

Analysis and Application of Lidar Inflow Measurements for Floating Offshore Wind Turbines

A thesis accepted by the Faculty of Aerospace Engineering and Geodesy of the
University of Stuttgart in partial fulfillment of the requirements for the degree of
Doctor of Engineering Sciences (Dr.-Ing.)

by

Moritz Johann Gräfe

born in Frankfurt am Main, Germany

Main referee:	Prof. Dr. Po Wen Cheng
Co-referees:	Prof. Dr. Sandrine Aubrun Prof. Dr.-Ing. Andrea Beck
Date of defense:	19.03.2025

Stuttgart Wind Energy at the Institute of Aircraft Design
University of Stuttgart
2025

© **Moritz Johann Gräfe**, 2025

This dissertation is licensed under the **Creative Commons Attribution 4.0 International License (CC BY 4.0)**.

This license permits use, distribution, and reproduction in any medium, provided the original author is credited.

Full license text: <https://creativecommons.org/licenses/by/4.0/>

Contents

Abbreviations	vii
List of Symbols	ix
Abstract	xiii
Kurzfassung	xvii
1 Introduction	1
1.1 Motivation	1
1.2 Related Work	2
1.2.1 Motion Influence and Uncertainty Quantification . .	2
1.2.2 Data-driven Virtual Sensors	7
1.3 Research Objectives and Methodology	10
1.4 Structure of the Thesis	12
2 Background	15
2.1 Wind	15
2.1.1 Vertical Wind Profiles	17
2.1.2 Turbulence	17
2.2 Floating Offshore Wind Turbines	19
2.2.1 Floater Types	19
2.2.2 Mooring Lines	22
2.2.3 Aeroelastic Wind Turbine Simulations	24
2.3 Wind Lidars	25
2.3.1 Wind field reconstruction	34
2.3.2 Lidar Simulations	35

2.3.3	Uncertainty Quantification	36
2.4	Virtual Sensors	38
2.4.1	Artificial Neural Networks	39
2.4.2	Damage Equivalent Loads	43
2.4.3	Performance Metrics	44
3	Simulation Environment and FOWT models	47
3.1	Lidar Simulation Requirements	47
3.2	Numerical Lidar Simulation	49
3.3	FOWT models	53
3.3.1	FLOATGEN	54
3.3.2	WindCrete	54
3.3.3	UMaine VoltturnUS-S	54
3.4	Analytical Lidar Simulation	56
4	Quantification and Correction of Motion Influence for Nacelle-based Lidar Measurements	61
4.1	Analysis of Measurement Campaign	62
4.2	Methodology	65
4.2.1	Analytical estimation of uncertainty in wind field characteristics	66
4.2.2	Uncertainty Propagation to Horizontal Wind Speed	67
4.2.3	Analytic Estimation of Bias	68
4.3	Uncertainty and Bias Quantification	70
4.3.1	Uncertainty Quantification	74
4.3.2	Bias Quantification	78
4.4	Correction Approaches	82
4.4.1	Model based Correction	84
4.4.2	Frequency Filtering	86
4.5	Evaluation of Correction Approaches	87
4.5.1	Model based Correction	88
4.5.2	Frequency Filtering	92
4.6	Chapter Discussion	96
5	Lidar Assisted Virtual Load Sensors for Mooring Lines	99
5.1	Methodology	100
5.1.1	Virtual Load Sensor Models	101

5.1.2	Feature Selection	106
5.1.3	Hyperparameter Tuning	108
5.2	Simulation Database	109
5.2.1	Lidar Configuration	109
5.2.2	Atmospheric Conditions	111
5.2.3	Measurement Noise	111
5.2.4	Creation of Training Database	112
5.3	Fairlead Tension Time Series Predictions	115
5.4	Fairlead Tension DEL Prediction	118
5.4.1	Prediction without Lidar Measurements	118
5.4.2	Predictions using Lidar Measurements	129
5.5	Chapter Discussion	135
6	Data-Driven Forecasting of FOWT Dynamics and Load Time Series	139
6.1	Methodology	140
6.1.1	Forecasting Model	141
6.1.2	Lidar Pattern and Ranges	146
6.2	Evaluation of Forecasting Accuracy	147
6.3	Chapter Discussion	151
7	Conclusions	153
7.1	Simulation Environment	153
7.2	Motion Influence and Correction Approaches	154
7.3	Virtual Sensors using Motion and Lidar Measurements	155
7.4	Recommendations for Future Work	158
A	Calculation Details	161
A.1	Uncertainty Estimation	161
A.2	Code Availability	162
A.3	Publications not included in this Thesis	163
	Bibliography	165
	Curriculum Vitae	177

Abbreviations

APE	Absolute percentage error
BEM	Blade element momentum theory
CNN	Convolutional neural network
DEL	Damage equivalent load
DOF	Degree of freedom
FC	Fully connected
FFT	Fast Fourier transform
FOWT	Floating offshore wind turbine
GNSS	Global navigation satellite system
GUM	Guide to the Expression of Uncertainty
IEC	International Electrotechnical Commission
IFB	Institut für Flugzeugbau (Institute of Aircraft Design)
IMU	Inertial measurement unit
lidar	light detection and ranging
LOS	Line of sight
LSTM	Long short term memory
MAE	Mean absolute error
ME	Mean error
NcIMUTV	Nacelle inertial measurement unit translational velocity
NREL	National Renewable Energy Laboratory
O&M	Operation & Maintenance
PSD	Power spectral density
PtfmPitch	Platform motion pitch

PtfmRoll	Platform motion roll
PtfmYaw	Platform motion yaw
ReLu	Rectified linear unit
RMSE	Root mean squared error
RMSEN	normalized root mean squared error
SCADA	Supervisory Control and Data Acquisition
Seq2One	Sequence-to-One
Seq2Seq	Sequence-to-Sequence
SNR	Signal to noise ratio
SWE	Stuttgart Wind Energy
TI	Turbulence intensity
TwrTpTD	Tower top translational displacement
ViConDAR	Virtual Constrained turbulence and liDAR measurements
WS	Wind speed

List of Symbols

Greek letters

α	Wind shear power law coefficient
α_{rec}	Lidar reconstructed wind shear power law coefficient
β	Floater pitch angle
β_{mean}	Floater mean pitch angle
Δ	Difference
γ_c	spatial correlation of velocity
γ	Floater roll angle
Λ	Turbulence length scale parameter
λ_L	Laser wave length
ϕ	Azimuth angle
φ	Wind direction
ψ	Floater yaw angle
σ	Standard deviation
σ_k	Standard deviation of wind field velocity component
θ	Elevation Angle

Latin letters

a	Deflection
A	Amplitude
c	Speed of light
D	Damage
d_{rotor}	Rotor diameter
f	Frequency
f_{center}	Center frequency of filter
f_D	Doppler frequency

f_L	Laser frequency
$f_{pass,lower}$	Lower passing frequency of filter
$f_{pass,upper}$	Upper passing frequency of filter
H	Dynamic measurement height
h_{lidar}	Height of lidar mounting position
H_s	Significant wave height
k	Mean deflection
L_k	Integral length scale
L_u	Coherence scale parameter
m	Wöhler exponent
N_{ref}	Number of reference cycles
r	Distance, correlation coefficient
R	Rotation matrix
S	Load amplitude
S_k	Frequency spectrum of velocity components
t	Time
T	Period
T_F	Fairlead tension force
T_p	Wave peak period
u	u-component of wind vector
U	Uncertainty
u_{rec}	reference wind speed
v	v-component of wind vector
$v_{corr.}$	Correction value
V_{hub}	Wind speed at hub height
v_{los}	Line of sight velocity
w	w-component of wind vector, weight
x	longitudinal coordinate, longitudinal displacement
x_L	longitudinal coordinate, longitudinal displacement
$\mathbf{x}_{vel}$	Translational velocity vector
y	lateral coordinate, output
Y	Target
Y_{pred}	Prediction
z	vertical coordinate, vertical displacement
z_{heave}	Heave elevation
z_{ref}	reference height above ground

Subscripts

$(\cdot)_a$	denotes deflection
$(\cdot)_\beta$	denotes pitch
$(\cdot)_i$	denotes running variable i
$(\cdot)_I$	denotes inertial coordinate system
$(\cdot)_j$	denotes running variable j
$(\cdot)_L$	denotes lidar coordinate system
$(\cdot)_{LOS}$	denotes line of sight
$(\cdot)_m$	denotes mounbting position
$(\cdot)_{mean}$	denotes mean
$(\cdot)_n$	denotes normalized
$(\cdot)_p$	denotes position
$(\cdot)_\psi$	denotes yaw
$(\cdot)_{rec}$	denotes reconstructed
$(\cdot)_{ref}$	denotes reference
$(\cdot)_{trans}$	denotes translation
$(\cdot)_{vel}$	denotes velocity

Abstract

Inflow wind field measurements from nacelle-based lidar systems offer great potential for different applications, including turbine and farm control, load validation, power performance measurements, and load monitoring. On floating offshore wind turbines (FOWT) nacelle-based lidar measurements are affected by the dynamic behavior of the floating foundations. Therefore, the effects on lidar wind speed measurements induced by floater dynamics must be understood and considered in the data application.

In this thesis, both topics are addressed using simulation-based approaches. First, two simulation environments for generating virtual lidar measurements considering the dynamics of the FOWT are created. The analytical uncertainty model of nacelle-based lidar measurements is developed explicitly as the basis for uncertainty estimation using the GUM methodology, which requires an analytical description of the measurement. Additionally, a numerical simulation environment for lidar measurements under motion influence is developed. This simulation environment is based on the aeroelastic wind turbine simulation code openFAST and an adapted version of the numerical lidar simulation tool ViConDAR. It uses simulated turbine responses along with synthetic turbulent wind fields for the simulation of lidar measurements considering the turbulent nature of real wind fields.

Further, the impact of floater movements on wind speed measurements from forward-looking nacelle-based lidar systems installed on FOWTs is investi-

gated. Approaches for correcting motion-induced effects are proposed. It is found that the uncertainty of lidar wind speed estimates is mainly caused by the fore-aft motion of the lidar, resulting from the pitch displacement of the floater. The bias of 10 min mean wind speed estimates is primarily influenced by the mean pitch angle of the floater and the pitch amplitude. Motion-induced biases in time-averaged lidar wind speed measurements are corrected with a model-based approach employing the developed analytical model for uncertainty and bias quantification. Testing the approach with simulated dynamics from two different FOWT concepts shows good results with remaining mean errors below 0.1 ms^{-1} . A frequency filter to correct fluctuations caused by floater pitch motions is used to correct motion-induced fluctuation in instantaneous measurements. The correction approach's performance depends on the pitch period and amplitude of the FOWT design. The second part of the thesis investigates a methodology for integrating lidar measurements in virtual sensors. Mooring line loads are intrinsically linked to the dynamics and the position of the floater. Wind speed measurements obtained via nacelle-based lidar on FOWTs are influenced inherently by the platform's dynamics, notably the rotational pitch displacement and surge displacement of the floater. Consequently, the lidar wind speed data indirectly contains the dynamic behavior of the floater, which, in turn, governs the fairlead loads. This thesis leverages lidar-measured Line of Sight (LOS) wind speeds to estimate mooring line tensions. Training data for the model is generated using the numerical lidar simulation environment developed as part of the thesis. The fairlead tension time series and damage equivalent loads (DELs) are predicted using different architectures of artificial neural networks. Results indicate that fairlead tension time series and DELs can be accurately estimated from floater motion time series. Further, it was found that lidar LOS measurements do not improve time series or DEL predictions if motion measurements are available. However, using lidar measurements as model inputs for DEL predictions leads to similar accuracies as using

displacement measurements of the floater as inputs.

Further, this thesis uses a data-driven approach that incorporates onboard sensor measurements and lidar inflow data to forecast the fairlead tension and floater dynamics time series of FOWTs. A data-driven forecasting methodology using the same data set as used for the prediction of time series and DELS is investigated. Utilizing a Long Short-Term Memory (LSTM) sequence-to-sequence model, forecasts of fairlead tension, surge, and pitch for time series are made for forecasting horizons of 20, 40, and 60 seconds, considering lidar ranges from 100 m to 500 m. The results indicate that incorporating lidar inflow measurements significantly improves the forecasts of fairlead tensions and platform motions.

Kurzfassung

Messungen der Anströmung von Windkraftanlagen, die von gondelbasierten Lidar-Systemen stammen, bieten großes Potenzial für verschiedene Anwendungen, einschließlich der Anlagenregelung, Lastvalidierung, Leistungsmessungen und Lastüberwachung. Bei schwimmenden Windkraftanlagen werden Messungen mit gondelbasierten Lidarsystemen durch das dynamische Verhalten der schwimmenden Plattformen beeinflusst. Daher müssen die Einflüsse, die durch die Dynamik der Plattformen induziert werden, verstanden und bei der Nutzung der Messdaten berücksichtigt werden. In dieser Arbeit werden beide Themen mithilfe von simulationsbasierten Ansätzen behandelt. Zuerst werden zwei Simulationsumgebungen für die Simulation virtueller Lidar-Messungen unter Berücksichtigung der Dynamik der schwimmenden Offshore-Windkraftanlagen erstellt. Ein analytisches Modell der Lidar-Windgeschwindigkeitsmessungen wird speziell als Grundlage für die Unsicherheitsschätzung unter Verwendung der GUM-Methodik (Leitfaden zur Angabe der Unsicherheit beim Messen) entwickelt. Zusätzlich wird eine numerische Simulationsumgebung für Lidarmessungen unter Bewegungseinfluss entwickelt.

Weiterhin wird der Einfluss von Plattformbewegungen auf Windgeschwindigkeitsmessungen von gondelbasierten Lidarsystemen untersucht und Ansätze zur Korrektur von bewegungsinduzierten Effekten vorgeschlagen. Die Ergebnisse zeigen, dass die Unsicherheit der Lidar-Windgeschwindigkeits-schätzungen

hauptsächlich durch die Vor- und Rückwärtsbewegung des Lidars verursacht wird, die aus der Nickbewegung des Schwimmers resultiert. Die Verzerrung von 10-minütigen mittleren Windgeschwindigkeitsschätzungen wird hauptsächlich durch den mittleren Nickwinkel des Schwimmers und die Nickamplitude beeinflusst. Bewegungsinduzierte Verzerrungen in zeitgemittelten Lidar-Windgeschwindigkeitsmessungen werden mit einem modellbasierten Ansatz korrigiert. Die Erprobung des Ansatzes mit simulierten Bewegungen von zwei verschiedenen Plattfortmtypen zeigt gute Ergebnisse mit verbleibenden mittleren Fehlern unter $0,1 \text{ ms}^{-1}$. Für die Korrektur von bewegungsinduzierten Messunsicherheiten bei Zeitreihenmessungen wird ein Frequenzfilter verwendet. Die Leistung des Korrekturansatzes hängt von der Nickperiode und -amplitude des FOWT-Designs ab.

Der zweite Teil der Arbeit befasst sich mit der Nutzung und Anwendung von Lidar-Anströmungsmessungen für die Modellierung von Lasten und Plattfortmbewegungen mittels virtueller Sensoren. In diesem Teil der Arbeit wird eine Methodik untersucht, bei der Messungen der Schwimmerbewegung und Lidar Windgeschwindigkeitsmessungen, als Inputs für verschiedene Arten von künstlichen neuronalen Netzwerken verwendet werden, um Fairlead-Lastzeitreihen und schadensäquivalente Lasten (DELs) zu modellieren. Diese Arbeit nutzt direkt vom Lidar gemessenen Line-of-Sight-Windgeschwindigkeiten, um Lasten von Ankerleinen zu schätzen. Trainingsdaten für das Modell werden mithilfe der im Rahmen dieser Arbeit entwickelten numerischen Lidar-Simulationsumgebung generiert. Die Fairlead-Spannungszeitreihen und DELs werden unter Verwendung von verschiedenen künstlichen neuronalen netzen modelliert. Die Ergebnisse zeigen, dass Fairlead-Spannungszeitreihen und DELs akkurat aus Plattfortmbewegungszeitreihen geschätzt werden können. Weiterhin wurde festgestellt, dass Lidar-Line-of-Sight Messungen die Vorhersagen von Zeitreihen oder DELs nicht verbessern, wenn Bewegungsmessungen verfügbar sind. Die Verwendung von Lidar-Messungen als Modellinput für DEL-Vorhersagen führt je-

doch zu ähnlichen Genauigkeiten wie die Verwendung von Positionsdaten der Plattform.

Neben der Echtzeitvorhersage konzentriert sich diese Arbeit auf die Zukunftsvorhersage der Fairlead-Spannungs- und Plattformdynamik-Zeitreihen von schwimmenden Windkraftanlagen, welche Messungen von Bewegungssensoren und Lidar-Windgeschwindigkeitsmessungen einbezieht. In dieser Arbeit wird eine datenbasierte Vorhersagemethodik untersucht. Unter Verwendung eines Long Short-Term-Memory (LSTM) Sequenz-zu-Sequenz-Modells werden Vorhersagen für Fairlead-Spannung, Vorwärtsbewegung und Nickbewegung für Zeitreihen über Prognosehorizonte von 20, 40 und 60 Sekunden gemacht, wobei Lidar-Reichweiten von 100 m bis 500 m berücksichtigt werden. Die Ergebnisse zeigen, dass die Einbeziehung von Lidar-Anströmungsmessungen die Prognose von Fairlead-Spannungen und Plattformbewegungen signifikant verbessert.

List of Figures

1.1	Overview of the thesis structure.	10
2.1	Floating substructure types [1].	22
2.2	Catenary mooring line.	23
2.3	Lidar measurement principle, adapted from [2].	26
2.4	Continuous wave lidar data processing [2].	28
2.5	Fraunhofer Wind Lidar Buoy during a trial next to the FINO1 met mast within the German bight [3].	30
2.6	Fixed beam nacelle based lidar system (left) and scanning lidar system (right) [4]	32
2.7	Nacelle-based lidar on top of the Floatgen (Copyright: Uni- versity of Stuttgart).	32
2.8	Left: Fundamental structure of the neural network. Right: Model of a neuron that applies the activation function f on the weighted sum of inputs.	40
2.9	Structure of a LSTM cell, where $c(t)$ is the cell state, $h(t)$ is the hidden state and $x(t)$ is the data input.	41
2.10	Left: Structure of a CNN with one convolutional layer and one pooling layer. Right: Convolution and pooling operation.	42
3.1	Motion influence on nacelle-based lidar systems.	49

3.2	Vicondar lidar simulation process steps.	49
3.3	Numerical lidar simulation coordinate systems.	53
3.4	Lidar pattern and coordinate systems for the analytical model.	59
4.1	Analysis of measurement campaign data. a): Mean and standard deviation of floater pitch angle over 10 min mean wind speed bins. Error bars denote the standard deviation of mean pitch values over all 10-minute samples. Standard deviation of translational velocity in the x-direction over wind speed bins. b) Time series of reconstructed u-component wind speed and pitch angle. c) PSD of floater pitch angle, LOS-1 velocity, and reconstructed u-component wind speed.	64
4.2	Utilization of analytical and numerical lidar measurement models.	65
4.3	a) Standard deviation of bias estimation within 100 random realizations over time window length. b) standard deviation of averaged bias estimations over the number of averaged random realizations, time window length 600 s.	70
4.4	Lidar patterns and coordinate systems	71
4.5	Modeled LOS velocities and reconstructed u- component wind speed as a function of yaw, pitch, roll and heave displacement for all four beams. Reference wind speed: 10 ms^{-1} . Top: $\alpha = 0$. Center: $\alpha = 0.1$. Bottom: $\alpha = 0.2$. α is the vertical shear exponent. VLOS1 and VLOS2 correspond to the two upper beams, VLOS3 and VLOS4 correspond to the two lower beams. The y-axis is normalized to the reconstructed wind speed at zero displacements.	72

4.6	Modeled LOS velocities as function of translational nacelle velocities in x-, y- and z- direction for all four beams. Reference wind speed: 10 ms^{-1} , vertical shear exponent $\alpha = 0.2$. The y-axis is normalized to the reconstructed wind speed at zero displacements.	73
4.7	Uncertainty estimation of u-component wind speed. Fixed parameters: U_{ref} : 10 ms^{-1} , $A_\psi = 0 \text{ deg}$, $A_\gamma = 0 \text{ deg}$, $A_{heave} = 0 \text{ m}$	76
4.8	Comparison between analytical and numerical uncertainty / MAE estimation. Plots a) to d) refer to cases in Table 4.1. Fixed parameters: U_{ref} : 10 ms^{-1} , $A_\psi = 0 \text{ deg}$, $A_\gamma = 0 \text{ deg}$, $A_{heave} = 0 \text{ m}$	78
4.9	Bias of u-component wind speed. Parameter according to Table 4.1. Fixed parameters: U_{ref} : 10 ms^{-1} , $A_\psi = 0 \text{ deg}$, $A_\gamma = 0 \text{ deg}$, $A_{heave} = 0 \text{ m}$	79
4.10	Comparison of bias wind speed estimation from analytical and numerical model. Fixed parameters: U_{ref} : 10 ms^{-1} , $A_\psi = 0 \text{ deg}$, $A_\gamma = 0 \text{ deg}$, $A_{heave} = 0 \text{ m}$, $\alpha = 0.1$	81
4.11	Absolute and relative ME of corrected u- wind speed component as function of mean wind speed for different mean pitch angles. Top: Uncorrected lidar estimates. Bottom: Corrected lidar estimates. Fixed Parameters: $A_\beta = 3 \text{ deg}$, $A_\psi = 0 \text{ deg}$, $A_\gamma = 0 \text{ deg}$, $A_{heave} = 0 \text{ m}$	89
4.12	Absolute and relative ME of corrected u- wind speed component as function of mean wind speed for different mean pitch angles. Top: Uncorrected lidar estimates. Bottom: Corrected lidar estimates. Fixed Parameters: $\beta_{mean} = 0 \text{ deg}$, $A_\psi = 0 \text{ deg}$, $A_\gamma = 0 \text{ deg}$, $A_{heave} = 0 \text{ m}$	90

4.13	MEs of u- wind speed component for FLOATGEN (top) and WindCrete (bottom) FOWT with and without correction for varying vertical shear exponents.	91
4.14	Left: Time series example of lidar estimated u-component wind speed, frequency corrected lidar u-component wind speed estimate and reference wind speed of the input wind field. Right: PSD of lidar estimated u-component wind speed and frequency corrected lidar u-component wind speed estimate. Dynamics parameters: U_{ref} : 12 ms ⁻¹ , A_β = 3 deg, T_β = 20 s, A_ψ = 0 deg, A_γ = 0 deg, A_{heave} = 0 m.	92
4.15	MAE of lidar u-component wind speed estimates with and without frequency correction for varying pitch amplitudes and vertical shear exponent of $\alpha = 0.1$. Fixed Parameters: A_ψ = 0 deg, A_γ = 0 deg, A_{heave} = 0 m.	93
4.16	Time Series and PSD of simulated Lidar wind speed estimate with and without frequency correction for wave case 3 (see Table 4.5). Top: FLOATGEN, Bottom: WindCrete.	93
4.17	MAE of u- wind speed component for FLOATGEN (top) and WindCrete (bottom) FOWT with and without correction for varying wave periods and vertical shear exponent of $\alpha = 0.1$	94
4.18	ME of u- wind speed component for FLOATGEN (top) and WindCrete (bottom) FOWT with and without application of frequency filter. Vertical shear exponent $\alpha = 0.1$	96
5.1	Overview of the simulation, training, and evaluation methodology. White boxes denote used tools and process steps, blue boxes denote used and generated data sets.	101
5.2	Sequence-to-Sequence time series prediction model architecture.	103
5.3	Seq2One model architecture.	104

5.4	One-dimensional CNN architecture for time series regression architecture.	105
5.5	Feedforward neural network with statistics vector input for DEL prediction.	106
5.6	Left: Lidar pattern and coordinate systems for numerical lidar simulation. Right: Floater geometry and lidar position. .	110
5.7	Lidar patterns considered in the analysis	110
5.8	Example of input dynamics with and without sensor noise. .	113
5.9	Sampling of wave parameters.	114
5.10	RMSEN of time series prediction for all cases and lidar patterns. Cases $A-D$ -Noise as well as cases $A_{Lidar}-F_{Lidar}$ -Noise denotes cases with the influence of measurement noise in dynamics and position measurements.	115
5.11	Example of time series predictions for cases $A-E$ -Noise. Top: Prediction versus reference time series. Bottom: PSD of prediction vs. reference time series.	116
5.12	Example of time series predictions for case F_{Lidar} , and pattern one to four. Top: Prediction versus reference time series. Bottom: PSD of prediction vs. reference time series.	117
5.13	APE of DELs for cases $A-E$ with and without influence of noise. Top: $m = 3$. Middle: $m = 6$. Bottom: $m = 9$. From left to right: Time series model, convolutional model, Seq2One model, statistics input model.	119
5.14	RMSE of DELs for cases $A-E$ with and without influence of noise. Top: $m = 3$. Middle: $m = 6$. Bottom: $m = 9$. From left to right: Time series model, convolutional model, Seq2One model, statistics input model.	122

5.15	One-to-One comparison between predicted and reference DELs for cases $A - E$ for $m = 3$ under the influence of noise. From top to bottom: Time series model, convolutional model, Seq2One model, statistics input model.	123
5.16	Sensitivity of relative Errors between predicted and reference DELs to environmental conditions for case A , time series model.	125
5.17	Sensitivity of relative Errors between predicted and reference DELs to environmental conditions for case A , convolutional model.	126
5.18	Sensitivity of relative Errors between predicted and reference DELs to environmental conditions for case A , Seq2One model.	127
5.19	Sensitivity of relative Errors between predicted and reference DELs to environmental conditions for case A , statistics input model.	128
5.20	APEs of DELs for cases F_{Lidar} for all lidar patterns and model architectures. Top: $m = 3$. Middle: $m = 6$. Bottom: $m = 9$.	130
5.21	One-to-One comparison between predicted and reference reference DELs for cases F_{Lidar} and all lidar patterns (top to bottom). From left to right: Time series model, convolutional model, seq2one model, statistics input model.	132
5.22	Sensitivity of relative Errors between predicted and reference DELs to environmental conditions for cases F_{lidar} and $m = 3$, 25P, time series model.	133
5.23	Sensitivity of relative Errors between predicted and reference DELs to environmental conditions for cases F_{lidar} and $m = 3$, 9P, convolutional model.	133
5.24	Sensitivity of relative Errors between predicted and reference DELs to environmental conditions for cases F_{lidar} and $m = 3$, 9P, seq2one model.	134

5.25	Sensitivity of relative Errors between predicted and reference DELs to environmental conditions for cases F_{lidar} and $m = 3$, 9P, statistics input model.	134
6.1	Methodology overview.	141
6.2	Target time series shifted by forecasting horizon.	141
6.3	Lidar pattern forecasting.	146
6.4	RMSEN across all models, forecasting horizons, and lidar ranges.	148
6.5	Time series forecasts example.	150
6.6	RMSEN difference between baseline and lidar case relative to environmental conditions.	151

List of Tables

3.1	Lidar DOFs and OpenFAST sensors used in the simulation. .	51
3.2	Floater natural frequencies WindCrete.	55
3.3	Floater natural frequencies VoltturnUS-S.	55
3.4	Considered FOWT dynamics parameters.	57
4.1	Dynamics parameters for uncertainty quantification.	75
4.2	Wind field parameters.	77
4.3	Parameter space correction look up table.	85
4.4	Wind field parameters.	88
4.5	Parameter space wave conditions, where H_s is the significant wave height and T_p is the peak wave period.	88
5.1	Summary of all modeling cases and input feaures.	107
5.2	Prediction models hyperparameters.	108
5.3	Turbulent wind field parameters	111
5.4	Inertial navigation system accuracy values.	112
5.5	Parameter space wave conditions, where H_s is the significant wave height and T_p is the peak wave period.	113
6.1	Modelling cases and input features.	144
6.2	Model target sensors.	144
6.3	Model hyperparameters.	145

1

Introduction

1.1 Motivation

Light Detection and Ranging (lidar) technology has achieved widespread acceptance in onshore environments for many applications within both operational and research contexts. While lidar measurements' main application has been quantifying and characterizing wind resources, recent years have witnessed the emergence of additional applications. These encompass turbine and wind farm control mechanisms, analyses of turbine-induced wake effects, evaluations of power performance, prognostic assessments, and load validation studies. Despite these advancements, the exploration of lidar applications on marine platforms, particularly nacelle-mounted lidar systems on FOWTs, remains underexplored, with the exception of buoy-based floating lidar systems for resource assessment purposes.

The deployment of nacelle-mounted lidar systems on FOWTs introduces the need for a comprehensive understanding and precise evaluation of the impact of motion induced by the dynamics of floating platforms. This requirement

is critical across various operational scenarios, each characterized by distinct precision requisites, permissible error thresholds, and potential demands for motion correction mechanisms.

The present thesis addresses this research topic by investigating the operational behavior of nacelle-mounted lidar systems on FOWTs. It focuses on examining the effects of platform motions on lidar-based inflow measurements and their consequent implications for various operational scenarios. While the primary utility of nacelle-mounted lidar systems in both bottom-fixed and floating wind turbines has been the measurement of inflow wind fields to facilitate advanced turbine control schemes, the continuous monitoring of the turbine presents potential value in the context of floating wind turbines. Given the anticipated growth in the installed capacity of floating wind power and its evolution towards extensive commercial deployment, the need for reliable FOWT monitoring systems is evident. This thesis aims to explore the potential, effectiveness, and usefulness of using lidar-based inflow measurements for load and motion prediction tasks. By demonstrating the additional benefits that come with using this technology, the study advocates for expanded adoption of lidar installations, which can lead to cost-efficiency and broader integration within the floating wind energy domain.

1.2 Related Work

1.2.1 Motion Influence and Uncertainty Quantification

For wind measurements in deep waters, met masts are often impractical due to high installation costs. Instead, floating lidar systems have been developed and are currently employed in both industry projects and research applications. A detailed discussion of this technology and its challenges is available in [5]. Forward-looking nacelle-based lidar systems are benefi-

cial for measuring inflow conditions to individual turbines. These systems are used for power performance monitoring, load monitoring, and turbine control.

In [6], power curve measurements using a nacelle-based pulsed lidar system on a multi-megawatt turbine were conducted and compared with data from a cup anemometer mounted on a met mast. Generally, the power curves from the lidar and cup anemometer measurements agreed well. The lidar-derived power curve exhibited less scatter, as the lidar-measured wind speeds more closely correlated with the rotor-effective wind speeds of the wind turbine. In a recent study published in [7], researchers conducted a power curve assessment campaign using a nacelle-based lidar on a 2 MW FOWT. The goal was to compare the lidar measurements to a nacelle-mounted sonic anemometer, while both signals were not corrected for floater dynamics. While the wind speed measurements from both references were found to be in good agreement, the power curves from the lidar measurements showed higher scatter compared to the nacelle cup-anemometer measurements. This increased scatter is likely caused by the influence of floater dynamics and the corresponding shift of measurement position on lidar measurements. However, the study did not present any systematic analysis or quantification of motion-induced effects.

Two studies have been conducted to improve load assessments for wind turbines. The first study [8] used lidar-estimated wind field characteristics to perform load simulations. The predicted loads were then compared to load measurements at the turbine. In the second study [9], a methodology was proposed to combine nacelle-based lidar measurements with constrained wind field reconstruction techniques. This was done to enhance the accuracy of load assessments for bottom-fixed wind turbines. However, this study did not consider the effects of floating dynamics. Therefore, it is necessary to investigate the impact of floater dynamics on measured wind speed time series to apply the proposed methodology to floating wind turbines.

Another application of nacelle-based lidar systems is using different lidar-assisted wind turbine control strategies. These control strategies aim to use knowledge about the approaching wind field to optimize the turbine's operation. Investigated concepts include collective and individual pitch control (see e.g. [10]), yaw control (see, e.g., [11]), and speed control (see, e.g., [12]). Above mentioned studies have not investigated the proposed control strategies for floating wind turbines, and did not consider the effect of floater dynamics on the inflow measurements used.

Although different applications require wind speed measurements in different temporal resolutions (e.g. 1 Hz for turbine control versus 10min average for performance measurements), quantifying uncertainties and biases in lidar measurements is essential for all the above-mentioned applications. The need for uncertainty quantification and the development of suitable tools and models has also been highlighted as an important step towards the broad application of nacelle-based lidar systems by [13].

While the above-mentioned studies have mainly investigated using nacelle-based lidar systems to measure inflow conditions of onshore or bottom-fixed offshore wind turbines, little experience exists for their use on FOWT. Since the floating dynamics of the FOWT cause translational and rotational displacement of nacelle-mounted lidars, it can be expected that these dynamics affect the measurements. Therefore, it is necessary to investigate motion-induced effects and evaluate the need for motion correction.

The quantification of uncertainties and correction of motion influence has, in general, already been approached by several authors for both floating and fixed lidar systems. In [14] motion induced effects on buoy-based lidar systems were investigated following a simulation-based and experimental approach. While mean wind speed measurements showed little deviation from fixed reference measurements, the authors found systematically increased turbulence intensity (TI) measurements. In [3] a simulation-based approach for the uncertainty estimation of buoy-based floating lidar sys-

tems under different met-ocean conditions is introduced. The authors of [15] quantified the motion-induced measurement errors for lidar buoys. Biases in the measurement were derived numerically and analytically using a mathematical model of the measurements under motion influence. Since the above-mentioned studies specifically address uncertainties of buoy-based lidar systems, their results are not directly transferable to nacelle-based systems on FOWT, which have significantly different dynamic characteristics. In [16] an analytical approach is followed to investigate uncertainties of nacelle-based lidar measurements. In this work, the methodology proposed by the guide for the expression of uncertainty in measurements (GUM) [17] is followed to estimate uncertainties due to LOS variations in range, elevation angle, and azimuth angles. While a high dependency of measurement uncertainty on the chosen beam elevation and azimuth angles is found, the study does not investigate the effect of floating dynamics.

For nacelle-based lidar systems on FOWT [18] demonstrated the influence of floater dynamics on lidar measurements. The main effects influencing the obtained lidar wind measurements are changing beam directions, changing positions of focus points, and superposition of translational velocities. Rotational displacements of the floater and the lidar system cause tilted beam directions compared to a fixed lidar system, which leads to changing LOS measurements. Changing beam directions also cause changing positions of focus points in space. The presence of vertical wind shear leads to errors in the wind speed estimates. Finally, floater dynamics cause translational displacements of the lidar system in space which creates the superposition of additional velocity components on the lidar measurements. The influence of floater dynamics on lidar measurements was investigated with a numerical simulation approach for a 15 MW spar-type FOWT. Results showed an increase in mean absolute error (MAE) between lidar estimated and true wind field rotor effective wind speed depending on the environmental conditions. An overestimation of mean rotor effective wind speed, due to

spatially shifted focus points was observed. The study is based on the simulation results for one specific FOWT design and does not investigate DOFs individually. Thus, results, are not directly transferable to other FOWT designs.

Different studies have addressed the correction of motion influence in lidar measurements. The authors of [19] suggest a motion compensation approach for TI estimates from buoy-mounted vertical azimuth display scanning lidar systems based on measured motion time series. Here, motion data from a motion reference unit is used to calculate the contribution of the buoy motions on the LOS measurements and the current LOS geometry. Further, this information is considered in the wind field reconstruction process for each measurement. Application of the suggested method yielded good agreement between motion-compensated and fixed reference measurements. While the proposed methodology generally applies to nacelle-based lidar measurements, results are not directly transferable due to different beam geometries and dynamics characteristics.

In [20] motion-induced contributions to LOS wind speed measurement variances are calculated based on 10 min mean motion data and used to correct the TI measured by the lidar. follows a similar approach citers10122037. Here, amplitudes and periods of the pitch and roll motion of a lidar buoy, in combination with information about the lidar configuration, are used to estimate the motion-induced variance of horizontal wind speed estimates. In [21] and [22] the use of Kalman Filters for motion correction of 10 min statistics from buoy-based lidar systems is investigated. Inertial measurement unit (IMU) signals from the buoy and a turbulence model are used to model the true wind velocity vector and correct the motion-corrupted lidar measurements. Again, the focus of these studies lies on the correction of buoy-based lidar TI estimates. The motion influence on nacelle-based lidar wind speed estimates cannot be derived from them.

1.2.2 Data-driven Virtual Sensors

The increasing deployment of FOWTs for commercial purposes necessitates reliable load-monitoring solutions. Although FOWTs come equipped with various sensors that provide useful data for controlling and monitoring individual turbines and farms, obtaining accurate measurements for certain physical quantities can be difficult or expensive. In such cases, virtual sensors offer a promising alternative. Mooring lines, which are critical components of FOWTs, are particularly susceptible to mechanical failures, and their failure can have catastrophic consequences. Fatigue, along with extreme loads, is a major cause of mechanical failure for mooring lines and fairleads [23]. Hence, precise load estimates for mooring lines and fairleads in FOWTs are essential for monitoring applications.

Although mooring lines perform critical functions, monitoring and assessing individual lines' remaining lifetime is difficult. Different authors (see, e.g., [24, 25]) have proposed methods to derive fatigue damage of mooring lines in the frequency domain while avoiding the need for rain flow-counting algorithms in the time domain. In principle, these methods could be used in operational settings assuming that representative spectral properties of the target loads are known. However, the harsh marine environment and logistical challenges make installing sensors and maintaining their accuracy difficult over long periods. Studies have investigated various approaches to model and predict mooring line loads in this context. An overview of modeling approaches for mooring line loads based on physical principles can be found in [26]. Physical mooring line models describe the mooring line behavior using knowledge about its mechanics and underlying physical laws. Different model fidelities, ranging from quasi-static to multi-body and finite element models, are described in the literature. While finite element models can calculate mooring line loads very accurately, the high computational costs make them impractical for monitoring applications. Multi-body

models, as described in [27], combine good accuracy with acceptable computational costs, making them applicable for general monitoring applications. However, the floater dynamics in 6 DoF must be known, which might not be the case in operational settings.

Data-driven models can make predictions without a physical description between input and output quantities at low computational costs. However, training of data-driven models typically involves large sets of training data that must be available through measurements or representative simulation models. The potential of data-driven models for predicting physical quantities has been demonstrated in different studies, not only for mooring line load predictions. For instance, in [28], measurable predictor signals have been used to train neural networks, predicting the load of a wind turbine gearbox in six degrees of freedom (DOFs). Similarly, in [29], different network designs have been investigated to predict blade root bending moments, wake center detection, and tip-tower clearance. In [30] Bayesian neural networks are used for a fleet monitoring approach, where models are trained on measured load data from one fully monitored turbine. At the same time, predictions are made for other turbines in the fleet. The study uses ten-minute statistics of different available time series measurements as input and predicts damage equivalent tower bending moments. Similarly, in [31] a fleet monitoring approach is used to predict long-term damage accumulation of tower bending moments employing physics-informed neural networks.

The authors of [32] developed data-driven digital twin models for predicting and forecasting mooring line tension based on measured operational time series data including floater dynamics signals and the ambient wind speed. The developed model could predict mooring line tension time series accurately and make near future (1 minute) tension forecasts. The use of predicted time series for DEL analysis was not investigated. In contrast to this work, our study is focused on leveraging lidar inflow measurements for mooring line load predictions and predicting DELs by utilizing different

modeling approaches.

Various studies have used nacelle-based lidar inflow measurements for turbine load calculation. For instance, in [33] and [9], besides lidar estimated wind field statistics for parameterization of constrained wind fields, measured lidar wind speed time series are used to constrain synthetic turbulent wind fields. These wind fields are further used to simulate turbine responses using an aeroelastic simulation code. While the method yields good load validation results, it is unsuitable for real-time monitoring applications. This thesis aims to demonstrate the ability of data-driven lidar-based models to predict mooring line tension in real-time.

The concept for this approach was initially introduced in [34], which demonstrated its feasibility but lacked a systematic analysis of all relevant aspects. This thesis extends the previous study by incorporating additional elements. It employs systematic feature selection to evaluate the impact of individual input features on prediction accuracy. Four different lidar patterns, ranging from sparse to dense focus points are investigated to assess their performance impact. Additionally, this work introduces a novel method for predicting DELs by using machine learning to directly predict DELs from input time series signals, rather than calculating them from predicted time series. The environmental conditions are sampled considering randomized atmospheric and oceanic conditions to better reflect the stochastic nature of real met ocean conditions. Additionally, this thesis considers and evaluates the influence of sensor noise in the models' input features on the prediction accuracy.

1.3 Research Objectives and Methodology

This thesis focuses on investigating nacelle-based lidar measurements on FOWTs. At its core, it addresses two main subject areas, which are the analysis of floater motion influence in lidar inflow measurements and the application of these measurements in virtual sensor models. Both parts rely on the simulation of lidar measurements under motion influence. Therefore, the first objective of this thesis is to develop lidar simulation environments, representing the influence of floater motion on nacelle-based lidar measurements and enabling the analysis of characteristics and uncertainties of these measurements.

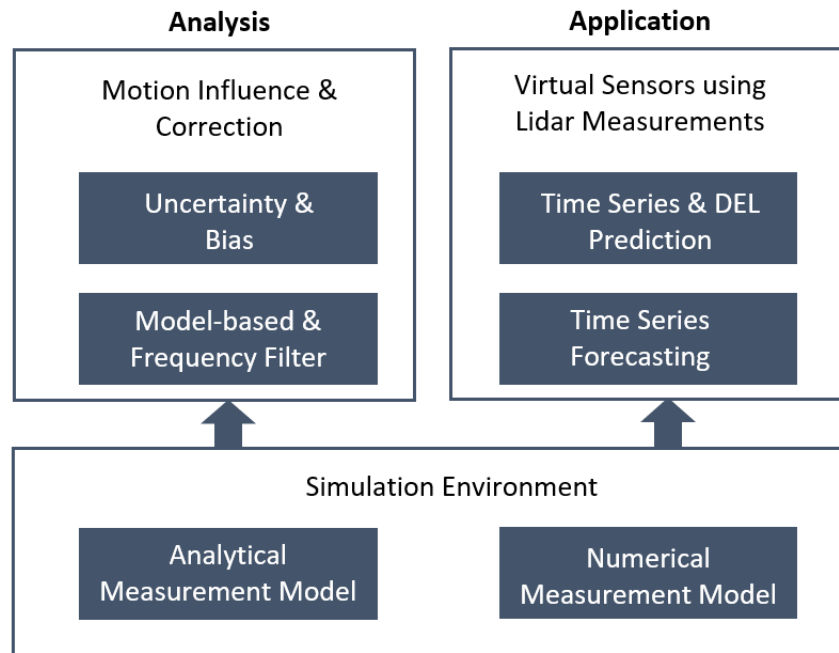


Figure 1.1: Overview of the thesis structure.

The influence of platform motions on lidar measurements is studied using these simulation environments. The behavior of different floater types in a wide array of environmental conditions and their implications for lidar measurements are investigated. Additionally, an analytical model of the

measurements is used for a parametric study on measurement uncertainty and bias. Here, the goal is to represent measurement uncertainty and bias as a function of environmental parameters and operational parameters of the FOWT. The methodology used for uncertainty quantification is closely linked to existing industry standards, to allow interpretability and transferability of results.

In the second part of the thesis, the developed numerical model and insights about the motion influence are used to investigate data-driven methods for FOWT load and dynamics predictions. Here, the focus lies on investigating the value of lidar measurements for real-time predictions and forecasting of mooring line loads and floater motions. Figure 1.1 provides an illustration of the primary subject areas.

Specifically, the research objectives of this thesis are:

- to develop simulation environments, capable of simulating nacelle-based lidar inflow measurements under the influence of floater motions.
- to quantify floater motion-induced uncertainties and biases in nacelle-based lidar wind speed measurements on FOWT
- to introduce correction methods for motion-induced effects on lidar wind speed measurements on different time scales
- to assess the introduced correction methods for different floater characteristics and atmospheric conditions
- to investigate the application of nacelle-based lidar inflow measurements for FOWT load predictions using machine learning methods
- to investigate the application of nacelle-based lidar inflow measurements approaches for the forecasting of fairlead tension time series and associated platform dynamics using machine learning methods

1.4 Structure of the Thesis

This thesis tackles multiple disciplines and diverse research objectives. The chapters are logically organized to consolidate relevant information for each topic.

Chapter 2 provides the background necessary for understanding the methods and approaches employed in this thesis. It begins with a basic explanation of the functional principles and operational and environmental conditions of FOWT. The chapter then introduces wind lidar technology, focusing on its use in wind energy and particularly within floating wind scenarios. Additionally, it lays the foundation for understanding uncertainty quantification in measurements and introduces data-driven methods for predicting and forecasting time-series signals.

In chapter 3 the numerical and analytical environments for the simulation of lidar wind measurements under motion influence are introduced. The numerical simulation environment for nacelle based lidar measurements on floating wind turbines is developed as part of this work and uses FOWT in six DOF provided by aeroelastic simulations. It is used throughout the thesis for motion influence and lidar-based prediction topics. The analytical model is developed explicitly for use as a basis for analytical uncertainty quantification.

Chapter 4 focuses on quantifying motion influence in nacelle-based lidar wind speed measurements on FOWT. First, it presents findings from the analysis of a lidar measurement campaign. Additionally, it presents a parametric measurement uncertainty study, which is based on numerical simulations as well as analytical derivation of uncertainties. Finally, the chapter provides possible correction approaches and discusses the relevance of motion induced uncertainties for different lidar data use cases.

