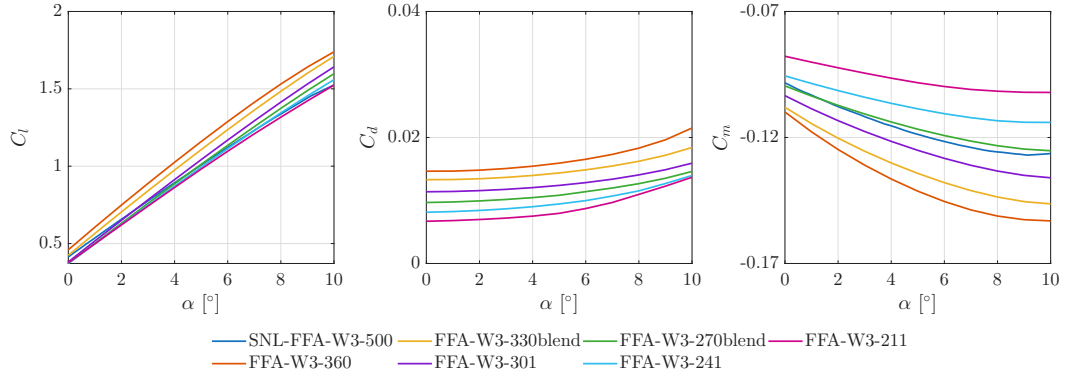


Figure 3.9: Aerodynamic coefficients of the six airfoils of the IEA 15MW wind turbine.

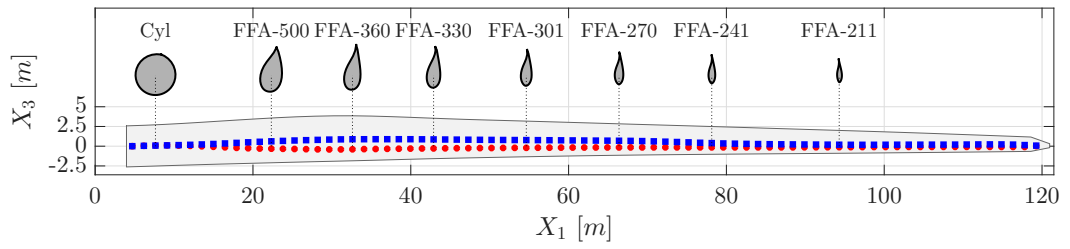


Figure 3.10: Aerodynamic centre (red), centre of mass (blue) and airfoils of the IEA 15MW wind turbine blade.

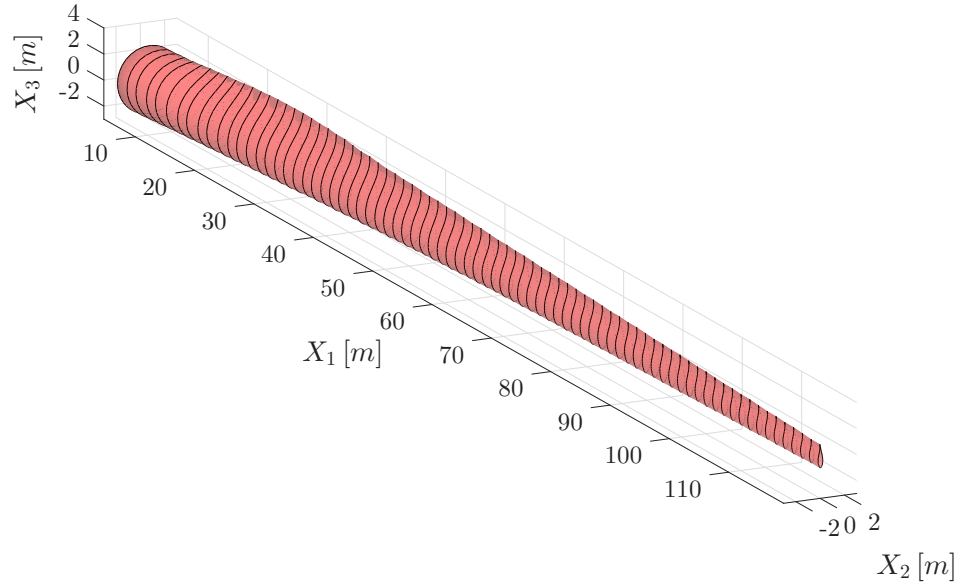


Figure 3.11: 3D-model of the IEA 15MW blade.

3.3 3-Bladed NREL Phase VI

The third turbine employed in this work is the NREL Phase VI [170], a small-scale rotor with a well-documented experimental database that makes it a

standard benchmark for aerodynamic and aeroelastic validation. Originally designed and tested in the NASA Ames wind tunnel as a two-bladed rotor, the model employed in this study has been specifically modified into a three-bladed configuration to better represent the standard topology of modern commercial wind turbines. The blade geometry, aerodynamic profiles, and structural properties are retained unchanged from the original two-bladed design; only the rotor configuration and the associated inertial parameters are adapted accordingly. The primary macroscopic specifications of this modified NREL Phase VI turbine are provided in Table 3.3.

Table 3.3: Macroscopic properties of the modified 3-bladed NREL Phase VI.

NREL Phase VI	
Rating	19.8 kW
Rotor Orientation	Upwind
Number of Blades	3
Control	Variable Speed
Rotor Diameter	10.0 m
Hub Height	12.2 m
Hub Diameter	0.50 m
Cut-In Wind Speed	6.0 m/s
Rated Wind Speed	11.0 m/s
Rated Rotor Speed	71.63 RPM
Design Tip-Speed Ratio	5.4

In contrast to large-scale offshore turbines, the NREL Phase VI is a much smaller machine with a rotor diameter of just 10.0 m. Consequently, its operational parameters are scaled differently, featuring a significantly higher rated rotor speed of 71.63 RPM and a lower design Tip-Speed Ratio ($TSR_{opt} = 5.4$). Figure 3.12 displays the global power and thrust coefficients (C_P and C_T) as a function of the TSR, highlighting the aerodynamic operational peak of this specific rotor configuration. Figure 3.13 illustrates the distributed structural properties along the nondimensional blade span, including the structural twist, cross-sectional stiffness, mass inertia, and linear density. While these blades are considerably stiffer and shorter than modern utility-scale blades, accurately representing their spanwise structural properties is nonetheless necessary to capture the relevant aeroelastic couplings in the simulations.

Aerodynamically, the Phase VI rotor relies on the S809 airfoil series, specifically designed by NREL to minimise sensitivity to roughness and provide a

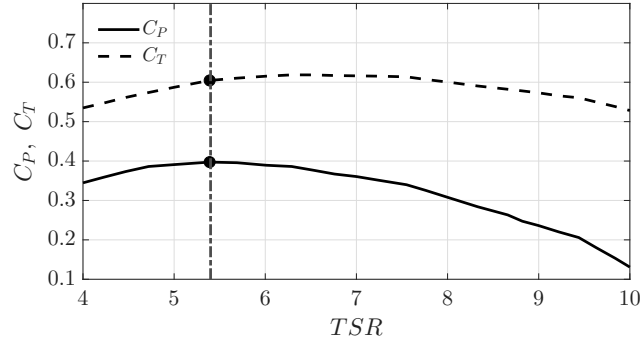


Figure 3.12: Power and thrust coefficients of the NREL Phase VI wind turbine as a function of the tip speed ratio. The dotted vertical line indicates the optimal tip speed ratio.

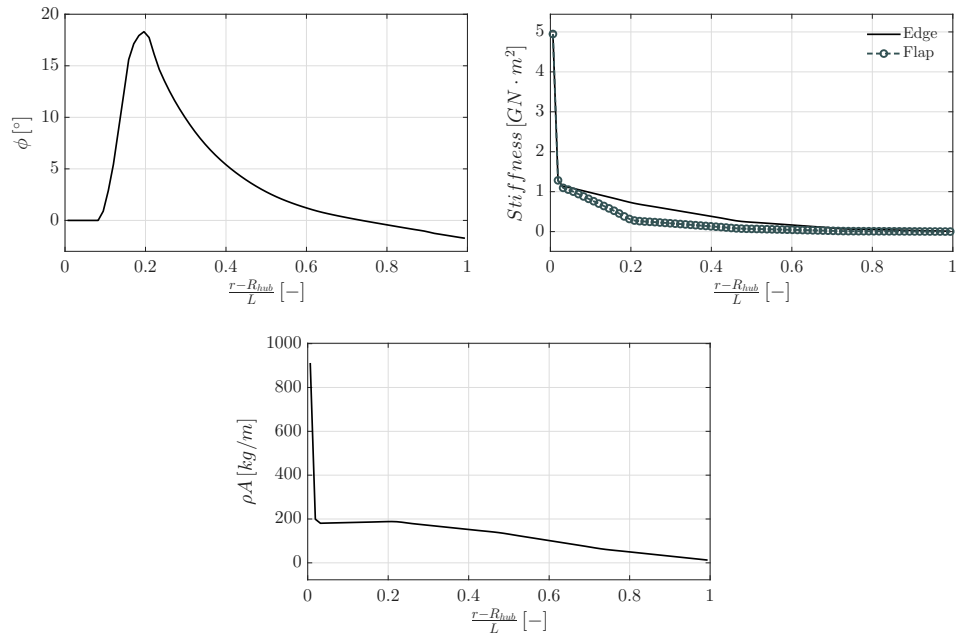


Figure 3.13: Structural properties of the blade along the span: local twist angle (top-left), stiffness (top-right), inertia (bottom-left), and density (bottom-right).

limited maximum lift coefficient, which aids in stall regulation. The static aerodynamic coefficients, lift (C_l), drag (C_d), and pitching moment (C_m), characterising the airfoil sections over a range of angles of attack are plotted in Figure 3.14.

Finally, Figure 3.15 shows the alignment of the 2D aerodynamic sections along the pitch axis, while Figure 3.16 shows the corresponding 3D blade geometry.

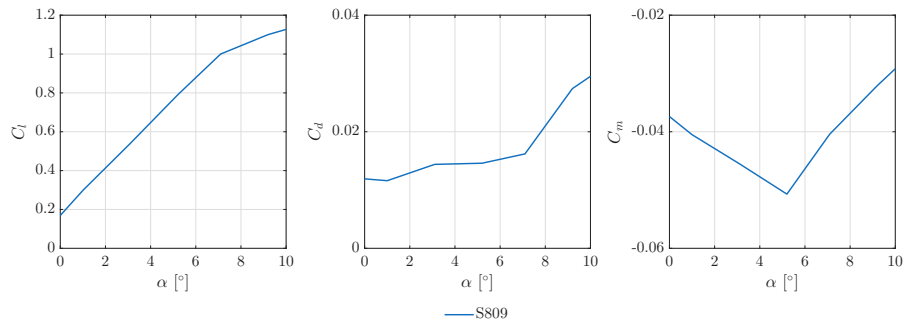


Figure 3.14: Aerodynamic coefficients (C_l, C_d, C_m) of the airfoil sections of the NREL Phase VI wind turbine.

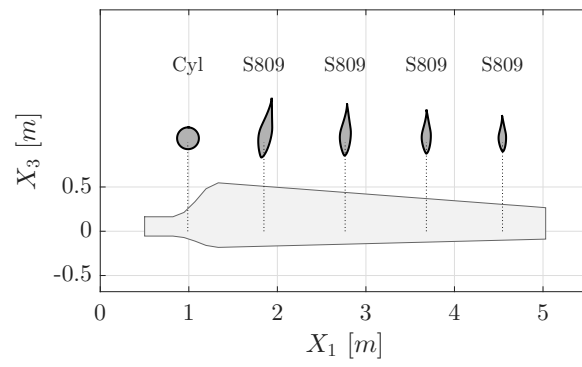


Figure 3.15: Aerodynamic centre (red), centre of mass (blue) and airfoils of the NREL Phase VI wind turbine blade.

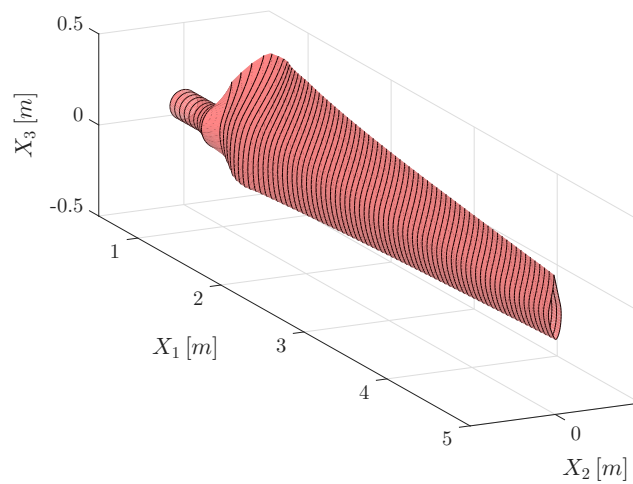


Figure 3.16: 3D-model of the NREL Phase VI blade.

Chapter 4

Validation and Verification of the Numerical Code

The numerical framework employed throughout this thesis for the aeroelastic analysis of wind turbines requires independent verification of both its structural and fluid-dynamic components against established reference solvers. Before the turbine-specific verification, a preliminary qualitative validation of the ALM wake implementation is presented against wind-tunnel measurements, providing confidence in the fluid-dynamic component of the framework. This chapter then presents a systematic comparison of the in-house UTD-WF solver [113, 114, 115, 46, 153] and the structural modal beam solver [46] against the OpenFAST engineering framework [39] for two reference turbines: the NREL 5MW and the IEA 15MW. The two OpenFAST structural modules used as benchmarks — ElastoDyn and BeamDyn, described in Appendix D — represent respectively a modal formulation without torsion and a geometrically exact beam formulation with torsion, providing complementary reference points for the assessment. For each turbine, two rotor configurations are considered: a *rotor-only* (RO) configuration, in which the tower and nacelle are absent, and a *tower-and-nacelle* (TN) configuration, in which the aerodynamic interaction with the tower is included while tower structural flexibility is neglected. This two-by-two matrix of structural model and rotor configuration isolates, respectively, the effect of torsional coupling and the effect of the periodic tower-passage event on the predicted aeroelastic response. The chapter is organised as follows. Section 4.1 presents the wake profile validation against experimental data. Section 4.2 addresses the NREL 5MW turbine, covering the eigenfrequency benchmark and the coupled aeroelastic response under sheared inflow. Section 4.3 addresses the IEA 15MW turbine; the complete verification procedure is presented in the companion study [171] and the main results are summarised here for completeness.

The contribution of this chapter is the systematic, cross-code verification of the in-house CFD-CSD framework against both the modal (ElastoDyn) and geo-

metrically exact (BeamDyn) OpenFAST modules for the NREL 5MW and IEA 15MW turbines, conducted within the IEA Wind TCP Task 47 TURBINA cross-validation activity. The verified solver underpins all aeroelastic investigations in the subsequent chapters.

4.1 Wake Profile Validation

The fluid-dynamic component of the in-house UTD-WF solver has been previously validated against both laboratory and field measurements. In the mesoscale–microscale coupling study of Santoni et al. [115], the UTD-WF LES predictions of wind farm power production and wake velocity profiles were assessed against SCADA power output data and scanning Doppler wind LiDAR measurements acquired at an onshore wind farm in North Texas, demonstrating the capability of the solver to reproduce field-scale wake dynamics under realistic atmospheric boundary layer conditions. A further qualitative assessment of the ALM implementation is provided here through comparison with the wind-tunnel measurements of Krogstad et al. [172] for an isolated turbine, following the validation study of De Cillis et al. [71]. Figure 4.1 presents vertical profiles of the time-averaged streamwise velocity $\bar{U}/U_\infty$ and the turbulent kinetic energy k/U_∞^2 extracted at $x/D = 3$ and $y/D = h_{hub}$ downstream of the rotor. The LES predictions are in reasonable agreement with the experimental data, with discrepancies attributable to differences in the experimental and numerical configurations: the absence of lateral walls, an extended wall-normal domain, and a modified tower-and-nacelle geometry result in a slightly lower velocity deficit within the wake and a higher free-stream velocity outside it compared with the measurements.

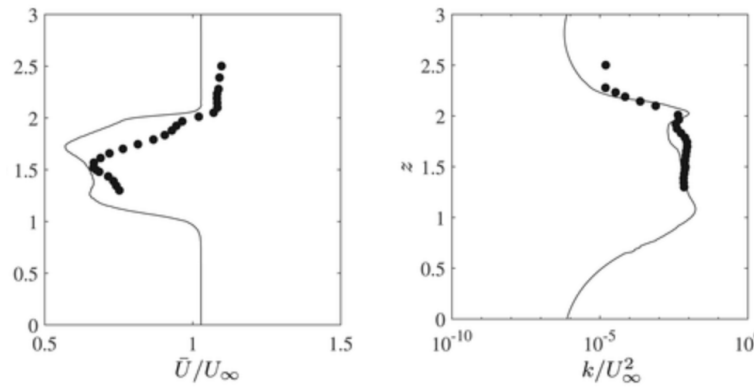


Figure 4.1: Turbulent kinetic energy profiles at $x/D = 3$ and $y/D = h_{hub}$: experimental results of [172] (—) and LES results (●). Adapted from [71].

4.2 NREL 5MW Turbine

The NREL 5MW is the most widely adopted benchmark turbine in the wind energy community [168], making it an ideal reference for assessing the reliability of the in-house solver against OpenFAST. Prior to the OpenFAST comparison, a preliminary verification of the aeroelastic framework was carried out by Della Posta et al. [173] against the HAWC2 engineering solver [174], with the aeroelastic results of Heinz et al. [48] used as an additional reference. That study demonstrated that the inclusion of the aeroelastic feedback produces significant variations in the instantaneous and phase-averaged structural and aerodynamic quantities, while time-averaged and flow-field features remain largely unaffected. The tower passage was identified as the dominant source of unsteadiness, driving both flapwise and torsional blade motion, and aerodynamic damping of the flapwise mode was confirmed consistently with the literature. Tip deformation analysis further suggested a non-negligible role of torsional deformation on the local angle of incidence, motivating the progressive inclusion of additional structural degrees of freedom in the present framework.

The structural and aeroelastic verification against OpenFAST is then conducted under a laminar sheared inflow (power-law exponent $\alpha = 0.05$, hub-height velocity $U_\infty = 9$ m/s) corresponding to Region-II operation at the optimal tip-speed ratio $\text{TSR} = 7.5$.

4.2.1 Blade Properties and Finite Element Model

The structural model follows the modal decomposition framework described in Section 4.3. The finite element discretisation of the NREL 5MW blade employs Euler–Bernoulli beam elements with six degrees of freedom per node, with linear shape functions for axial and torsional deformations and a lumped-mass representation that accounts for the local offset of the centres of mass with respect to the pitching axis X_1 . The blade spans $L = 61.5$ m, and its total mass is 17,740 kg per blade.

For ElastoDyn, the blade is parameterised by the mode-shape polynomial coefficients that encode the first flapwise, second flapwise, and first edgewise modes; torsion is not included. For BeamDyn, the full 6×6 cross-sectional stiffness and mass matrices are used directly, making all six structural degrees of freedom available without prior mode-shape assumptions.

4.2.2 Eigenfrequency Benchmark

The first six natural frequencies of the undeformed, non-rotating NREL 5MW blade computed by the present structural model are listed in Table 4.1 alongside the OpenFAST reference values and the results of Jonkman et al. [168]. A graphical comparison against additional literature models is provided in Figure 4.2.

Table 4.1: Natural frequencies of the first six structural modes of the NREL 5MW blade (non-rotating, in vacuum).

Mode	Description	Present
1	1st flapwise	0.6763
2	1st edgewise	1.0858
3	2nd flapwise	1.9485
4	2nd edgewise	4.0037
5	3rd flapwise	4.5167
6	1st torsional	5.5837

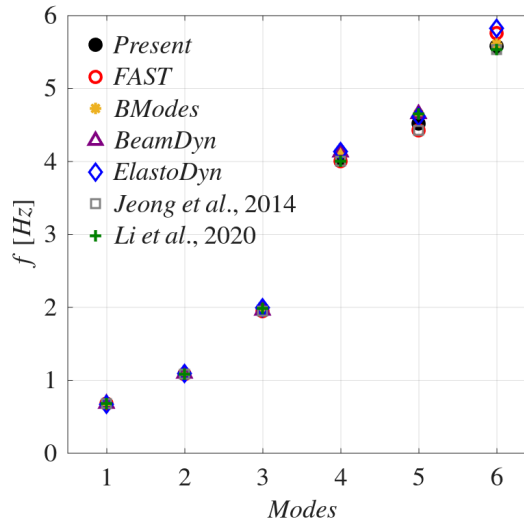


Figure 4.2: First six natural frequencies of the NREL 5MW blade computed by the present structural model (●) compared against FAST (○), BModes (*), BeamDyn (◇), ElastoDyn (△), Jeong et al. (2014) (□), and Li et al. (2020) (+).

The computed eigenfrequencies are in good agreement with both OpenFAST modules and the reference values of Jonkman et al. [168]. The slight overestimate across all models with respect to the BModes reference ($\approx 3\text{--}5\%$ for the first three modes) is consistent with the use of Euler–Bernoulli beam theory in the present FEM formulation, as opposed to the Timoshenko formulation employed by BModes, which additionally accounts for shear deformation and rotary inertia. The first torsional mode appears at $f_6 = 5.58\text{ Hz}$, well above the bending modes; its relatively high frequency, compared to the IEA 15MW (Section 4.3), reflects the greater torsional stiffness of the shorter, stiffer NREL 5MW blade and confirms the secondary role of torsional dynamics at this scale.

4.2.3 Coupled Aeroelastic Response

The fully coupled aeroelastic solver is verified against OpenFAST under the sheared inflow described above for both the RO and TN configurations. Throughout this section, tower and nacelle *structural* flexibility are neglected; the TN configuration therefore isolates the aerodynamic effect of the tower passage from any structural tower response. Four reference cases are considered: ElastoDyn rotor-only (ED-RO), ElastoDyn tower-and-nacelle (ED-TN), BeamDyn rotor-only (BD-RO), and BeamDyn tower-and-nacelle (BD-TN). Two variants of the in-house solver are compared: CFD-CSD/OV, in which structural coupling modifies only the deformation velocity in the angle-of-attack computation; and CFD-CSD/T, which additionally incorporates the instantaneous torsional angle.

Spanwise Aerodynamic Loads

Figure 4.3 shows the time-averaged distributions of the angle of attack α , pitching moment M_{aero} , flapwise force F_2 (normal to the rotor plane), and edgewise force F_3 (in the rotor plane) along the blade span. Because the loads are time-averaged over many rotor revolutions, the RO and TN variants of each structural solver collapse onto the same curve in this view: the tower-passage event, being periodic and short in duration, contributes negligibly to the mean. The dominant difference is therefore between ElastoDyn and BeamDyn.

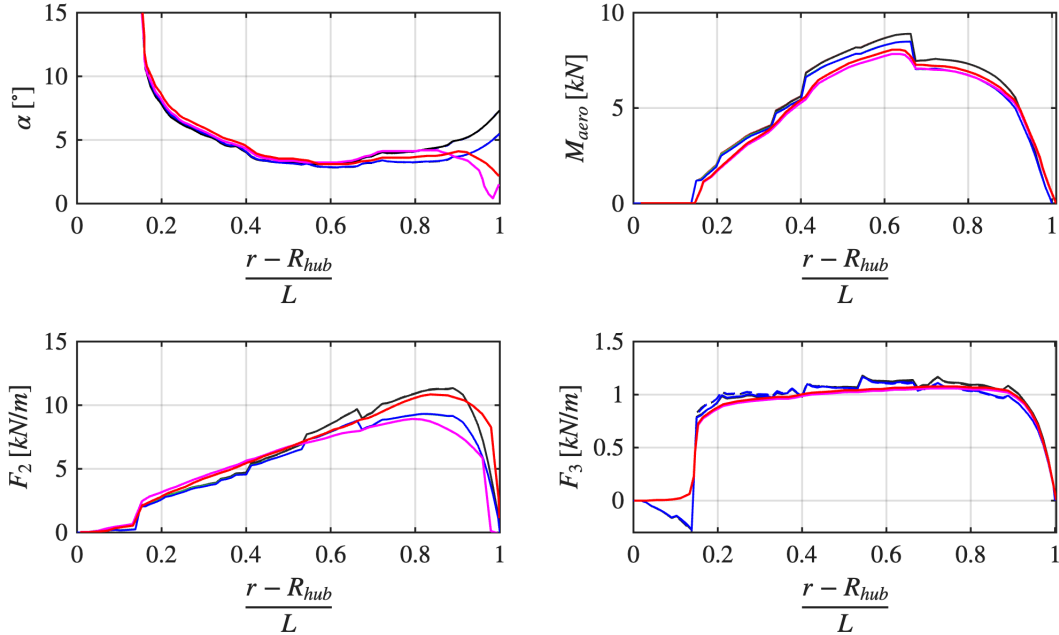


Figure 4.3: Time-averaged aerodynamic quantities along the NREL 5MW blade span. CFD-CSD/OV (—), CFD-CSD/T (—), *BeamDyn* (—), *ElastoDyn* (—). RO and TN variants overlap in the time-averaged view.

Good agreement is observed across all solvers from 20 % to 80 % blade span; discrepancies near the root are attributable to different hub modelling strategies. In the outer 20 % of the span, the incidence angle predicted by CFD-CSD/T and BD diverges from the non-torsional solvers, confirming that torsional deformation modifies the local angle of attack at the tip, although the effect is more moderate at this scale than for the IEA 15MW. The flapwise force of CFD-CSD/T agrees with BeamDyn to within $\approx 3\%$.

Structural Deformations

Figure 4.4 reports the structural response of the NREL 5MW blade in two complementary representations. The left column shows the *time-averaged spanwise profiles* of the out-of-plane (flapwise), in-plane (edgewise), and torsional deformations. The right column shows the corresponding *phase-averaged tip deflections* as a function of the azimuth angle θ , where $\theta = 180^\circ$ marks the blade passage in front of the tower.

Time-averaged spanwise profiles. All four OpenFAST cases (ED-RO, ED-TN, BD-RO, BD-TN) are shown on the same axes; the RO and TN curves of each solver are nearly indistinguishable in this view, confirming that the mean deformation state is insensitive to the presence of the tower. The comparison between ElastoDyn and BeamDyn isolates the effect of the structural model: the out-of-plane deformation predicted by BD exceeds that of ED by $\approx 8\%$ at the tip, attributable to the additional geometric softening captured by the geometrically exact formulation. The torsional profile (Figure 4.4f) is shown for the BeamDyn cases only, as ElastoDyn does not include a torsional degree of freedom.

Phase-averaged tip deflections. The phase-averaged representation reveals the influence of the tower passage that is averaged out in the time-mean. In the TN cases, a clear local minimum at $\theta = 180^\circ$ is visible in the out-of-plane deflection, corresponding to the instantaneous load reduction as the blade crosses the tower wake. The amplitude of this dip is comparable between ElastoDyn and BeamDyn, suggesting that the tower-shadow-induced load excursion is captured consistently by both structural models. The in-plane deflection is dominated by the gravity-induced once-per-revolution oscillation and shows good agreement across all four cases. The torsional tip angle predicted by BeamDyn (Figure 4.4e, BD-RO and BD-TN) remains small throughout the revolution, consistent with the high torsional stiffness of the NREL 5MW blade; the TN variant shows a slight additional perturbation at $\theta = 180^\circ$ due to the aerodynamic moment fluctuation induced by the tower passage. The out-of-plane deformation of the NREL 5MW is significantly smaller than that of the IEA 15MW, reflecting the greater structural stiffness of the shorter blade. The in-plane deformation is dominated by the gravitational loading and agrees

well across all solvers. The torsional response is markedly smaller than that observed for the 15MW machine, consistent with the higher torsional stiffness and the secondary role of torsion-bending coupling at this scale — a contrast that directly motivates the greater emphasis placed on torsional dynamics in the 15MW studies of Chapters 6 and 7.

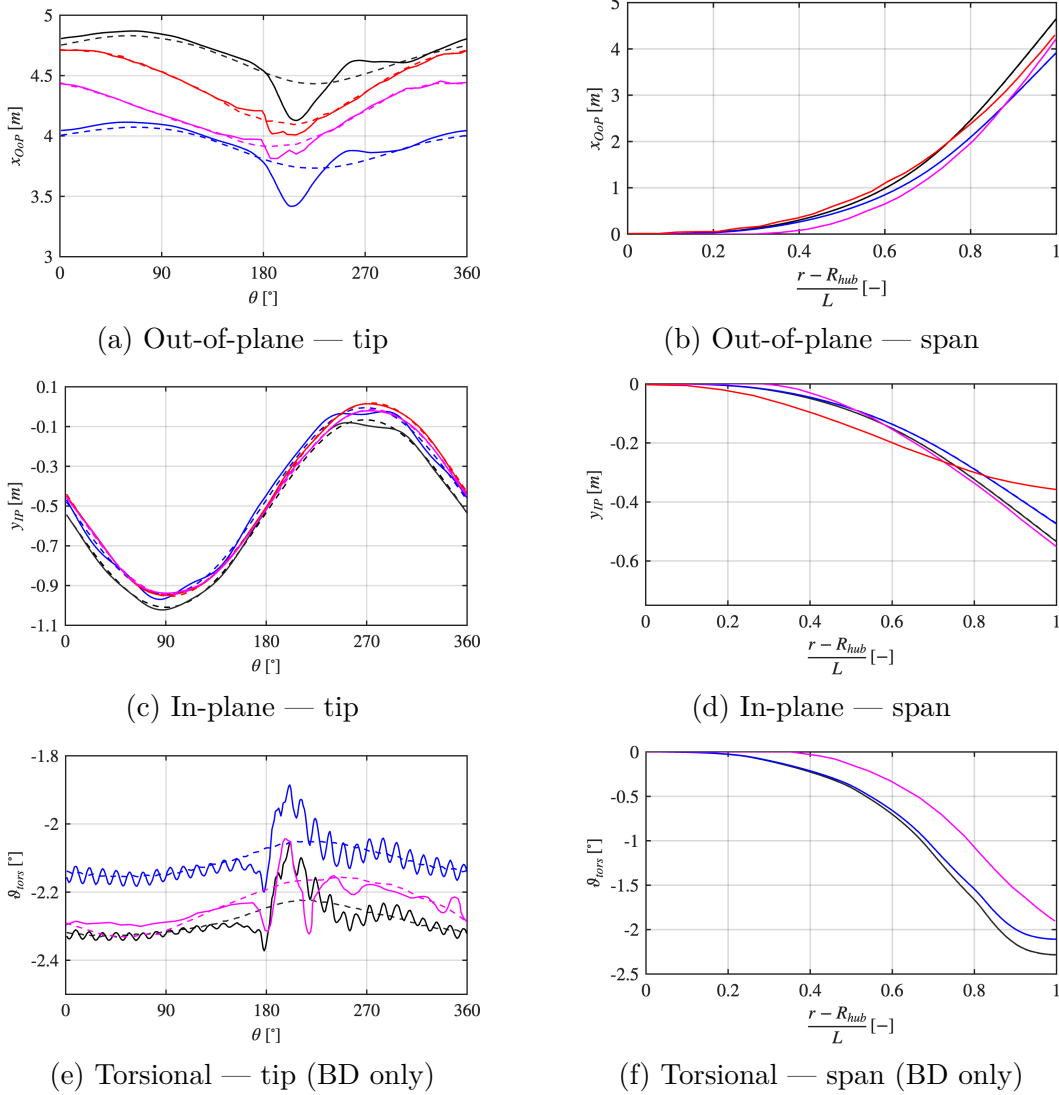


Figure 4.4: Phase-averaged spanwise deformation profiles (left column) and time-averaged tip deflections (right column) for the NREL 5MW blade. *ElastoDyn*: TN (—), RO (---); *BeamDyn*: TN (—), RO (---). The torsional panels (e–f) show *BeamDyn* results only; *ElastoDyn* does not include a torsional degree of freedom.

Power and Thrust Coefficients

The phase-averaged power coefficient C_p and thrust coefficient C_t are shown in Figure 4.5 for all four OpenFAST cases alongside the in-house solver predictions. In the RO configuration, both C_p and C_t are nearly constant over the revolution; residual oscillations reflect blade-to-blade inflow asymmetry induced by the shear profile. In the TN configuration, the blade passage in front of the tower produces a $\approx 15\%$ drop in C_p at $\theta = 180^\circ$, more pronounced than the $\approx 10\%$ observed for the IEA 15MW, attributable to the relatively larger tower-to-rotor diameter ratio of the NREL 5MW ($d_{\text{twr}}/D \approx 0.047$, versus 0.027 for the 15MW). The recovery after the tower shadow event is well captured by all four OpenFAST cases; the dip amplitude predicted by ElastoDyn and BeamDyn is consistent with one another, confirming that the tower-shadow-induced load loss is insensitive to the choice of structural model.

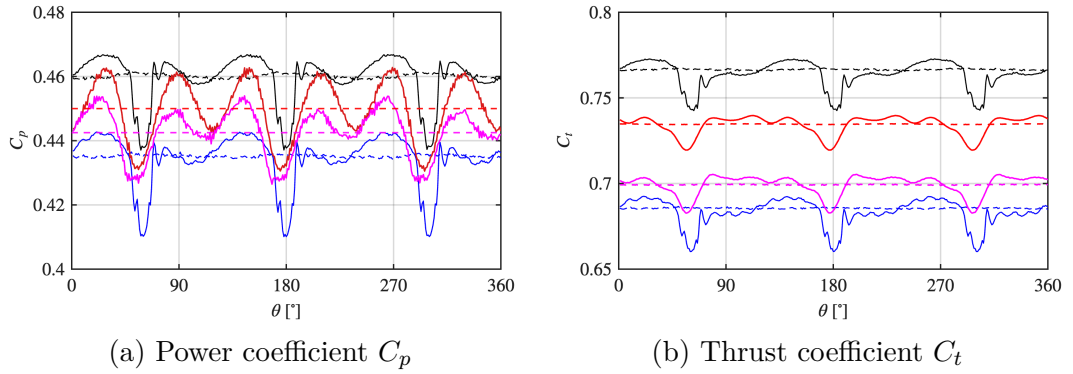


Figure 4.5: Phase-averaged power (a) and thrust (b) coefficients over one rotor revolution for the NREL 5MW. CFD-CSD/OV (—), CFD-CSD/T (—); ElastoDyn: TN (—), RO (---); BeamDyn: TN (—), RO (---).

4.2.4 Summary

The eigenfrequency benchmark and the comparison of aerodynamic loads, structural deformations, and integral performance coefficients confirm the reliability of the CFD-CSD framework for the NREL 5MW turbine. The computed natural frequencies agree with both OpenFAST modules and the BModes reference of Jonkman et al. [168] to within 5% for all modes. The coupled aeroelastic response is consistent with the OpenFAST predictions across both structural models (ElastoDyn and BeamDyn) and both rotor configurations (RO and TN), with the main discrepancies confined to the root region and to the tower-shadow event. In particular, the tower-shadow-induced drop in C_p is underestimated by the BEM-based OpenFAST model relative to the LES prediction — a limitation that grows with the tower-to-rotor diameter ratio and is therefore more pronounced here than for the IEA 15MW. These

findings establish the in-house framework as a reliable tool for aeroelastic analysis at the NREL 5MW scale and directly motivate the extension to the larger, more flexible IEA 15MW turbine in the following sections.

4.3 IEA 15MW Reference Turbine

The IEA 15MW reference wind turbine [11] represents a significant step up in scale from the NREL 5MW: the rotor diameter doubles to $D = 240$ m, the blade length increases to $L = 117$ m, and the combined flexibility and torsion-bending coupling become substantially more pronounced. The verification of the in-house CFD-CSD framework against OpenFAST for this turbine is presented comprehensively in the companion study [171], conducted within the IEA Wind TCP Task 47 TURBINIA cross-validation activity [175], in which the present research group contributed the UTD-WF CFD-CSD results for both the NREL 5MW and IEA 15MW reference turbines. The present section summarises the main findings in the same four-case format (ED-RO, ED-TN, BD-RO, BD-TN) used in Section 4.2, highlighting the aspects that most directly support the aeroelastic studies of the following chapters. The structural solver definitions and solver variants (CFD-CSD/OV and CFD-CSD/T) are as described in Section 4.2. The inflow is a laminar power-law shear profile with exponent $\alpha_s = 0.05$ and hub-height velocity $U_\infty = 10$ m/s.

4.3.1 Blade Properties and Finite Element Model

The structural model is based on a modal decomposition of the elastic displacement along the blade span. The finite element model of the undeformed, non-rotating blade employs beam elements with six degrees of freedom, using Euler–Bernoulli behaviour for flapwise (X_2) and edgewise (X_3) bending and linear shape functions for axial and torsional deformations.

4.3.2 Eigenfrequency Benchmark

The first eight natural frequencies of the undeformed, non-rotating IEA 15MW blade are listed in Table 4.2 and compared graphically in Figure 4.6 against five independent reference models: the prismatic Timoshenko model without torsion (H2-PTNT), the Timoshenko model with a fully populated stiffness matrix (H2-FPM) from [176], a three-dimensional FEA from [177], and the OpenFAST modules ElastoDyn and BeamDyn. This benchmark was conducted within the cross-validation activity of IEA Wind TCP Task 47 TURBINIA [175, 178].

The computed eigenfrequencies are consistent with all reference models; minor discrepancies in the higher-order modes are attributable to differences in the cross-sectional stiffness representation. The first torsional mode appears

Table 4.2: Classification and natural frequencies of the first eight structural modes of the IEA 15MW blade (non-rotating, in vacuum).

Mode #	Description	f_n [Hz]
1	1st flapwise	0.5369
2	1st edgewise	0.7267
3	2nd flapwise	1.577
4	2nd edgewise	2.267
5	3rd flapwise	3.113
6	1st torsional	3.642
7	3rd edgewise	4.571
8	4th flapwise	5.385

as the sixth mode at $f_6 = 3.642$ Hz, well separated from the leading bending modes yet within a frequency range that can be aerodynamically excited by the blade loading at rated conditions. The sectional angle of attack is sensitive to torsional feedback. By contrast, for the NREL 5MW the first torsional mode appears at 5.58 Hz (Table 4.1), well above the relevant aerodynamic excitation frequencies and therefore dynamically inactive — a key qualitative difference between the two turbines.

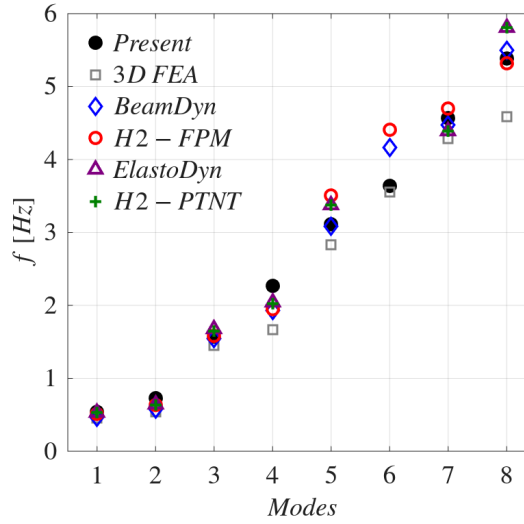


Figure 4.6: First eight natural frequencies of the IEA 15MW blade computed by the present structural model (●) compared against 3D FEA (□), H2-FPM (○), ElastoDyn (△), H2-PTNT (+).

4.3.3 Aerodynamic loads on the blade

Both solvers employ the same laminar sheared inflow (power-law exponent $\alpha_s = 0.05$, hub-height velocity $U_\infty = 10$ m/s), yet the underlying aerodynamic and structural formulations remain distinct. In the LES, the inflow profile is imposed several diameters upstream and evolves naturally before reaching the rotor, so the flow actually impinging on the blade is not identical to that seen by the BEM solver. As a consequence, observed differences cannot always be unambiguously attributed to the aerodynamic model alone or to the structural formulation, and both effects must be kept in mind when interpreting the comparisons that follow.

Time-averaged spanwise distributions. Figure 4.7 collects the time-averaged spanwise profiles of four aerodynamic quantities: the local angle of attack α (panel a), the aerodynamic pitching moment per unit length M_{aero} (panel b), and the force components normal and tangential to the rotor plane, F_2 and F_3 (panels c–d), sometimes referred to as flapwise and edgewise loading, respectively. Because the time average is taken over many complete revolutions, the rotor-only and tower-and-nacelle configurations of each solver collapse onto a single curve in this representation: the brief, periodic tower-passage event contributes negligibly to the mean. The primary axis of variation is therefore the structural model (ElastoDyn vs. BeamDyn), not the rotor configuration.

Satisfactory agreement among all four solvers is found throughout the 20%–80% span range; near-root deviations are ascribed to the different hub geometries used by the two frameworks, which affect the local inflow in that region. In the outermost 20% of the span the torsional solvers (BeamDyn, CFD-CSD/T) predict a markedly lower incidence angle than their non-torsional counterparts: the nose-down elastic twist of the section reduces the effective angle of attack, in turn relieving the aerodynamic loading. This torsion-induced effect is considerably stronger than for the NREL 5MW (Section 4.2), in line with the lower first torsional eigenfrequency and the greater chord-to-span ratio of the IEA 15MW blade. The flapwise force F_2 of CFD-CSD/T matches BeamDyn to within $\approx 2\%$ despite the linearity of the in-house structural model. Conversely, CFD-CSD/OV produces results in close agreement with ElastoDyn, confirming that the structural coupling scheme — torsional feedback included or excluded — is the controlling factor in load prediction accuracy, overriding the differences between the LES and BEM aerodynamic frameworks. The aerodynamic pitching moment M_{aero} shows a maximum relative gap of $\approx 8\%$ between the BEM-based and the LES-based predictions.

