Survivability control using data-driven approaches and reliability analysis for wave energy converters

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Abstract


Wave energy, with five times the energy density of wind and ten times the power density of solar, offers a compelling carbon-free electricity solution. Despite its advantages, ongoing debates surround the reliability and economic feasibility of wave energy converters (WECs). To address these challenges, this doctoral thesis is divided into four integral parts, focusing on optimizing the prediction horizon for power maximization, analyzing extreme waves' impact on system dynamics, ensuring reliability, and enhancing survivability in WECs.

Part I emphasizes the critical importance of the prediction horizon for maximal power absorption in wave energy conversion. Using generic body shapes and modes, it explores the effect of dissipative losses, noise, filtering, amplitude constraints, and real-world wave parameters on the prediction horizon. Findings suggest achieving optimal power output may be possible with a relatively short prediction horizon, challenging traditional assumptions.

Part II shifts focus to WEC system dynamics, analyzing extreme load scenarios. Based on a 1:30 scaled wave tank experiment, it establishes a robust experimental foundation, extending into numerical assessment of the WEC. Results underscore the importance of damping to alleviate peak forces. Investigating various wave representations highlights conservative characteristics of irregular waves, crucial for WEC design in extreme sea conditions.

Part III explores the computational intricacies of environmental design load cases and fatigue analyses for critical mechanical components of the WEC. The analysis is conducted for hourly sea state damage and equivalent two-million-cycle loads. Finally, a comparison of safety factors between the ultimate limit state and fatigue limit state unfolds, illustrating the predominant influence of the ultimate limit state on point-absorber WEC design.

Part IV centers on elevating survivability strategies for WECs in extreme wave conditions. Three distinct controller system approaches leverage neural networks to predict and minimize the line force. Distinct variations emerge in each approach, spanning from rapid detection of optimal damping to integrating advanced neural network architectures into the control system with feedback. The incorporation of a controller system, refined through experimental data, showcases decreases in the line force, providing a practical mechanism for real-time force alleviation.

This thesis aims to contribute uniquely to the goal of advancing wave energy conversion technology through extensive exploration.

Keywords: power maximization, prediction horizon, extreme wave conditions, wave tank experiment, numerical WEC-Sim analysis, reliability analysis, statistical methods, environmental design load, fatigue analysis, statistical methods, survivability analysis, neural network methods

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URN urn:nbn:se:uu:diva-524903 (http://urn.kb.se/resolve?urn=urn:nbn:se:uu:diva-524903)
To Reza, the symphony of my heart, and my dear family
List of papers

This thesis is based on the following papers, which are referred to in the text by their Roman numerals.

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The author has also contributed to the following papers which are not included in the thesis.


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List of Symbols

Part I

\( \dot{\theta} \)  Angular velocity of a 1-DOF flap
\( \eta \)  Position of a 1-DOF floater
\( \gamma \)  Non-dimensional shape parameter of JONSWAP spectrum
\( \gamma' \)  Velocity of a 1-DOF floater in frequency domain
\( \gamma_{\text{opt}} \)  Optimal velocity in frequency domain
\( \nu \)  Velocity of a 1-DOF floater
\( \nu_{\text{opt}} \)  Optimal velocity in time domain
\( \nu_{\text{opt}}^{th} \)  Suboptimal finite-horizon velocity in time domain
\( \omega_p \)  Peak angular frequency of surface elevation
\( \sigma \)  Spectral width parameter of JONSWAP spectrum
\( \sigma_f \)  Standard deviation of excitation force
\( \sigma_n \)  Standard deviation of noise signal
\( \tau_{\text{exc}} \)  Excitation torque
\( \tau_{\text{PTO}} \)  Power take-off torque
GOF  Goodness-of-fit
\( \theta \)  Rotation angle of a 1-DOF flap
\( A_{\gamma} \)  Normalization factor of JONSWAP spectrum
\( E_u \)  Useful energy
\( f_{\text{exc}} \)  Complex excitation force coefficient
\( F_l \)  Loss force
\( F_r \)  Radiation force
\( F_{\text{exc}} \)  Excitation force
\( F_{\text{PTO}} \)  Power take-off force
\( H_{\text{opt}} \)  Optimal transfer function in frequency domain
\( h_{\text{opt}} \)  Optimal transfer function in time domain
\( H_s \)  Significant wave height
$H_{s,n}$  Significant wave height of noise signal