Chapter 5 uses insights on the motion influence of lidar measurements from the previous chapter and the numerical simulation environment introduced

in chapter 3 to establish a training database, including turbine responses and corresponding lidar measurements. Based on this database, data-driven methods for predicting FOWT fairlead tension loads using lidar measurements. The demonstration and analysis of predictions of time series signals and DELs are discussed separately, while the value of lidar inflow measurements for the predictions is investigated. The chapter ends with a critical discussion of the real-world applicability of the presented methods.

In chapter 6, the training database generated in chapter 5 is used to investigate the value of lidar inflow measurements to forecast fairlead tension time series and related platform dynamics. Forecasts are based on data-driven models and benchmarked against a simple persistence model.

Chapter 7 concludes the thesis by summarizing the main results and providing a conclusion about using a nacelle-based lidar system on FOWT. Further, it provides suggestions and ideas for further research in the field.

2

Background

This section provides background on concepts, technologies, methods and metrics used throughout this work.

2.1 Wind

Wind turbines operate under the influence of their location-specific environmental conditions. The wind, being a key element, provides kinetic energy that is harnessed for electricity generation. Simultaneously, it imposes structural loads on the turbine system. Wind is the movement of air relative to the rotating earth's surface. Its formation is fundamentally driven by the unevenly distributed solar energy intake across the earth's surface. The amount of solar energy received by the earth's surface is larger at the equator compared to the poles. This results in unevenly distributed heat in the atmosphere. Warmer equatorial air masses will rise while colder polar air masses will sink, resulting in different pressure zones around the earth. Additionally, the Earth's rotation introduces Coriolis forces, which make the

wind veer depending on its direction and the specific location on the planet. The combination of pressure gradients in the atmosphere and the influence of Coriolis forces is responsible for the large-scale flow patterns known as equatorial trade winds and midlatitude westerlies. For wind energy, especially the westerlies, are highly relevant as they are responsible for the good wind resources at high latitudes (North America, Europe, Asia) and low latitudes (Africa, South America, Australia).

Superimposed on global atmospheric circulation are various regional patterns influenced by the differential heating of land and ocean. Land masses heat and cool more rapidly than oceans. Furthermore, even within land areas, there are differences in surface heating, such as between a snow-covered mountain peak and a valley, or between a desert and a cultivated field. These temperature variations create what are known as mesoscale atmospheric circulations. An example of such a circulation is the sea breeze. On a typical summer day, as the land heats up faster than the ocean, the air above the land expands and rises, drawing in cooler, denser air from the ocean. Conversely, at night, this process reverses, leading to a land breeze. For the planning and operation of wind turbines, the wind needs to be characterized. Besides the mean wind speed at a specific site, the variability in speed, direction, and density in time and space are essential characteristics. On small time scales, in the order of seconds and minutes, variations in wind are called turbulence. In an offshore context turbulence is mainly caused by frictional forces and the presence of wind shear as well as thermal gradients in the atmosphere. On time scales, in the order of 12 to 24 hours, variations are associated with diurnal patterns of solar heating and nightly cooling of the Earth's surface.

The characteristics of the offshore wind resource differ significantly from the onshore wind resource for several reasons. On one hand, the surface roughness is often significantly lower for water surfaces than for land surfaces, which indicates that shear effects are less pronounced offshore. On the

other hand, the relative temperature variations during the day are smaller, which is caused by the high heat capacity of water compared to land. This effect has an influence on the stability of the atmosphere and, thus, on shear and TI, which are usually smaller offshore. In general, it can be stated that the offshore wind resource is spatially more homogeneous than the onshore wind resource [35].

2.1.1 Vertical Wind Profiles

The frictional influence of the sea surface on the wind decreases with height above the sea surface. Therefore, in general, the wind speed increases with height. This change in wind speed as a function of height is referred to as vertical wind shear. Typically, the wind profile is either described through a logarithmic law, which is derived from physical processes in the boundary layer, or a power law wind profile, which is a purely mathematical description of the wind profile. In this work wind profiles for are described using the power law profile given by:

$$u(z) = u_{ref} \left(\frac{z}{z_{ref}} \right)^\alpha \quad (2.1)$$

where u_{ref} is the reference wind speed at height z_{ref} , z is the height and α is the power law exponent.

2.1.2 Turbulence

On small time scales, in the order of seconds and minutes, variations in wind are called turbulence. Turbulence refers to rapid fluctuations in wind speed caused by pressure differences or eddies in the wind field stemming from frictional or thermal effects. While variations in the order of seconds are mostly relevant for the structural loading of wind turbines, on larger time

scales, in the order of minutes, variations in the wind field cause fluctuations in the power output of wind turbines. The consideration of turbulence is part of the design requirements of IEC 61400-3 [36]. It is typically quantified as:

$$TI = \frac{\sigma}{U} \quad (2.2)$$

where σ is the standard deviation of the 10-minute mean wind speed U . IEC 61400-3 recommends estimating σ for offshore conditions, where no measurement data is available.

For the aeroelastic simulation of wind turbines spectral models of the wind field are used to represent the statistical variation of the wind in time and space. In this work, wind synthetic turbulent wind fields are used for the aeroelastic simulation of FOWT and for the simulation of lidar measurements. The synthetic wind fields used in this work are based on the Kaimal spectral turbulence model as described in IEC 61400-1 [37].

The Kaimal model describes the wind as velocity fluctuations with zero mean Gaussian statistics. The spectra of the three wind vector components u, v, w are given by:

$$S_k(f) = \frac{4\sigma_k^2 \frac{L_k}{V_{hub}}}{(1 + 6f \frac{L_k}{V_{hub}})^{5/3}} \quad (2.3)$$

where f is the frequency in hertz and the subscript k denotes the index of the velocity component in the longitudinal, lateral, and upward direction, respectively. The single-sided velocity component spectrum is denoted as S_k , while σ_k and L_k represent the standard deviation and integral length scale parameters the respective velocity component, respectively. The wind speed at hub height is denoted as V_{hub} .

For the longitudinal velocity component u , σ_1 is the representative value of the turbulence standard deviation. The standard deviations of the lateral

and upward components are defined as:

$$\sigma_2 = 0.8\sigma_1 \quad \sigma_3 = 0.5\sigma_1 \quad (2.4)$$

The integral length scale L_k is given by

$$L_1 = 8.1\Lambda_1 \quad L_2 = 2.7\Lambda_1 \quad L_3 = 0.66\Lambda_1 \quad (2.5)$$

where Λ is the length scale parameter. For a modern wind turbine, the hub height is typically above $z > 60$ m, and the longitudinal length scale parameter is $\Lambda_1 = 42$ m. According to IEC 61400-1, the following exponential coherence model can be used in conjunction with the Kaimal model to describe the spatial correlation of the longitudinal velocity component.

$$\gamma_c(r, f) = \exp \left[-12 \left(\left(\frac{fr}{V_{hub}} \right)^2 + \left(\frac{0.12r}{L_c} \right)^2 \right)^{0.5} \right] \quad (2.6)$$

where r is the magnitude of the distance between the two points projected onto a plane normal to the averaged wind direction and L_c is the coherence scale parameter.

2.2 Floating Offshore Wind Turbines

2.2.1 Floater Types

Offshore wind turbines are a leading renewable energy technology with a significant potential to support a carbon-free economy. Worldwide the installed capacity of offshore wind has reached 64.3 GW in 2023 with further potential to grow [38]. However, the installation of offshore wind turbines until today mostly relies on bottom fixed substructures like monopiles, space frame jacket structures, or tripods, which are limited to relatively shallow

waters up to approximately 50 meters in depth. As the availability of shallow water sites with good wind resources declines, FOWTs can play a leading role. Projections indicate that the global installed capacity of floating wind power will increase to 16.5 GW by 2030 [39].

A fundamental difference between fixed and floating wind turbine support structures is the additional motions of the platform and the turbine introduced by environmental forces acting on the structure. These motions have to be kept within acceptable limits for the operation, station keeping, and safety of the turbine. Various floater concepts are discussed in the literature or are currently employed in demonstration or first commercial projects. A classification of floater types is possible through the physical principles that are used to counter the wind turbine's overturning thrust load and achieve stability of the system. Although real floater designs can be a combination of floater types, four main floater types (refer to figure 2.1) can be distinguished:

- Semisubmersible platforms use a combination distributed buoyancy of typically three or four buoyancy bodies, which are connected through a space frame structure to provide platform stability and gravity forces. Designs with the turbine tower mounted to a central column [40], or on one of the radial columns, [41] exist. Stationkeeping is realized through catenary mooring systems. This makes semisubmersible platforms suitable for installation in shallow waters down to 25 meters [42]. Important design considerations are the positioning of the floating bodies to ensure that wave loads are out of phase with design critical waves. Additional damping can be provided through the introduction of heave plates [41] or tuned liquid dampers, as discussed in [43].
- Spar-type floaters (see, e.g., [44]) use gravity in the form of a ballast keel to realize platform stability. The turbine tower is mounted on one

slender body which provides buoyancy and stability through ballast at the base of the spar. In some concepts, the spar buoy and the turbine tower are designed as a single member (see, e.g., [45]). While the slender structure at the water surface makes a spar design less susceptible to wave loads, spar-type floaters tend to heel over during operation. Stationkeeping is realized through a catenary or taught mooring systems. The high draft of spar-boys (eg. 78 m for Hywind Tampen) makes this floater design suitable only for deep water sites and can be a challenging factor for assembly and installation.

- Tension Leg platforms use a taught mooring system to attach the platform to the seabed and to provide platform stability [46]. Buoyancy bodies provide an upwards-directed force greater than the weight of the structure. Since the mooring lines are axial rigid tension, leg platforms are highly stable with very little heave, pitch, and roll motions, even in severe weather conditions.
- Barge-type floating platforms are characterized by a large surface area and relatively small drafts. Similar to semi-submersible platforms, stability is achieved through buoyancy forces. Stationkeeping is realized through catenary mooring systems. While barge-type floaters show good weight-carrying capacities, they are susceptible to wave loadings and high pitching and rolling motions [47]. A damping pool in the center of the structure can mitigate these characteristics and provide additional damping to the structure [48, 49]. The principle of this design is that the water entrapped within the hull can oscillate under the effects of the floater motion, but also of incoming waves. The water mass behaves as a mass-spring system. This technology is employed by BW Ideols FLOATGEN demonstrator platform [50].

In the context of this work, especially, the different dynamic characteristics

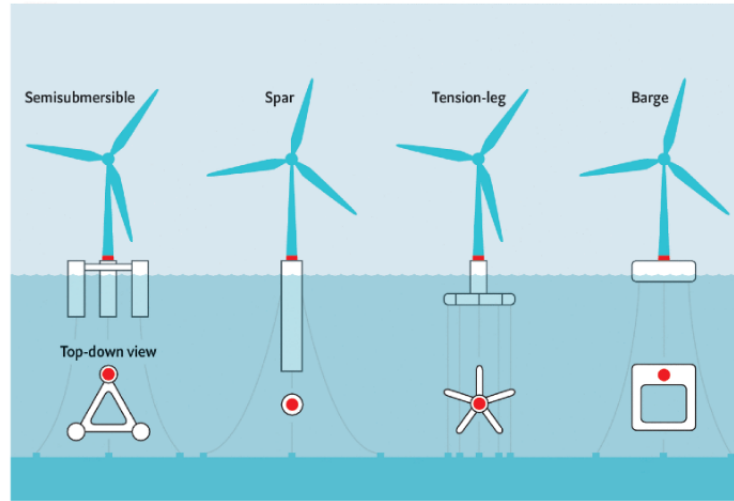


Figure 2.1: Floating substructure types [1].

of the floater types are relevant as they determine the motion influence on lidar measurements. Throughout the thesis, different floater types are used to analyze lidar inflow measurements. Chapter 4 employs a barge type design (FLOATGEN) and a spar design (WindCrete), while chapter 5 and 6 is based on a semisubmersible platform (UMaine VoltturnUS-S).

2.2.2 Mooring Lines

The design and configuration of mooring lines for station-keeping systems in FOWTs are determined by the need for stabilization and the characteristics of the sea bed. Current floater designs predominantly utilize either taut or catenary mooring lines to ensure stability and maintain position. Taut lines are characterized by their pre-tensioning, while catenary lines rely on their weight to provide stability. The catenary lines, governed by the principles of the catenary shape (see figure 2.2), are subject to dynamic loading that fluctuates with the motions of the platform.

In the case of catenary mooring lines, as investigated in this work, the forces exerted at the fairlead, both vertical and horizontal, can be collectively described as the fairlead tension force T_F . This variable force responds to

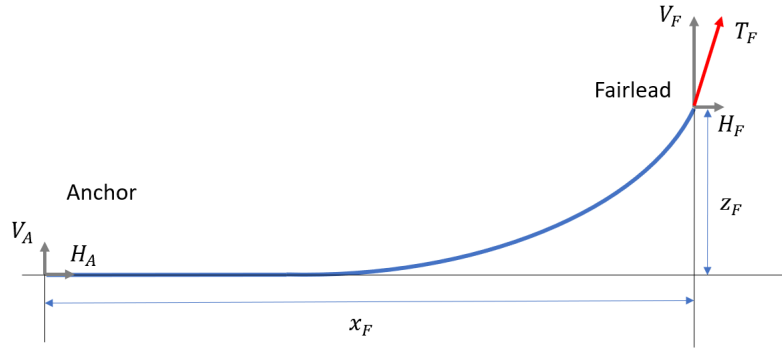


Figure 2.2: Catenary mooring line.

changing environmental conditions such as wave action, ocean currents, and wind forces. Consequently, the dynamic tension experienced by the mooring lines of a FOWT is subject to frequent fluctuations, as detailed in [51] and [52].

Fairlead tensions are intrinsically linked to the dynamics of the floater, which moves in six DOFs. The floater's translational and rotational movements dictate the fairlead's relative positioning to the anchor point. Therefore, the quasi-static loading experienced by a catenary mooring line is primarily governed by this displacement. Moreover, additional loading components on the mooring line arise due to the translational velocities of the fairlead about the anchor. The efficiency of a lidar-based model for predicting fairlead tensions, as introduced in chapter 5, hinges on its ability to accurately interpret turbine displacement and velocity patterns from the measured lidar radial wind speed data. The performance of such a model relies on its capacity to discern these patterns, which are indicative of the underlying dynamics influencing the fairlead tensions.

2.2.3 Aeroelastic Wind Turbine Simulations

Aeroelastic simulation codes model the response of a wind turbine system to wind and wave conditions by coupling aerodynamic, hydrodynamic, structural, electrical, and control effects. In the context of this work, aeroelastic simulations of FOWTs are used to model the turbine motions, which serve as input to the lidar simulations. In this work, the aeroelastic simulation code openFAST provided by the National Renewable Energy Laboratory (NREL) is used [53]. OpenFast is built using a modular approach. A short introduction to openFAST modules and underlying modeling approaches is given hereafter.

The AeroDyn module calculates the aerodynamic loads on a wind turbine's blades and tower. At each time step, it processes the undisturbed wind flow and structural motions, using blade element momentum (BEM) theory to determine the loads.

The ElastoDyn module models the turbine's structural motion. It simulates the turbine's structural dynamics by combining multibody simulation with modal analysis. The dynamics of the blades and tower are modeled using modal analysis that focuses on the most significant modes, while the dynamics of other components, such as the nacelle, generator, shaft, and hub, are modeled using multibody simulations.

Besides the interaction with the wind FOWTs interact with ocean waves. Hydrodynamics forces play an important role in the platforms' stability and contribute to the structural loading. Ocean waves can vary greatly in their characteristics and origins. For example, tidal waves are driven by the rotation of the earth in combination with the sun and the moon and periods of 12-24 hours. On the other extreme, capillary waves are driven by the local wind and have periods of less than 0.1s. The most relevant waves for the operation of FOWT are ocean surface waves with periods between 0.1 and 30s [42]. These waves are dominated by gravity and driven by the wind

blowing across the sea surface. For aeroelastic simulation, either deterministic regular waves or irregular, stochastic waves can be used to represent sea-states. Common parametric wave spectra are the Pierson-Moskowitz spectrum and the Jonswap spectrum (see, e.g., [54]). They are defined as a function of the peak spectral period T_p and the significant wave height H_s , which is the mean of the highest third crest heights. In this work, the Jonswap wave spectrum defines irregular, stochastic waves. The HydroDyn module generates waves based on the provided spectral parameters and calculates the hydrodynamic loads using a potential-flow theory solution, a strip-theory solution, or a hybrid combination of these two. MoorDyn models the dynamics of mooring lines and their interaction with the floating platform. It uses a lumped mass formulation that accounts for a mooring line's axial elasticity, hydrodynamic forces from Morison's equation, and seabed contact forces based on horizontal friction coefficients and vertical spring-damper coefficients. The ServoDyn module represents the turbine controller. ServoDyn's inputs include the turbine structure motions, while its outputs include the turbine blade pitch angles and generator torque.

2.3 Wind Lidars

Wind lidars are optical remote sensing devices that probe the atmospheric flow using light signals. Lidar measurements are used to reconstruct information about the atmospheric flow, such as wind speed, TI, or wind shear. In onshore environments lidar systems are already well established in the wind industry for measuring the wind resource. Especially in cases where the installation of met masts is costly or technically challenging to implement, lidar wind measurements are advantageous. While anemometers can only measure wind characteristics in the installation position, wind lidars can be adjusted to measure at different points in space. In this way, measurements at different heights or across the rotor plane area can be realized, which

makes it possible to assess the spatial distribution of wind fields, for example, in the inflow or wake of a wind turbine. Additionally, compared to met masts, lidar devices can be moved relatively easily, which makes it possible to to characterize the wind resource across larger project areas without the need to install several metmasts.

As for onshore wind measurements, lidar devices can be advantageous for characterizing offshore flow conditions. Especially in areas with high water depths, installing met-mast installation becomes technically complex and costly. The installation of lidar devices on floating platforms is a possible alternative with the potential to decrease costs for wind measuring campaigns significantly. Besides the wind resource assessment before the operation of the wind turbines, lidar wind measurements can serve other objectives like wind turbine control, performance measurement and monitoring, wake measurements, or characteristics of complex coastal flow patterns. Depending on the application, installing lidar devices on different floating platforms is possible. In the following section an overview of different floating lidar systems will be presented after a brief introduction into the lidar technology.

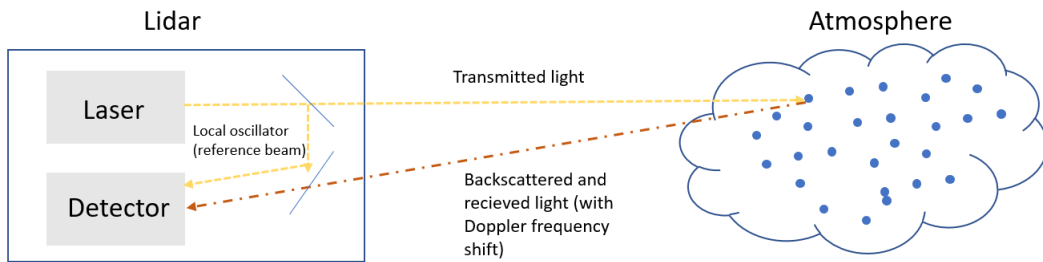


Figure 2.3: Lidar measurement principle, adapted from [2].

A wind lidar probes the atmospheric flow by transmitting laser light signals into the atmosphere and detecting the backscattered light which is reflected by aerosols in the air. Due to the speed of aerosols moving with the wind flow, there is a Doppler shift between the transmitted and backscattered

light. Motion towards the lidar leads to a compression of the wave and an increase in its frequency (blue shift). Movements away from the lidar lead to wave stretching and decreased frequency (red shift). The frequency shift is accurately detected by mixing the return signal with a portion of the emitted signal (local oscillator) and sensing the beats in the resulting frequency with a photodetector. This principle is depicted in figure 2.3. The Doppler shift is proportional to the wind speed in the direction of the beams. This wind speed is also referred to as radial wind speed (RWS) or line of sight (LOS) wind speed.

The LOS wind speed as a function of the transmitted and backscattered laser frequency (f_L, f_D), the speed of light c , and the wavelength of the laser λ_L are given by:

$$v_{los} = \frac{cf_D}{2f_L} = \frac{\lambda_L f_D}{2} \quad (2.7)$$

Lidars cannot measure the wind speed at a single point in space. The detected frequency shift is rather the result of the interaction of the light with aerosols in a probe volume. Based on the type of emitted laser signals two types categories of lidars are distinguished:

- Pulsed lidar systems: transmits a sequence of coherent light signals into the atmosphere and uses the time of flight of the backscattered light to measure a specific volume in the atmosphere. In contrast to the continuous wave type lidar, several ranges can be measured simultaneously.
- Continuous wave lidar: transmits a continuous laser signal into the atmosphere and focuses the laser beam at a specific volume in the atmosphere. The continuous wave lidar needs to refocus the laser beam to probe the wind at different points in space.

The continuous wave lidar is based on focusing a Gaussian laser beam to a specific point in space and detecting the backscattered light. However, the

energy of the laser beam is not focused precisely in one point but distributed around the focus length [55]. Therefore, the atmosphere is probed in a probe volume rather than in one point. The energy distribution is characterized by a spatial weighting function which can, according to [55], be approximated by a Lorentzian function. It is important to note that the weighting function is sensitive to the focus distance, meaning that the probe volume increases with larger distances. The processing steps for the calculation are summarized in figure 2.4. Initially, the detector captures a time series, which is divided into numerous blocks. A Fast Fourier Transform (FFT) is then applied to each block to estimate their power spectra. Subsequently, these spectra from all blocks are averaged. The LOS speed is derived from this averaged spectrum, as outlined in Equation 2.7. Various methods can be employed to determine the LOS speed from the averaged spectrum, including the centroid, median, or maximum value methods. Among these, the centroid method is more commonly utilized.

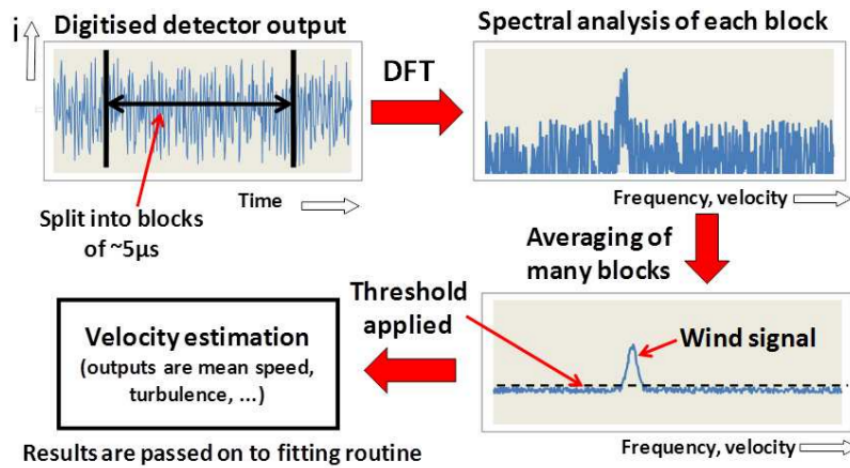


Figure 2.4: Continuous wave lidar data processing [2].

Pulsed lidar systems transmit short pulses of light into the atmosphere. Due to the travel time of the light, the backscattered light detected at a specific time can only originate from a range of distance. As for the continuous wave lidar, this means that wind speed is measured in a probe

volume rather than a point in space. In contrast to the continuous wave lidar the range gate length is no function of the measurement distance. The process of LOS wind speed calculation can be summarized as follows. The time series data from the detector is initially segmented into blocks, each corresponding to a different measurement range gate. The size of these blocks influences the probe volume-averaging effect. A FFT is applied for each range gate to estimate its power spectrum. Subsequently, after emitting the next pulse, the process is repeated to acquire the spectrum for each block. Once the spectra from many pulses are collected, they are averaged for each measurement gate to produce the mean Doppler spectrum. Finally, the LOS speed at each range gate is calculated from this averaged spectrum. Irrespective of pulsed or continuous wave lidar technology, devices can be distinguished by their ability to move the laser beam in space. Scanning lidar systems can move the laser beam to measure either on predefined or freely user-defined trajectories. This flexibility is valuable for advanced measurement objectives. For instance, a scanning lidar installed on a fixed point in a wind farm can reach arbitrary (besides blocked areas and depending on design characteristics) points in the wind field of the wind farm or site of interest by moving the laser beam and measuring at multiple distances. For resource assessment, a scanning lidar could potentially be placed on existing offshore structures or on land to measure the wind characteristics in defined points of the area of interest. In contrast, fixed beam lidars, are not able to move the laser beam during operation. Therefore, the measurement points in space form a fixed pattern.

Lidars are applied to different floating platforms in deep water environments. Below is a brief overview of these systems.

Buoy based Lidars: In general, buoy-based floating lidar systems consist of a floating platform that carries the lidar device and its auxiliary equipment and, in most cases, additional met ocean measurement equipment. Figure 2.5 shows a lidar buoy during a measurement campaign in the Ger-

man bight. The two main concepts for the buoy itself are spar buoys or tension leg platforms and free-floating marine buoys. Spar buoy concepts are either stabilized by gravity or tension legs and can be tuned not to follow wave motions. This is advantageous since the motions of the platform will be small and may be negligible for the accuracy of the lidar measurements. However, spar buoys require water depths deeper than 40m to be deployed, which makes them unsuitable for shallow waters. Marine buoys are buoyancy stabilized and typically follow the wave motions, which makes motion compensation, either mechanical or with a software algorithm, necessary in some cases [56]. In general, a floating lidar system can move in six DOFs. While these DOFs apply in general for all floating platforms, the actual intensity of motion and the influence on measurements depend on the floater type.



Figure 2.5: Fraunhofer Wind Lidar Buoy during a trial next to the FINO1 met mast within the German bight [3].

Until now, several floating lidar systems have been developed and deployed by different research groups and companies. An overview of existing floating lidar systems can be found in [57], including information about maturity level, conducted measurement campaigns, and the number of deployments and technical information. It is shown that the total number of floating lidar system deployments increased significantly in recent years. However, it is indicated that further development is needed toward full commercialization and industry acceptance.

Ship based lidars: Analog to the mounting of lidars on floating platforms with a station-keeping system, it is possible to mount wind lidars on ships. One obvious advantage of ship-based lidars is the spatial flexibility, which can be valuable for different applications like analyzing wind farm level wakes. In [58], a ship-based lidar measurement campaign in the wind farm Alpha Ventus has been performed. In this study, a Leosphere WindCube V2 lidar was installed on an offshore support vessel, and measurement equipment was used to capture the motions and exact position of the vessel. With this measurement setup, the different patterns of the ship (fixed positions, translational with wake, translational perpendicular to wake) were performed while VAD scanning measurements were performed. After motion correction of the measured wind speed, the results showed good agreement compared to the reference measurements from the FINO1 research platform. Similarly, in [59], a ship-based lidar is used to evaluate low-level jets in the baltic sea.

Nacelle based lidars: Nacelle-based lidars, as investigated in this work, are mounted on top of a turbine's nacelle, either pointing upwind or downwind to measure the inflow wind characteristics or the wake behind the turbine (see, e.g., [7, 60]). The measurements of nacelle-based lidars can serve different objectives, including power performance measurements, wind turbine control, detection of wake flows, and forecasting of power production. Today, several commercial lidar devices specifically developed for the use of nacelle lidars are available. Typically, these lidars can measure the wind speed at different heights and different distances, as depicted in figure 2.6. Examples of commercially available lidar systems are:

- WindIris TC: 4-Beam, pulsed lidar, measuring in 10 distances up to 200 meters [61]
- ZX TM Turbine: Continuous wave scanning lidar, measuring multiple ranges between 10 and 550 meters distance [62]

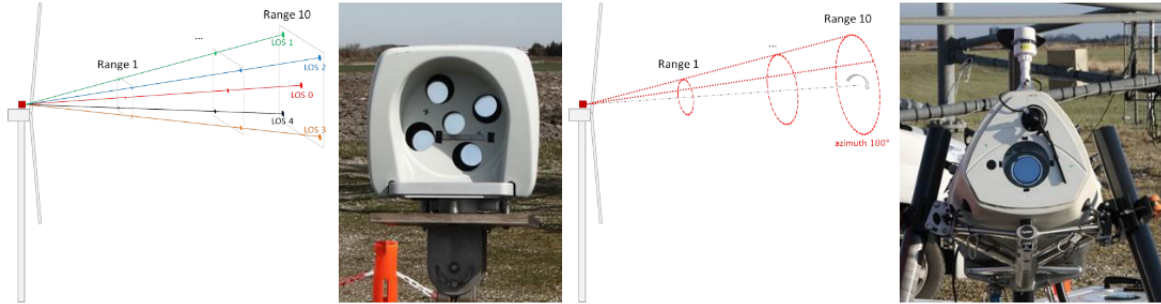


Figure 2.6: Fixed beam nacelle based lidar system (left) and scanning lidar system (right) [4]

Measuring at multiple heights and distances allows for reconstructing wind field characteristics such as shear, TI, horizontal wind speed, and rotor effective wind speed using the measured LOS velocities. Commercial lidar systems equipped with software algorithms estimate these wind field characteristics. Nacelle-based lidars have been successfully implemented on onshore and fixed bed offshore turbines, with various studies exploring different wind field reconstruction methods and assessing related uncertainties. However, deploying nacelle-based lidars on FOWTs has been less extensively studied. The first full-scale measurement campaign on a FOWT was conducted under the VAMOS research project, where a WindIris TC lidar was installed on the nacelle of the FLOATGEN demonstrator floating wind turbine. Data from this measurement campaign is utilized in this thesis.



Figure 2.7: Nacelle-based lidar on top of the Floatgen (Copyright: University of Stuttgart).

Possible applications and use cases of measurements from nacelle-based lidar systems are diverse and include:

- **Power Monitoring and Forecasting:** Wind turbines performing below the ideal power performance given by the manufacturer's power curve are a common cause of efficiency losses. This can be due to various reasons like the wake effects of neighboring turbines or operations outside of specified atmospheric conditions. A nacelle-based lidar system could provide the required wind field information needed to verify the turbine's power curve and take countermeasures if underperformance is detected.
- **Wind turbine and farm control:** Lidar-assisted feedforward pitch control approaches utilize incoming wind field speed data to adjust an additional control loop. This loop compensates for wind speed variations, such as gusts, by altering the rotor blade pitch angles to stabilize rotor speed. This method has effectively reduced platform motions and rotor speed fluctuations caused by wind disturbances (see [63] and [64] for examples). In wind farm control, nacelle-based lidar measurements provide crucial data for accurate power production prediction (see, e.g, [65]) and enable closed-loop wake steering approaches by estimating wake positions in the inflow wind field of turbines (see, e.g, [66]).
- **Load validation and monitoring:** For load validation studies lidar measurements can be used for characterizing real inflow conditions to be represented in aeroelastic simulations. (see, e.g., [8, 33]). Possible applications also include integrating inflow information into real-time load prediction models, as investigated in this thesis.
- **O&M support:** In the context of O&M, predicting the motions of FOWTs using lidar inflow measurements could be valuable for enhancing safety systems. The dynamics of FOWTs significantly influence the

accessibility of turbines for crew transfer vessels. Accurate forecasts of floater motions enable the identification of optimal times for the safe and efficient transfer of maintenance personnel to and from the turbines. Unforeseen movements of these floating structures present safety hazards. Operators can improve safety protocols for maintenance staff by accurately forecasting these movements based on lidar inflow measurements.

2.3.1 Wind field reconstruction

A Doppler lidar measures the Doppler frequency shift between transmitted and backscattered light. Since movements of reflecting particles perpendicular to the LOS will not produce a Doppler shift, only wind speed in the direction of the LOS can be detected. For the simplifying assumption of a point measurement at a specific point $[x, y, z]$ in space, the LOS wind speed for each beam i is given by the projection of the wind vector $[u, v, w]$ on the LOS vector:

$$v_{los,i} = x_{n,i}u_i + y_{n,i}v_i + z_{n,i}w_i \quad (2.8)$$

where $[x_{n,i}, y_{n,i}, z_{n,i}]$ is the normalized LOS vector.

Since the lidar can only provide measurements of the LOS wind speed, the wind vector $[u, v, w]$ in an earth-fixed coordinate system needs to be reconstructed from the LOS measurements. In general, it is not possible to reconstruct the 3-dimensional wind vector from a single LOS measurement unambiguously. This problem is known as the Cyclops dilemma. Different approaches to this problem like the Velocity-Azimuth Display technique [67] are discussed in literature. More sophisticated approaches combine several LOS measurements and use assumptions about spatial and temporal relationships between the measurements to reconstruct the wind vector (see eg.[68, 69]).

In this work, horizontal wind speed from a four-beam nacelle-based lidar system is reconstructed, making simplifying assumptions about the wind field. It is assumed that the v and w components of the wind vector are both equal to zero. With this assumption, the reconstructed u-component of the wind speed at each beam is given by:

$$u_i = \frac{v_{los,i}}{x_{n,i}} \quad (2.9)$$

with $v_{los,i}$ being the LOS wind speed of beam i , $x_{n,i}$ being the normalized x-coordinate of beam i .

2.3.2 Lidar Simulations

To evaluate the influence of motion on lidar measurements and to generate training datasets for data-driven methods, this work employs the lidar simulation environment ViConDAR [70]. ViConDAR is an open-source, modular framework designed for various lidar applications in wind energy. It comprises different modules, each offering specific functionalities, including the simulation of lidar measurements, the generation of constrained wind fields based on these measurements, and functionalities for statistical analysis. These modules can operate either independently or in sequence as part of a toolchain. In this work, only the lidar simulation functionality is used and, therefore, briefly introduced hereafter. The adaption to the framework for consideration of floating dynamics is described in chapter 3.2.

In the lidar simulation framework of ViConDAR, any arbitrary scanning pattern can be represented by defining the number and position of focus points in the rotor plane. The scanning pattern, whether a single point or multiple points, is specified in Cartesian coordinates. The time lag between consecutive measurement points can be freely defined, resulting in a time series with shifted timestamps according to this lag. The scans are repeated

across the entire length of the turbulence box, simulating the box moving toward the lidar system at the wind field's mean velocity. To accommodate both pulsed and continuous wave lidar technologies, a specific focal distance along the LOS is set, defining the center of the lidar's probe volume. Wind speed measurements at each point in the scanning pattern are captured by taking a weighted average, with a definable weighting function. Current implementations include a simple non-weighted average. In this way, the lidar's properties can be adjusted to match the specifications of specific devices. To calculate the LOS velocity at each pattern point, the wind speed components in the inertial system (u , v , w) are transformed into the LOS coordinate system. This transformation uses rotation matrices based on azimuth and elevation angles. Since lidar can only measure speed in the LOS direction, only the velocity component parallel to the LOS is retained and used in further processing steps.

2.3.3 Uncertainty Quantification

Uncertainty of measurement means doubt about the validity of the result of a measurement. More specifically, there are different measures of uncertainty that are used to describe uncertainty quantitatively [71]. In general, measurements of physical quantities are always an approximation of the real physical condition, and therefore, uncertainty about the difference between reality and measurements does exist. In most cases, the physical quantity of interest, like wind speed, cannot be measured directly. Instead, the quantity of interest is derived from measurable physical quantities. In the case of lidar wind measurements, the wind speed is derived from the detection of frequency shift between transmitted and backscattered light. Relevant characteristics of the wind field are reconstructed based on assumptions and constraints. In all process steps, from installation to measurement and signal processing, uncertainty occurs either due to systematic or random

errors. Random errors occur due to unpredictable or stochastic temporal and spatial variations of measured quantities. This type of uncertainty is often referred to as type A uncertainty. In contrast, systematic errors do not occur randomly but are introduced by an inaccuracy inherent to the system. This uncertainty is often referred to as type B uncertainty. Often known, systematic errors in measurements can be corrected but not completely eliminated. The evaluation of wind measurements with lidars and uncertainty quantification is highly relevant since, depending on the use case, errors in wind measurements will influence, for instance, controller behavior or turbine performance estimations.

Following the guide to the expression of uncertainty in measurements (GUM) methodology [72] the total uncertainty of

$$y = f(x_1, x_2, \dots, x_n) \quad (2.10)$$

with N correlated input quantities x_i is given by:

$$U_y^2 = \sum_{i=1}^N \left(\frac{\delta f}{\delta x_i} \right)^2 U_{x,i}^2 + 2 \sum_{i=1}^{N-1} \sum_{j=i+1}^N \frac{\delta f}{\delta x_i} \frac{\delta f}{\delta x_j} U_{x,i} U_{x,j} r_{i,j} \quad (2.11)$$

Where $U_{x,i}$ is the standard uncertainty of input quantity x_i and $r_{i,j}$ is the correlation coefficient between input quantity i and j . This equation sums up the uncertainty from each input variable and considers the correlation between the uncertainties of each input variable. In practical application, difficulty arises due to unknown variable uncertainties and correlation coefficients. In case the correlation coefficients are zero or assumed to be zero the equation 2.11 simplifies to:

$$U_y^2 = \sum_{i=1}^N \left(\frac{\delta f}{\delta x_i} \right)^2 U_{x,i}^2 \quad (2.12)$$

In the context of nacelle-based lidar measurements, as investigated in this

work, in IEC 61400-50-3 [73], it is suggested to use the GUM methodology for the analytical expression of uncertainty in lidar measurements. Therefore, an analytical expression of the measurement, including relevant sources of uncertainty, must be found. It is important to note that in most applications of lidar measurement campaigns, specific wind field characteristics that are reconstructed from the LOS of measurements are of interest. Therefore another source of uncertainty is the applied wind field reconstruction algorithm and the propagation of measurement uncertainties to the reconstructed wind field characteristics. This must be reflected in the analytical expression used in the GUM methodology. The application to uncertainty estimation of lidar measurements under motion influence is discussed in chapter 4.

2.4 Virtual Sensors

In the context of wind turbine operation, control, and monitoring, the measurement of key physical parameters is crucial. Nonetheless, there are scenarios where direct measurement through conventional sensors is impractical or unattainable. In such instances, the use of virtual sensors presents a viable alternative. These sensors perform indirect estimations of the target quantities by utilizing available measurement data as inputs to model the desired outputs. The nature of the model employed in this process varies based on the understanding of the input-output relationship. When this relationship is clearly defined, physical models can be utilized. Conversely, in situations where the relationship is either unknown or too complex for a physical model to encapsulate, data-driven models can be employed. An example of this is the prediction and forecasting of fairlead tensions from platform positions, dynamics, and lidar inflow measurements. In this work, virtual load sensors are developed based on artificial neural networks.

2.4.1 Artificial Neural Networks

The generic structure of a multi-layer artificial neural network with an input layer, a hidden layer, and an output layer is shown in figure 2.8. The goal of a neural network is to map a set of input data to a set of target data. In its simplest form, each neuron is modeled by:

$$x_i = f\left(\sum_{j=1}^n w_{ij}x_j\right) \quad (2.13)$$

where f is the activation function, x_j is the output from the previous layers output and w_{ij} is the weight of the connection between neuron i and neuron j . Different linear and nonlinear activation functions exist and are chosen depending on the neural network's individual task.

Training data is required to determine the network's weights so that the network best predicts the target data based on input data, using the back-propagation algorithm. This algorithm computes the gradient of a loss function with respect to the weights of the network. The process involves two main phases: a forward pass and a backward pass. In the forward pass, input data is passed through the network, layer by layer, to compute the output predictions and the loss, which measures the discrepancy between the predicted and actual outputs. During the backward pass, the gradient of the loss function is computed backward from the output layer to the input layer. This is achieved by applying the chain rule to compute the loss gradient with respect to each weight in the network. These gradients are then used to update the weights in the opposite direction of the gradient to minimize the loss. Detailed explanations and mathematical formulations are in [74].

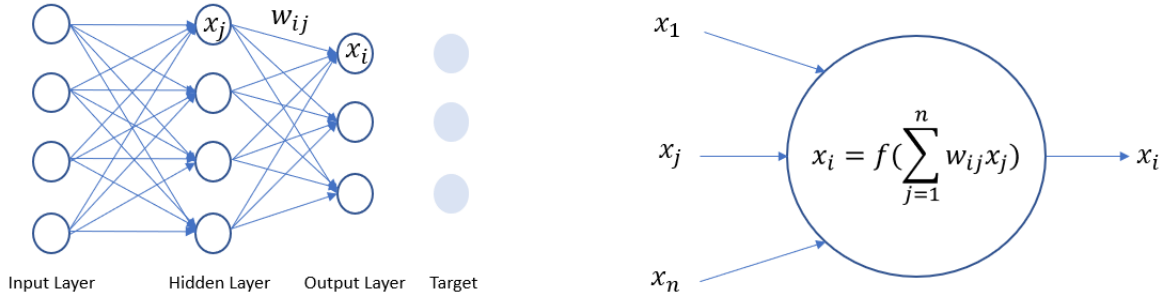


Figure 2.8: Left: Fundamental structure of the neural network. Right: Model of a neuron that applies the activation function f on the weighted sum of inputs.

LSTM Networks

LSTM networks are a type of recurrent artificial neural network, that has proven to be particularly effective in capturing time dependencies in input data. The key feature of LSTMs is their ability to remember or forget previous inputs over extended sequences of input data selectively. LSTM networks have been introduced by [75] as a solution to the vanishing exploding gradient problem. The exploding gradient problem refers to the phenomenon in recurrent neural networks where gradients become excessively large during backpropagation, leading to unstable training dynamics and impeding learning. An in-depth discussion of the problem is given in [76].

LSTM networks are characterized by the use of specialized memory cells that can store information over multiple steps. Unlike traditional neural networks, LSTMs have a gating mechanism that regulates the flow of information between cells, allowing them to selectively retain or discard information based on its relevance to the current state of the network. Figure 2.9 shows the structure of an LSTM cell.

The initial phase in the operation of an LSTM involves determining the

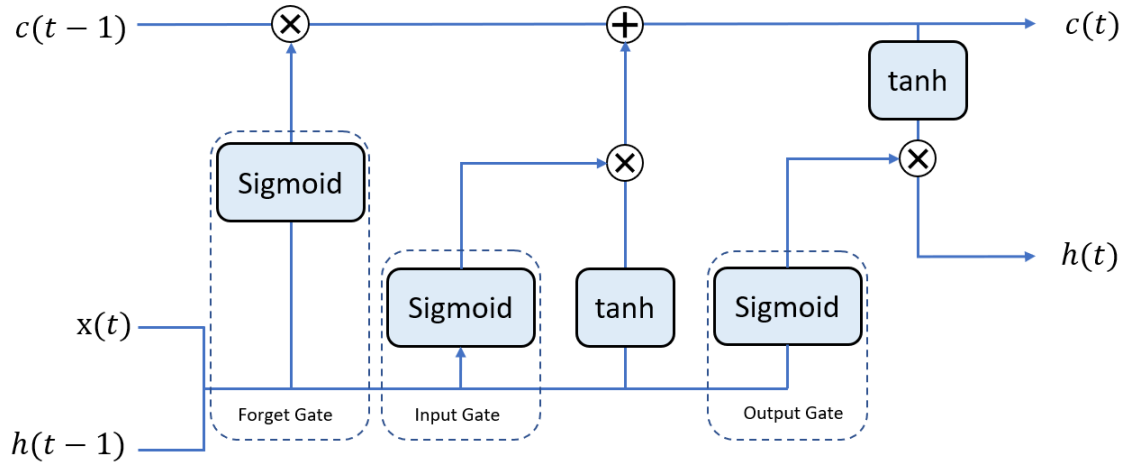


Figure 2.9: Structure of a LSTM cell, where $c(t)$ is the cell state, $h(t)$ is the hidden state and $x(t)$ is the data input.

information to be discarded from the cell state. This process is governed by a sigmoid function, denominated as the "forget gate" which evaluates h_{t-1} and x_t , subsequently emitting a value within the range of 0 to 1 for each element in the cell state c_{t-1} . Herein, a value of 1 signifies the complete retention of the information, whereas a value of 0 denotes its total elimination.

The input gate in an LSTM cell manages the influx of new information into the cell state. It consists of two parts: a sigmoid function that determines which values will be updated, and a tanh function that generates a vector of candidate values for addition to the cell state. This gate effectively decides the extent of the update to the cell state with new, relevant information, ensuring that only significant updates are made while preserving the integrity of the cell's existing state.

The output gate controls what part of the cell state is passed to the output. It employs a sigmoid function to select parts of the cell state for output based on the current inputs and the previous state. Then, it applies a tanh function to the cell state, scaling it between -1 and 1, multiplying this result by the sigmoid output. This process filters the cell state, ensuring that only

relevant information, as determined by the output gate, is transmitted to the next network stage or as the final output.

Convolutional Neural Networks

Convolutional Neural Networks (CNNs) have traditionally been associated with image processing tasks, but they have also proven to be effective for time series classification. CNNs can extract meaningful features from sequential data by using 1D convolutional layers to scan through the time series, identifying patterns within the data. These learned features can capture essential temporal information, such as trends and frequencies, making CNNs useful in applications like the prediction of DELs. Figure 2.10 shows the schematic structure of a CNN.