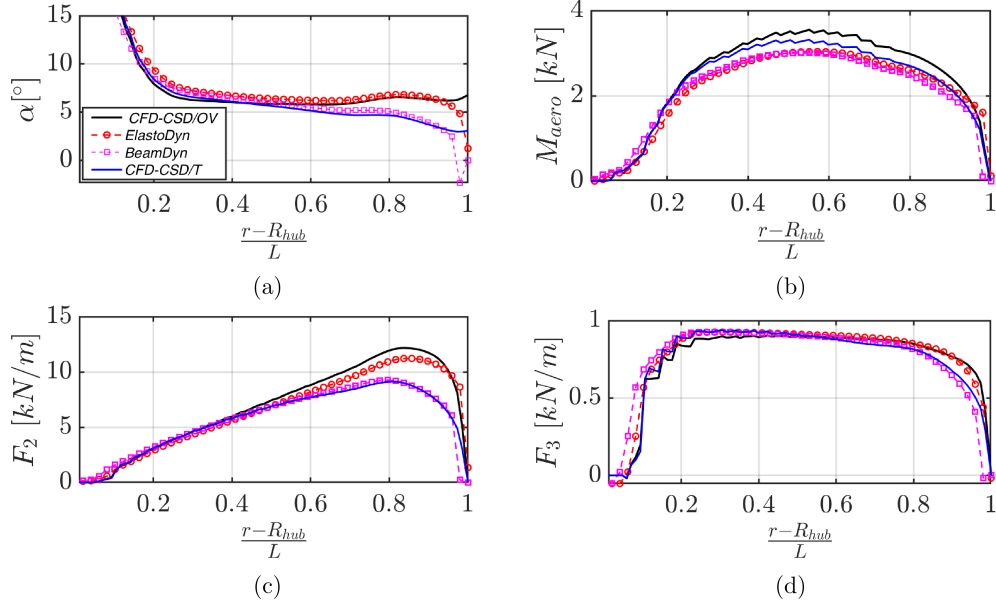


Figure 4.7: Time-averaged spanwise aerodynamic distributions for the IEA 15MW blade: (a) angle of attack α , (b) pitching moment per unit length M_{aero} , (c) flapwise force F_2 (normal to the rotor plane), (d) edgewise force F_3 (tangential to the rotor plane). CFD-CSD/OV (—), CFD-CSD/T (—), *ElastoDyn* ($\circ$), *BeamDyn* ($\square$). RO and TN curves are superimposed in the time-averaged view.

Phase-averaged response at 80% span. The outer portion of the blade is structurally the most critical: near the tip the aerodynamic loads remain high while the cross-sectional stiffness drops substantially [179]. Figure 4.8 therefore presents the phase-averaged evolution of α , F_2 , and F_3 at $(r - R_{\text{hub}})/L = 0.80$ as a function of the blade azimuth angle θ .

In the RO configuration all three quantities remain nearly constant throughout the revolution; a slight once-per-revolution modulation reflects the shear-induced asymmetry of the approaching flow. When the tower is present, the blade passage at $\theta = 180^\circ$ excites an oscillation in both the incidence angle and the aerodynamic forces, which marks the tower shadow as the dominant source of unsteadiness under the inflow conditions considered. Interestingly, this excursion is of greater amplitude in the BEM-based predictions (*ElastoDyn* and *BeamDyn*) than in the LES-based ones, in contrast to the opposite trend observed for the NREL 5MW turbine [42]. As discussed in that reference, the intricate flow field that develops between the blade and the tower — characterised by a region of reduced streamwise velocity ahead of the tower that the blade traverses — is only approximated by the potential-flow tower model employed in the BEM framework. For the IEA 15MW, the slender tower ($d_{\text{twr}}/D \approx 0.027$) makes this approximation more adequate than for the thicker

relative tower of the NREL 5MW ($d_{\text{tower}}/D \approx 0.047$), which would explain the improved agreement for the larger turbine. The sheared inflow further reduces the mean wind velocity in the lower half of the rotor, further limiting the relative impact of the tower shadow.

Away from $\theta = 180^\circ$, CFD-CSD/OV and ElastoDyn reproduce each other closely for both α and F_3 , while CFD-CSD/T and BeamDyn agree on F_2 to within $\approx 2\%$ and on F_3 to within $\approx 5\%$ near $\theta = 0^\circ$; the angle of attack discrepancy between the two torsional solvers reaches $\approx 8\%$. When torsional deformation is included in the coupling, high-frequency oscillations — at a frequency close to the first torsional eigenfrequency — appear in both CFD-CSD/T and BeamDyn, indicating that torsion is dynamically active at this scale and can be driven by the periodic aerodynamic loads.

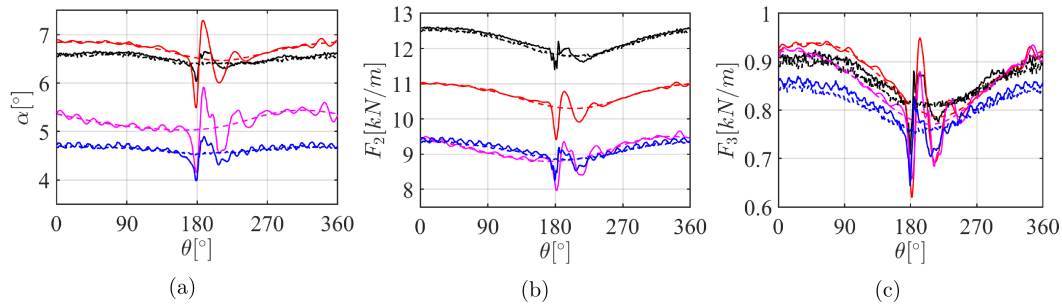


Figure 4.8: Phase-averaged aerodynamic quantities at $(r - R_{\text{hub}})/L = 0.80$: (a) angle of attack α , (b) flapwise force F_2 , (c) edgewise force F_3 . *ElastoDyn*: TN (—), RO (---); *BeamDyn*: TN (—), RO (---); CFD-CSD/OV: TN (—), RO (---); CFD-CSD/T: TN (—), RO (---).

Rotor-plane error maps. To extend the local 80%-span comparison to the entire span and azimuth range, Figure 4.9 presents phase-averaged contour maps of the relative percentage difference in α , F_2 , and F_3 , computed separately for the non-torsional pair ($|\langle \Delta q/q^{\text{CFD/OV}} \rangle|$, left column) and the torsional pair ($|\langle \Delta q/q^{\text{CFD/T}} \rangle|$, right column).

For the non-torsional pair, the incidence-angle error is largest in the azimuthal sector immediately following the tower ($17\% - 25\%$), driven by the different treatment of the tower wake between the two solvers. For the torsional pair, the dominant pattern is a radial gradient: the discrepancy in α grows from root to tip, reaching $35\% - 60\%$ in the outermost 20% of the span where three-dimensional effects and torsion-induced angle-of-attack changes accumulate. A discontinuity is also visible near $\theta = 180^\circ$ in both columns. The flapwise force map (panel b) mirrors the incidence-angle pattern, while the edgewise force (panel c) concentrates its largest errors towards the tip for both pairs of solvers. Taken together, the error maps confirm that the tip region is where the two families of solvers diverge most, owing to the combined

influence of tip-vortex three-dimensional effects, torsional compliance, and the aerodynamic pitching moment.

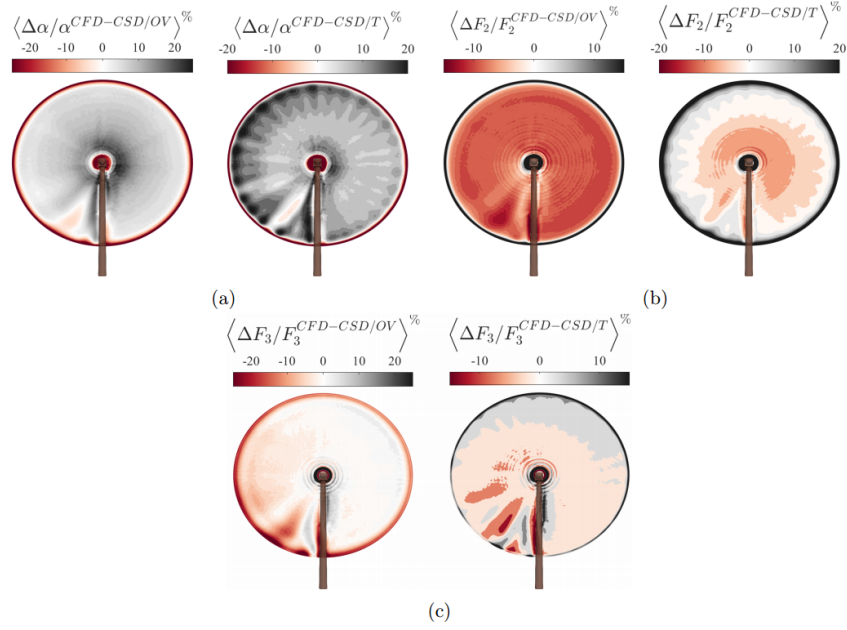


Figure 4.9: Phase-averaged rotor-plane contour maps of the relative percentage differences in aerodynamic quantities: CFD-CSD/OV vs. *ElastoDyn* (left) and CFD-CSD/T vs. *BeamDyn* (right). (a) α , (b) F_2 , (c) F_3 .

4.3.4 Power and thrust coefficients

The integral aerodynamic performance is characterised by the power and thrust coefficients

$$C_p = \frac{P_d}{\frac{1}{2}\rho AU_\infty^3}, \quad C_t = \frac{T_{\text{aero}}}{\frac{1}{2}\rho AU_\infty^2}, \quad (4.1)$$

where $A = \pi D^2/4$ is the rotor swept area, P_d the aerodynamic power delivered to the shaft, and T_{aero} the total rotor thrust.

Phase-averaged C_p and C_t . Figure 4.10 shows the phase-averaged time histories of C_p and C_t for all four solver combinations, with the results of Bernardi et al. [42] (LES+CSD and OpenFAST-AeroDyn for the same turbine) included for reference. In the RO configuration both coefficients are nearly steady over the revolution; a weak once-per-revolution oscillation arises from the shear-induced variation of the local inflow velocity. For the TN configuration, the blade sweeping through the tower wake at $\theta = 180^\circ$ produces a drop of $\approx 10\%$ in C_p , after which the elastic recovery of the blade restores performance to its pre-event level. The drop is less severe than the $\approx 15\%$ measured for

the NREL 5MW, consistent with the smaller relative tower obstruction of the 15MW machine.

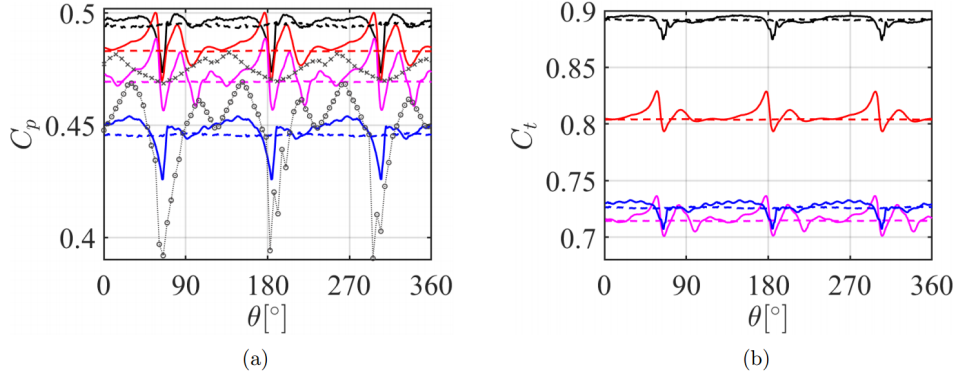


Figure 4.10: Phase-averaged power (a) and thrust (b) coefficients over one rotor revolution for the IEA 15MW turbine. *ElastoDyn*: TN (—), RO (---); *BeamDyn*: TN (—), RO (---); CFD-CSD/OV: TN (—), RO (---); CFD-CSD/T: TN (—), RO (---). Reference from [42]: $\circ$ LES+CSD flexible, $\times$ OpenFAST-AeroDyn.

Both BEM and CFD predict a similar drop amplitude for this turbine, in contrast to the 5MW case where the BEM framework significantly underestimated the excursion [42]. Two factors may contribute to this improved agreement: the slender tower makes the potential-flow approximation more accurate, and the sheared inflow lowers the average velocity in the lower half of the rotor, reducing the relative weight of the tower-shadow event on the total power. Nevertheless, this should not be interpreted as a general verification of the BEM tower model: the spanwise error maps of Figure 4.9 show that substantial local discrepancies persist in the tip region.

The mean C_p is higher for the non-torsional solvers than for the torsional ones, a direct consequence of the load reduction induced by the nose-down elastic twist; the same trend is found in both the BEM and LES frameworks. Consistently with the aerodynamic loads analysis, *BeamDyn* predicts higher edgewise forces than CFD-CSD/T because it computes a smaller torsional deformation, leading to a larger effective angle of attack and a higher extracted power.

Spectral content of C_p and C_t . Figure 4.11 shows the pre-multiplied, variance-normalised PSD $f \text{ PSD} / \sigma^2$ of C_p and C_t for the TN configuration, plotted against f/f_{rot} where $1P = f_{\text{rot}}$ corresponds to 7.5 RPM. The strongest spectral peaks in all solvers occur at $3P$, $6P$, $9P$, and $12P$, driven by the three-bladed symmetry and the tower-passage excitation, in agreement with URANS results reported by Pagamonci et al. [43] for the same and similar turbines. At these harmonics the BEM and CFD-CSD predictions agree well in both frequency and relative amplitude.

The two families of solvers diverge in the sub- $1P$ range and in the frequency bands between the discrete harmonics. The BEM-based solvers concentrate energy at the isolated $1P$ and $2P$ peaks, producing a spectrum with well-defined lines and little energy elsewhere. The CFD-CSD solvers, by contrast, show a broader and more continuous spectral distribution, without sharp peaks below $1P$. This broadband character stems from the large-scale coherent structures of the developing LES boundary layer, which introduce energy across a range of frequencies not representable by the time-periodic, two-dimensional BEM model. Moreover, in the LES the imposed power-law profile evolves for several diameters upstream, so the velocity field at the rotor has a non-trivial low-frequency content beyond what any periodic BEM prescription can capture. The practical implication is that the BEM solvers underestimate the oscillation energy at frequencies that do not coincide exactly with $1P$ or $2P$, a limitation potentially relevant for fatigue life estimates based on spectral methods.

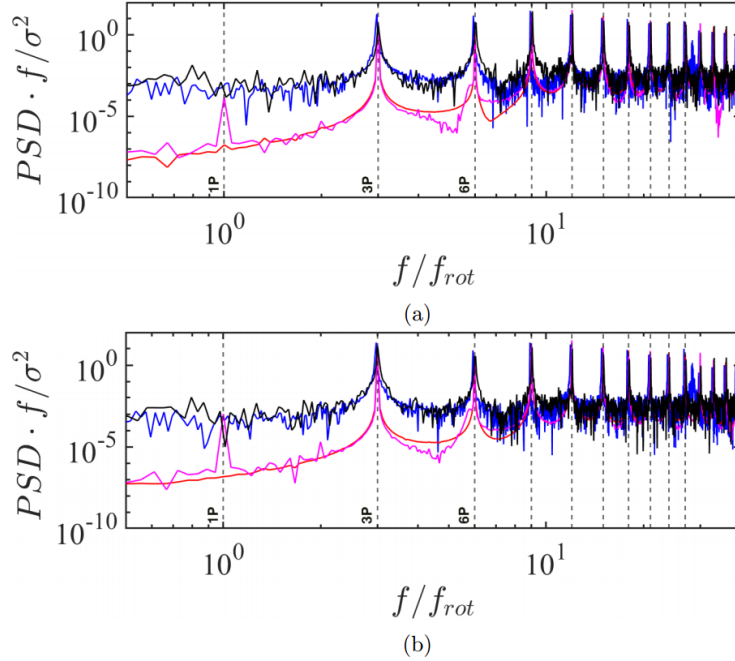


Figure 4.11: Pre-multiplied variance-normalised PSD of C_p (a) and C_t (b) for the TN configuration. Vertical dashed lines indicate $1P = f_{rot} = 7.5$ RPM and its $3P$ multiples. CFD-CSD/OV (—), CFD-CSD/T (—), *ElastoDyn* (—), *BeamDyn* (—).

4.3.5 Structural response

Figure 4.12 presents the structural response of the IEA 15MW blade in two complementary representations: the phase-averaged tip deflection as a function of azimuth (left column) and the time-averaged deformation along the span

(right column), for all three degrees of freedom — out-of-plane (flapwise), in-plane (edgewise), and torsional.

Out-of-plane deformation. The out-of-plane tip deflection (panel a) follows the phase-averaged behaviour of the flapwise force discussed above: the blade stiffens slightly as it sweeps through the faster-wind upper half of the rotor and deflects most as it approaches $\theta = 180^\circ$, where the tower shadow causes an abrupt reduction followed by an elastic overshoot before the next revolution. This dynamic signature is present in both the ElastoDyn and BeamDyn TN curves with comparable amplitude, indicating that the tower-passage load excursion is governed primarily by the aerodynamic forcing rather than by the structural formulation. The time-averaged spanwise profile (panel b) reaches ≈ 16 m at the blade tip, in good agreement with the LES results of Trigaux et al. [49], and larger than the URANS prediction of Pagamonci et al. [43]. Consistent with the aerodynamic load analysis, the non-torsional solver (CFD-CSD/OV) overestimates the reference BeamDyn deformation by $\approx 17\%$, while CFD-CSD/T undershoots it by $\approx 13\%$. These bounds reflect the sensitivity of the flapwise response to the torsional coupling strategy; the fact that the LES non-torsional result brackets the BeamDyn reference from above, and the LES torsional result from below, confirms that torsion is the single most consequential modelling choice for the 15MW blade at this operating point.

In-plane deformation. The edgewise tip deflection (panel c) is dominated by the gravitational loading and oscillates once per revolution without any discernible tower-shadow signature, as expected from the primarily gravity-driven nature of the lag deformation. The CFD-CSD/OV and CFD-CSD/T predictions are nearly superimposed, while ElastoDyn departs from BeamDyn: this discrepancy is attributed to the limited number of polynomial mode shapes available in ElastoDyn for describing the in-plane translation, not to any difference in the torsional coupling. The amplitude of the oscillation (approximately -2.3 m to $+0.2$ m) is consistent with that reported by Trigaux et al. [49]; the opposite sign convention reflects the different blade reference frames adopted in that study.

Torsional deformation. The torsional tip angle (panel e, CFD-CSD/T and BeamDyn only) exhibits a periodic oscillation synchronised with the rotor frequency, superimposed on a non-zero mean; an additional perturbation appears at $\theta = 180^\circ$ in the TN cases. Significant quantitative differences are observed between the LES-based and BEM-based torsional predictions that are not easily attributed to the structural model alone: both CFD-CSD/T and BeamDyn account for the torsional deformation in the aerodynamic coupling [41], yet the gap between the two reaches approximately 20 % of the local deformation value. A detailed assessment of the aerodynamic-model

contribution to this discrepancy can be found in the IEA Task 47 TURBINIA report [175]. The time-averaged spanwise torsional profile (panel f) confirms the concentration of twist in the outer 30 % of the span with a maximum relative gap with respect to BeamDyn of $\approx 29\%$ for CFD-CSD/OV and $\approx 24\%$ for CFD-CSD/T. Crucially, the lower torsional deformation predicted by BeamDyn leads directly to higher aerodynamic forces (see Figure 4.7c), providing a quantitative link between structural and aerodynamic discrepancies.

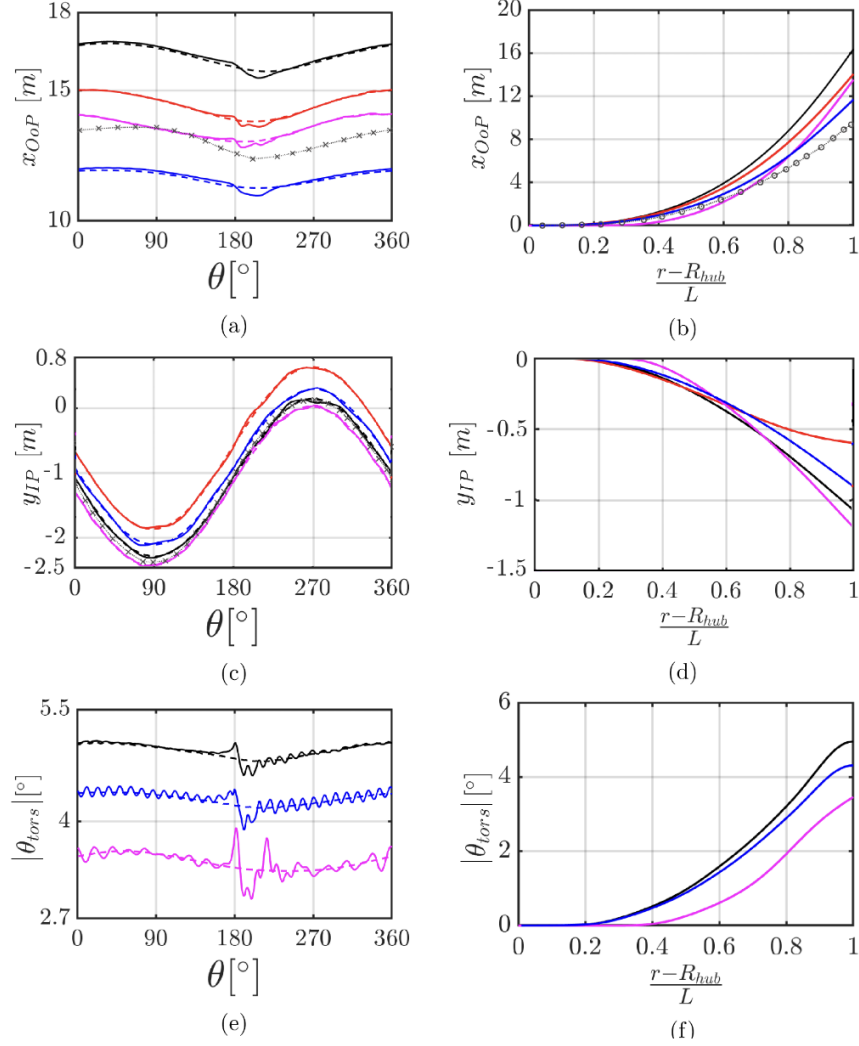


Figure 4.12: Phase-averaged tip deflections (left column) and time-averaged spanwise profiles (right column) for the IEA 15MW blade: (a–b) out-of-plane, (c–d) in-plane, (e–f) torsional. *ElastoDyn*: TN (—), RO (---); *BeamDyn*: TN (—), RO (---); CFD-CSD/OV: TN (—), RO (---); CFD-CSD/T: TN (—), RO (---). Torsional panels (e–f): *BeamDyn* and CFD-CSD/T only. Reference data from [43] (○) and [49] (×).

Spectral content of the tip deformations. Figure 4.13 shows the pre-multiplied variance-normalised PSD of the three tip-deflection components for the TN configuration, normalised by the rotor frequency. Spectral estimates were obtained with both the Welch and the Lomb-Scargle algorithms, which yielded consistent results.

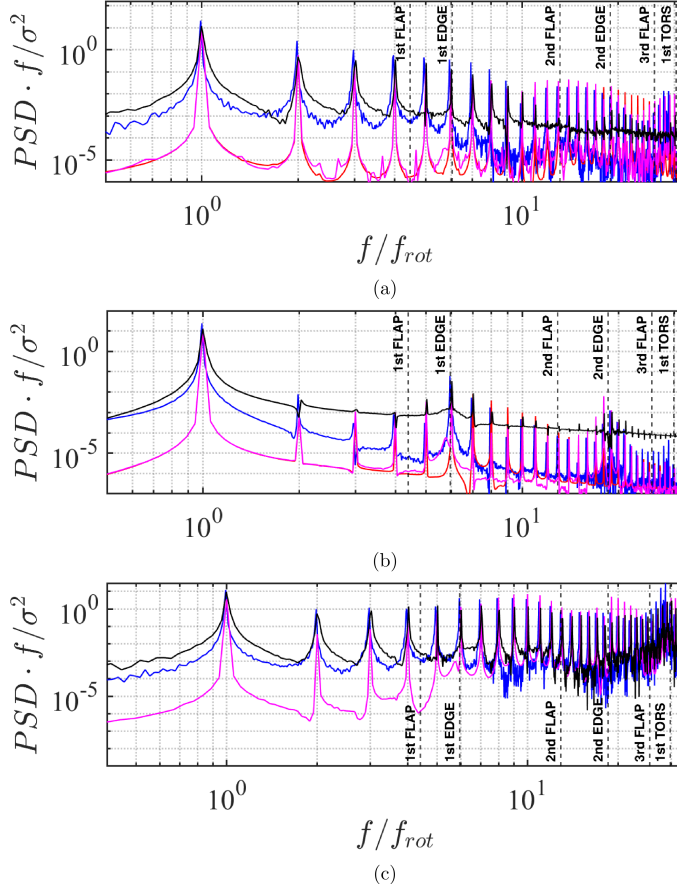


Figure 4.13: Pre-multiplied variance-normalised PSD of the blade tip deformation components for the TN configuration: a) out-of-plane X_{OoP} , (b) in-plane y_{IP} , (c) torsional θ_{tors} . Vertical dashed lines mark the first eight structural eigenfrequencies. CFD-CSD/OV (—), CFD-CSD/T (—), *ElastoDyn* (—), *BeamDyn* (—).

For the out-of-plane component (panel a), no peak associated with the first flapwise natural frequency is visible in any solver, suggesting that quasi-steady aerodynamic loading governs the flapwise response and that the first mode is not resonantly excited under the conditions considered; the same observation is reported by Trigaux et al. [49] for identical inflow conditions. Peaks near the second and third flapwise eigenfrequencies are present and coincide with the $13P$ and $26P$ harmonics of the rotor frequency. At low frequencies the CFD-CSD solvers predict substantially larger spectral energy than the BEM

codes, reflecting three-dimensional large-scale flow structures captured by the LES that are absent in the BEM framework. BeamDyn tracks the CFD-CSD spectral peaks at higher frequencies more faithfully than ElastoDyn, likely due to its larger number of active degrees of freedom. The in-plane PSD (panel b) is dominated by the $1P$ gravity peak; the broadband excess at low frequencies is again more pronounced in the LES predictions. For the torsional component (panel c, CFD-CSD/T and BeamDyn only), the two solvers agree well in the neighbourhood of the first torsional eigenfrequency, confirming that the linear in-house model and the geometrically exact BeamDyn formulation produce consistent torsional responses at this scale.

4.3.6 Summary

The eigenfrequency benchmark and the systematic comparison against both OpenFAST modules across all four load categories — spanwise aerodynamic loads, performance coefficients, structural deformations, and their spectral content — establish the reliability of the in-house CFD-CSD framework for the IEA 15MW turbine. The following conclusions are of direct relevance to the aeroelastic studies presented in subsequent chapters.

1. **Torsion governs outer-span loads and mean performance.** Including the torsional degree of freedom consistently reduces flapwise loading, out-of-plane deformation, and mean C_p relative to non-torsional counterparts, regardless of whether the aerodynamic framework is BEM or LES. CFD-CSD/T reproduces BeamDyn flapwise forces to within $\approx 2\%$ and tip deflections to within $\approx 13\%$, sufficient accuracy for the design studies of the following chapters.
2. **The tower-passage event has a moderate but non-negligible effect.** The $\approx 10\%$ drop in C_p at $\theta = 180^\circ$ is well reproduced by both BEM and LES for the IEA 15MW, in contrast to the NREL 5MW where BEM underestimates the larger drop ($\approx 15\%$). The difference is attributed to the smaller relative tower diameter and the sheared inflow, which together render the potential-flow tower model more adequate at the 15MW scale.
3. **BEM and LES spectra diverge at sub-harmonic frequencies.** Both solver families agree on the $3P$ harmonics of C_p , C_t , and the tip deformations, but the BEM codes suppress energy between harmonics while the LES predicts a broadband continuum driven by the three-dimensional inflow turbulence. This distinction is relevant when assessing fatigue loads at frequencies not coinciding with integer multiples of the rotor frequency.

The verified four-case framework is employed as the reference baseline in the aeroelastic and wake studies of the following chapters.

Chapter 5

Effects of Atmospheric Wind Veer on Wake Dynamics

This chapter analyses the coherent structures developing in the wake of the NREL 5MW reference wind turbine [168]. Specifically, the study aims to isolate and evaluate the impact of atmospheric wind veer induced by the Coriolis acceleration. To this end, two distinct turbulent inflow conditions are generated and compared: an idealized pressure-driven boundary layer and a fully developed Ekman layer. LES combined with modal decomposition is used to characterise the role of large-scale coherent structures in wake recovery and to derive a corresponding Reduced-Order Model (ROM).

The contribution of this chapter is the first LES-based modal analysis of wind turbine wake coherent structures contrasting pressure-gradient-driven and Coriolis-driven inflow, providing the physics-informed modal basis for the Reduced-Order Models developed at the end of the chapter (Contribution 1 of Section 1.4).

5.1 Simulations Setup

This section outlines the numerical and analytical framework adopted in the present study. It begins with the description of the precursor simulations used to generate two distinct, physically consistent atmospheric inflow conditions: one driven purely by a pressure gradient and one incorporating the Coriolis acceleration to account for wind veer. Subsequently, the detailed LES setup for the NREL 5MW wind turbine is presented.

Precursor simulations

To properly investigate the influence of the Earth's rotation on the turbine wake, two precursor simulations were carried out to generate the turbulent inflow conditions. The first scenario considers a neutral ABL driven solely by

a pressure gradient, in the absence of the Coriolis force ($f_c = 0$, $\mathbf{f}_{PI} = 0$). This case, hereafter referred to as the “pressure gradient” case, excludes Earth’s rotation effects and serves as the reference baseline. In this configuration, the momentum conservation equation incorporates a pressure gradient term calibrated to maintain a constant mass flow rate across the domain. The second precursor simulation accounts for the Coriolis force and is driven by a geostrophic wind at the top boundary. This configuration reproduces the characteristic Ekman spiral [59], resulting in a continuous variation of the streamwise and spanwise velocity components along the wall-normal direction. A Coriolis frequency of $f_c \approx 1.2 \times 10^{-4} \text{ s}^{-1}$ is assumed, representing typical mid-latitude North Sea offshore conditions. Before generating the inflow, the Coriolis forcing implementation was verified against the results of Jiang et al. [180]. As shown in Figure 5.1, the mean velocity profiles are in good agreement with the reference data.

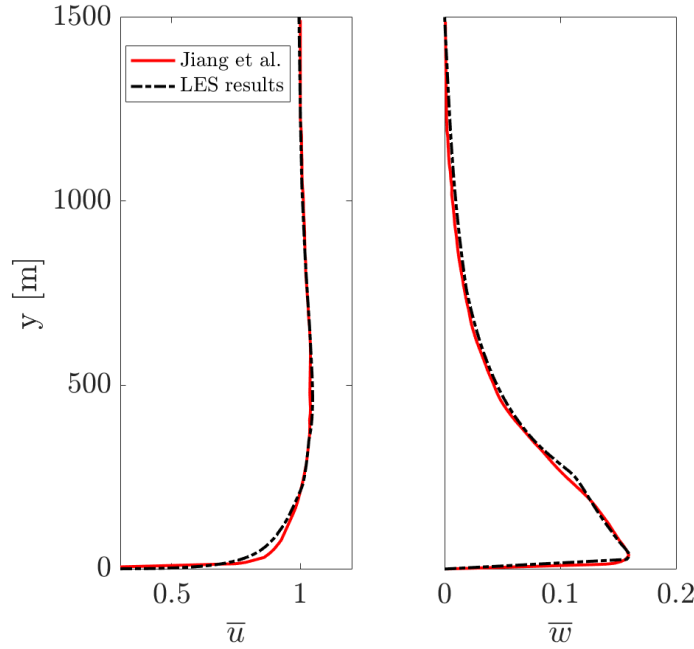


Figure 5.1: Verification of the Coriolis forcing implementation. The velocity profile obtained from the present LES framework (dash-dotted black line) is compared against the reference data (red line) from Jiang et al. [180].

Because the wind vector inherently rotates with altitude in the Ekman layer, setting the geostrophic velocity components to achieve a specific flow direction at the turbine hub height is non-trivial. To prevent yaw misalignment between the incoming mean velocity profile and the turbine rotor, the PI controller proposed by Sescu and Meneveau [116]—previously detailed in Section 2.6—is

adopted. Following a dedicated tuning phase, the proportional and integral gains were set to $K_P = 1$ and $K_I = 0.1$, respectively. The control loop is automatically deactivated once the directional error drops below a strict tolerance of $e(t) = \theta - \theta_{desired} < 0.1^\circ$.

The computational domain for both precursor simulations spans $6 \times 11 \times 3$ rotor diameters (D) in the streamwise (x), vertical (y), and spanwise (z) directions, respectively. The vertical extent is deliberately chosen to be exceptionally large compared to previous LES campaigns on the same turbine [181], ensuring that the Ekman layer can fully develop up to the top boundary without artificial confinement. The domain is discretised using a Cartesian grid of $1025 \times 513 \times 513$ cells. Periodic boundary conditions are applied in the horizontal directions, while no-slip and free-slip conditions govern the bottom and upper boundaries, respectively.

Turbine flow simulations

The statistically stationary, fully developed velocity fields extracted from the two precursor simulations are subsequently employed as dynamic inflow boundary conditions for the main wind turbine domain. This computational box measures $12 \times 11 \times 3$ diameter units and is discretised using a staggered grid of $2049 \times 513 \times 513$ points. The grid features uniform spacing in the horizontal plane and a stretched distribution in the wall-normal direction, maintaining a constantly refined resolution within the rotor region. This grid topology has been previously verified [79, 182], confirming that the selected cell size yields highly satisfactory outcomes compared to experimental benchmarks.

Table 5.1: Operating parameters and main characteristics of the NREL 5MW wind turbine considered in this study.

NREL 5MW	
Blades number	3
Rotor diameter - D	126 m
Hub height	90 m
Design Tip-Speed Ratio - TSR	7
Wind speed - U_{ref}	11.4 m/s
Rotor speed Ω	12.1 RPM

The boundary conditions mirror those of the precursor setup, with the exception of the streamwise boundaries. The time-varying turbulent velocity fields are injected at the inlet, while a radiative boundary condition [183]

with a uniform convection velocity $c = 0.9 U_{ref}$ is applied at the outlet. The target turbine is the NREL 5MW model, operating at rated conditions with a Reynolds number on the order of 10^8 . Its macroscopic and structural properties have been extensively detailed in Section 3.1, while the main features for this study are summarised in Table 5.1. The turbine tower and nacelle are modelled via the IBM, whereas the blades are simulated using the ALM [144]. The rotor is centrally positioned in the spanwise direction and placed $4D$ downstream of the inflow plane. An $8D$ downstream development region is provided to capture the full morphological evolution of the far wake.

5.2 Results

5.2.1 Precursor simulations

Time-averaged velocity fields

Mean velocity profiles were extracted from the precursor simulations by performing time and horizontal spatial averaging once statistically stationary conditions were achieved. Figure 5.2 presents the mean streamwise ($\bar{u}$), spanwise ($\bar{w}$), and wind direction profiles (θ). Thanks to the active PI controller, there is virtually no yaw misalignment at hub height (90 m). In the pressure gradient case, the lateral wind component is effectively zero, and the inner region of the boundary layer adheres perfectly to the theoretical log-law profile. Conversely, the Coriolis case clearly exhibits the characteristic Ekman spiral, visualized in 3D in Figure 5.3. Notably, both precursor setups achieve a turbulence intensity of approximately 7% at hub height.

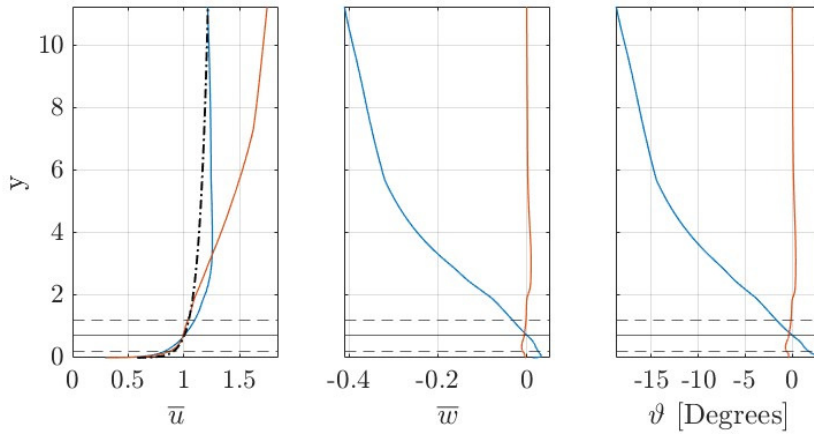


Figure 5.2: Streamwise (left), spanwise (center), and wind direction θ (right) components of the time- and horizontally-averaged velocity. Orange: pressure gradient case; blue: Coriolis case; black dash-dotted: log-law profile. Horizontal solid line: hub height; dashed lines: blade tip.

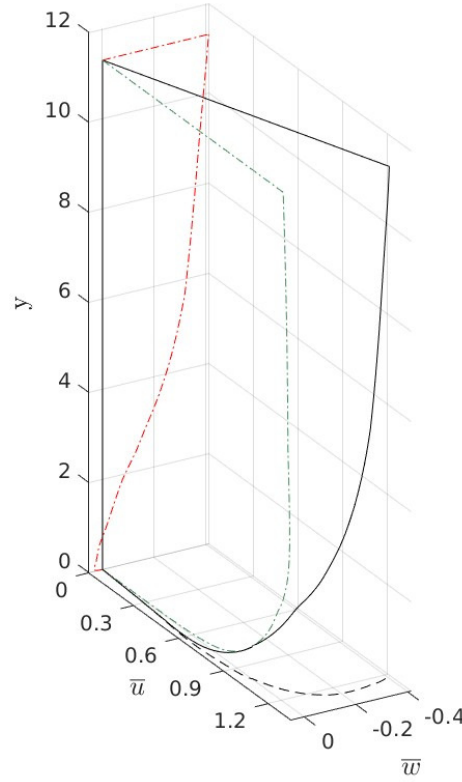


Figure 5.3: Time- and horizontally-averaged dimensionless Coriolis ABL velocity profiles (black solid line). The green dash-dotted line is the $\bar{u}$ -component, the red dash-dotted line is the $\bar{w}$ -component and the black dashed line is the Ekman spiral.

POD and DMD modes

Modal analysis was performed on the two precursor datasets to isolate the dominant structures of the incoming turbulence. Snapshots of the velocity field (with the time-averaged field subtracted) were extracted at intervals of $\Delta t = 0.025$ time units over a reduced domain, yielding 2370 snapshots per case. Figure 5.4 illustrates the singular value distribution of the leading 400 POD modes, revealing a notable energy reduction within the first 20 modes, followed by a more gradual decrease. In accordance with the convergence criteria established by De Cillis et al. [79], a POD subspace of rank $r = 400$ was retained as the basis for the DMD. The complex frequency of the DMD modes, denoted as ω , is derived from the eigenvalues μ of the approximated linear operator $\tilde{A}$ via the relation:

$$\omega = -\frac{\log(\mu)}{i\Delta t}, \quad (5.1)$$

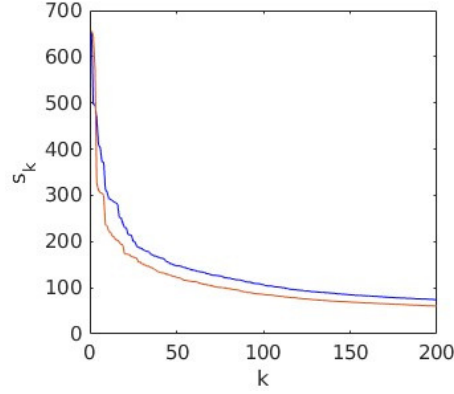


Figure 5.4: Singular values of the first 400 POD modes for the pressure gradient (orange) and the Coriolis (blue) precursor cases.

where Δt represents the temporal step between consecutive snapshots and i is the imaginary unit. The complex variable ω decomposes into a real part, $\mathbf{R}(\omega)$, corresponding to the angular frequency, and an imaginary part, $\mathbf{I}(\omega)$, dictating the growth rate. Figure 5.5a compares the angular frequency distributions of the DMD modes for both inflow cases. The green markers represent the unpenalised DMD amplitudes, while the black markers denote the results filtered through the SPDMD algorithm for a specific sparsity parameter. Prior to sparsity penalisation, the spectral distributions appear broadly similar; however, the geostrophic forcing scenario notably recovers peak amplitudes over a wider and higher range of frequencies.

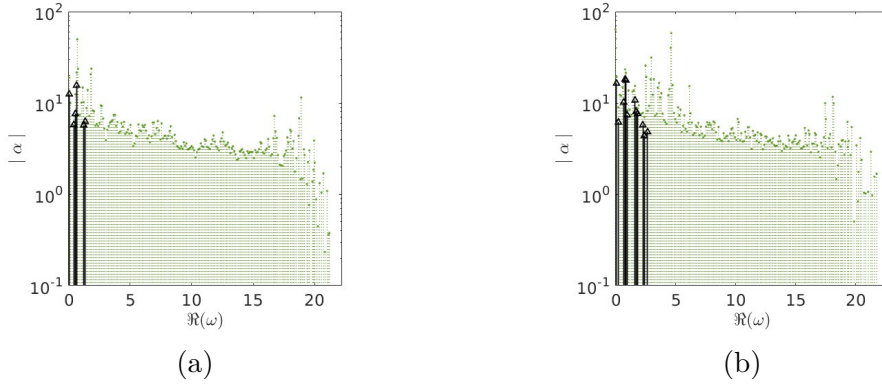


Figure 5.5: DMD amplitude $|\alpha_i|$ versus angular frequency $\mathbf{R}(\omega)$ for the pressure gradient (a) and Coriolis (b) cases. Green circles: DMD modes; black triangles ($\gamma = 10000$): SPDMD modes.