$M$  Mass of wave-absorber body

$M_a$  Added mass at finite frequencies

$M_r$  Total added mass

$M_\infty$  Added mass at infinite frequency

$N_P$  Normalized useful power

$N_R$  Normalized radiation resistance

$N_T$  Normalized prediction horizon

$P_e$  Excitation power

$P_l$  Loss power

$P_r$  Radiation power

$P_u$  Useful power

$P_u^{opt}$  Optimal useful power

$r_d$  Normalized damping

$R_l$  Dissipative loss coefficient

$R_r$  Radiation resistance

$r_r$  Impulse response of radiation resistance

$R_\theta$  Angular damping coefficient

$S_{exc}$  Excitation spectrum

$S_b$  Hydrostatic stiffness coefficient

$S_J$  JONSWAP spectrum

$S_{PM}$  Pierson-Moskowitz spectrum

$T_f$  Full length of time series

$T_p$  Peak period of surface elevation

$Z_i$  Intrinsic impedance

$Z_r$  Radiation impedance

**Part II**

$\beta$  Radius of the circular contour line in u-space

$\beta^*$  Radius of the inflated circular contour line in u-space

$\ddot{z}_{PTO}$  PTO translator acceleration in vector form

$\dot{z}_{PTO}$  PTO translator velocity in vector form

$\epsilon$  Standard deviation of the Gaussian amplitude spectrum
\( \eta \)  \quad \text{Threshold in marginal PDF of } H_s \\
\( \eta_G \)  \quad \text{Surface elevation of a Gaussian wave packet} \\
\( \mu(h_s) \)  \quad \text{Conditional mean of } \ln t_p \text{ given } h_s \\
\( \mu_p \)  \quad \text{Pulley friction coefficient} \\
\( \nu_{\text{brk}} \)  \quad \text{Breakaway friction velocity} \\
\( \nu_{\text{Coul}} \)  \quad \text{Coulomb velocity threshold} \\
\( \nu_{\text{St}} \)  \quad \text{Striebeck velocity} \\
\( \Phi \)  \quad \text{Standard Gaussian CDF} \\
\( \sigma(h_s) \)  \quad \text{Conditional standard deviation of } \ln t_p \text{ given } h_s \\
\( \mathbf{F}_{\text{line}} \)  \quad \text{Line force in vector form} \\
\( \mathbf{F}_{\text{endstop}} \)  \quad \text{End-stop force in vector form} \\
\( \mathbf{F}_{f_P} \)  \quad \text{Pulley friction force in vector form} \\
\( \mathbf{F}_{f_{\text{PTO}}} \)  \quad \text{PTO friction force in vector form} \\
\( g \)  \quad \text{Gravitational acceleration} \\
\( \bar{a} \)  \quad \text{Mean of } \ln h_s \text{ in marginal PDF of } H_s \\
\( \bar{b} \)  \quad \text{Variance of } \ln h_s \text{ in marginal PDF of } H_s \\
\( \bar{c} \)  \quad \text{Scale parameter of Weibull tail distribution in marginal PDF of } H_s \\
\( \bar{d} \)  \quad \text{Shape parameter of Weibull tail distribution in marginal PDF of } H_s \\
\( A_0 \)  \quad \text{Amplitude crest of Gaussian wave packet} \\
\( c_{\text{st}} \)  \quad \text{Equivalent viscous damping coefficient of the structure} \\
\( F_{\text{brk}} \)  \quad \text{Breakaway friction force} \\
\( F_{\text{heave}} \)  \quad \text{Heave force on buoy} \\
\( F_{\text{surge}} \)  \quad \text{Surge force on buoy} \\
\( F_{C_p} \)  \quad \text{Pulley Coulomb force} \\
\( F_{C_{\text{PTO}}} \)  \quad \text{PTO Coulomb force} \\
\( F_{D_0} \)  \quad \text{PTO sliding friction damping force in } D_0 \text{ configuration} \\
\( F_{D_1} \)  \quad \text{PTO sliding friction damping force in } D_1 \text{ configuration} \\
\( F_{D_2} \)  \quad \text{PTO sliding friction damping force in } D_2 \text{ configuration} \\
H  \quad \text{Wave height} \\
h_5  \quad \text{Pitch angle} \\
H_s  \quad \text{Significant wave height} \\
k  \quad \text{Wavenumber} \\
k_p  \quad \text{Wavenumber at peak frequency}
\( k_{es} \) Spring coefficient of the end-stop
\( k_{st} \) Equivalent spring coefficient of the structure
\( L \) Wavelength
\( l_0 \) Uncompressed length of end-stop spring
\( l_c \) Fully-compressed length of end-stop spring
\( l_s \) Stroke length
\( M_{\text{pitch}} \) Pitch moment on buoy
\( m_{PTO} \) PTO translator mass
\( p_{H_s,T_p} \) Joint PDF of sea state
\( P_{H_s} \) Marginal CDF of \( H_s \)
\( p_{H_s} \) Marginal PDF of \( H_s \)
\( S_G \) Gaussian shape amplitude spectrum
\( T \) Wave period
\( T_e \) Energy period of surface elevation
\( T_p \) Peak period of surface elevation
\( T_r \) Return period
\( T_z \) Zero-crossing period of surface elevation
\( T_{ss} \) Sea state duration
\( z \) PTO translator position