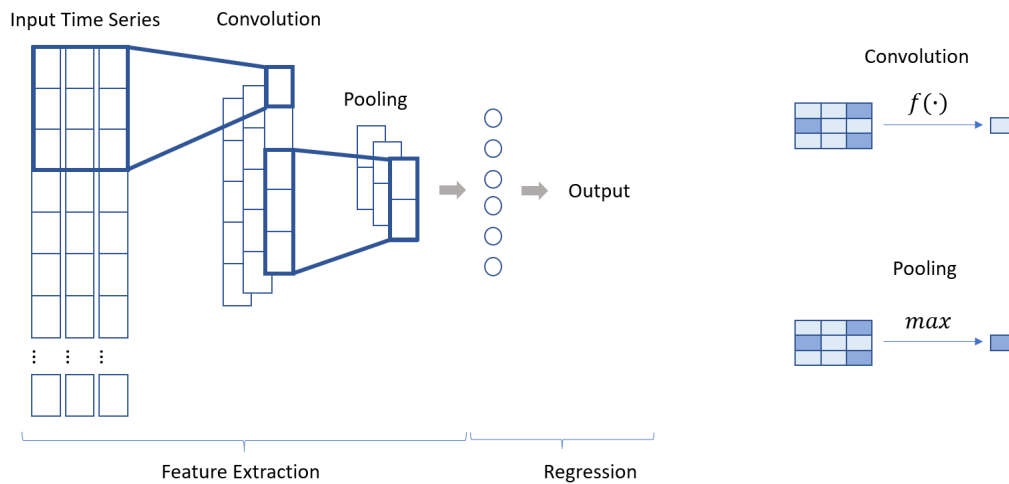


Figure 2.10: Left: Structure of a CNN with one convolutional layer and one pooling layer. Right: Convolution and pooling operation.

The convolutional operation in neural networks involves sliding a filter, with learned weights during training, across the input data to produce a feature map. This process captures patterns by computing the dot product between the filter and input segments. The output, a feature map, highlights detected features and is activated by functions like ReLU to introduce non-

linearity, enabling complex pattern recognition.

The pooling operation aims to reduce the spatial dimensions of feature maps, thus decreasing the computation and parameter requirements. Pooling is performed after the convolutional layers and the activation function. The most common form of pooling is max pooling, where the operation divides the input feature map into non-overlapping rectangles and outputs the maximum value from each rectangle. This effectively retains the most prominent features while discarding less significant information. In section 5, CNNs using a ReLU activation function and a *max*-pooling layer are employed to predict DELs of failed tensions.

2.4.2 Damage Equivalent Loads

The fatigue damage to wind turbine structures is strongly influenced by the stochastic inflow to the turbine, which is mainly composed of wind turbulence and spatial variations such as shear and veer. For offshore substructures, irregular ocean waves also result in dynamic loads leading to fatigue damage. The Palmgren–Miner rule [77] is the standard approach followed in the design of wind turbines by which it is ensured that the linear damage sum over an intended lifetime is lower than unity after considering required safety margins. This damage definition is based on the Wöhler curve which defines the maximum allowable number of load cycles N_i for each load amplitude S_i . The damage is given as a summation of all load contributions in a load spectrum.

$$D = \sum_{i=1}^{i=j} \frac{n_i}{N_i} = \sum_{i=1}^{i=j} n_i S_i^m \quad (2.14)$$

where n_i is the number of cycles at load amplitudes S_i in the load spectrum and m is the Wöhler exponent. Since the Miner damage variable is not a physically measurable quantity, a substitute for damage is used, which

is the damage equivalent load (DEL). This is the load level at a particular number of cycles N_{ref} which results in the same damage as the original summation of a multitude of different load cycles n_i with different amplitudes S_i . DEL provides a measurable quantity from an operating turbine that can be compared with results from simulations made in the design phase. DEL is calculated by

$$DEL = \sqrt[m]{\frac{1}{N_{ref}} \sum_i n_i S_i^m}. \quad (2.15)$$

The load amplitudes S_i and corresponding cycle counts are determined using a rain flow counting algorithm. In chapter 5 where different approaches for predicting DELs of fairlead tension using neural networks are investigated the calculation procedure is used.

2.4.3 Performance Metrics

The performance of the time series prediction and forecasting models in this work is assessed using the RMSEN (Root Mean Squared Error Normalized) metric. RMSEN is the root mean squared error between the predicted time series Y_{pred} and the actual target time series Y , normalized by the standard deviation σ_y of the reference time series. The RMSEN is mathematically represented as follows:

$$RMSEN = \frac{1}{\sigma_y} \sqrt{\frac{\sum_{i=1}^N (Y_{pred} - Y)^2}{N}} \quad (2.16)$$

In this equation, Y_{pred} represents the predicted values, Y denotes the actual reference values, and N is the total number of data points in the sequence. For a comprehensive evaluation across the entire testing dataset, both Y_{pred} and Y are concatenated, encompassing all test sequences. In this context, N

refers to the total count of data points across the complete testing dataset, and σ_y is the standard deviation calculated over the entire reference dataset. RMSEN is selected as the error metric for its ability to facilitate both qualitative and quantitative comparisons of forecasting accuracy for different target features across varying scales.

DEL predictions are evaluated using absolute percentage errors (*APE*) which allow an easier interpretation of results. *APEs* between predicted and reference DELs are calculated by:

$$APE = \left| \frac{DEL_{pred} - DEL_{ref}}{DEL_{ref}} \right| * 100 \quad (2.17)$$

where DEL_{ref} is the reference DEL and DEL_{pred} is the predicted DEL value. To represent absolute error values, the root mean squared error (RMSE) is used, where N is the number of samples in the testing data set. RMSE is given by:

$$RMSE = \sqrt{\frac{\sum_{i=1}^N (DEL_{pred} - DEL_{ref})^2}{N}}. \quad (2.18)$$

3

Simulation Environment and FOWT models

3.1 Lidar Simulation Requirements

FOWT dynamics affect the lidar measurements in different ways. A simulation environment for lidar measurements on FOWT must reflect these effects to realistically reproduce lidar measurements under motion influence. Motion-influencing effects considered in developing the numerical and analytical simulation environments are summarized below. See figure 3.1 for a schematic representation.

- **Beam direction:** Depending on the floater type, the met ocean conditions, and the mounting position of the lidar, the lidar system will be subject to translational and rotational motions. The rotational motion of the lidar will cause a tilted beam direction compared to a fixed lidar system. Wind lidars can only measure the wind speed in

the direction of the LOS. Mathematically, this can be described by a projection of the wind vector $[u, v, w]$ on the vector $[x, y, z]$ defining the LOS. In case the LOS direction changes due to the FOWT dynamics, the lidar will measure the LOS wind speed differently. Wind field reconstruction algorithms, as discussed in section 2.3.1, rely on the knowledge of beam direction to reconstruct the wind vector from the LOS measurements. The reconstruction will yield erroneous results if the exact beam direction is unknown due to floater dynamics.

- **Position of focus points:** A changing beam direction also changes the location of the lidar focus points in space. Assuming a horizontal LOS and a measurement distance of 350 m, a pitch angle of 5 deg would cause a vertical shift of the focus point of ca. 30 m. Thus, the measurement is taken from a different location than intended, which can yield erroneous results. Wind speed measurements may be systematically biased under the presence of wind field characteristics like vertical wind shear.
- **Superimposed translational velocities:** The wind speed measured by a lidar is derived from the Doppler shift between transmitted and backscattered light. If the lidar system moves in space with a certain velocity the relative velocity between the reflecting particles in the air and the lidar devices changes. This leads to a change in the backscattered frequency and, thus, to a bias in the measured LOS wind speed.

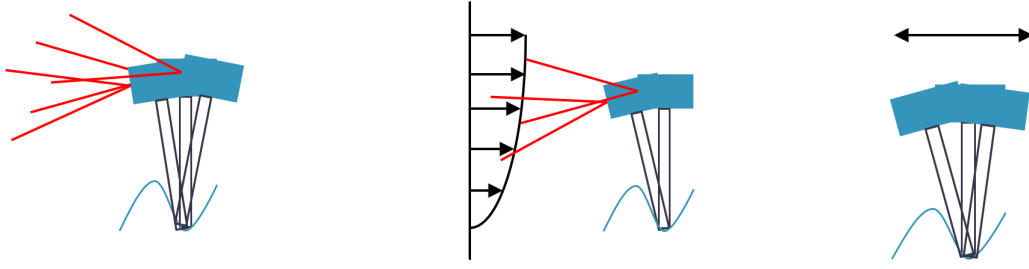


Figure 3.1: Motion influence on nacelle-based lidar systems.

3.2 Numerical Lidar Simulation

The studies on motion influence, uncertainty quantification, and lidar-based virtual sensors in this thesis rely on numerical simulations of lidar measurements under the influence of FOWT. Therefore, as part of this work, the numerical lidar simulation framework introduced in 2.3.2 is adapted to account for platform motions in six DOFs. This extension is described in this section.

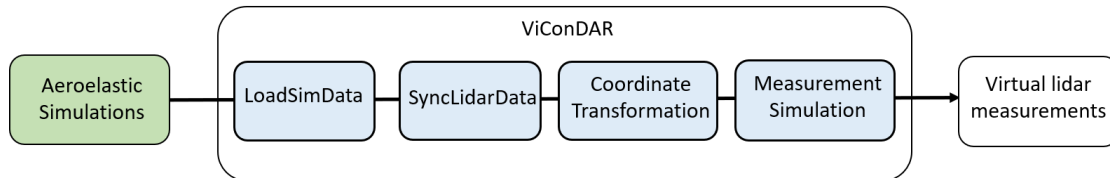


Figure 3.2: ViConDAR lidar simulation process steps.

A floating platform has six DOFs. Three DOFs define the rotational displacement around the x , y , and z axes, and three DOFs define translational displacements along the x , y , and z axes. With the assumption of a rigid floater-turbine assembly, these DOFs are directly transferred from the floater coordinate system to the mounting position of the lidar atop the nacelle. Due to the lever arm between the platform and the mounting position of the lidar, additional translational displacements of the nacelle result from rotations of the platform. Additionally, the lidar's translational velocities

resulting from the floater's combined translational and rotational motion must be considered. Consequently, the dynamics summarized in table 3.1 are considered for the numeric lidar simulation. The table also provides the names of the OpenFAST sensors used for this work. In general, other sensors representing the same DOFs could be used.

The data handling and processing steps are depicted in figure 3.2. The LoadSimData module reads the simulated FOWT responses and extracts relevant channels according to table 3.1. For the rotational displacement angles, a rigid floater-tower assembly is assumed. Therefore, the platform rotational displacement signals (pitch, roll, and yaw) from the aeroelastic simulation are directly used by ViConDAR as input for the rotational displacement of the lidar system. If the nacelle yaw DoF is enabled in the aeroelastic simulations, such as in the simulations in chapter 5 and 6 to align the rotor for different wind directions, the rotational displacements are rotated to the lidar coordinate system, considering the yaw position of the nacelle.

The tower top displacements are used for the translational displacement of the lidar system. These output signals reflect the translational displacement at the tower top, which is not equal to the mounting position of the nacelle-based lidar. Since the distance between the tower top and the lidar mounting position is small compared to the tower height, the influence of this inaccuracy is neglected. Equivalent to the rotational displacements, the translational displacements are transferred to the lidar coordinate system, considering the yaw position of the nacelle. The translational velocities of the lidar system are given in the nacelle coordinate system of the turbine model, which reflects the translational velocities of the nacelle relative to an earth-fixed coordinate system. The position of the nacelle coordinate system might not exactly coincide with the mounting position of the lidar. This inaccuracy is neglected, assuming that both coordinate systems coincide.

The SyncLidar module matches the time steps of the aero-elastic simula-

Table 3.1: Lidar DOFs and OpenFAST sensors used in the simulation.

Group	DOF	OpenFAST Sensor
Rotational Displacements	Ptich Roll Yaw	PtfmPitch PtfmRoll PtfmYaw
Translational Displacements	Surge Sway Heave	TwrTpTDxi TwrTpTDyi TwrTpTDzi
Translational velocities	x_{vel} y_{vel} z_{vel}	NcIMUTVxs NcIMUTVys NcIMUTVzs

tions with the time steps where lidar measurements take place. Here, the temporal distance between individual focus points in the pattern, as well as the temporal distance between the full scans, is considered. In this way, the turbine dynamics are extracted for all points in time where a lidar measurement is simulated.

The coordinate transformation module computes the positions of the focus points based on the defined pattern and the dynamic position of the lidar device. In this module, the position of the lidar focus points is determined, considering the displacement of the lidar system. Mathematically, the positions of lidar focus points after rotational displacement are obtained by multiplication of the LOS vectors without displacement with a rotation matrix $R(\psi, \beta, \gamma)$. The translational displacement of the lidar system does not affect the angular beam directions but shifts the lidar system and the focus in space. After consideration of translational displacements the positions of focus points are given by:

$$\begin{bmatrix} x_{p,I} \\ y_{p,I} \\ z_{p,I} \end{bmatrix} = R(\psi, \beta, \gamma) \cdot \begin{bmatrix} x_{p,L} \\ y_{p,L} \\ z_{p,L} \end{bmatrix} + \begin{bmatrix} x_{trans} \\ y_{trans} \\ z_{trans} \end{bmatrix} \quad (3.1)$$

where $[x_{p,L}, y_{p,L}, z_{p,L}]$ are the focus point position in lidar coordinates, $[x_{trans}, y_{trans}, z_{trans}]$ are the translational displacements and include the surge, sway, and heave DOFs of the floating platform.

The LOS measurements of the individual beams are modeled as a projection of the wind vector $[u, v, w]$ on the current normalized LOS vector $[x_{pn,I}, y_{pn,I}, z_{pn,I}]$:

$$v_{los} = \int_{-\infty}^{\infty} (x_{pn,I}u + y_{pn,I}v + z_{pn,I}w)f(a_d)da_d + v_{los,trans} \quad (3.2)$$

where $f(a_d)$ is the range weighting function and a_d is the distance between the lidar and the focus point. The translational velocities $[x_{vel}, y_{vel}, z_{vel}]$ of the lidar in x, y, z direction superimpose an additional velocity component on the LOS measurements:

$$v_{los,trans} = (x_{vel}x_{pn,I} + y_{vel}y_{pn,I} + z_{vel}z_{pn,I}) \quad (3.3)$$

In the simulation, the range weighting function is represented by a definable length of the range gate and discretized by a number of points along the beam. The x-coordinate of the focus points in space is converted to the time coordinate of the synthetic turbulence box using Taylors' frozen turbulence hypothesis. The wind vector is then sampled from the closest point to the $[x, y, z]$ grid of the synthetic turbulence box (see Figure 4.4).

The spatial and temporal resolution of the turbulence box is a limiting factor of the numerical simulation approach. The magnitude of the spatial shift of the lidar focus points position, which the simulation can capture,

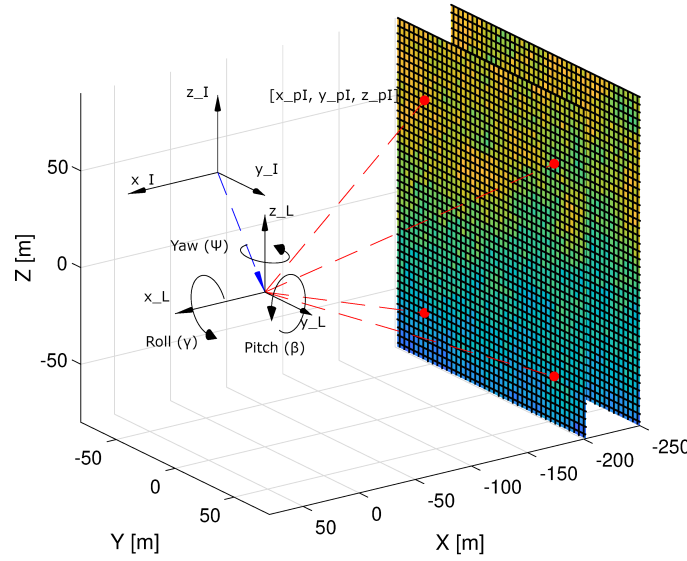


Figure 3.3: Numerical lidar simulation coordinate systems.

is determined by the distance of the grid points. If the spatial shift of focus points is much smaller than the grid resolution, it will not alter the grid point queried for the derivation of the wind vector and, therefore, not change the simulated measurement.

The model is available as an open-source tool by the chair for wind energy at the University of Stuttgart (SWE) on "<https://github.com/SWE-UniStuttgart/ViConDAR>".

3.3 FOWT models

In this thesis, lidar measurements are simulated and investigated for different FOWT concepts. This chapter briefly introduces the three FOWT models used throughout the thesis. The FLOATGEN and WindCrete FOWT concepts are employed for the motion influence quantification in chapter 4. The UMaine VoltturnUS-S reference FOWT model is used to generate model training data in chapter 5 and 6.

3.3.1 FLOATGEN

The floating substructure is a barge-type floater employing BWideol's damping pool design. It is installed on the SEMREV test site [78] located near the Atlantic coast of Brittany. The wind turbine employed for this demonstrator is a 2 MW Vestas V80 turbine with a rotor diameter of 90 m and a hub height of 60 m. Further information on the FLOATGEN demonstrator can be found in [50].

3.3.2 WindCrete

The WindCrete floater design concept [45] in combination with the International Energy Agency (IEA) 15 MW reference wind turbine [79] is a monolithic spar design with a draft of 155 m and a tower height of 129.5 m. The spar and the tower are designed as one single concrete member with an overall mass of 3.665×10^7 kg including the ballast. Station keeping of the WindCrete concept is realized with three delta-shaped catenary mooring lines with an overall length of 615 m and a mass of 561.25 kgm^{-1} . Details on the WindCrete design parameters and the dynamic behavior can be found in [45]. Additionally, to assist in analyzing frequency contents of predicted time series in chapter 5, table 3.2 lists the natural frequencies of the FOWT model.

3.3.3 UMaine VoltturnUS-S

The University of Maine's VoltturnUS-S reference floating wind turbine, detailed in [40], features a semisubmersible substructure paired with the International Energy Agency's (IEA) 15-240-RWT 15 MW reference wind turbine, as described in [79]. This turbine has a rotor diameter of 240 meters and a hub height of 150 meters. The floating support structure is a steel

Table 3.2: Floater natural frequencies WindCrete.

DOF	natural frequency
Surge	0.012 Hz
Sway	0.012 Hz
Heave	0.030 Hz
Roll	0.030 Hz
Pitch	0.024 Hz
Yaw	0.092 Hz

design, comprising three radial and one central cylindrical body, with the turbine tower connected to the central column. Stability and positioning are achieved through three mooring lines, each 850 meters long and weighing 685 kgm^{-1} , attached to the radial bodies. A visual representation of the floater, including its geometric layout, the locations of fairleads, and the lidar installation point, is depicted in Figure 5.6 (right). Comprehensive details on the design specifications of both the floater and the mooring lines are available in [40]. Table 3.3 lists the natural frequencies of the FOWT model.

Table 3.3: Floater natural frequencies VoltturnUS-S.

DOF	natural frequency
Surge	0.007 Hz
Sway	0.007 Hz
Heave	0.049 Hz
Roll	0.036 Hz
Pitch	0.036 Hz
Yaw	0.011 Hz

3.4 Analytical Lidar Simulation

The analytical uncertainty model of nacelle-based lidar measurements is specifically developed as a basis for uncertainty estimation using the GUM methodology, which requires an analytical description of the measurement. For nacelle-based lidar measurements on a FOWT, the model must contain the relevant dynamic behavior of the FOWT, a description of the wind field, and a model of the measurement itself.

The dynamic behavior of the FOWT is modeled considering four DOFs, namely the rotational displacement in yaw, pitch, and roll direction, as well as the heave displacement of the floater (see Figure 3.4). The low-frequency displacements of the floater in surge and sway direction typically cause slow translational displacements of the nacelle compared to the effect of rotational floater displacements. Therefore, the model does not consider the floater's sway and surge displacement individual DOF. The temporal behavior of the considered DOFs, a , is modeled by harmonic oscillations around a defined mean value:

$$a = A_a \cdot \left(\sin \frac{2\pi}{T_a} t \right) + k_a \quad (3.4)$$

where A_a is the amplitude, T_a is the period, k_a is the mean value of the respective DOF and t is the time. A rigid floater-tower assembly is assumed to transfer the modeled floater dynamics to the dynamics of the lidar device mounted on the turbine's nacelle. Therefore, the rotational displacement and the translational heave displacement of the lidar device are equivalent to the displacement of the floater. The rotational displacements of the floater cause relevant translational displacements at the mounting position of the lidar. The translational displacements $[x_{trans}, y_{trans}, z_{trans}]$ are modeled by defining the mounting position of the lidar, $[x_m, y_m, z_m]$, in the floater coordinate system and the multiplication with a rotation matrix

R :

$$\begin{bmatrix} x_{trans} \\ y_{trans} \\ z_{trans} \end{bmatrix} = R(\psi, \beta, \gamma) \cdot \begin{bmatrix} x_m \\ y_m \\ z_m \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ z_{heave} \end{bmatrix} \quad (3.5)$$

where z_{heave} is heave elevation of the floater (see figure 3.4). The definition of the rotation matrix R is given in Appendix A.1. The translational velocities at the lidar mounting position are found by calculation of the first time derivative of the translational displacement:

$$\vec{x}_{vel} = \frac{\Delta \vec{x}_{trans}}{\Delta t} \quad (3.6)$$

where $\vec{x}_{trans}$ denotes the vector of translational displacements $[x_{trans}, y_{trans}, z_{trans}]$ and $\vec{x}_{vel}$ is the vector of translational velocities $[x_{vel}, y_{vel}, z_{vel}]$.

The model parameters defining the dynamic behavior of the FOWT are summarized in Table 3.4.

Table 3.4: Considered FOWT dynamics parameters.

DOF	Amplitude	Period	mean
Yaw	A_ψ [deg]	T_ψ [s]	0
Pitch	A_β [deg]	T_β [s]	k_β [deg]
Roll	A_γ [deg]	T_γ [s]	0
Heave	A_{heave} [m]	T_{heave} [s]	0

In reality, the LOS measurement of a lidar is influenced by various atmospheric and technical parameters. A simplified model of the atmosphere and the lidar measurement is introduced for the analytical calculation of motion-induced uncertainties. The horizontal wind speed is modeled using a power law profile given by equation 2.1 where V_{ref} is the reference wind

speed, H_{ref} is the reference height, H is the height above ground and α is the vertical wind shear exponent. Horizontally, the wind field is assumed to be homogeneous. The v and w wind speed components are assumed to be zero. While these assumptions avoid the introduction of a turbulence model and enable the analytical derivation of uncertainty following the GUM methodology, it should be pointed out that model results do not reflect any effects originating from the turbulent nature of real wind fields.

Two coordinate systems are introduced to consider dynamic LOS position due to floater motion. Following the notation of [69], the I coordinate system is an earth-fixed reference coordinate system, and the L coordinate system is the coordinate system of the lidar device. The coordinates of the lidar focus points are defined in terms of angles from the center line θ (opening angle) and angles around the center line ϕ (polar position):

$$\begin{bmatrix} x_{p,L} \\ y_{p,L} \\ z_{p,L} \end{bmatrix} = \begin{bmatrix} \cos \theta \\ \sin \theta \cos \phi \\ \cos \theta \sin \phi \end{bmatrix} \quad (3.7)$$

Considering the rotational displacement of the lidar system due to the yaw, pitch, and roll DOF of the floater, the coordinates of the rotated focus points in the earth fixed coordinate system are obtained by multiplication with a rotation matrix R :

$$\begin{bmatrix} x_{p,I} \\ y_{p,I} \\ z_{p,I} \end{bmatrix} = R(\psi, \beta, \gamma) \cdot \begin{bmatrix} x_{p,L} \\ y_{p,L} \\ z_{p,L} \end{bmatrix} \quad (3.8)$$

where ψ, β, γ is the current roll, pitch, and yaw angle respectively, and $[x_{p,I}, y_{p,I}, z_{p,I}]$ is the current position of the lidar focus points in earth fixed

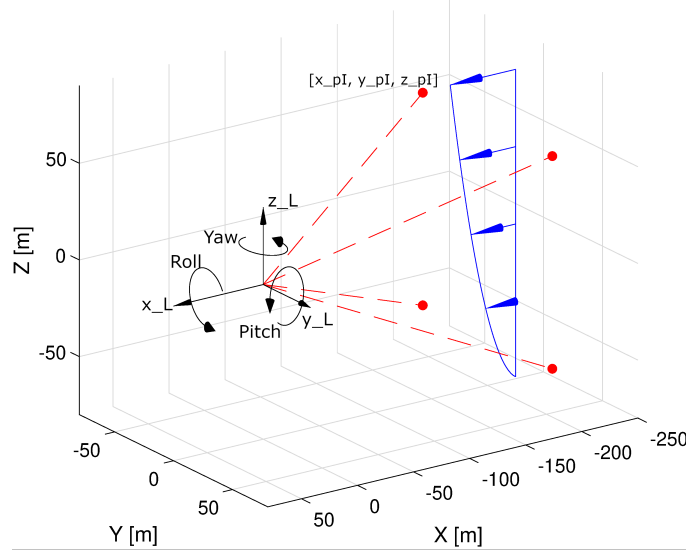


Figure 3.4: Lidar pattern and coordinate systems for the analytical model.

coordinates (see Figure 3.4). The rotation matrix R is given in Appendix A.1.

Finally, the LOS velocity is mathematically described by a projection of the local wind vector $[u, v, w]$ on the vector describing the LOS. In the remainder of the thesis, the u-component of the wind field is referred to as u .

$$v_{los} = x_{pn,I}u + y_{pn,I}v + z_{pn,I}w + (x_{In}x_{vel} + y_{pn,I}y_{vel} + y_{pn,z_{vel}}) \quad (3.9)$$

where $x_{pn,I}, y_{pn,I}, z_{pn,I}$ is the normalized LOS vector. The wind speed components u, v, w are derived using equation 2.1. To enable a straightforward analytical uncertainty derivation probe volume averaging effects are not considered. The translational velocities $[x_{vel}, y_{vel}, z_{vel}]$ are added to the local wind vector as additional velocity components.

The dynamic measurement height H is given by:

$$H = z_{p,I} + h_{lidar} + h_{heave} \quad (3.10)$$

where $z_{p,I}$ is the z-coordinate of the focus point, h_{lidar} is the height of the

lidar mounting position above mean sea level, and h_{heave} is the elevation due to the heave motion of the floating platform.

Considering the vertical wind profile, the wind direction φ and assuming the vertical wind speed component w to be zero yields:

$$v_{los} = V_{ref} \left(\frac{z_{p,I} + h_{lidar} + h_{heave}}{H_{ref}} \right)^\alpha \cdot (\sin \varphi \cdot x_{pn,I} + \cos \varphi \cdot y_{pn,I}) + (x_{pn,I} \cdot x_{vel} + y_{pn,I} \cdot y_{vel} + y_{pn,I} \cdot z_{vel}) \quad (3.11)$$

4

Quantification and Correction of Motion Influence for Nacelle-based Lidar Measurements

This chapter aims to provide missing insights into the impact of floater dynamics on nacelle-based lidar inflow wind speed measurements for FOWT. Therefore, motion-induced effects from individual platform DOFs are analyzed, and correction methods are proposed. In short, the objectives of this chapter are:

- quantify the uncertainties and biases caused by floater motion in lidar wind speed measurements on FOWT
- Propose correction methods for these motion-induced effects across various time scales
- Evaluate the effectiveness of these methods under different floater

characteristics and atmospheric conditions

This chapter expands upon the findings and methodologies previously documented in [80].

4.1 Analysis of Measurement Campaign

To gain a general understanding of the characteristics of real measurement data from a nacelle-based lidar system on a FOWT, this section analyzes a dataset from a lidar installed on the nacelle of the FLOATGEN demonstrator floating wind turbine, as referenced in [50]. The dataset was collected during a measurement campaign from December 2020 to April 2021. Specifically, the analysis focuses on the data gathered in January 2021.

The measurement campaign utilized a WindIris TC lidar, as detailed in [61]. This system is characterized by four pulsed beams and a sampling frequency of 1 Hz, capturing LOS velocities at distances ranging from 50 m to 200 m. Additionally, the system includes an IMU that records the lidar's rotational displacements in both pitch and roll orientations. The methodology for reconstructing the wind field, as described in [81], involves recalculating the horizontal wind speed components u and v by integrating the LOS measurements from all four beams.

The rotational displacement measurements obtained from the lidar's IMU were found to significantly overestimate the displacement amplitudes compared to those from other nacelle-mounted sensors. Consequently, the inclination data utilized in this study were adjusted using a linear correction factor that aligns the IMU's inclination measurements with those from other nacelle-mounted inclinometers. This correction method is elaborated upon in [82].

Figure 4.1a presents the 10-minute averaged mean pitch angles from the inclination sensor, categorized by wind speed, and includes the standard

deviation of these mean pitch angles for each wind speed bin within the dataset. The data illustrate a significant correlation between the mean pitch angle and the wind speed, along with the associated thrust force. Notably, the observed mean pitch angles are below 1 degree, which is relatively low compared to those recorded for other types of floating wind turbines, such as the WindCrete FOWT concept detailed in [45].

The analysis further includes the standard deviation of the pitch angle, calculated for each 10-minute interval and organized by wind speed bin. The data reveal that the standard deviations increase in tandem with wind speed and related wave-induced motions of the floater. Hydrodynamic forces predominantly drive the pitch dynamics of this particular floater and are notably pronounced when compared with other floater designs, such as spar-type floaters. This significant pitch movement induces translational velocities of the nacelle along the x-axis. In Figure 4.1a, the black line represents the standard deviation of these translational velocities in the x-direction.

The velocity component, being superimposed on the measurements, is likely to result in considerable variations in the lidar data due to the pitch motion and associated translational velocities of the nacelle. However, the impact of mean pitch angles and the consequent shift in measurement positions are anticipated to exert a lesser effect on the measurements for this type of floater.

The time series depicted in Figure 4.1b confirms this observation, showing the lidar's reconstructed wind speed estimates alongside the measured pitch inclination signals. This demonstrates a significant correlation between the floater's pitch angle and the wind speed measurements obtained by the lidar. The power spectral density (PSD) plots for the inclination pitch signal, one LOS velocity signal, and the reconstructed u-component of the wind speed are presented in Figure 4.1c. These PSDs exhibit peaks corresponding to the floater's pitch frequency across the LOS velocities from individual beams, the pitch signal, and the reconstructed u-component of the wind speed,

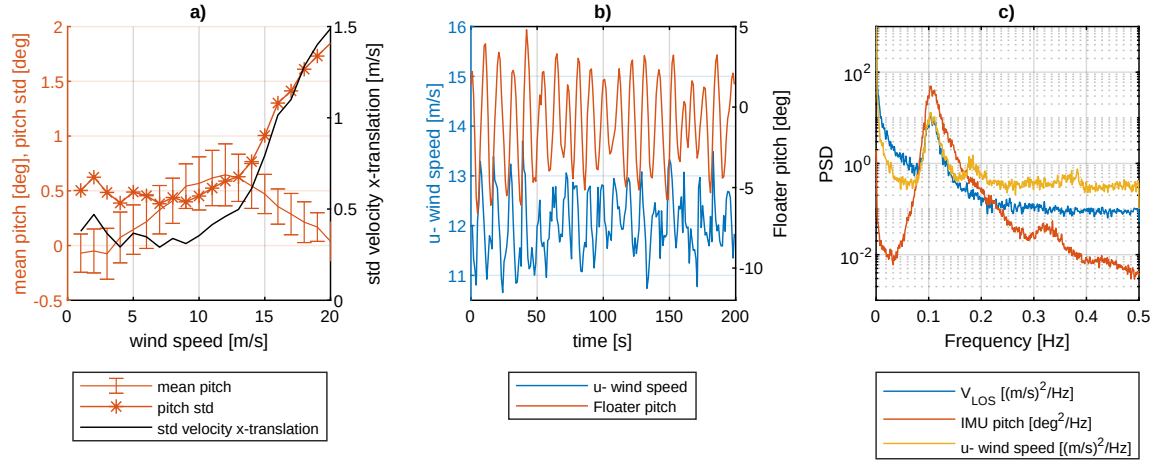


Figure 4.1: Analysis of measurement campaign data. a): Mean and standard deviation of floater pitch angle over 10 min mean wind speed bins. Error bars denote the standard deviation of mean pitch values over all 10-minute samples. Standard deviation of translational velocity in the x-direction over wind speed bins. b) Time series of reconstructed u-component wind speed and pitch angle. c) PSD of floater pitch angle, LOS-1 velocity, and reconstructed u-component wind speed.

indicating a distinct correlation between the lidar's pitch signal and the reconstructed u-component of the wind speed. The analysis shows the impact of the floater's rotational DOFs, especially the pitch motion, on the LOS measurements and the nacelle-mounted lidar's wind speed reconstruction. Without a reference wind speed measurement, such as from a met-mast, it is challenging to quantify the exact influence of floater motions on the lidar readings. Nevertheless, the observed correlations underscore the necessity for further detailed investigation and quantification of motion impacts on lidar measurements. The subsequent section will address this by quantifying the motion's influence through a simulation-based approach.

4.2 Methodology

Figure 4.2 provides a schematic representation of the methodology and the application of both analytical and numerical lidar measurement models used in this chapter. These models operate within a defined dynamics parameter space, encompassing a range of rotational and translational displacements. The analytical model, in conjunction with the GUM methodology, and the numerical model, paired with statistical metrics, are utilized to quantify the uncertainties and biases in lidar measurements mounted on nacelles. As recommended by [73], the GUM approach assesses the uncertainty of LOS velocity (v_{los}) based on specific input parameters delineated in Equation 3.11. This uncertainty is then propagated through a wind field reconstruction algorithm to estimate the uncertainties associated with the reconstructed u-component of the wind vector. Additionally, the analytical model calculates the bias in the lidar-estimated u-component wind speed, considering the dynamic input parameters.

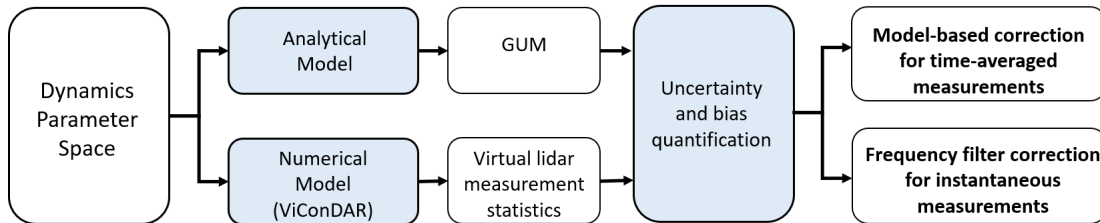


Figure 4.2: Utilization of analytical and numerical lidar measurement models.

Using this quantification of uncertainties and biases, two correction approaches are introduced.

4.2.1 Analytical estimation of uncertainty in wind field characteristics

Following the GUM methodology for expression of uncertainty [72] the total uncertainty of $y = f(x_1, x_2, \dots, x_n)$ with n uncorrelated input quantities x_i is given by equation 2.12. Accordingly, the total uncertainty in the LOS measurements, induced by floater dynamics is given by:

$$U_{v_{los}} = \sqrt{\left(\frac{\delta v_{los}}{\delta \psi}\right)^2 U_{\psi}^2 + \left(\frac{\delta v_{los}}{\delta \beta}\right)^2 U_{\beta}^2 + \left(\frac{\delta v_{los}}{\delta \gamma}\right)^2 U_{\gamma}^2 + \left(\frac{\delta v_{los}}{\delta h_{heave}}\right)^2 U_{h_{heave}}^2 + \frac{\delta v_{los}^2}{\delta \mathbf{x}_{vel}} U_{\mathbf{x}_{vel}}^2} \quad (4.1)$$

Where $\psi, \beta, \gamma, h_{heave}, \mathbf{x}_{vel}$ denote the roll, pitch, yaw, heave and translational velocity DoFs and $U_{\psi}, U_{\beta}, U_{\gamma}, U_{h_{heave}}, U_{\mathbf{x}_{vel}}$ are the standard uncertainties of these input quantities. The formulation in Equation 4.1 assumes that the considered input quantities are uncorrelated. As the input quantities represent the dynamics of the floater which are closely connected to wave forces acting on the floater, they are modeled as harmonic oscillations. Following [72] the standard uncertainties of this type of input quantities are given by:

$$U_{a_i} = \frac{\Delta a_i}{\sqrt{2}} \quad (4.2)$$

where a_i is the amplitude of the assumed oscillation of the input quantity i . The derivatives in Equation 4.1 are the partial derivatives of Equation 3.11 with respect to the considered input quantities. The solutions of the partial derivatives are presented in appendix A.1.

4.2.2 Uncertainty Propagation to Horizontal Wind Speed

In this section, uncertainties in the reconstructed wind field characteristics based on previously defined LOS uncertainties are derived.

For the analytical derivation of uncertainty, a simple wind field reconstruction algorithm that assumes the v and w components of the wind field to be zero is employed. Under this assumption, all contributions to the measured radial velocity are attributed to the u -component of the wind field, which can lead to an overestimation of this component. The uncertainty related to this effect increases with growing magnitudes of v - and w - components. The implementation of other reconstruction approaches is possible but requires modifying the corresponding partial derivatives. The reconstructed u -component of the wind speed at each beam is calculated using equation 2.9, with $v_{los,i}$ being the LOS wind speed of beam 1 to 4, $x_{p,L,n,i}$ being the normalized focus point x - coordinate of beam i . Further, the measurements of all four beams are combined by averaging the wind speed estimates of the individual beams.

Thus, the reconstructed wind speed component u_{rec} is given by:

$$u_{rec} = \frac{1}{4} * \left(\frac{v_{los,1}}{x_{p,L,n,1}} + \frac{v_{los,2}}{x_{p,L,n,2}} + \frac{v_{los,3}}{x_{p,L,n,3}} + \frac{v_{los,4}}{x_{p,L,n,4}} \right) \quad (4.3)$$

Again, the uncertainty of the reconstructed horizontal wind speed components can be estimated by combining the standard of uncertainties of the input quantities by following the GUM methodology. The combined uncertainty of n correlated input quantities is given by equation 2.11. Considering Equation 4.3 the reconstructed wind speed component u_{rec} is a function of the four LOS velocities. Thus the total uncertainty of u_{rec} given by:

$$U_{u_{rec}}^2 = \sum_{i=1}^N \left(\frac{\delta u_{rec}}{\delta v_{los,i}} \right)^2 * U_{los,i}^2 + 2 \sum_{i=1}^{N-1} \sum_{j=i+1}^N \frac{\delta u_{rec}}{\delta v_{los,i}} \frac{\delta u_{rec}}{\delta v_{los,j}} U_{los,i} U_{los,j} r_{i,j} \quad (4.4)$$

Where $U_{los,i}$ is the standard uncertainty of beam i as calculated in Equation 4.1. In this case, the LOS velocities of the four beams cannot be assumed uncorrelated. The correlation is considered by the correlation coefficient $r_{i,j}$ of the LOS velocities of beam i and j . The partial derivatives can be found in Appendix A.1.

The correlation coefficients between the LOS measurements of the individual beams are needed as a parameter for the calculation of uncertainty of reconstructed wind field characteristics. They are influenced by the changing LOS directions, the position of focus points in space, and the assumed wind field. Thus, correlation coefficients depend on the set of dynamic input parameters and the phasing between the single DOF. In the model, the correlation coefficients are calculated for the present set of model input parameters. This is done by evaluating Equation 3.11 over time for each LOS and calculating the correlation between the resulting LOS time series.

4.2.3 Analytic Estimation of Bias

The lidar measurement model introduced in section 3.4 is also used to estimate systematic biases in reconstructed wind field characteristics that occur due to floater dynamics. Using Equation 3.11, which combines the temporal evolution of all dynamic input quantities the LOS velocity is calculated for a defined parameter space over a defined time span. Further, the wind field reconstruction approach introduced before is applied to calculate the horizontal wind speed component u_{rec} . The bias of the reconstructed u-component wind speed is calculated by

$$Bias_u = u_{ref} - u_{rec,mean} \quad (4.5)$$

where u_{ref} is the reference wind speed and, $u_{rec,mean}$ is the mean value of the reconstructed wind speed component. The reference wind speed is calculated as the average over a rotor plane. The rotor diameter for this hypothetical rotor is chosen to be $d_{rotor} = 150$ m. The results of the bias estimation are very sensitive to the exact calculation procedure of the reference value. Therefore, to make the results comparable to the numerical model results, the calculation procedure is the same as in the numerical model. In the numerical model, the u-wind speed components of all grid points of the synthetic wind field, which are within the rotor plane, are averaged. For the reference values u_{ref} of the analytical model the wind speed components of the same grid points are calculated according to the assumed power law wind profile. The average of these points is taken to calculate u_{ref} .

Equation 3.11 combines the temporal evolution of all dynamic input quantities. Therefore, different effects can potentially influence the estimation of bias. First, it must be ensured that the length of the time window of calculation is large enough to avoid any relevant influence of time window length on the bias estimation. Second the phasing between the individual dynamic input quantities could influence the bias estimation.

Figure 4.3a) shows the standard deviation within 100 realizations of the bias estimation of the wind speed u-component for one set of input parameters as a function of time window length. The phasing of input dynamics (yaw, pitch, roll, and heave) is randomized for each realization. It can be seen that the standard deviation fluctuates over the time window length depending on the ratio between time window length and dynamics frequencies, with minima for time window lengths being multiples of dynamics frequencies. This effect is small for longer time window lengths where the averaging pe-

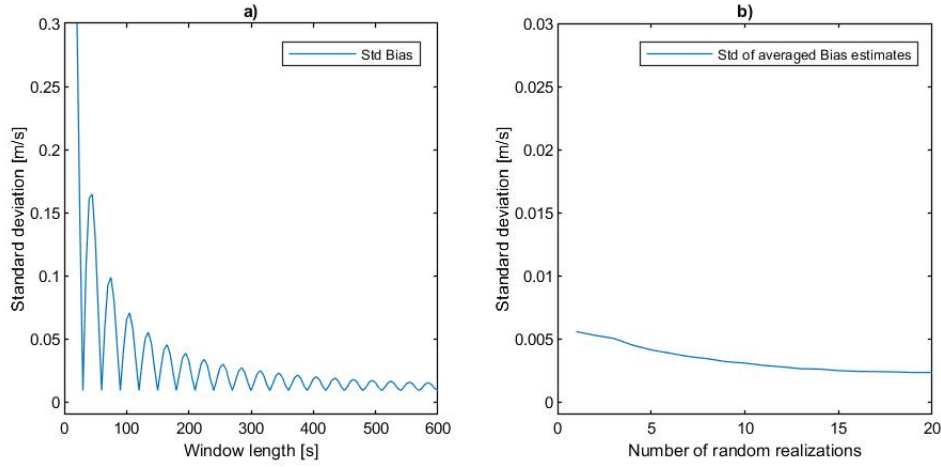


Figure 4.3: a) Standard deviation of bias estimation within 100 random realizations over time window length. b) standard deviation of averaged bias estimations over the number of averaged random realizations, time window length 600 s.

riod is one order of magnitude higher than the period of input dynamics. The remaining fluctuation in standard deviation for a time window length of 600 s is small and can be neglected. However, the standard deviation is not converging to zero, since the random phasing between the individual dynamics input quantities is part of the standard deviation. Therefore, several random realizations with a time window length of 600 s are averaged. Figure 4.3b) shows the standard deviation of averaged bias estimates as a function of the number of random realizations, averaged for one bias estimate. For the remainder of the work, all bias estimates of the analytical model are calculated for a time window length of 600 s and averaged over 10 random realizations.

4.3 Uncertainty and Bias Quantification

In this section, the findings from uncertainty and bias estimation of lidar measurements under motion influence, as discussed earlier, are presented for both the analytical and numerical approaches. The lidar configuration investigated in the numerical and analytic uncertainty estimation follows

the one used in the real measurement campaign.

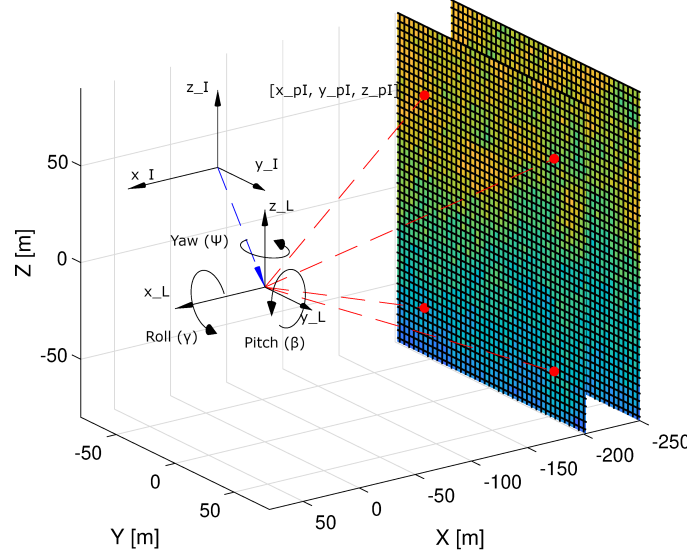


Figure 4.4: Lidar patterns and coordinate systems

This configuration (see figure 4.4) represents a fixed-beam lidar system with 4 beams, arranged in a rectangular pattern. The opening angle (angle to the center line) of all four beams is set to $\theta = 19.8$ deg and the angle around the center line is set to $\phi = 39.6, 140.4, -39.6, -140.4$ deg. The range of the lidar is assumed to be 200 m. The LOS measurements from all 4 beams are taken sequentially with a delay of $T_{meas} = 0.25$ s. For this pattern, the duration of a full scan is 1 s. The resulting scanning pattern is visualized in Figure 4.4. For both the analytical model and the numerical model, a hub height, which is also the installation height of the lidar, of 100m and a rotor radius of 75m, is assumed.