The application of the SPDMD algorithm underscores the core dynamical differences between the two precursors. Because the flow fields differ markedly in complexity, the algorithm necessarily retains a different number of modes

for a given sparsity coefficient (γ). This disparity is particularly evident under stringent sparsity constraints (e.g., $\gamma = 10000$), where the algorithm selects only 6 complex conjugate mode pairs for the pressure gradient case, but necessitates 12 pairs for the Coriolis case. As illustrated in Figures 5.5a and 5.5b (which display only the positive real parts for clarity), the maximum frequency retained for the pressure-driven inflow does not exceed $\mathbf{R}(\omega) = 1.4$. The Coriolis-driven inflow, by contrast, clearly surpasses this threshold, confirming that a broader spectral range is required to adequately capture its dynamics. Nevertheless, both datasets are predominantly governed by low-frequency modes, a finding consistent with previous investigations of turbulent inflows [79].

Evaluating the spatial topology of the selected DMD modes provides further physical insight. Figures 5.6 and 5.7 visualize the isosurfaces of the streamwise velocity fluctuations for the leading modes in the pressure gradient and Coriolis cases, respectively. Blue surfaces indicate positive fluctuations, while orange surfaces denote negative ones.

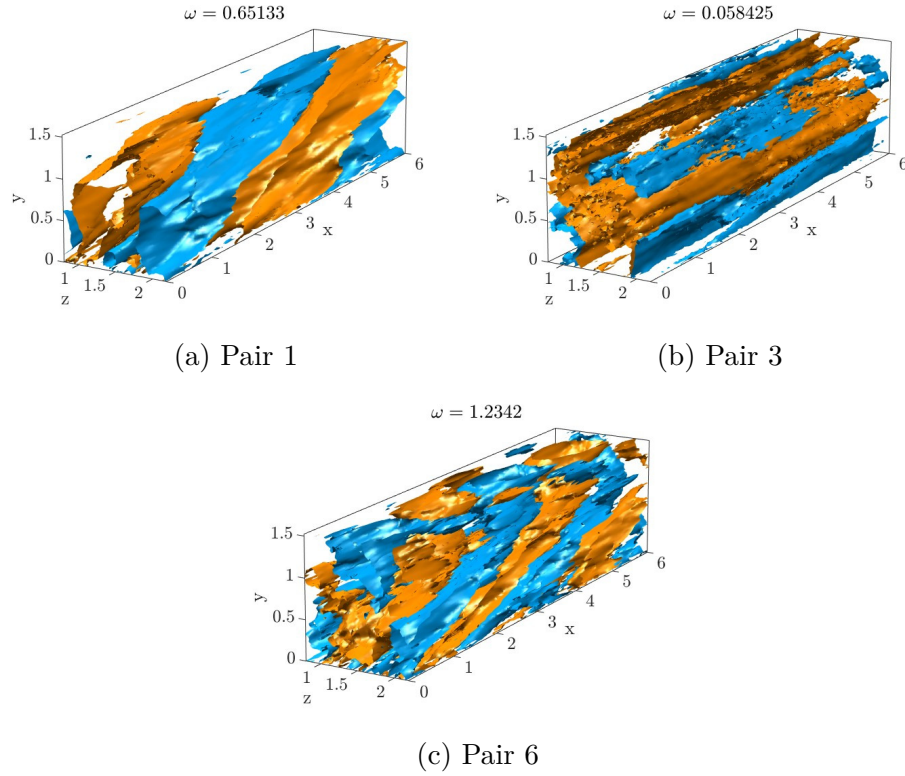


Figure 5.6: Streamwise velocity fluctuation iso-surfaces for three SPDMD modes ($\gamma = 10000$, pressure gradient precursor). Blue: $u = +0.0008$, orange: $u = -0.0008$.

In both precursor scenarios, the lowest-frequency modes ($\mathbf{R}(\omega) < 0.1$) emerge as large-scale, streamwise-elongated streaks ($\lambda_x \approx 5$, $\lambda_z \approx 1$). These structures are well-documented as fundamental components of the self-sustaining

cycle of turbulence in shear flows [184]. Within the pressure gradient precursor, intermediate modes ($\mathbf{R}(\omega) \in [0.40 - 0.67]$) maintain large streamwise wavelengths ($\lambda_x \approx 5$), whereas the highest-frequency modes selected ($\mathbf{R}(\omega) > 1.20$) exhibit shorter wavelengths ($\lambda_x \approx 3$) with fluctuations alternating along both the streamwise and spanwise axes.

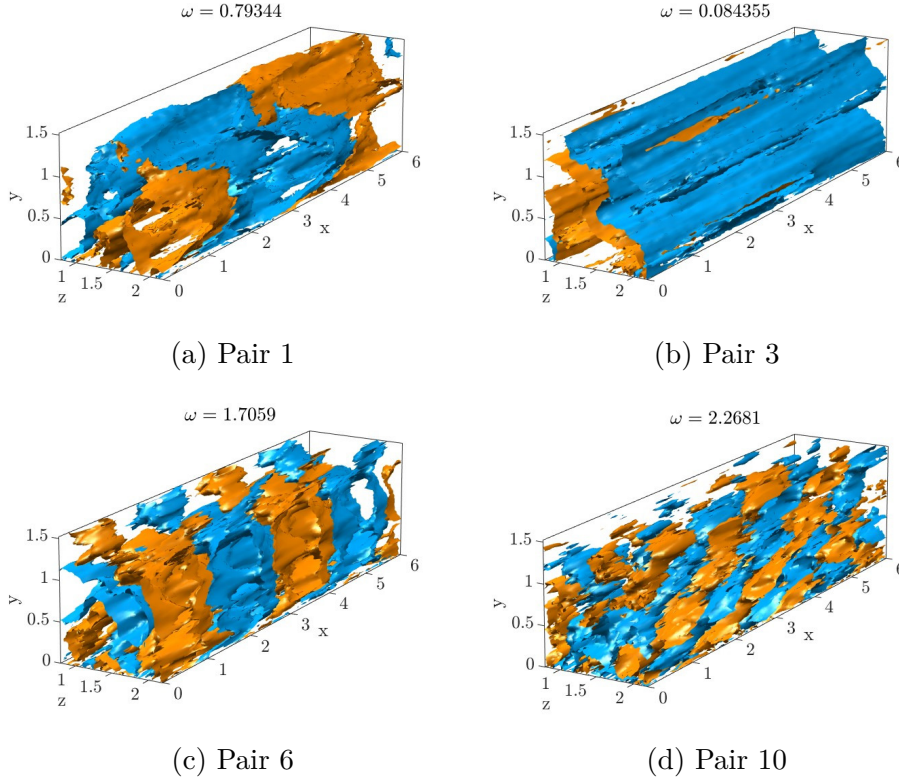


Figure 5.7: Streamwise velocity fluctuation iso-surfaces for four SPDMD modes ($\gamma = 10000$, Coriolis precursor). Blue: $u = +0.0008$, orange: $u = -0.0008$.

When the geostrophic forcing is introduced, the spatial footprint evolves. Modes within the $\mathbf{R}(\omega) \in [0.67 - 1.00]$ range display alternating patterns ($\lambda_x \approx 5$) that remain predominantly aligned with the primary axes. Frequencies falling between $\mathbf{R}(\omega) \in [1.62 - 1.85]$ show streamwise-modulated fluctuations highly comparable to those observed in the pressure gradient case. However, the Coriolis case uniquely selects higher-frequency modes ($\mathbf{R}(\omega) > 2.0$), which are characterised by shorter structures ($\lambda_x \approx 2$) that permeate the domain. Overall, the characteristic length scales extracted from both precursors exhibit a strong correlation with the established kinematics of large-scale motions in turbulent boundary layers [184, 185].

5.2.2 Wind turbine wake

Time-averaged velocity fields of turbine wakes

Analysing the time-averaged velocity field provides clear insights into the spatial evolution of a wind turbine wake structure. In the absence of incoming wind veer, the wake maintains a nearly symmetric profile along the vertical axis. In contrast, geostrophic forcing generates a strong cross-flow component [65], which severely skews the rotor wake as it propagates downstream. It is also well established that the presence of the tower amplifies wake deformation, particularly under geostrophic conditions. As illustrated by the Q-criterion iso-surfaces colored by streamwise velocity in Figure 5.8a (pressure gradient-inflow) and Figure 5.8b (Coriolis), the structural differences are evident. Without wind veer (Figure 5.8a), the downstream wake preserves its streamwise alignment and vertical symmetry. In contrast, geostrophic forcing severely distorts the wake, causing it to adopt an almost elliptical cross-section further downstream. Additionally, driven by the cross-flow component, the tower wake experiences a distinct positive lateral deflection as it expands outwards. These spatial

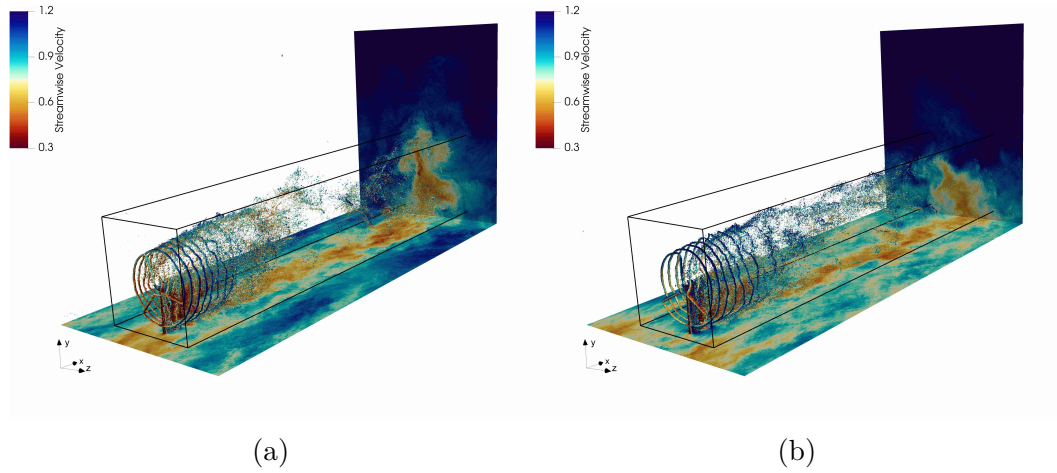


Figure 5.8: Q-criterion iso-surfaces, colored by the streamwise velocity values, for the pressure-gradient (a) and Coriolis case (b). The box sketches the dimensions of the subdomain in which the modal decompositions are performed.

dynamics are corroborated by analysing the velocity deficit field, defined as $\Delta u = u_{in} - u$, where u_{in} represents the time-averaged streamwise inflow velocity. Figures 5.9a and 5.9b depict these fields without and with wind veer, respectively. While the wake cross-section remains largely circular in the absence of veer, the introduction of wind veer causes it to progressively stretch into an ellipse as it moves away from the rotor. These findings align closely with the analytical framework proposed by Abkar [186]; however, the inclusion of the tower in the present study highlights a more pronounced downstream deformation than previously modelled.

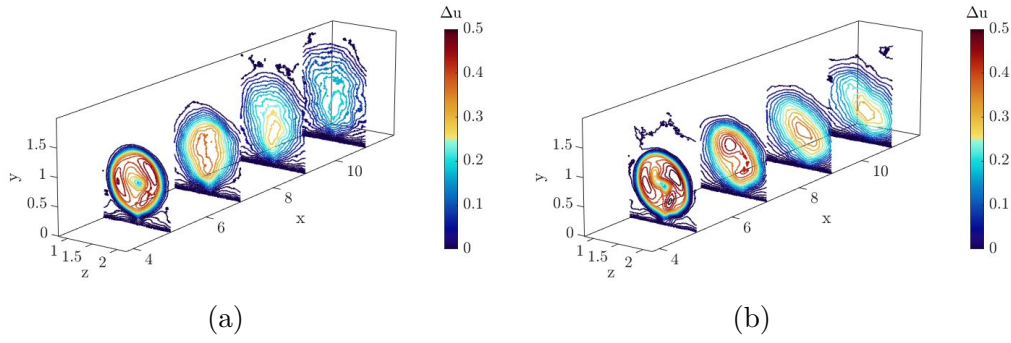


Figure 5.9: Time-averaged streamwise velocity-loss field obtained by LES, in the $y-z$ plane at $x = 5, 7, 9, 11$ diameter units downstream of the wind turbine for (a) the pressure gradient-inflow case and (b) the Coriolis-inflow case.

POD and DMD modes

For the POD and SPDMD evaluations of the wind turbine wake, two distinct datasets were utilized, each comprising 2370 snapshots representing the Coriolis and pressure gradient inflow scenarios. Velocity field snapshots were sampled at a constant time step of $\Delta t = 0.0125$, which equates to a 10° blade rotation. This sampling occurred within a restricted spatial domain spanning $[3.8 - 11.9] \times [0 - 1.55] \times [0.8 - 2.2]$ along the x , y , and z axes, respectively, as delineated by the box in Figure 5.8. Prior to analysis, the temporal mean velocity field was subtracted from all individual snapshots. The singular value distribution corresponding to the leading 600 POD modes is depicted in Figure 5.10. An initial steep drop in energy is observed across the first ≈ 10 modes, transitioning into a more gradual decline thereafter. In accordance

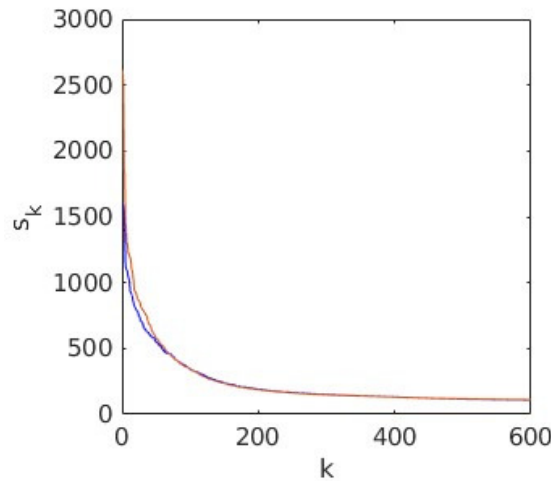


Figure 5.10: Singular values of the first 600 POD modes for the pressure gradient (orange) and the Coriolis (blue) wind turbine cases.

with the convergence criteria established by De Cillis et al. [79], an energy plateau emerges around the 600th mode. Consequently, a reduced basis of $r = 600$ POD modes was selected to conduct the subsequent DMD analysis.

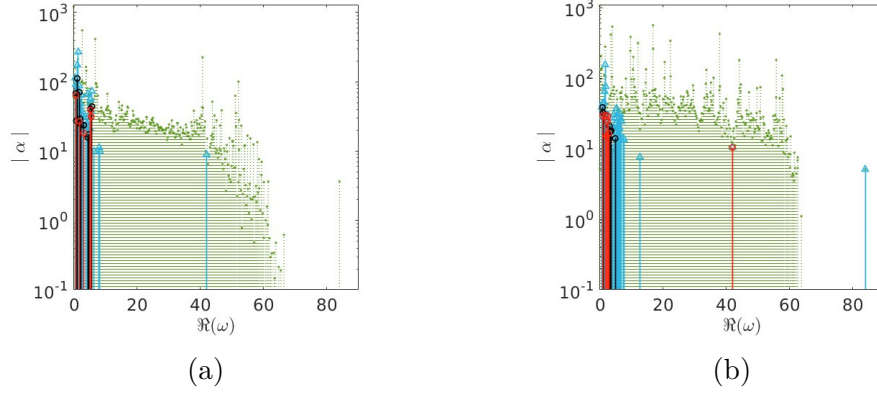


Figure 5.11: Absolute value of DMD amplitudes α_i versus the angular frequency $\mathbf{R}(\omega)$ for the pressure gradient (a) and the Coriolis (b) turbine's wake cases. Green circles represent the DMD modes, whereas blue triangle ($\gamma = 10000$), black circles ($\gamma = 21300$), and red circles ($\gamma = 33500$) are the SPDM modes.

Figures 5.11a and 5.11b illustrate the absolute DMD amplitudes, α_i , plotted against the angular frequency, $\mathbf{R}(\omega)$, for the pressure gradient and Coriolis cases. In these plots, standard DMD modes are denoted by green circles, while the SPDM outcomes are differentiated by red circles ($\gamma = 33500$), black circles ($\gamma = 21300$), and blue triangles ($\gamma = 10000$). Raising the sparsity parameter γ yields sparser representations, meaning the algorithm isolates a more restricted subset of dynamically dominant coherent structures alongside their optimised α values. Notably, at the highest γ value, the algorithm selects only low-frequency modes in both scenarios; however, lower sparsity thresholds allow one or two high-frequency modes to persist. For instance, under pressure gradient conditions, a high-frequency mode is captured by SPDM only at the lowest parameter ($\gamma = 10000$). Specifically, this is the mode at $\mathbf{R}(\omega) = 42.0$, representing tip vortices and matching three times the turbine's rotational frequency. This suggests that, at equivalent sparsity levels, higher-frequency coherent structures play a more prominent role in the turbine's dynamics when the Coriolis effect is present, whereas low-frequency structures are more representative for the flow devoid of wind veer. Subsequent discussions will focus exclusively on the results obtained using a sparsity coefficient of $\gamma = 33500$. It is important to highlight that at this specific γ value, the SPDM algorithm extracts 5 mode pairs for the pressure gradient scenario compared to 7 for the Coriolis case. This discrepancy implies that the Coriolis-driven flow possesses a higher number of non-negligible modes—particularly in the higher frequency spectrum—due to its increased dynamic complexity. This difference in mode numbers mirrors observations from the precursor simulation results. This

outcome could have been anticipated by examining the unpenalised DMD frequency distributions (green circles, Figure 5.11b), where the Coriolis case exhibits elevated amplitudes across a considerably broader frequency band than the pressure gradient case (Figure 5.11a). Table 5.2 provides a concise overview of the frequencies associated with the leading 10 modes under varying sparsity coefficients for both analysed cases.

Table 5.2: Frequencies of the first 10 modes selected by the SPDMD algorithm for different sparsity coefficients, for both wind turbine's flow cases considered.

	Pressure gradient			Coriolis		
	$\gamma = 10000$	$\gamma = 21300$	$\gamma = 33500$	$\gamma = 10000$	$\gamma = 21300$	$\gamma = 33500$
1 st mode	2.6944	1.1271	0.6703	1.7443	0.9013	1.8870
2 nd mode	1.4539	1.7749	5.3333	1.8870	1.0643	0.9013
3 rd mode	1.1271	0.6703	5.5488	1.5741	1.8870	2.6218
4 th mode	0.4676	5.7808	1.7749	1.3671	2.6218	2.4076
5 th mode	0.6703	5.3332	3.2131	0.9013	2.4073	2.8588
6 th mode	1.7749	5.5488	-	0.68845	3.0971	4.6195
7 th mode	5.7808	2.0448	-	5.3586	3.6489	42.0000
8 th mode	0.8426	0.8426	-	6.4352	3.3264	-
9 th mode	4.4801	2.2016	-	4.4959	2.8588	-
10 th mode	2.4539	3.2131	-	2.6218	2.1559	-

Turning to the spatial topology of the extracted modes, the SPDMD algorithm applied to the pressure gradient case exclusively filters low-frequency modes within the $\mathbf{R}(\omega) \in [0.45 - 5.57]$ range. These correspond to coherent structures of varying scales that span the entire computational domain. Specifically, modes bounded by $\mathbf{R}(\omega) \in [0.45 - 0.67]$ represent large-scale structures with a streamwise wavelength of $\lambda_x \approx 7.5$ (see Figure 5.12a). Moderate-scale structures, by contrast, characterise the mode at $\mathbf{R}(\omega) = 1.45$ ($\lambda_x \approx 3.7$) and those within the $\mathbf{R}(\omega) \in [3.20 - 5.50]$ band ($\lambda_x \approx 1.6$), as depicted in Figure 5.12c and Figure 5.12d. At higher frequencies near $\mathbf{R}(\omega) \approx 5.50$, the structures exhibit wavelengths below ≈ 1 (Figure 5.12b). Overall, the presence of the turbine does not result in the formation of discernible geometric patterns directly linked to the blades and/or tower/nacelle within the selected modes. Regarding the Strouhal numbers St of these modes, it is of interest to ascertain whether they align with documented wake meandering values [187, 188]. Consistent with the findings of De Cillis et al. [79] for this same reference turbine without Coriolis forcing, modes where $\mathbf{R}(\omega) < 1$ yield a Strouhal number of $St \leq 0.2$. This agreement with typical literature ranges reinforces the conjecture that wake meandering is primarily a consequence of external

factors associated with ABL turbulence, rather than an effect inherent to the turbine itself.

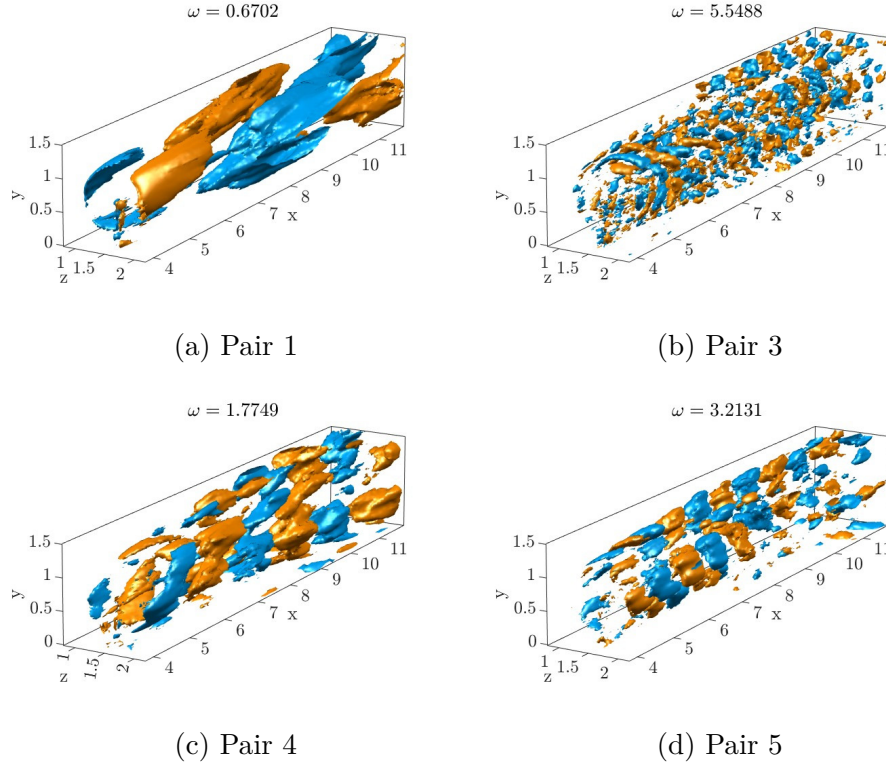


Figure 5.12: Streamwise velocity fluctuation iso-surfaces for three SPDMD modes ($\gamma = 33500$, pressure gradient-inflow wake). Blue: $u = +0.001$, orange: $u = -0.001$.

Analysing the Coriolis inflow case, structures associated with frequencies $\mathbf{R}(\omega) < 1$ exhibit a streamwise length mostly equal to that of the sub-domain, $\lambda_x \approx 7.4$, as shown in Figure 5.13b. Coherent structures of medium wavelengths ($\lambda_x \approx 3.4$) are observed for modes in the $\mathbf{R}(\omega) \in [1.50 - 1.90]$ range, while structures with a length scale on the order of $1.5 - 2$ correlate with $\mathbf{R}(\omega) \in [2.87 - 4.62]$ (see Figure 5.13a and Figure 5.13c, respectively). Figure 5.13d highlights the DMD mode at $\mathbf{R}(\omega) \approx 42.0$, which corresponds to an angular frequency triple the turbine's rated speed. It is worth noting that relaxing the sparsity constraint would allow the algorithm to capture the mode at a frequency of ≈ 84 (six times the rotational frequency), which is associated with the tip vortices. The Strouhal number value reported for the pressure gradient case is also recovered when the Coriolis effect is present.

A key observation is that in the pressure gradient case, the SPDMD algorithm more readily discards high-frequency modes related to tip vortices as the sparsity parameter increases. The addition of wind veer, however, preserves such high-frequency wave structures to a greater extent. This implies that the

presence of wind veer delays the breakdown of these structures, potentially negatively impacting wake recovery, a phenomenon that will be further investigated in Section 5.2.2. Notably, as these structures propagate away from the rotor region, they extend towards the left side of the computational domain. The behaviour of these same structures in the far-wake region indicates that the tower's wake is off-center in the z -direction (see Figure 5.13c).

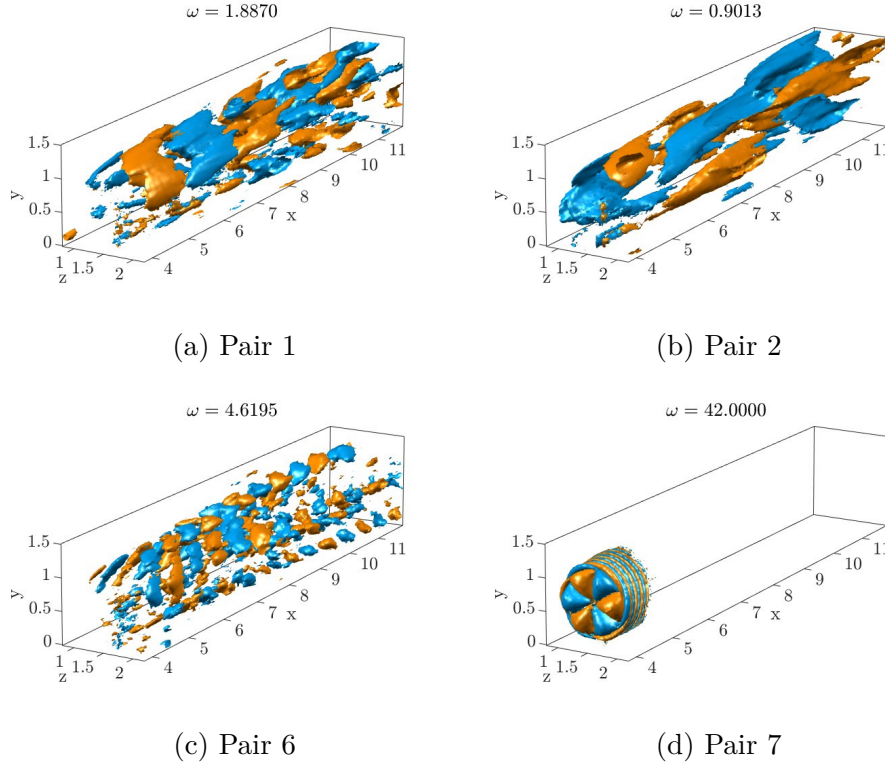


Figure 5.13: Streamwise velocity fluctuation iso-surfaces for three SPDMD modes ($\gamma = 33500$, Coriolis forcing-inflow wake). Blue: $u = +0.001$, orange: $u = -0.001$.

Figure 5.14 provides clear evidence that streamwise fluctuation structures are strongly influenced by the presence of wind veer. The figure displays three slices in $x - z$ planes at varying elevations for both inflow scenarios, utilizing the 4th mode pair for the pressure gradient and the 1st mode pair for the Coriolis case. Below hub height, the Coriolis case reveals a rightward deflection of the structures (Figure 5.14b), a trend entirely absent without wind veer (Figure 5.14a). The opposite deflection occurs in the slices above hub height (Figure 5.14e and Figure 5.14f). Unsurprisingly, exactly at hub height (Figure 5.14c and Figure 5.14d), neither case exhibits lateral deflection due to the expected local absence of veer.

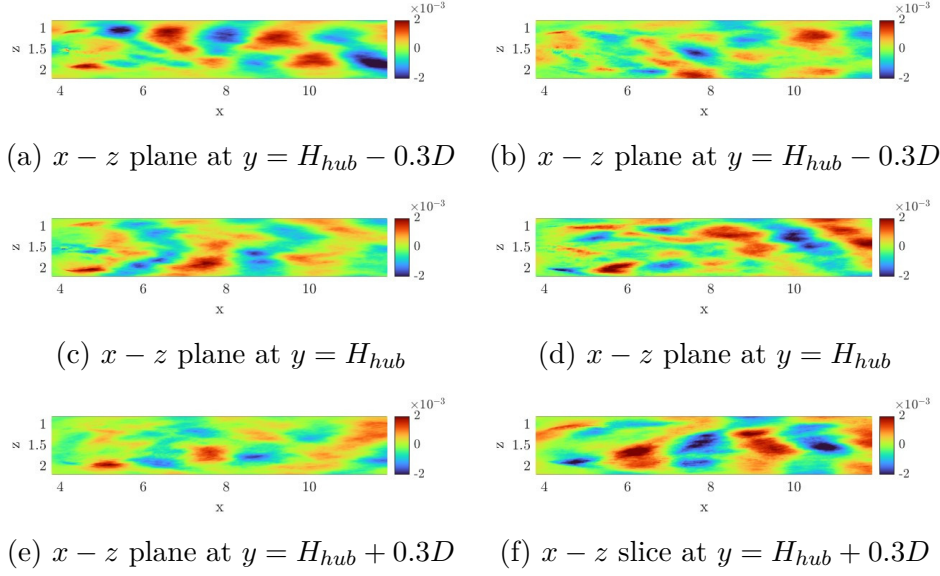


Figure 5.14: Streamwise velocity fluctuation in $x - z$ planes at three different heights of the 4th mode pair of the pressure gradient case (left) and of the 1st mode pair of Coriolis turbine's wake case (right).

The principal distinguishing feature between these two scenarios is the presence of a spanwise velocity component within the inflow. An examination of the transverse velocity isosurfaces within the wake is therefore warranted. In the pressure gradient case, coherent structures associated with lateral velocity are notably weak at frequencies $\mathbf{R}(\omega) < 1.45$, as depicted in Figure 5.15a. While strong lateral flows can be identified in high-frequency modes, they remain largely confined to the wake region away from the tower (see Figure 5.15b).

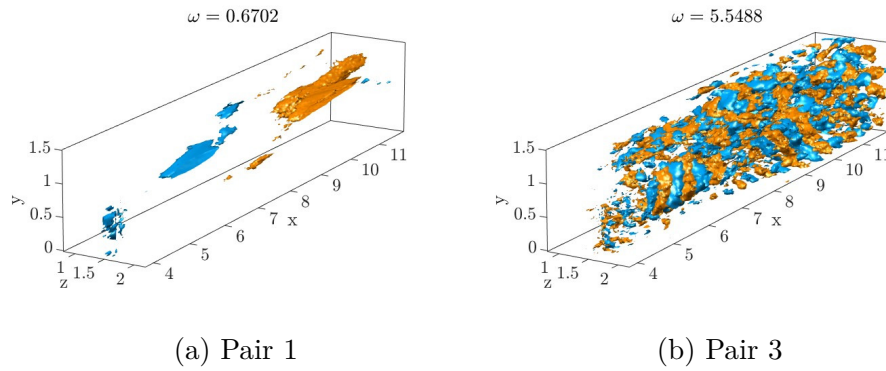


Figure 5.15: Spanwise velocity fluctuation iso-surfaces for three modes selected by SPDMD with $\gamma = 33500$ for the pressure gradient-inflow turbine's wake simulation. The iso-surfaces colored in blue indicate a positive fluctuation $w = 0.001$, whereas the orange ones represent a negative fluctuation $w = -0.001$.

When the Coriolis force is applied, however, transverse flow becomes dominant. As illustrated in Figure 5.16a and Figure 5.16b, these structures adopt an oblique orientation, reflecting the deformation dictated by the Coriolis effect. An intriguing observation is that, unlike the streamwise velocity component, the low-frequency spanwise structures appear minimally influenced by the physical geometry of the tower, nacelle, and rotor (see Figure 5.16a). However, for frequencies exceeding $\mathbf{R}(\omega) > 3.10$, the tower and nacelle exert a non-negligible influence on the flow, a phenomenon clearly evidenced by the spanwise iso-contours in Figure 5.16b.

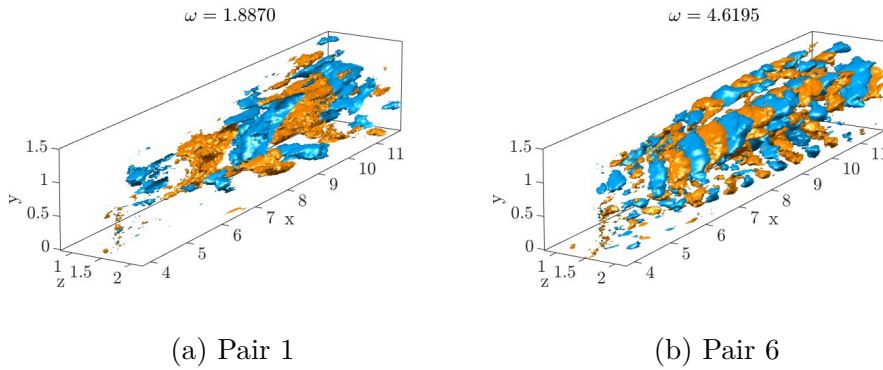


Figure 5.16: Spanwise velocity fluctuation iso-surfaces for three modes selected by SPDMD with $\gamma = 33500$ for the Coriolis-inflow simulation. The iso-surfaces colored in blue indicate a positive fluctuation $w = 0.001$, whereas the orange ones represent a negative fluctuation $w = -0.001$.

In summary, the spanwise velocity component is instrumental in shaping the coherent structures within the wind turbine wake, driven by the effects of Coriolis acceleration. This underscores the pronounced impact of wind veer on wake dynamics. A comparison of the relevant DMD modes reveals that, under geostrophic forcing, the streamwise and spanwise velocity components share comparable amplitudes and spatial extensions. Therefore, when the inflow features a strong cross-flow velocity profile, spanwise momentum exchange is a critical factor that cannot be overlooked. Furthermore, the wavelengths associated with the DMD modes are highly comparable across both studied scenarios. This similarity is particularly evident in the Coriolis case, where spanwise structures are more extensively developed, especially at lower frequencies. This serves as additional evidence that bi-directional coherent structures fundamentally dictate wake evolution within the evaluated sub-domain.

Mean kinetic energy entrainment

Following the methodology established in Section 2.7, the turbulent MKE flux is decomposed to evaluate how the most energetic coherent structures

facilitate wake recovery. Given their inherent orthogonality and dominance in energy capture, the leading POD modes serve as the basis for this analysis. Figure 5.17a illustrates the local turbulent MKE flux under pressure gradient inflow conditions. Evaluated at a radial distance of $R_c = 0.5$, the data reveal that the five most energetic, low-frequency POD modes consistently yield a positive local MKE flux. For each of these individual modes, the local flux reaches its maximum in the near-to-transition wake region—peaking at distinct streamwise locations between 7 and 10 rotor diameters—before gradually decaying into the far wake. The total MKE flux, computed across varying values of R_c , is depicted in Figure 5.17b. Highlighting the cumulative impact of these top five POD mode pairs, it is evident that all of them actively drive MKE entrainment, with the first two modes providing the most substantial contributions.

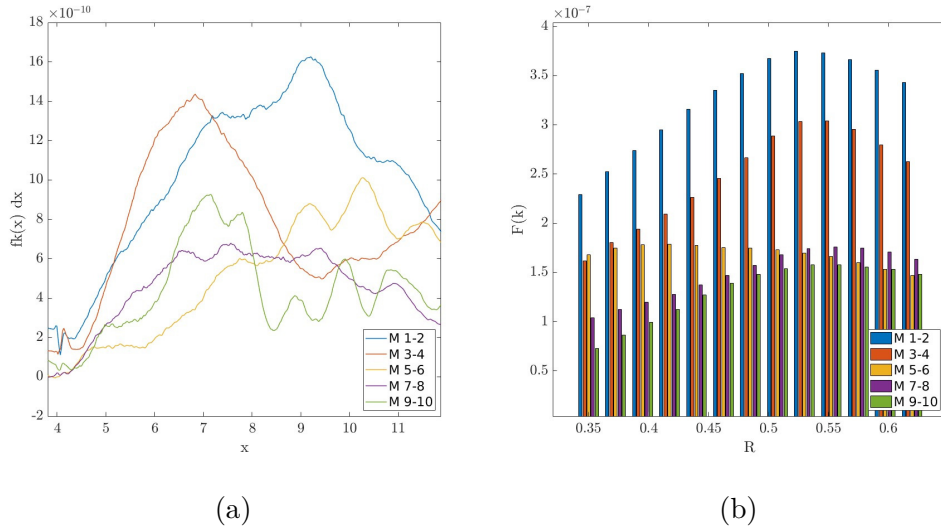


Figure 5.17: MKE entrainment for Pressure gradient-inflow case: (a) local (at $R_c = 0.5$) and (b) total fluxes.

Transitioning to the Coriolis-inflow scenario, the leading five mode pairs similarly demonstrate a positive influence on both the local and total MKE fluxes. However, a comparison of the local flux profiles (Figure 5.18a) reveals a distinct spatial shift: the peaks are more tightly concentrated upstream, occurring around $x \approx 6 - 7$ diameters. Regarding the total flux (Figure 5.18b), MKE entrainment reaches its maximum near $R \approx 0.5$ but experiences a much steeper radial decline for $R > 0.5$ compared to the pressure gradient counterpart. This indicates that while wind veer strongly enhances entrainment within the inner core of the wake, this momentum exchange dissipates rapidly along the radial outward direction. This phenomenon aligns with the geometric observations from Figure 5.8, indicating that the Coriolis-affected wake is more radially compressed (flattened), thereby spatially restricting the entrainment zone.

The primary (first) mode, moreover, overwhelmingly dictates the entrainment dynamics in the Coriolis case, whereas the secondary mode maintains a more substantial relative influence under pressure gradient conditions.

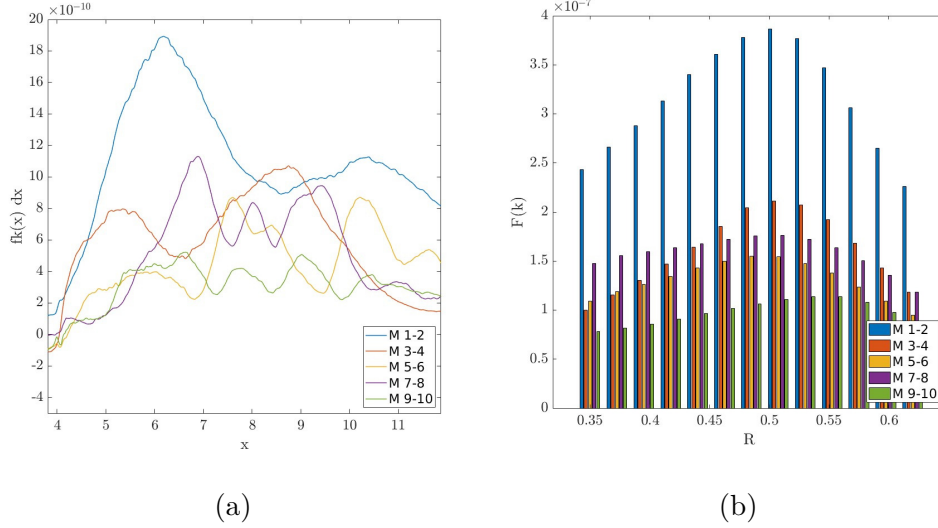


Figure 5.18: MKE entrainment for Coriolis-inflow case: (a) local (at $R_c = 0.5$) and (b) total fluxes.

Interestingly, the first two mode pairs share similar spatial topologies across both inflow scenarios, yet their energetic ranking is inverted. The long-wavelength structure dominates in the pressure gradient case (Figure 5.19a), while the medium-wavelength one becomes the most energetic when the Coriolis force is introduced (Figure 5.20a).

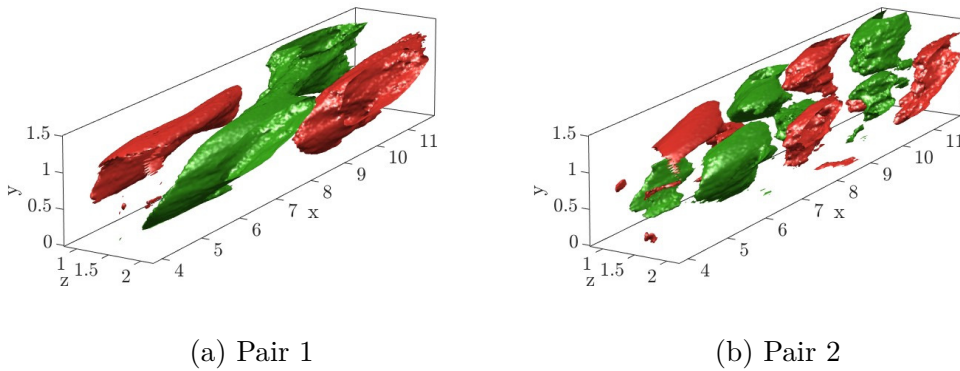


Figure 5.19: Streamwise velocity fluctuation iso-surfaces for the first 2 POD modes of the pressure gradient-inflow turbine wake. Green: $u = 0.001$; red: $u = -0.001$.

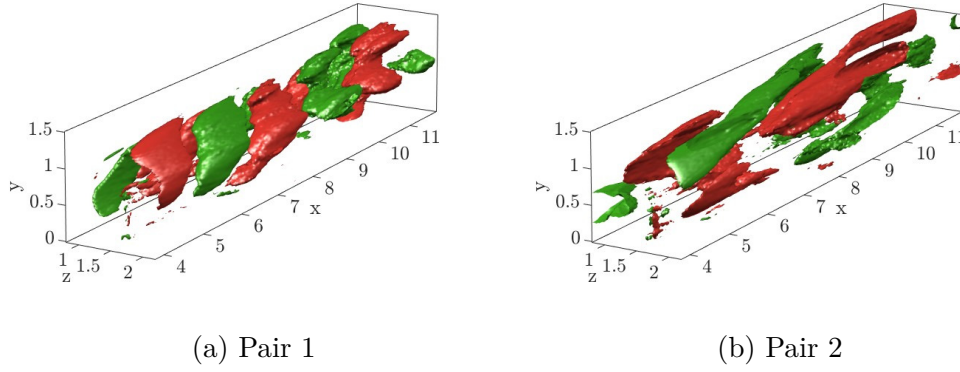


Figure 5.20: Streamwise velocity fluctuation iso-surfaces for the first 2 POD modes of the Coriolis-inflow turbine wake. Green: $u = 0.001$; red: $u = -0.001$.