Part III
\( \alpha \) Scale parameter of general Pareto distribution
\( \bar{P}_{lt} \) Long-term survival function (CCDF) of line force peaks
\( \bar{P}_{st} \) Short-term survival function (CCDF) of line force peaks
\( \Delta_{st} \) Short-term extreme simulation period
\( \Delta t_{st} \) Total simulation period
\( \eta_f \) Fatigue safety factor
\( \mu_{\text{exc}} \) Mean of exceedances
\( \mu_{xp} \) Mean of peak forces
\( \sigma_{\text{exc}} \) Standard deviation of exceedances
\( \sigma_{xp} \) Standard deviation of peak forces
\( \tilde{S} \) Wave spectrum
\( A_c \) Cross-sectional area of the load-bearing material
$d$ Diameter of the load-bearing cross-section

$D_s$ Damage in each sea state

$D_{1h}$ Total damage over 1 hour

$D_{50y}$ Total damage over 50 years

$E_i$ The $i^{th}$ peak or trough in the stress history

$F_{\text{max}}$ Maximum line force

$F_{DL}$ Ultimate limit state design load

$F_{eq}$ Fatigue equivalent constant amplitude force

$k$ Shape parameter of general Pareto distribution

$m$ Fatigue exponent of material

$m_{0,j}$ Zero spectral moment of the $j^{th}$ sea state

$m_{1,j}$ First spectral moment of the $j^{th}$ sea state

$N$ Number of stress cycles

$N_t$ Total number of force peaks

$N_{\text{POT}}$ Number of force peaks above threshold

$n_{eq}$ Number of cycles for which $S_{eq}$ is calculated

$N_{st}$ Average number of peaks in each short-term extreme simulation

$P_{GPD}$ CDF of general Pareto distribution

$p_{H_s,T_p}$ PDF of sea state

$p_{jH_s,T_p}$ Probability of the $j^{th}$ grid module in sea states contour

$P_{P,GPD}$ CDF of line force peaks based on GPD

$P_p$ CDF of line force peaks

$P_{st}$ Short-term extreme CDF of force peaks

$R_a$ Surface roughness

$S$ Material stress

$S_y$ Yield stress of the material

$S_{eq}$ Fatigue equivalent constant amplitude stress

$S_{f,2M}$ Fatigue stress amplitude for two million cycles

$S_{m,DL}$ Stress in material based on design load

$T_{\text{avg},j}$ Average period of the $j^{th}$ sea state

$x_P$ Line force peaks in general Pareto distribution

$z_P$ Exceedance of the line force peaks above threshold in general Pareto distribution
Part IV

\(\alpha\) Weight cost in \(R_{L2}\)

\(\beta_1, \beta_2\) Decay rates of the Adam optimizer

\(\dot{z}\) PTO translator acceleration

\(\delta^l\) Gradient of the loss with respect to the \(l^{th}\) layer output

\(\dot{z}\) PTO translator velocity

\(\eta\) Surface elevation

\(\eta_n\) Normalized surface elevation

\(\eta_{\text{noise}}\) Surface elevation noise

\(\gamma\) Learning rate in the update rule

\(\hat{M}_{\theta}\) Bias-corrected first moment of the gradient in the Adam optimizer