In the first analysis step, the influence of displacement in individual DOF on the measured LOS velocities is examined with the help of the analytical model. Figure 4.5 shows the LOS velocity per beam as a function of displacement for the yaw, pitch, roll, and heave displacement for three values of the vertical shear exponent α . Additionally, the reconstructed u- component of the wind field is shown as a function of each DOF. In this analysis, quasi-static displacements are assumed. Velocity components resulting from

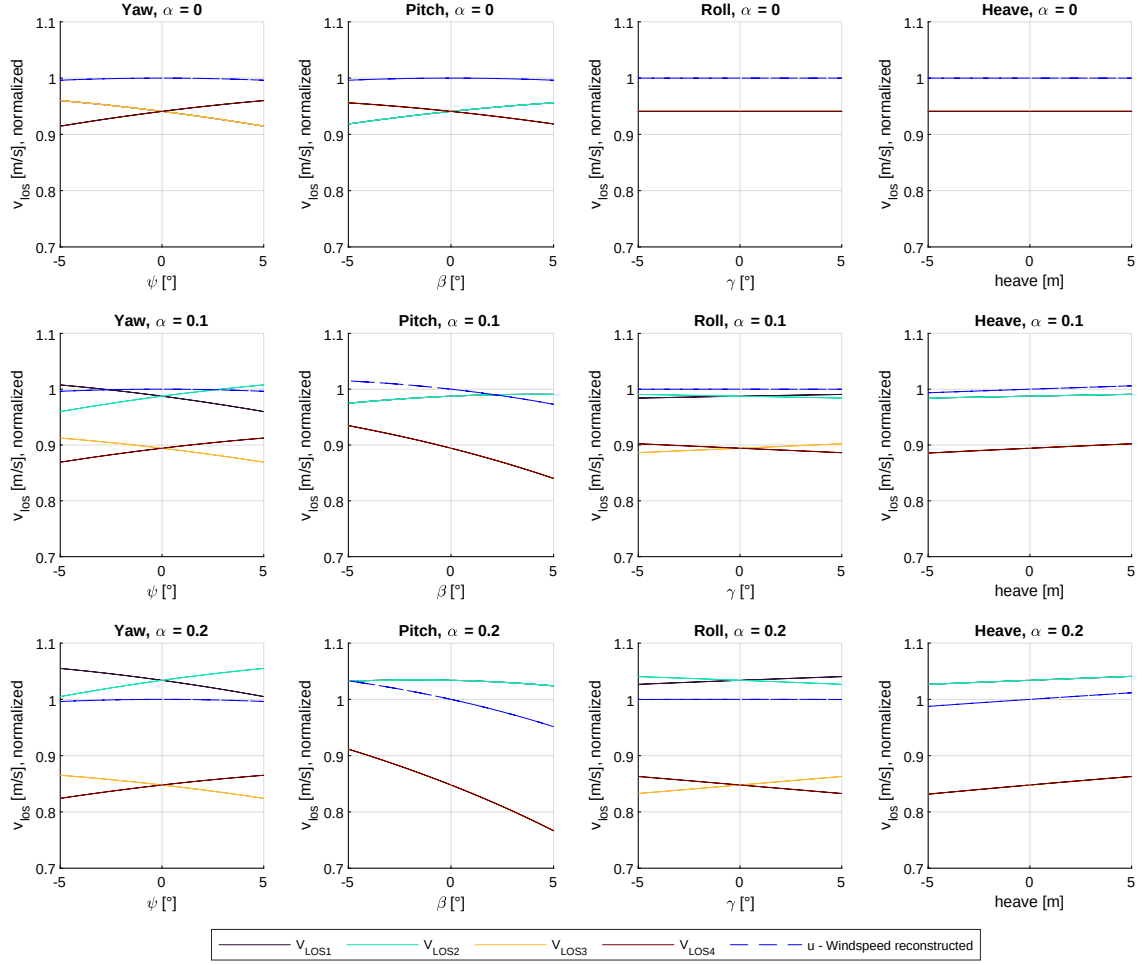


Figure 4.5: Modeled LOS velocities and reconstructed u- component wind speed as a function of yaw, pitch, roll and heave displacement for all four beams. Reference wind speed: 10 ms^{-1} . Top: $\alpha = 0$. Center: $\alpha = 0.1$: Bottom: $\alpha = 0.2$. α is the vertical shear exponent. V_{LOS1} and V_{LOS2} correspond to the two upper beams, V_{LOS3} and V_{LOS4} correspond to the two lower beams. The y-axis is normalized to the reconstructed wind speed at zero displacements.

changing quasi-static conditions are not considered.

For a vertical shear exponent of $\alpha = 0$, the individual LOS velocities differ for changing pitch and yaw angles. However, the reconstructed wind speed shows no significant fluctuation over the respective DOF due to the symmetric beam pattern. this effect is small for the expected range of floater heave elevations. The yaw and roll displacement cause fluctuations in the LOS velocities. Again the reconstructed wind speed stays nearly constant

due to the symmetric beam pattern.

For the pitch DOF, the upper and lower beam's LOS velocities have different characteristics. Therefore, the reconstructed wind speed fluctuates. It is also important to note that the relationship between reconstructed wind speed and pitch angle is non-linear. This non-linear relationship can cause bias in averaged lidar wind speed estimates. Heave displacement, in combination with a non-linear vertical wind shear profile, causes fluctuation in the reconstructed wind speed due to changing measurement elevation. As a result, the reconstructed u-component wind speed will show a small negative bias because horizontal wind speeds increase slower with increasing height than they decrease with decreasing height. However, for the expected range of floater heave elevations, this effect is small compared to the effect of floater pitch motion.

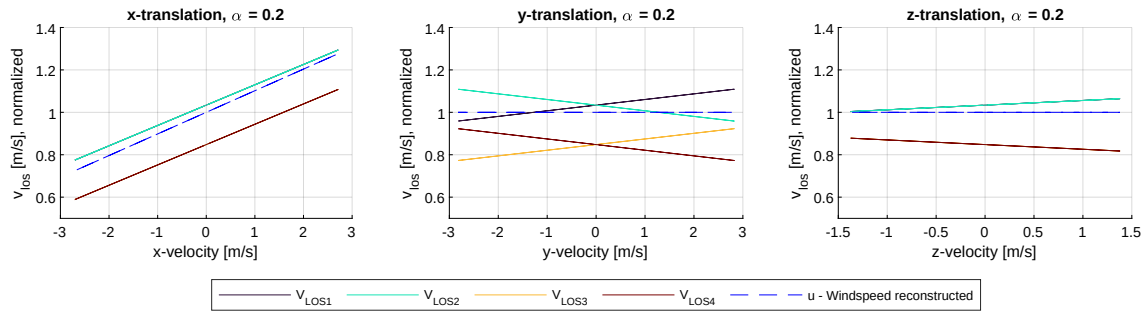


Figure 4.6: Modeled LOS velocities as function of translational nacelle velocities in x-, y- and z- direction for all four beams. Reference wind speed: 10 ms^{-1} , vertical shear exponent $\alpha = 0.2$. The y-axis is normalized to the reconstructed wind speed at zero displacements.

Figure 4.6 illustrates the dependency of measured LOS velocities and reconstructed wind speed on translational velocities of the lidar device for quasi-static conditions. No fluctuation of translational velocities is considered. It can be seen that the translational velocity components are directly projected on the LOS direction of the beam and thus cause significant changes in the measured LOS velocities. For the translational displacement in the x-direction, this directly translates into changing reconstructed wind speeds. For the y- and z-direction the reconstructed u- component wind

speed remains constant since the effects on the left/right and upper/lower beams compensate for each other. However, it is important to note that the relationship is strictly linear, meaning that zero mean fluctuations in translational velocities will cause zero mean fluctuations in LOS velocities and, thus, not cause any bias in the LOS velocity and reconstructed u-component of the wind speed.

This analysis shows that the most relevant DOF for the influence of nacelle-based lidar wind measurements is pitch motion. Under the presence of a vertical wind shear profile, the rotational pitch displacement causes a significant variation in reconstructed wind speed. This variation is non-linear as a function of pitch displacement, indicating that the displacement could introduce bias in the measurement. The rotational pitch motion also causes translational velocities of the nacelle in the x-direction. These translational velocities cause fluctuations in the reconstructed wind speed. Consequently, the following sections focus on analyzing the influence of the pitch DOF in combination with the present vertical shear profile.

4.3.1 Uncertainty Quantification

In this section, motion-induced uncertainties in reconstructed lidar wind speed estimates are quantified as a function of dynamic input parameters using the analytical and numerical models. For the analytical model, the wind field is only defined by the inflow wind speed of 10 ms^{-1} and the vertical shear exponent α . The dynamics parameters are summarized in table 4.1. Figure 4.7 a) and b) shows the u-component wind speed uncertainty estimates from the analytical model as functions of shear exponent, mean pitch angle, and pitch amplitude.

The resulting uncertainty of the reconstructed u- wind speed component mainly depends on the pitch amplitude, which determines the magnitude of different effects. With a given pitch period of 30 s, the pitch amplitude

Table 4.1: Dynamics parameters for uncertainty quantification.

Parameter / case	a)	b)	c)	d)
Pitch Amplitude [deg]	0 : 1 : 5	0 : 1 : 5	2	2
Mean Pitch [deg]	0	-5 : 1 : 0	0	-5 : 1 : 0
Pitch Period [s]	30	30	10 : 5 : 50	10 : 5 : 50
Vertical shear [-]	0 : 0.1 : 0.2	0.1	0 : 0.1 : 0.2	0.1

determines the magnitude of the translational velocity in the fore-aft direction. In this case, this is the main source of uncertainty in the reconstructed wind speed. Additionally, the pitch amplitude determines the uncertainty resulting from changed beam direction and shifted focus points. The overall uncertainty of the u- wind speed component is found to be in the region of up to 15 % of the reference wind speed. No significant influence of the inflow shear exponent and the mean pitch angle on the overall uncertainty estimate of the u-component wind speed component can be observed.

In the next step, the influence of the frequency of rotational pitch movement was investigated. Figure 4.7 c) and d) shows the uncertainty of u-component wind speed as a function of shear exponent, mean pitch angle, and period of floater pitch movement. The corresponding parameter space is summarized in Table 4.1. Results show a strong dependency on the period of the rotational pitch movement of the floater. This parameter determines the magnitude of the translational velocities at the lidar mounting position. Therefore, short periods of rotational movement, in general, cause high uncertainty in u-component wind estimates. No significant influence of the inflow shear exponent and the floater mean pitch angle can be observed.

Verification of the analytical results is done employing the numerical model. Turbulent synthetic wind fields used in the simulations are generated for a mean wind speed of 10 ms^{-1} and a TI of 6 %. 10 random turbulence

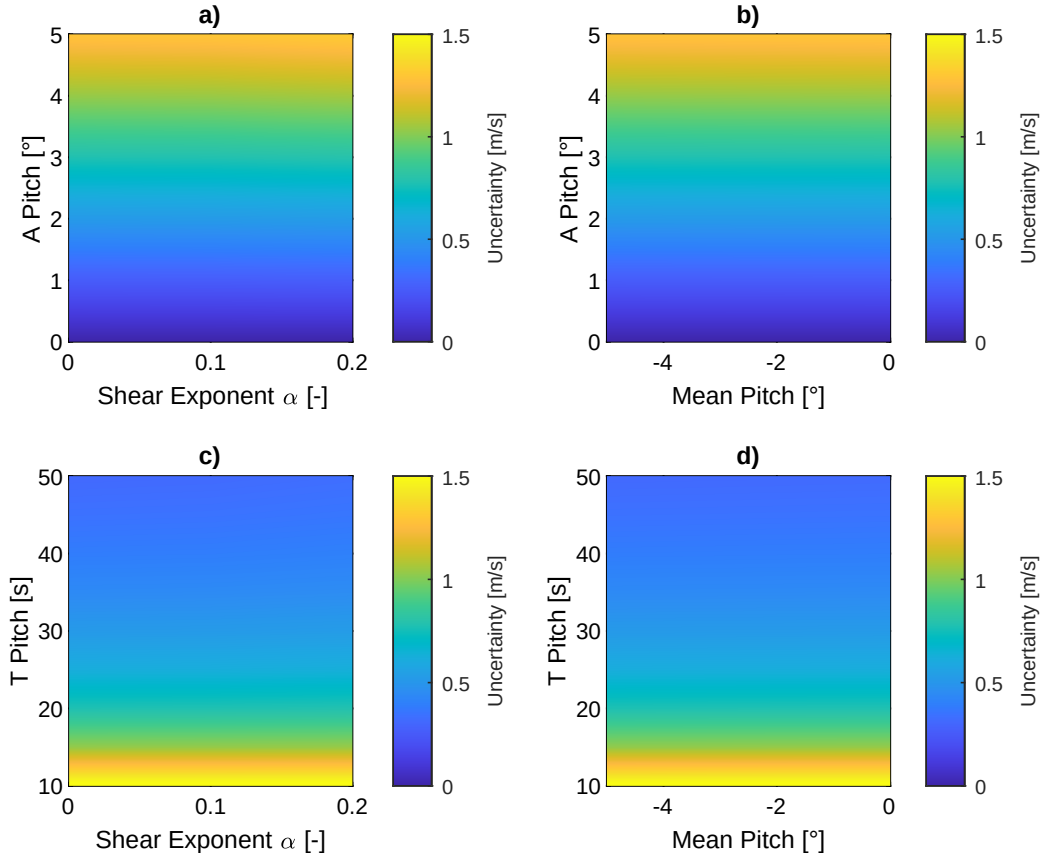


Figure 4.7: Uncertainty estimation of u-component wind speed. Fixed parameters: U_{ref} : 10 ms^{-1} , $A_\psi = 0 \text{ deg}$, $A_\gamma = 0 \text{ deg}$, $A_{heave} = 0 \text{ m}$.

realizations are generated for each wind condition and the presented results are averaged over all random realizations. Turbulence is taken into account to represent the floater under turbulent inflow loading conditions. Table 4.2 summarizes additional wind field parameters.

Figure 4.8 shows a comparison of the analytical and numerical uncertainty estimation for selected dynamic input parameters. The MAE metric represents uncertainty for the numerical model. The MAE is the mean of the absolute error between the time series of lidar estimated wind speed and the reference time series of the full input wind field. The MAE represents the instantaneous error between the reconstructed wind speed and the input wind

Table 4.2: Wind field parameters.

Parameter	Value
Wind speed [ms^{-1}]	10
Turbulence Intensity[%]	6
Surface Roughness [m]	0.03
Shear exponent [-]	0.0 : 0.1 : 0.2
Spatial Grid Resolution [m]	4
Gridsize [m]	180x180
Timestep [s]	0.1
Usable Time [s]	600
Seeds	10

field. Therefore, it contains the fluctuations resulting from assumed FOWT dynamics. This metric can be compared qualitatively and quantitatively to the uncertainty results from the analytic model.

In general, the pattern of the numerical results follows the estimation of the analytical uncertainty model. The MAE is heavily dependent on the pitch amplitude and period, which determine the magnitude of the lidar system's fore-aft motion. The shear exponent and mean pitch angle variation show no significant effect on the MAE. Quantitatively, both models show similar magnitudes of uncertainty and MAE values, respectively. It can be seen that there is a linear relationship between uncertainty in the u-component wind speed estimate and the amplitude of the pitch DOF of the floater. A nonlinear relationship between uncertainty in the u-wind speed estimate and pitch period, with lower uncertainties for increasing pitch periods, can also be observed.

This analysis shows, that the uncertainty in reconstructed u-component wind speed measurements is dominantly determined by the fore-aft motion of the nacelle, which is mainly caused by the pitch rotation of the floater. High pitch amplitudes and high frequencies cause high uncertainties in wind

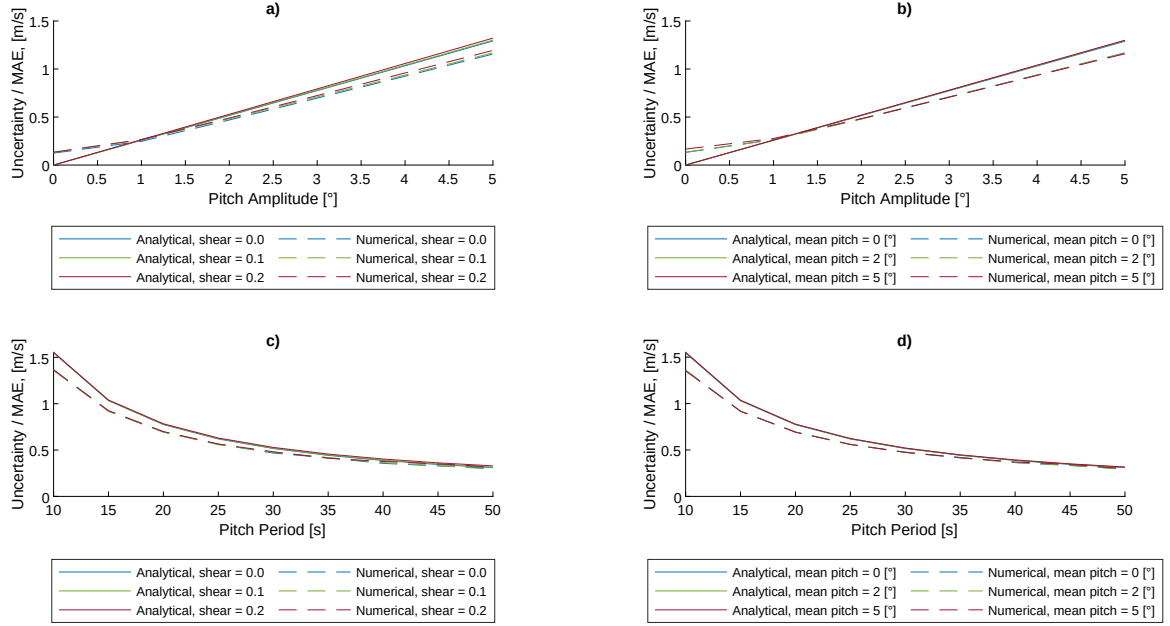


Figure 4.8: Comparison between analytical and numerical uncertainty / MAE estimation. Plots a) to d) refer to cases in Table 4.1. Fixed parameters: U_{ref} : 10 ms^{-1} , $A_\psi = 0 \text{ deg}$, $A_\gamma = 0 \text{ deg}$, $A_{heave} = 0 \text{ m}$.

speed estimates. For the conditions and models considered this uncertainty is found to be in the order of magnitude of 1 ms^{-1} .

4.3.2 Bias Quantification

In this section, the motion-induced bias in reconstructed lidar wind speed estimates as a function of dynamic input parameters using the analytical and numerical models is quantified. The input wind fields for the numerical model and the dynamics parameter space are the same as previously used for the uncertainty quantification.

Figure 4.9 a) and b) shows the analytical model's estimation of bias in the reconstructed u-component wind speed. As a function of vertical shear exponent and pitch amplitude, results show a negative bias in the reconstructed u-component wind speed which is increasing for higher shear exponents. A slightly negative trend in the wind speed estimation can be observed for in-

creasing pitch amplitudes, which is more pronounced for high vertical shear conditions. This is caused by the combined effect of a nonlinear vertical wind shear profile and the nonlinear relationship between beam directions and measured LOS velocity.

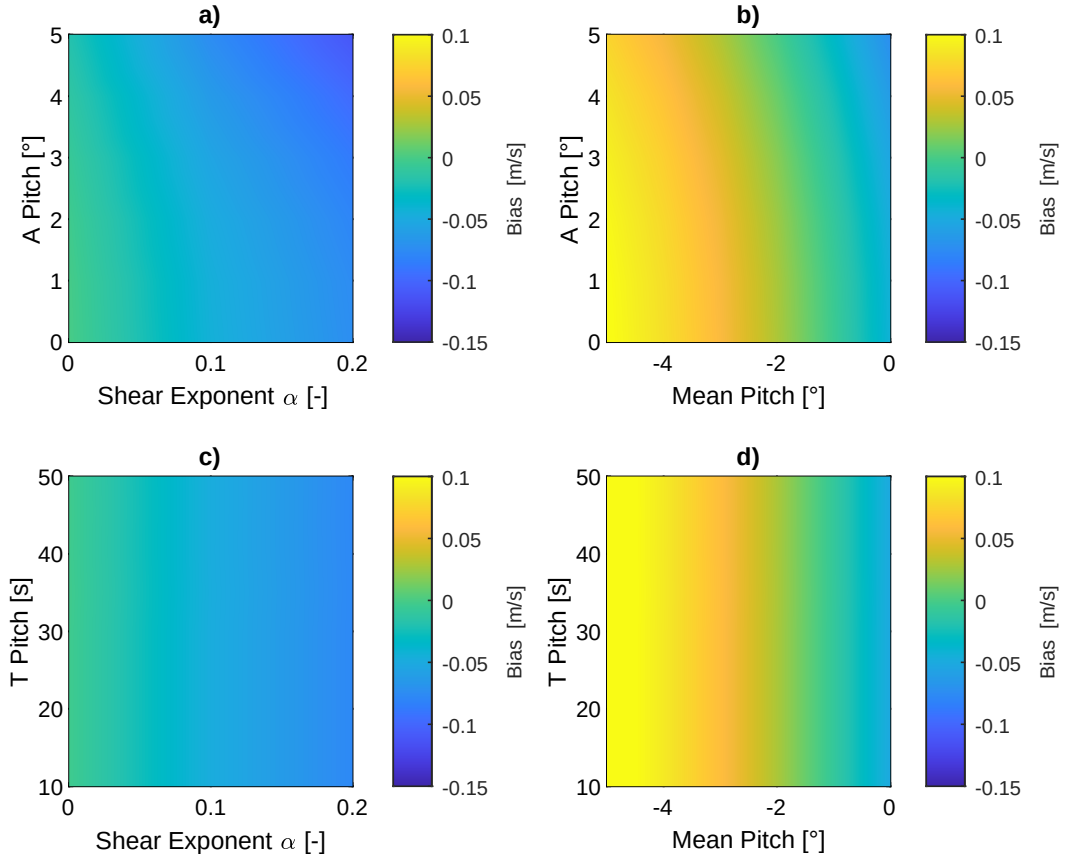


Figure 4.9: Bias of u-component wind speed. Parameter according to Table 4.1. Fixed parameters: U_{ref} : 10 ms^{-1} , $A_\psi = 0 \text{ deg}$, $A_\gamma = 0 \text{ deg}$, $A_{heave} = 0 \text{ m}$.

Non-zero mean pitch angles generally result in upwards or downwards-shifted focus points. Negative mean pitch angles (upwards-shifted focus points) and the assumption of a power law wind profile result in a positive bias in the LOS measurements. Depending on the magnitude of vertical shear, this effect exceeds the negative effect from the pitch motion and leads to an overestimation of wind speed. Consequently, the overestimation

is most pronounced for high negative mean pitch and low pitch amplitudes. For the relationship between vertical shear, pitch amplitude, and resulting bias, it can be seen that the calculated bias is not zero, even in the presence of zero pitch amplitude. Any dynamics do not introduce this bias but is a result of the definition of the reference value used for bias calculation. As detailed in section 4.2.3, the reference for bias calculation is defined as the average wind speed over the rotor plane. Depending on the present shear profile, the assumed rotor size, and the lidar pattern, this reference value differs from the lidar u-component wind speed estimate. Therefore, only the change of bias over the varying dynamics parameters can be attributed to the influence of the dynamics.

Figure 4.9 c) and d) shows the bias of u-component wind speed as a function of shear exponent, mean pitch angle, and pitch period. No significant dependency of wind speed bias to the frequency of the floater pitch motion can be observed.

The analytical model results are verified using the numerical model. Figure 4.10 compares the numerical and analytical bias estimation. For the numerical model, the bias is expressed in terms of the mean error (ME) which is the error between the mean of the lidar estimated time series and the mean of the full wind field time series over the full simulation length of 600 seconds. The ME can be compared to the bias metric from the analytical model. As for the uncertainty estimation, the ME follows the pattern of the analytical bias estimation. Quantitatively, the results of both models show good agreement. Observed deviations between the model results are in the region below 0.015 ms^{-1} for the given reference wind speed of 10 ms^{-1} .

This analysis shows that the bias in reconstructed u-component wind speed is determined by the mean pitch angle of the floater and the pitch amplitude. In the presence of vertical wind shear, negative mean pitch angles cause upwards shifted focus points which result in positive bias in u-component wind speed estimates. High pitch amplitudes cause negative bias in u-component

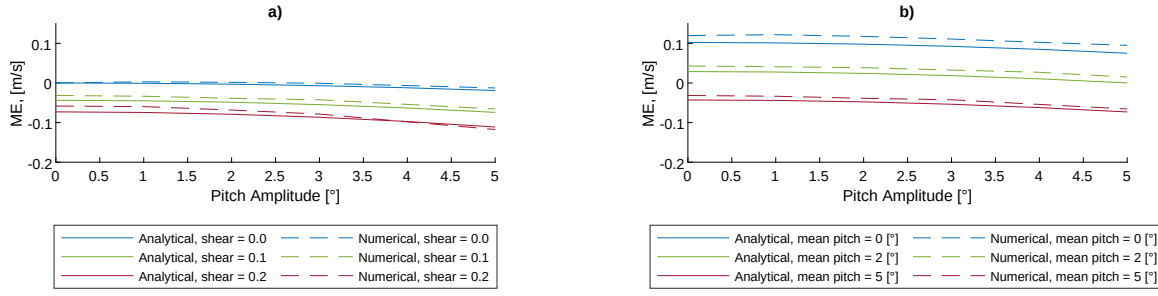


Figure 4.10: Comparison of bias wind speed estimation from analytical and numerical model. Fixed parameters: U_{ref} : 10 ms^{-1} , $A_\psi = 0 \text{ deg}$, $A_\gamma = 0 \text{ deg}$, $A_{heave} = 0 \text{ m}$, $\alpha = 0.1$.

wind speed estimates. This bias is in the order of magnitude of 0.1 ms^{-1} .

4.4 Correction Approaches

The results of the numerical and analytic uncertainty and bias estimation have identified the main dynamic effects influencing the measurements of nacelle-based lidars on floating wind turbines. Motion-induced uncertainty in measurement time series is mainly influenced by:

- translational velocity components caused by the fore-aft movement of the nacelle due to floater pitch motion cause fluctuation of horizontal wind speed estimates.

Motion-induced biases in time-averaged wind speed measurements are mainly influenced by:

- rotational oscillations of the beam direction due to floater pitch motion cause an underestimation of horizontal wind speed components.
- negative mean pitch angles of the FOWT are causing upwards shifted focus point resulting in an overestimation of wind speed.

It is important to note, that these effects have different orders of magnitude and are relevant at different time scales. Translational velocities cause fluctuations of the measurement time series which can be in the order of 1 ms^{-1} and must be considered when using measurement time series data. Over- and under-estimation of mean wind speeds due to rotational movement is one order of magnitude smaller and found to be in the region of 0.1 ms^{-1} . This is most relevant in cases where accurate estimates of mean wind speed are necessary.

Depending on the intended use of the measurement a correction of these effects can be necessary. Power performance measurement of wind turbines is a key application of lidar wind measurements. According to IEC 61400-12-1 [83] the performance measurements should be performed by measuring

the 10-minute average power output of the wind turbine and the 10-minute average inflow wind speed. A wind turbine power curve is then obtained by binning the wind speeds from 4 ms^{-1} to 16 ms^{-1} and plotting against the corresponding power outputs. While the standard procedure requires the use of met mast-mounted cup anemometers, the use of nacelle-based lidar is an attractive alternative. However, the question arises if wind speed measurements from nacelle-mounted lidars introduce uncertainty or bias in the power performance measurements and if motion-induced effects need to be corrected. The findings from section 4.3.2 show that mean wind speed estimates from nacelle-based lidars can be biased depending on the dynamic condition of the wind turbine. For power performance measurements, bias in the order of 0.1 ms^{-1} or around 1 % could be significant. This suggests that a correction of the estimated 10 min mean wind speed used for power performance assessment will be necessary for using nacelle-based lidar systems on floating wind turbines under specific dynamic conditions.

Several studies have investigated the use of lidar inflow measurements for turbine load validation using different methods. In [8] 10 min statistics of lidar estimated wind field characteristics are used for the parameterization of synthetic turbulent wind fields for aeroelastic turbine simulations and evaluation of loads. It was found that uncertainties in the lidar-estimated mean wind speed and the lidar-estimated TI used for the parameterization of synthetic wind fields are the main sources of uncertainty in predicted loads. The dynamics-induced bias in lidar wind speed measurements can be expected to affect load estimations. In [33], besides lidar estimated wind field statistics for parameterization, measured lidar wind speed time series are used to constrain synthetic wind fields for load validation studies. In this method, it can be expected, that motion-induced fluctuations in the wind speed measurements will significantly influence the resulting wind field and load estimates. This suggests that the correction of instantaneous errors in lidar wind speed measurements is necessary for use in load validation

studies.

Another application of nacelle-based lidar systems on FOWT is the use of lidar wind speed measurements for turbine pitch control. Here the wind speed information of the inflow wind field is used as an input to an additional control loop that aims to compensate for changes in wind speed, e.g. through gusts, by changing the rotor blade pitch angles in order to maintain the rotor speed. This control approach can significantly reduce platform motions and variations in rotor speed due to disturbance in the form of wind gusts (see e.g. [63]). The application relies on instantaneous time series information of the inflow wind speed with sampling frequencies in the region of 1 Hz. Since these measurements contain motion-induced fluctuations, correcting the lidar wind speed measurement time series data is necessary to avoid undesired effects on the pitch controller. In [69] this is considered by using a model-based wind field reconstruction algorithm that considers the lidar system's instantaneous displacements and velocities to provide a motion-compensated wind speed estimate.

The above-mentioned use cases show that motion correction of measurements from nacelle-based lidar systems is necessary, while different time scales must be considered. This work suggests a method for correcting fore-aft motion-induced fluctuation based on frequency filtering and a simple model-based correction approach of the turbine mean pitch employing the analytical model.

4.4.1 Model based Correction

As shown in chapter 4.3.2, the bias in the wind speed estimation is mainly caused by a non-zero mean pitch angle which causes upwards shifted measurement positions and oscillating beam directions caused by the floater pitch motion.

Instead of correcting lidar measurement time series based on the instan-

taneous turbine tilt angles, correcting the reconstructed wind speed with a model-based approach is proposed. The analytical model introduced in section 3.4 is used to calculate the ME in the reconstructed u-component wind speed estimation as a function of the wind speed WS , vertical shear exponent α , turbine mean pitch β_{mean} and pitch amplitude A_β .

$$v_{corr.} = f(WS, \alpha, \beta_{mean}, A_\beta) \quad (4.6)$$

In this way a four-dimensional look-up table with correction values $v_{corr.}$ is created for the parameter space given in Table 4.3.

Table 4.3: Parameter space correction look up table.

Parameter	Value
Wind speed [ms^{-1}]	4 : 4 : 20
Shear [-]	0.0 : 0.05 : 0.3
$\beta_{mean}[\text{deg}]$	0 : 0.1 : 5
$A_\beta[\text{deg}]$	0 : 0.1 : 5

The remaining model parameters are set to fixed values of $T_\beta = 30$ s, $A_\psi = 0$, $A_\gamma = 0$, $A_{heave} = 0$ as results are only evaluated for these values. It should be mentioned that the dimension of the created correction look-up table can easily be extended to other model parameters if a significant sensitivity is found for a specific setup.

Assuming the mean pitch angle and the mean pitch amplitude is known for each 10 min period through inclination measurements and using the lidar estimated u-component wind speed and vertical shear exponent the correction value can be extracted from the look-up table and subtracted from the lidar estimated u- component wind speed:

$$u_{corr.} = u_{rec} - v_{corr.}(u_{rec}, \alpha_{rec}, \beta_{mean}, A_\beta) \quad (4.7)$$

The approach avoids the need for synchronized motion time series data, which might not be available in all cases. Inclination sensor signals might be noisy or not accurate enough due to the influence of nacelle acceleration on the sensor. Thus, the suggested approach is easy to implement for practical applications. However, it relies on the availability and accuracy of floater dynamics statistics. Inaccuracies could occur in transient conditions, where mean floater dynamics do not sufficiently represent the actual floater dynamics.

4.4.2 Frequency Filtering

In this section, the use of frequency filters to correct motion-induced fluctuations is investigated. Applying a frequency filter on the time series of reconstructed u- component wind speed estimates is proposed. As shown in Figure 4.1, the time series of LOS wind speed and the reconstructed u-wind speed show peaks at the floater pitch frequency. The application of a frequency filter aims to correct the influence of floater pitch displacement and the resulting translational velocities in the fore-aft direction, without introducing bias or error in estimating the real wind field properties.

For frequency filtering, a bandstop filter characterized by three parameters is used. The stopband frequency range is given by a *width* parameter, defining the upper and lower frequency limit of the stop band. The peak pitch frequency of the floater is used as the center frequency f_{center} of the applied band stop filter, while the upper and lower bounds of the filter are defined at $f_{pass,lower} = f_{center} - width/2$ and $f_{pass,upper} = f_{center} + width/2$. The filtering depth is defined by the stop band attenuation parameter, *depth* in dB. A steepness parameter defines the steepness of the filter's transition region.

The filter parameters applied in section 4.5 are optimized with a parametric study, evaluating the ME and the MEA between the corrected lidar wind

speed and the full wind field reference. The goal of this optimization is to find the filter parameterization, that minimizes the MEA while not increasing the ME significantly. The filter has been implemented using the MATLAB [84] bandstop filtering function.

4.5 Evaluation of Correction Approaches

The correction approaches are evaluated using the numerical lidar simulation framework introduced in chapter 3.2. Lidar measurements are simulated by coupling an aeroelastic simulation of specific FOWT models to ViConDAR. In this way, the dynamics input response to wind and wave conditions is used as input to the lidar simulation. The first FOWT model employed for the simulation of FOWT dynamics is the WindCrete floater design concept in combination with the International Energy Agency (IEA) 15 MW reference wind turbine as introduced in 3.3.2. The second FOWT model is the numerical model of the FLOATGEN demonstrator introduced in 3.3.1.

Both FOWTs are modeled in the open-source aeroelastic simulation code OpenFAST (see chapter 2.2.3). The wind field parameters used for aeroelastic simulations are summarized in Table 4.4. It should be noted, that no correlation between turbulence intensity and shear exponent is considered as a simplifying assumption. The first 600 s of each simulation are discarded to minimize the influence of transient effects. Simulations are created for three sets of wave conditions using a Jonswap wave spectrum with parameters given in Table 4.5. For all testing cases, the same lidar configuration as described in section 4.3 is used.

Table 4.4: Wind field parameters.

Parameter	Value
Wind speed [ms^{-1}]	4 : 4 : 20
Turbulence Intensity[%]	6
Surface Roughness [m]	0.03
Shear exponent [-]	0.1, 0.2, 0.3
Spatial Grid Resolution [m]	5
Timestep [s]	0.05
Usable Time [s]	1200
Seeds	6

Table 4.5: Parameter space wave conditions, where H_s is the significant wave height and T_p is the peak wave period.

Parameter	Wave 1	Wave 2	Wave 3
H_s [m]	1	2	5
T_p [s]	6	9	11

4.5.1 Model based Correction

The correction approach is first tested using the lidar simulation framework ViConDAR and prescribed dynamics inputs. IEC 61400-12-1 [83] suggests verifying lidar wind measurements against reference wind speed measurements. The measurements from the remote sensing device and the reference sensor (e.g., a cup anemometer) shall be compared bin-wise for wind speeds from 4ms^{-1} to 16ms^{-1} . Following this approach, figure 4.11 and 4.12 show the relative uncertainty of a typical cup anemometer used for power performance measurements over an averaging period of 10 minutes as a reference. The reference values are extracted from [83].

Figure 4.11, first row shows the resulting MEs between the input wind field

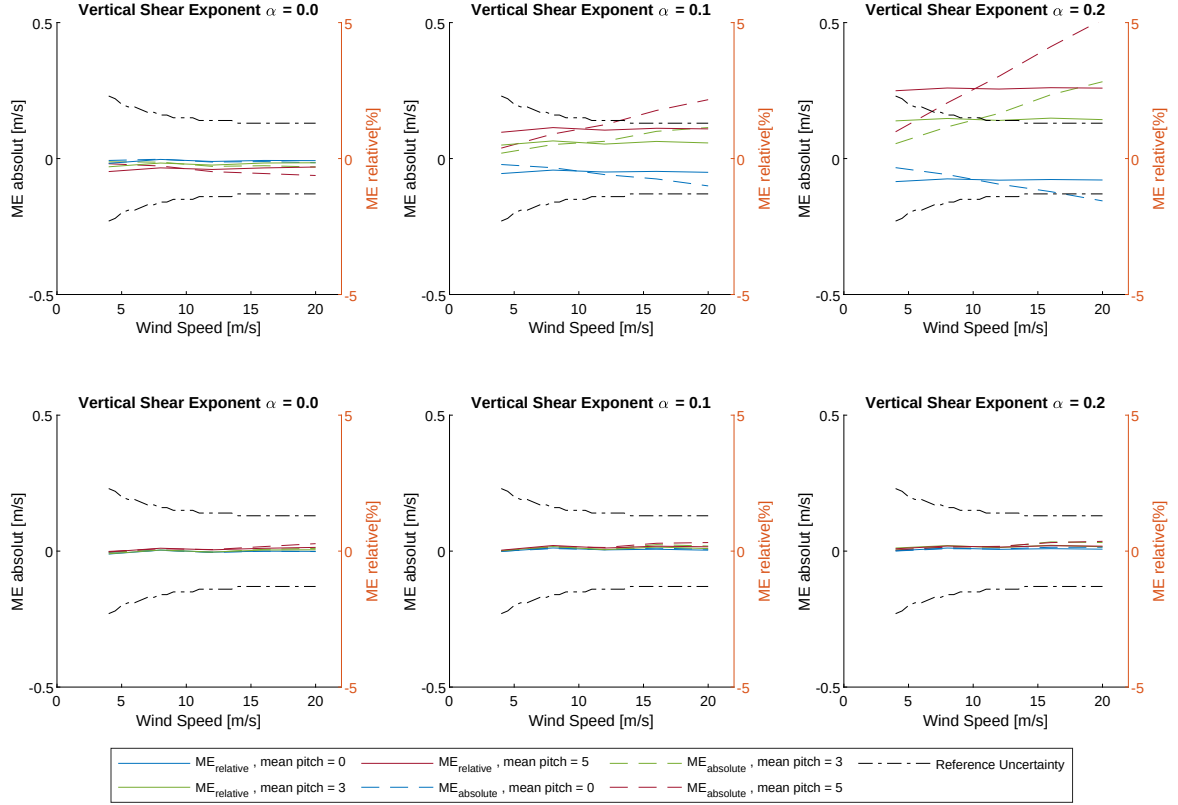


Figure 4.11: Absolute and relative ME of corrected u- wind speed component as function of mean wind speed for different mean pitch angles. Top: Uncorrected lidar estimates. Bottom: Corrected lidar estimates. Fixed Parameters: $A_\beta = 3$ deg, $A_\psi = 0$ deg, $A_\gamma = 0$ deg, $A_{heave} = 0$ m.

and the lidar estimates of the u- wind speed component without correction. It can be seen, that the mean pitch angle mainly influences the relative ME in combination with the present vertical wind shear profile, while it is almost constant over wind speed. For a vertical shear exponent of 0.2 and a mean pitch angle of 3 deg, the overestimation of wind speed is in the region of around 3%, which exceeds the shown reference uncertainty.

Figure 4.11, the second row shows the ME for the same parameter space after correction. It can be seen, that the ME can be reduced significantly and is below 1% of the wind speed over the entire range of wind speeds.

Similarly, figure 4.12 shows the ME before (first row) and after correction (second row) for different pitch amplitudes. While the higher pitch ampli-

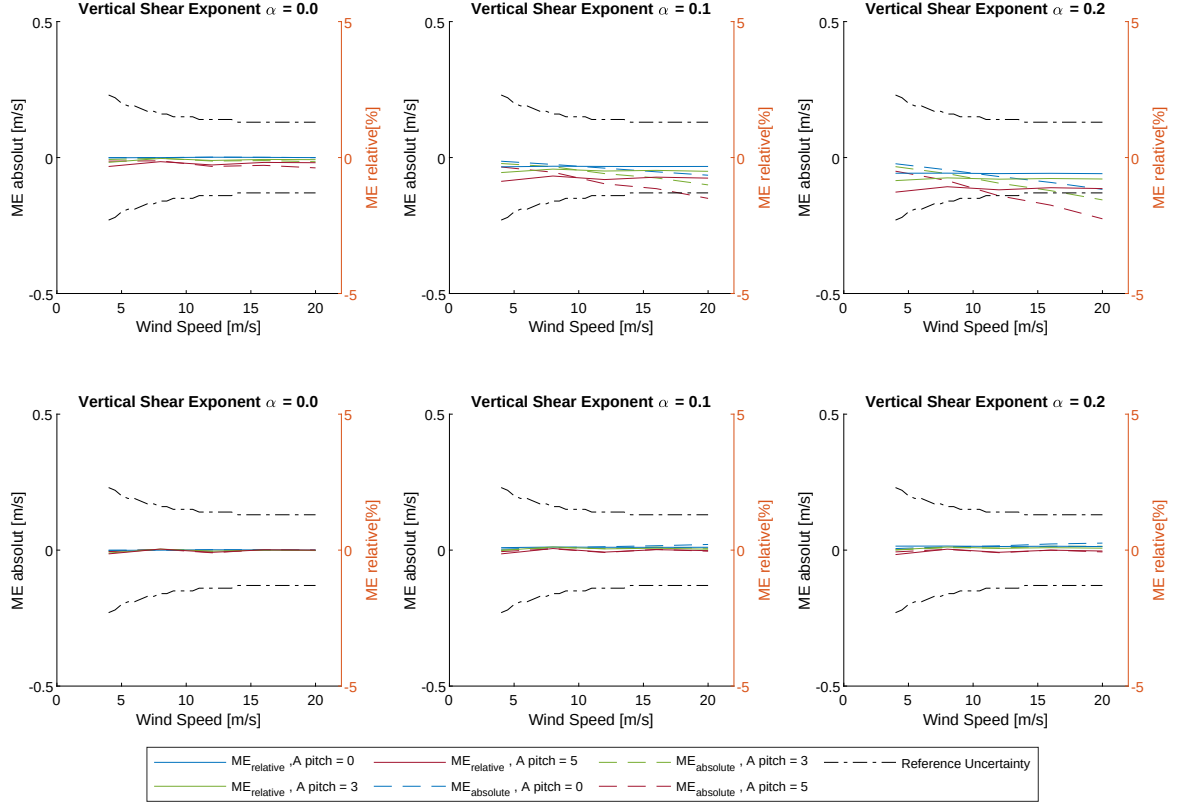


Figure 4.12: Absolute and relative ME of corrected u- wind speed component as function of mean wind speed for different mean pitch angles. Top: Uncorrected lidar estimates. Bottom: Corrected lidar estimates. Fixed Parameters: $\beta_{mean} = 0$ deg, $A_\psi = 0$ deg, $A_\gamma = 0$ deg, $A_{heave} = 0$ m.

tudes, combined with positive vertical shear exponents, cause a negative ME for the uncorrected u-wind speed estimations, the correction approach can significantly reduce the effect. The remaining errors are in the region below 1% of the wind speed.

Figure 4.13 shows the model-based correction results for simulated dynamics for the FLOATGEN (first row) and WindCrete (second row) FOWT. Before the correction, FLOATGEN shows negative MEs in u-component wind speed, which increases with wind speed. This pattern is more pronounced under wind conditions with high vertical shear values. The dynamic characteristics of FLOATGEN can explain this behavior. As a barge-type floater, FLOATGEN shows insignificant mean pitch angles for the given conditions.

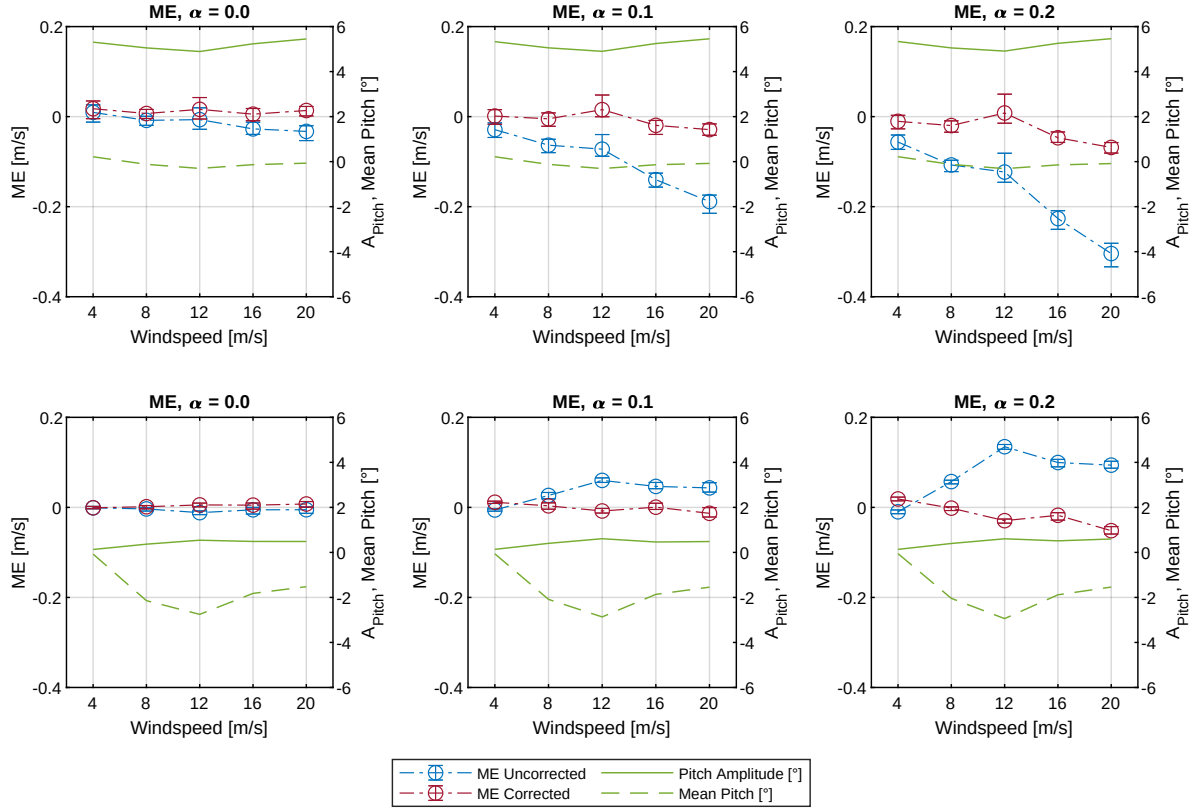


Figure 4.13: MEs of u- wind speed component for FLOWTGEN (top) and WindCrest (bottom) FOWT with and without correction for varying vertical shear exponents.