Wakefield reconstruction

A key application of DMD is the construction of ROMs that extend the prediction of the flow's temporal evolution beyond the original sampling window, at a fraction of the computational cost of a full simulation. However, achieving this efficiency requires identifying an optimal balance between the size of the retained DMD modal basis and the corresponding approximation error, which is defined by the following expression:

$$error[\%] = \frac{1}{N} \sum_{j=1}^N \frac{\|q_{CFD}^j - x_{ROMF}^j\|}{\|q_{CFD}^j\|} \times 100, \quad (5.2)$$

where q_{CFD}^j represents the j^{th} reference snapshot extracted from the simulation, and x_{ROMF}^j denotes the reconstructed flow field at the identical time step, evaluated via Equation 2.69.

Table 5.3 details the reconstruction errors relative to the actual reference datasets for both investigated inflow scenarios, tabulated against the number of modes selected by the SP algorithm. Notably, for an equivalent number of SPDMD modes, the reconstructed fields under wind veer conditions demonstrate a slightly higher degree of accuracy than those in the pressure gradient scenario. As anticipated, truncating the modal basis invariably leads to an increase in the error margin for both flows. Nevertheless, the quantitative deviation from the reference flow field remains reasonably bounded even when deploying a highly restricted basis—specifically, just 12 complex conjugate mode pairs. Ultimately, the optimal number of modes depends on the specific requirements of the application, striking a compromise between the target predictive accuracy and the necessity to lower computational costs.

Table 5.3: Comparative analysis of the error of the DMD flow field reconstructions with respect to the original snapshot for the pressure gradient and Coriolis flow cases, as a function of the number of DMD mode pairs selected by the sparsity promoting algorithm.

	Pressure gradient	Coriolis
300 mode pairs	6.75 %	4.79 %
75 mode pairs	7.14 %	5.25 %
12 mode pairs	12.5 %	8.87 %

Figure 5.21 provides a visual comparison of velocity field slices extracted in the $x-y$ plane. The top row displays the original reference snapshots, while the subsequent rows (from second to fourth) illustrate the SPDMD reconstructions utilizing a progressively decreasing number of modes for both aerodynamic cases.

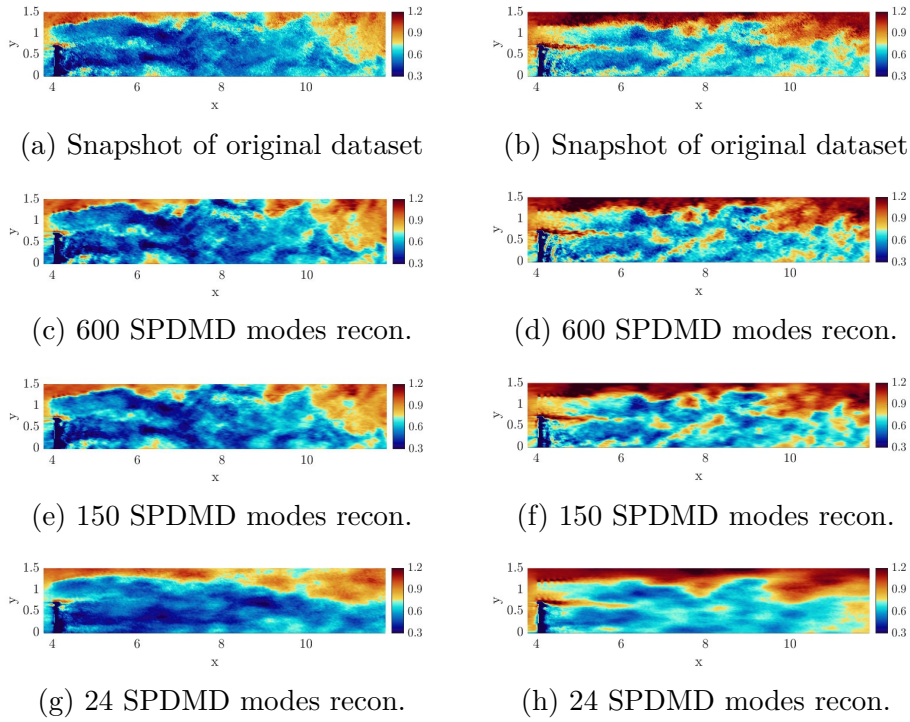


Figure 5.21: Pressure gradient (left) and Coriolis (right) wakefield reconstruction results: original snapshot (a,b), wakefield reconstructed by SPDMD with different number of modes (c-h).

Across all test scenarios, incorporating 600 dynamic modes (equivalent to 300 complex conjugate pairs) yields a spatial wake structure practically

indistinguishable from the original LES data. Conversely, as the modal basis is increasingly truncated, the algorithm struggles to resolve the small-scale vortical details of the wake. Under the most aggressive truncation (retaining only 12 mode pairs), these fine-scale turbulent structures are completely dissipated; however, the reconstruction successfully preserves the overarching macroscopic flow footprint of the original snapshots. Overall, the analysis concludes that utilizing a subset of 75 DMD mode pairs serves as an excellent compromise, reliably capturing the structural complexities of the flow down to the small scales while maintaining a highly acceptable error threshold of 5 – 7%.

5.3 Conclusions

This chapter has examined how wind veer, induced by Coriolis acceleration within the ABL, affects the coherent structures developing in the wake of the NREL 5MW turbine.

The DMD technique was applied to extract the dominant mono-frequency modes from the wake, effectively decomposing the turbulent flow field into distinct coherent structures. To refine this representation, the SPDMD algorithm was utilized. By imposing a constrained minimisation on the reconstruction error, the SPDMD method filters the modal basis, retaining only an optimal, limited subset of dynamically relevant flow features. This approach was instrumental in comparing the wake topologies with and without wind veer, ultimately facilitating the construction of an efficient, ROM that accurately accounts for geostrophic forcing.

A critical finding emerges from comparing the modal velocity components under both inflow scenarios: the introduction of wind veer markedly amplifies the importance of the spanwise velocity component, leading to an increase in oblique flow features. In the Coriolis-affected scenario, the dynamically dominant DMD modes exhibit spanwise velocity amplitudes and spatial extents highly comparable to their streamwise counterparts. Under pure pressure gradient conditions, however, transverse flow structures remain weak or entirely absent, particularly within the low-frequency modal spectrum. When wind veer is present, these spanwise structures adopt a distinct oblique orientation in the far wake, directly reflecting the continuous distortion driven by the Coriolis effect.

In both aerodynamic cases, the wake is predominantly governed by low-frequency coherent structures originating from the inherent turbulent properties of the incoming ABL. Endogenously generated structures, such as tip and hub vortices, exert a comparatively minor dynamic influence. However, it is notable that the modes extracted from the pressure gradient case consistently display a much more pronounced structural footprint related to the physical presence of the turbine tower.

To assess how these coherent structures govern wake recovery, a POD

was executed to quantify each mode's contribution to mean kinetic energy MKE entrainment. POD was specifically chosen for this task because it ranks modes by their turbulent kinetic energy content and provides the necessary orthonormal basis for an exact energy decomposition. The analysis of the leading POD modes reveals a fascinating dynamic: while the spatial topologies of the first two modes are structurally similar across both inflow cases, their relative energetic importance is inverted.

Under pressure gradient conditions, the longer-wavelength mode dominates MKE entrainment, though subsequent modes also contribute substantially to wake recovery. When the Coriolis force is active, the shorter-wavelength mode becomes the primary recovery driver, with an entrainment rate approximately twice that of the secondary modes. Moreover, the Coriolis case localizes peak MKE entrainment closer to the rotor and at a smaller radial distance, producing the radially flattened downstream wake shape characteristic of wind veer environments.

As highlighted, a pivotal outcome of this study is the successful derivation of highly accurate, DMD-based reduced-order models that encapsulate both ABL turbulence characteristics and Coriolis-induced phenomena. When the SPDMD algorithm retains a substantial number of modes, it accurately reconstructs both large- and small-scale vortical structures, with an L_2 -norm velocity error of $\approx 5\%$. The resolution of small-scale structures is highly sensitive to modal truncation; as the basis size decreases, the accurate reconstruction of fine turbulence details deteriorates rapidly. The global reconstruction error scales inversely with the number of retained modes, peaking at $\approx 10\%$ when the basis is drastically reduced to just 12 mode pairs. Overall, the analysis establishes that a basis of ≈ 70 DMD mode pairs represents an optimal threshold, successfully capturing the flow physics down to the small scales while maintaining a stringent error margin of $5 - 7\%$.

By thoroughly contrasting turbine wakes with and without wind veer, the results indicate that realistic wake modeling requires the inclusion of Coriolis forcing. The spanwise velocity component plays a dominant role in shaping the coherent structures of both turbine- and boundary-layer origin, making geostrophic effects necessary for accurate wake predictions.

Finally, while this investigation focused on the NREL 5MW turbine, wind veer effects are expected to become more pronounced as rotor size increases. Next-generation installations, such as the IEA 15MW [11] or NREL 22MW [189] reference turbines (featuring diameters more than double the one studied here), will likely experience profoundly amplified Coriolis interactions. The current findings confirm that even at the 5 MW scale, geostrophic wind veer fundamentally alters wake morphology and coherent structure dynamics. Consequently, future work should address these phenomena on ultra-large turbines and explore the complex wake-interaction dynamics of multi-turbine arrays operating under wind veer conditions.

Chapter 6

Effects of Flexibility

This chapter compares the aerodynamic performance and aeroelastic response of the NREL 5MW and the IEA 15MW reference turbines. To separate the effects of structural scaling from environmental variables, both models are subjected to identical sheared inflow conditions. The analysis is conducted entirely within the UTD-WF computational framework [115], relying on a fully coupled CFD-CSD solver. Special attention is given to the role of the torsional degree of freedom across the two scales, comparing simulations with and without coupled torsional feedback to quantify its impact on blade loading, dynamic deformation, and wake-tower interactions.

The contribution of this chapter is the first fully coupled LES-CSD comparison of the NREL 5MW and IEA 15MW turbines under identical inflow, isolating the effect of rotor scale on torsion-bending coupling and demonstrating its counter-intuitive consequence: the torsional degree of freedom reduces mean deflection but increases fatigue accumulation, a trade-off quantified in a LES fluid-structure interaction environment (Chapter 4).

6.1 Flow and structural setup

In this work, two stand-alone reference turbines are considered in their monopile configurations: the NREL 5MW [168] and the IEA 15MW [11]. While the 5MW turbine represents a standard utility-scale machine, the 15MW turbine embodies the next generation of highly flexible offshore rotors, featuring a rotor diameter $D = 240$ m and blades of length $L = 117$ m, while the 5MW dimensions are $D = 126$ m and $L = 61.5$ m. For more details, see Sections 3.1 and 3.2.

For both configurations, the computational domain is scaled relative to the respective rotor diameter, maintaining dimensions of $12D \times 11D \times 3D$ in the streamwise, vertical, and spanwise directions, respectively. The distance of the turbine from the inlet is set to $4D$, a value determined based on reference data available in the literature, which typically ranges from $2D$ to $5D$ for numerical

simulations [190, 191, 192, 193]. The spanwise length of 3D was verified to be sufficient to render the blockage effect negligible when employing periodic boundary conditions [194, 191, 192].

Following a rigorous convergence study, the computational box is discretised by a staggered orthogonal grid composed of $2049 \times 513 \times 513$ points. The grid is equally spaced in the streamwise and spanwise directions and is stretched vertically, with a gradually wider spacing starting from the region above the rotor. The chosen resolution yields an actuator line discretised by 86 points per blade. The time resolution of the LES computation is tied to the spatial resolution to satisfy the stability requirements of the numerical scheme. Simulations are carried out at a constant CFL number [134] equal to 0.65.

To isolate the scaling effects, both turbines are subjected to an identical sheared laminar inflow, defined by a power law with the exponent $\alpha = 0.05$. The streamwise undisturbed velocity at the respective hub height is kept constant at $U_\infty \simeq 9$ m/s, while $U_{ref} = 10$ m/s at the top of domain. A convective boundary condition is applied at the outlet, while slip and no-slip conditions are enforced at the top and bottom boundaries, respectively. The turbines operate at their nominal tip speed ratios (TSR). The simulations were conducted for a sufficiently long time interval over the initial transient to guarantee statistically converged data over multiple rotor revolutions. ALM is adopted to model the wind turbine blades, while IBM is used to represent the tower and nacelle. A Prandtl loss model is applied to account for the tip and root effects.

The aeroelastic coupling is handled entirely by the in-house UTD-WF solver. While engineering tools based on modal approaches (e.g., *ElastoDyn* [40]) or geometrically exact beam theories (e.g., *BeamDyn* [41]) are widely used in the literature for structural verification, this study relies exclusively on the CFD-CSD framework to capture the fully resolved fluid-structure interactions. The reliability of this framework against both OpenFAST modules has been established in Chapter 4; the comparisons presented there are not repeated here. To thoroughly investigate the impact of torsional coupling, two distinct structural configurations are simulated for each turbine:

- **CFD-CSD/OV**: a model where the structural deformation velocity alters the local angle of attack, but the structural torsional twist is neglected;
- **CFD-CSD/T**: a fully coupled model that actively incorporates the instantaneous torsional deformation into the definition of the local effective incidence.

To identify the optimal configuration for the structural model, a preliminary sensitivity analysis was conducted; the natural frequencies of the undeformed, non-rotating blade were then benchmarked against reference values from the

literature. A total of $M_s = 15$ modes and a discretisation of $N = 80$ equally-spaced nodes per blade were retained.

6.2 Results

This section analyses the aerodynamic loads distributed along the blades, comparing the outcomes between the NREL 5MW and IEA 15MW turbines. Subsequently, the overall turbine performance and the dynamic blade deformations are assessed to highlight the scaling effects.

6.2.1 Aerodynamic loads on the blade

The analysis of the aerodynamic loads relies exclusively on the UTD-WF CFD-CSD models. Imposing identical laminar sheared inflow conditions allows any observed behavioural differences to be attributed directly to the distinct architectural and structural properties of the two turbines.

Figure 6.1 depicts the time-averaged aerodynamic quantities along the blade span, including the local angle of attack α , the aerodynamic pitching moment M_{aero} , and the flapwise (F_2) and edgewise (F_3) components of the aerodynamic force. Comparing the two turbines, the IEA 15MW rotor exhibits a markedly different load distribution. All forces and torque curves show higher loads acting on the blade. As shown in Figure 6.1, the aerodynamic load distributions for the NREL 5MW turbine exhibit localised discontinuities or a 'step-like' behaviour along the span, particularly evident in the pitching moment M_{aero} . This is a well-documented numerical artifact stemming from the original NREL 5MW specification [168], wherein the spanwise transition between different discrete airfoil families is strictly abrupt. Since the Actuator Line Model evaluates local forces based on tabulated 2D polars, the lack of continuous spanwise blending manifests as sudden jumps in the aerodynamic coefficients, as previously discussed in the literature [48, 46]. In contrast, the modern IEA 15MW utilises a smoothly interpolated FFA airfoil series, yielding perfectly continuous load distributions. When comparing the two coupling strategies, it is evident that neglecting the torsional feedback (CFD-CSD/OV) leads to a systematic overprediction of the angle of attack towards the tip, which consequently alters the F_2 and F_3 force distributions. This overprediction is markedly more severe for the highly flexible 15MW blade than for the stiffer 5MW blade, underlining the necessity of torsional coupling (CFD-CSD/T) for ultra-large rotors.

To capture the unsteady dynamics, a phase average of the aerodynamic quantities was performed at 80% of the blade span ($\frac{r-R_{\text{hub}}}{L} = 0.8$). As shown in Figure 6.2, the dynamical behaviour of the aerodynamic forces during the blade revolution demonstrates that the passage of the blade in front of the tower constitutes the primary source of flow unsteadiness. As the blade aligns

with the tower ($\theta = 180^\circ$), a sharp oscillation in the incidence angle and the aerodynamic forces is observed.

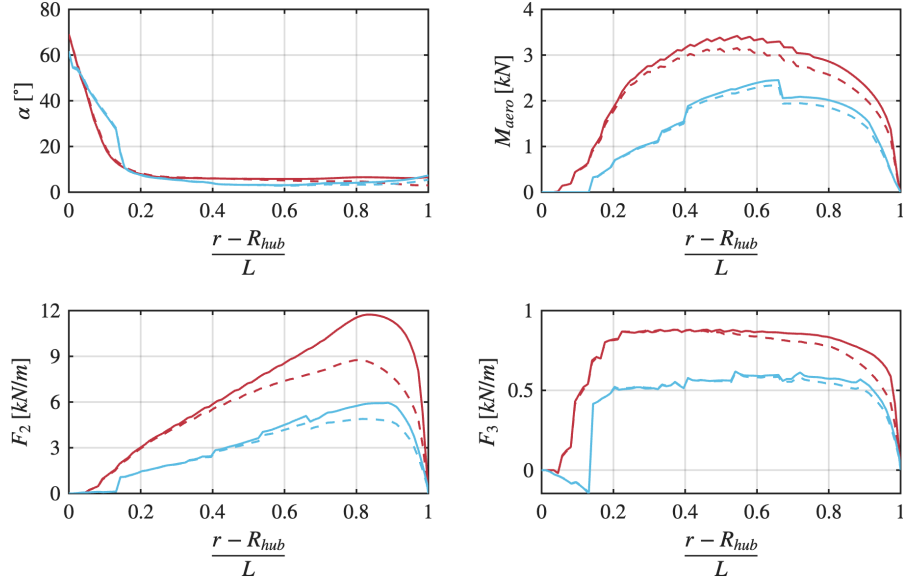


Figure 6.1: Time-averaged radial distribution of the local angle of attack (α), aerodynamic pitching moment (M_{aero}), flapwise (F_2) and edgewise (F_3) forces. CFD-CSD/OV: IEA 15MW —, NREL 5MW —. CFD-CSD/T: IEA 15MW ---, NREL 5MW ---.

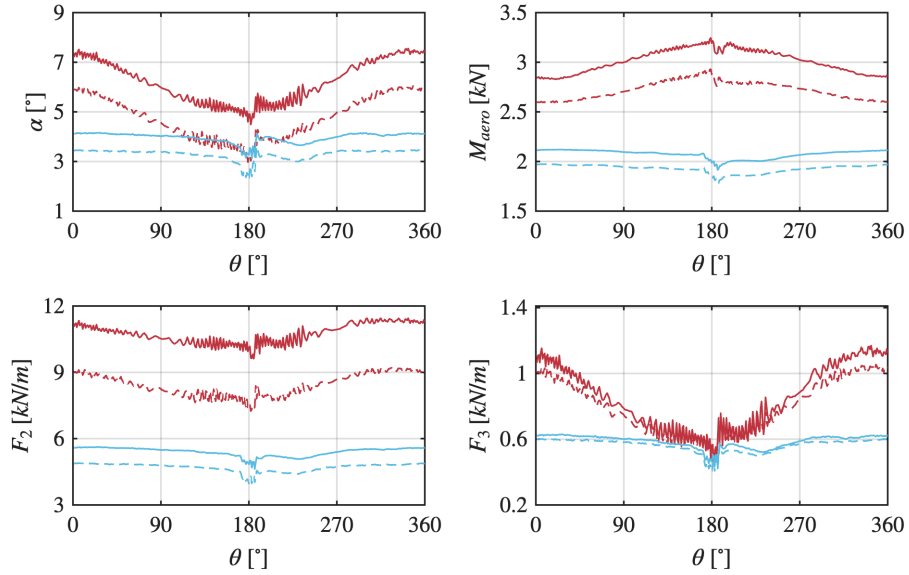


Figure 6.2: Phase-averaged aerodynamic quantities at 80% of the blade span. CFD-CSD/OV: IEA 15MW —, NREL 5MW —. CFD-CSD/T: IEA 15MW ---, NREL 5MW ---.

Interestingly, a distinct scaling effect emerges when comparing the tower

shadow impact on the two turbines. For the NREL 5MW, the blade-tower interaction generates a profound and abrupt alteration of the aerodynamic forces. Conversely, for the IEA 15MW turbine, despite its huge size, the localised effect of the tower shadow appears relatively less disruptive in terms of percentage load variations. This can be attributed to the different relative geometry: the flow induced by a thinner tower (in diameter units)—as in the case of the 15MW wind turbine—produces a more confined velocity deficit compared to the one induced by the relatively thicker tower of the 5MW turbine. Moreover, the variation of loads during the rotation appears larger as the rotor diameter increases.

Furthermore, analysing the phase-averaged percentage differences between the CFD-CSD/OV and CFD-CSD/T models confirms that the torsional degree of freedom acts as an aeroelastic damper. Including torsion systematically reduces the amplitude of the load fluctuations encountered during the tower passage, an effect that is paramount for mitigating fatigue in the ultra-large 15MW blades.

6.2.2 Power and thrust coefficients

The integration of the previously discussed aerodynamic loads yields the global performance metrics: the power coefficient (C_P) and the thrust coefficient (C_T). They are defined as follows:

$$C_P = \frac{P_d}{\frac{1}{2}\rho AU_\infty^3}, \quad C_T = \frac{T_{\text{aero}}}{\frac{1}{2}\rho AU_\infty^2}, \quad (6.1)$$

where $A = \pi D^2/4$ represents the rotor area, P_d is the aerodynamic power transferred to the rotor and T_{aero} is the overall aerodynamic thrust on the turbine.

The phase-averaged evolution of C_P and C_T (Figure 6.3) clearly reflects the tower shadow effect. The periodic passage of the blades in front of the tower produces a distinct drop in the performance curves. However, the magnitude of this performance loss scales differently for the two machines. The performance drop induced by the tower is less pronounced for the 15MW turbine ($\approx 4.5\%$) compared to the 5MW turbine ($\approx 7.4\%$). This behaviour is strongly linked to the inflow conditions and the rotor dimensions. Because the inflow is sheared, the ultra-large 240 m rotor of the 15MW turbine operates across a much wider velocity gradient. The lower wind speed in the bottom half of the rotor plane naturally yields a lower power production in the region where the tower is located. Consequently, the localised deficit caused by the tower represents a smaller fraction of the total produced power compared to the smaller rotor.

Comparing the structural models, the average value of the power coefficient is noticeably larger when the torsional deformation is neglected (CFD-CSD/OV). Incorporating the torsional feedback (CFD-CSD/T) causes the

blade to naturally twist towards lower angles of attack under load, reducing the aerodynamic loading through a pitch-to-stall twisting response and slightly reducing the predicted C_P . This trend is consistent across both turbine scales but is heavily magnified in the 15MW case.

Figure 6.3b shows the same phenomenon for the thrust coefficient C_T .

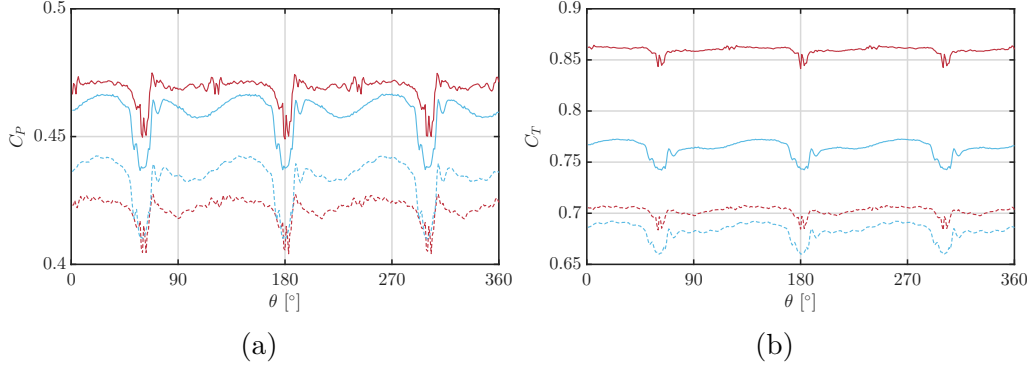


Figure 6.3: Phase-averaged power (a) and thrust (b) coefficients. CFD-CSD/OV: IEA 15MW —, NREL 5MW —. CFD-CSD/T: IEA 15MW - - -, NREL 5MW - - -.

6.2.3 Structural response

The structural response of the blades reveals the aeroelastic scaling effects between the utility-scale NREL 5MW and the ultra-large IEA 15MW turbines. Figure 6.4 illustrates the time-averaged spatial distribution of the out-of-plane, in-plane, and torsional deflections along the normalized blade span.

The out-of-plane deformation (x_{OoP}) is primarily governed by the aerodynamic thrust. As expected, the absolute deflection of the 15MW blade is substantially larger compared to the 5MW model. For the uncoupled CFD-CSD/OV model, the 15MW blade tip deflection reaches approximately 13% of the rotor radius ($R = 120$ m), translating to a physical displacement of nearly 15.6 m. In contrast, the stiffer 5MW blade reaches roughly 7% of its radius (≈ 4.4 m). Crucially, neglecting the torsional feedback (CFD-CSD/OV) leads to a severe overestimation of the out-of-plane deformation. By actively simulating the pitch-to-stall twisting behaviour of the blade under load, the fully coupled CFD-CSD/T solver effectively relieves the aerodynamic thrust, resulting in a structural deformation that is noticeably lower (dropping to $\approx 9\%$ of R for the 15MW model).

A similar trend is starkly evident in the torsional deflection (ϑ_{tors}). The torsional coupling actively unloads the blade, resulting in a maximum time-averaged twist of about -4.1° for the 15MW blade, compared to an overestimated -4.8° when torsional feedback is neglected. This confirms that ignoring

the aeroelastic twist loop not only artificially inflates the aerodynamic loads but also severely misrepresents the torsional state of the structure.

Conversely, the in-plane deformation (y_{IP}) exhibits a distinctly different behaviour. Because it is heavily influenced by gravity, centrifugal, and Coriolis forces rather than purely aerodynamic loading, the in-plane deflection is largely insensitive to the chosen coupling strategy. The curves for both the OV and T models almost perfectly overlap, converging to similar normalized values near the tip.

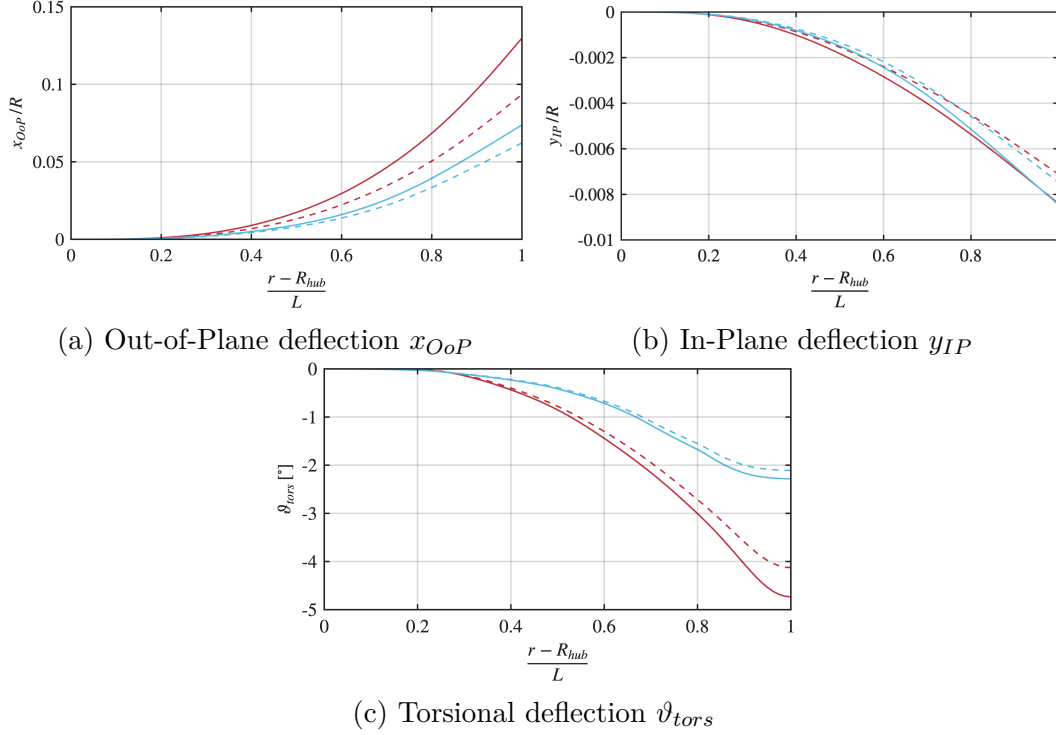


Figure 6.4: Structural deflection along the blade. CFD-CSD/OV: IEA 15MW —, NREL 5MW —. CFD-CSD/T: IEA 15MW - - -, NREL 5MW - - -.

To provide a more intuitive understanding of the structural response, Figure 6.5 presents a two-dimensional visualization of the deformed blades across the simulated cases. This rendering highlights the true scale of the aeroelastic deflections relative to the overall blade dimensions, as accurately captured by the employed fluid-structure interaction model.

To evaluate the dynamic response during a full rotation, Figure 6.6 presents the phase-averaged deflections extracted at the outer portion of the blade (80% of the span). The azimuthal angle $\theta = 0^\circ$ corresponds to the blade pointing vertically upward. The passage of the blade in front of the tower at $\theta = 180^\circ$ acts as a dominant impulsive forcing. For both the out-of-plane and torsional deflections, the tower shadow triggers a distinct, sudden drop due to the localised velocity deficit, immediately followed by an elastic rebound. The

phase-averaged data reiterate how harmful neglecting the torsional degree of freedom is, particularly for next-generation rotors: the gap between the OV and T curves is significant for the highly flexible 15MW turbine, whereas it remains relatively contained for the 5MW model.

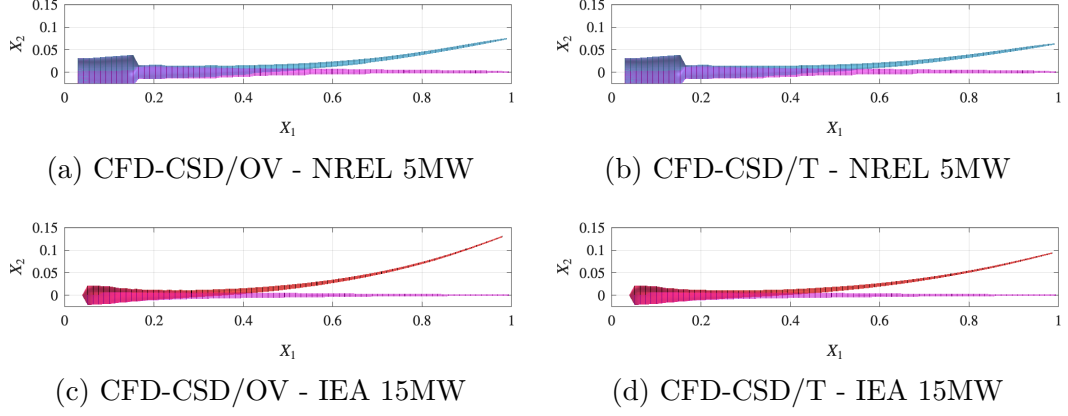


Figure 6.5: Two-dimensional visualization of the deformed blades. The undeformed blade is superimposed in magenta to provide a direct baseline for comparison, highlighting the scale of aeroelastic deflections relative to the overall blade dimensions.

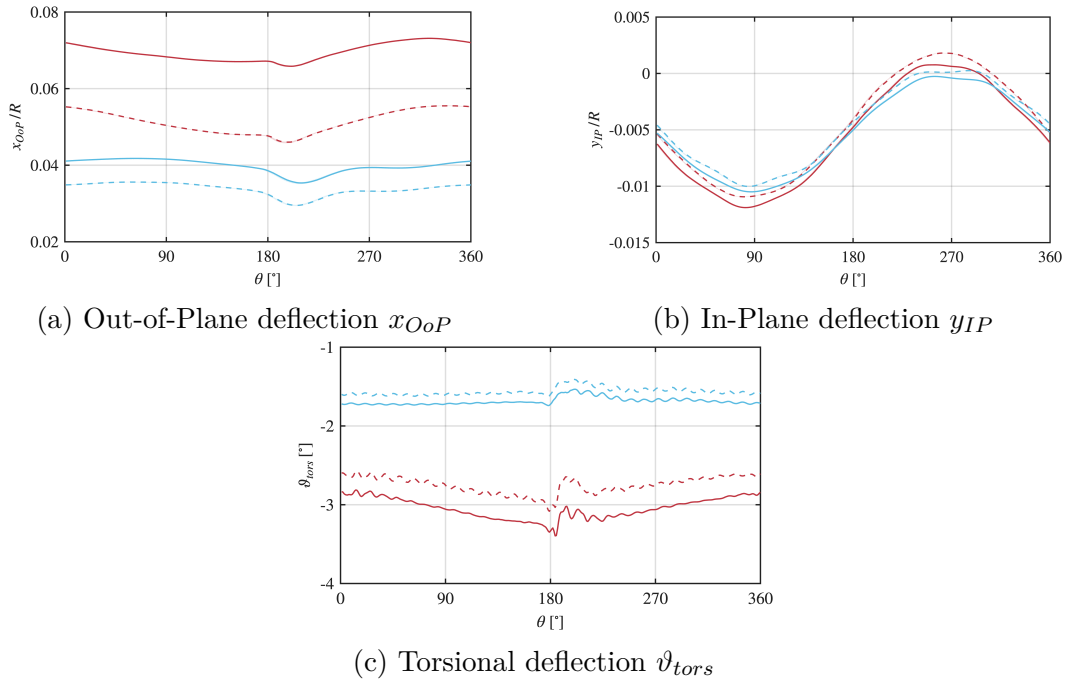


Figure 6.6: Phase-averaged deflections response along the blade. CFD-CSD/OV: IEA 15MW —, NREL 5MW —. CFD-CSD/T: IEA 15MW - - -, NREL 5MW - - -.

The phase-averaged in-plane deformation, on the other hand, follows a clear sinusoidal trajectory governed by the gravitational vector. The deflection remains predominantly negative throughout the revolution, reaching its maximum magnitude when the blade is horizontal and moving downwards ($\theta = 90^\circ$). It only approaches zero—or becomes slightly positive—when the blade is horizontal and moving upwards ($\theta = 270^\circ$), where gravity actively opposes the prevalent bending direction. Notably, the relative percentage difference between the OV and T solvers for the in-plane response is negligible across the entire 360° rotation.

Finally, Figure 6.7 illustrates the premultiplied Power Spectral Density (PSD) of the tip deflections, normalized by the respective rotational frequency of the rotor (f/f_{rot}). A fundamental observation is that the spectral energy distributions of the OV and T models are virtually identical across all deformation components. While the torsional coupling substantially alters the absolute mean amplitude of the deflections, it does not modify the underlying frequency content of the aeroelastic excitation.

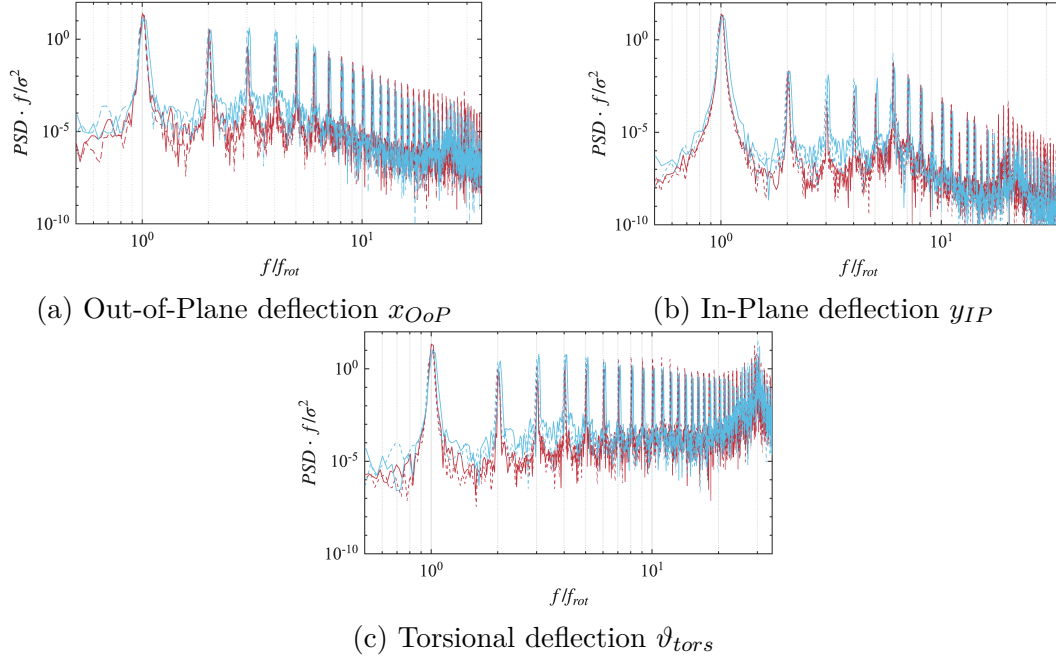


Figure 6.7: Power Spectral Density (PSD) of deflections response of the blade. CFD-CSD/OV: IEA 15MW —, NREL 5MW —. CFD-CSD/T: IEA 15MW - - -, NREL 5MW - - -.

Furthermore, despite the immense difference in physical dimensions and structural stiffness between the NREL 5MW and IEA 15MW machines, their normalized PSD shapes are remarkably similar. Both turbines exhibit dominant, closely aligned resonant peaks at integer multiples of the rotational frequency (1p, 2p, 3p, etc.). This confirms that the primary aeroelastic exci-

tation mechanisms—namely the tower shadow, wind shear, and broadband turbulence—scale linearly with the rotational speed, dictating a universal dynamic signature that remains consistent across vastly different utility-scale rotor sizes.

6.2.4 Blade Root Reactions and Fatigue Load Analysis

To comprehensively assess the structural integrity and the scaling effects on the turbines' lifespan, the dynamic reactions at the blade root were analysed alongside a rigorous fatigue assessment. Figure 6.8 illustrates the phase-averaged root reaction forces and moments over a full rotor revolution, while Table 6.1 summarises the Damage Equivalent Loads (DEL).

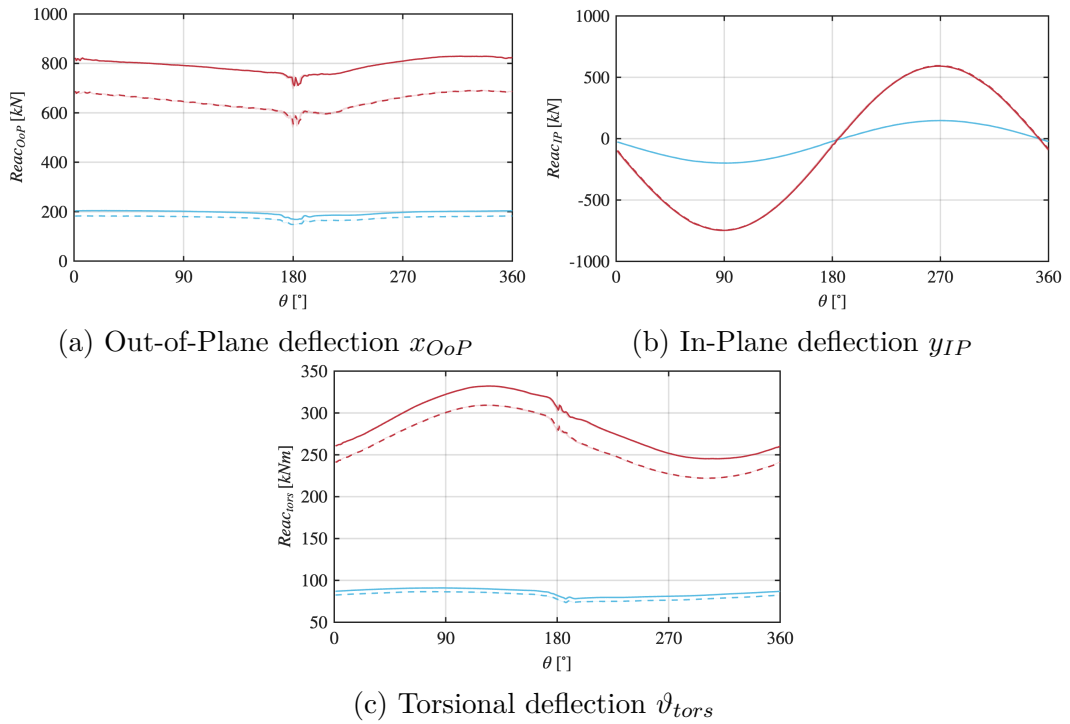


Figure 6.8: Phase-averaged root reaction forces and moments over a full rotor revolution. CFD-CSD/OV: IEA 15MW —, NREL 5MW —. CFD-CSD/T: IEA 15MW - - -, NREL 5MW - - -.

The phase-averaged Out-of-Plane reaction ($Reac_{OoP}$) directly mirrors the aerodynamic thrust distribution. For both machines, a distinct drop is recorded at $\theta = 180^\circ$ due to the tower shadow effect. The difference in scale is immediately apparent, with the 15MW turbine generating root forces almost four times larger than the 5MW model. More importantly, Figure 6.8a confirms the "load-shedding" mechanism introduced by the torsional coupling. By allowing the blade to actively twist under load, the fully coupled CFD-CSD/T solver predicts a substantial reduction in the mean out-of-plane root reaction for the

highly flexible 15MW rotor compared to the uncoupled CFD-CSD/OV model. A similar proportional reduction is observed in the torsional root moment ($Reac_{tors}$), as depicted in Figure 6.8c.