On the other hand, floater pitch amplitudes show relatively high values for the given wave condition. Consequently, the negative effect of pitch movement is predominant. The model-based correction approach is able to reduce the ME significantly resulting in ME below 0.1 ms^{-1} or 0.5% .

The WindCrest FOWT model shows a different behavior. The ME of the u-component wind speed before correction increases with the wind speed up to the rated wind speed of the turbine and slightly decreases for above-rated wind conditions. The effect is more pronounced for high vertical shear conditions. The spar-type floater only shows small pitch amplitudes, below one degree, for the given wind and wave conditions. In contrast to FLOWTGEN, the mean pitch angle shows relatively high values, especially at rated wind speed. Consequently, the positive effect of upward-shifted

lidar focus points is predominant. In this case, the model-based correction approach can reduce the ME significantly over the full wind speed range. The remaining MEs are below 0.1 ms^{-1} or 0.5% .

4.5.2 Frequency Filtering

The filtering approach is tested using the lidar simulation framework Vi-conDAR for a random realization of a synthetic turbulent wind field with prescribed floater dynamics.

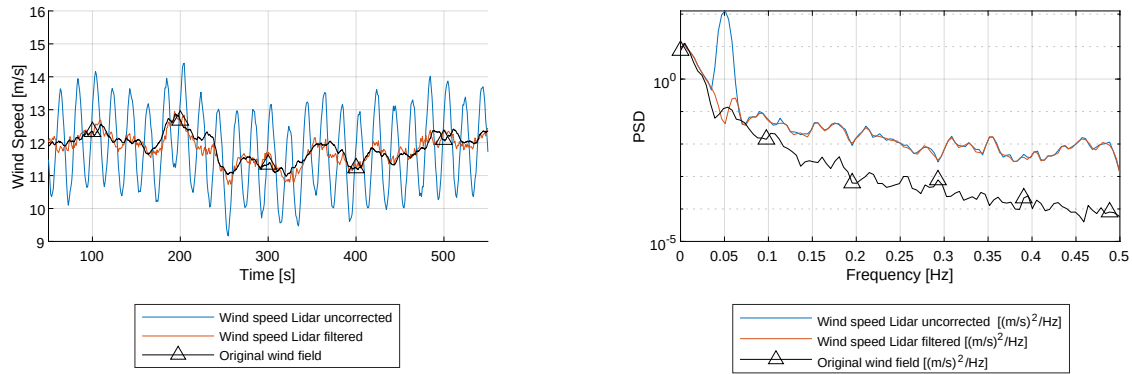


Figure 4.14: Left: Time series example of lidar estimated u-component wind speed, frequency corrected lidar u-component wind speed estimate and reference wind speed of the input wind field. Right: PSD of lidar estimated u-component wind speed and frequency corrected lidar u-component wind speed estimate. Dynamics parameters: U_{ref} : 12 ms^{-1} , $A_\beta = 3 \text{ deg}$, $T_\beta = 20 \text{ s}$, $A_\psi = 0 \text{ deg}$, $A_\gamma = 0 \text{ deg}$, $A_{heave} = 0 \text{ m}$.

Figure 4.14 shows an exemplary time series plot of lidar estimated u-component wind speed with and without application of the frequency filter. Additionally, the u-component wind speed component of the original wind field averaged over the rotor plane is shown as a reference. Since the floater pitch frequency is defined by only one frequency in this case, a narrow peak in the resulting PSD of the lidar measured u-component is observed. The application of the bandstop filter corrects the pitch-induced fluctuations accurately. Figure 4.15 shows the MAE after application of the frequency correction approach over wind speeds from 4 ms^{-1} to 20 ms^{-1} and different pitch frequen-

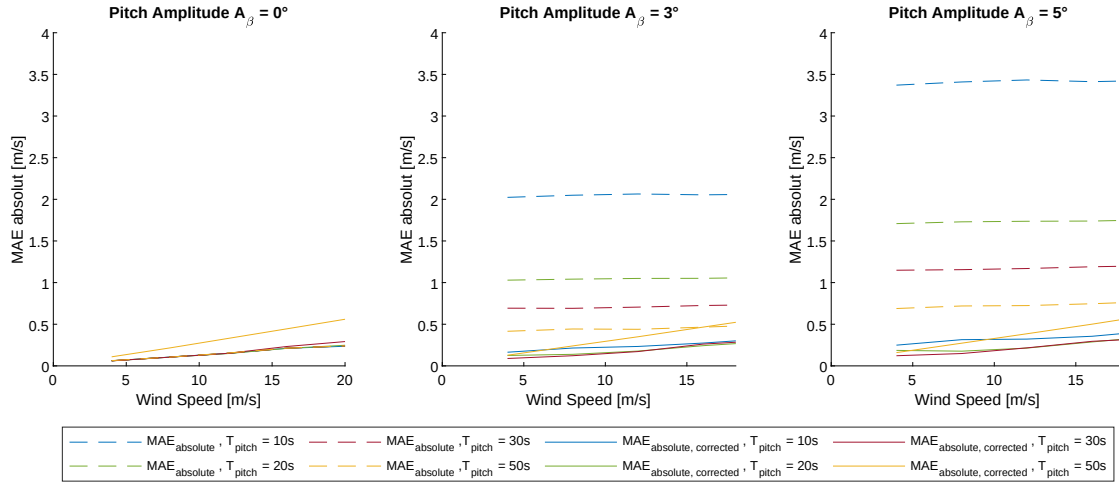


Figure 4.15: MAE of lidar u-component wind speed estimates with and without frequency correction for varying pitch amplitudes and vertical shear exponent of $\alpha = 0.1$. Fixed Parameters: $A_\psi = 0$ deg, $A_\gamma = 0$ deg, $A_{heave} = 0$ m.

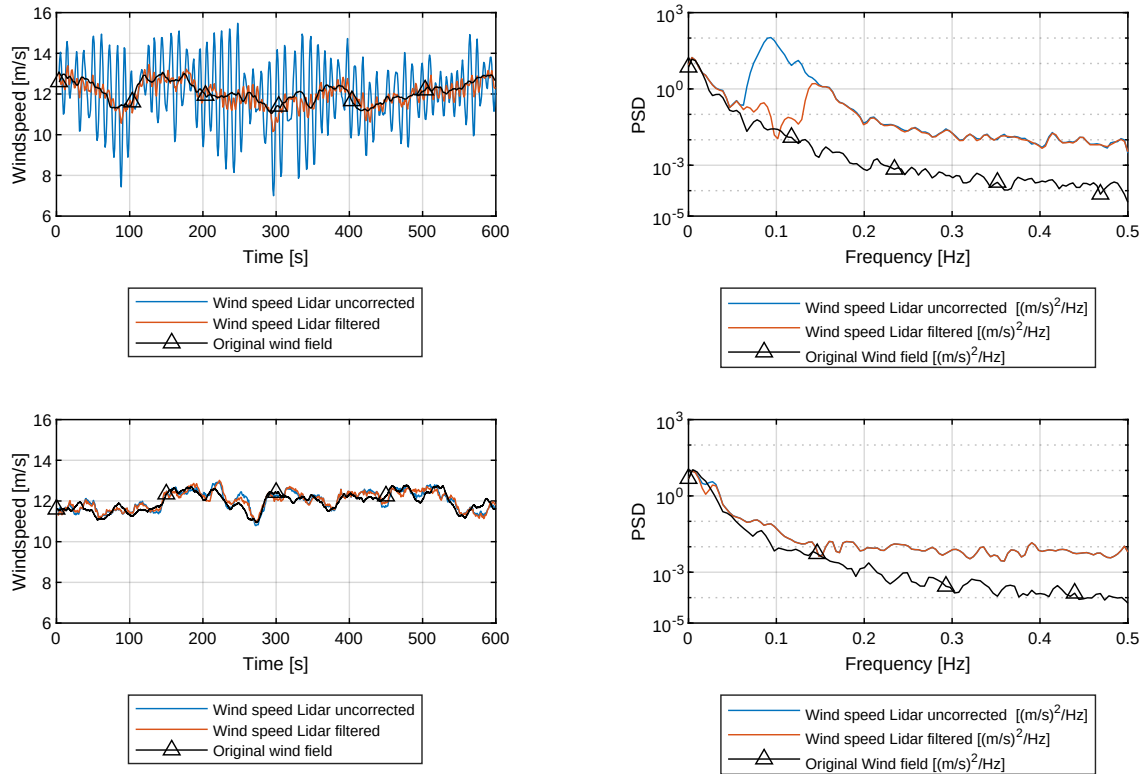


Figure 4.16: Time Series and PSD of simulated Lidar wind speed estimate with and without frequency correction for wave case 3 (see Table 4.5). Top: FLOATGEN, Bottom: WindCrete.

cies for three different pitch amplitudes. As a reference, the figure shows the MAE without frequency filtering. The remaining MAE after filtering is reduced to values of around 2% of the inflow wind speed.

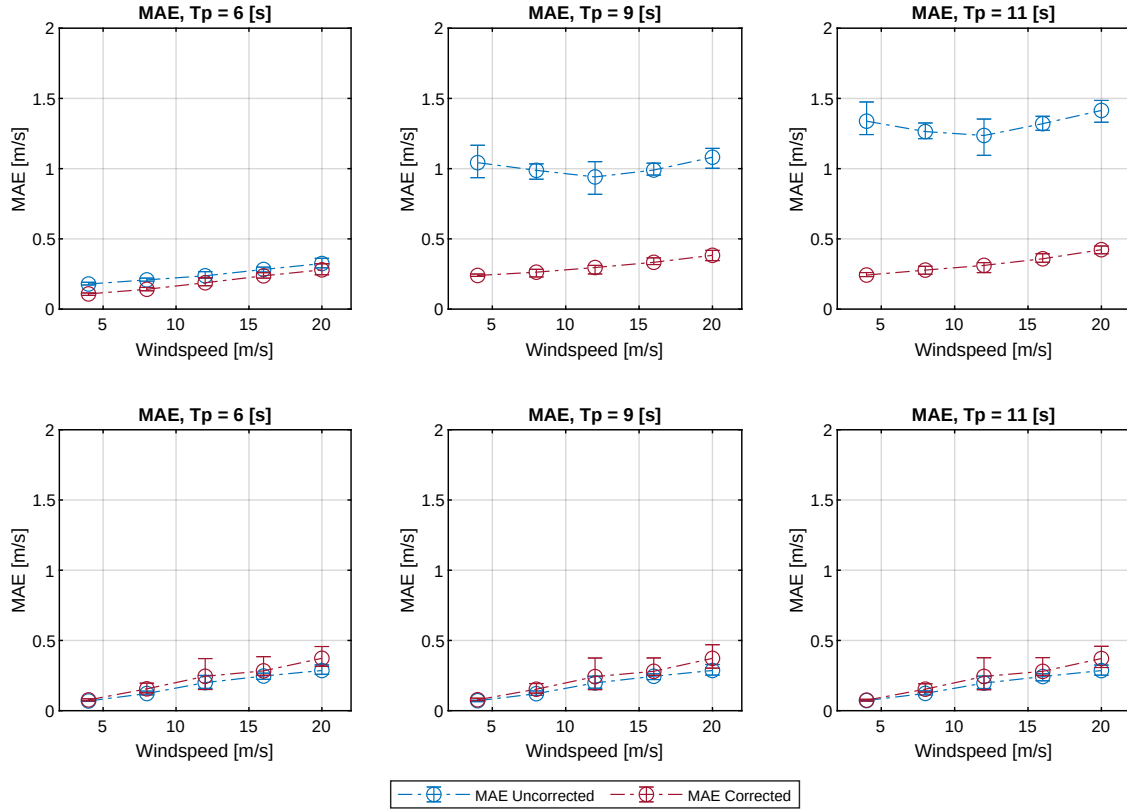


Figure 4.17: MAE of u -wind speed component for FLOATGEN (top) and WindCrete (bottom) FOWT with and without correction for varying wave periods and vertical shear exponent of $\alpha = 0.1$.

In Figure 4.16, example time series and corresponding PSD plots for simulated lidar measurements on the FLOATGEN and WindCrete FOWT before and after applying the bandstop filter are shown. As a reference, the wind speed average over the rotor plane is shown. The uncorrected measurements for FLOATGEN are characterized by periodic fluctuations caused by the floater's response to wave excitation. Application of the frequency filter reduces the fluctuations significantly. For the WindCrete FOWT, no clear influence of pitch motion can be observed in the time series and the corresponding PSD. Consequently, application of the frequency filtering cannot

reduce the error between the lidar-measured wind speed and the full wind field reference. The reference PSD of the original wind field represents an average over all points in the rotor plane. Therefore, the spectrum lies below the lidar estimated spectra. It should be noted, that the lidar spectrum does contain the combined effect of probe volume averaging and cross contamination due to spatially separated measurement volumes.

Figure 4.17 shows the MAE results of the frequency filter-based correction approach for simulated dynamics of FLOATGEN (first row) and WindCrete (second row) FOWT. For FLOATGEN, the pitch motion of the floater is mainly determined by the wave conditions with high pitch excitation for wave frequencies, close to the natural pitch frequency of the floater at 0.1 Hz. The frequency filtering of the present floater pitch frequency can significantly reduce the MAE.

For the given wind and wave conditions the WindCrete Floater shows very small pitch excitation, resulting in small translational velocities of the nacelle and no significant peak in the frequency spectrum. In this case, the frequency filtering approach does not affect the MAE. On the contrary, the MAE of the filtered lidar wind speed estimates is slightly higher than the uncorrected value, because the applied frequency acts on the measured wind field spectrum itself. Wave conditions do not significantly influence MAE values because of the small dependency between floater pitch response and different wave conditions.

Besides MAE, the second metric used to evaluate the performance of frequency filtering is ME. While for FLOATGEN, filtering of the pitch frequency does not introduce additional bias, for WindCrete bias of up to 0.2 ms^{-1} is introduced in the time series. A comparison of ME before and after applying the frequency filter is shown in Figure 4.18. The MAE and ME results of this simulation study show, that the proposed frequency filtering approach for motion correction is able to reduce MAE while not introducing bias. This applies only to floaters that cause a distinct peak

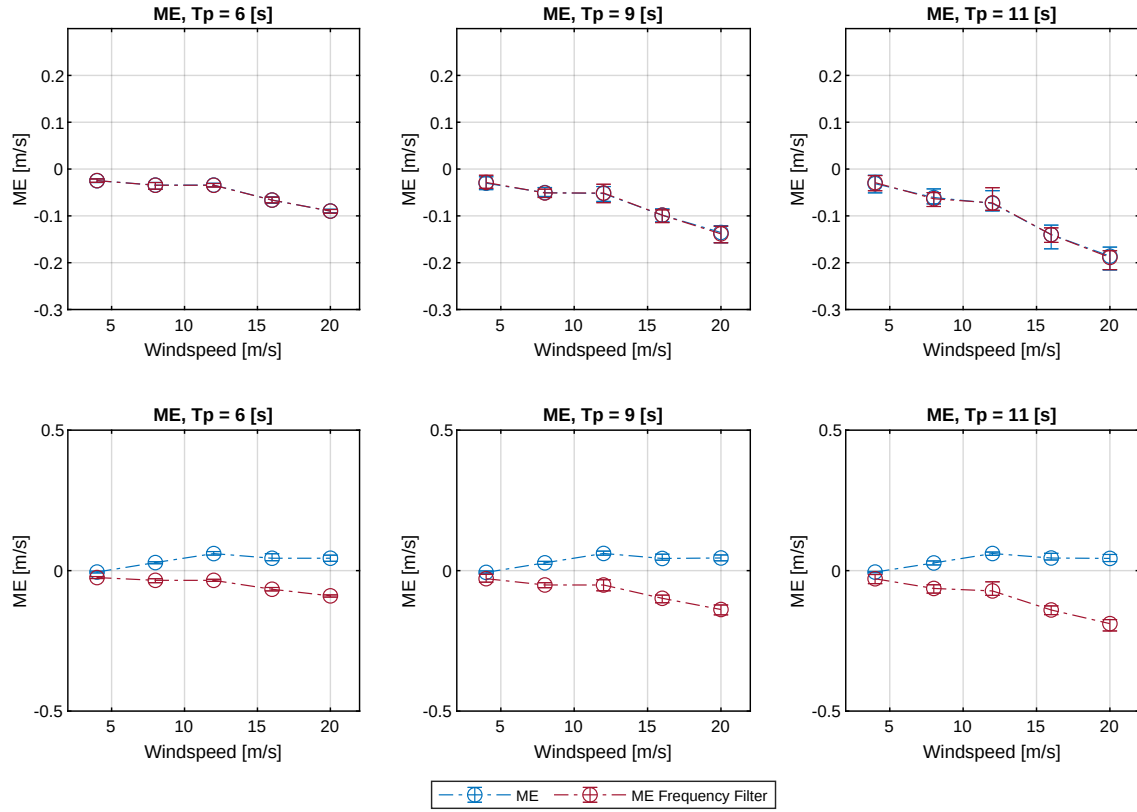


Figure 4.18: ME of u- wind speed component for FLOWTGEN (top) and WindCrest (bottom) FOWT with and without application of frequency filter. Vertical shear exponent $\alpha = 0.1$.

around the pitch frequency of the floater in the frequency spectrum of the lidar wind speed measurements.

4.6 Chapter Discussion

Two different approaches for correcting these effects were introduced and tested using the numerical lidar simulation framework. The model-based bias correction approach uses bias estimates from the analytical model to calculate correction values as a function of pitch amplitude, frequency, and present shear conditions.

The correction approach yields very accurate results for the testing case using prescribed dynamics based on amplitude and frequency parameters.

Here, it should be noted that the analytical and the numerical models use the same dynamic inputs. In reality, the modeled floater dynamics of the analytical model might not exactly represent the real floater dynamics. Also, the parameters determining the correction value for every 10 minutes are not constant for real floaters and need to be averaged, which adds uncertainties. However, the testing cases with the aero-elastic simulation of a spar type and a barge type FOWT with very different pitch characteristics still yield good results with remaining MEs of below 0.1 ms^{-1} . For all testing cases, it is assumed that the parameters necessary for determining correction values can be measured accurately. In reality, determining these parameters (mean pitch angle and pitch amplitude) would rely on inclination measurements which could add uncertainty to the corrected wind speed estimates. A sensitivity study, quantifying the effect of these uncertainties, and further verification with real measurements is needed before applying the methodology.

For higher pitch periods, translational velocities of the nacelle caused by floater pitch motions are not increasing the MEA significantly. Thus, the MEA is not predominantly determined by the pitch motion of the floater. Filtering of these frequencies yields increased MAEs since relevant parts of the wind field spectrum are filtered out. Here, it should also be mentioned that the pitch frequency is assumed to be exactly known for each simulation run and not changing over time which does not accurately represent the behavior of FOWTs under varying environmental conditions.

The testing cases using the simulated dynamics from FLOATGEN and WindCrete FOWT confirm the findings of the idealized conditions. For FLOATGEN, which has a relatively low natural pitch period of around 11 seconds and high pitch amplitudes, the pitch motion of the floater predominantly determines the MEA. Here, the MAE can be reduced significantly using the filtering approach. The filtering approach does not yield satisfactory results for WindCrete, which has a natural pitch period of around 50

seconds and smaller pitch amplitudes. For applications on real measurement data, the filtering frequencies need to be determined through measurements, e.g., based on a peak detection algorithm, which might introduce additional uncertainties. Therefore, the method must be verified with real measurements in future work on the topic.

5

Lidar Assisted Virtual Load Sensors for Mooring Lines

In the previous chapter the influence of floater motion on nacelle-based measurements has been analysed and quantified. The need for motion correction has been discussed based on different use cases. In this chapter, the use of nacelle-based lidar inflow measurements for virtual load sensors is investigated. Hereby, a novel approach is followed. Instead of reconstructing wind field characteristics from the lidar; the lidar LOS measurements are directly used as input to different machine learning models, which are trained to predict fair tension load time series and DELs. Mooring lines and fairlead loads are intrinsically linked to the dynamics and the position of the floater of an FOWT. Therefore, the individual contribution of floater dynamics on the prediction quality of fairlead tension time series and DELs is analyzed. Wind speed measurements obtained via nacelle-based lidar on FOWTs are inherently influenced by the platform's dynamic motions, notably the rotational pitch displacement and surge displacement of the

floater. Consequently, the lidar wind speed data encapsulates insights into the dynamic behavior of the floater, which, in turn, governs the fairlead loads. This chapter directly leverages lidar-measured LOS wind speeds to estimate mooring line tensions. In short, the objectives of this chapter are:

- to investigate machine learning approaches suitable for constructing virtual sensor models to predict fairlead tension time series and DELs
- to analyze the contribution of individual input features to the models' performance. Considered input features include platform dynamics and position measurements, supervisory control and data acquisition (SCADA) signals, and lidar inflow measurements.
- to evaluate the influence of noise in platform position and dynamics input signals on the model prediction accuracy.
- to investigate the value of lidar inflow measurements for fairlead tension prediction and analyze the sensitivity to different lidar patterns.

This chapter expands upon the findings and methodologies previously documented in [85].

5.1 Methodology

A numerical approach is employed to provide model training data and demonstrate prediction performance. OpenFAST, an aero-elastic wind turbine simulation tool [53], in combination with ViConDAR, a numerical lidar simulation framework [70, 18], to generate the input and output variables for the neural network. Turbulent wind fields are created using the open-source windfield generator TurbSim [86], and the aero-elastic simulation code openFAST version 3.2.1 is used to simulate relevant FOWT responses, including mooring line loads. Subsequently, the simulated wind fields and turbine

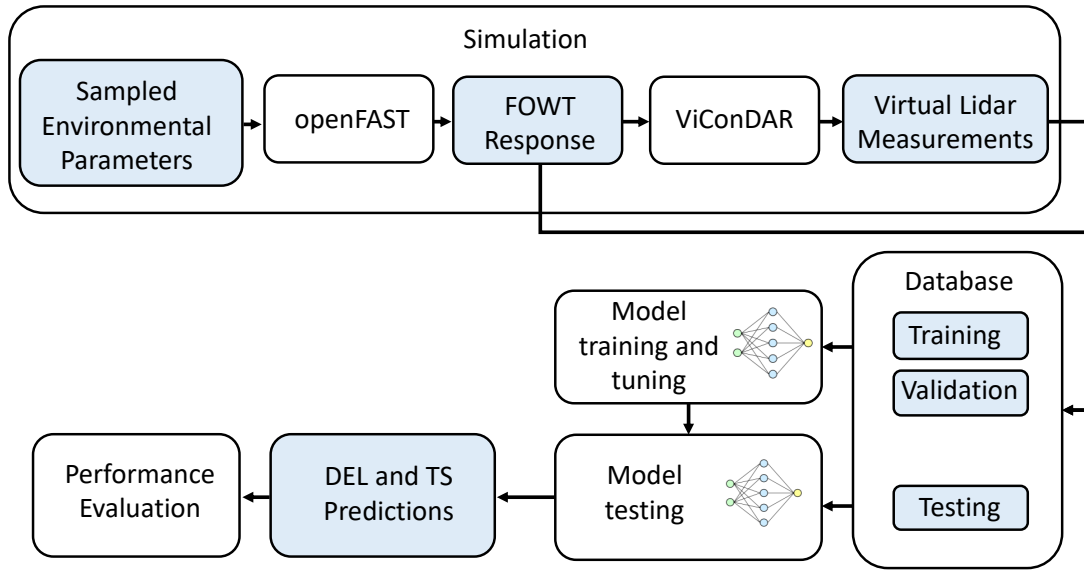


Figure 5.1: Overview of the simulation, training, and evaluation methodology. White boxes denote used tools and process steps, blue boxes denote used and generated data sets.

dynamics are utilized as input to the open-source numerical lidar simulator, which generates virtual lidar measurements under the influence of all six DOFs. The fairlead tensions, turbine dynamics, and turbine responses characterized by blade pitch, power output, and nacelle yaw angles, along with corresponding lidar measurements, are used to train neural networks for predicting fairlead tension time series and DELs. Finally, the predictions of the neural networks are evaluated against the simulated time series. An overview of the approach is shown in Figure 5.1.

5.1.1 Virtual Load Sensor Models

This study delves into two distinct applications of virtual load sensor models. A sequence-to-sequence model for predicting the time series of fairlead tension loads. Additionally, four different modeling approaches for predicting fairlead tension DELs are investigated. The models are introduced hereafter.

Time Series Prediction Model

The virtual load sensor time series model is built as a sequence-to-sequence LSTM model, which uses sequences of input time series to predict target time series sequences. The network structure that has been chosen for this model consists of six layers. These layers include a sequence input layer, an LSTM layer, a hidden fully connected (FC) layer, a Dropout layer, an output FC layer, and a regression output. The sequence input layer allows data from all input channels to enter as a sample sequence, with the length determined by the window size parameter. These samples are then passed to the LSTM layer. These neurons learn when to forget, update, and output the cell value based on the current and previous input values, as well as the cell memory value. The output of the LSTM layer is then fed into the hidden FC layer, which, along with the output FC layer, processes the features extracted by the LSTM layer. A dropout layer is placed between the hidden FC layer and the output FC layer. This dropout layer randomly sets a fraction of inputs to zero with a specified probability. This helps reduce the network's reliance on individual features from the LSTM layer and prevents overfitting. Finally, the regression output layer produces the final predictions for the target values. The window size defines the number of timesteps in the input features. Predictions are made for the same number of target time series time steps, while no forecasts into the future are made. A hyperparameter tuning process determines the window size used in this study. Since the predicted time series are further used for calculations of DELs an overall sequence length of 600s is needed. Therefore, input sequences are divided into several shorter sequences based on the optimized window size in the prediction step. Predictions are then made in succession while remembering the LSTM cell states for each sub-sequence. Sub-sequences are concatenated after the prediction for the calculation of DELs. Figure 5.2 shows the layer architectures of the model.

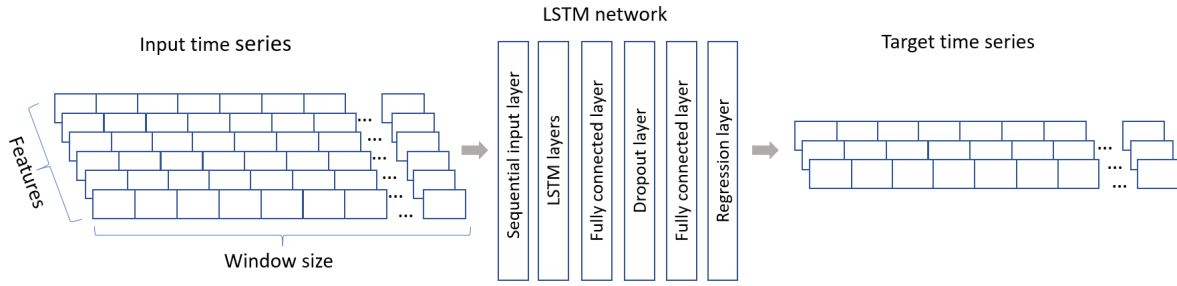


Figure 5.2: Sequence-to-Sequence time series prediction model architecture.

DEL Prediction Models

Considering the possible use and application of virtual load sensors for fairlead tensions, the ability to accurately predict DELs is important. DELs are used for monitoring fatigue loads and estimation of remaining lifetimes. A rain flow counting algorithm counts the number of cycles n_i with load amplitudes S_i in each sequence. DELs are calculated using equation 2.15. The number of reference cycles N_{ref} for a reference cycle frequency of 1 Hz is chosen to be 600. DNVGL-OS-E301 [87] recommends a Wöhler coefficient of $m = 3$ for a studless mooring chain made of steel. While this value of the Wöhler coefficient is used as a realistic baseline case, additionally the performance of DEL prediction models is investigated for Wöhler coefficients of $m = 6$ and $m = 9$. In this way the sensitivity of the Wöhler coefficient on the DEL prediction performance is tested.

The prediction quality of fairlead tension DELs is evaluated for four different modeling approaches. First, the time series model as described in 5.1.1 is trained to predict fairlead tension time series in sequences of 600s. The fairlead DELs are then calculated from the predicted time series using equation 2.15. Second, a sequence-to-one regression model architecture is used to predict DELs directly from the input time series sequences. In this case, the model is trained to predict a single estimate of DEL for each set of input time series. In contrast to the Seq2Seq model for time series prediction the sequence-to-one architecture uses only the last output of the LSTM layers

for a given input sequence to produce the DEL prediction. This LSTM output is then passed through a FC layer and a regression layer to produce the final DEL estimate for the given input sequence. The model architecture is shown in figure 5.3.

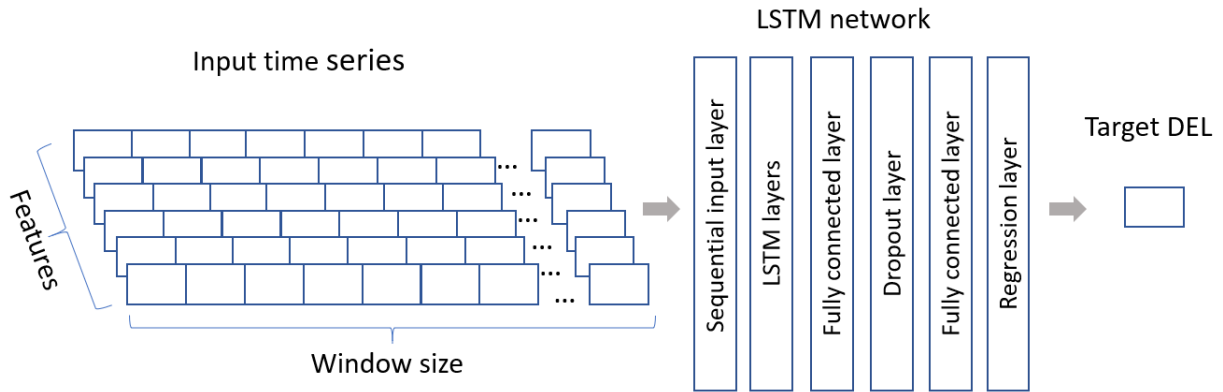


Figure 5.3: Seq2One model architecture.

The third investigated DEL prediction approach employs a CNN. CNNs have traditionally been associated with image processing tasks, but they have also proven to be effective for time series classification. CNNs can extract meaningful features from sequential data by using 1D convolutional layers to scan through the time series, identifying patterns within the data. These learned features can capture essential temporal information, such as trends and frequencies, making CNNs useful in applications like the prediction of DELs. The architecture of the model employed in this study is shown in figure 5.4. The input time series are fed through a one-dimensional convolutional layer, which applies filters to the input time series, allowing the network to detect patterns and relevant features at various scales and positions within the data. The pooling layer follows the convolutional layers and serves to reduce the spatial dimensionality of the feature maps. This dimensionality reduction helps retain essential information while making the network more computationally efficient. The FC layer connects all the

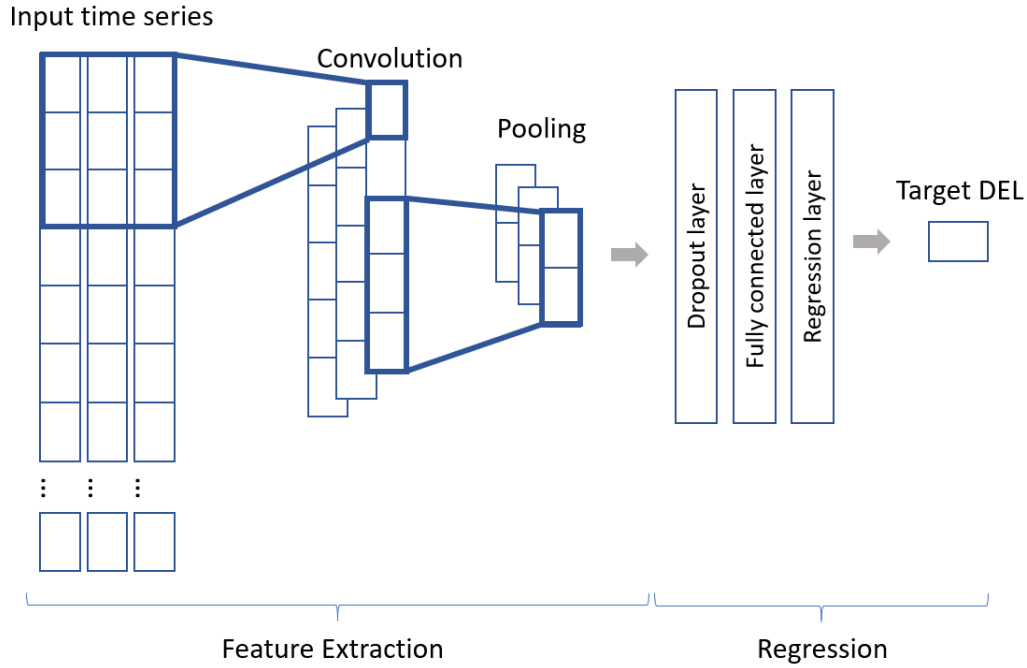


Figure 5.4: One-dimensional CNN architecture for time series regression architecture.

neurons from the previous layer to each neuron in itself. This layer learns to map the extracted features to the output. Finally, the regression layer consists of a single neuron which produces the final regression output for DEL estimation.

The last investigated model architecture follows a different approach. Here, only pre-calculated time-series statistics are used as model input. The model is built as a simple feedforward neural network with a network architecture as presented in figure 5.5. The minimum, maximum, mean, and standard deviation are calculated in a preprocessing step for each input time series. All input feature metrics are concatenated in a single vector used as model input. The model is trained to predict the DEL value corresponding to the original input sequence.

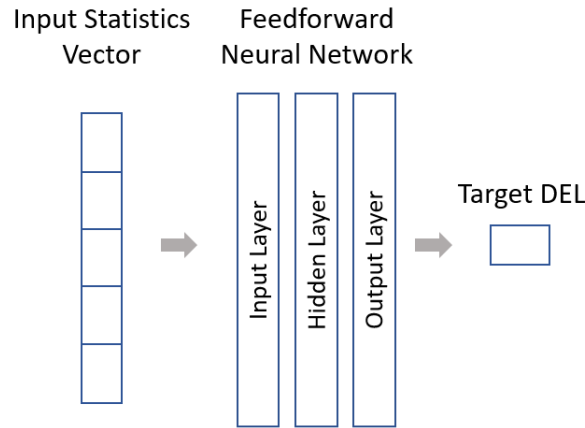


Figure 5.5: Feedforward neural network with statistics vector input for DEL prediction.

5.1.2 Feature Selection

The selection of input features for various models is carried out manually, aligning with the study's objective to assess the impact of individual input features on prediction accuracy. Consequently, different scenarios combining platform dynamics, SCADA signals, and lidar measurements were distinctly categorized. As outlined in section 2.2.2, the platform dynamics in six DOFs are crucial in determining fairlead tensions, leading to the inclusion of both platform displacements and velocities in our analysis. Additionally, standard SCADA system outputs like blade pitch, power, and nacelle yaw signals were considered, given their potential relevance to the prediction task. Lidar Line-of-Sight (LOS) signals were also incorporated additionally for each case to ascertain their specific contribution to prediction accuracy. To manage the scope of the investigation, platform dynamics were grouped into four categories: translational displacements, rotational displacements, translational velocities, and rotational velocities, with each category encompassing signals in the x, y, and z coordinates. For cases A to E , the model inputs were restricted to platform dynamics, SCADA signals, and nacelle yaw position. In contrast, cases A_{Lidar} to E_{Lidar} were expanded to include

radial wind speed measurements from the lidar, facilitating a focused analysis of lidar signals' impact. Case F_{Lidar} is unique, using only the lidar LOS wind speeds and nacelle yaw position; the latter is included to inform the model about the global wind direction, a parameter not directly evident from the radial wind speeds. This particular case is designed to evaluate the potential of a model based solely on lidar data in predicting fairlead tensions. A summary of all these scenarios is presented in table 5.1.

Table 5.1: Summary of all modeling cases and input feaures.

Feature	A	B	C	D	E
LOS velocities [ms^{-1}]	x	x	x	x	x
Nac. Yaw [deg]	✓	✓	✓	✓	✓
Bld. Pitch [deg], Power [W] [deg]	✓	✓	✓	✓	✓
Platform transl. displ. (surge, sway, heave) [m]	✓	✓	✓	✓	x
Platform rot. displ. (pitch, roll, yaw) [deg]	✓	✓	✓	x	x
Platform transl. velocities (x, y, z) [m/s]	✓	✓	x	x	x
Platform rot. velocities (x, y, z) [deg/s]	✓	x	x	x	x

Feature	A_{Lidar}	B_{Lidar}	C_{Lidar}	D_{Lidar}	E_{Lidar}	F_{Lidar}
LOS velocities [ms^{-1}]	✓	✓	✓	✓	✓	✓
Nac. Yaw [deg]	✓	✓	✓	✓	✓	✓
Bld. Pitch [deg], Power [W] [deg]	✓	✓	✓	✓	✓	x
Platform transl. displ. (surge, sway, heave) [m]	✓	✓	✓	✓	x	x
Platform rot. displ. (pitch, roll, yaw) [deg]	✓	✓	✓	x	x	x
Platform transl. velocities (x, y, z) [m/s]	✓	✓	x	x	x	x
Platform rot. velocities (x, y, z) [deg/s]	✓	x	x	x	x	x

5.1.3 Hyperparameter Tuning

Model hyperparameters define the configuration of the model and the learning process. Since model hyperparameters can not be learned based on the training data they need to be defined prior to the training process. To increase the performance of each model, hyperparameters are optimized in a tuning process. Similar to the approach of [29], two types of hyperparameters are distinguished. The first set of parameters determines the architecture and training characteristics of the LSTM model, while the second set of parameters defines the number of training data sequences and the window length of the input and target time series.

Table 5.2: Prediction models hyperparameters.

Model	Hyperparameter	Parameter space	case A	case A_{Lidar}
DEL TS	Number of LSTM layers	1-3	1	1
	Number of LSTM units per layer	50-200	130	100
	Number of fully connected layers	1-3	1	1
	Window length	50:50:600	100	100
	Number of units in fully connected layers	50-200	190	60
	Dropout rate	0-0.5	0.25	0.3
	Number of training sequences	200-1800	1800	1800
DEL Seq2One	Number of LSTM layers	1-3	1	1
	Number of LSTM units per layer	50-200	130	110
	Number of fully connected layers 1	1-3	1	1
	Number of units in fully connected layers	50-200	80	150
	Dropout rate	0-0.5	0.3	0.26
	Number of training sequences	200-1800	1800	1800
DEL Convolution	Number of Convolutions	1-3	2	2
	Filter size	1-30	25	17
	Number of filters	1-100	55	67
	Pool size	1-50	6	1
	Dropout rate	0-0.5	0.2	0.2
	Number of training sequences	200-1800	1800	1800
DEL Stat	Number of hidden layers	1-5	3	3
	Number of Neurons per layer	10- 50	20	20
	Number of training sequences	200-1800	1800	1800

Since the model architectures used in this study require different hyperparameters, the optimization is done for each model architecture indepen-

dently. A Bayesian optimization approach was employed to optimize these parameters, utilizing the experiment manager functionality of the MATLAB statistics and machine learning toolbox [84]. Due to computational limitations, the optimization is not carried out for each case and lidar pattern individually. Each model architecture has been optimized for case A and A_{Lidar} separately and the optimized parameters have been applied to all cases. Hyperparameters, including the parameter space and the optimized values for the time series prediction network, are summarized in table 5.2. The adaptive moment estimation (ADAM) algorithm was utilized during the training process to optimize the model parameters. With the specified hyperparameters, training a single virtual load sensor model typically takes around 1 hour, while predicting a ten-minute target sequence requires less than 1 second.

5.2 Simulation Database

A training database of simulated environmental conditions, turbine response, and lidar measurements is created to develop virtual sensor models in this chapter, as well as chapter 6. The numerical lidar simulation developed in chapter 3.2 in combination with the numerical model of the UMaine VoltturnUS-S reference floating wind substructure (see figure 5.6, right), introduced in chapter 3.3.3, is employed to create the database.

5.2.1 Lidar Configuration

Four different lidar patterns, as depicted in figure 5.7, with an increasing number of focus points are investigated in this chapter. The figure shows the position of focus points in the y-z-plane (see figure 5.6) in front of the turbine. The measurements for each focus point are taken sequentially with a temporal distance of $1/n_{beam}$ seconds, where n_{beam} is the number

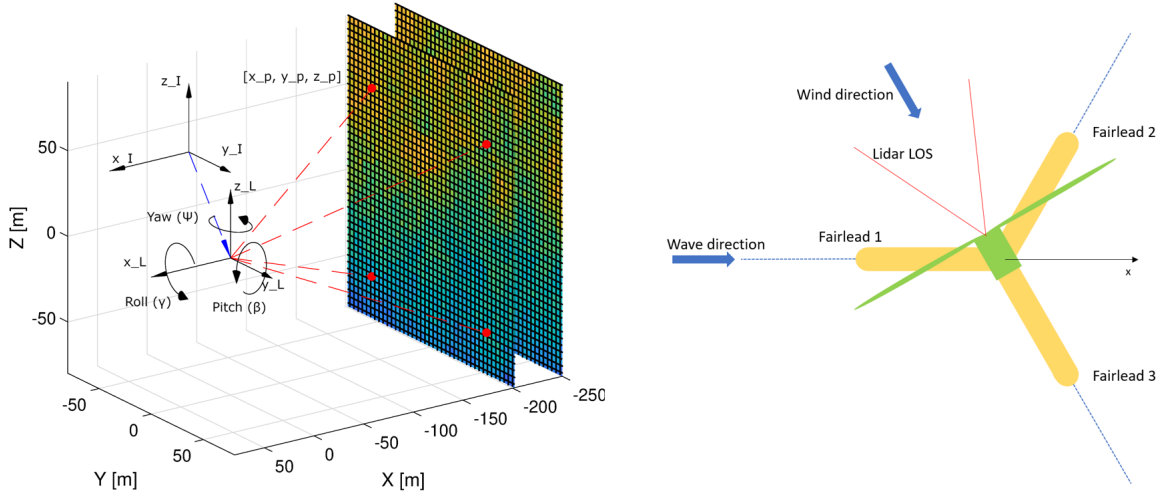


Figure 5.6: Left: Lidar pattern and coordinate systems for numerical lidar simulation. Right: Floater geometry and lidar position.

of focus points in the pattern. In this way, the time series of each LOS velocity has a sampling frequency of 1 Hz. The measurement range is set to 300m. The beam range gate length is set to 30 m and discretized by 10 equispaced points along the range gate. Additionally, Gaussian white noise of $SNR = 20db$ is added to each measurement. This is done to reflect uncertainties of real lidar measurements, which could originate from hardware or software components.

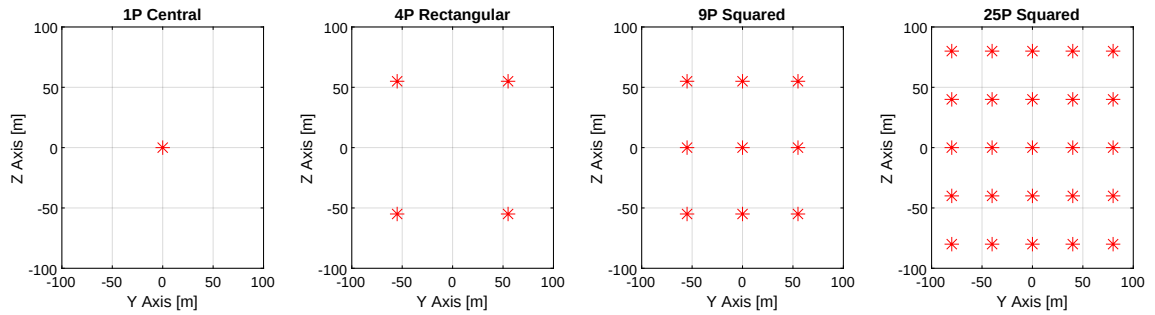


Figure 5.7: Lidar patterns considered in the analysis

5.2.2 Atmospheric Conditions

Using the Veers method for turbulence creation [88], a set of synthetic wind fields is generated. The total number of windfields is limited to 500 due to limited computational capacities. The mean wind speed of each wind field is randomized between 4ms^{-1} and 20ms^{-1} , the TI is randomized between 4% and 16%, and the power law shear exponent is randomized between 0 and 0.2. All wind field parameters are listed in table 5.3.

Table 5.3: Turbulent wind field parameters

Parameter	Value
Wind speed [ms^{-1}]	4:1:20
Turbulence Intensity [%]	4:1:16
Surface Roughness [m]	0.03
Shear exponent [-]	0.0:0.1:0.2
Spatial Grid Resolution [m]	5
Gridsize [m]	300x250
Timestep [s]	0.05
Usable Time [s]	600

5.2.3 Measurement Noise

The required input data would be obtained via diverse sensor systems in a pragmatic utilization context of the trained predictive models. Each distinct sensor category may be subject to measurement inaccuracies. To address the influence of noise present in the acquired measurement data, a noise modeling procedure has been implemented for every individual input feature of the models, subsequently introducing it into the simulated time series. It is assumed that an integrated GNSS/IMU sensor obtains the position and dynamics measurement, which combines an IMU with a global navigation

satellite system (GNSS). The IMU includes an accelerometer, a gyroscope, and a magnetometer. Based on this setup, a sensor fusion model creates measurements from the simulated ground truth dynamics and position signals. The noise of integrated systems is dominated by white sensor noise (see, e.g., [89]). Therefore, the measurement noise of the output signals is modeled using a white noise process. The accuracy of output signals used in this study is based on fact sheets of commercially available GNSS/IMU receivers (see, e.g., [90]). Accuracy parameters are summarized in table 5.4. Figure 5.8 shows exemplary input dynamics with and without modeled sensor noise.

Table 5.4: Inertial navigation system accuracy values.

Parameter	Value
Pitch / Roll [deg]	0.1
Yaw [deg]	0.2
Position accuracy [m]	[1 1 0.05]
Velocity accuracy [m/s]	0.05
Angular velocity accuracy [deg/s]	0.001
Acceleration accuracy [m/s ²]	$2 \cdot 10^{-4}$

5.2.4 Creation of Training Database

Overall, a dataset comprising 2200 simulations, each lasting 600 seconds, encompassing floater dynamics, lidar measurements, fairlead tensions, and DEL values, is created. For each simulation, one turbulent wind field is randomly selected from the aforementioned database of 500 wind fields. To mitigate the impact of transient effects typically present at the start of simulation runs, each simulation is extended to a total duration of 1200 seconds, with the initial 600 seconds being excluded from analysis. Moreover, all

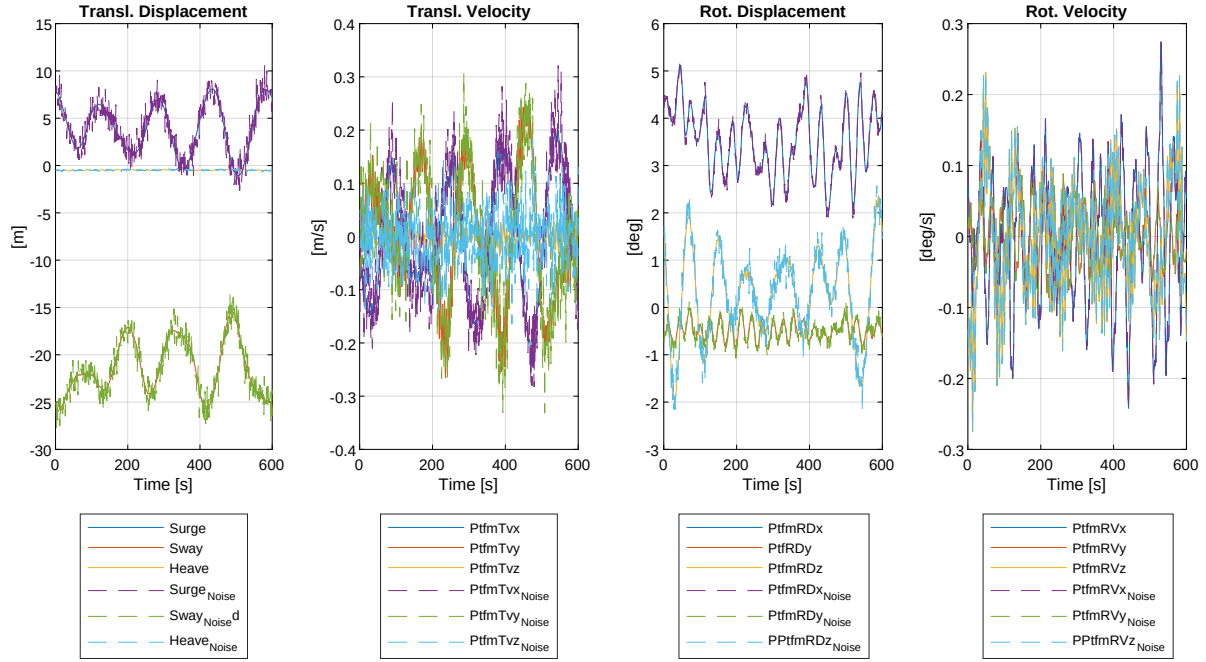


Figure 5.8: Example of input dynamics with and without sensor noise.

sequences utilized in the training, validation, and testing phases are standardized, ensuring a mean of zero and a standard deviation of one across the entire dataset.

Table 5.5: Parameter space wave conditions, where H_s is the significant wave height and T_p is the peak wave period.

Parameter	LR1 [min, max]	LR2 [min, max]	LR3 [min, max]
Wind speed range [m/s]	4:10	11:14	15:20
H_s [m]	0.3, 3.2	0.5, 5.0	0.7, 7.0
T_p [s]	1.7, 13.3	1.2, 12.3	0.9, 11.9

The ocean conditions in the aeroelastic simulations are determined based on the methodology proposed by [91], which accounts for a basic correlation between wind speed, wave height, and wave period. To do this, wind speed is categorized into three distinct load ranges: below-rated, rated, and above-

rated. Each range has specified upper and lower limits for wave height and period. Depending on the mean wind speed of the chosen wind field, wave conditions are randomly sampled within these predefined boundaries. The specific parameters for wave conditions, corresponding to the different wind speed ranges, are detailed in table 5.5. The dependency between wind speed and the sampled wave parameters is shown in figure 5.9.

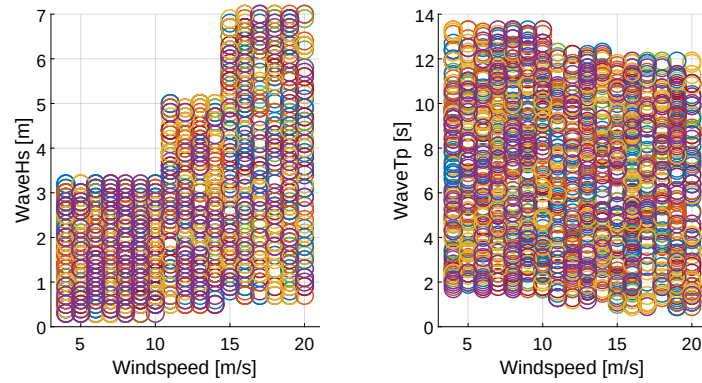


Figure 5.9: Sampling of wave parameters.

In each aeroelastic simulation conducted for this study, radial wind speed measurements are generated for four distinct lidar patterns. The wind direction, relative to a fixed Earth coordinate system, is randomly chosen within a range of 0 to 359 degrees, while the nacelle is always aligned with the wind direction. Similarly, the wave heading, also about the Earth-fixed system, is randomly selected across the same 0 to 359-degree range. To align with the 1 Hz sampling rate of the lidar radial wind speed measurements, all feature and target time series within the simulations are downsampled accordingly. All predictions and performance evaluations for time series and DELs are only based on the downsampled time series. To develop the models, up to 1800 of these simulations are allocated for training. Additionally, 200 simulations are used for model validation during the hyperparameter optimization phase, and another 200 are reserved for the final testing of the model.

5.3 Fairlead Tension Time Series Predictions

Figure 5.10 shows the RMSEN values across the testing data set for all modeling cases and lidar patterns with and without the presence of noise in the dynamics measurements. Comparing cases A to E to the cases A_{Lidar} to F_{Lidar} for all four lidar patterns, the LOS wind speed measurements from the lidar to the model features does not improve the prediction accuracy. This indicates, that the use of lidar signals as predictors for fairlead tensions does not provide additional value compared to dynamics and SCADA signals.

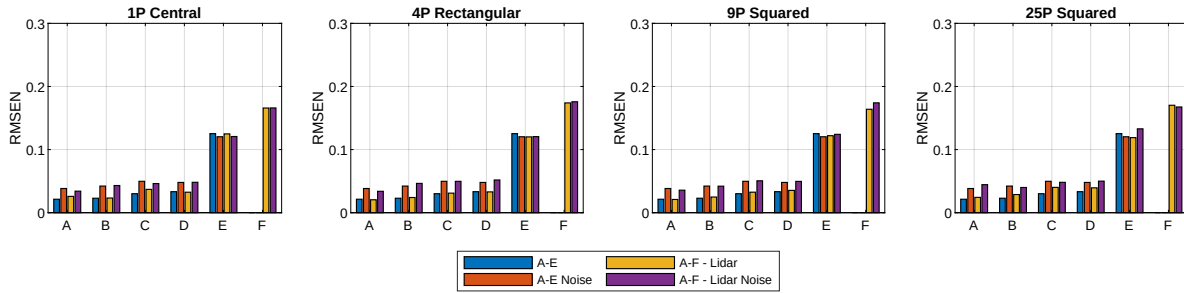


Figure 5.10: RMSEN of time series prediction for all cases and lidar patterns. Cases $A - D$ -Noise as well as cases $A_{Lidar} - F_{Lidar}$ -Noise denotes cases with the influence of measurement noise in dynamics and position measurements.

The best performance is observed in case A , which incorporates all categories of platform dynamics, showing their collective importance in predicting fairlead tensions. A gradual increase in RMSEN is noted with the sequential removal of specific dynamics categories: rotational displacement, translational velocities, and then rotational velocities. Case D exhibits an RMSEN increase of approximately 0.015 compared to case A for noisy input signals. This relatively minor increase suggests that the translational position of the floater plays a pivotal role in time series signal prediction, with additional dynamics groups having less impact on the RMSEN. In case F_{Lidar} , all lidar patterns demonstrate elevated RMSEN values. A noteworthy trend is the reduction in RMSEN as the number of focus points in the lidar pattern increases, up to the 9P squared pattern. This implies that the ratio of in-

formative content to the number of input features may be more favorable in the 9P pattern than in the others. Regarding the impact of noise in the dynamics model inputs, a consistent pattern is seen across cases A to D, with RMSEN values rising by around 0.02. This uniform increase indicates that the effect of noise is independent of the type of input feature used and generally introduces an additional layer of uncertainty to the predictions.

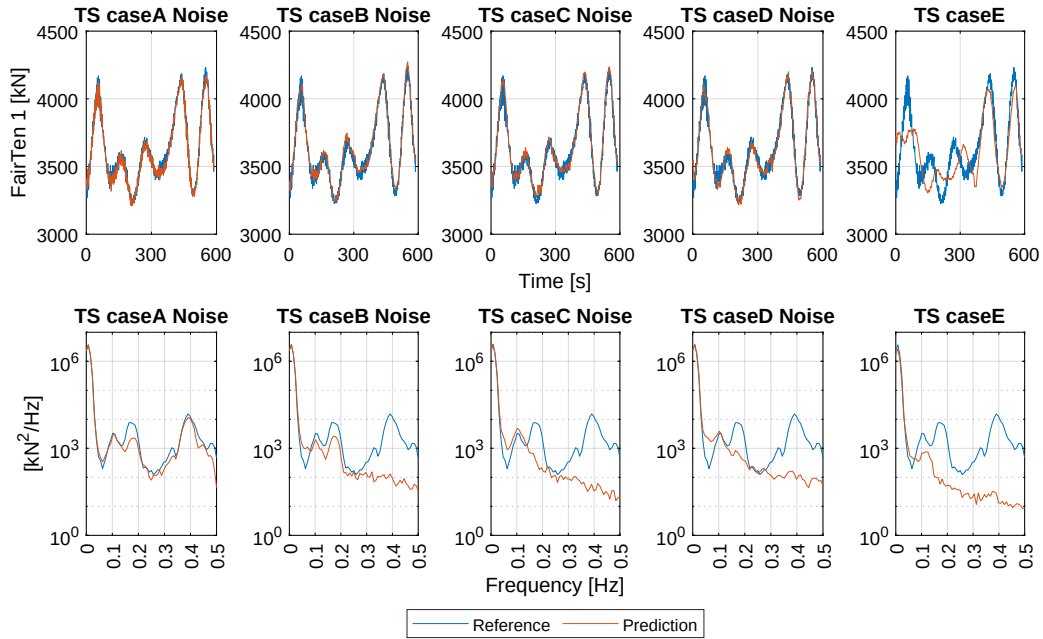


Figure 5.11: Example of time series predictions for cases *A* – *E*-Noise. Top: Prediction versus reference time series. Bottom: PSD of prediction vs. reference time series.

Figure 5.11 illustrates a comparison between predicted time series and reference values, along with their PSD plots, for cases *A* through *E*. In case *A*, which includes both rotational and translational displacements and velocities, the model successfully predicts time series with frequency components accurately up to 0.5 Hz. In case *B*, the predictions fail to capture frequency contents above 0.25 Hz, highlighting the significant role of rotational velocity inputs in the model's predictive capability. For cases *C* and *D*, which lack data on both translational and rotational velocities, the model is limited to accurately reflecting only lower frequency fluctuations, up to approximately

0.15 Hz. Despite these variations in frequency content, it is important to note that the RMSEN differences between these cases are relatively minor (as shown in figure 5.10). Therefore, the necessity and benefit of including additional input features largely depend on the specific application of the time series predictions. In contexts like the calculation of DELs, discussed in section 5.4, the ability of a model to account for higher frequency contents could significantly influence the resulting DEL values.

Figure 5.12 shows a time series prediction example of case F_{Lidar} , which only uses the lidar LOS and nacelle yaw information as an input for the four different lidar patterns. This model can reproduce low-frequency fluctuations originating from variations in the wind field. Frequencies originating from the floater's response to the wave excitation and higher frequency dynamics of the floater are not captured by the model.

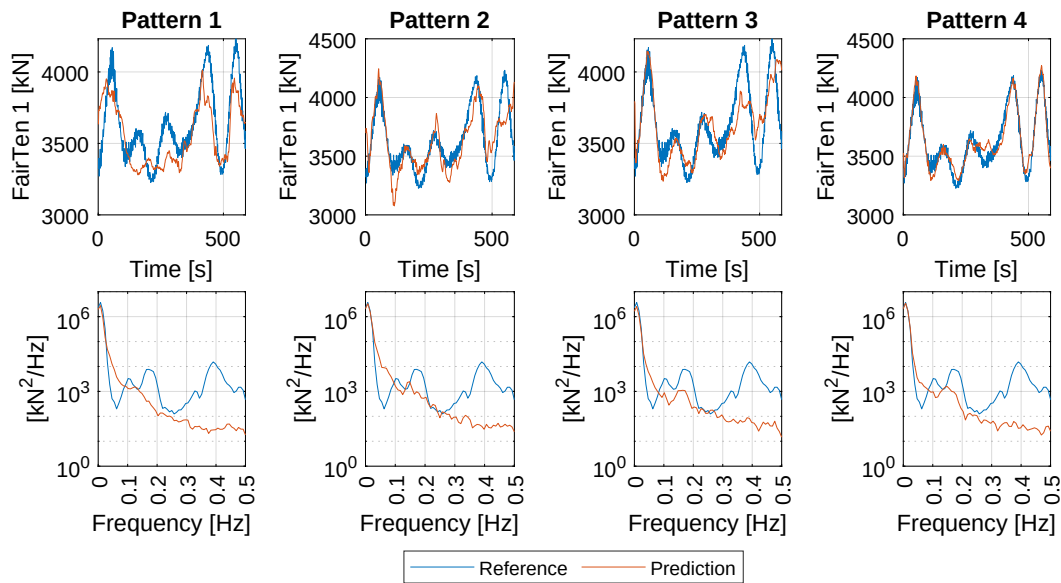


Figure 5.12: Example of time series predictions for case F_{Lidar} , and pattern one to four. Top: Prediction versus reference time series. Bottom: PSD of prediction vs. reference time series.

5.4 Fairlead Tension DEL Prediction

5.4.1 Prediction without Lidar Measurements

Figure 5.13 displays the prediction accuracy for DELs using three different model architectures, covering cases A through E for three different values of the Wöhler exponent. In each boxplot, the lower and upper bounds of the box represent the 25th and 75th percentiles of the data distribution, respectively. The median of the sample is indicated by the horizontal line situated in each box. Any data point marked as a circle is classified as an outlier; these are values that lie more than 1.5 times the interquartile range beyond the box's upper or lower boundaries. The whiskers of the boxplot extend from the edges of the box to the furthest data points that fall within the range defined by the whisker length. The whisker range is defined through the highest/lowest values which do not fall in the definition of outliers.

Across different model architectures, several consistent trends are observed in this study. Case A outperforms other cases for time series and convolutional models, suggesting that both rotational and translational displacements, along with their respective velocities, significantly contribute to the accuracy of DEL predictions. This pattern is inconsistent for the sequence-to-one model and statistics input model, especially across different values of m . The similarity in the median error magnitude, error value distribution, and outlier count across all models suggests that each modeling architecture is generally effective for DEL prediction tasks.

The gap in prediction accuracy between cases A and B is marginal for all models, hinting at a relatively minor role of rotational velocity inputs in overall DEL prediction accuracy. Conversely, cases C and D exhibit higher APEs than A and B across all models, with this effect being more pronounced in the convolutional and Seq2One models. These cases also show a

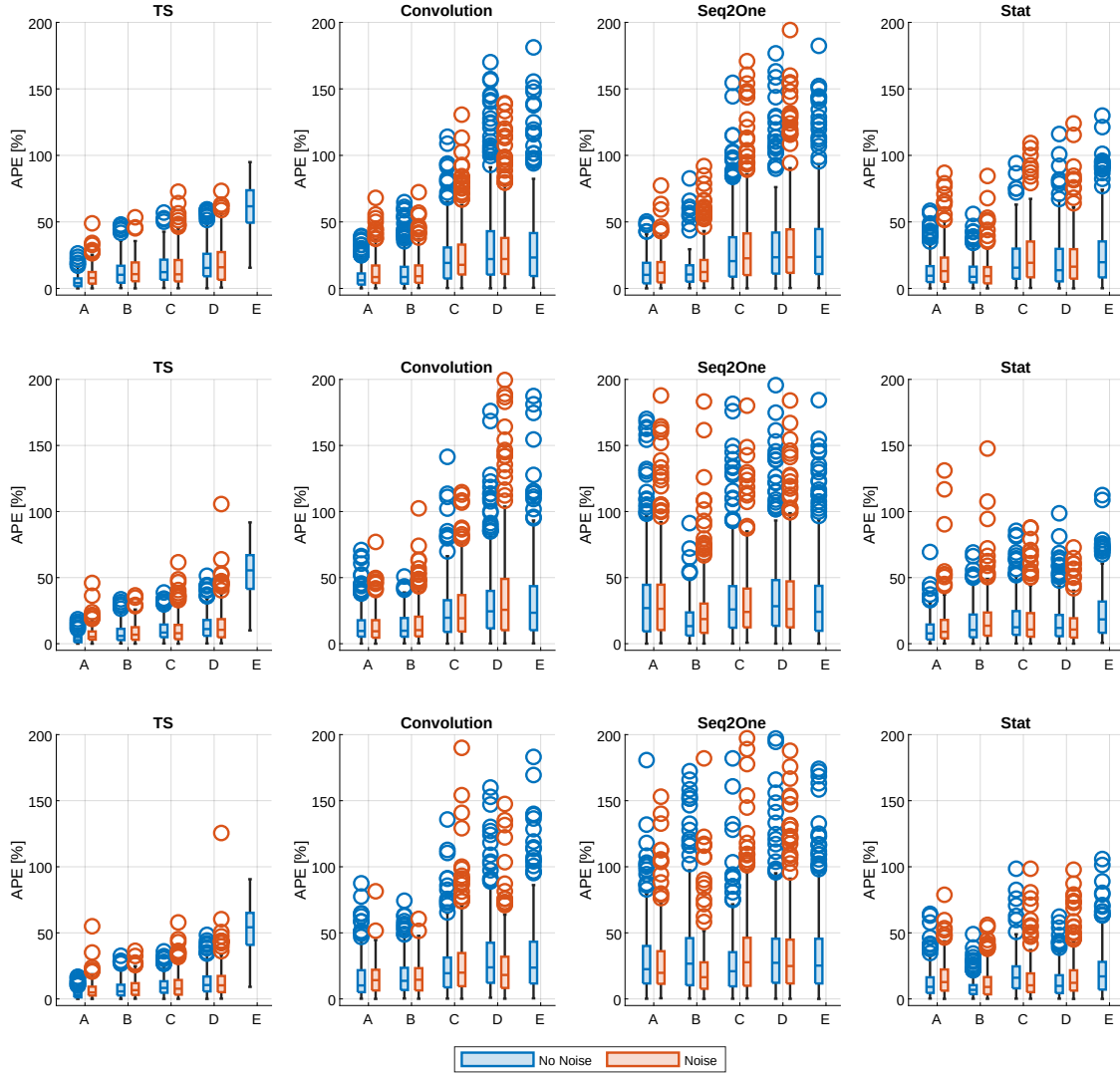


Figure 5.13: APE of DELs for cases $A - E$ with and without influence of noise. Top: $m = 3$. Middle: $m = 6$. Bottom: $m = 9$. From left to right: Time series model, convolutional model, Seq2One model, statistics input model.

broader range of prediction errors and increased outliers. The difference in prediction accuracy between cases C and D is relatively small for all models, indicating that rotational displacements have a smaller impact than translational displacements in predicting DELs.

Interestingly, the influence of noise on the input data is either minimal or inconsistent across all models, suggesting that the level of introduced noise does not significantly contribute to uncertainty in DEL predictions.

Besides these similarities, the four models show significant differences in their ability to predict fairlead tension DELs. While the median error values for cases A and B show similar values for all four models, cases C and D show approximately 10 % higher median errors, for the convolutional and Seq2One models. The statistics input model shows inconsistent trends across different values of the Wöhler exponent m . While the performance pattern for $m = 3$ is similar to the convolutional and Seq2One model, for higher values of m no significant performance difference can be observed for cases A to D.

The approach for calculating the DELs based on time series predictions shows a notably narrower range of error values, especially apparent in cases B, C, and D. Furthermore, the convolutional, the Seq2One, and statistic input models tend to predict a higher number of outliers, and the errors generated by these models span a wider range of magnitudes. This difference in performance can be attributed to the intrinsic characteristics of the different modeling approaches used. For the time series prediction model, DEL values are derived analytically. This method is robust in situations where the predicted time series are reasonably accurate in terms of scale, and capture the low-frequency fluctuations of the signal. Under these conditions, the DEL calculation algorithm is less likely to yield DEL results with high errors. On the other hand, the convolutional, Seq2One, and statistic input models derive DEL predictions only on a statistical basis. They lack an inherent representation of the analytical procedures of the DEL calculation. Consequently, as observed in this work, these models are more prone to higher prediction uncertainties. The statistics inputs model outperforms the convolutional and Seq2One models. This is especially evident in cases C to E.

Interestingly, the error median for case E is significantly higher for the time series model, compared to convolution, Seq2One, and statistics inputs models although the spread of error and the number of outliers is smaller. The

quality of the time series prediction can explain this. As shown in figure 5.11, the time series model for case E is not able to predict the low-frequency fluctuations of the signal correctly. Consequently, the calculated DEL values show higher median errors.

The variation of the Wöhler exponent m of the predicted DELs reveals a notable pattern. The time series DEL calculation approach shows only marginal sensitivity to the variation of the Wöhler exponent. Relative errors are slightly smaller for higher values of m . In contrast, the Seq2One prediction model shows significantly higher prediction errors for higher values of m . This is particularly true for cases *A* and *B*. The convolutional model shows a similar trend, while the error increase with higher values of m is less pronounced. The dependency of the realization-to-realization uncertainty on the Wöhler exponent can explain this behavior. Due to the definition of the DEL metric (see equation 2.15), any variation in the time series signals is exponentiated by the power of m , leading to an amplification in the DEL values. This leads to a larger realization-to-realization uncertainty compared to other metrics such as the mean or the standard deviation of a time series. While this variation is well captured by the time series prediction in combination with analytical DEL prediction, the purely statistical time series input models perform inferiorly in capturing these uncertainties. The statistical input model performs similarly to the time series prediction model.

When interpreting the sensitivity of error values to the Wöhler exponent, it should be emphasized that *APE* is a relative metric that does not reflect the absolute error values. An absolute representation of error values is given in figure 5.14, where the RMSE is presented across the same cases and variations of m . While the variation of error values between cases and model architectures is consistent with the *APE* results discussed above, it can be seen that the absolute prediction errors increase significantly with higher values of m .

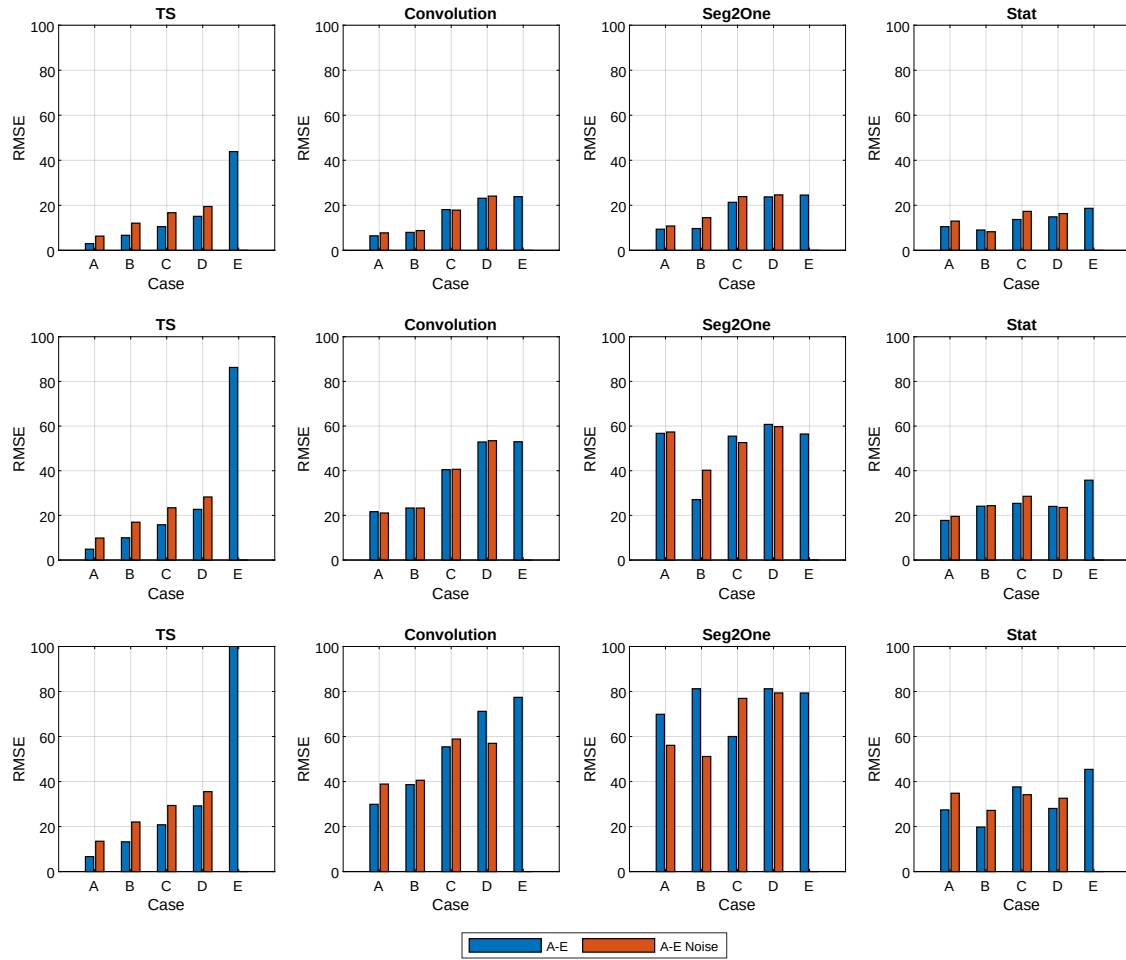


Figure 5.14: RMSE of DELs for cases A–E with and without influence of noise. Top: $m = 3$. Middle: $m = 6$. Bottom: $m = 9$. From left to right: Time series model, convolutional model, Seg2One model, statistics input model.

Figure 5.15 shows the model predicted DELs about the reference DELs, calculated from the reference time series for all model architectures and cases A to D. Additionally, the result of a linear regression and the coefficient of determination is shown for each case. As indicated by figure 5.13 case A provides the best prediction accuracy for all models except the statistics input model. For convolutional, Seg2One, and statistics input models, higher scatter around the 1-1 reference can be observed. Although the time series prediction show the least scatter around the 1-1 reference, a negative bias or underestimation of DELs predictions can be observed for the time

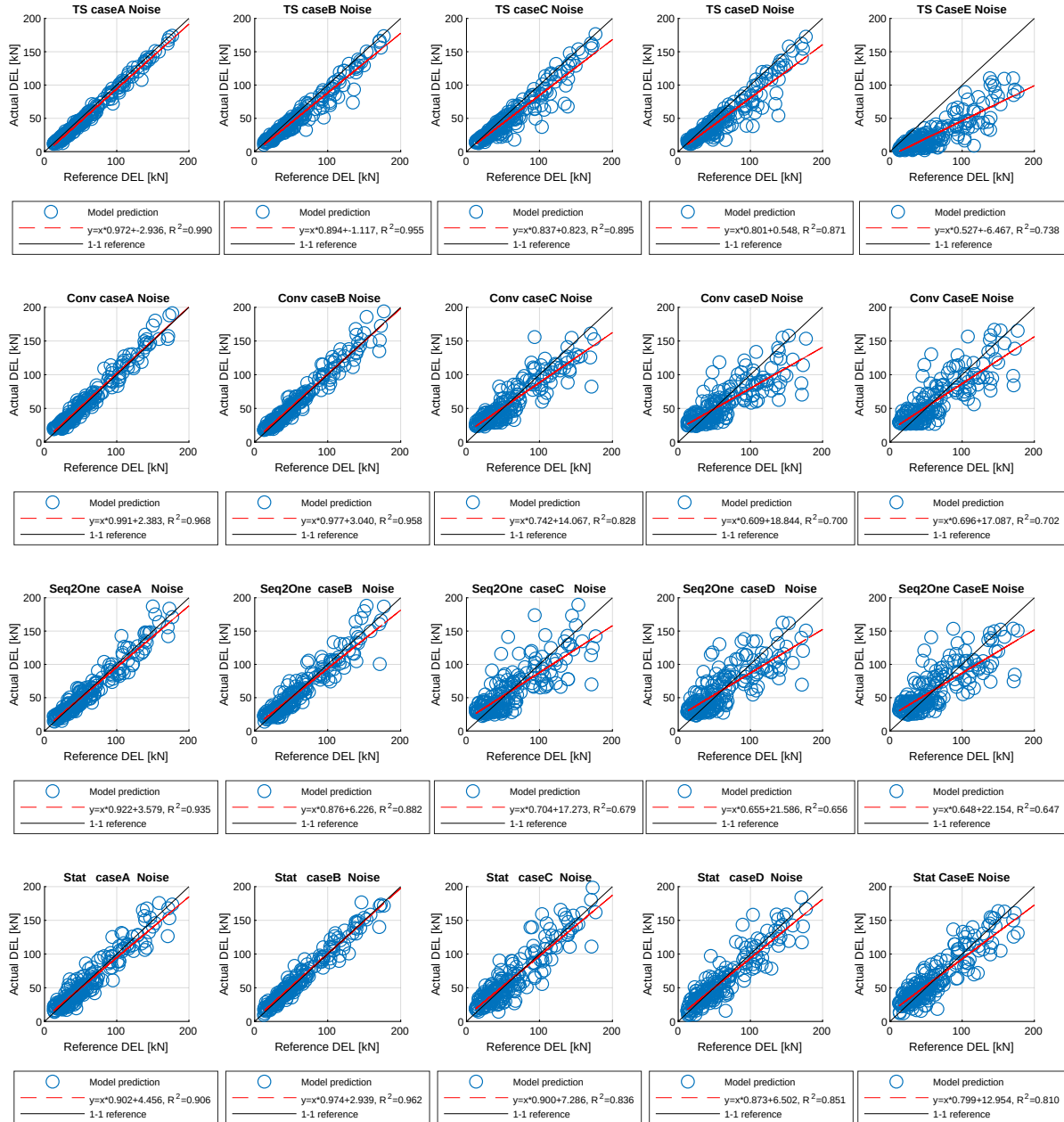


Figure 5.15: One-to-One comparison between predicted and reference DELs for cases A – E for $m = 3$ under the influence of noise. From top to bottom: Time series model, convolutional model, Seq2One model, statistics input model.

series approach. While this bias is relatively small for case A, it is more pronounced for cases with fewer model input features. Particularly, large DEL values are strongly underestimated (See TS case E). The behavior of

the time series prediction itself can explain this. As shown in figure 5.11 the correct representation of the time series signals frequency content depends on the availability of input features. Consequently, the calculated DEL values are negatively biased if the frequency content of the reference signal is not reflected in the time series predictions.

The convolutional and Seq2One models exhibit different characteristics. A notable pattern is observed where both models tend to overestimate smaller DEL values and underestimate larger ones. As a result, their predictions tend to be shifted towards the center of the DEL distribution. This effect becomes more evident when the models are provided with fewer input features. This trend is especially evident in cases C, D, and E, where the models' inability to predict smaller DEL values is observable accurately. The underlying reason for this effect possibly stems from the purely statistical nature of these models. Unlike the analytical DEL calculations approach, the convolutional and Seq2One models cannot effectively distinguish between various low-load conditions. In contrast, the time series prediction model, combined with the analytical DEL calculation method, shows a better ability to discern these subtle differences in low-load scenarios. Again, this observation can be explained by the high realization-to-realization uncertainty of DELs, which the purely statistical models do not so well capture. This distinction in model performance highlights the limitations of a purely statistical approach, particularly in contexts where distinguishing between closely related load conditions is crucial for accurate DEL prediction. Interestingly, the statistics input model results show significantly less variation across cases *A* to *E* regarding scatter and bias, with case *B* showing the best prediction accuracy. Similar to the convolutional and Seq2One models, a tendency to overestimate small DEL values while underestimating large DEL values is observed.

Figures 5.16, 5.17, 5.18, and 5.19 show the relative error between predicted and reference DELs for the time series, convolutional, Seq2One and statis-

tics input model. All plots show results for case *A* including measurement noise and a Wöhler exponent of $m = 3$. The error is shown relative to the randomized environmental conditions used as input for the aeroelastic simulations. The colors of individual data points reflect the absolute magnitude of the respective DEL prediction.

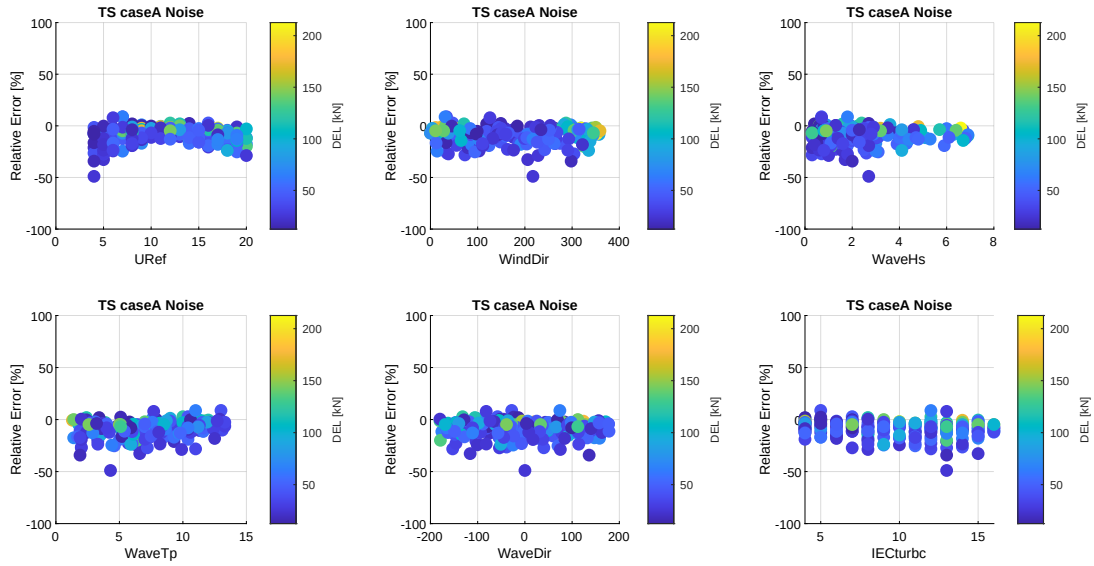


Figure 5.16: Sensitivity of relative Errors between predicted and reference DELs to environmental conditions for case *A*, time series model.

For TS Case A, the negative bias in DEL prediction is reflected by the distribution of relative Errors. It can also be observed, that high relative errors occur for relatively small absolute DEL values. Conversely, data points with relatively large absolute DEL values, show comparatively small relative errors. Concerning the sensitivity to environmental conditions, a dependency of the relative error with the wave conditions can be seen. High relative errors cumulate for low wave heights, indicating difficulties in predicting DEL values correctly for low hydrodynamic loading scenarios. Similarly, large relative errors cumulate for low wind speeds indicating inaccurate predictions for low aerodynamic loads and related turbine excitations. No clear influence of wind direction, wave period, wave direction, and turbulence can be observed.

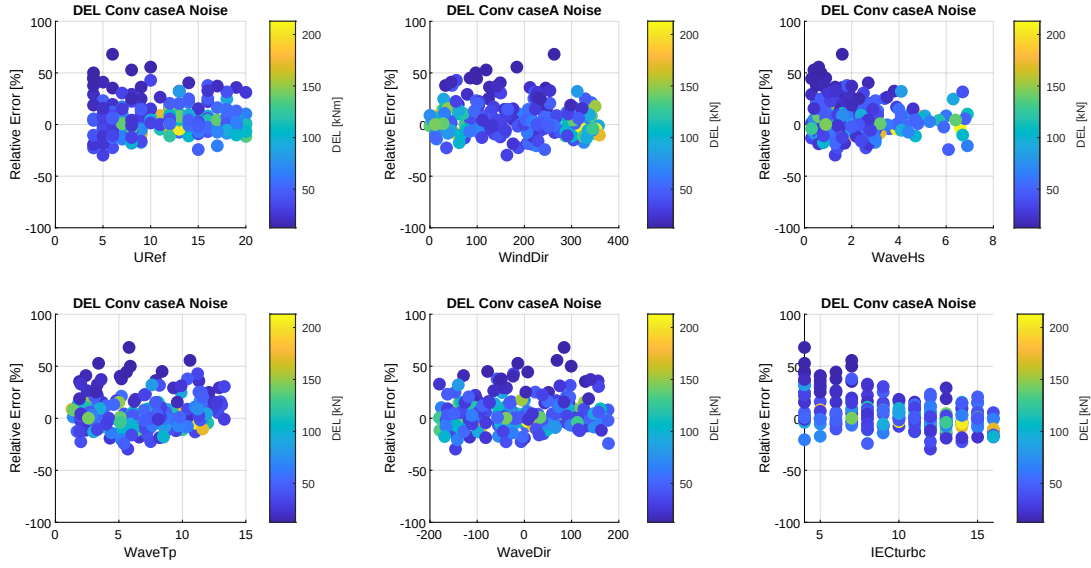


Figure 5.17: Sensitivity of relative Errors between predicted and reference DELs to environmental conditions for case A, convolutional model.

For Case A, convolution (figure 5.17) different patterns can be observed. Overall increased scatter of DEL predictions is reflected in the relative errors. Similar to TS case A, large relative errors occur for low absolute DEL values. However large relative errors tend to be positive, indicating an overestimation of DELs. High relative errors tend to cumulate for low wave heights and low turbulence conditions. Case A, Seq2One (figure 5.18) shows a pattern consistent with the previously discussed convolutional network results, indicating a similar error sensitivity between the models. The statistics input model 5.19 displays a consistent trend, although it is less pronounced.

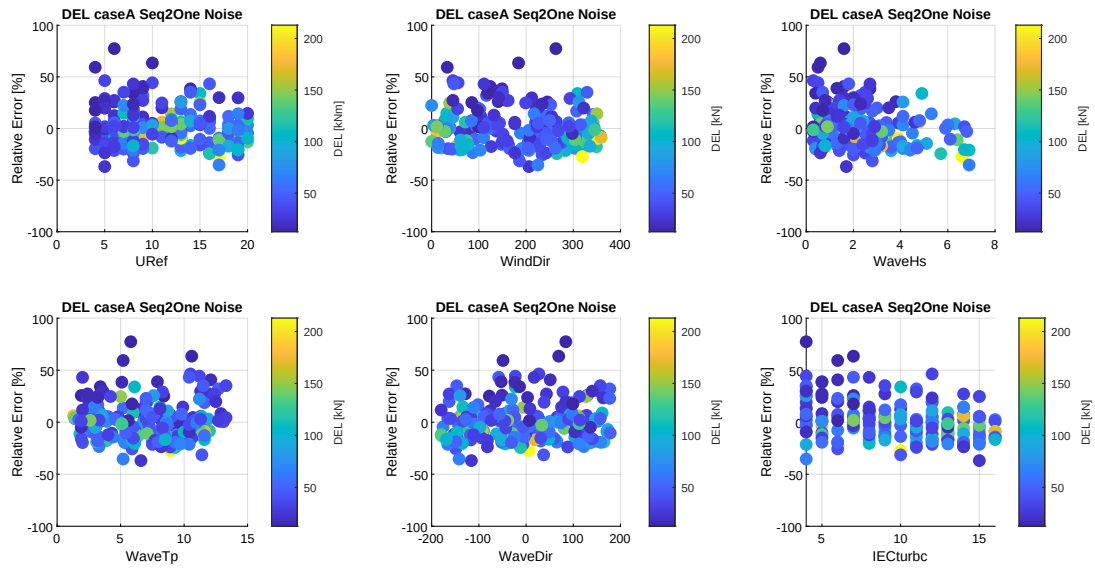


Figure 5.18: Sensitivity of relative Errors between predicted and reference DELs to environmental conditions for case A, Seq2One model.

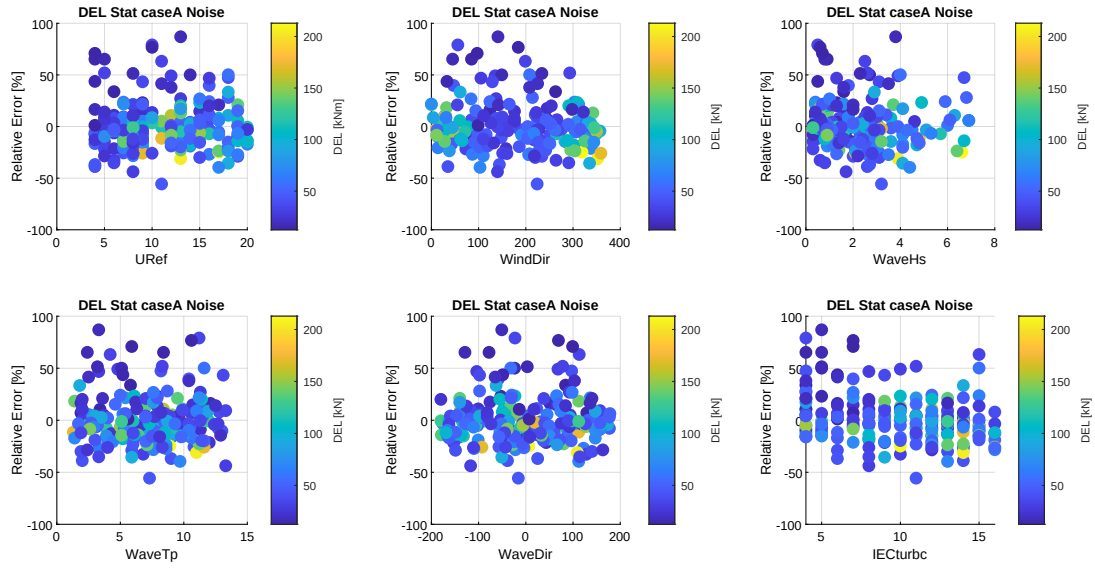


Figure 5.19: Sensitivity of relative Errors between predicted and reference DELs to environmental conditions for case A, statistics input model.

5.4.2 Predictions using Lidar Measurements

In this section, the results of the DEL prediction using lidar inflow measurements are presented. The analysis of time series predictions for cases A_{Lidar} to E_{Lidar} (see section 5.3) revealed that the additional use of lidar measurements as model input features is not improving the prediction accuracy. This is also true for DEL prediction with all investigated model architectures and lidar patterns. Therefore, the following discussion focuses on the discussion of predictions made only based on lidar measurements (case F_{Lidar}).

Figure 5.20 shows the APE for case F_{Lidar} for all four model architectures over the four investigated lidar patterns for three different values of the Wöhler exponent m . The definition of the boxplots is the same as in the previous section. The comparison of results for different lidar patterns suggests a correlation between prediction accuracy and the density of points within the pattern. For time series predictions, there is a tendency for smaller errors in predictions for patterns with a higher number of points. For the time series prediction model, the most accurate predictions, as indicated by the median error, are observed for the 25-point (25P) pattern. In contrast, for the convolutional, Seq2One, and statistics input models, the 9P pattern shows the best performance (lowest median error).