Conversely, the In-Plane reaction ($Reac_{IP}$) in Figure 6.8b is governed almost entirely by the gravitational mass of the blade, resulting in a pronounced, zero-mean sinusoidal behaviour. Because aerodynamic forces have a negligible impact on this plane compared to the extreme weight of the structure, the curves for the OV and T coupling strategies strongly overlap, unaffected by the aeroelastic twist.

While the phase-averaged results confirm that torsional coupling successfully mitigates the *mean* extreme loads, a thorough fatigue analysis is required to evaluate the impact of cyclic fluctuations. DELs were computed applying the Rainflow-counting algorithm to the time-histories of the root reactions. According to standard practices for fibreglass composite blades, the Palmgren-Miner linear damage accumulation rule was applied utilising a Wöhler material exponent of $m = 10$. The equivalent load is formulated as:

$$DEL = \left(\frac{\sum_i n_i S_i^m}{N_{eq}} \right)^{\frac{1}{m}} \quad (6.2)$$

where S_i is the amplitude of the i -th load cycle, n_i is the number of cycles counted at that amplitude, both extracted via the Rainflow-counting algorithm, and N_{eq} is the total equivalent number of cycles.

The DEL results reported in Table 6.1 reveal a critical aeroelastic phenomenon. The highest fatigue loads are systematically recorded in the in-plane direction (DEL_{IP}), reaching an enormous 1,225 kN for the 15MW turbine (CFD-CSD/T model). This phenomenon can be attributed to the blade's exposure to extreme gravitational cycles of considerable amplitude, which dominate the fatigue spectrum, thereby surpassing the impact of aerodynamic out-of-plane fluctuations.

However, comparing the OV and T structural models reveals a critical counter-trend. Despite the fact that the torsional coupling actively *reduces* the mean out-of-plane and torsional loads, it systematically *increases* the DEL across all components. This increase is particularly pronounced for the damage equivalent load in the out-of-plane direction (DEL_{OoP}) of the 15MW turbine, which surges from 79.6 kN (OV) to 95.3 kN (T). Similarly, a noticeable increment is observed in the torsional fatigue (DEL_{tors}), which rises from 65.7 kNm (OV) to 67.1 kNm (T) for the 15MW model. Although its absolute magnitude is smaller than the bending moments, it confirms that enabling the torsional degree of freedom amplifies load fluctuations within the torsional channel itself.

While seemingly counterintuitive, this increase in fatigue is physically consistent with the dynamics of highly flexible rotors. The incorporation of the torsional degree of freedom renders the blade more dynamically responsive to

the continuous, rapid variations induced by the sheared turbulent inflow and the tower wake. This enhanced aeroelastic responsiveness introduces larger, high-frequency load fluctuations. It is evident that, since the Wöhler exponent for composites is exceptionally high ($m = 10$), the calculation exhibits exponential sensitivity to the amplitude of these alternating cycles. Consequently, even minor increases in the amplitude of dynamic load variations have been observed to have a substantial detrimental effect on the fatigue life, thereby completely offsetting any benefits that may be obtained from a reduced static mean load.

This analysis confirms that neglecting the torsional coupling in mega-watt scale turbines results in the inaccurate representation of mean deflections and severely underestimates the accumulated fatigue damage to the structure during operation.

Table 6.1: Damage Equivalent Loads (DEL) calculated for the blade root reactions, utilising a Wöhler exponent of $m = 10$.

	NREL 5MW		IEA 15MW	
	CFD-CSD/OV	CFD-CSD/T	CFD-CSD/OV	CFD-CSD/T
DEL_{OoP}	22.6 kN	23.1 kN	79.6 kN	95.3 kN
DEL_{IP}	298.2 kN	298.5 kN	1,214 kN	1,225 kN
DEL_{tors}	8.8 kNm	8.9 kNm	65.7 kNm	67.1 kNm

6.3 Conclusions

This chapter investigated the scaling effects on the aeroelastic response of wind turbines by directly comparing the NREL 5MW and the IEA 15MW reference models. Utilising the UTD-WF solver, which couples LES with a CSD module, the study isolated the impact of structural flexibility and rotor scale under identical sheared inflow conditions. Furthermore, the role of structural coupling was systematically evaluated by comparing a model driven solely by deformation velocity (CFD-CSD/OV) against a fully coupled formulation encompassing torsional feedback (CFD-CSD/T).

The results show that aerodynamic scaling between utility-scale and ultra-large offshore turbines is not linear. The localised performance drop and load fluctuations induced by the tower shadow were found to be proportionally less severe for the 15MW turbine ($\approx 4.5\%$ drop) compared to the 5MW turbine ($\approx 7.4\%$ drop). This behaviour is attributed to the thinner relative geometry of the 15MW tower and the vast velocity gradient characterising the sheared

inflow over the 240 m rotor disk, which naturally reduces the aerodynamic contribution of the lower rotor half.

Crucially, the results confirm the importance of incorporating the torsional degree of freedom when modelling next-generation flexible blades. For both machines, neglecting torsional feedback led to an overprediction of the local angle of attack, artificially inflating the aerodynamic loads, the overall power coefficient, and the maximum out-of-plane deflections. This discrepancy is considerably larger for the highly flexible 15MW blade. The fully coupled CFD-CSD/T model proved that the torsional twist acts as an intrinsic aeroelastic damper, shedding loads through a pitch-to-stall mechanism and effectively mitigating extreme static deflections.

However, a comprehensive fatigue analysis revealed a critical aeroelastic trade-off associated with this torsional flexibility. While the structural coupling successfully reduced the *mean* aerodynamic loads, it systematically *increased* the DEL across the structure. Incorporating the torsional degree of freedom renders the slender blades more dynamically responsive to the continuous, rapid variations induced by the sheared inflow and the tower wake. These enhanced high-frequency fluctuations, heavily penalised by the high Wöhler exponent characteristic of composite materials ($m = 10$), sharply accelerate fatigue accumulation, completely offsetting the benefits of a reduced mean load. In parallel, the in-plane fatigue remained largely uninfluenced by the aeroelastic formulation, being entirely dominated by the immense one-period gravitational cycles of the large-scale rotors.

Spectral analysis of the deformations further corroborated these findings. Despite the vast differences in physical dimensions and mass, the normalized PSD of the two turbines exhibited remarkably similar shapes, with dominant, perfectly aligned resonant peaks at integer multiples of the rotational frequency. This confirms that the primary aeroelastic excitation mechanisms, such as tower shadow and wind shear, scale linearly with the rotational speed, dictating a universal dynamic signature across vastly different utility-scale sizes.

In conclusion, the CFD-CSD framework captures the broadband flow-structure interactions and unsteady dynamics that scale with rotor size and cannot be resolved by lower-fidelity approaches. The findings establish that as turbines grow in capacity, lower-fidelity structural assumptions—particularly those neglecting torsional twist and under-resolving fatigue fluctuations—become increasingly inadequate. The inflow conditions adopted here are deliberately simplified (laminar power-law shear) to isolate the aeroelastic scaling effects; the coupled response of the IEA 15MW rotor under fully turbulent, Coriolis-driven atmospheric inflow is examined in Chapter 7 for the two-turbine array configuration.

Chapter 7

Turbine Array Aeroelasticity

This chapter investigates the aeroelastic response of a two-turbine in-line array of IEA 15MW reference turbines [11] under Coriolis-driven inflow, examining the combined effects of upstream yaw misalignment and atmospheric wind veer on farm performance, wake morphology, and blade fatigue loading. The CFD-CSD framework employed here has been systematically verified against the OpenFAST reference solvers (ElastoDyn and BeamDyn) in Chapter 4; those benchmarks are not repeated in the present study.

The contribution of this chapter is the first LES-based aeroelastic characterisation of yaw-based wake steering in a two-turbine IEA 15MW array under Coriolis-driven atmospheric inflow, establishing the directional asymmetry of wake deflection and its simultaneous impact on farm power output and downstream blade fatigue loading (Contribution 3).

7.1 Simulations setup

7.1.1 Precursor simulations

To ensure realistic inflow conditions for the wind turbine simulations, a precursor LES was first performed. This simulation generates a turbulent, neutrally-stratified ABL, characterised by the development of an Ekman spiral [59], induced by the Coriolis force. The Coriolis frequency was set to $f_c = 1.2 \times 10^{-4}$ Hz, representative of the conditions typically observed in the North Sea. The geostrophic velocity was prescribed as $G = 10$ m/s. The corresponding Rossby number is approximately equal to 350. To eliminate yaw misalignment between the mean velocity vector at hub height and the geostrophic wind direction, a Proportional-Integral (PI) controller, as proposed by Sescu et al. [116], was employed, consistent with the methodology detailed in Section 2.6.

The computational domain has dimensions $6 \times 11 \times 3$ diameter units in the streamwise (x), vertical (y), and spanwise directions (z), respectively, and is discretised by a Cartesian grid composed of $1025 \times 513 \times 513$ points.

Periodic boundary conditions are imposed in both the streamwise and spanwise directions, whereas a no-slip condition is applied at the bottom wall and a free-slip condition at the top boundary. Given the periodic spanwise boundary and a domain width of $3D$, the configuration is equivalent to an infinite array of side-by-side turbines with spacing equal to the box width. Bernardoni et al. [194] investigated turbine interactions in clustered arrangements and found that turbines spaced $3D$ apart exhibited negligible mutual interference, thus justifying the present configuration.

Uniform grid spacing is applied in the x and z directions, while a stretching is imposed in the vertical direction to enhance resolution near the rotor region. A turbulence intensity (TI) of 6.3% is obtained at hub height. The integral length scale L_u^z is computed based on the spanwise correlation of the streamwise velocity component. The resulting value at hub height, $L_{u,\text{hub}}^z = 45.6 \text{ m}$ ($0.19D$), is consistent with values reported in the literature for neutral atmospheric conditions [195]. Figure 7.1 shows the time- and horizontally-averaged velocity components in the streamwise and spanwise directions, as well as the wind direction angle, defined as $\bar{\theta} = \tan^{-1}(\bar{w}/\bar{u})$. All velocity components are non-dimensionalized using the freestream velocity U_∞ , set equal to the geostrophic velocity. Owing to the action of the PI controller, the wind direction aligns with the x -axis at hub height, eliminating yaw misalignment.

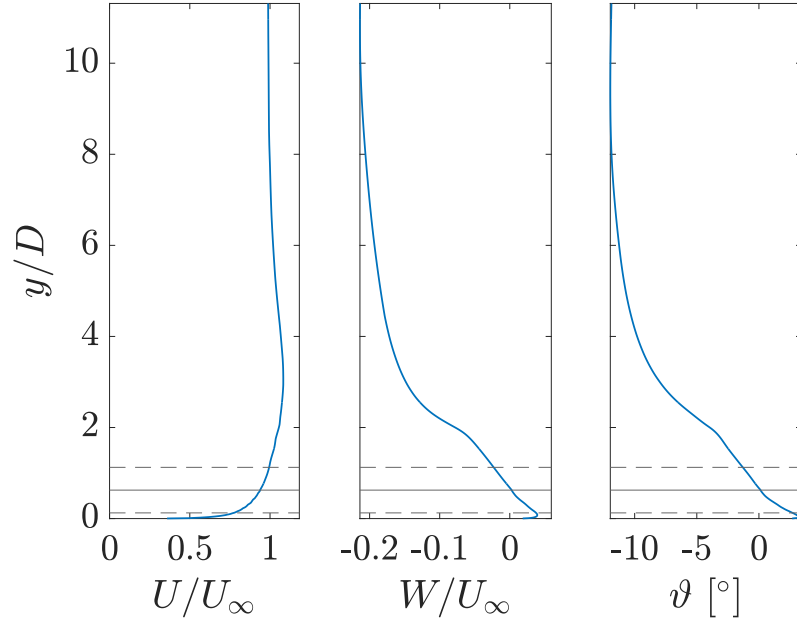


Figure 7.1: Time- and horizontally-averaged streamwise (left) and spanwise (center) velocity components, and wind direction angle θ (right). The solid horizontal line denotes hub height; dashed lines represent blade tips.

7.1.2 Array wind turbines

A series of simulations was performed on a two-turbine in-line array consisting of IEA 15MW reference wind turbines [11]. The main characteristics of the turbine are reported in Table 7.1.

Table 7.1: Key specifications of the IEA 15MW reference wind turbine.

Parameter	Value
Power rating	15 MW
Blades number	3
Rotor diameter – D	240 m
Blade length – L	117 m
Hub radius – R_{hub}	3.97 m
Hub height	150 m
Design Tip-Speed Ratio – TSR	9
Rated wind speed – U_{ref}	10.59 m/s
Rated rotor speed – Ω	7.56 RPM

The computational domain measures $12 \times 11 \times 3$ diameter units and is discretised with a Cartesian grid of $2049 \times 513 \times 513$ points, maintaining the same grid refinement strategy as in the precursor simulation. This resolution has been validated in prior studies, notably by De Cillis et al. [79], and shown to provide satisfactory agreement with experimental observations. The inflow boundary condition is provided by the velocity field extracted from the precursor ABL simulation. All other boundary conditions remain consistent with those previously described.

The upstream turbine (UT) is positioned $3D$ downstream from the inflow boundary, while the downstream turbine (DT) is placed $5D$ behind the upstream one. Both turbines are centered in the spanwise direction. The actuator line is discretised using 86 points per blade, dictated by the local grid spacing. The Reynolds number, based on D and U_∞ , is on the order of $\mathcal{O}(10^8)$.

The fluid-structure interaction model for the IEA 15MW turbine has been verified by Bernardi et al. [171] (see Section 4.3 for a detailed account of the structural and CFD verification). The structural model employs $M_s = 15$ modes and a discretisation of $N = 80$ equally spaced nodes per blade.

In each case, the upstream turbine was subjected to a specific yaw misalignment, with different yaw angles applied depending on the scenario under investigation. The aeroelastic response of the turbines is analysed for each configuration. Yaw angles for the upstream turbine range from -30° to $+30^\circ$.

Figure 7.2 shows the visual definition of the yaw angle convention. The inclusion of negative yaw angles is strictly necessary to capture the asymmetric wake behavior introduced by the Coriolis force and the consequent atmospheric veer.

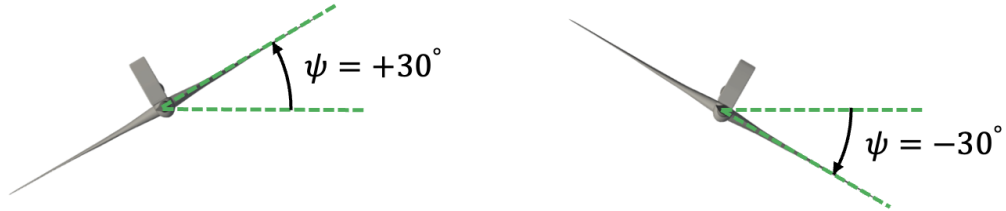


Figure 7.2: Sketch of the yaw misalignment convention.

Simulations are run for 480 s after the initial transient period, corresponding to approximately 60 rotor revolutions.

7.2 Results

This section presents the results of the aeroelastic simulations conducted on the two-turbine in-line array, focusing on three key aspects: flow dynamics, turbine performance, and structural response. The influence of upstream turbine yaw misalignment is examined for yaw angles ranging from -30° to $+30^\circ$ under Coriolis-driven flow conditions. Unless otherwise specified, results are reported for both turbines and compared against the baseline (aligned) configuration, thereby highlighting the coupled effects of wake steering and atmospheric veer.

7.2.1 Flow analysis

To optimise power at the farm level, active wake steering via yaw misalignment is frequently employed. Following the convention established in Figure 7.2, yaw misalignment (ψ) introduces a lateral thrust component that deflects the momentum deficit away from downstream machines. However, the efficacy and nature of this deflection are highly dependent on the incoming ABL regime.

The time-averaged wake velocity contours (Figure 7.3) reveal the complex morphology of the wake in the simulated Coriolis-driven environment. The interaction between the turbine's induced rotation, the yaw misalignment, and the background atmospheric wind veer generates highly complex, three-dimensional flow structures. The wake cross-sections distort into characteristic elliptical shapes, with the velocity deficit curling as it advects downstream. Because the ambient wind veer continuously pushes the upper and lower halves of the wake in opposite lateral directions, intentional yaw misalignment either constructively amplifies or destructively counteracts this natural atmospheric

deflection. As a result, wake steering in a Coriolis-driven environment becomes an asymmetric physical process by nature.

Consequently, the downstream rotor is typically subjected to an asymmetric and highly sheared wake, resulting in severe flow variations as the blades rotate. In scenarios involving larger arrays or varying inter-turbine spacing, the wake interactions would be further modified by Earth's rotation, which continuously forces the flow to deform and shift laterally as it propagates. It is also noteworthy that, as the absolute yaw angle increases, the wake not only deflects but also exhibits enhanced recovery by the time it reaches the downstream rotor. This accelerated mixing allows the downstream turbine to recover a greater amount of power than what is initially sacrificed by the upstream turbine due to its misalignment.

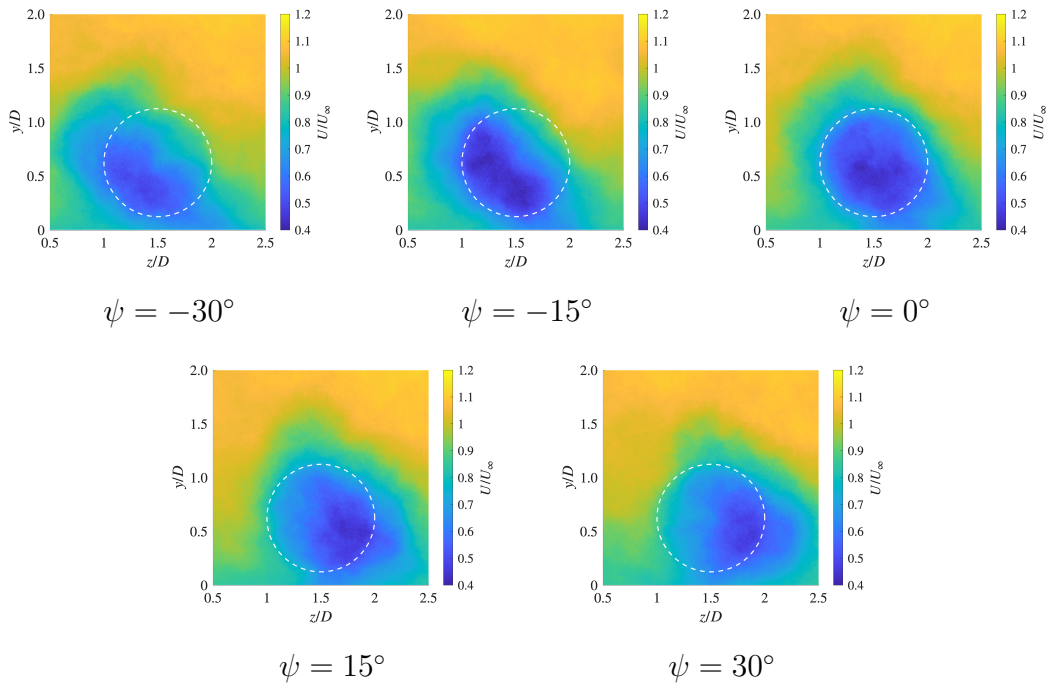


Figure 7.3: Time-averaged velocity on the z-y plane 0.1D upstream of the second rotor.

As illustrated in Figure 7.4, velocity slices at $x = 12D$ (equivalent to $4D$ downstream of the DT) exhibit a skewness characteristic of wakes developing within a Coriolis-affected ABL. In the case of positive yaw misalignment, the wake deficit is concentrated on the right side of the domain. Interestingly, the wake primarily thickens on this side without adopting a fully elliptical shape. Conversely, under negative yaw angles, the wake displays a much greater propensity for three-dimensional deformation, curling into a pronounced elliptical structure.

Analysing the effective area intercepted by the downstream rotor (delineated

by the white dashed circle) reveals that employing a $+30^\circ$ yaw angle could yield a more uniform inflow for a hypothetical third turbine in the array. However, this configuration results in lower velocities on the right side of the DT rotor. In contrast, at a -30° yaw angle, a low-velocity flow region interacts with a much larger portion of the lower-left DT rotor plane, imposing distinct aerodynamic consequences.

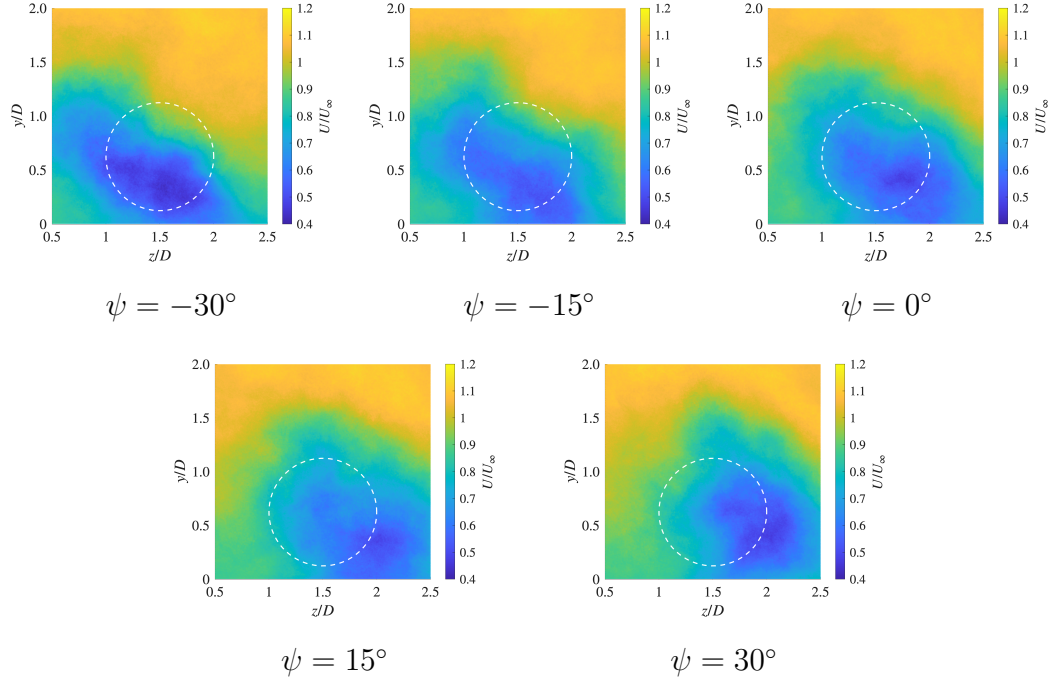


Figure 7.4: Time-averaged velocity on z - y plane 4D downstream the second rotor. White dotted circle represents the downstream wind turbine rotor.

7.2.2 Performance

The aerodynamic asymmetries observed in the wake directly dictate the energy harvesting performance of the wind farm. Figure 7.5 presents the time-averaged power output (P_d) as a function of the upstream turbine's yaw angle. For the upstream turbine (UT), the power penalty follows a roughly symmetric cosine-law decay (red curve), whereas the downstream turbine (DT) exhibits a radically asymmetric power recovery profile (blue curve). Because atmospheric wind veer deflects the wake in a preferential direction, yawing the UT toward positive angles proves substantially more effective at steering the velocity deficit away from the downstream rotor. The combined farm power confirms that optimisation algorithms trained on pressure-driven models will predict sub-optimal yaw setpoints in Coriolis-affected environments.

Yaw-based control successfully enhances array performance, though the benefit is direction-dependent at $\psi = +30^\circ$ total power increases by roughly

15%, against approximately 10% at $\psi = -30^\circ$. Ciri et al. [191] previously noted that energy output is asymmetric with respect to yaw angle due to crossflow and blade velocity variations. Here, Coriolis-driven wind veer governs wake morphology, forcing an elliptical shape and dictating the asymmetric power recovery of the downstream turbine, with a clear preference for the positive yaw direction.

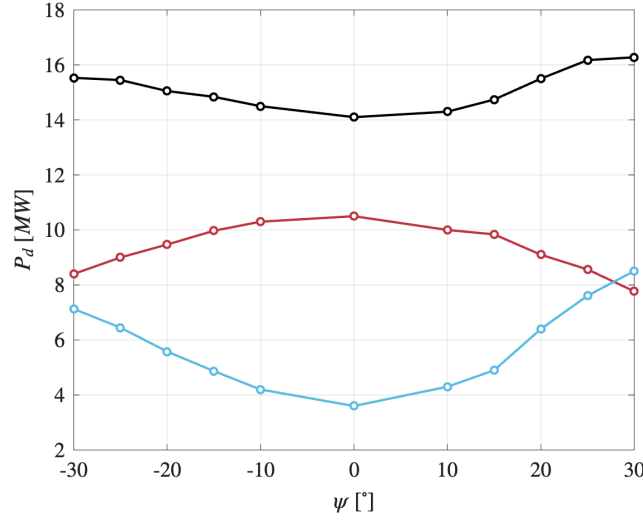


Figure 7.5: Time-averaged power output as a function of the upstream turbine yaw angle (UT —, DT —, UT+DT —).

7.2.3 Structural response

While active wake steering maximises farm-level aerodynamic efficiency, it simultaneously alters the structural demands on the turbine blades. The FSI framework allows a detailed assessment of the aeroelastic response under varying conditions, as illustrated by the time-averaged (Figures 7.6–7.8) and phase-averaged (Figures 7.9–7.14) structural data.

The mean out-of-plane (x_{OoP}), in-plane (y_{IP}), and torsional (ϑ_{tors}) deformations are strictly coupled with the aerodynamic state. Yaw misalignment reduces the mean aerodynamic thrust on the UT, directly reflected in reduced x_{OoP} deflections at higher yaw angles, as the upstream turbine operates within a directionally sheared inflow that distributes loads asymmetrically across the rotor disk.

As yaw misalignment increases, the UT and DT out-of-plane deformations converge (Figure 7.6), with similar trends for the in-plane (Figure 7.7) and torsional (Figure 7.8) components. Time-averaged data alone can be misleading, as it obscures the unsteady phenomena across the rotor plane; a phase-averaged analysis is therefore required to fully characterise the fluid-structure interaction.

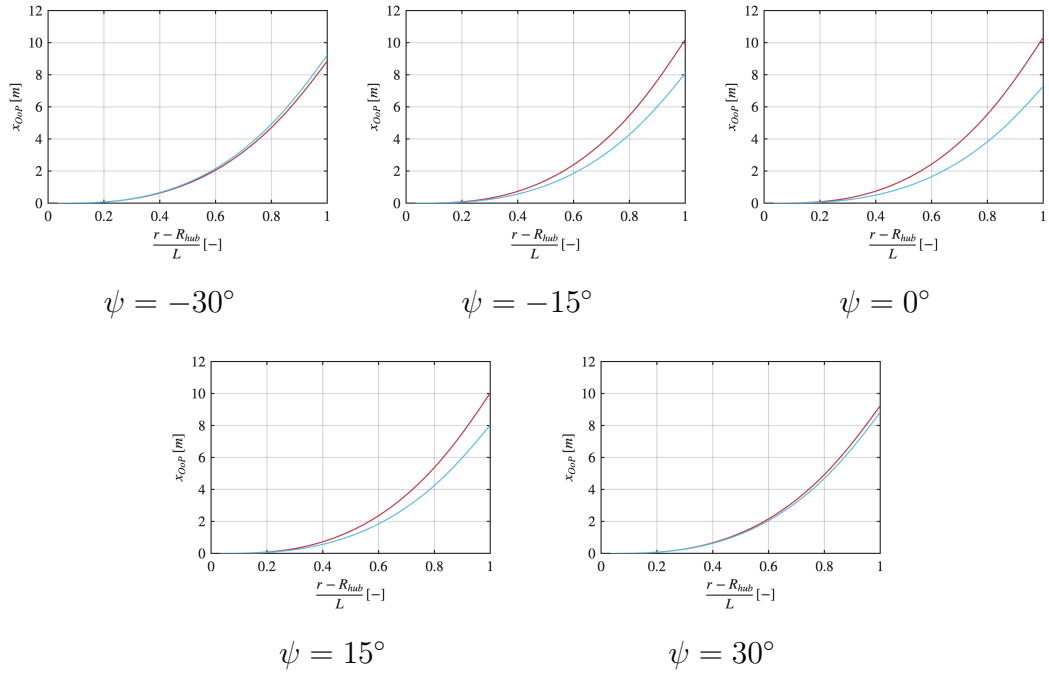


Figure 7.6: Time-averaged out-of-plane deformation (x_{OoP}) along the blade span (UT —, DT —).

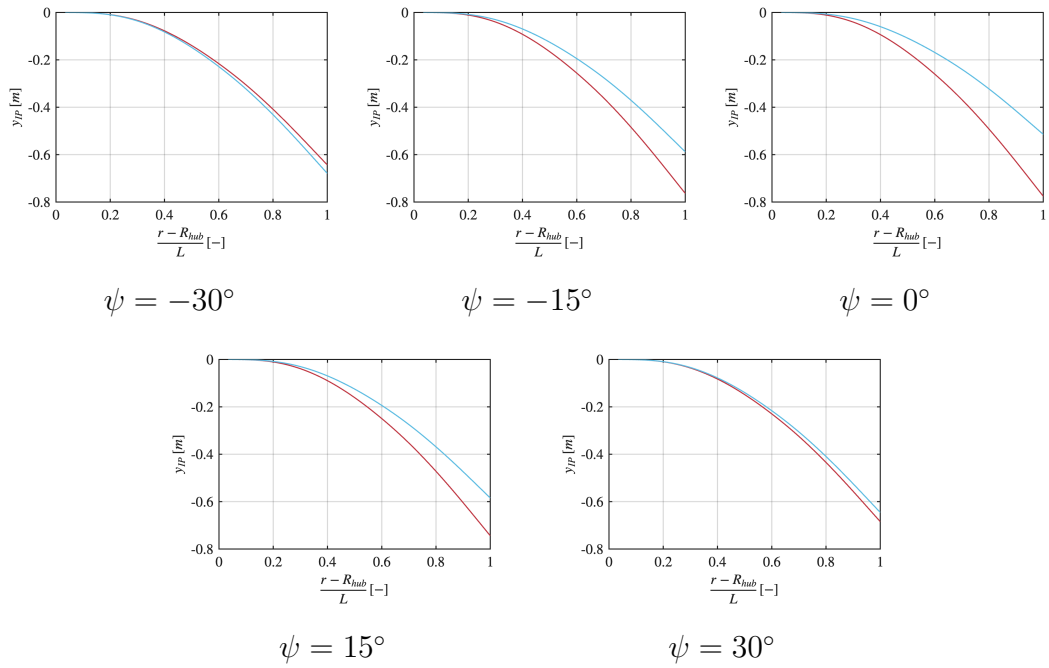


Figure 7.7: Time-averaged in-plane deformation (y_{IP}) along the blade span (UT —, DT —).

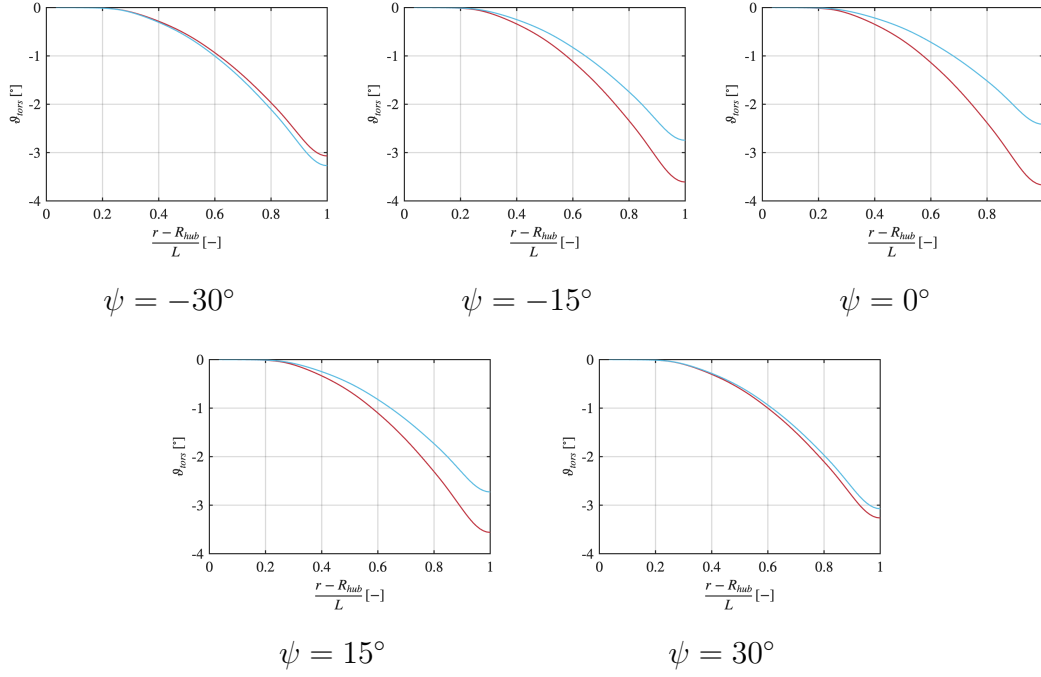


Figure 7.8: Time-averaged torsional deformation (ϑ_{tors}) along the blade span (UT —, DT —).

Figure 7.9 displays the phase-averaged out-of-plane blade deformations. In the aligned configuration ($\psi = 0^\circ$), the UT exhibits a distinct deformation drop as the blade passes through the lower rotor region (180° azimuth), attributed to the reduced wind speed near the ground due to atmospheric shear and the aerodynamic interference of the tower shadow. The DT, impinged by the asymmetrical UT wake (Figure 7.3, $\psi = 0^\circ$), shows a markedly different phase-averaged response, reflecting the complex wake structure generated by the upstream machine.

Upon introducing yaw misalignment, the overall deformation of the UT decreases, while the DT deformations increase, driven by the varying wake dynamics. For the UT, the cyclic trend is preserved, though the fluctuation amplitude is reduced at negative yaw angles due to the altered angle of attack distribution relative to positive misalignments. The DT response, however, is heavily influenced by the Ekman effect and wake steering. For positive yaw angles, deformations are naturally higher on the left side of the DT rotor, corresponding to the region exposed to the higher-velocity freestream flow. For negative yaw angles, the highly curled, elliptical wake impinges on the lower and left portions of the DT rotor with low velocity, causing markedly higher deformations on the right side of the rotor, followed by a pronounced drop as the blade rotates into the wake deficit.

In-plane deformations (y_{IP}) exhibit a distinct sinusoidal trend for both UT and DT blades (Figure 7.10). This response is predominantly driven by

gravitational forces and structural mass distribution rather than aerodynamic loads, and the differences induced by wake steering are therefore minimal, confirming that yaw misalignment does not significantly alter the in-plane structural behaviour of either rotor.

The torsional response (ϑ_{tors} , Figure 7.11) is more complex. Generally, the UT exhibits higher absolute torsional deformations than the DT, though this gap narrows progressively as yaw misalignment increases. The altered inflow caused by yawing modifies how the flow interacts with the blade leading edge: for positive yaw angles, ϑ_{tors} increases near the tower passage, whereas the opposite trend is observed for negative angles. For positive yaw angles, deformations are higher on the left side of the DT rotor, corresponding to the region exposed to the undisturbed freestream flow. Conversely, for negative yaw angles, the highly curled, elliptical wake impinges on the lower and left portions of the DT rotor, locally reducing the aerodynamic loading in that region. As a result, the right side of the rotor — still exposed to the higher-velocity freestream — experiences comparatively larger torsional deformations. The blade therefore undergoes a pronounced load drop as it rotates from the high-velocity right side into the low-velocity wake region on the left, amplifying the amplitude of the cyclic torsional fluctuation and, in turn, accelerating fatigue accumulation over the turbine lifetime.

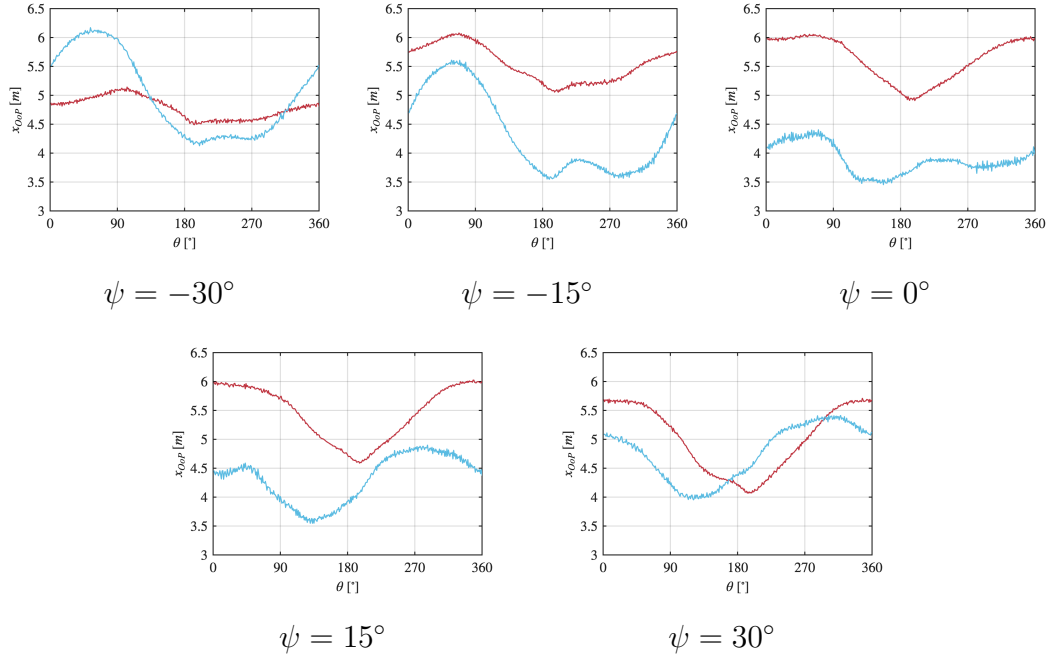


Figure 7.9: Phase-averaged out-of-plane deformation (x_{OoP}) at 80% of the blade span (UT —, DT —).

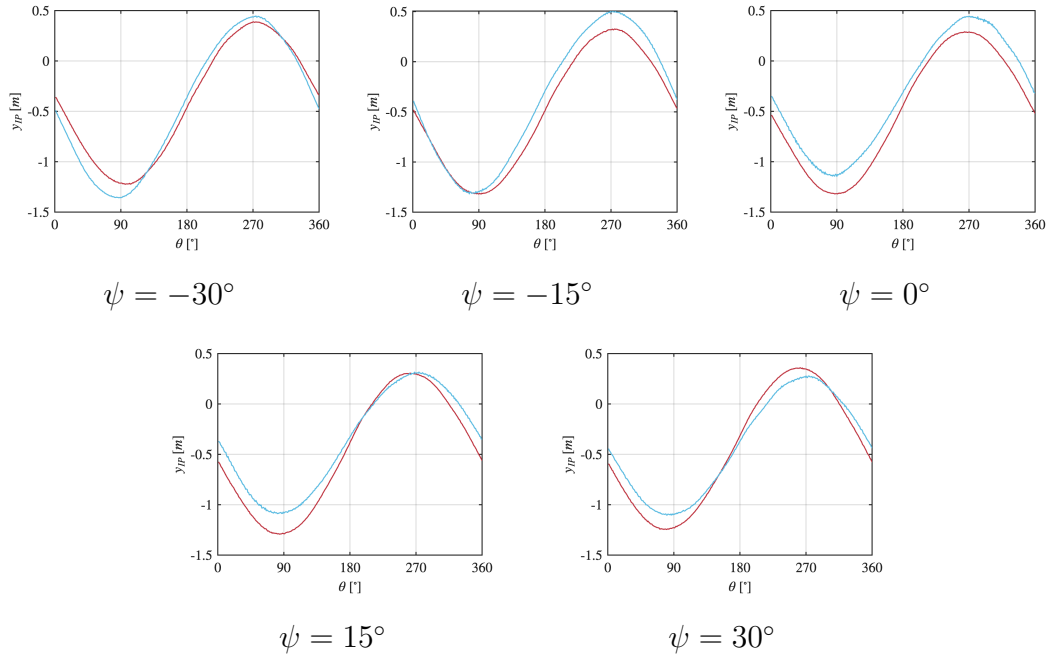


Figure 7.10: Phase-averaged in-plane deformation (y_{IP}) at 80% of the blade span (UT —, DT —).

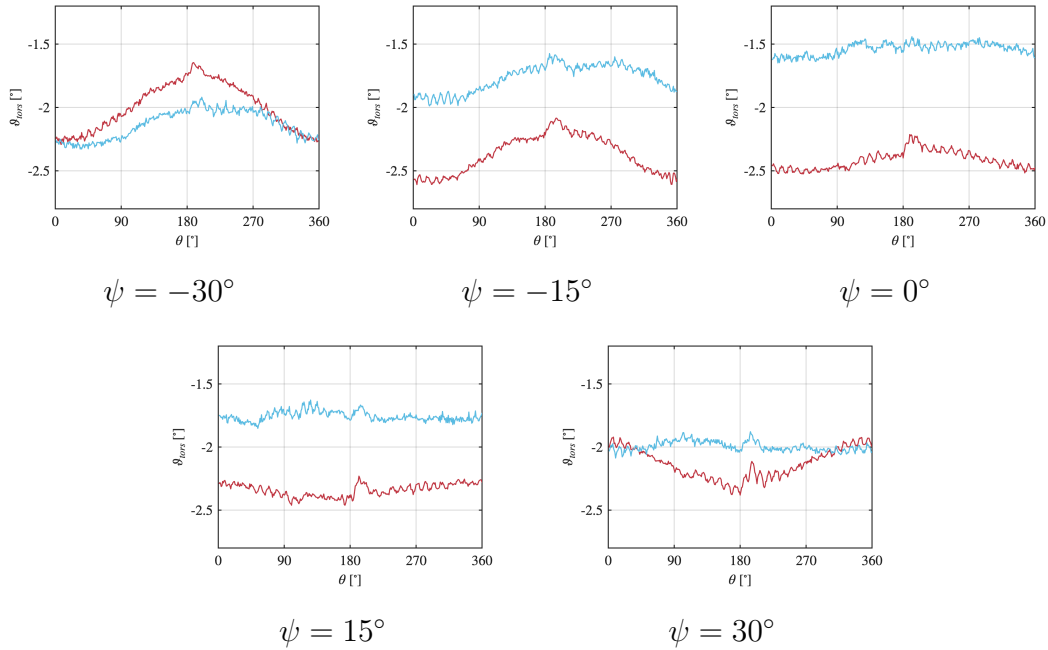


Figure 7.11: Phase-averaged torsional deformation (ϑ_{tors}) at 80% of the blade span (UT —, DT —).

Fatigue and Damage Equivalent Loads (DEL)

Finally, the blade root reactions must be analysed to evaluate the impact of wake steering on the structural lifetime of the blades. Figures 7.12 and 7.14

confirm that out-of-plane and torsional reactions closely follow the trends of their respective deformations, being strongly governed by aerodynamic forces, and reflecting the same directional asymmetries observed in the phase-averaged deformation fields. In-plane reactions ($Reac_{IP}$, Figure 7.13), meanwhile, are almost entirely dominated by blade mass and gravity, and remain largely insensitive to the yaw misalignment angle.

To rigorously quantify the fatigue impact of this cyclic loading, Damage Equivalent Loads (DEL) were computed using a Rainflow-counting algorithm with a Wöhler exponent $m = 10$, standard for composite wind turbine blades. Table 7.2 summarises the DEL for the out-of-plane (DEL_{OoP}), in-plane (DEL_{IP}), and torsional (DEL_{tors}) root reactions.

The in-plane fatigue is predominantly governed by gravity and structural inertia, resulting in relatively constant DEL_{IP} values (around 1050–1100 kN) across all configurations, with negligible sensitivity to yaw angle. The aerodynamic influence is instead highly evident in the DEL_{OoP} and DEL_{tors} results, where the wake morphology plays a decisive role. For the downstream turbine, negative yaw angles ($\psi = -15^\circ$ and $\psi = -30^\circ$) produce the most severe fatigue loading, with DEL_{OoP} exceeding 200 kN. This occurs because the highly distorted, elliptical wake generated by the Coriolis effect directly impinges on the downstream rotor under negative yaw misalignment, creating steep velocity gradients that the blades must repeatedly traverse during each revolution, significantly amplifying the cyclic load amplitude.

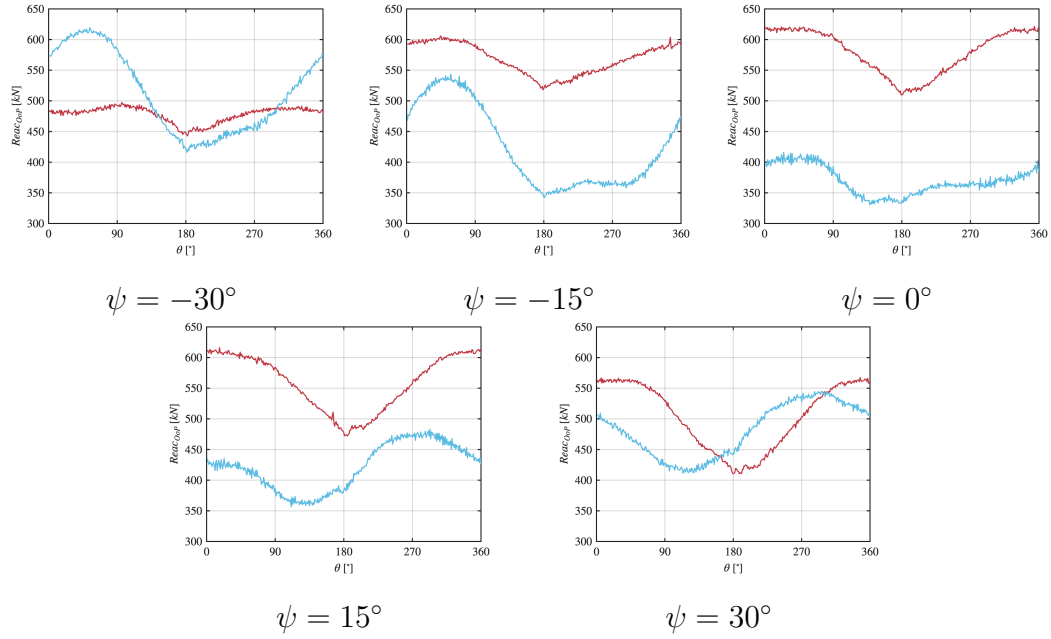


Figure 7.12: Phase-averaged out-of-plane reaction ($Reac_{OoP}$) at 80% of the blade span (UT —, DT —).

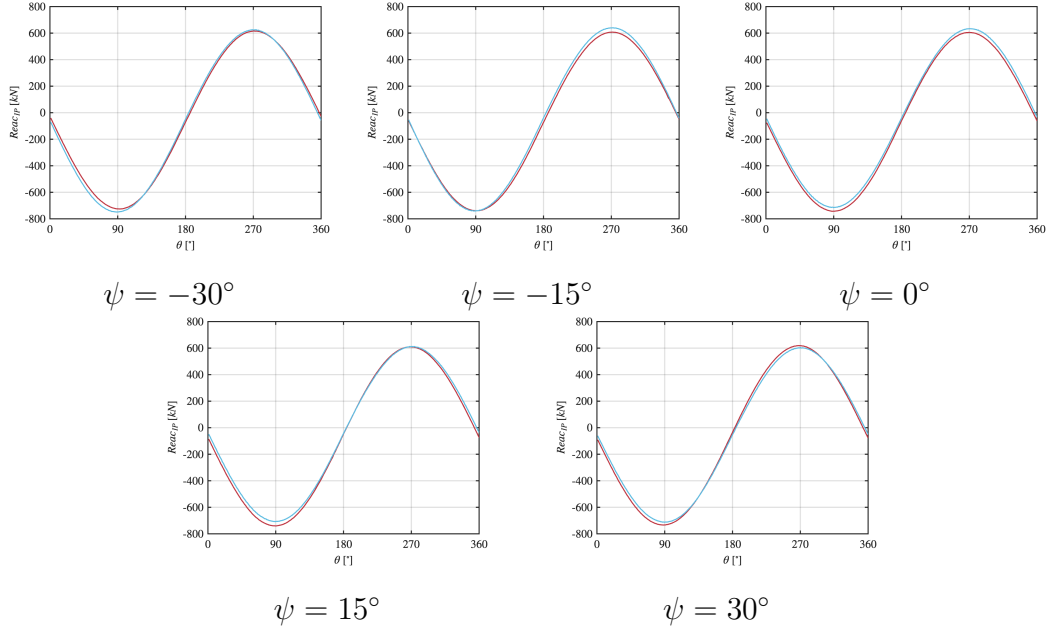


Figure 7.13: Phase-averaged in-plane reaction ($Reac_{IP}$) at 80% of the blade span (UT —, DT —).

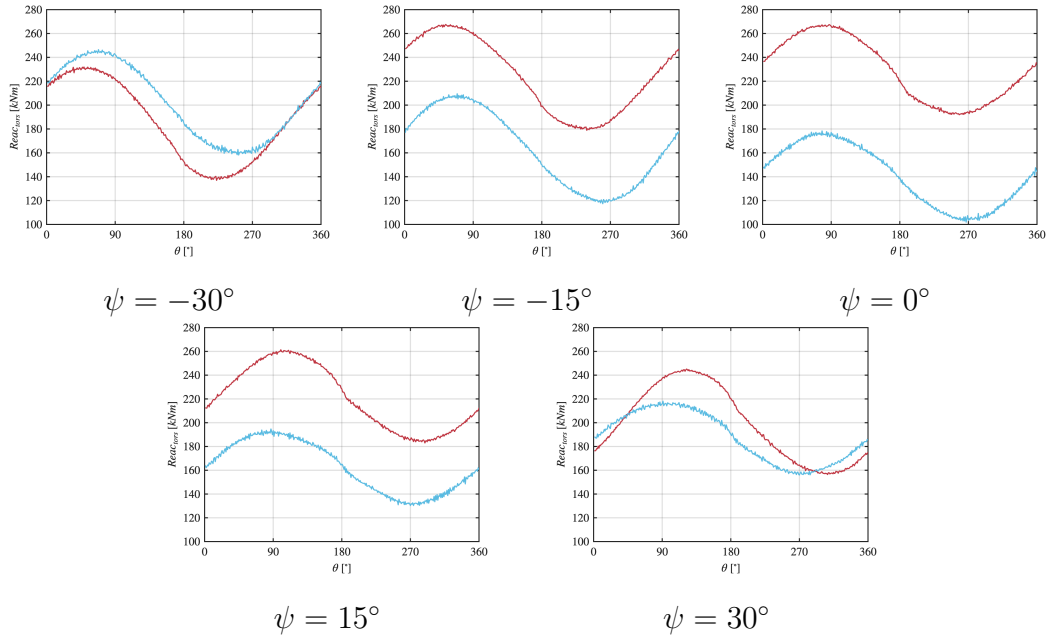


Figure 7.14: Phase-averaged torsional reaction ($Reac_{tors}$) at 80% of the blade span (UT —, DT —).

Crucially, these structural findings are consistent with the aerodynamic performance results. Negative yaw directions, which yield inferior farm-level power recovery, simultaneously impose the greatest structural penalty on the downstream turbine. Conversely, the positive yaw configuration ($\psi = +30^\circ$) emerges as a synergistic operational strategy: it maximises array power capture through effective wake steering while avoiding the severe fatigue amplification associated with the Coriolis-distorted wake structures observed at negative angles.

Table 7.2: Damage Equivalent Loads (DEL) at the blade root for out-of-plane, in-plane, and torsional reactions. Rainflow-counting algorithm, Wöhler exponent $m = 10$.

	DEL_{OoP} [kN]		DEL_{IP} [kN]		DEL_{tors} [kN · m]	
	<i>UT</i>	<i>DT</i>	<i>UT</i>	<i>DT</i>	<i>UT</i>	<i>DT</i>
$\psi = -30^\circ$	103.9	200.4	1099.6	1089.5	79.1	86.3
$\psi = -15^\circ$	116.8	204.2	1092.8	1083.4	69.7	77.8
$\psi = 0^\circ$	149.6	185.9	1095.8	1065.6	71.2	77.1
$\psi = 15^\circ$	153.1	175.6	1093.8	1055.4	70.3	66.9
$\psi = 30^\circ$	147.8	177.3	1110.8	1056.4	71.7	62.0

7.3 Conclusions

This chapter presented an LES-based aeroelastic investigation of a two-turbine array composed of 15MW reference wind turbines, operating within a fully developed, Coriolis-driven Atmospheric Boundary Layer. By coupling Large Eddy Simulation with a structural multi-body solver, the study successfully captured the intricate dynamics of active wake steering and its direct consequences on farm performance and structural fatigue.

The inclusion of the Coriolis force proved fundamental in determining wake morphology. The resulting atmospheric wind veer continuously interacts with the rotor-induced rotation, breaking the lateral symmetry of wake deflection. Consequently, active wake steering via yaw misalignment was shown to be an asymmetric process by construction. Negative yaw angles resulted in a highly curled, elliptical wake that impinged heavily on the downstream rotor, whereas positive yaw angles led to a more effective deflection of the velocity deficit.

This aerodynamic asymmetry directly translated into array power performance. Wake steering employing positive yaw angles allowed the downstream turbine to recover significantly more power, leading to a peak total array

power increase of approximately 15% at $\psi = +30^\circ$, compared to only a 10% enhancement at $\psi = -30^\circ$. These results suggest that wind farm control strategies optimised on simplified, non-rotating atmospheric models will yield suboptimal or erroneous setpoints under realistic Coriolis-affected conditions.

Most importantly, the fluid-structure interaction analysis revealed a clear directional preference for wake steering. Unlike traditional wake steering scenarios that often present a strict trade-off between aerodynamic power gains and downstream structural fatigue, the Coriolis-driven environment establishes a preferred steering direction. While negative yaw misalignments trapped the downstream turbine in highly sheared velocity gradients that drastically amplified out-of-plane and torsional cyclic loads (with DEL_{OoP} exceeding 200 kN), the positive yaw configurations successfully maximised energy yield while simultaneously circumventing the most severe fatigue penalties. Therefore, the implementation of next-generation wind farm control strategies should account for these ABL physics to exploit the directional asymmetry of wake steering, improving both power production and structural lifetime.

Chapter 8

Diffuser-Augmented Wind Turbines

This chapter presents a comprehensive aerodynamic analysis of flow augmentation techniques, moving beyond conventional open rotors to investigate Diffuser-Augmented Wind Turbines (DAWTs). Specifically, the study aims to evaluate the impact of a static diffuser enclosing the rotor on the overall energy yield and wake recovery mechanisms. To this end, distinct geometrical configurations are generated and compared: a conventional Open Wind Turbine (OWT) serving as the baseline, and three ducted variants featuring progressively expanded diffuser exit areas. Through the application of LES coupled with the Actuator Line Model and the Immersed Boundary Method, the complex dynamics of the confined flow and its propagation downstream are systematically investigated under partial-load Maximum Power Point Tracking (MPPT) conditions. Ultimately, this LES-based approach allows us to quantify the direct influence of the diffuser geometry on the turbine's aerodynamic forces, torque generation, and the structural morphology of the downstream wake.

The contribution of this chapter is the first LES-IBM assessment of Diffuser-Augmented Wind Turbines under MPPT conditions, resolving the tip-vortex suppression mechanism and the blade loading redistribution responsible for the power augmentation, and establishing the monotonic scaling of torque gain with diffuser exit area across three duct geometries (Contribution 4).

8.1 Simulation Setup

This section details the numerical setup used to evaluate the aerodynamic effects of enclosing a wind turbine rotor within a diffuser. The analysis contrasts a conventional Open Wind Turbine (OWT) with three Diffuser-Augmented Wind Turbine (DWT) variants. The rotor geometry derives from the NREL Phase VI turbine, utilizing the S809 airfoil profile [170], with a minimal clearance

maintained between the blade tips and the diffuser's inner wall. Operating at a Reynolds number of approximately $\mathcal{O}(10^6)$, the rotor features a diameter of $D = 10.06$ m and a hub radius of $R_{\text{hub}} = 0.501$ m. The left panel of Figure 8.1 illustrates the baseline ducted geometry (DWT-V2), designed according to the guidelines proposed by Bontempo et al. [196]. To assess the sensitivity of the aerodynamic performance to the duct geometry, two additional variants were created by modifying the exit area of the divergent section: DWT-V1 features a 10% smaller outlet, whereas DWT-V3 features a 10% larger outlet, as shown in the right panel of Figure 8.1.

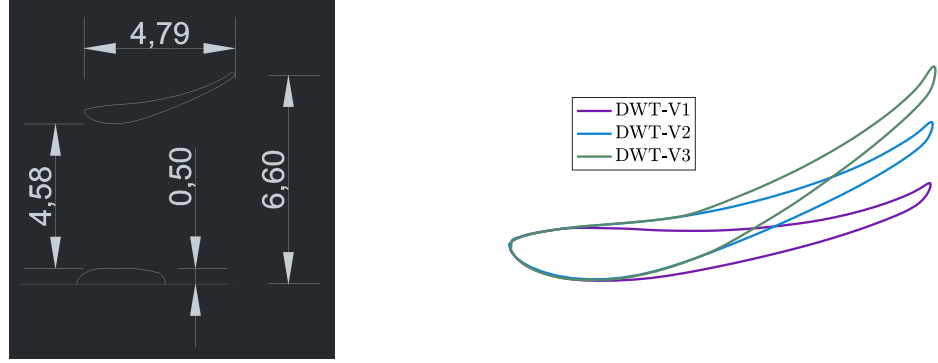


Figure 8.1: Left: corresponding dimensional measurements of the DWT-V2 (expressed in meters, m). Right: longitudinal sections of the DWT for the three configurations.

The computational domain spans $12.0 \times 11.0 \times 6.0$ in diameter units in the streamwise, vertical, and spanwise directions, respectively. The rotor is centered laterally and vertically, positioned $3D$ downstream of the inlet. The domain is discretised using a structured grid of $2049 \times 513 \times 1025$ points, featuring uniform spacing in the streamwise and spanwise directions and stretching along the vertical axis. The ALM represents the blades, utilizing 86 points along the span; considering the transverse force-spreading procedure, each actuator line interacts with approximately 4500 fluid cells.

A partial-load Maximum Power Point Tracking (MPPT) strategy is employed to govern the turbine operation for all configurations. The system aims to maintain an optimal TSR of 5.4 under a constant inflow velocity of $U_\infty = 7$ m/s. The rotor dynamics under this control scheme are modelled via the angular momentum balance:

$$I \frac{d\omega}{dt} = T_{\text{aero}} - T_{\text{gen}}, \quad (8.1)$$

where I represents the rotor inertia, ω the angular velocity, and T_{aero} the aerodynamic torque. The generator torque is defined quadratically as:

$$T_{\text{gen}} = k \omega^2, \quad (8.2)$$

with the constant k calibrated to sustain the target TSR. Finally, the boundary conditions consist of periodicity on the lateral walls, free-slip at the top and bottom patches, and a convective outflow condition at the domain exit.

8.2 Results

Table 8.1 summarises the time-averaged performance metrics for both the baseline OWT and the three ducted configurations operating under MPPT control. The results demonstrate a substantial power enhancement across all DWT cases, confirming that the diffuser effectively accelerates the incoming flow. Compared to the 6.78 kW generated by the OWT, power output rises monotonically with the diffuser exit area, reaching 8.77 kW (+29.35%) for DWT-V1 and peaking at 12.11 kW (+78.61%) for DWT-V3. This trend proves that a wider divergent section induces a stronger pressure drop across the rotor plane, driving a higher mass-flow rate. Consequently, both aerodynamic torque and rotational speed increase significantly; for instance, torque grows from 0.90 kNm (OWT) to 1.32 kNm (DWT-V3). This indicates that the diffuser not only boosts energy capture but also shifts the optimal operational state toward higher torque-speed combinations without requiring physical modifications to the rotor.

Table 8.1: Time-averaged power output, relative power increase (ΔP), aerodynamic torque, and rotational speed for the OWT and DWT configurations operating under MPPT control.

Geometries	Power [kW]	ΔP [%]	T_{aero} [kNm]	ω [RPM]
OWT	6.78	-	0.90	72.36
DWT – V1	8.77	+29.35	1.06	78.87
DWT – V2	10.93	+61.21	1.23	84.90
DWT – V3	12.11	+78.61	1.32	87.77

The radial distribution of tangential forces, F_t , presented in Figure 8.2, clearly illustrates the aerodynamic advantages introduced by the diffuser. For the baseline OWT, tangential forces remain elevated up to approximately 60% of the blade span before experiencing a sharp decline and collapsing near the tip. This drop is primarily driven by tip losses, strong vortex shedding, and radial flow leakage from the pressure side to the suction side. Conversely, all DWT configurations sustain a nearly constant tangential force profile across the majority of the blade span, with a reduction occurring only at the very tip. This sustained loading is governed by three primary mechanisms induced by the

duct: (i) the suppression of tip losses, as the diffuser acts as a physical boundary that mitigates radial leakage and weakens tip vortices; (ii) the generation of a more uniform axial flow through the rotor plane, preserving higher relative velocities at the outboard blade sections; and (iii) the attenuation of three-dimensional flow effects, establishing quasi-2D aerodynamic conditions along the blade due to the guided flow. It should be noted that the tangential force still experiences a reduction near the tip in the ducted cases—a consequence of the finite blade length and localized flow adjustments at the diffuser exit. However, this drop occurs much further outboard and is significantly less gradual than in the OWT.

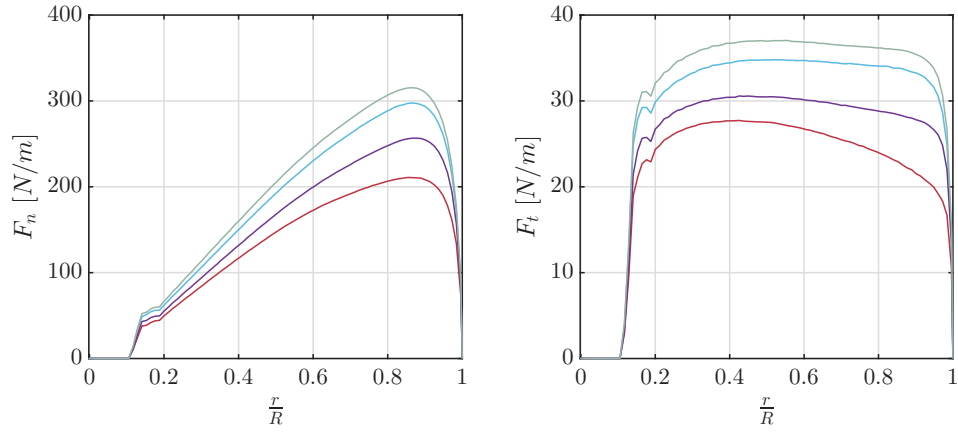


Figure 8.2: Time-averaged radial distribution of normal (F_n) and tangential (F_t) forces. Colors refer to the baseline **OWT**, and the ducted configurations **DWT-V1**, **DWT-V2**, and **DWT-V3**.

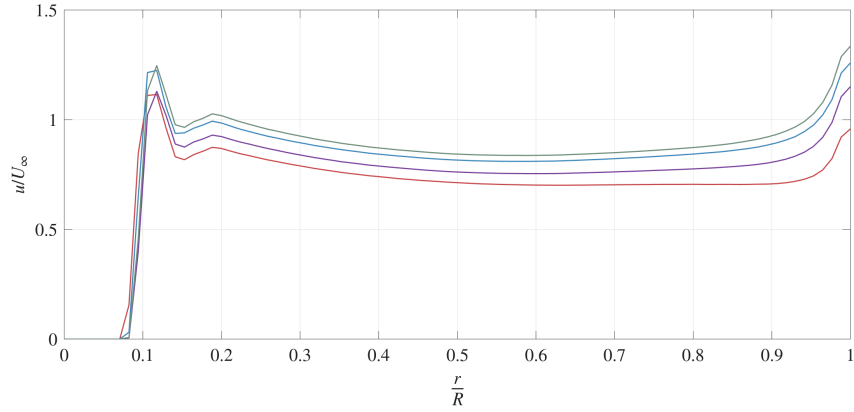


Figure 8.3: Apparent wind speed at the rotor plane. Colors refer to the baseline **OWT**, and the ducted configurations **DWT-V1**, **DWT-V2**, and **DWT-V3**.

As depicted in Figure 8.3, the diffuser actively accelerates the incoming flow, yielding a higher axial velocity at the rotor plane. This acceleration

directly amplifies the magnitude of the relative wind speed encountered by the blade sections. Because aerodynamic lift scales with the square of the relative velocity, this enhanced inflow translates to higher overall aerodynamic loading, evidenced by a substantial increase in the normal force, F_n , relative to the OWT. Consequently, the aerodynamic load is redistributed toward the outer portions of the rotor. This shift allows the blade sections possessing the largest moment arms to extract energy with greater efficiency, ultimately driving the elevated torque and power outputs characteristic of the DWT configurations. The corresponding rise in the normal force F_n across the entire blade span directly reflects this overall enhancement in lift induced by the diffuser.

Figures 8.4 and 8.5 illustrate how the presence of the diffuser actively modifies both the near-wake topology and the downstream flow recovery. The time-averaged streamwise velocity contours on the $x - y$ plane (Figure 8.4) reveal that, as the configuration shifts from the baseline OWT to DWT-V3, the wake structure becomes progressively wider and shorter. This visual spreading is indicative of enhanced lateral entrainment and vigorous mixing induced by the duct. Concurrently, the nacelle shadow shortens as the diffuser exit area expands, providing further evidence of an accelerated recovery process. Immediately downstream of the rotor, the DWT models exhibit a distinctly pronounced low-velocity region (visible as a darker area). This pronounced local velocity deficit reflects the augmented extraction of kinetic energy from the flow, aligning consistently with the elevated power and torque metrics previously discussed.

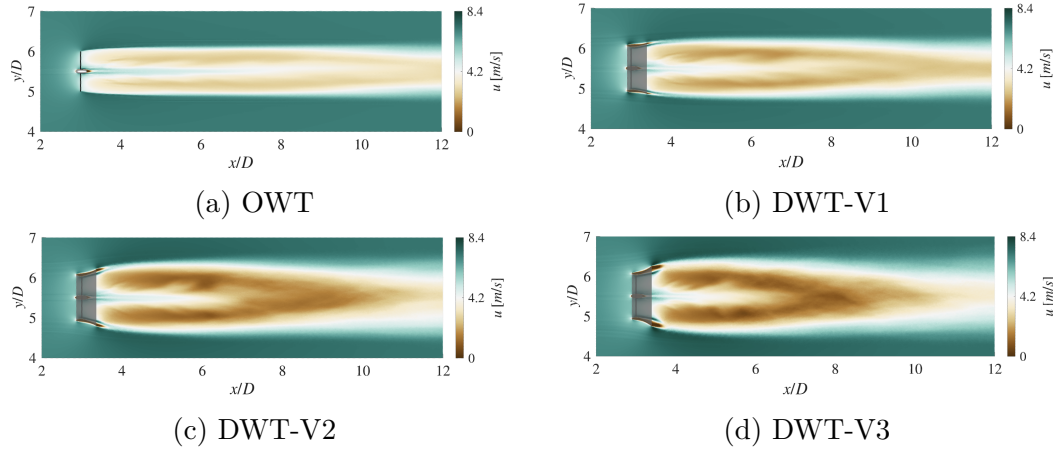


Figure 8.4: Time-averaged streamwise velocity slices of the 4 configurations.

These flow structures are reflected in the wake recovery profiles in Figure 8.5. A localized velocity peak is evident at the diffuser inlet (marked by the dashed vertical line), representing the flow acceleration driven by mass-flow entrainment. The amplitude of this peak scales with the diffuser size, growing from DWT-V1 to DWT-V3, thereby emphasizing the intensified suction effect associated with a larger divergent area. In the downstream region, while the

ducted turbines produce a deeper initial velocity deficit due to their superior energy extraction, they simultaneously demonstrate a considerably faster wake recovery compared to the baseline OWT. This combination of enhanced energy capture and accelerated recovery confirms that expanding the diffuser exit area improves turbine performance while simultaneously fostering highly efficient downstream mixing.

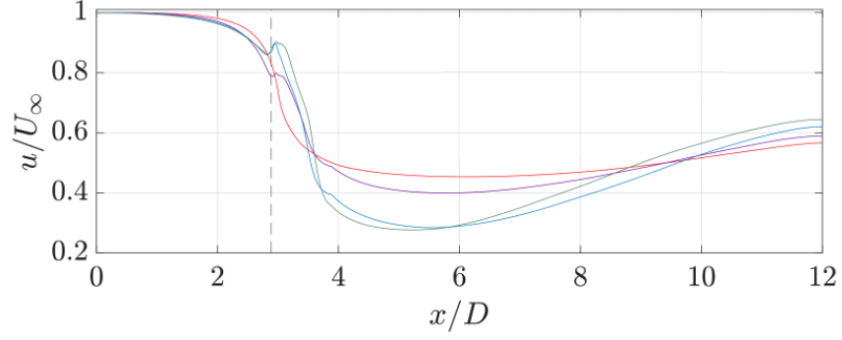


Figure 8.5: Wake recovery of the 4 configurations (**OWT**, and the ducted configurations **DWT-V1**, **DWT-V2**, and **DWT-V3**), computed by integrating the velocity over the rotor swept area and then extruding this quantity along the entire streamwise length of the domain. Black dashed line represents the rotor.

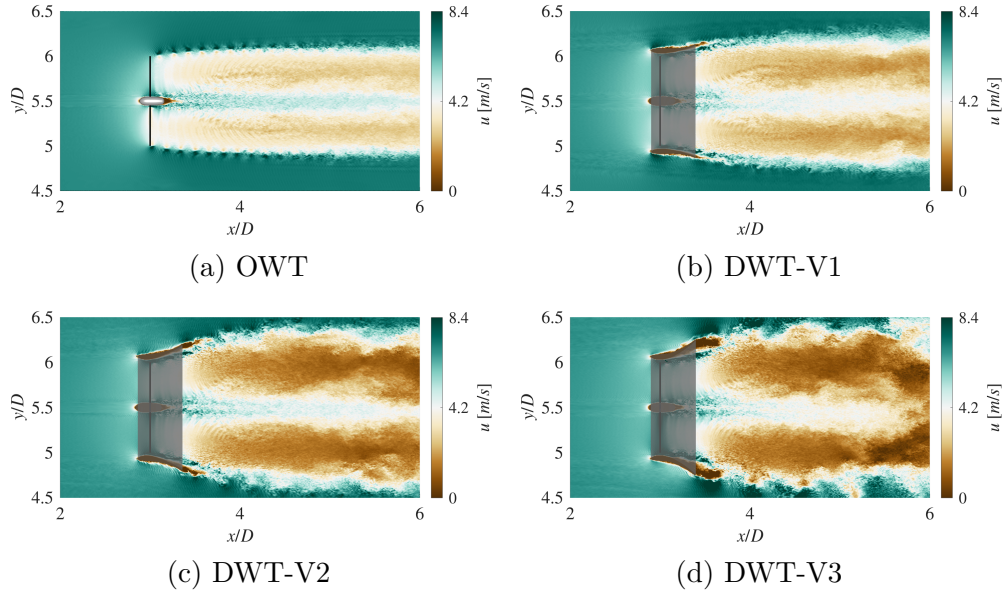


Figure 8.6: Instantaneous streamwise velocity slices of the 4 configurations. Black solid line represents the rotor.

The instantaneous streamwise velocity slices on the $x - y$ plane, presented

in Figure 8.6, offer deeper insights into these recovery mechanisms. Consistent with the time-averaged data, the instantaneous wake clearly broadens when transitioning from the open rotor to the ducted variants, with DWT-V3 exhibiting the most substantial lateral spreading due to its maximal entrainment capability. In the OWT simulation (Figure 8.6a), distinct low-velocity patches are visible along the wake boundaries, corresponding to the tip vortices shed by the blades. These coherent structures persist stably for several rotor diameters downstream, indicating a relatively slow breakdown of the vortex system. Conversely, in all DWT configurations (Figures 8.6b–8.6d), comparable coherent structures are strictly confined to the immediate vicinity of the rotor and undergo rapid destabilization within the downstream diffuser region. This accelerated dissipation of tip vortices is a direct consequence of flow confinement and the high shear layers generated by the duct, which collectively trigger intense turbulence and mixing. The swift breakdown of these coherent structures mechanically explains the faster wake recovery observed in the ducted cases, confirming the direct connection between diffuser geometry, wake behavior, and aerodynamic performance.

8.3 Conclusions

This chapter employed Large Eddy Simulations to investigate the aerodynamic performance and wake dynamics of Diffuser-Augmented Wind Turbines (DWTs) relative to a conventional Open Wind Turbine (OWT) operating under uniform laminar inflow. By analysing three distinct diffuser geometries, each featuring a progressively enlarged exit area, the study quantified the direct influence of the duct shape on both energy production and downstream flow topology.

All evaluated ducted configurations yielded a substantial power augmentation compared to the baseline OWT, achieving a +78.6% gain for the variant with the largest exit area (DWT-V3). Operating under an MPPT control strategy, this surge in power was consistently accompanied by higher aerodynamic torque and elevated rotational speeds. These results confirm that enclosing the rotor within a diffuser increases the kinetic energy available for extraction and shifts the turbine's optimal operating point toward higher torque-speed regimes. Furthermore, the monotonic performance improvement observed from DWT-V1 to DWT-V3 establishes the diffuser's divergent exit area as a critical design parameter that actively regulates the mass flow rate traversing the rotor plane.

Blade-resolved aerodynamic analyses revealed that the duct allows a significantly larger span of the blade to operate near its optimal aerodynamic limit. This is achieved through the flattening of the axial velocity profile and the mitigation of detrimental three-dimensional flow phenomena, specifically radial leakage and strong tip vortices. While the ALM intrinsically evaluates two-dimensional aerodynamics at each blade section—relying on analytical cor-

rections to approximate tip losses—the physical presence of the diffuser actively guides the flow and minimises these 3D losses, establishing a highly uniform axial velocity distribution. Concurrently, wake investigations demonstrated that although the enhanced energy extraction of DWTs inherently generates a deeper near-wake velocity deficit, these configurations simultaneously achieve a markedly faster wake recovery, propelled by vigorous lateral entrainment and enhanced fluid mixing.

While these macroscopic trends are consistent with existing literature based on engineering models, deploying an LES framework provides temporally and spatially resolved flow data that successfully captures unsteady separation and coherent 3D flow structures—such as the rapid breakdown of tip vortices. Establishing this aerodynamic baseline is a crucial step for accurately resolving the flow physics of DWTs.

In conclusion, this study not only substantiates the distinct aerodynamic benefits of flow augmentation but also underscores the dominant role of duct geometry in dictating rotor loading and wake morphology. Future work will extend this framework to realistic ABL inflows and incorporate structural flexibility, enabling the assessment of aeroelastic interactions and fatigue loading under operational scenarios.

Chapter 9

MARL for Wind Farm Control

The MARL framework and its underlying theoretical foundations — the Dec-POMDP formulation, the PPO, SAC, and TD3 engines, the independent, multi-agent, and centralised coordination paradigms, and the multi-fidelity transfer strategy — are described in detail in the preceding methodology chapter (Section 2.8). The present chapter applies that framework to two wind farm configurations of increasing geometric complexity: a canonical 3-turbine in-line array and the irregular Ablaincourt Energies farm. Nine algorithms are benchmarked, spanning three algorithmic families (PPO, SAC, TD3) crossed with three coordination paradigms (independent, centralised-critic, fully centralised). Training is conducted using the FLORIS engineering surrogate; the resulting policies are transferred to the LES environment to assess the sim-to-real fidelity gap in terms of power gain and structural loading. The chapter is organised as follows: Section 9.1 defines the experimental setup; Section 9.2 introduces the nine algorithms and their architectural differences; Sections 9.3 and 9.4 present the training and performance results for each farm; Section 9.5 reports the sim-to-real transfer for the best policies; Section 9.6 discusses cross-algorithm trends; and Section 9.7 summarises the main findings. The contribution of this chapter is a comprehensive benchmark of nine MARL algorithms for wind farm yaw control, including the first sim-to-real transfer to a turbulence-resolving LES environment with structural load monitoring. The study identifies PPO and entropy-regularised SAC as the most reliable families for deployment-scale operation, and characterises a fixed-point instability in deterministic TD3 policies that constitutes a previously unreported deployment risk (Contribution 5).

9.1 Simulation Setup

9.1.1 Wind Farm Configurations

3-Turbine In-Line Array

The first test case is a canonical 3-turbine in-line array of NREL 5MW wind turbines (Section 3.1), aligned with the mean inflow direction and spaced $4D$ apart, where $D = 126\text{ m}$ is the rotor diameter. This configuration isolates the sequential wake interaction problem in its simplest form: each downstream turbine operates in the fully developed wake of its upstream neighbour, providing a controlled benchmark in a low-dimensional action space ($M = 3$ agents, $|\mathcal{A}| = 6$). The regularity of the layout makes credit assignment straightforward — the causal chain from yaw command to power recovery is direct and unambiguous — and therefore serves as the reference case for verifying algorithmic behaviour before scaling to a more complex geometry.

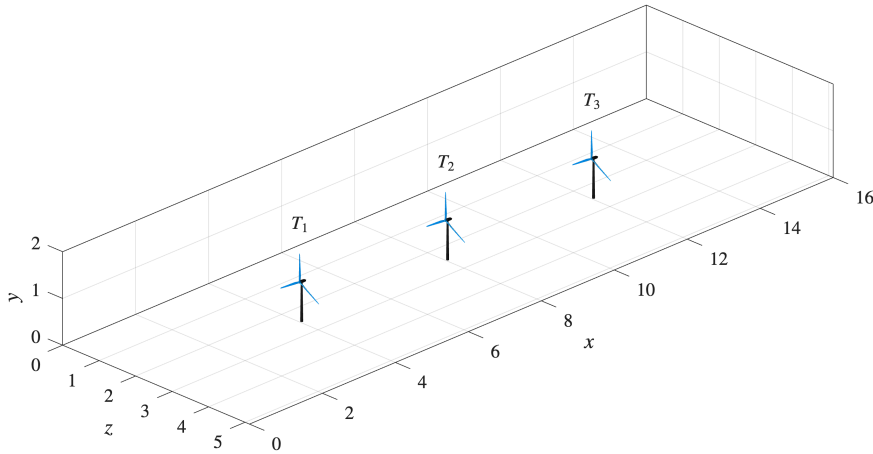


Figure 9.1: 3-turbine in-line array layout. Turbines are aligned with the mean inflow and separated by $4D$.

Ablaincourt Energies Wind Farm

The second configuration is the Ablaincourt Energies onshore wind farm, located in the Somme département, northern France. The farm comprises seven NREL 5MW equivalent turbines arranged in an irregular layout, representative of real-world deployment constraints imposed by land use and grid connectivity. The non-collinear turbine arrangement introduces partial and asymmetric wake overlaps, demanding a more flexible control strategy than the structured in-line case and exposing the limits of the Gaussian wake model adopted in FLORIS. With $M = 7$ agents and $|\mathcal{A}| = 14$, this case stresses the scalability of

all nine algorithms, particularly those whose credit-assignment mechanism is conditioned on local observations only.

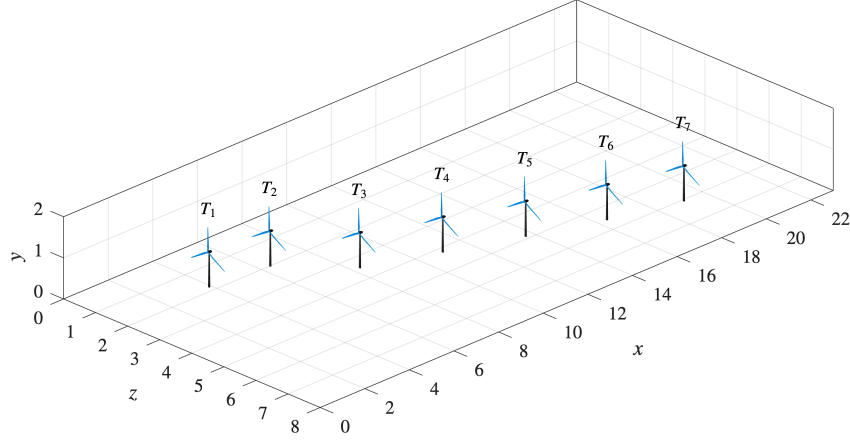


Figure 9.2: Ablaincourt Energies wind farm layout. The seven turbines are arranged in an irregular pattern representative of real-world onshore deployment constraints.

9.1.2 Inlet Conditions

All experiments correspond to **Wind Scenario I** (constant free-stream conditions, Section 2.8). The inflow is prescribed as a power-law shear profile:

$$U(y) = U_h \left(\frac{y}{y_h} \right)^\alpha, \quad (9.1)$$

where $U_h = 8 \text{ m/s}$ is the hub-height reference velocity, $y_h = 90 \text{ m}$ the hub height, and $\alpha = 0.05$ the shear exponent, representative of near-neutral onshore conditions. The wind direction is fixed at 270° for the in-line array and at the dominant inflow bearing of the Ablaincourt site for the farm case. All quantities reported in this chapter are non-dimensionalised using $D = 126 \text{ m}$ and $U_h = 8 \text{ m/s}$ as reference length and velocity scales.

9.1.3 LES Numerical Setup

The LES computational domains are configured independently for the two farm geometries. For the 3-turbine in-line array, the domain extends $16D \times 10D \times 5.12D$ in the streamwise, wall-normal, and spanwise directions, discretised on a $801 \times 193 \times 257$ grid. For the Ablaincourt farm, the larger turbine footprint requires a domain of $23D \times 10D \times 8D$, resolved on a $1153 \times 193 \times 401$ grid. In both cases the wall-normal grid is non-uniform: uniform spacing is maintained

throughout the rotor-swept region to resolve blade-induced velocity gradients at constant resolution, while the grid is progressively stretched above the rotor top to reduce computational cost. The Reynolds number based on hub-height velocity and rotor diameter is $Re = U_h D / \nu \sim 10^7$ for both configurations.

Boundary conditions are applied consistently across both configurations. The power-law profile of Equation 9.1 is prescribed at the inlet; a convective outflow condition is imposed at the exit; periodic boundary conditions are enforced in the spanwise direction; a no-slip condition is applied at the bottom wall; and a free-slip condition is imposed at the top boundary. In the FLORIS environment, rotor–wake interactions are modelled through the Gaussian wake model (Appendix C.2); in the LES environment, each rotor is represented by the Rotating Actuator Disc Model (Section 2.4).

For the MARL evaluation campaigns reported in Section 9.5, the inlet profile is kept strictly constant, with no synthetic turbulence superimposed at the inflow boundary. The only time-varying quantities in the domain are therefore the wake-induced velocity fluctuations generated by the rotors themselves. This choice enables a direct, one-to-one comparison with the FLORIS steady-state results and, crucially, isolates algorithmic behaviour from inflow variability: any instability observed in the controller output can be attributed to the policy itself rather than to environmental noise.

9.1.4 Wake Convection Time and RL Rollout Interval

A key design parameter of the RL–LES coupling is the rollout step duration — the interval between successive policy queries. This interval must be long enough for the flow field to respond to a yaw change and reach a new quasi-steady wake state, yet short enough to allow a sufficient number of control actions per episode. To determine this interval, a dedicated campaign of precursor LES step-response simulations was carried out for each farm configuration. The rollout interval was then set equal to the wake convection time T_c , defined as the time required for the deflected wake to reach the last downstream turbine and for the farm-averaged power to settle.