When comparing the overall performance, the convolutional, Seq2One, and statistics input models demonstrate significantly lower median errors than the time series model. However, they also exhibit a higher incidence of outliers. This indicates that the time series model, DEL calculation procedure is more robust against high relative prediction errors, as it is less affected by realization-to-realization uncertainties. In this case, the median prediction accuracy is determined by the underlying prediction of fairlead tension time series based on lidar measurements.

The influence of the value of the Wöhler coefficient is marginal. As for

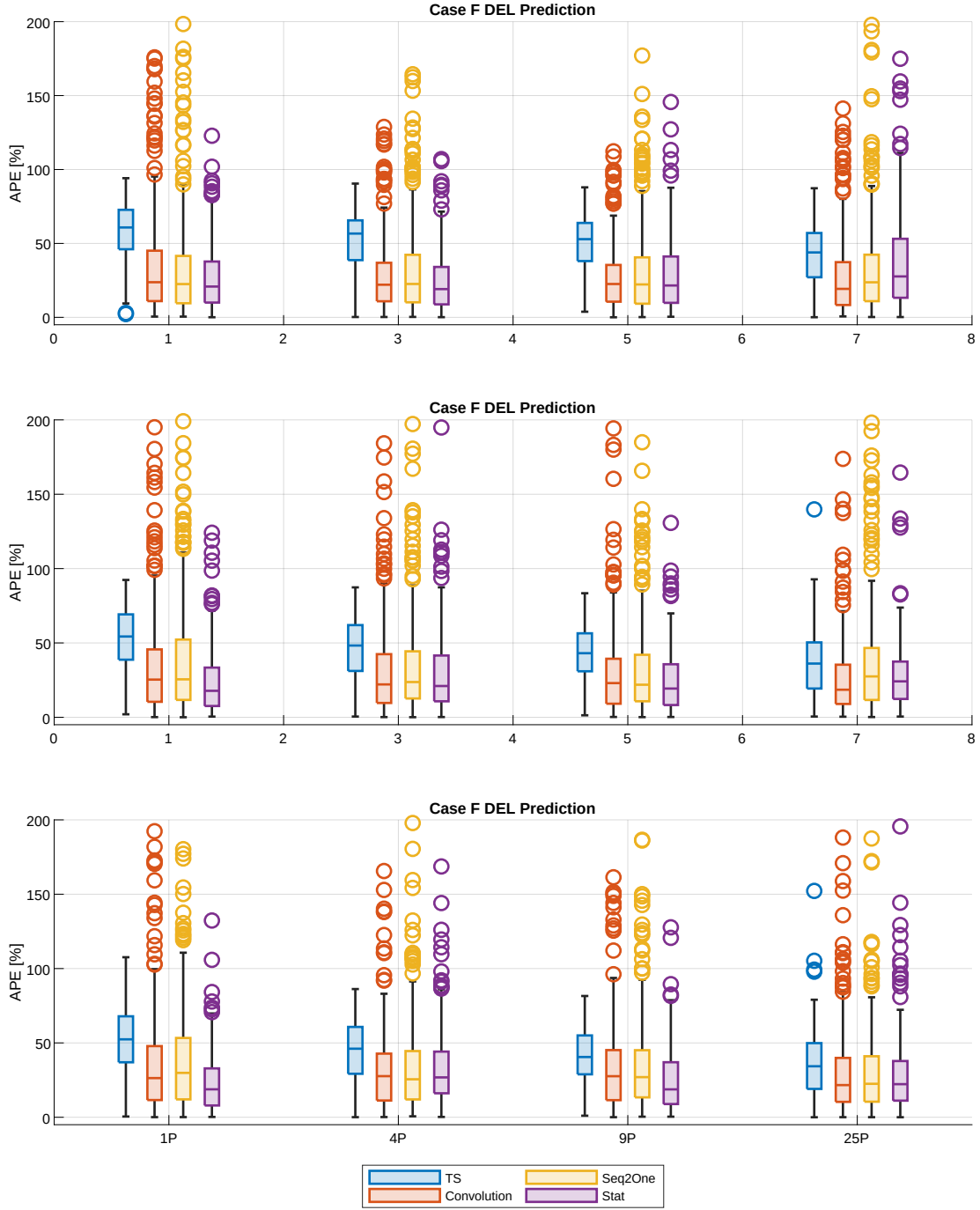


Figure 5.20: APEs of DELs for cases F_{Lidar} for all lidar patterns and model architectures. Top: $m = 3$. Middle: $m = 6$. Bottom: $m = 9$.

the cases without lidar inputs (see figure 5.13), the relative errors for the time series prediction model are slightly smaller for higher values of m .

The influence of m on the error distribution of the convolutional, SeqOne, and statistics input model predictions is small. This indicates that the uncertainty stemming from the DEL calculation carries less significance for the lidar cases, where overall prediction errors are higher than in cases *A* to *C*.

Figure 5.21 shows predicted versus references DELs for the 25P patterns and the four model architectures. The observed trends are similar to those observed for the non-lidar cases in the previous section. The time series model exhibits high negative bias, increasing with the absolute magnitude of DEL Values. The Convolution, Seq2One, and statistics input models overestimate small DELs and underestimate large DELs. Their inability to predict small DEL values correctly is particularly evident.

Figure 5.22 shows the sensitivity of prediction errors to the randomized environmental conditions in the input data for the time series prediction model, 9P lidar pattern and a Wöhler exponent of $m = 3$. As suggested by the one-to-one comparison, a strong negative bias in the error values is observed. A tendency for relatively higher error values is visible for low wave heights. Higher relative errors also occur for low wind speeds and high, while the relative errors around the rated wind speed are smaller. This could be attributed to better time series prediction capabilities of the model around the rated wind speed and related high thrust forces.

Figures 5.23, 5.24, and 5.25 show the sensitivity of prediction error for the convolutional, Seq2One, and statistics input models, 9P lidar pattern and a Wöhler exponent of $m = 3$, respectively. While overall much higher relative error values and a wider range of error can be observed compared to the non-lidar cases, the visible trends are similar. High relative errors occur for small absolute DEL values while a positive bias for small DEL predictions and a negative bias for large DEL predictions is visible. No clear dependency of relative error values with wind speed, wind direction, and wave direction is visible. High relative errors occur for low wave heights, indicating that the

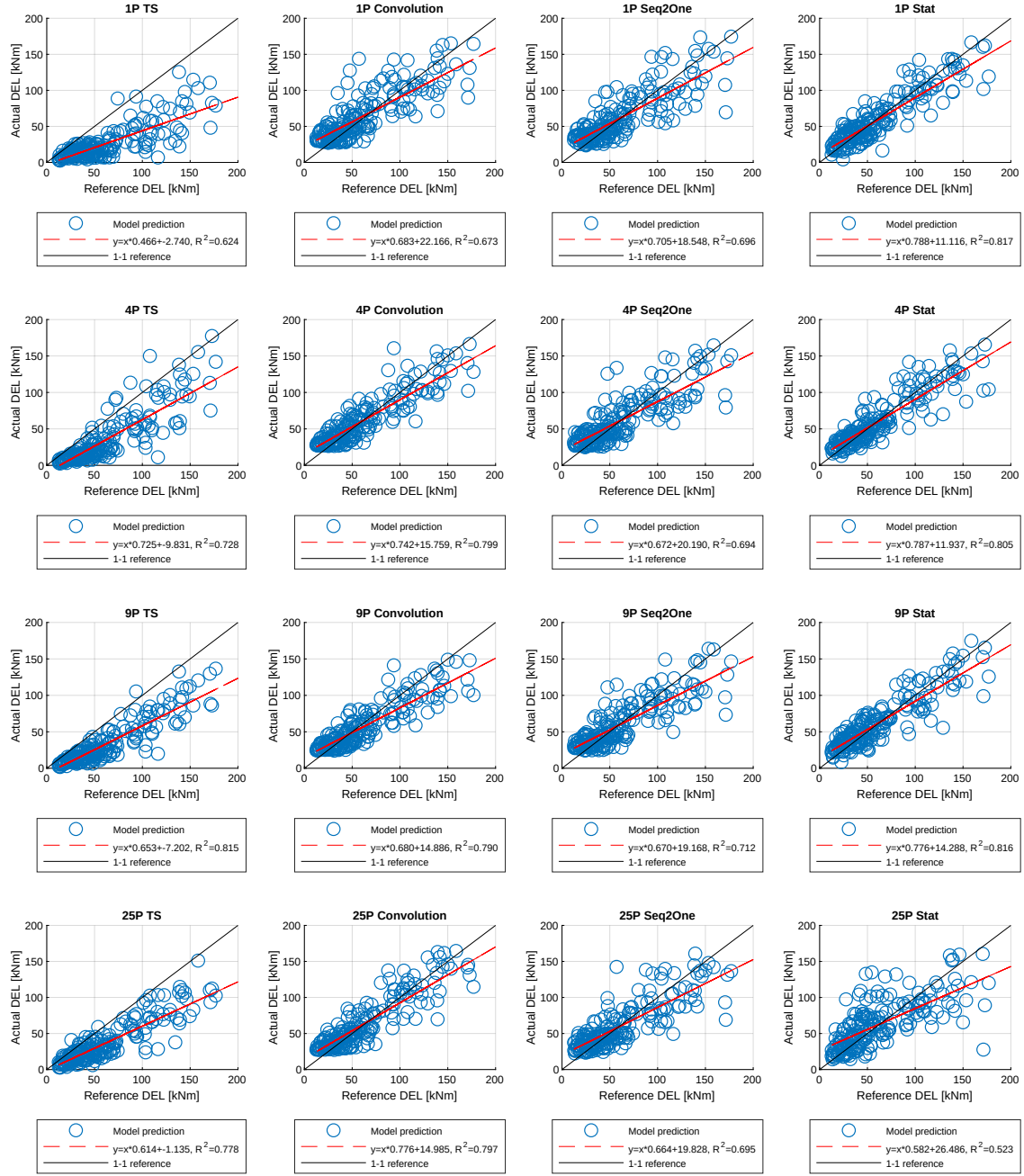


Figure 5.21: One-to-One comparison between predicted and reference reference DELs for cases F_{Lidar} and all lidar patterns (top to bottom). From left to right: Time series model, convolutional model, seq2one model, statistics input model.

floaters motion in these conditions cannot be extracted from measured lidar signals. Similarly high relative errors occur for low turbulence conditions. These trends are consistent for the three model architectures.

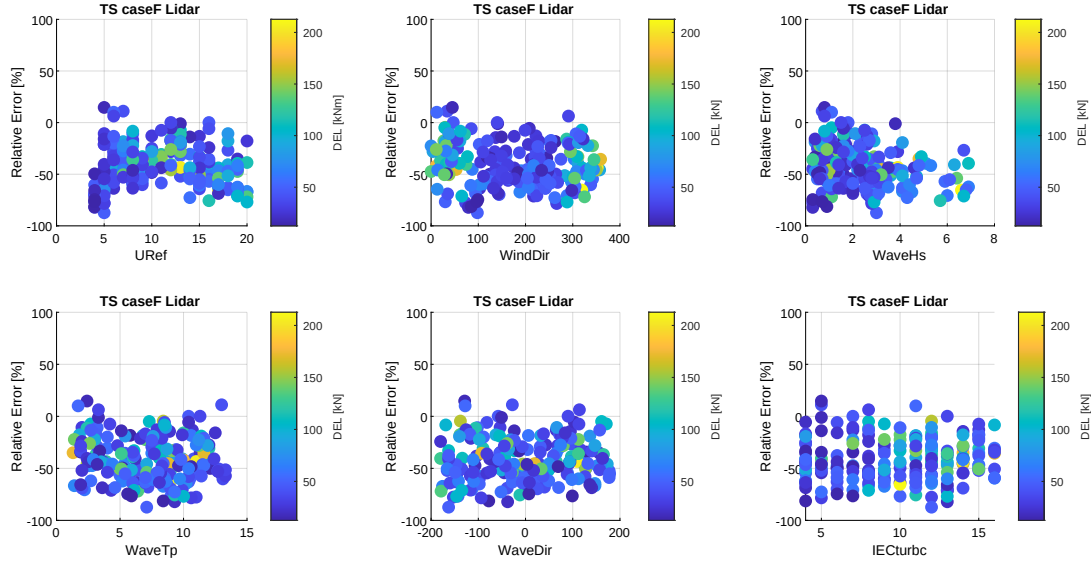


Figure 5.22: Sensitivity of relative Errors between predicted and reference DELs to environmental conditions for cases F_{lidar} and $m = 3, 25P$, time series model.

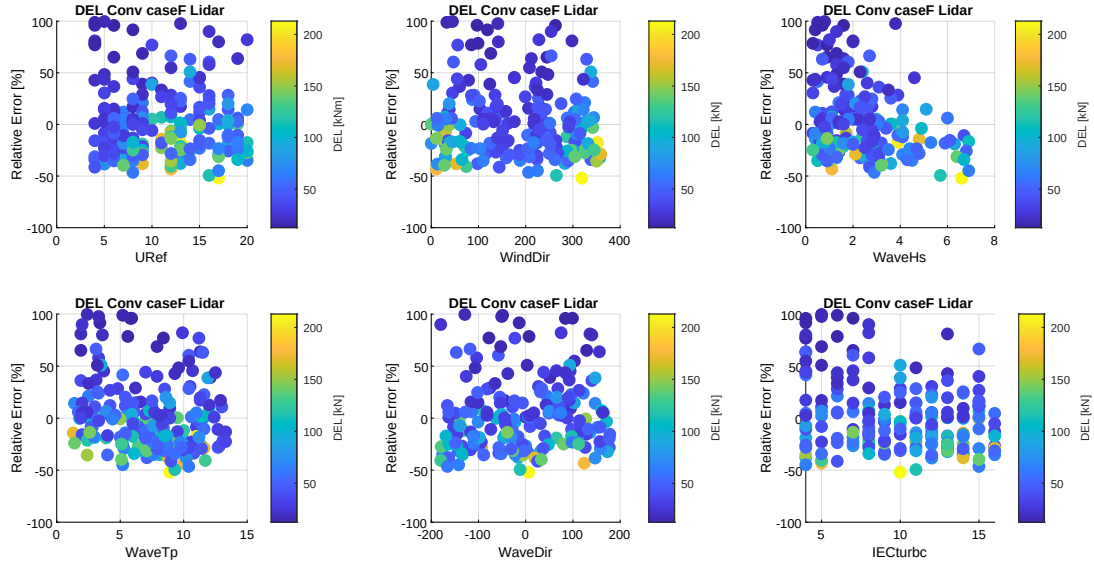


Figure 5.23: Sensitivity of relative Errors between predicted and reference DELs to environmental conditions for cases F_{lidar} and $m = 3, 9P$, convolutional model.

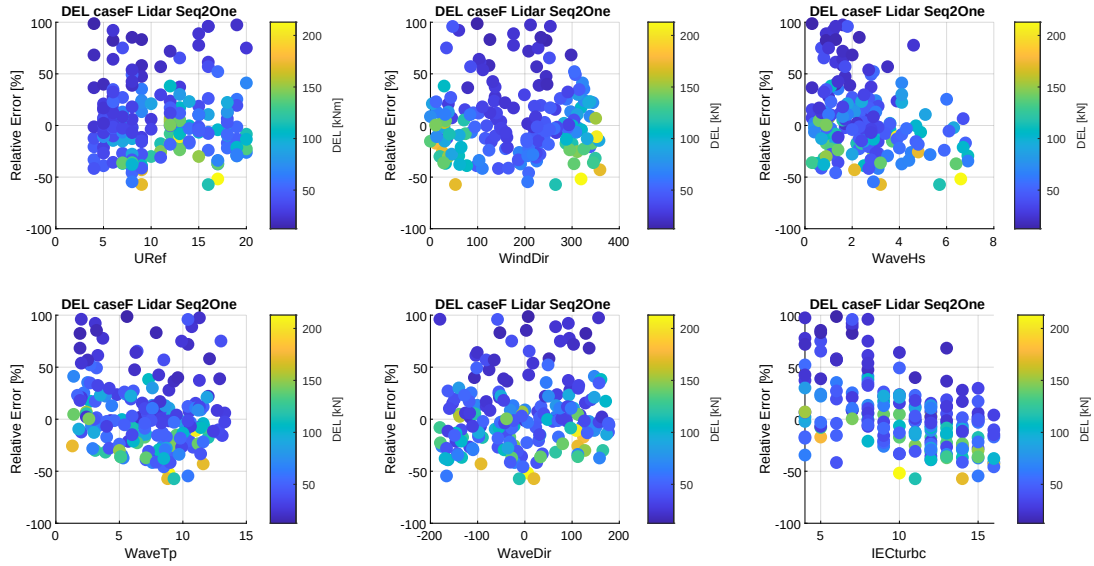


Figure 5.24: Sensitivity of relative Errors between predicted and reference DELs to environmental conditions for cases F_{lidar} and $m = 3, 9P$, seq2one model.

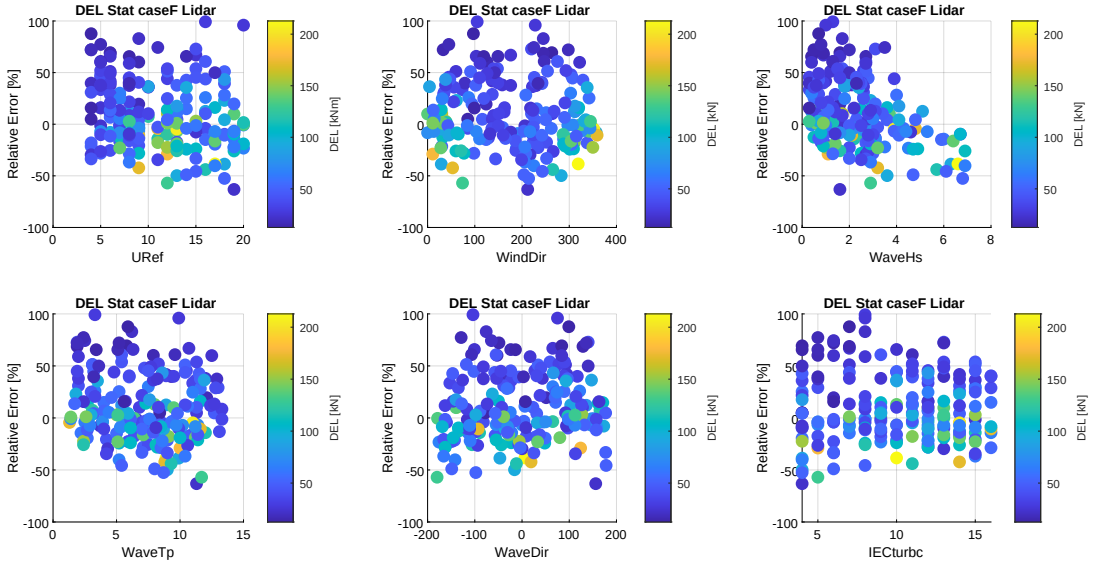


Figure 5.25: Sensitivity of relative Errors between predicted and reference DELs to environmental conditions for cases F_{lidar} and $m = 3, 9P$, statistics input model.

5.5 Chapter Discussion

In this chapter, different models for predicting fairlead tension time series and DEL have been developed. All models are trained to predict fairlead tension 1 (see figure 5.6). Due to the symmetry of the floater and the mooring line layout and the randomized wind and wave direction considered in the training data, it can be expected that the presented results represent all three fairleads. For a non-symmetric floater design or mooring line layout, individual models for each fairlead would need to be trained.

The findings discussed here are derived from a specific floater model employed in this research. However, it can be expected that the core outcomes of this study do apply to other floater designs. This statement is based on the assumption that the dynamics of the platform fundamentally determine fairlead tension loads. In scenarios where these dynamics are accurately captured through measurements, as in cases *A* to *D*, it can be expected that training the model architectures presented in this study would yield similar results for different floater designs.

The accuracy of predicting fairlead tension using nacelle-based lidar inflow measurements is likely to be significantly influenced by the specific dynamic behavior of the floater. As detailed in [34], the frequency and amplitude of movements in various DOFs, such as pitch or surge predominantly govern the impact of floater motions on nacelle-based lidar measurements. Consequently, the effectiveness of lidar in capturing floater dynamics heavily depends on the design of the floater and the configuration of its mooring lines. In the case of the floater model used in this study, the effect of its motion on lidar measurements is relatively minor. As a result, lidar data demonstrated limited efficacy in accurately predicting fairlead tensions. Furthermore, the analysis revealed only marginal differences among various lidar patterns, indicating that a simplistic representation of inflow, captured by a single time series signal, is adequate for achieving the observed results. This im-

plies that similar measurements could potentially be obtained using simpler instruments like cup or sonic anemometers.

The data set used for model training, validation, and testing in this study is simulated using an aeroelastic wind turbine simulation code in combination with a numerical lidar simulator. While this simulation-based approach can show its general feasibility, several considerations have to be made for a real application. In a practical setting, the model training data could either be acquired through real measurements or a simulation model. If real fairlead tension measurement data is used, it must be ensured that the data set reflects all relevant environmental conditions. Especially for extreme conditions, gathering data in sufficient quantities could be challenging. The use of training data sets for other turbines of the same type, eg. in a fleet of FOWT, could be possible. However, even for FOWT identical in construction, differences in the orientation or the mooring line layout could lead to unexpected effects or bias in the load predictions. Suppose a FOWT simulation is used for the generation of the training database. In that case, it is essential that the simulation model is validated and reflects the behavior of the real system accurately across all relevant environmental conditions. Also, more sophisticated methods using a combination of simulated and measured data, as suggested by [92], e.g. through a transfer learning approach, could be beneficial in this context.

In this study, sensor noise was modeled to represent model input data realistically. The analysis indicates that this modeled noise has a relatively small impact on time series predictions, though the exact magnitude of this influence is not specified. For the prediction of DELs, the effect of noise appears to be negligible, suggesting that other sources of uncertainty in the model play a more significant role than sensor noise. This finding underscores the potential practicality of using a virtual load sensor approach. However, it is important to note that the study only accounted for sensor noise. Other factors, such as systematic errors, sensor malfunctions, or uncorrected biases in

measurements, were not considered and could lead to larger discrepancies in DEL predictions. In scenarios where such issues are present, supplementing predictions with lidar measurements could provide a valuable redundancy or serve as a reference to identify erroneous predictions. This is especially true if a lidar inflow measurement system is already available due to its use in the turbine's control system.

Four different model architectures were evaluated for the prediction of DELs. While the inputs for the time series, convolution, and Seq2One prediction models are sequences of feature time series, the last model, a feed-forward neural network, uses minimum, maximum, mean, and standard deviation statistics as input. Among these, the procedure that calculates DELs from predicted time series, particularly for cases *A* to *D* that utilize floater dynamics as inputs, exhibited superior performance. This is true regarding both median errors and scatter of prediction errors and consistency over different values of the Wöhler exponent. This finding indicates that this procedure is the preferred modeling choice in cases where floater dynamics are available as measurements (Cases *A* to *D*). The statistics input model outperforms the convolutional and Seq2One models, particularly for higher values of m . This indicates that the more complex model architectures (Convolutional and Seq2One) do not offer benefits compared to the simple feed-forward neural network structure in combination with statistics inputs. This finding is also relevant from a practical application perspective, where time-series statistics might be readily available through existing SCADA systems and require fewer storage capacities.

For the predictions based on lidar measurements, the convolutional and statistics input network architectures yielded the best results. Similar to the cases without lidar, this indicates that the statistics input feed-forward model is the preferable model choice for lidar-based DEL predictions due to its simplicity and data requirements. High relative errors were more frequent in instances of small absolute DEL values. This finding carries significance

in scenarios where DELs are accumulated for long-term damage estimations, such as in calculating the remaining lifetime of a structure. In this case, the impact of high relative errors on overall damage is mitigated due to the nonlinear relationship between DEL and damage, depending on the specific value of the Wöhler coefficient. This aspect highlights the importance of understanding the error characteristics in DEL predictions, especially in their application to long-term structural health monitoring and life cycle analysis.

The hyperparameters for each model were fine-tuned using a Bayesian optimization process, employing a distinct validation dataset for this purpose. However, due to constraints in computational resources and the extensive range of cases and pattern combinations, it was not feasible to optimize every scenario. Consequently, optimization was performed explicitly for cases A and A_{Lidar} across each model architecture. While the impact of optimized parameters on model performance was generally found to be modest, fine-tuning hyperparameters for all individual cases might enhance prediction accuracy in certain instances.

6

Data-Driven Forecasting of FOWT Dynamics and Load Time Series

In this chapter, a data-driven approach to provide forecasts of fairlead tensions and associated platform dynamics, namely surge and platform pitch signals, is investigated. Besides typically available measurement signals, such as inclination sensors, inflow measurements from a forward-looking nacelle-based lidar system are used as input features for the forecasting model. The lidar's ability to measure the inflow wind field before interacting with the FOWT provides valuable information for forecasting time series.

Such forecasts hold potential for application in advanced control strategies, which could focus on reducing mooring line loads or minimizing platform motions. This is particularly relevant for transient effects such as gusts or ramps in the inflow wind field. Additionally, they have relevance in operations and maintenance (O&M) contexts. Forecasting the motions of FOWTs could be valuable for enhancing safety systems. The dynamics of

FOWTs significantly influence the accessibility of turbines for crew transfer vessels. Accurate forecasts of floater motions enable the identification of optimal times for the safe and efficient transfer of maintenance personnel to and from the turbines. Unforeseen movements of these floating structures present safety hazards. By accurately forecasting these movements, operators can improve safety protocols for maintenance staff. Another approach involves model predictive control strategies for wind turbines, where a turbine model is utilized to foresee the system's future response and accordingly adjust control parameters to meet predefined objectives. In such scenarios, data-driven forecasts of mooring line loads and associated platform dynamics could serve as valuable inputs for these advanced control systems, enhancing their effectiveness and precision.

This chapter is solely focused on the development and evaluation of short-term forecasting models. The investigation of possible applications is not investigated. In short, the objectives of this chapter are to:

- Investigate data-driven approaches for the forecasting of fairlead tension time series and associated platform dynamics
- Evaluate forecasting accuracy for different lidar measurement ranges and forecasting horizons

This chapter presents methodologies and findings previously published in [93].

6.1 Methodology

The methodology used in this chapter is closely linked to the methodology introduced in the previous chapter (see figure 6.1). The same simulated data set is used for model training and evaluation.

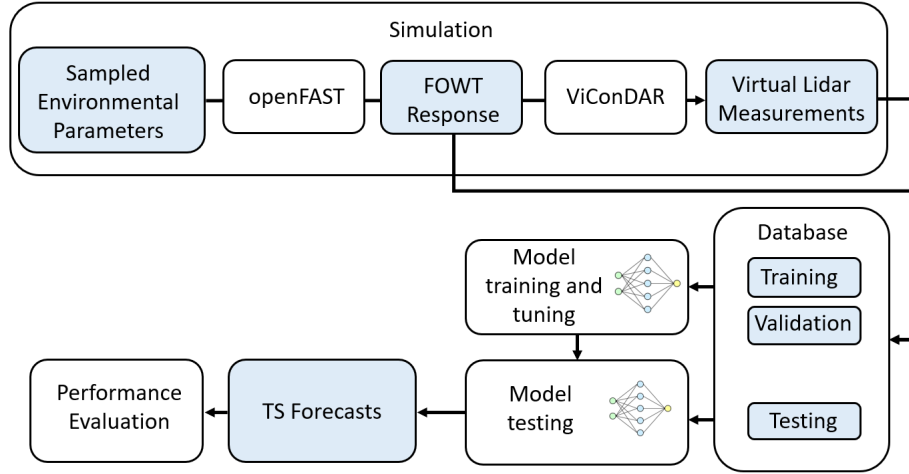


Figure 6.1: Methodology overview.

6.1.1 Forecasting Model

The forecasting models in this study are developed as sequence-to-sequence LSTM models. Other authors already used this approach for times series forecasting tasks (see, e.g., [33]). These models utilize sequences of input time series data to forecast corresponding target time series sequences.

LSTM networks, a variant of recurrent artificial neural networks, are particularly effective at capturing temporal dependencies in input data. A distinctive aspect of LSTM networks is their capacity to preserve or disregard previous inputs over a long duration selectively. This property makes LSTM networks particularly effective in forecasting tasks.

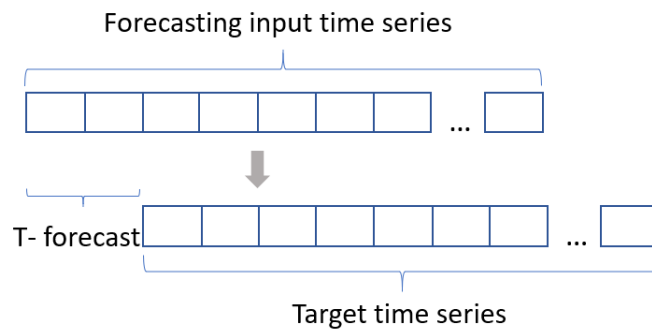


Figure 6.2: Target time series shifted by forecasting horizon.

The chosen architecture for this model comprises six layers. The structure includes a sequence input layer, an LSTM layer, a hidden FC layer, a dropout layer, an output FC layer, and a regression output layer. The sequence input layer receives data from all input channels as a sequence, with its length determined by the window size parameter. This input is then processed by the cells in the LSTM layer. The information from the LSTM layer is subsequently relayed to the hidden FC layer, which, together with the output FC layer, further processes the LSTM-extracted features. To mitigate over-reliance on specific features and to prevent overfitting, a dropout layer is positioned between the hidden and output FC layers. This layer randomly nullifies a fraction of inputs based on a predetermined probability. The final stage of the network is the regression output layer, which generates the predictions for the target values. The window size parameter is pivotal, defining the time step count in the input features. Predictions are correspondingly made for an equivalent number of time steps in the target time series.

The model's forecasting capability for future time steps is established by shifting the target time series by a set number of time steps, denoted as T_{fc} , relative to the input series (see figure 6.2). This training approach enables the model to effectively predict values across the defined forecasting horizon T_{fc} .

Benchmark Model using Persistence

In this work, a simple persistence model is employed as a benchmark to evaluate the performance of the developed time series forecasting models. Persistence models are extensively used as benchmarks for models in forecasting tasks involving environmental conditions (see, e.g., [94, 95]). This model assumes that the value at a given time step will remain unchanged in the subsequent time step. In the context of multi-step time series forecast-

ing, as conducted in this research, the persistence model projects the target time series as a constant signal throughout the entire forecasting horizon. This straightforward approach provides a benchmark against which the performance of more complex forecasting models can be measured and evaluated.

Feature and Target Selection

In alignment with the primary objective of this chapter, which is to assess the utility of using lidar LOS wind speed measurements as input for data-driven forecasting models, two specific cases were explored (see table 6.1). These cases incorporate a combination of platform dynamics and lidar measurements. The platform dynamics features are categorized into four groups: translational displacements, rotational displacements, translational velocities, and rotational velocities, with each group encompassing signals in the x, y, and z coordinates. In the *Baseline* case, all platform dynamics, along with additional operational signals such as blade pitch, power output, and nacelle yaw, are utilized as input features. As shown in chapter 5, all platform dynamics signals contribute to the prediction quality of fairlead time series. Therefore, the full set of platform dynamics is chosen for this case. Conversely, case *Lidar* extends this input set by including four LOS signals from the lidar, thus augmenting the data inputs with wind field information. The influence of measurement noise in the dynamics input data is not considered. Based on the results of chapter 5 it can be expected that the introduction of noise in the dynamics input time series will not have a major impact on the results when comparing the *Baseline* and *Lidar* case. This work is focused on assessing the value of lidar inflow measurements for the forecasting of mooring line tension and the physical quantities most relevant for mooring line loads. Therefore, the developed forecasting models are trained and tested for three sensors (see table 6.2).

Table 6.1: Modelling cases and input features.

Feature	Baseline	Lidar
LOS velocities [ms^{-1}]	x	✓
"SCADA" (Bld. Pitch [deg], Power [W], Nac. Yaw [deg])	✓	✓
Platform transl. displ. (surge, sway, heave) [m]	✓	✓
Platform rot. displ. (pitch, roll, yaw) [deg]	✓	✓
Platform transl. velocities (x, y, z) [m/s]	✓	✓
Platform rot. velocities (x, y, z) [deg/s]	✓	✓

Table 6.2: Model target sensors.

Target	Sensor name	Unit
Fairlead Tension	FairTen1	[N]
Platform Surge	PtfmSurge	[m]
Platform Pitch	PtfmPitch	[deg]

Due to the symmetric floater and mooring line design and the randomized sampling of the wind and wave direction, the forecasting of the platform's three fairlead tension sensors are equivalent prediction tasks. Therefore, only the results for fairlead tension one (see figure 5.6) are presented herein. Forecasting of sway and roll motions has been considered. However, the observed results show the same trends and patterns as the surge and pitch results respectively. Therefore, the results for sway and roll sensors are not discussed in the results section of this chapter.

Hyperparameter Tuning

Model hyperparameters, which define the architecture, training characteristics, and properties of the time series sequences used for training, are optimized using the same procedure introduced in chapter 5. The parameter space, as well as the optimized parameters for each investigated sensor, are presented in table 6.3.

Table 6.3: Model hyperparameters.

Hyperparameter	Parameter space	FairTen1	PtfmSurge	PtfmPitch
Num. of LSTM layers	1-3	2	3	2
Num. of LSTM units per layer	50-200	150	80	140
Num. of units in fully connected layers	50-200	190	90	110
Dropout rate	0-0.8	0.3	0.3	0.3
Number of training sequences	200-1800	1800	1800	1800
Window length [s]	100:100:500	400	200	200

Due to computational limitations, hyperparameter optimization was not feasible for each sensor, lidar range, and forecasting horizon independently. Instead, it was carried out specifically for a 500m lidar range and a 60s forecasting horizon for each sensor under investigation. This constraint could impact the results when comparing performances across different lidar ranges and forecasting horizons. However, based on the experience with model training, hyperparameter variations tend to have a marginal effect and are unlikely to significantly alter the overall performance trends observed in the model outcomes.

The Adaptive Moment Estimation (ADAM) algorithm was used to train the model parameters. Under the established hyperparameters, the training duration for one virtual load sensor model is approximately one hour, while predicting a target sequence can be achieved in less than a second. The performance of the time series forecasting model is assessed using the RMSEN metric.

6.1.2 Lidar Pattern and Ranges

For the forecasting study in this chapter a four-beam lidar configuration as illustrated in Figure 6.3. The focal points of the beams are positioned at $[-55, 55, -55, 55]$ meters along the y-axis, and $[55, 55, -55, -55]$ meters along the z-axis are employed. This arrangement represents a design, similar to commercially available lidar systems with a rectangular scanning pattern. Measurements at each focus point were taken sequentially, at intervals of 0.25 seconds, resulting in a 1 Hz sampling frequency for each LOS velocity time series.

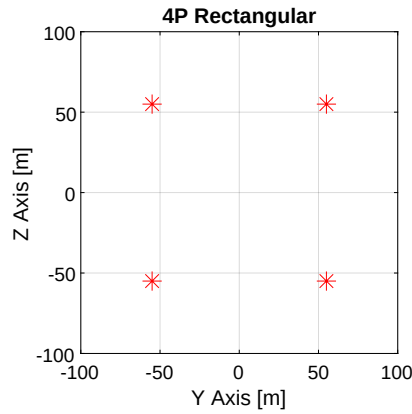


Figure 6.3: Lidar pattern forecasting.

To evaluate the effectiveness of lidar in forecasting turbine responses, five different lidar ranges (distances from the measurement plane to the lidar mounting position): 100m, 200m, 300m, 400m, and 500m are considered. Notably, the focal point's positions remained constant across all ranges, altering only the beam's opening angles while keeping their coordinates in the y-z plane fixed. This is done to avoid the influence of different pattern geometries on forecasting accuracy results. The beam range gate length is set at 30 meters, subdivided into 10 equally spaced points, irrespective of the range. Additionally, Gaussian white noise with a signal-to-noise ratio

(SNR) of 20 dB was added to each measurement to simulate uncertainties found in real lidar measurements.

6.2 Evaluation of Forecasting Accuracy

Figure 6.4 shows the RMSEN values for all target sensors, containing various forecasting horizons and lidar ranges. To illustrate the relationship between forecasting accuracy, lidar range, and wind speed, the results are categorized based on the mean wind speed in the order of below-rated conditions (4m/s to 7m/s), rated conditions (8m/s to 12m/s), and above-rated conditions (13m/s to 20m/s). Each plot in the figure presents the forecasting accuracy for three different models: the persistence model, the forecasting model without lidar input, and the forecasting model incorporating lidar inputs. The persistence model and the non-lidar forecasting models, which do not depend on the lidar range, are represented as horizontal lines in the plots. Across all sensors in the study, both forecasting models consistently outperform the persistence model prediction accuracy with and without lidar inputs. This finding suggests that the input data sequences are informative for forecasting the sensor outputs and that the selected model architecture can utilize this information to make forecasts.

In the fairlead tension forecasting for a 20s horizon, the error values of both lidar-based and non-lidar-based forecasts are nearly identical. This similarity suggests that the wind field preview provided by lidar signals does not significantly influence forecasts over this short time horizon, a trend consistent across all wind conditions. For a 40s forecasting horizon, lidar-based forecasts demonstrate superior performance over the *Baseline* case, especially for larger lidar ranges. This is particularly true in rated power conditions.

However, for the 60s forecast, the advantage of the lidar-based model becomes more pronounced, with a clear relationship emerging between range

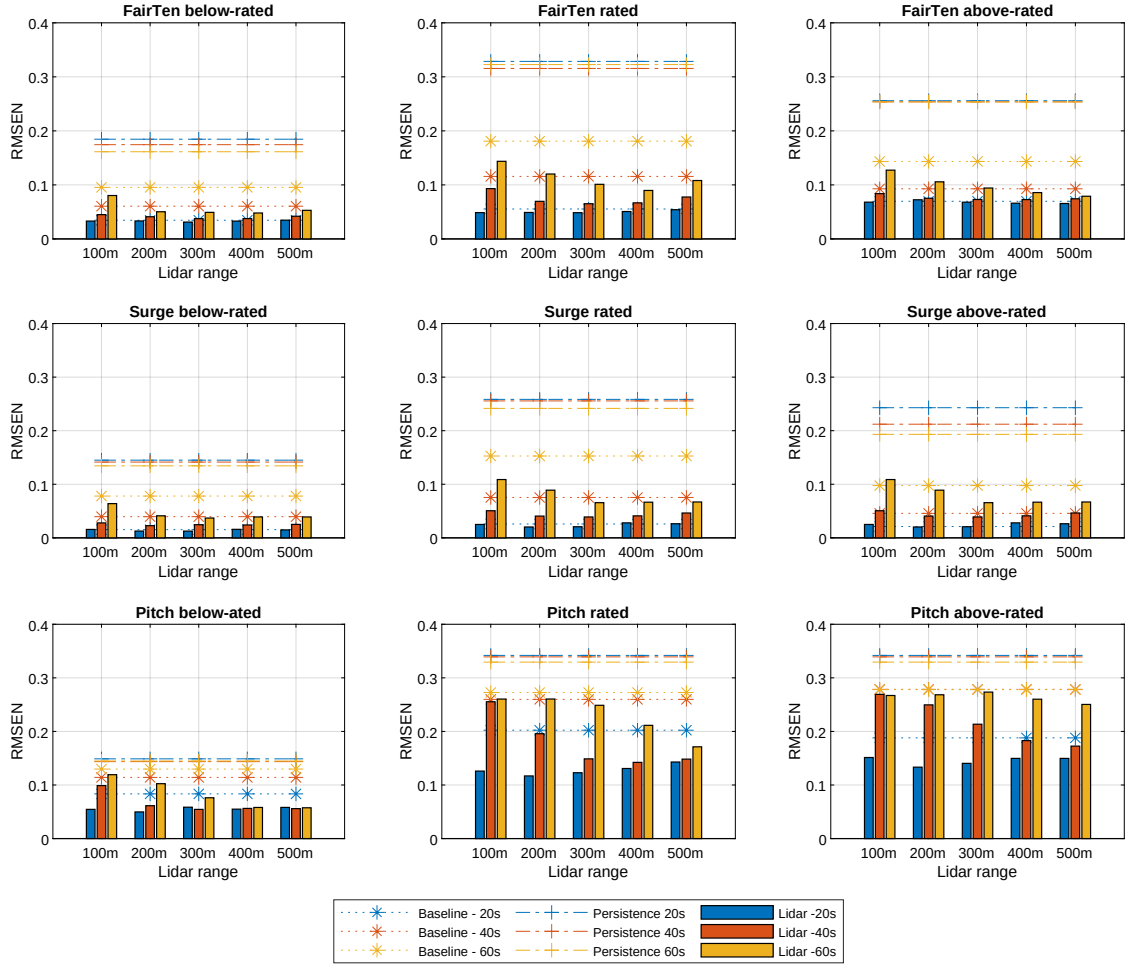


Figure 6.4: RMSEN across all models, forecasting horizons, and lidar ranges.

and forecasting accuracy, particularly in rated wind speed conditions. In these scenarios, forecasting error diminishes with an increasing lidar range, reaching optimal accuracy at a 400m range. This pattern can be attributed to the interplay between mean wind speed and lidar range, which determines the wind field's travel time from the lidar focus points to the rotor. When this travel time exceeds the forecasting horizon, the lidar input time series effectively covers the entire forecast period.

For the platform surge forecasting, the overall trend is similar to that observed in fairlead tension, albeit with generally lower error levels. This indicates a better capacity of the forecasting model to predict the surge

displacement compared to fairlead tensions, also reflecting the close link between fairlead tensions and the surge position of the floater.

Pitch forecasts for the platform display a distinct pattern. In below-rated conditions, the lidar-based model outperforms the non-lidar model across all forecasting horizons, with the best performance observed at 400m and 500m ranges for 20s, 40s and 60s forecasts, respectively. In contrast, in rated and above-rated conditions, the overall error magnitudes increase significantly compared to below-rated conditions. Nevertheless, depending on the forecasting horizon, the lidar-based model surpasses the non-lidar model.

Figure 6.5 presents examples of time series forecasts alongside reference time series for all sensors, across three forecasting horizons, focusing specifically on a lidar range of 500m. Consistent with the RMSEN analysis, the forecasts for fairlead tension and surge signals at the 20s horizon exhibit no substantial differences in replicating the reference time series, regardless of whether lidar input is used or not. However, for longer forecasting horizons of 40s and 60s, the advantage of incorporating lidar input becomes evident. The lidar-based model more accurately mirrors the reference time series in these cases. Notably, the forecasts for pitch signals demonstrate an enhanced accuracy with lidar measurements across all forecasting horizons, underscoring the value of lidar data in improving forecast quality.

Figure 6.6 illustrates the differences in fairlead tension forecasting errors between the lidar-based model and the non-lidar model at a 500m lidar range and a 60s forecasting horizon. In this context, negative values signify a better performance of the lidar-based model compared to its non-lidar counterpart. The analysis reveals several patterns. The effectiveness of the lidar-based model is linked to wind speed, with the most significant differences in forecasting accuracy occurring just above and below the turbine's rated wind speed of 10m/s. For high ($>15\text{m/s}$) and low ($<7\text{m/s}$) wind speeds the performance difference is less pronounced. The reduced performance of the lidar-based compared to the baseline model at higher wind

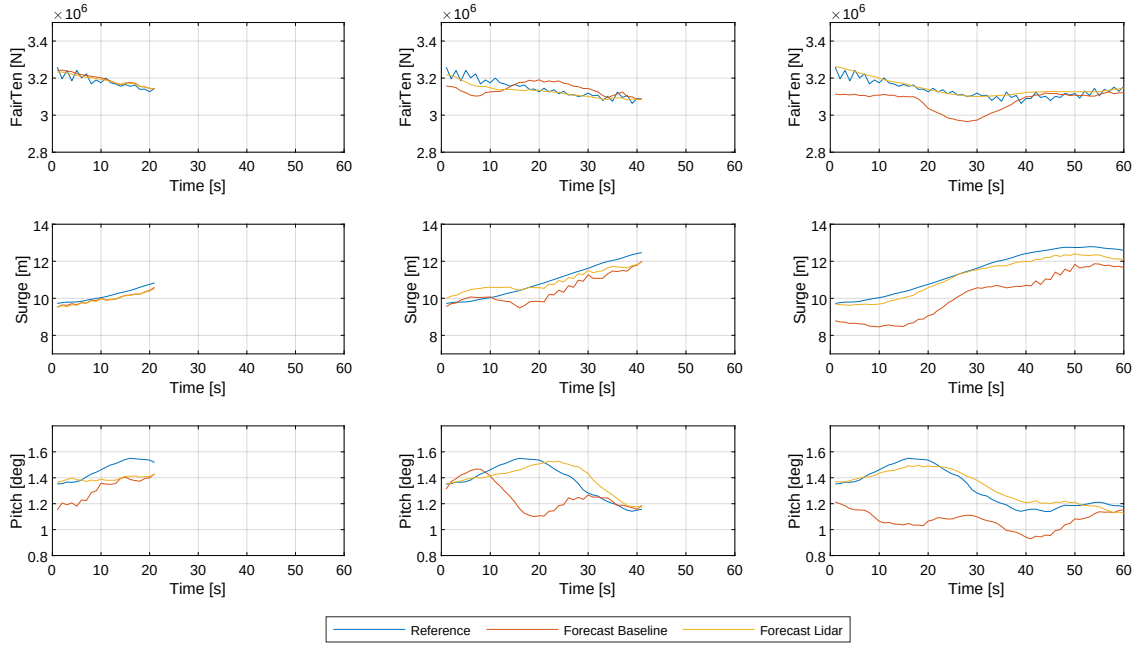


Figure 6.5: Time series forecasts example.

speeds suggests that lidar-based forecasts are particularly advantageous in rated conditions, where the turbine is subject to maximum thrust forces and the transition region of the turbine controller. Another dependency is observed for wave heights, with the lidar-based model performing better for small wave heights. This indicates that the lidar signals provide less advantage in conditions where wave forces heavily influence the floater motions, because they do not provide a preview of the approaching waves. Larger differences in error levels are also notable in high turbulence conditions, underscoring the value of lidar data for accurately forecasting the FOWT system's response to turbulent wind.