9.1.5 Training Hyperparameters

The hyperparameters for each algorithmic family are reported in Tables 9.1, 9.2 and 9.3. The PPO values follow the benchmark of Monroc et al. [197], which established a standardised experimental protocol for MARL wind farm control. For SAC and TD3 the hyperparameters were tuned to ensure fair comparison in terms of sample budget and exploration strategy. To quantify sensitivity to random initialisation, every configuration is repeated with **20 independent random seeds**, yielding a statistically robust characterisation of each algorithm’s convergence reliability and steady-state performance.

Table 9.1: PPO hyperparameters used during training in FLORIS (IPPO, MAPPO, CPPO).

Parameter	Value
Learning rate	$3 \times 10^{-4} \rightarrow 0$ (linear annealing)
Discount γ	0.99
GAE λ	0.95
Clip coefficient ε	0.2
Entropy coefficient	0.01
Value loss coefficient	0.5
# steps between updates	2048
# epochs	10
# minibatches	32
Minibatch size	64
Max. gradient norm	0.5
Normalise advantages	True
Target KL (per agent)	0.015
Hidden layers	(64, 64)

Table 9.2: SAC hyperparameters used during training in FLORIS (ISAC, MASAC, CSAC).

Parameter	Value
Learning rate	1×10^{-4}
Discount γ	0.99
Soft update τ	0.005
Replay buffer size	10^6
Batch size	512
Learning starts	5 000
Policy frequency	2
Entropy coefficient α	autotune (target $H = -\dim(\mathcal{A})$)
Hidden layers	(64, 64)

Table 9.3: TD3 hyperparameters used during training in FLORIS (ITD3, MATD3, CTD3).

Parameter	Value
Learning rate	1×10^{-4}
Discount γ	0.95
Soft update τ	0.01
Replay buffer size	10^6
Batch size	512
Learning starts	10 000
Policy frequency	2
Exploration noise (init)	$0.3 \rightarrow 0.05$ (linear decay)
Policy smoothing noise	0.2
Noise clip	0.5
Hidden layers	(64, 64)

A remark on the discount factor γ is in order. PPO and SAC use $\gamma = 0.99$, which yields an effective planning horizon of approximately 100 steps on 150-step episodes ($\gamma^{100} \approx 0.37$). For TD3, preliminary experiments showed that $\gamma = 0.99$ destabilises training due to the amplified Bellman backup error in the absence of entropy regularisation (Section 9.6.3); $\gamma = 0.95$ — corresponding to an effective horizon of roughly 20 steps — was found to give the best trade-off between stability and performance and is therefore retained for the TD3 family.

The uncontrolled **baseline** is defined as the greedy configuration with all yaw angles fixed at zero ($\psi_i = 0 \forall i$), corresponding to full rotor alignment with the mean inflow. The action space is bounded by $|\psi_i| \leq 40^\circ$ and incremental cap $|\Delta\psi_i| \leq 5^\circ$. In the LES environment a finite yaw rotation rate of $\dot{\psi} = 1^\circ \text{ s}^{-1}$ is additionally enforced. For evaluation, a single representative seed is selected per algorithm and farm configuration according to the criterion described in Section 9.5.

9.2 Algorithm Families and Coordination

The nine algorithms benchmarked in this chapter span three *algorithmic families* — Proximal Policy Optimisation (PPO), Soft Actor-Critic (SAC), and Twin Delayed Deep Deterministic Policy Gradient (TD3) — each instantiated under three *coordination paradigms*, as summarised in Table 9.4 and illustrated architecturally in Figure 9.3.

Table 9.4: The 3×3 algorithm matrix. Rows: algorithmic family; columns: coordination paradigm.

	Independent	Multi-Agent (CTDE)	Centralised
PPO	IPPO	MAPPO	CPPO
SAC	ISAC	MASAC	CSAC
TD3	ITD3	MATD3	CTD3

Independent paradigm (IPPO, ISAC, ITD3). Each agent i maintains its own actor $\pi_{\theta_i}(a_i | o_i)$ and its own critic $V_{\phi_i}(o_i)$ or $Q_{\phi_i}(o_i, a_i)$, both conditioned exclusively on the local observation o_i . No information is shared between agents during either training or execution. The key advantage is scalability and architectural simplicity; the key limitation is that the critic cannot observe the contributions of other agents to the joint reward, introducing non-stationarity that worsens as the number of agents grows or as inter-agent coupling intensifies. In a seven-turbine farm with strong wake interactions, the local critic observes only one seventh of the reward as a meaningful signal, while the remaining six sevenths appear as noise from its perspective. This fundamental limitation makes the independent paradigm particularly ill-suited for tightly coupled systems where individual actions produce far-reaching downstream consequences.

Multi-Agent paradigm with Centralised Training and Decentralised Execution (MAPPO, MASAC, MATD3). Each agent i retains a decentralised actor $\pi_{\theta_i}(a_i | o_i)$ for execution, but during training a centralised critic $V_{\phi}(o_g)$ or $Q_{\phi}(o_g, \mathbf{a})$ — conditioned on the global observation $o_g = (o_1, \dots, o_M)$ and, for value-based critics, on the joint action $\mathbf{a} = (a_1, \dots, a_M)$ — provides a shared value signal to all actors. This *Centralised Training, Decentralised Execution* (CTDE) paradigm eliminates the non-stationarity of independent critics while preserving fully decentralised execution. Each actor’s optimisation problem remains low-dimensional regardless of farm size, making CTDE the natural sweet spot between representational capacity and optimisation difficulty.

Centralised paradigm (CPPO, CSAC, CTD3). A single actor $\pi_{\theta}(\mathbf{a} | o_g)$ and a single critic jointly observe the global state and produce the joint action $\mathbf{a} \in \mathbb{R}^{2M}$ for the entire farm. This formulation treats the multi-agent problem as a single-agent one with a large action space. While the centralised actor can exploit the full observability of the farm state and is not subject to partial observability bias, its policy gradient is computed over an action space that grows linearly with M : for seven turbines, $|\mathbf{a}| = 14$. The success of this

paradigm depends critically on whether the underlying optimisation algorithm provides sufficient implicit regularisation to navigate a high-dimensional action landscape reliably.

Algorithmic families. The three families differ in how they generate and use the value signal. **PPO** is on-policy: it collects rollout data under the current policy, computes Generalised Advantage Estimates (GAE), and performs multiple gradient steps per batch before discarding the data. The clip objective limits policy updates to a trust region, providing implicit variance control. **SAC** is off-policy and entropy-regularised: it stores transitions in a replay buffer, optimises a soft Bellman objective that augments the standard return with an entropy bonus $\alpha \mathcal{H}[\pi]$, and uses automatic tuning of the temperature α to balance exploration and exploitation. The entropy regularisation acts as a continuous stochasticity incentive that prevents premature convergence and stabilises Q-value estimation. **TD3** is off-policy and deterministic: it uses clipped double-Q learning to reduce overestimation bias and a delayed policy update to decouple critic and actor learning. Unlike SAC, TD3 has no explicit entropy term; exploration is driven entirely by a linearly decaying Gaussian noise added to the deterministic actor output.

Figure 9.3 summarises the actor–critic wiring for all nine algorithms.

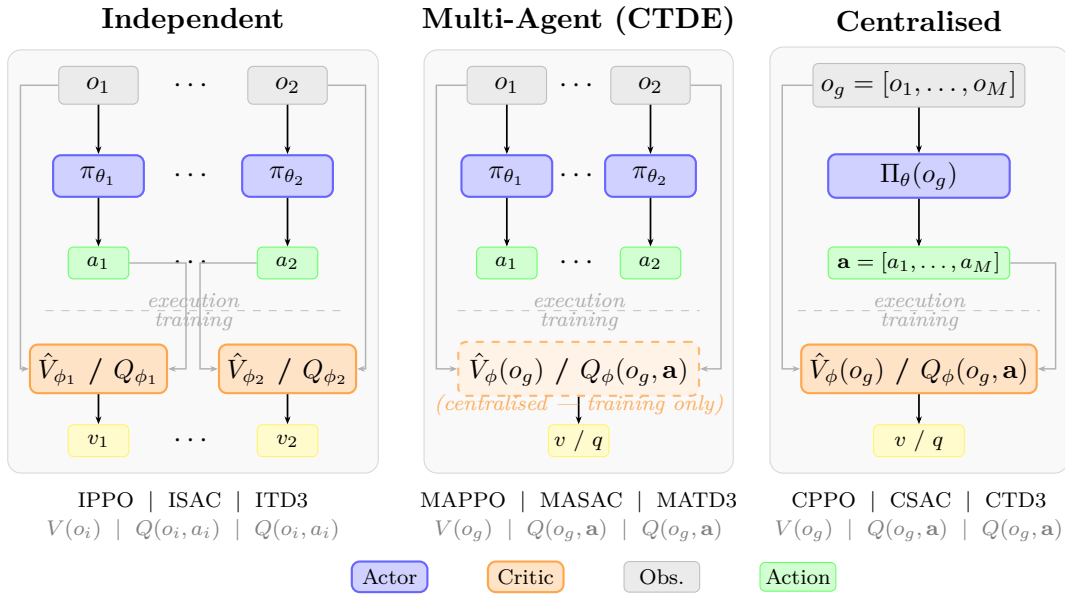


Figure 9.3: Actor–critic wiring for the nine benchmarked algorithms. **Blue**: actor networks; **orange**: critic networks (dashed in CTDE = training only); **grey**: observations; **green**: action outputs. PPO uses a state-value function $V(\cdot)$; SAC and TD3 use an action-value function $Q(\cdot, \cdot)$.

9.3 Results: 3-Turbine In-Line Array

9.3.1 Training Convergence

Figure 9.4 shows the smoothed episode reward as a function of environment interactions for all nine algorithms on the 3-turbine array. Each curve reports the mean across seeds; shaded bands indicate one standard deviation. The horizontal dashed line marks the convergence threshold $\mathcal{S} = 233.5$.

PPO-family algorithms converge within approximately 10^5 environment interactions, consistent with the on-policy rollout structure and the linear learning-rate schedule. SAC-family algorithms, leveraging the replay buffer, begin exploiting stored transitions after the initial 5000-step warm-up phase and reach steady state by $7\text{--}10 \times 10^4$ steps. TD3-family algorithms exhibit a later onset of learning due to the larger learning-starts budget of 10000 steps and the deterministic policy noise annealing, but converge comparably by $10\text{--}15 \times 10^4$ steps.

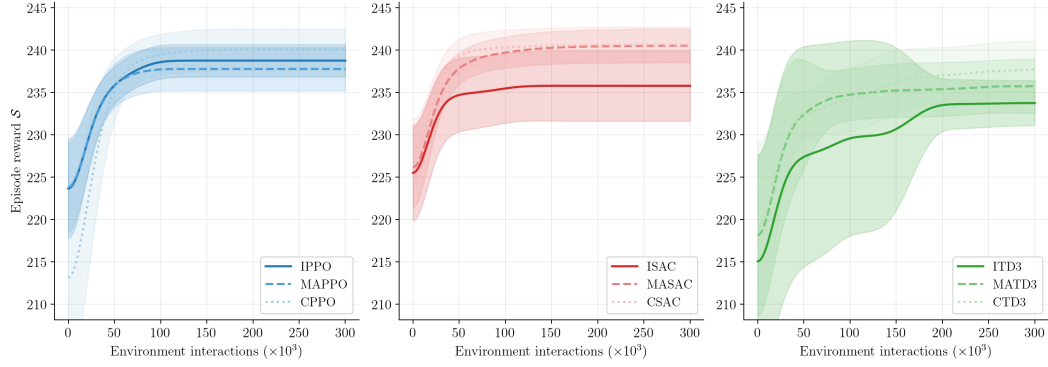


Figure 9.4: Smoothed training curves for the 3-turbine array. Mean $\pm$ 1 std across seeds. Colour encodes the algorithmic family (blue: PPO; orange: SAC; green: TD3); line style encodes the paradigm (solid: independent; dashed: multi-agent; dotted: centralised).

9.3.2 Final Performance Statistics

Table 9.5 summarises the steady-state performance across all seeds. The episode reward $\mathcal{S}$ is computed as the mean over the last 50 episodes of each training run, and the reported statistics are taken over the full seed ensemble. Convergence is defined as $\mathcal{S} \geq 233.5$, a threshold chosen to reflect a meaningful and stable improvement over the uncontrolled baseline.

Figure 9.5 presents the corresponding box plots, where each box spans the inter-quartile range of the per-seed final scores, the central line marks the median, and whiskers extend to 1.5 times the IQR. On this configuration

the PPO family and the SAC centralised variants achieve complete or near-complete convergence. The best-performing algorithms — CPPO, CSAC, and MASAC — differ from the weakest (ITD3, ISAC) by approximately 5–8 points, equivalent to a relative difference of roughly 2–3%. TD3 algorithms, by contrast, show partial convergence even on this simpler layout: ITD3 reaches the threshold in only 35% of seeds, foreshadowing the more severe failures observed on the larger farm.

Table 9.5: Steady-state training performance on the 3-turbine array. Convergence defined as $\mathcal{S} \geq 233.5$.

Family	Algorithm	N	Mean $\bar{\mathcal{S}}$	Std $\sigma_{\mathcal{S}}$	Conv.%
PPO	IPPO	20	239.78	2.00	100
	MAPPO	20	237.85	2.58	100
	CPPO	20	241.79	2.44	100
SAC	ISAC	20	235.69	4.11	70
	MASAC	20	241.51	2.00	100
	CSAC	20	241.71	2.13	100
TD3	ITD3	20	233.77	2.67	35
	MATD3	20	236.09	3.19	65
	CTD3	20	237.03	3.34	85

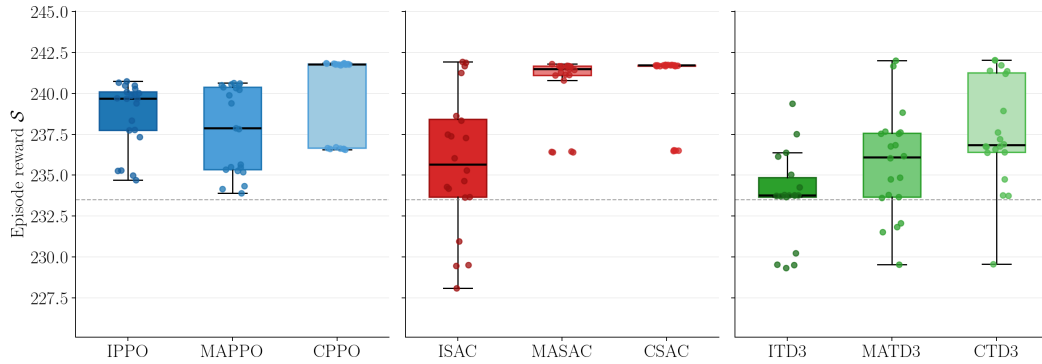


Figure 9.5: Box plots of the steady-state episode reward for the 3-turbine array. Algorithms are grouped by family. The dashed horizontal line marks the convergence threshold ($\mathcal{S} = 233.5$ for the 3-turbine array).

9.3.3 Per-Family Analysis

PPO family. All three paradigms converge on the large majority of seeds and produce comparable performance. CPPO marginally outperforms IPPO and MAPPO ($\Delta\bar{\mathcal{S}} \approx 2\text{--}4$) because the centralised actor can directly exploit the sequential wake structure of the three-turbine topology, issuing coordinated yaw commands without the information latency of decentralised policies. The target-KL early-stopping mechanism in CPPO is scaled proportionally to the number of agents (effective threshold = $0.015 \times M$), ensuring that the per-agent KL divergence remains comparable across farm sizes regardless of the joint-probability formulation of the PPO update.

SAC family. MASAC and CSAC match the top PPO scores and achieve 100% convergence. The automatic entropy tuning successfully calibrates the exploration–exploitation trade-off, and the replay buffer reuse provides a sample-efficiency advantage: SAC reaches 90% of its final score roughly $3\times$ faster than PPO in terms of environment interactions. ISAC is the weakest SAC variant: 6 out of 20 seeds fail to converge, a consequence of the local critic $Q_\phi(o_i, a_i)$ receiving a partially corrupted reward signal due to wake interactions that are not visible in the individual observation o_i .

TD3 family. TD3 algorithms show partial convergence even on the simpler 3-turbine array. ITD3 converges in only 35% of seeds, the first indication of the credit-assignment instability that becomes severe on the 7-turbine farm. MATD3 fares better (65% convergence) by virtue of its centralised critic, and CTD3 reaches 85%. When convergence does occur, the achieved scores (233.5–240) are approximately 2–5 points below the best PPO and SAC results, a gap attributed in part to the shorter effective planning horizon imposed by $\gamma = 0.95$ and in part to the deterministic exploration strategy, which is less well-matched to the quasi-static FLORIS environment (Section 9.6.3).

9.4 Results: Ablaincourt Energies Farm

9.4.1 Training Convergence

Figure 9.6 shows the training curves for all nine algorithms on the Ablaincourt farm. The contrast with the 3-turbine results is striking: the algorithms diverge markedly in both convergence reliability and steady-state performance as the farm complexity increases from $M = 3$ to $M = 7$.

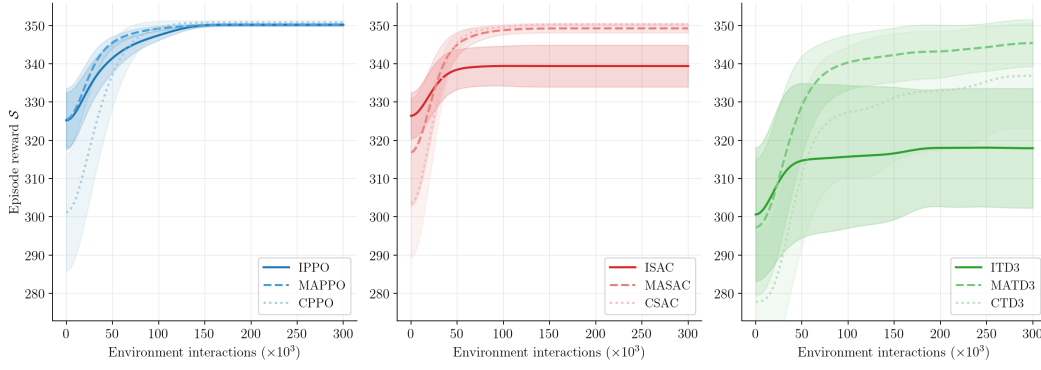


Figure 9.6: Smoothed training curves for the Ablaincourt farm. Same colour and line-style convention as Figure 9.4. The horizontal dashed line marks the convergence threshold $\mathcal{S} = 348$.

9.4.2 Final Performance Statistics

Table 9.6 summarises the Ablaincourt results. Convergence is defined as $\mathcal{S} \geq 348$.

Table 9.6: Steady-state training performance on the Ablaincourt farm. Convergence defined as $\mathcal{S} \geq 348$.

Family	Algorithm	N	Mean $\bar{\mathcal{S}}$	Std $\sigma_{\mathcal{S}}$	Conv.%
PPO	IPPO	20	350.37	0.41	100
	MAPPO	20	350.14	0.16	100
	CPPO	20	351.07	0.37	100
SAC	ISAC	20	340.73	5.20	0
	MASAC	20	349.74	1.12	80
	CSAC	20	350.42	0.34	100
TD3	ITD3	20	317.83	15.54	0
	MATD3	20	350.23	6.00	55
	CTD3	20	338.06	13.19	30

Figure 9.7 presents the corresponding box plots. The spread across algorithms now amounts to nearly 70 points — one full order of magnitude larger than on the 3-turbine array. Three clear performance tiers emerge: (i) the PPO family and CSAC ($\bar{\mathcal{S}} \approx 350$ – 351 , 100% convergence); (ii) MASAC and MATD3 ($\bar{\mathcal{S}} \approx 350$, 55–80% convergence); and (iii) ISAC, CTD3, and ITD3 ($\bar{\mathcal{S}} \leq 341$, 0–30% convergence).

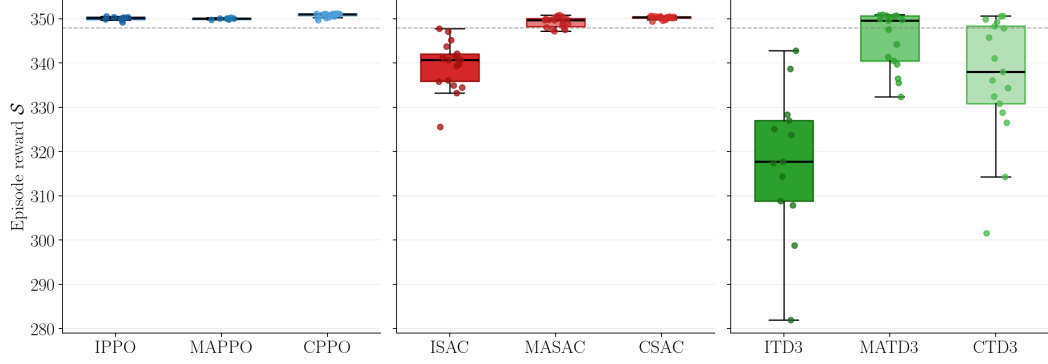


Figure 9.7: Box plots of the steady-state episode reward for the Ablaincourt farm. Algorithms are sorted by median performance. The dashed horizontal line marks the uncontrolled baseline.

9.4.3 Convergence Reliability Across Farm Scales

The convergence reliability of each algorithm shows not whether an algorithm can find a good policy, but how consistently it does so across independent training runs.

The four most significant reliability drops are:

- **ITD3**: 35% $\rightarrow$ 0%. All 20 Ablaincourt seeds plateau far below the threshold ($\bar{S} \approx 318$). This is a structural failure attributable to the local critic $Q_\phi(o_i, a_i)$: with seven turbines the per-agent reward signal carries only one seventh of the meaningful information, the remainder being noise from the local perspective. No hyperparameter adjustment can remedy this.
- **ISAC**: 70% $\rightarrow$ 0%. Despite automatic entropy tuning, ISAC reaches a mean of $\bar{S} = 340.7$ but no seed crosses the 348 threshold. The ceiling is set by the same local-Q structural limitation as ITD3, partially mitigated by the entropy regularisation but not eliminated.
- **CTD3**: 85% $\rightarrow$ 30%. The centralised actor must navigate a 14-dimensional action space; only 6 of 20 seeds converge. When convergence does occur, the achieved score (≈ 350) is indistinguishable from the PPO ceiling, confirming that the architecture is not fundamentally capacity-limited but rather susceptible to initialisation-dependent training instabilities.
- **MATD3**: 65% $\rightarrow$ 55%. The moderate drop suggests that the CTDE paradigm partially mitigates the TD3 instability by keeping each actor’s gradient low-dimensional; however, the 45% failure rate on Ablaincourt remains too high for reliable deployment.

By contrast, PPO-family algorithms, MASAC, and CSAC maintain 80–100% convergence on the larger farm, demonstrating that on-policy training or entropy-regularised off-policy training provides the robustness needed for practical deployment at scale.

9.4.4 Per-Family Analysis

PPO family. All three PPO variants converge on every seed with negligible inter-seed variance ($\sigma_S < 0.5$ for all). CPPO achieves the highest mean (351.07) and the highest reliability, a finding that might appear counter-intuitive given the centralised actor’s larger action space. The key enabler is the on-policy nature of PPO: the clip objective and the target-KL early stopping — scaled proportionally to M to preserve a constant per-agent threshold — together constrain update steps to a safe trust region, preventing the initialisation-dependent policy collapse that afflicts CTD3. IPPO and MAPPO deliver essentially identical performance ($\Delta\bar{S} < 0.3$), confirming that for the Ablaincourt topology the marginal value of centralised critic information is small at steady state.

SAC family. CSAC achieves the highest overall SAC score (350.42, 100% convergence) because the entropy regularisation stabilises the centralised actor in a way that the purely deterministic CTD3 cannot. The entropy bonus prevents the policy from prematurely committing to a suboptimal joint action, effectively acting as a continuous implicit exploration mechanism in the 14-dimensional action space. MASAC, despite its CTDE architecture, exhibits moderate convergence failures (20% of seeds); post-hoc analysis reveals that failing seeds reach a plateau at ≈ 344 – 346 without further improvement, suggestive of a saddle point in the loss landscape. ISAC is the weakest SAC variant for the structural reasons detailed above.

TD3 family. The TD3 results on Ablaincourt exhibit the highest variance of any family. Crucially, MATD3 outperforms CTD3 in both mean reward (350.2 vs 338.1) and convergence reliability (55% vs 30%), despite CTD3’s theoretically higher representational capacity. This inversion of the expected centralised $>$ CTDE hierarchy is the most significant finding of the TD3 analysis: MATD3’s decentralised actors each solve a 2-dimensional action problem, whereas CTD3’s single actor must optimise a 14-dimensional policy — a six-fold increase in dimensionality that amplifies sensitivity to initialisation without any regularisation mechanism to counteract it. Furthermore, the distribution of CTD3 final scores is markedly bimodal: seeds that converge cluster tightly around 350–351 (identical to IPPO), while seeds that fail scatter between 300 and 338. This bimodality indicates the coexistence of two distinct attractors in the loss landscape, and suggests that early training dynamics

largely determine which basin the algorithm falls into.

9.5 Sim-to-Real Transfer

Following training and FLORIS evaluation, the centralised variant of each algorithmic family is selected for LES evaluation: CPPO, CSAC, and CTD3. This enables a direct cross-family comparison at a uniform coordination level, focusing the expensive LES campaigns on the best-performing policies. The representative seed for each algorithm is selected as

$$s^* = \arg \min_{s \in \mathcal{S}_{\text{conv}}, |\psi_i^*| < 39.5^\circ \forall i} |\mathcal{S}_s - \text{median}(\mathcal{S}_{\text{conv}})|, \quad (9.2)$$

where $\mathcal{S}_{\text{conv}}$ is the set of converged seeds and the yaw constraint $|\psi_i^*| < 39.5^\circ$ excludes policies saturating the action boundary. The selected seeds are reported in Table 9.7.

Table 9.7: Policies selected for LES evaluation. †: anti-saturation filter of Equation (9.2) active.

Farm	Algorithm	Seed s^*	$\mathcal{S}_{s^*}$
3-turbine	CPPO	18	241.79
3-turbine	CSAC	11	241.71
3-turbine	CTD3	16	240.52 †
Ablaincourt	CPPO	7	351.07
Ablaincourt	CSAC	14	350.42
Ablaincourt	CTD3	4	349.86

The † symbol flags CTD3 on the 3-turbine farm, where a subset of seeds saturated the yaw constraint — an indicator of a boundary optimum rather than a genuine wake-steering strategy.

9.5.1 Instantaneous Flow Structure

Figure 9.8 and Figure 9.9 show the representative instantaneous hub-height streamwise velocity fields from the CPPO LES campaign on the 3-turbine array and Ablaincourt wind farm, respectively. The turbulent wake structure — tip-vortex roll-up, shear-layer instabilities, and the characteristic meandering of the deflected wake — is fully resolved, highlighting the extent of the approximations introduced by the Gaussian steady-state surrogate. This figure motivates the LES campaigns: the physical mechanisms governing wake recovery in the

high-fidelity simulation are absent from the FLORIS model, and quantifying their effect on the transferred policies is the primary objective of this section.

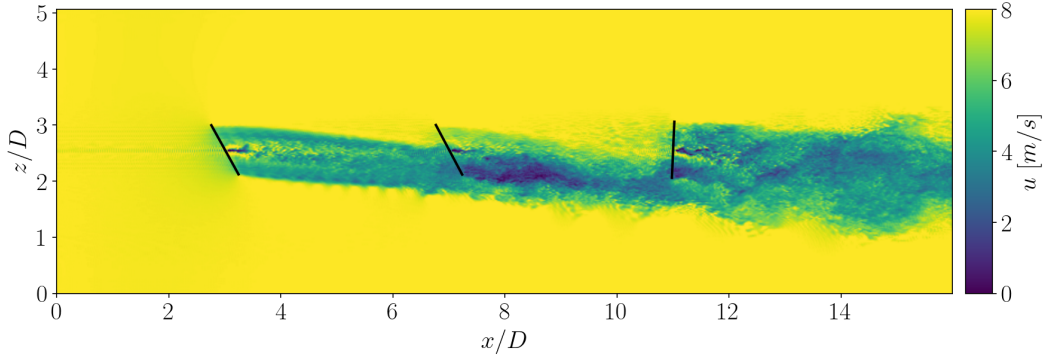


Figure 9.8: Instantaneous hub-height streamwise velocity from the CPPO LES evaluation – 3-turbine array.

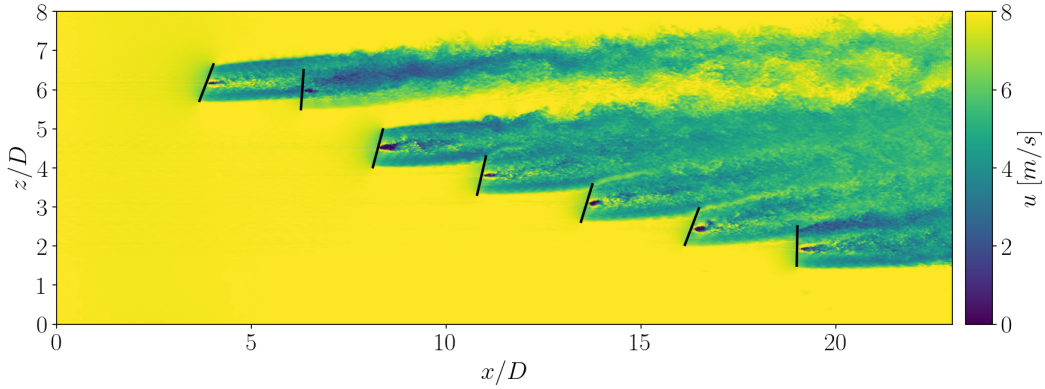


Figure 9.9: Instantaneous hub-height streamwise velocity from the CPPO LES evaluation – Ablaincourt farm.

9.5.2 Yaw Convergence and Steady-State Power

Figure 9.10 and Figure 9.12 show the yaw angle trajectories for all three policies on the 3-turbine array and the Ablaincourt farm, respectively. In both configurations, CPPO and CSAC converge rapidly and stably to yaw angles that closely reproduce the FLORIS evaluation results, confirming that the policies learned in the surrogate environment transfer with high fidelity to the high-fidelity LES framework. The agreement between surrogate and LES yaw setpoints is particularly encouraging, as it validates the use of the computationally inexpensive FLORIS model as a reliable training environment for downstream deployment. CTD3, by contrast, exhibits persistent yaw oscillations following the initial convergence transient, rather than settling to

a fixed steady-state configuration. This unsteady behaviour prevents a clean extraction of optimal setpoints and introduces uncertainty in the power output estimates. The origin of this behaviour is discussed in detail in Section 9.6.3.

Table 9.8 reports the time-averaged farm power computed during the LES regime phase, alongside the corresponding FLORIS evaluation results, providing a quantitative assessment of the sim-to-real transfer fidelity for each policy. Discrepancies between the two columns reflect the combined effect of modelling assumptions in FLORIS and the inherent unsteadiness of the LES flow field.

Table 9.8: Steady-state farm power [MW] from FLORIS evaluation and LES campaigns. LES values are time-averaged over the regime phase (steps > 50 for 3T, steps > 30 for Ablaincourt). $\Delta P = (P_{\text{LES}} - P_{\text{Floris}})/P_{\text{Floris}}$.

Farm	Algo	P_{Floris} [MW]	P_{LES} [MW]	ΔP [%]
3-turbine	CPPO	2.890	2.869	−0.7
	CSAC	2.890	2.855	−1.2
	CTD3	2.877	2.708	−5.9
Ablaincourt	CPPO	9.218	9.568	+3.8
	CSAC	9.216	9.686	+5.1
	CTD3	9.188	9.702	+5.6

3-Turbine array. The LES farm power of CPPO and CSAC agrees with FLORIS to within 0.7–1.2%, and the steady-state yaw angles differ by less than 3° on all turbines (Figure 9.10). The distribution of power among turbines does change: the second turbine receives substantially less power in the LES (CPPO: 0.41 vs 0.63 MW in FLORIS) because the turbulent wake is more intense and narrower than the Gaussian approximation predicts, reducing the velocity in the wake core. The upstream and downstream turbines compensate, leaving the farm total essentially unchanged (Figure 9.11).

CTD3 loses 5.9% in total power and converges to lower yaw angles ($\approx 20^\circ$ vs the 28° of CPPO and CSAC), indicating that the policy found a shallower local optimum in the LES environment. The reward standard deviation of CTD3 during the regime phase ($\sigma = 0.044$) is approximately three to four times that of CPPO (0.010) and CSAC (0.013), reflecting the persistent yaw oscillations visible in Figure 9.10. The mechanism responsible for this behaviour — the absence of a stable fixed point in the deterministic policy map — is analysed in Section 9.6.3.

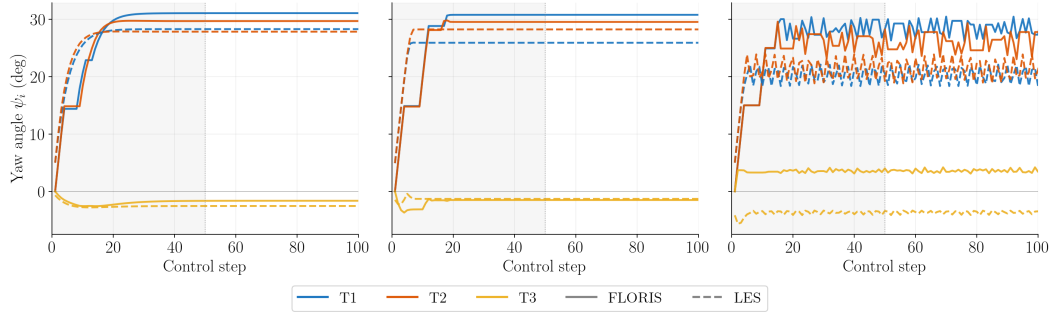


Figure 9.10: Yaw angle trajectories during evaluation on the 3-turbine array. Solid lines: FLORIS; dashed lines: LES. Each colour identifies one turbine (T1–T3). The shaded region marks the transient phase (steps ≤ 50) excluded from regime-phase statistics.

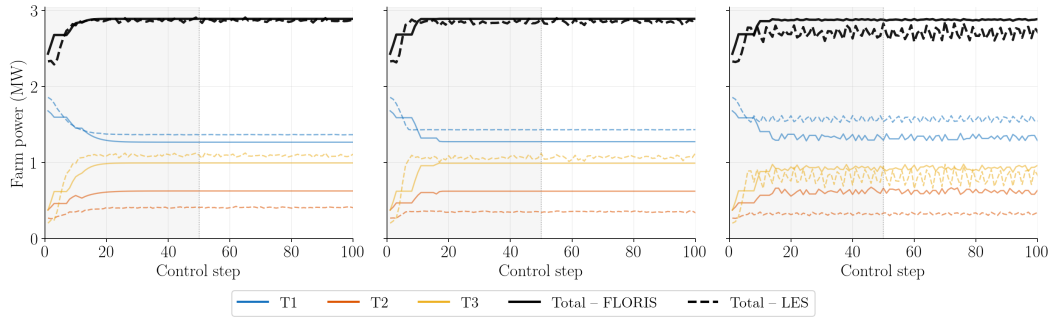


Figure 9.11: Per-turbine power (coloured lines) and total farm power (black) during evaluation on the 3-turbine array. Solid: FLORIS; dashed: LES.

Abblaincourt farm. The LES produces $\approx 5\%$ more total farm power than FLORIS for all three algorithms (Table 9.8), a systematic gap that warrants physical explanation. The Gaussian steady-state wake model represents each turbine’s velocity deficit as a fixed profile whose recovery is governed by a single empirical parameter; it does not resolve the turbulent mechanisms — tip-vortex roll-up, shear-layer instabilities, wake meandering — that actively re-energise the flow between turbines. In the LES, this turbulent entrainment accelerates wake recovery beyond what the surrogate predicts, and the effect is amplified on an irregular layout where inter-turbine corridors are not aligned: partial wakes overlap asymmetrically, creating acceleration channels that the Gaussian model cannot represent. The result is that the LES consistently delivers higher downstream turbine power (Figure 9.13), an effect that FLORIS cannot capture regardless of the controller in use.

Importantly, the yaw angles adopted by CPPO and CSAC in the LES are virtually identical to their FLORIS counterparts (differences $< 3^\circ$ on all seven turbines, Figure 9.12), confirming that the policies transfer faithfully. The $\approx 5\%$ power gap is therefore a property of the physical environment, not of the

controller. CTD3 shows one qualitative discrepancy: turbine T2 converges to $+17.9^\circ$ in the LES versus -0.5° in FLORIS, indicating that the deterministic policy settled into a different local optimum when exposed to the turbulent wake dynamics absent from the training environment.

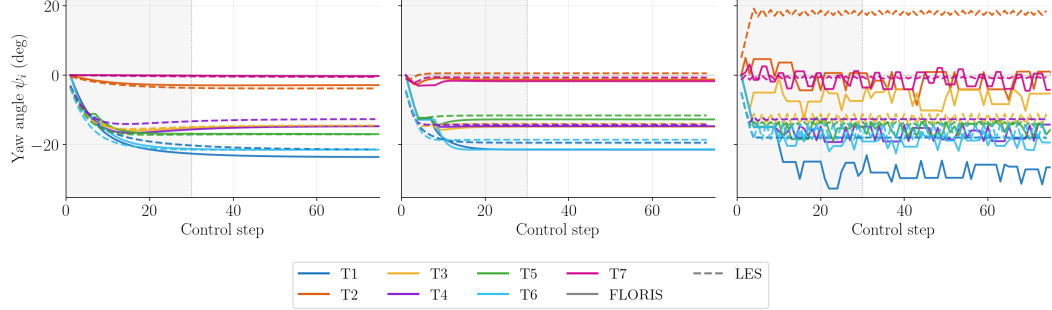


Figure 9.12: Yaw angle trajectories during evaluation on the Ablaincourt farm. Solid lines: FLORIS; dashed lines: LES. Each colour identifies one turbine (T1–T7). The shaded region marks the transient phase (steps ≤ 30).

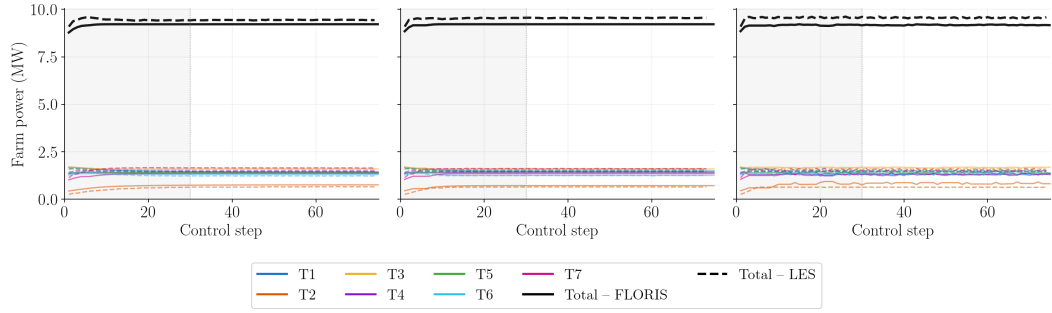


Figure 9.13: Per-turbine power (coloured lines) and total farm power (black) during evaluation on the Ablaincourt farm. Solid: FLORIS; dashed: LES.

9.5.3 Time-Averaged Flow Field

Figures 9.14 compare the time-averaged hub-height streamwise velocity from the CPPO LES campaign with the FLORIS steady-state prediction at the same yaw configuration. On the 3-turbine array the two fields agree qualitatively, with deflected wake cores consistent with the yaw angles of Figure 9.10; quantitatively, the LES wake recovers faster due to turbulent entrainment, which the Gaussian model underestimates. On the Ablaincourt farm the discrepancy is more pronounced: the irregular layout generates asymmetric partial wake overlaps and inter-turbine acceleration corridors that the Gaussian model cannot reproduce, explaining the systematic $\approx 5\%$ power surplus reported in Table 9.8.

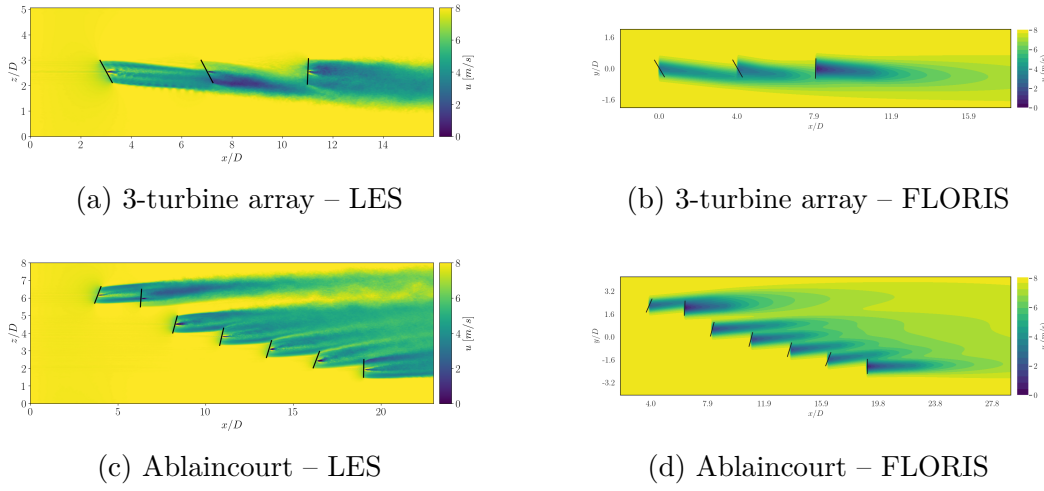


Figure 9.14: Hub-height streamwise velocity: LES time-averaged (left) vs FLORIS steady-state (right), for the CPPO policy at steady-state yaw.