The pattern observed for wind direction sensitivity results from the mooring line layout (see figure 5.6). Better performance is achieved if the mooring line and wind direction are aligned. No correlations are observed between forecasting accuracy differences and wave period or wave direction.

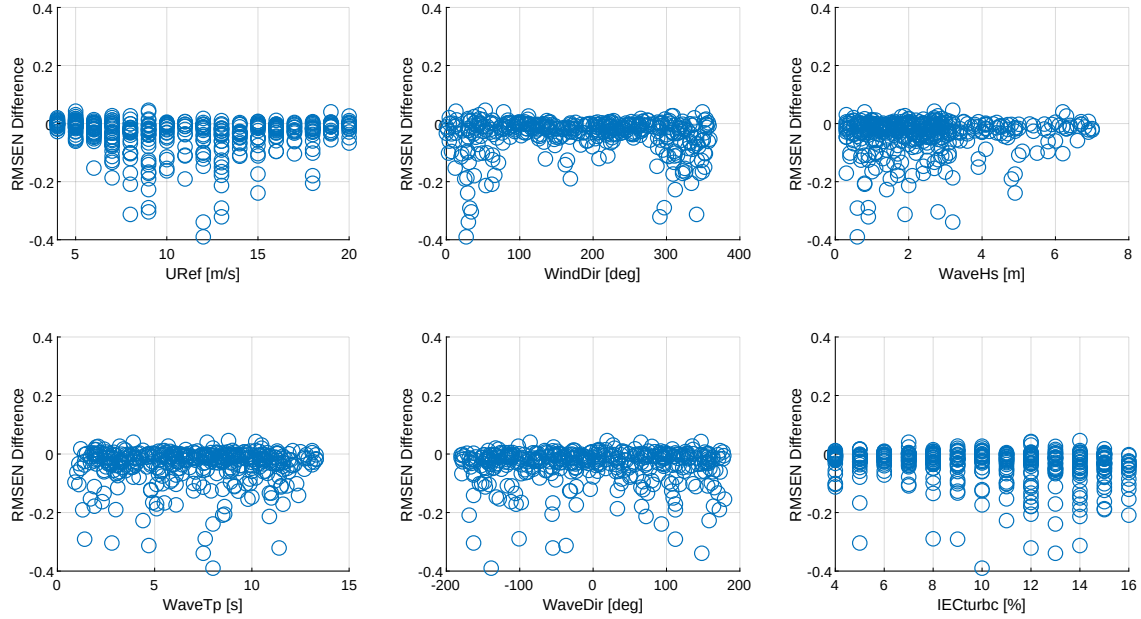


Figure 6.6: RMSEN difference between baseline and lidar case relative to environmental conditions.

6.3 Chapter Discussion

In interpreting the results of this chapter, it is important to recognize the limitations of the numerical simulation framework used for generating the lidar measurements and corresponding turbine responses. This framework is based on Taylor's frozen turbulence hypothesis, which assumes that the wind field does not evolve between its measurement and its interaction with the wind turbine. However, the wind field is evolving during this interval in real-world scenarios. In this context, the effect of wake from neighboring turbines should also be considered, as this can also alter the wind field. Such evolution of the wind field can potentially degrade the forecasting accuracy of the models used in this study. For practical applications, it is, therefore, essential that the training data for such models adequately reflects the dynamic nature of wind evolution for the specific conditions of the site in question. An advanced modeling approach, which incorporates

lidar measurements from multiple range gates simultaneously, could prove beneficial in addressing this aspect of wind field dynamics. The evolution of the wind field could be integrated into FOWT and lidar simulation using an advanced wind field modeling approach as discussed in [96].

Like the prediction models discussed in Chapter 5, this study exclusively used simulated data. The applicability of models trained on simulated data to real-world scenarios remains unexamined. Thus, these results should be viewed as a preliminary proof of concept, and verification with actual measurement data is necessary.

In practical applications of the trained predictive models, input data is sourced from various sensor systems, including accelerometers, inclinometers, gyroscopes, and global navigation satellite systems. It is important to note that each type of sensor may introduce measurement inaccuracies. Based on the investigation in chapter 5 it can be expected that the influence of sensor noise on the forecasting accuracy is small. While this study does not address the impact of sensor noise or other measurement errors on the forecasting quality, it is important to acknowledge that such inaccuracies could potentially affect the performance of the forecasting models.

7

Conclusions

The goal of this work was to provide a comprehensive understanding of the characteristics of nacelle-based lidar inflow measurements on floating wind turbines. Therefore, a numerical and analytical measurement simulation environment was developed. A parametric study based on the developed models analyzed and discussed the influence of motion on measurement uncertainties and biases. Further, the use of lidar inflow measurements for load and floater dynamics predictions and forecasts was investigated using the numerical lidar simulation environment and employing different machine learning models.

7.1 Simulation Environment

In chapter 3 two environments for simulating nacelle-based lidar measurements under the influence of FOWT platform motions were introduced. Using the GUM methodology, a new analytical model was developed to estimate uncertainty and bias in wind speed measurements determined by

lidar. In this model, the dynamics of FOWT were represented using the amplitudes and periods of floater DOFs in yaw, pitch, roll, and heave directions, with the wind field modeled using a power law profile.

Additionally, the numerical lidar simulation code ViConDAR was adapted to consider floater dynamics. This approach integrates floater dynamics, simulated using the aero-elastic wind turbine simulation code openFAST, into the simulation of lidar measurements. Thus, it considers full floater dynamics in six DOFs. Additionally, it uses the same representation of the wind field used in the aeroelastic simulation of the FOWT, thus modeling the measurement of the turbulent wind field under the influence of realistic floater-specific motions.

7.2 Motion Influence and Correction Approaches

Chapter 4 analyzed the motion-induced effects on lidar measurements from forward-looking, nacelle-mounted lidars on FOWTs. The focus was on quantifying floater motion-induced uncertainties and biases in wind speed measurements and introducing correction methods for these effects over various time scales.

The GUM methodology was employed using the analytical measurement model to derive combined uncertainties in LOS measurements and the reconstructed wind field components. Validation of the model involved comparisons with uncertainties obtained from the more detailed ViConDAR numerical lidar simulation, which incorporates turbulent wind fields.

The study found that the primary source of uncertainty in lidar-estimated wind speeds arises from the lidar's fore-aft motion due to the floater's pitch displacement, heavily influenced by the amplitude and frequency of the pitch motion. Furthermore, biases in 10-minute averaged wind speeds were found to be mainly affected by the mean pitch angle of the floater, pitch amplitude, and vertical wind shear.

Two correction approaches were introduced to mitigate motion-induced effects. The analytical model was used to create a lookup table of correction values for 10-minute averaged wind speeds, showing successful results when tested with simulated dynamics from two different FOWT designs, with mean errors remaining below 0.1 ms^{-1} for both models. A frequency filter was also employed to correct fluctuations in instantaneous measurements caused by floater pitch motions. This method significantly reduced the MAE under conditions characterized by harmonic pitch oscillation with low pitch periods and high pitch amplitudes. However, the frequency filter did not effectively reduce the error in wind speed estimates for varying pitch oscillations or conditions with high pitch periods and low amplitudes.

7.3 Virtual Sensors using Motion and Lidar Measurements

In chapter 5, various machine learning approaches were explored for predicting fairlead tension time series and DELs, utilizing simulated dynamics and SCADA data from the UMaine VoltturnUS-S reference FOWT. The potential of incorporating inflow measurements from a forward-looking, nacelle-mounted lidar system based on simulated lidar data was examined. Additionally, the impact of noise on the dynamics input measurements was assessed by introducing realistic noise levels into the simulated signals.

An LSTM neural network was employed for time series predictions. Our findings indicate that incorporating rotational and translational displacements and velocities achieves the highest prediction accuracy. The effect of noise in the dynamics input measurements on prediction accuracy was found to be small. Augmenting the input feature set with lidar measurements did not enhance prediction accuracy in any studied cases. Predictions based solely on lidar data broadly captured the reference sequences' order of magnitude and low-frequency fluctuations. However, the prediction accuracy was found to be significantly smaller.

Four methodologies were investigated for predicting DELs. First, DELs were calculated based on time series predictions; second, using a Sequence-to-One (Seq2One) LSTM network; third, employing a CNN architecture; and last, using a simple feedforward neural network with time series statistics input. Instead of time series sequences, statistics of feature time series, including minimum, maximum, and standard deviation, are calculated in a pre-processing step and used as input to the networks.

Consistent with the time series predictions, including all examined platform dynamics inputs led to the highest accuracies for the time series prediction and convolutional model. For the Seq2One and the statistics input model, the difference in prediction accuracy between cases *A* and *B* is indifferent, indicating a negligible role of the rotational velocity for these models.

The variation of the Wöhler exponent m had differing impacts on various model architectures. The time series DEL calculation approach and the statistics input model exhibited only marginal sensitivity to changes in m , with relative errors slightly smaller at higher values of m . In contrast, the Seq2One prediction model demonstrated significantly higher prediction errors as m increased, particularly in cases *A* and *B*. The convolutional model displayed a similar trend, though the increase in error was less pronounced. Overall, the time series prediction and DEL calculation procedure provided the best prediction accuracy regarding both median and scatter of errors and showed the least sensitivity to variations in the Wöhler exponent. It is therefore recommended to employ the time series DEL calculation approach in cases where dynamics measurements of the platform are available, such as in the modeling cases *A* to *D*. Adding lidar measurements to the dynamics input features did not improve accuracies for any of the investigated model architectures. This leads to the conclusion that including lidar inflow measurements in the model input features is not beneficial in cases where platform dynamics measurements are available.

However, the modeling case, relying solely on lidar measurements for pre-

dictions (case F_{Lidar}) achieved comparable accuracies (with an APE of approximately 20%) to those utilizing platform displacement inputs. Here, the performance differences between the modeling approaches show a different pattern compared to modeling cases A to E . The convolutional, Seq2One, and statistics input model consistently outperformed the time series prediction, DEL calculation approach across all lidar patterns and values of the Wöhler exponent, indicating that a purely statistical prediction, without calculation from time series, is preferable in this case. Overall, for case F_{Lidar} , the best performance was achieved for the convolutional and statistics input model for the 4P and 9P lidar pattern, suggesting that both are favorable approaches for fairlead tension DEL prediction based on lidar inflow measurements.

Notably, measurement noise in the platform dynamics inputs had a negligible effect on the outcomes of this study. This indicates that the presence of noise when training and applying the models on real measurement data will likely not have a large impact on prediction accuracy. However, it should be noted that effects like sensor drift, unavailability of single input features, or bias in measurement data were not considered and could have a more significant impact on the results. Overall, our results suggest that measurements from a GNSS/INS sensor are crucial for accurately predicting fairlead tension time series and DELs. The integration of lidar inflow measurements could serve as a beneficial backup in cases of sensor failures or as a reference system to verify the proper functioning of the actual load prediction model. Chapter 6 investigated a data-driven forecasting approach using motion and lidar inflow measurements to predict fairlead tension, surge, and platform pitch time series. An LSTM sequence-to-sequence model was trained to forecast these target time series over three forecasting horizons: 20s, 40s, and 60s, with lidar ranges from 100m to 500m. The findings show, that lidar inflow measurements significantly enhance the forecasting of mooring line loads, surge, and pitch dynamics. Specifically, including lidar data

improved pitch predictions across all horizons and enhanced fairlead tension and surge predictions at the 40s and 60s horizons. The results highlight the importance of considering the interplay among lidar range, mean wind speed, and forecasting horizon to optimize forecast accuracy. Although this thesis did not investigate forecasting applications for high-load events or platform motions due to gusts or wind ramps, the integration of lidar inflow measurements is beneficial for similar forecasting tasks.

7.4 Recommendations for Future Work

The following points summarize recommendations for future work on the topic.

- The presented motion correction approaches are not entirely transferable to different floater types. Therefore, a more advanced motion correction approach should be investigated, considering the measured dynamics of the floating platform in real time. For this approach, lidar measurements and IMU signals must be synchronized, e.g., through a common data acquisition system. Uncertainties arising from changed measurement positions in space can not be corrected through a post-processing approach. This is especially relevant for long-range lidar measurements. Here, the investigation of an adaptive lidar LOS trajectory is a promising approach. Initial work in this direction has already been published in [82].
- Following the idea of data-driven approaches explored in this thesis, the data-driven reconstruction of wind field characteristics should be investigated. Besides estimating rotor effective wind speed, reconstructing other wind field characteristics, such as TI and wind shear, could be interesting. In this context, the provision of training data will

be crucial. Questions on the usability and transferability of synthetic training data should be investigated.

- Further work is needed to accept power curve assessments using nacelle-based lidar systems, especially in the context of floating wind turbines. While it is shown in this work that the influence of floater motion on 10-minute average lidar measurements is small, it can be a relevant source of uncertainty depending on the floater type and its dynamic characteristics. A standardized procedure for motion correction should be developed and implemented in relevant standards.
- Nacelle-based lidar measurements could be a valuable resource for the identification and characterization of FOWT wakes. A forward-looking lidar system could be used to identify the wake characteristics in the inflow wind field and thus enable wind farm control strategies involving wake steering. The ability of fixed-beam lidar systems, typically used for turbine control, to sufficiently capture the spatial and temporal characteristics of the wake needs to be studied. Again, the use of data-driven should be considered. A first study investigating the general feasibility of wake measurements using field measurements and wind farm simulations has been addressed as part of the Ph.D. project. Findings are documented in [60].
- The investigation of motion-induced uncertainty and bias in lidar inflow measurement addressed in the thesis has only demonstrated the motion-related uncertainty of lidar measurements based on simulated data. Modeling uncertainties, stemming, for example, from the representation of wind field in the simulation environments, have not been quantified. Therefore, validating the findings using real measurement data, including lidar measurements and a reference measurement, would be valuable.

- The virtual sensor approaches investigated in this thesis purely relied on simulated training data. The question of whether models trained on simulated data from validated simulation models can be used in operational scenarios needs to be investigated. In this context, more sophisticated approaches should be considered, such as incorporating a mix of simulated and operational data, e.g., through a transfer learning approach.
- Apart from the DEL prediction approach, using a combination of data-driven time series prediction and analytical formulation, the virtual sensor models explored in this thesis are purely data-driven. It is recommended to examine the combination of data-driven and first-principle models, for example, through physics-informed neural networks. This could especially prove beneficial in cases where the model must capture complex structural dynamics.
- The integration of lidar inflow information into wind farm control schemes is a promising field of research. In this context, lidar measurements could facilitate wake steering approaches by providing a real-time representation of the inflow wind field affected by the wake of neighboring turbines. Short-term forecasting of power prediction based on lidar inflow information could benefit grid integration and balancing approaches.

A

Calculation Details

A.1 Uncertainty Estimation

Partial derivatives

$$\frac{\delta v_{los}}{\delta \psi} = -V_{ref} \left(\frac{z_L + h_{lidar} + h_{heave}}{H_{ref}} \right)^\alpha (\sin \varphi (x_L \sin \psi + y_L \cos \psi)) + \cos \psi (y_L \sin \psi - x_L \cos \psi) \quad (A.1)$$

$$\frac{\delta v_{los}}{\delta \beta} = \frac{\alpha V_{ref} (-x_L \cos \beta - z_L \sin \beta) (\sin \varphi (x_L \cos \beta + z_L \sin \beta) + y_L \cos \varphi) \left(\frac{h_{lidar} + h_{heave} - x_L \sin \beta + z_L \cos \beta}{H_{ref}} \right)^{\alpha-1}}{H_{ref}} + V_{ref} \sin \varphi (z_L \cos \beta - x_L \sin \beta) \left(\frac{h_{lidar} + h_{heave} - x_L \sin \beta + z_L \cos \beta}{H_{ref}} \right)^\alpha \quad (A.2)$$

$$\frac{\delta v_{los}}{\delta \gamma} = \frac{\alpha V_{ref} (y_L \cos \gamma - z_L \sin \gamma) (x_L \sin \varphi + \cos \varphi (y_L \cos \gamma - z_L \sin \gamma))^{\frac{h_{lidar} + h_{heave} + x_L \sin \gamma + z_L \cos \gamma}{H_{ref}} \alpha - 1}}{H_{ref}} + V_{ref} \cos \varphi (-y_L \sin \gamma - z_L \cos \gamma) \left(\frac{h_{lidar} + h_{heave} + y_L \sin \gamma + z_L \cos \gamma}{H_{ref}} \right)^\alpha \quad (A.3)$$

$$\frac{\delta v_{los}}{\delta h_{heave}} = \frac{\alpha V_{ref} \left(\frac{h_{heave} + h_{lidar} + z_L}{H_{ref}} \right)^\alpha (x_L \sin \varphi + y_L \cos \varphi)}{h_{heave} + h_{lidar} + z_L} \quad (A.4)$$

$$\frac{\delta v_{los}}{\delta x_{vel}} = x_I \quad \frac{\delta v_{los}}{\delta x_{vel}} = y_I \quad \frac{\delta v_{los}}{\delta z_{vel}} = z_I \quad (A.5)$$

$$\frac{\delta u}{\delta v_{los,i}} = \frac{1}{4} \frac{1}{x_{L,i}} \quad (A.6)$$

Rotation matrices

The rotation matrix is given by:

$$R(\psi, \beta, \gamma) = \begin{bmatrix} \cos \psi & -\sin \psi & 0 \\ \sin \psi & \cos \psi & 0 \\ 0 & 0 & 1 \end{bmatrix} * \begin{bmatrix} \cos \beta & 0 & \sin \beta \\ 0 & 1 & 0 \\ -\sin \beta & 0 & \cos \beta \end{bmatrix} * \begin{bmatrix} 1 & 0 & 0 \\ 0 & \cos \gamma & -\sin \gamma \\ 0 & \sin \gamma & \cos \gamma \end{bmatrix} \quad (A.7)$$

A.2 Code Availability

- (a) The numerical lidar simulation environment ViConDAR is available as an open-source tool by the chair for wind energy at the University of Stuttgart (SWE) on "<https://github.com/SWE-UniStuttgart/ViConDAR>".
- (b) The analytical lidar uncertainty estimation tool FLIDU available as an open-source tool by the chair for wind energy at the University of

Stuttgart (SWE) on "<https://github.com/SWE-UniStuttgart/FLIDU>".

A.3 Publications not included in this Thesis

The following peer-reviewed publications were published during the Ph.D project but are not included in this thesis.

- (a) M. Gräfe, V. Pettas, and P. W. Cheng, “Wind field reconstruction using nacelle based lidar measurements for floating wind turbines,” *Journal of Physics: Conference Series*, vol. 2265, no. 4, p. 042022, may 2022. [Online]. Available: <https://doi.org/10.1088/1742-6596/2265/4/042022>
- (b) M. Gräfe, U. Özinan, and P. W. Cheng, “Lidar-based virtual load sensors for mooring lines using artificial neural networks,” *Journal of Physics: Conference Series*, vol. 2626, no. 1, p. 012036, oct 2023. [Online]. Available: <https://dx.doi.org/10.1088/1742-6596/2626/1/012036>
- (c) Özinan U, Gräfe M, Schulz C W, Cheng P W.: Near-wake measurements and simulations of a floating wind turbine using a four-beam nacelle-based lidar, In Press, *Journal of Physics: Conference Series*, 2024

Bibliography

- [1] X. Mei and M. Xiong, “Effects of second-order hydrodynamics on the dynamic responses and fatigue damage of a 15 mw floating offshore wind turbine,” *Journal of Marine Science and Engineering*, vol. 9, no. 11, 2021. [Online]. Available: <https://www.mdpi.com/2077-1312/9/11/1232>
- [2] A. Peña, C. B. Hasager, M. Badger, R. J. Barthelmie, F. Bingöl, J.-P. Cariou, S. Emeis, S. T. Frandsen, M. Harris, I. Karagali, S. E. Larsen, J. Mann, T. Mikkelsen, M. Pitter, S. Pryor, A. Sathe, D. Schlipf, C. Slinger, and R. Wagner, *Remote Sensing for Wind Energy DTU Wind Energy E-Report Remote Sensing for Wind Energy*, 2015, vol. DTU Wind E.
- [3] O. Bischoff, G. Wolken-Möhlmann, and P. W. Cheng, “An approach and discussion of a simulation based measurement uncertainty estimation for a floating lidar system,” *Journal of Physics: Conference Series*, vol. 2265, no. 2, p. 022077, may 2022. [Online]. Available: <https://doi.org/10.1088/1742-6596/2265/2/022077>
- [4] A. Borraccino, D. Schlipf, F. Haizmann, and R. Wagner, “Wind field reconstruction from nacelle-mounted lidar short-range measurements,” *Wind Energy Science*, vol. 2, no. 1, pp. 269–283, 2017.
- [5] J. Gottschall, B. Gribben, D. Stein, and I. Würth, “Floating lidar as an advanced offshore wind speed measurement technique: current

- technology status and gap analysis in regard to full maturity,” *WIREs Energy and Environment*, vol. 6, no. 5, p. e250, 2017. [Online]. Available: <https://wires.onlinelibrary.wiley.com/doi/abs/10.1002/wene.250>
- [6] R. Wagner, T. Friis Pedersen, M. Courtney, I. Antoniou, S. Davoust, and R. Rivera, “Power curve measurement with a nacelle mounted lidar,” *Wind Energy*, vol. 17, no. 9, p. 1441–1453, 2014.
- [7] U. Özınan, D. Liu, R. Adam, T. Choynet, and P. W. Cheng, “Power curve measurement of a floating offshore wind turbine with a nacelle-based lidar,” *Journal of Physics: Conference Series*, vol. 2265, no. 4, p. 042016, may 2022. [Online]. Available: <https://doi.org/10.1088/1742-6596/2265/4/042016>
- [8] D. Conti, N. Dimitrov, and A. Peña, “Aeroelastic load validation in wake conditions using nacelle-mounted lidar measurements,” *Wind Energy Science*, vol. 5, no. 3, pp. 1129–1154, 2020.
- [9] D. Conti, V. Pettas, N. Dimitrov, and A. Peña, “Wind turbine load validation in wakes using wind field reconstruction techniques and nacelle lidar wind retrievals,” *Wind Energy Science*, vol. 6, no. 3, pp. 841–866, 2021.
- [10] E. A. Bossanyi, A. Kumar, and O. Hugues-Salas, “Wind turbine control applications of turbine-mounted LIDAR,” *Journal of Physics: Conference Series*, vol. 555, p. 012011, dec 2014. [Online]. Available: <https://doi.org/10.1088/1742-6596/555/1/012011>
- [11] P. A. Fleming, A. K. Scholbrock, A. Jehu, S. Davoust, E. Osler, A. D. Wright, and A. Clifton, “Field-test results using a nacelle-mounted lidar for improving wind turbine power capture by reducing yaw misalignment,” *Journal of Physics: Conference Series*, vol. 524, p. 012002, jun 2014. [Online]. Available: <https://doi.org/10.1088/1742-6596/524/1/012002>
- [12] D. Schlipf, P. Fleming, S. Kapp, A. Scholbrock, F. Haizmann, F. Belen,

- A. Wright, and P. W. Cheng, “Direct speed control using lidar and turbine data,” pp. 2208–2213, 2013.
- [13] A. Clifton, P. Clive, J. Gottschall, D. Schlipf, E. Simley, L. Simmons, D. Stein, D. Trabucchi, N. Vasiljevic, and I. Würth, “Iea wind task 32: Wind lidar identifying and mitigating barriers to the adoption of wind lidar,” *Remote Sensing*, vol. 10, no. 3, 2018. [Online]. Available: <https://www.mdpi.com/2072-4292/10/3/406>
- [14] J. Gottschall, G. Wolken-Möhlmann, and B. Lange, “About offshore resource assessment with floating lidars with special respect to turbulence and extreme events,” *Journal of Physics: Conference Series*, vol. 555, p. 012043, dec 2014.
- [15] F. Kelberlau and J. Mann, “Quantification of motion-induced measurement error on floating lidar systems,” *Atmospheric Measurement Techniques*, vol. 15, no. 18, pp. 5323–5341, 2022. [Online]. Available: <https://amt.copernicus.org/articles/15/5323/2022/>
- [16] P. J. Meyer and J. Gottschall, “Evaluation of the “fan scan” based on three combined nacelle lidars for advanced wind field characterisation,” *Journal of Physics: Conference Series*, vol. 2265, no. 2, p. 022107, may 2022. [Online]. Available: <https://doi.org/10.1088/1742-6596/2265/2/022107>
- [17] “Uncertainty of measurement Part 3: Guide to the expression of uncertainty in measurement (GUM:1995),” International Organization for Standardization (ISO), Standard, 2008.
- [18] M. Gräfe, V. Pettas, and P. W. Cheng, “Wind field reconstruction using nacelle based lidar measurements for floating wind turbines,” *Journal of Physics: Conference Series*, vol. 2265, no. 4, p. 042022, may 2022. [Online]. Available: <https://doi.org/10.1088/1742-6596/2265/4/042022>
- [19] F. Kelberlau, V. Neshaug, L. Lønseth, T. Bracchi, and J. Mann, “Taking the motion out of floating lidar: Turbulence intensity estimates with a continuous-wave wind lidar,” *Remote Sensing*, vol. 12, no. 5,

- 2020.
- [20] T. Désert, G. Knapp, and S. Aubrun, “Quantification and correction of wave-induced turbulence intensity bias for a floating lidar system,” *Remote Sensing*, vol. 13, no. 15, 2021. [Online]. Available: <https://www.mdpi.com/2072-4292/13/15/2973>
 - [21] A. Salcedo-Bosch, F. Rocabenbosch, and J. Sospedra, “Enhanced dual filter for floating wind lidar motion correction: The impact of wind and initial scan phase models,” *Remote Sensing*, vol. 14, no. 19, 2022. [Online]. Available: <https://www.mdpi.com/2072-4292/14/19/4704>
 - [22] A. Salcedo-Bosch, F. Rocabenbosch, and J. Sospedra, “A robust adaptive unscented kalman filter for floating doppler wind-lidar motion correction,” *Remote Sensing*, vol. 13, no. 20, 2021. [Online]. Available: <https://www.mdpi.com/2072-4292/13/20/4167>
 - [23] M. Shafiee, “Failure analysis of spar buoy floating offshore wind turbine systems,” *Innovative Infrastructure Solutions*, vol. 8, 2022.
 - [24] Z. Gao and T. Moan, “Fatigue damage induced by nongaussian bimodal wave loading in mooring lines,” *Applied Ocean Research*, vol. 29, no. 1, pp. 45–54, 2007. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S0141118707000442>
 - [25] D. Benasciutti and R. Tovo, “Spectral methods for lifetime prediction under wide-band stationary random processes,” *International Journal of Fatigue*, vol. 27, no. 8, pp. 867–877, 2005, cumulative Fatigue Damage Conference - University of Seville 2003. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S0142112305000617>
 - [26] M. Borg, M. Collu, and A. Kolios, “Offshore floating vertical axis wind turbines, dynamics modelling state of the art. part ii: Mooring line and structural dynamics,” *Renewable and Sustainable Energy Reviews*, vol. 39, pp. 1226–1234, 2014. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S1364032114005747>
 - [27] M. Hall, “Moordyn v2: New capabilities in mooring system

- components and load cases: Preprint,” 9 2020. [Online]. Available: <https://www.osti.gov/biblio/1669566>
- [28] B. Azzam, R. Schelenz, B. Roscher, A. Baseer, and G. Jacobs, “Development of a wind turbine gearbox virtual load sensor using multibody simulation and artificial neural networks,” *Forschung im Ingenieurwesen*, vol. 85, p. 241–250, 2021.
- [29] N. Dimitrov and T. Göçmen, “Virtual sensors for wind turbines with machine learning-based time series models,” *Wind Energy*, vol. 25, no. 9, pp. 1626–1645, 2022. [Online]. Available: <https://onlinelibrary.wiley.com/doi/abs/10.1002/we.2762>
- [30] N. Hlaing, P. G. Morato, F. d. N. Santos, W. Weijtjens, C. Devriendt, and P. Rigo, “Farm-wide virtual load monitoring for offshore wind structures via bayesian neural networks,” *Structural Health Monitoring*, Aug. 2023. [Online]. Available: <http://dx.doi.org/10.1177/14759217231186048>
- [31] F. de N Santos, P. D’Antuono, K. Robbelein, N. Noppe, W. Weijtjens, and C. Devriendt, “Long-term fatigue estimation on offshore wind turbines interface loads through loss function physics-guided learning of neural networks,” *Renewable Energy*, vol. 205, pp. 461–474, 2023. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S0960148123001027>
- [32] J. Walker, A. Coraddu, M. Collu, and L. Oneto, “Digital twins of the mooring line tension for floating offshore wind turbines to improve monitoring, lifespan, and safety,” *Journal of Ocean Engineering and Marine Energy*, vol. 8, 2022.
- [33] N. Dimitrov, A. Borraccino, A. Peña, A. Natarajan, and J. Mann, “Wind turbine load validation using lidar-based wind retrievals,” *Wind Energy*, vol. 22, no. 11, pp. 1512–1533, 2019. [Online]. Available: <https://onlinelibrary.wiley.com/doi/abs/10.1002/we.2385>
- [34] M. Gräfe, U. Özinan, and P. W. Cheng, “Lidar-based virtual load

- sensors for mooring lines using artificial neural networks,” *Journal of Physics: Conference Series*, vol. 2626, no. 1, p. 012036, oct 2023. [Online]. Available: <https://dx.doi.org/10.1088/1742-6596/2626/1/012036>
- [35] M. C. Brower, B. H. Bailey, J. Doane, and M. J. Eberhard, *ASSESSMENT WIND RESOURCE ASSESSMENT to Developing a Wind Project with contributions from*, 2015.
- [36] “IEC61400-3-1 Design requirements for fixed offshore wind turbines,” International Electrotechnical Commission (IEC), Standard, 2019.
- [37] “IEC61400-1 Design requirements ,” International Electrotechnical Commission (IEC), Standard, 2019.
- [38] “Global offshore wind report 2023,” Tech. Rep.
- [39] “Floating offshore wind - a global opportunity,” Global Wind Energy Council, Report, 2022. [Online]. Available: <https://gwec.net/wp-content/uploads/2022/03/GWEC-Report-Floating-Offshore-Wind-A-Global-Opportunity.pdf>
- [40] C. Allen, V. Anthony, D. Habib, G. Andrew, G. Evan, A. Nikhar, H. Matthew, and B. Garrett, “Definition of the umaine volturnus-s reference platform developed for the iea wind 15-megawatt offshore reference wind turbine,” National Renewable Energy Laboratory, Report, 2020. [Online]. Available: <https://www.nrel.gov/docs/fy20osti/76773.pdf>
- [41] *Heave Plate Hydrodynamic Coefficients for Floating Offshore Wind Turbines – A Compilation of Data*, ser. International Conference on Offshore Mechanics and Arctic Engineering, vol. ASME 2023 5th International Offshore Wind Technical Conference, 12 2023. [Online]. Available: <https://doi.org/10.1115/IOWTC2023-119414>
- [42] J. Cruz and M. Atcheson, *Floating Offshore Wind Energy*. Springer Cham, 2016.
- [43] W. Yu, S. T. Zhou, F. Lemmer, and P. W. Cheng, “Control

- co-design optimization of floating offshore wind turbines with tuned liquid multi-column dampers,” *Wind Energy Science Discussions*, vol. 2023, pp. 1–25, 2023. [Online]. Available: <https://wes.copernicus.org/preprints/wes-2023-131/>
- [44] B. Skaare, F. G. Nielsen, T. D. Hanson, R. Yttervik, O. Havmøller, and A. Rekdal, “Analysis of measurements and simulations from the hywind demo floating wind turbine,” *Wind Energy*, vol. 18, no. 6, pp. 1105–1122, 2015. [Online]. Available: <https://onlinelibrary.wiley.com/doi/abs/10.1002/we.1750>
- [45] M. Y. Mahfouz, C. Molins, P. Trubat, S. Hernández, F. Vigarà, A. Pegalajar-Jurado, H. Bredmose, and M. Salari, “Response of the international energy agency (iea) wind 15 mw windcrete and active-float floating wind turbines to wind and second-order waves,” *Wind Energy Science*, vol. 6, no. 3, pp. 867–883, 2021.
- [46] E. E. Bachynski and T. Moan, “Design considerations for tension leg platform wind turbines,” *Marine Structures*, vol. 29, no. 1, pp. 89–114, 2012.
- [47] J. Jonkman and D. Matha, “Quantitative comparison of the responses of three floating platforms,” 01 2009.
- [48] T. Choisnet, S. Vasseur, and E. Rogier, “Performance and mooring qualification in floatgen : The first french offshore wind turbine project,” 06 2018.
- [49] F. Borisade, T. Choisnet, and P. W. Cheng, “Design study and full scale mbs-cfd simulation of the ideol floating offshore wind turbine foundation,” *Journal of Physics: Conference Series*, vol. 753, no. 9, p. 092002, sep 2016. [Online]. Available: <https://dx.doi.org/10.1088/1742-6596/753/9/092002>
- [50] BWIdeol. (2019) FLOATGEN. [Online]. Available: <https://floatgen.eu/>
- [51] M. Hall and A. Goupee, “Validation of a lumped-mass mooring

- line model with deepcwind semisubmersible model test data,” *Ocean Engineering*, vol. 104, pp. 590–603, 2015. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S0029801815002279>
- [52] U. Özinan, M. Kretschmer, F. Lemmer, and P. W. Cheng, “Effects of yaw misalignment on platform motions and fairlead tensions of the oo-star wind floater semi 10mw floating wind turbine,” *Journal of Physics: Conference Series*, vol. 1618, no. 5, p. 052081, sep 2020. [Online]. Available: <https://dx.doi.org/10.1088/1742-6596/1618/5/052081>
- [53] J. M. Jonkman, “Dynamics modeling and loads analysis of an offshore floating wind turbine,” National Renewable Energy Laboratory NREL, Tech. Rep., 2007.
- [54] J. Journée and W. Massie, *OFFSHORE HYDROMECHANICS*. Delft University of Technology, 2001.
- [55] N. Angelou, J. Mann, M. Sjöholm, and M. Courtney, “Direct measurement of the spectral transfer function of a laser based anemometer,” *Review of Scientific Instruments*, vol. 83, no. 3, 2012.
- [56] J. Gottschall, B. Gribben, D. Stein, and I. Würth, “Floating lidar as an advanced offshore wind speed measurement technique: current technology status and gap analysis in regard to full maturity,” *Wiley Interdisciplinary Reviews: Energy and Environment*, vol. 6, no. 5, 2017.
- [57] J. Cocks, B. Gribben, M.-A. Cowan, D. Stein, and J. Gottschall, “Deployments of Floating LiDAR Systems,” Tech. Rep., 2018.
- [58] G. Wolken-Möhlmann, J. Gottschall, and B. Lange, “First verification test and wake measurement results using a Ship-LIDAR system,” *Energy Procedia*, vol. 53, no. C, pp. 146–155, 2014.
- [59] H. Rubio, M. Kühn, and J. Gottschall, “Evaluation of low-level jets in the southern baltic sea: a comparison between ship-based lidar observational data and numerical models,” *Wind Energy Science*, vol. 7, no. 6, pp. 2433–2455, 2022. [Online]. Available: <https://wes.copernicus.org/articles/7/2433/2022/>

- [60] U. Özinan, M. Gräfe, C. W. Schulz, and P. W. Cheng, “Near-wake measurements and simulations of a floating wind turbine using a four-beam nacelle-based lidar,” In Press.
- [61] Vaisala. (2022) Wind iris turbine control. [Online]. Available: <https://www.vaisala.com/sites/default/files/documents/WindIrisTurbineControlBrochure.pdf>
- [62] ZX. (2024) Zx tm turbine mounted wind lidar. [Online]. Available: <https://www.zxlidars.com/wind-lidars/zx-tm/>
- [63] D. Schlipf, E. Simley, F. Lemmer, L. Pao, and P. W. Cheng, “Collective Pitch Feedforward Control of Floating Wind Turbines Using Lidar,” 06 2015, iSOPE-I-15-755.
- [64] F. Guo and D. Schlipf, “Assessing lidar-assisted feedforward and multi-variable feedback controls for large floating wind turbines,” *Wind Energy Science*, vol. 8, no. 8, pp. 1299–1317, 2023.
- [65] I. Würth, “Minute-scale forecasting of wind power using long-range lidar data,” Ph.D. dissertation, University of Stuttgart, 2012.
- [66] S. Raach, “Lidar-assisted wake redirection control,” Ph.D. dissertation, University of Stuttgart, 2016.
- [67] K. Browning and R. Wexler, “The determination of kinematic properties of a wind field using doppler radar,” *Journal of Applied meteorology and climatology*, vol. 7, no. 1, pp. 105–113, 1968.
- [68] A. Borraccino, D. Schlipf, F. Haizmann, and R. Wagner, “Wind field reconstruction from nacelle-mounted lidars short range measurements,” *Wind Energy Science*, vol. 2, pp. 269–283, 2017.
- [69] D. Schlipf, “Lidar-assisted control concepts for wind turbines,” Ph.D. dissertation, University of Stuttgart, 2016.
- [70] V. Pettas, F. García, M. Kretschmer, J. Rinker, A. Clifton, and P. Cheng, “A numerical framework for constrainin synthetic wind fields with lidar measurements for improved load simulations,” in *Proceedings of AIAA Scitech 2020 Forum*. Aerospace Research Central (ARC),

- 2020.
- [71] Joint Committee For Guides In Metrology, “Evaluation of measurement data — Guide to the expression of uncertainty in measurement,” *International Organization for Standardization Geneva ISBN*, vol. 50, no. September, p. 134, 2008. [Online]. Available: <http://www.bipm.org/en/publications/guides/gum.html>
 - [72] K.-D. Sommer and B. R. L. Siebert, “Praxisgerechtes bestimmen der messunsicherheit nach gum (practical determination of the measurement uncertainty under gum),” *tm - Technisches Messen*, vol. 71, no. 2, pp. 52–66, 2004. [Online]. Available: <https://doi.org/10.1524/teme.71.2.52.27068>
 - [73] “IEC61400-50-3 ED1 Use of nacelle-mounted lidars for wind measurements,” International Electrotechnical Commission (IEC), Standard, 2022.
 - [74] S. L. Brunton and J. N. Kutz, *Data-Driven Science and Engineering: Machine Learning, Dynamical Systems, and Control*, 2nd ed. Cambridge University Press, 2022.
 - [75] S. Hochreiter and J. Schmidhuber, “Long Short-Term Memory,” *Neural Computation*, vol. 9, no. 8, pp. 1735–1780, 11 1997. [Online]. Available: <https://doi.org/10.1162/neco.1997.9.8.1735>
 - [76] G. Philipp, D. Song, and J. G. Carbonell, “The exploding gradient problem demystified - definition, prevalence, impact, origin, tradeoffs, and solutions,” 2018.
 - [77] M. Miner, “Cumulative Damage in Fatigue,” *Journal of Applied Mechanics*, vol. 3, no. 3, pp. 159–164, 1945.
 - [78] ECN. (2017) Centrale Nantes offshore test site. [Online]. Available: <https://sem-rev.ec-nantes.fr/>
 - [79] E. Gaertner, J. Rinker, F. Sethuraman L.and Zahle, B. Anderson, G. Barter, F. Abbas, N.and Meng, W. Bortolotti, P.and Skrzypinski, G. Scott, R. Feil, H. Bredmose, K. Dykes, C. Sheilds, M.and Allen, and

- A. Viselli, “Definition of the iea 15-megawatt offshore reference wind turbine, tech. rep.” Tech. Rep., 2014.
- [80] M. Gräfe, V. Pettas, J. Gottschall, and P. W. Cheng, “Quantification and correction of motion influence for nacelle-based lidar systems on floating wind turbines,” *Wind Energy Science*, vol. 8, no. 6, pp. 925–946, 2023. [Online]. Available: <https://wes.copernicus.org/articles/8/925/2023/>
- [81] D. Schlipf, M. Koch, and S. Raach, “Modeling uncertainties of wind field reconstruction using lidar,” *Journal of Physics: Conference Series*, vol. 1452, no. 1, p. 012088, jan 2020. [Online]. Available: <https://doi.org/10.1088/1742-6596/1452/1/012088>
- [82] Y. Chen, W. Yu, F. Guo, and P. W. Cheng, “Adaptive measuring trajectory for scanning lidars: proof of concept,” *Journal of Physics: Conference Series*, vol. 2265, no. 2, p. 022099, may 2022. [Online]. Available: <https://doi.org/10.1088/1742-6596/2265/2/022099>
- [83] “IEC61400-12-1 Power performance measurements of electricity producing wind turbines,” International Electrotechnical Commission (IEC), Standard, 2016.
- [84] MATLAB, *9.9.0.1495850 (R2020b)*. Natick, Massachusetts: The MathWorks Inc., 2020.
- [85] M. Gräfe, V. Pettas, N. Dimitrov, and P. W. Cheng, “Machine-learning-based virtual load sensors for mooring lines using simulated motion and lidar measurements,” *Wind Energy Science*, vol. 9, no. 11, pp. 2175–2193, 2024. [Online]. Available: <https://wes.copernicus.org/articles/9/2175/2024/>
- [86] B. J. Jonkman, “Turbsim user’s guide v2,” Tech. Rep., 2014. [Online]. Available: <https://nwtc.nrel.gov/TurbSim>
- [87] “DNVGL-OS-E301 Position Mooring,” DNV, Standard, 2004.
- [88] P. S. Veers, D. C. Powell, and J. R. Connell, “Three-dimensional wind simulation,” 1998.

- [89] C. Blum and J. Dambeck, “Analytical assessment of the propagation of colored sensor noise in strapdown inertial navigation,” *Sensors*, vol. 20, no. 23, 2020. [Online]. Available: <https://www.mdpi.com/1424-8220/20/23/6914>
- [90] SBG-Systems. (2023) Ellipse Series. [Online]. Available: https://www.sbg-systems.com/wp-content/uploads/Ellipse_Series_Leaflet.pdf
- [91] K. Müller and P. W. Cheng, “A Surrogate Modeling Approach for Fatigue Damage Assessment of Floating Wind Turbines,” 06 2018, v010T09A065. [Online]. Available: <https://doi.org/10.1115/OMAE2018-78219>
- [92] L. Schröder, N. K. Dimitrov, D. R. Verelst, and J. A. Sørensen, “Using transfer learning to build physics-informed machine learning models for improved wind farm monitoring,” *Energies*, vol. 15, no. 2, 2022. [Online]. Available: <https://www.mdpi.com/1996-1073/15/2/558>
- [93] M. Gräfe, V. Pettas, and P. W. Cheng, “Data-driven forecasting of fowft dynamics and load time series using lidar inflow measurements,” *Journal of Physics: Conference Series*, vol. 2767, no. 3, p. 032025, jun 2024. [Online]. Available: <https://dx.doi.org/10.1088/1742-6596/2767/3/032025>
- [94] H. S. Dhiman and D. Deb, “A review of wind speed and wind power forecasting techniques,” 2020.
- [95] Y.-K. Wu and J.-S. Hong, “A literature review of wind forecasting technology in the world,” pp. 504–509, 2007.
- [96] Y. Chen, F. Guo, D. Schlipf, and P. W. Cheng, “Four-dimensional wind field generation for the aeroelastic simulation of wind turbines with lidars,” *Wind Energy Science*, vol. 7, no. 2, pp. 539–558, 2022. [Online]. Available: <https://wes.copernicus.org/articles/7/539/2022/>

Curriculum Vitae

Dipl.-Ing. Moritz Johann Gräfe, MSc.

ORCID:

0000-0002-8541-2324

LinkedIn:

<https://www.linkedin.com/in/moritz-gräfe/>

ResearchGate:

<https://www.researchgate.net/profile/Moritz-Graefe>



Professional experience

10/2020 - 04/2024

University of Stuttgart – Chair for Wind Energy (SWE), Stuttgart, Germany

Doctoral Researcher – Floating Wind

- Early Stage Researcher in the International Training Network FLOWER
- Research Topics: Floating Lidar Wind Field and Power Performance Measurements; Motion Influence and Uncertainty Quantification, Virtual Load Sensors for Mooring Lines using Machine Learning
- PhD Thesis: “Analysis and Application of Lidar Inflow Measurements for Floating Offshore Wind Turbines”

06/2018 - 09/2022

Uptime Engineering GmbH, Graz, Austria

Consultant Reliability Engineering, Project Manager

- Project Lead Horizon 2020 ROMEO Project: Development of a fully integrated methodology for offshore wind turbine failure diagnostics and prognostics; Development of O&M Information Management and decision support platform

03/2016–06/2017

Mercedes Benz G GmbH, Graz, Austria

Intern / Working Student, Change Management Department

Education

10/2016–04/2019

Master’s degree course: Production Science and Management

Graz University of Technology, Austria

09/2017–09/2018

Master’s degree course: Renewable Energy Engineering

Double Degree Scholarship Program, Cranfield University, UK

09/2011–02/2016

Bachelor’s degree course: Mechanical Engineering and Business Economics

Graz University of Technology, Austria

2001–2010

Higher education entrance qualification (Abitur)

High School (Ricarda-Huch Gymnasium), Dreieich, Germany