9.6 Cross-Algorithm Discussion

9.6.1 Radar Summary

Figure 9.15 provides a multi-dimensional summary of each algorithm's performance profile through a set of radar charts, one per algorithmic family, shown for both the 3-turbine array (Figure 9.15a) and the Ablaincourt farm (Figure 9.15b).

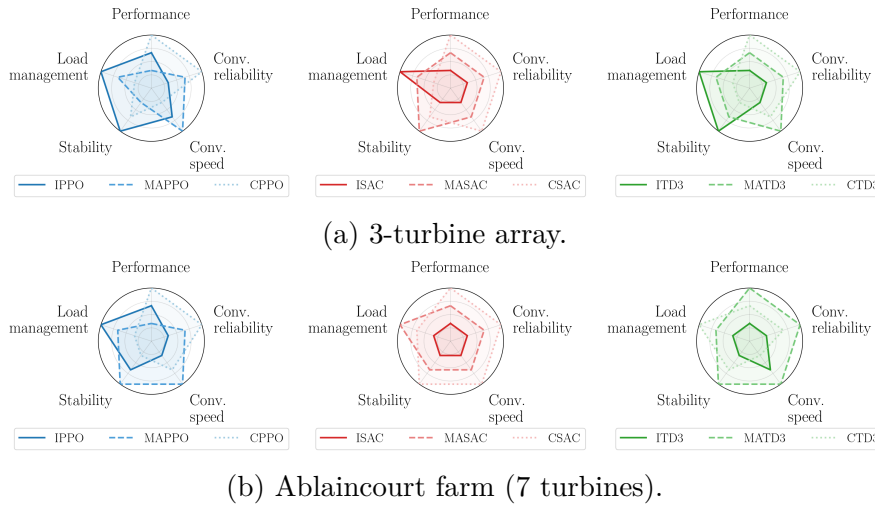


Figure 9.15: Radar charts for each algorithmic family. Axes are rank-normalised within the family. Vertices: Performance, Conv. reliability, Conv. speed, Stability, Load management.

Five axes are reported for each algorithm: final performance (mean $\bar{S}$ normalised by rank), convergence reliability (fraction of seeds converging), convergence speed (inverse median steps to convergence), training stability (inverse inter-seed standard deviation), and load management (inverse final load, normalised by rank). Each axis is rank-normalised so that the best algorithm within each family reaches the outer edge.

9.6.2 Centralisation Trade-off

A consistent pattern across all three algorithmic families is that the benefit of centralisation is algorithm-dependent:

- **PPO:** full centralisation (CPPO) is beneficial on both farms. The trust-region mechanism and the per-agent-scaled target-KL prevent destabilisation despite the large joint action space.
- **SAC:** full centralisation (CSAC) is similarly beneficial and outperforms MASAC on the larger farm. The entropy bonus fulfils the same stabilising role as the PPO clip objective, maintaining stochastic exploration in the high-dimensional action space.
- **TD3:** full centralisation (CTD3) is harmful on the larger farm relative to MATD3. Without entropy regularisation or a trust-region constraint, the centralised deterministic actor is prone to initialisation-dependent convergence failures when the policy gradient is computed over a 14-dimensional action space.
- **Design principle:** full centralisation is viable only when the optimisation algorithm provides sufficient implicit regularisation — either through stochastic gradient noise (PPO’s on-policy sampling with clip objective) or through explicit entropy incentives (SAC’s temperature term). Deterministic off-policy algorithms such as TD3 are better matched to the CTDE paradigm on complex farms, where the policy gradient remains low-dimensional.

9.6.3 Effect of the Quasi-Static Environment on TD3

The FLORIS model employed in this study is a *steady-state* wake model: given fixed wind conditions and turbine yaw angles, it returns the instantaneous farm power at equilibrium, without resolving any wake dynamics. This implies that successive environment states are nearly identical: $s' \approx s$ when the wind is constant (Wind Scenario I). As a consequence, the Bellman backup becomes approximately circular:

$$Q(s, a) \approx r + \gamma \cdot Q(s, \pi(s)), \quad (9.3)$$

and the Q-function must learn to distinguish the value of different actions from essentially the same state rather than using temporal transitions to propagate credit.

This structure is intrinsically better matched to on-policy algorithms (PPO) and entropy-regularised off-policy algorithms (SAC) than to a purely deterministic off-policy algorithm (TD3):

- **PPO** computes advantages from observed rollout data under the current policy, relying on direct reward comparisons rather than bootstrapped Q-values. The circular Bellman structure does not directly enter the PPO update.
- **SAC** augments the Bellman target with an entropy bonus that continuously incentivises action diversity, effectively performing a form of stochastic search over the action space at each state. This is well-suited to the near-bandit structure of the problem.
- **TD3** relies entirely on bootstrapped Q-values and deterministic policy gradients. The circular Bellman equation inflates Q-value estimation errors, which are then amplified by the policy gradient, leading to the observed training instabilities and initialisation sensitivity.

This structural mismatch manifests not only during training but also at deployment. The LES evaluation campaigns use strictly constant inlet conditions (no superimposed turbulence), so that the only time-varying quantity in the RL observation is the yaw state itself. Under these conditions the dynamical system reduces to the iterated map

$$\psi(t+1) = \psi(t) + \pi_{\theta}(\psi(t), U_h, \theta_0). \quad (9.4)$$

A stable fixed point of this map requires $\pi_{\theta}(\psi^*, U_h, \theta_0) = 0$ exactly — a condition that finite-episode training does not enforce. During training on 150-step episodes, the policy learns to steer towards the optimal yaw efficiently, but the reward signal provides no gradient information on whether to output *exactly zero* once the optimum is reached. SAC avoids this failure mode through the entropy term $\alpha \mathcal{H}[\pi]$, which explicitly penalises large actions and induces $\Delta\psi \rightarrow 0$ near the optimum. PPO achieves the same effect through the Gaussian policy, whose variance collapses to zero in the optimal region. TD3’s deterministic policy has no such mechanism: it continues issuing small non-zero $\Delta\psi$ commands at every step, producing the limit cycle visible in Figure 9.10.

The four-fold higher reward variance of CTD3 relative to CPPO and CSAC in the LES regime phase ($\sigma = 0.044$ vs 0.010–0.013 on the 3-turbine array) provides direct empirical evidence of this limit-cycle behaviour. The implication for deployment is practical: an algorithm that scores well in a finite-episode evaluation may still exhibit undesirable yaw chattering in a physical system.

Adding a dead-band penalty on $|\Delta\psi|$ to the reward function, or constraining the policy to output zero below a threshold, are straightforward remediations that should be considered when deploying deterministic policies in real turbines.

9.6.4 Sample Efficiency

Despite the differences in convergence reliability, all algorithms that do converge reach comparable final scores. The question then becomes how many environment interactions are required. SAC is the most sample-efficient family: convergence is achieved in approximately $7\text{--}10 \times 10^4$ interactions, compared to $\sim 10^5$ for PPO and $1\text{--}2 \times 10^5$ for TD3 (when it converges). The replay buffer reuse in SAC effectively multiplies the informational content of each environment step by the buffer sampling ratio, partially offsetting the variance of the off-policy correction. In practice, for a fixed compute budget, SAC can run approximately three independent seeds in the time that PPO runs one, making convergence reliability a secondary concern when resources are plentiful.

9.6.5 Scalability from 3 to 7 Turbines

Table 9.9 compares the convergence reliability and mean performance between the two farms, quantifying how each algorithm degrades as the problem scale increases from $M = 3$ to $M = 7$.

Table 9.9: Scalability summary. ΔConv is the change in convergence percentage from $M = 3$ to $M = 7$ (positive: improvement; negative: degradation).

Algo	ΔConv	Conv.%		Mean score	
		3T	AB	3T	AB
IPPO	0	100	100	239.8	350.4
MAPPO	0	100	100	237.9	350.1
CPPO	0	100	100	241.8	351.1
ISAC	−70	70	0	235.7	340.7
MASAC	−20	100	80	241.5	349.7
CSAC	0	100	100	241.7	350.4
ITD3	−35	35	0	233.8	317.8
MATD3	−10	65	55	236.1	350.2
CTD3	−55	85	30	237.0	338.1

The algorithms with zero degradation (IPPO, MAPPO, CPPO, CSAC) share a common property: they use on-policy training or entropy regularisation, both of which provide robustness to the non-stationarity and dimensionality growth associated with a larger farm. The algorithms with the largest degradation (ITD3 -30% , CTD3 -55% , ISAC -70%) are those where the local critic (ITD3, ISAC) or the unregularised deterministic centralised actor (CTD3) amplifies the credit-assignment problem as M grows.

9.7 Conclusions

This chapter has presented a comprehensive benchmark of nine MARL algorithms — spanning the PPO, SAC, and TD3 families under independent, CTDE, and centralised coordination paradigms — on two wind farm configurations under constant power-law inflow. The main findings are as follows.

All algorithms converge on the 3-turbine array, but TD3 shows early signs of instability. The sequential wake problem with $M = 3$ agents is tractable by every tested algorithm, with final scores within 3% of the best achievable value. However, ITD3 converges in only 35% of seeds, foreshadowing the structural failure that becomes total on the larger farm. CPPO, CSAC, and MASAC achieve the highest mean scores, consistent with a power gain of approximately 25% over the uncontrolled baseline.

Algorithms diverge dramatically on the 7-turbine Ablaincourt farm. The transition from $M = 3$ to $M = 7$ turbines reveals three distinct performance tiers. The PPO family and CSAC maintain 100% convergence and mean scores of ≈ 350 – 351 , delivering a 10% power gain over the baseline. MASAC and MATD3 achieve comparable scores when they converge (80% and 55% of seeds, respectively). ISAC, CTD3, and ITD3 suffer severe convergence degradation (0–35%) driven by architectural mismatches that cannot be addressed through hyperparameter tuning.

The CTDE paradigm provides the most robust coordination strategy for TD3. On the Ablaincourt farm, MATD3 outperforms CTD3 in both mean reward and convergence rate — the only case in the benchmark where the CTDE paradigm beats the centralised one. This inversion confirms that the benefit of centralisation is conditional on the optimisation algorithm providing sufficient regularisation to navigate the resulting high-dimensional action space.

Entropy regularisation enables reliable full centralisation. CSAC achieves 100% convergence on the 7-turbine farm despite its fully centralised

actor, while CTD3 — architecturally equivalent but without entropy regularisation — converges in only 30% of seeds. This comparison isolates the role of the entropy term as a stabiliser of high-dimensional policy gradients, an effect achieved via a different mechanism by PPO’s trust-region constraint.

FLORIS is a reliable training surrogate for PPO and SAC, but not for TD3. On the 3-turbine array, CPPO and CSAC transfer to LES with farm power agreements within 0.7–1.2% and yaw angles differing by less than 3° . On Ablaincourt, the LES delivers $\approx 5\%$ more total power than FLORIS for all three evaluated policies. This systematic gap is not a failure of the controller: the yaw angles transfer faithfully, and the additional power stems from turbulence-enhanced wake recovery that the Gaussian steady-state model cannot represent. CTD3, by contrast, exhibits qualitative discrepancies between FLORIS and LES results — a different local optimum on Ablaincourt and persistent yaw oscillations on both farms — confirming that deterministic policies trained on a steady-state surrogate are more susceptible to the mismatch between training and deployment environments.

Deterministic policies require explicit fixed-point constraints for deployment. The CTD3 LES campaigns reveal that a well-trained deterministic policy may exhibit persistent yaw chattering even under constant inflow, because finite-episode training does not guarantee a stable fixed point in the yaw iterated map. This constitutes a practical deployment concern distinct from training convergence. Adding a dead-band penalty on $|\Delta\psi|$ to the reward function, or constraining the policy output to zero below a threshold, are straightforward remediations that should be incorporated in future work targeting physical deployment of deterministic wind farm controllers.

Conclusions

This thesis set out to address a fundamental limitation of current wind energy research: the inability of standard engineering tools to capture the multiscale coupled physical processes that govern the behaviour of utility-scale wind turbines and farms. To overcome this, an LES-based numerical framework integrating Large Eddy Simulation, Computational Structural Dynamics, advanced modal analysis, and data-driven control was developed and systematically applied across five interconnected investigations. The common thread running through all of them is the demonstration that physical fidelity is not merely a quantitative refinement — it consistently reveals phenomena that are structurally absent in lower-order models and that carry direct consequences for turbine design and farm control.

Summary of Contributions

Wake dynamics under atmospheric boundary layer forcing. Coherent structures in the wake of the NREL 5MW turbine were examined under two inflow regimes: an idealised pressure-driven boundary layer and a fully developed, Coriolis-driven Ekman layer. The application of POD, DMD, and Sparsity-Promoting DMD to the LES flow fields revealed that atmospheric wind veer introduces a lateral asymmetry in wake recovery that is absent in pressure-driven simulations and that standard engineering wake models — which assume axial symmetry — are structurally incapable of reproducing. The dominant spatial modes extracted provide the basis for physics-informed Reduced-Order Models, showing that the gap between computational tractability and physical realism can be partially bridged through modal decomposition without abandoning the high-fidelity flow description.

Aeroelastic scaling from 5MW to 15MW. A fully coupled aeroelastic comparison was performed between the NREL 5MW and IEA 15MW reference turbines under identical sheared inflow, isolating the effect of rotor size on structural response and wake morphology. The results established that the torsional degree of freedom, which plays a secondary role at 5MW scale, becomes a primary driver of blade loading at 15MW scale through torsion-

bending coupling. This nonlinear feedback modifies the sectional angle of attack distribution along the blade and alters the downstream wake in ways that linearised structural models cannot capture. The implication is unambiguous: the design and certification of next-generation turbines cannot rely on tools that suppress torsional dynamics.

Wake steering and fatigue loading in a two-turbine array. The coupled framework was extended to a two-turbine in-line array of IEA 15MW machines under Coriolis-driven inflow, introducing active yaw misalignment for wake steering. The combined effect of yaw offset and atmospheric wind veer was found to be strongly asymmetric with respect to the deflection sign: positive and negative yaw angles of equal magnitude produce qualitatively different wake deflection morphologies, farm power outputs, and downstream fatigue loading distributions. This asymmetry, which arises from the directional shear introduced by the Ekman layer, cannot be captured by symmetric wake models and has direct consequences for the design of yaw control strategies — particularly for farms operating under significant wind veer.

Flow augmentation through diffuser-augmented wind turbines. Flow augmentation through Diffuser-Augmented Wind Turbines was investigated using LES coupled with the Immersed Boundary Method. The systematic evaluation of three duct geometries of progressively increasing exit area under partial-load MPPT operation demonstrated a monotonic improvement in rotor torque augmentation, reaching a power gain of +78.6 % for the largest diffuser relative to the open-rotor baseline. LES resolved the suppression of tip vortices by the duct walls, the enhanced lateral entrainment that accelerates near-wake recovery, and the shift of aerodynamic loading toward the outer blade sections — phenomena that one-dimensional actuator-disk analyses cannot represent, underscoring the necessity of high-fidelity simulation for reliable DAWT design.

Multi-agent reinforcement learning for wind farm yaw control. A Multi-Agent Reinforcement Learning framework was developed for wind farm yaw control, benchmarking nine algorithms spanning the PPO, SAC, and TD3 families under independent, CTDE, and fully centralised coordination paradigms on a canonical three-turbine array and the irregular Ablaincourt Energies farm. All PPO variants and entropy-regularised SAC (MASAC, CSAC) achieved 100 % convergence reliability and power gains of approximately 25 % on the three-turbine case and 10 % on the seven-turbine farm. Deterministic TD3 policies exhibited severe convergence degradation at scale, a structural limitation traced to the absence of a stable fixed point in the deterministic policy map. Transfer of the best policies to LES confirmed the power gains in sign; on the Ablaincourt farm, LES delivered 14–16 % more power than FLORIS due to turbulence-enhanced wake recovery absent from the Gaussian

surrogate. Blade root bending moment analysis in LES revealed an asymmetric redistribution of fatigue loading: out-of-plane moments increase at the yawed upstream turbine and decrease at downstream machines, an effect entirely absent from the FLORIS load proxy and with significant implications for life-time load assessment under active control.

Cross-Cutting Findings

Beyond the individual contributions, several conclusions emerge from reading the five studies as a whole.

Scale-dependent physics. Physical effects that are secondary at 5MW scale — blade torsion, wake asymmetry under veer, torsion-bending coupling — become primary at 15MW scale. This is not a gradual quantitative shift but a qualitative change in the dominant physics: as the industry moves towards rotor diameters exceeding 200 m, the engineering tools calibrated on smaller machines will increasingly misrepresent the very phenomena that drive fatigue loading and wake interaction.

Systematic bias of surrogate models. In every chapter where a surrogate prediction was compared against LES, the LES result consistently corrected the surrogate in the same direction — smaller power gains, larger structural costs, and more complex wake morphology. This is not a deficiency specific to any particular model; it is a structural property of steady-state, linearised, and axisymmetric formulations when applied to problems involving turbulent inflow, atmospheric shear, and aeroelastic coupling.

The power–fatigue trade-off. The yaw offset that maximises farm power is never the offset that minimises fatigue loading. This behaviour appears clearly in both the farm aeroelastic study and the RL evaluation, and it cannot be resolved within a single-objective optimisation framework — any practically deployable control strategy must account for this conflict explicitly, either through multi-objective reward formulations or through hard constraints on allowable loading.

Computational tractability of the integrated framework. The coupled framework established in this thesis — LES with ALM/ADM rotor models, modal beam structural solver, and MARL agents communicating via SmartRedis — represents one of the few examples in the open literature of data-driven wind farm control evaluated in a fully aeroelastic, turbulence-resolving environment, establishing that such integration is computationally tractable on modern HPC systems.

Limitations

Wind conditions and meteorological variability. In the RL chapter, all training and evaluation were conducted under Wind Scenario I — a stationary, single-direction inflow — which does not reflect the meteorological variability of operational wind farms.

Rotor representation in the RL study. The ADM rotor representation adopted in the LES evaluation, while computationally efficient, does not resolve the blade-level aerodynamics captured by the ALM used in the aeroelastic chapters; the blade root bending moments are therefore modelled at a lower level of fidelity than in the structural studies.

Atmospheric stratification. All simulations were performed under neutral atmospheric stratification, neglecting the effects of thermal stability that can significantly alter turbulence structure and wake recovery in real boundary layers.

Terrain effects. The Ablaincourt farm was evaluated with an idealised flat terrain, without the orographic effects present at the actual site.

Future Perspectives

Extension of the MARL framework. The benchmark conducted in this thesis establishes that PPO and entropy-regularised SAC variants provide the most robust combination of convergence reliability and scalability for farm-level yaw control, while deterministic TD3 policies require explicit fixed-point constraints to avoid persistent yaw chattering at deployment. The most immediate continuation is the extension to Wind Scenario II, subjecting the trained policies to realistic meteorological variability (sampled wind speed and direction), and the incorporation of axial induction control alongside yaw to widen the optimisation action space.

Meteorological variability and transient wind conditions. A parallel priority is the extension to Wind Scenario II, in which free-stream velocity and direction are sampled from a Weibull–Normal wind rose at episode initialisation, exposing trained policies to realistic meteorological variability and allowing the score metric to incorporate direction-weighted power gains. The characterisation of the closed-loop system response to abrupt wind shifts — direction changes and velocity ramps occurring within an episode — is equally important before any real-world deployment can be considered.

Load-aware reward formulations. On the reward side, the structural findings of the LES evaluation motivate load-aware formulations that directly penalise M_{op} and M_{ip} during surrogate training, rather than relying on the turbulence intensity proxy currently used in FLORIS.

Physics-informed surrogate environments. At the medium-term horizon, the physics-informed ROMs derived from the Ekman layer wake in the first study offer a natural path toward surrogate environments that are more faithful than FLORIS while remaining orders of magnitude cheaper than full LES. Using these ROMs as training environments for MARL agents would reduce the sim-to-real gap without incurring the full computational cost of LES rollouts.

Extension of the aeroelastic framework. The farm-level aeroelastic framework verified for the two-turbine IEA 15MW array should be extended to larger configurations under Coriolis-driven inflow, where the interaction between multiple deflected wakes and the Ekman-layer veer produces multi-body aeroelastic effects that have not yet been characterised at this level of physical resolution.

Diffuser-augmented wind turbine arrays. The DAWT analysis — currently limited to isolated duct geometries — should be extended to array configurations, where diffuser-to-diffuser interference and wake recovery between consecutive augmented turbines remain open problems.

Physics-informed digital twins. In the longer term, at the intersection of the computational framework developed here and operational wind energy lies the concept of a physics-informed digital twin: a system in which SCADA measurements from an operating farm are assimilated into a reduced-order model — derived from the LES database through modal decomposition — to continuously update the farm state and recalibrate the control policy online. The building blocks for such a system — LES-based flow solutions, physically grounded ROMs, and data-driven MARL policies capable of operating in real time — have all been established in this thesis. Their integration into a unified, field-deployable framework represents the natural long-term trajectory of this line of research.

Appendix A

CPU/GPU Scalability

Porting and GPU Acceleration of the LES Solver

This appendix describes the process of porting the LES solver from a CPU-based implementation to a GPU-accelerated one, detailing the programming model adopted, the optimizations carried out, and the performance gains achieved on the high-performance computing systems used in this work.

Introduction and Architectural Context

Large-Eddy Simulation is among the most computationally demanding approaches in turbulence research. Even with optimal parallelisation on multi-core CPU clusters, the wall-clock time required for high-resolution runs can span weeks, severely limiting the parameter space that can be explored within a research project.

In recent years, the High Performance Computing (HPC) landscape has undergone a significant architectural shift, transitioning from purely multi-core architectures (CPUs) to heterogeneous architectures dominated by hardware accelerators (GPUs). Modern GPU accelerators offer peak floating-point throughputs and memory bandwidths that far exceed those of conventional CPU nodes, and they have become the dominant hardware in the latest generations of leadership-class supercomputers. Porting the solver to GPUs was therefore the logical next step, targeting a reduction in time-to-solution of approximately one order of magnitude and enabling the use of larger meshes.

The accelerated code was developed, tested, and verified on various international-level HPC infrastructures:

- **Leonardo** (CINECA, Italy) [198] – NVIDIA A100 80 GB SXM4 GPUs, used as the primary platform for scalability studies.
- **Lonestar6** (TACC, USA) [199] – NVIDIA A100 40 GB PCIe GPUs.

- **Juno** (University of Texas at Dallas, USA) [200] – NVIDIA GPU cluster used for development and verification tests.
- **Ganymede2** (University of Texas at Dallas, USA) [200] – used for additional performance benchmarks.

Programming Model and Algorithmic Restructuring

The GPU port is based on a combination of **CUDA** and **OpenACC**, retaining the existing MPI layer for distributed-memory parallelism. OpenACC compiler directives (`#pragma acc`) were used to offload structured loop nests — such as the convection, diffusion, and forcing terms — with minimal source-code changes. Performance-critical kernels requiring fine-grained control over thread organisation and shared-memory usage were implemented directly in CUDA C/C++. The two approaches are fully integrated within the same codebase: OpenACC regions are compiled by the NVIDIA HPC SDK, which generates PTX code equivalent to hand-written CUDA.

To maximize the efficiency of the High Bandwidth Memory (HBM), memory layouts were reorganized from an *Array of Structures* (AoS) to a *Structure of Arrays* (SoA) approach, ensuring coalesced memory access by the GPU threads. The pressure Poisson equation — typically the computational bottleneck due to its elliptic, globally coupled nature — was offloaded to the **cuFFT** library, substantially reducing computation times compared to traditional iterative CPU solvers.

Profiling and Numerical Verification

Kernel-level profiling was carried out using **NVIDIA Nsight Systems** and **NVIDIA Nsight Compute** to identify memory-bandwidth bottlenecks, suboptimal occupancy, and instruction-level inefficiencies (Figure A.1). Key metrics monitored included achieved memory bandwidth relative to the hardware roof, SM occupancy, and warp efficiency. Iterative optimisation cycles guided by Nsight profiling substantially reduced the execution time of the dominant kernels relative to the initial ported version. From a numerical standpoint, the GPU results were verified against the original CPU version, confirming that deviations are at the level of machine precision with no physically relevant differences in the resolved flow fields.

Performance and Scalability

Performance was quantified across three mesh sizes: Coarse ($321 \times 129 \times 129$), Fine ($641 \times 257 \times 257$), and Ultrafine ($1281 \times 513 \times 513$). Both strong and weak scaling tests were conducted on the Leonardo cluster.

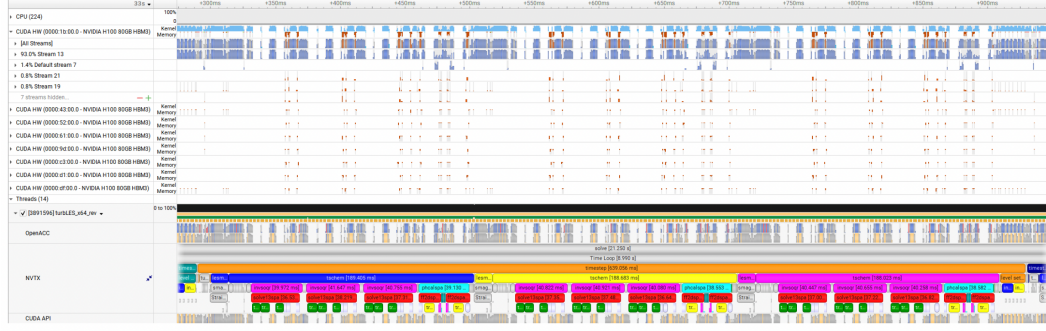
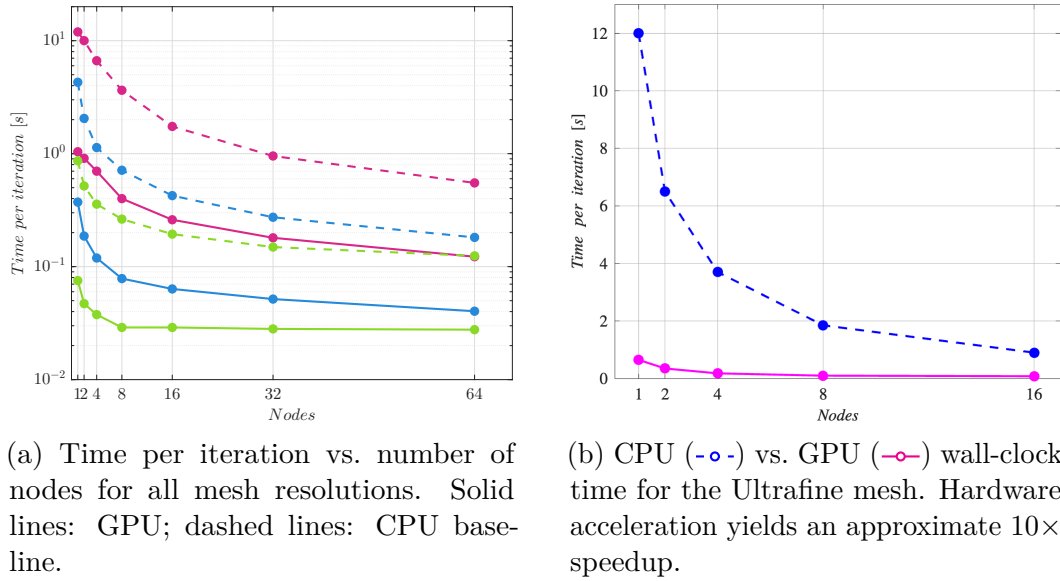


Figure A.1: Representative snapshot of the NVIDIA Nsight Systems timeline, highlighting CUDA kernel execution, OpenACC regions, and memory transfers.

Figure A.2 shows the time per iteration as a function of the number of nodes (left) and a direct CPU-vs-GPU comparison for the Ultrafine mesh (right). GPU acceleration yields a speedup of approximately one order of magnitude across all resolutions, enabling LES simulations on domains and at resolutions that would otherwise be prohibitive.



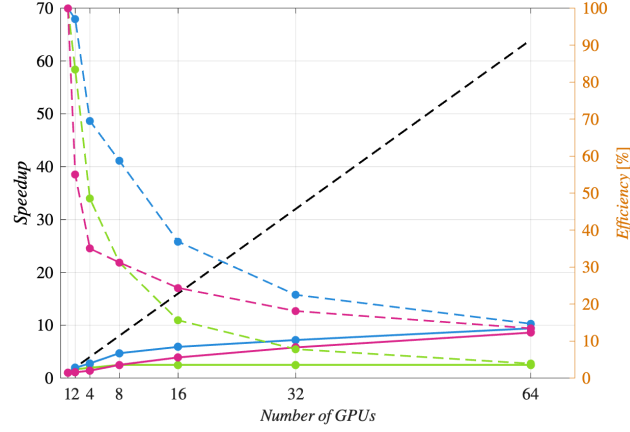
(a) Time per iteration vs. number of nodes for all mesh resolutions. Solid lines: GPU; dashed lines: CPU baseline.

(b) CPU (-o-) vs. GPU (-o-) wall-clock time for the Ultrafine mesh. Hardware acceleration yields an approximate 10× speedup.

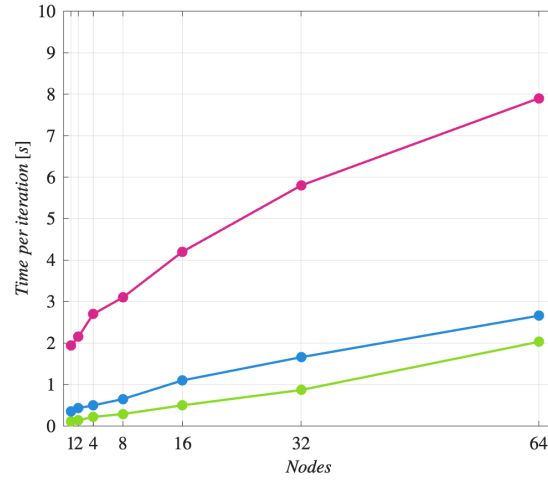
Figure A.2: Strong scaling: time per iteration as a function of node count for the **Coarse**, **Fine**, and **Ultrafine** meshes.

Strong Scaling. Figure A.3(a) details speedup and parallel efficiency. As expected from Amdahl's Law, efficiency degrades at high GPU counts, particularly for the Coarse mesh: as the local sub-domain shrinks, the computational load becomes insufficient to saturate the streaming multiprocessors, and MPI halo exchanges begin to dominate. The Ultrafine mesh maintains a substantially higher efficiency profile throughout.

Weak Scaling. Figure A.3(b) reports the weak scaling behaviour, where the problem size per GPU is kept approximately constant. The slight upward trend is a known characteristic of incompressible flow solvers, driven by the global *all-to-all* communications required by the distributed cuFFT pressure solver, which introduce a logarithmic scaling penalty that cannot be completely hidden.



(a) Speedup (solid, left axis) and parallel efficiency (dashed, right axis). The black dashed line is the ideal linear speedup.



(b) Weak scaling: time per iteration with fixed local domain size per GPU.

Figure A.3: Parallel scalability of the GPU solver on the Leonardo cluster for the **Coarse**, **Fine**, and **Ultrafine** meshes.

Appendix B

SmartRedis Ecosystem

B.1 Overview

Coupling high-fidelity physics solvers with machine learning workflows presents a significant software engineering challenge: numerical simulations are typically implemented in compiled languages like Fortran or C++, while modern RL frameworks operate almost exclusively in Python. Connecting these two environments at runtime, without introducing severe communication bottlenecks or requiring intrusive modifications to the solver codebase, necessitates a dedicated middleware layer.

SmartRedis [201] is an open-source client library developed by Hewlett Packard Enterprise (HPE) for this purpose on HPC systems. It acts as the communication interface for a shared, in-memory database architecture, handling runtime data exchange between heterogeneous processes such as simulation codes, ML model servers, and training scripts.

B.2 Architectural Design

The core of the infrastructure is an in-memory key-value database based on Redis [202], extended with the RedisAI module for on-database model inference. All processes communicate exclusively through this database via the SmartRedis client library, which provides native bindings for C, C++, Fortran, and Python. This architecture completely decouples the CFD solver from the RL framework: both interact only with the shared database through a unified API. Figure B.1 illustrates the communication loop adopted in this thesis.

B.3 Client API and Key Primitives

Tensor exchange. `put_tensor` and `get_tensor` transmit multi-dimensional arrays. Instantaneous rotor quantities (e.g., shaft power P_i and wake velocity

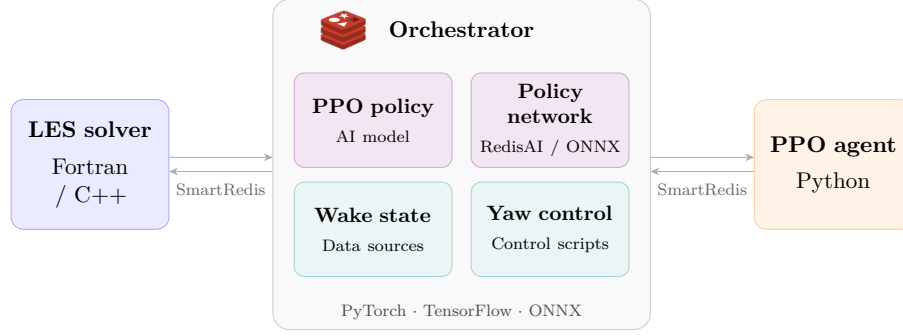


Figure B.1: Communication architecture between the LES solver and the PPO agent via the SmartRedis in-memory database.

profiles) are pushed to the database at every control step; the Python agent retrieves them, formats the observation vector, computes the policy, and writes the resulting yaw actions back through the same mechanism.

Dataset aggregation. The `DataSet` abstraction groups multiple tensors and metadata under a single logical key, transmitting structured observation dictionaries as atomic units and preventing partial reads.

On-database inference. Pre-trained networks (TorchScript or ONNX) can be loaded via `set_model` and executed in-place via `run_model`, minimising data transfer latency during frequent policy queries.

B.4 Integration with the RL Training Pipeline

During pre-training on the FLORIS surrogate (Chapter 9), SmartRedis ensures a consistent observation-action interface even though no solver coupling is required. During LES fine-tuning, it serves as the exclusive communication link: at each control step t , the solver writes $\mathbf{o}_t$ to the database; the agent retrieves it, queries $\pi_\theta(\mathbf{a}_t \mid \mathbf{o}_t)$, and writes back the yaw action vector $\mathbf{a}_t = \{\gamma_i\}_{i=1}^N$. The solver then updates the actuator boundary conditions and advances the simulation, requiring only targeted API calls at specific points in the time-stepping loop.

Appendix C

FLORIS and the Gaussian Wake Model

C.1 Overview

FLORIS (FLOw Redirection and Induction in Steady State) is an open-source engineering framework developed by NREL [100]. Instead of solving the Navier–Stokes equations, FLORIS employs analytical wake models to evaluate wind farm flow fields in milliseconds, making it an ideal surrogate environment for pre-training RL agents before transitioning to computationally expensive LES evaluations. This work relies on the Gaussian wake model of Bastankhah and Porté-Agel [203], which provides a reliable far-wake velocity deficit approximation while maintaining a differentiable structure suitable for optimization.

C.2 The Gaussian Wake Model

Velocity Deficit

The normalized streamwise velocity deficit $\Delta u/U_\infty$ is described as a self-similar Gaussian profile in the lateral (y) and vertical (z) directions:

$$\frac{\Delta u(x, y, z)}{U_\infty} = \left(1 - \sqrt{1 - \frac{C_T}{8\sigma_y\sigma_z/D^2}}\right) \exp\left(-\frac{y^2}{2\sigma_y^2} - \frac{(z - z_h)^2}{2\sigma_z^2}\right), \quad (\text{C.1})$$

where U_∞ is the freestream velocity, C_T the thrust coefficient, D the rotor diameter, z_h the hub height, and σ_y, σ_z the lateral and vertical wake widths. These expand linearly with the downstream distance x :

$$\sigma_y(x) = k_y(x - x_0) + \sigma_{y,0}, \quad \sigma_z(x) = k_z(x - x_0) + \sigma_{z,0}. \quad (\text{C.2})$$

The expansion coefficients satisfy $k_y = k_z = a_s I_0 + b_s$, where I_0 is the ambient turbulence intensity and a_s, b_s are calibration constants. The near-wake origin x_0 and the initial widths $\sigma_{y,0}, \sigma_{z,0}$ follow from momentum conservation at the rotor plane [203].

Wake Deflection under Yaw Misalignment

When an upstream turbine operates at yaw angle γ , the lateral thrust component deflects the wake trajectory. The lateral centerline displacement $\delta(x)$ is:

$$\delta(x) = \frac{\theta_{c,0}}{14.7} \sqrt{\frac{\cos \gamma}{k_y k_z C_T}} \left(2.9 + 1.3 \sqrt{1 - C_T} - C_T \right) * \ln \left[\frac{(1.6 + \sqrt{C_T})(M - \sqrt{C_T})}{(1.6 - \sqrt{C_T})(M + \sqrt{C_T})} \right], \quad (\text{C.3})$$

where $\theta_{c,0} = 0.3 \gamma C_T \cos \gamma / \cos(\gamma/2)$ is the initial cross-stream velocity component and $M = 1.6 \sqrt{8 \sigma_y \sigma_z / (D^2 \cos \gamma)}$. This mechanism allows the RL agents to redirect wakes laterally, mitigating aerodynamic interference on downstream turbines. For multi-turbine setups, FLORIS superimposes the velocity deficits of all upstream turbines using a standard linear superposition method [204].

C.3 Limitations of the FLORIS Surrogate

While computationally efficient, FLORIS relies on simplifying assumptions that limit its physical fidelity:

- **Steady-state formulation:** transient phenomena such as wake meandering and dynamic turbulent fluctuations are not resolved.
- **Simplified atmospheric boundary layer:** the model assumes uniform inflow and does not account for complex atmospheric forcing, such as the Coriolis-driven wind veer characterizing the Ekman layer used in the LES simulations.
- **Absence of aeroelastic coupling:** turbines are modelled as rigid actuator disks via static C_T and C_P look-up tables; the dynamic feedback between blade deformation and rotor loading is neglected.

These limitations make the subsequent fine-tuning step in the high-fidelity LES environment (via SmartRedis, Appendix B) essential for bridging the sim-to-real fidelity gap.

Appendix D

OpenFAST Framework

D.1 Overview

OpenFAST [205] is an open-source, modular multi-physics engineering tool developed by NREL for the aeroelastic simulation of wind turbines, and serves as the de facto reference standard in the wind energy community. Its modular architecture allows individual physics modules to be activated or replaced independently, enabling systematic comparisons between formulations of different fidelity. In this thesis, it is employed as the verification reference for the aeroelastic framework described in Chapter 4, relying on two structural modules — **ElastoDyn** and **BeamDyn** — both driven by the **AeroDyn** [206] aerodynamic module.

D.2 AeroDyn: Aerodynamic Module

AeroDyn solves rotor aerodynamics via Blade-Element/Momentum (BEM) theory, augmented with Prandtl tip/hub loss corrections, the Glauert correction for the turbulent wake state ($a > 0.4$), a dynamic inflow model (DBEMT [207]), and a skewed wake correction for yaw misalignment. Sectional forces are computed from tabulated polars $C_l(\alpha)$, $C_d(\alpha)$, with dynamic stall handled via a Beddoes–Leishman formulation. Since BEM assumes azimuthal inflow uniformity, it cannot resolve the three-dimensional turbulent structures of the atmospheric boundary layer or the blade–wake interaction — a fundamental limitation with respect to the high-fidelity LES approach adopted in this thesis.

D.3 ElastoDyn: Modal Structural Solver

ElastoDyn [205] models the turbine as a system of interconnected rigid and flexible bodies, where blade elasticity is expressed as a truncated linear superposition of pre-computed mode shapes. The generalized modal coordinates

$q_k(t)$ satisfy:

$$M_{kj} \ddot{q}_j + C_{kj} \dot{q}_j + K_{kj} q_j = Q_k^{\text{aero}} + Q_k^{\text{grav}}, \quad (\text{D.1})$$

retaining by default the first two flapwise and first edgewise modes. Its main limitations are geometric linearity (mode shapes are fixed on the undeformed geometry), complete absence of a torsional degree of freedom — a significant gap for flexible multi-megawatt blades where bend-twist coupling substantially modifies the local angle of attack — and truncation errors when higher-frequency dynamics are excited by turbulent inflow.

D.4 BeamDyn: Geometrically Exact Beam

BeamDyn [208] implements the geometrically exact beam theory (GEBT) of Hodges [209], derived from Hamilton’s principle applied to a spatial Cosserat rod. The constitutive behaviour is governed by a fully populated 6×6 cross-sectional stiffness matrix:

$$\begin{pmatrix} \mathbf{F} \\ \mathbf{M} \end{pmatrix} = \mathbf{K}_{\text{cs}}(s) \begin{pmatrix} \boldsymbol{\varepsilon} \\ \boldsymbol{\kappa} \end{pmatrix}, \quad (\text{D.2})$$

which captures bend-twist coupling from anisotropic composite laminates. The blade is discretized via a Legendre Spectral Finite Element Method on Gauss–Legendre–Lobatto points and integrated in time with the generalized- α scheme. Relative to ElastoDyn, BeamDyn handles arbitrarily large deflections and rotations exactly and fully resolves the torsional degree of freedom, at the cost of increased computational expense from non-linear solver iterations.

D.5 Summary

The two structural modules address complementary modelling regimes. ElastoDyn offers a computationally efficient modal description well suited to moderate deflection regimes, but its geometric linearity and the absence of a torsional degree of freedom limit its accuracy for flexible multi-megawatt blades. BeamDyn removes both constraints through a geometrically exact formulation with a fully populated cross-sectional stiffness matrix, at the cost of increased computational expense.

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