\(\hat{V}_{\theta}\) Bias-corrected second moment of the gradient in the Adam optimizer

\(\hat{Y}\) Predicted output vector

\(\hat{y}\) Predicted output value

\(\lambda\) Wavelength

\(\mu\) Average value of a feature

\(\omega\) Angular frequency

\(\phi_{\text{rand}}\) Random phase

\(\sigma\) Standard deviation of a feature

\(\sigma_n\) Standard deviation of noise

\(\sigma_\eta\) Standard deviation of surface elevation

\(\theta^k\) Model parameters (weights and biases) in the \(k^{th}\) iteration

\(\theta_{ij}\) Model parameters (weights and biases)

\(\zeta\) Attention factor

\(a\) Amplitude of frequency components

\(b^{[l]}\) Bias of the \(l^{th}\) layer

\(c\) Complex amplitude

\(C_r\) correlation between the true and predicted output vector

\(c_{ij}\) Elements of the covariance matrix

\(F_D\) Sliding friction damping force

\(F_{\text{line}n}\) Normalized peak line force

\(F_Dn\) Normalized sliding friction damping force

\(g^{[l]}\) Activation function of the \(l^{th}\) layer
\( H \) Wave height
\( H_s \) Significant wave height
\( L(y, \hat{y}) \) Loss function
\( M_\theta \) First moment of the gradient in the Adam optimizer
\( n_b \) Batch size
\( R_{L_2} \) L\(_2\) regularization
\( T_p \) Peak period
\( V_\theta \) Second moment of the gradient in the Adam optimizer
\( W[l] \) Weight of the \( l^{th} \) layer
\( Y \) True output vector
\( y \) True output value
\( y_c \) Predicted probability of extreme peak line force
\( y_n \) Normalized true output value
\( y_r \) Regression output of the network
\( z \) PTO translator position
\( z[l] \) Output of the \( l^{th} \) layer
\( z_n \) Normalized PTO translator position
\( z_{\text{noise}} \) PTO translator position noise
<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Full Form</th>
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<tbody>
<tr>
<td>ACER</td>
<td>Average Conditional Exceedance Rate</td>
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<td>ALS</td>
<td>Accidental Limit State</td>
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<tr>
<td>API</td>
<td>Application Programming Interface</td>
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<tr>
<td>BCE</td>
<td>Binary Cross Entropy</td>
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<tr>
<td>CAD</td>
<td>Computer-aided Design Software</td>
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<tr>
<td>CCDF</td>
<td>Complementary Cumulative Distribution Function (Short-term Survival Function)</td>
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<tr>
<td>CDF</td>
<td>Cumulative Distribution Function</td>
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<tr>
<td>CFD</td>
<td>Computational Fluid Dynamics</td>
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<tr>
<td>CNN</td>
<td>Convolutional Neural Network</td>
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<tr>
<td>DL</td>
<td>Design Load</td>
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<tr>
<td>DLC</td>
<td>Design Load Case</td>
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<tr>
<td>DNN</td>
<td>Deep Neural Network</td>
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<tr>
<td>ECDF</td>
<td>Empirical Cumulative Distribution Function</td>
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<td>ED</td>
<td>Exponential Distribution</td>
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<tr>
<td>FEM</td>
<td>Finite Element Method</td>
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<tr>
<td>FLS</td>
<td>Fatigue Limit State</td>
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<td>GEV</td>
<td>Generalized Extreme Value</td>
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<tr>
<td>GOF</td>
<td>Goodness-of-fit</td>
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<tr>
<td>GPD</td>
<td>Generalized Pareto Distribution</td>
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<tr>
<td>HPC</td>
<td>High-performance Computing</td>
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<tr>
<td>IEC</td>
<td>International Electrotechnical Commission</td>
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<tr>
<td>IQR</td>
<td>Interquartile Range</td>
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<tr>
<td>LCOE</td>
<td>Levelized Cost of Energy</td>
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<td>LSTM</td>
<td>Long Short-term Memory</td>
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<td>Abbreviation</td>
<td>Full Form</td>
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<tr>
<td>MCMC</td>
<td>Markov Chain Monte Carlo</td>
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<td>MLE</td>
<td>Maximum Likelihood Estimates</td>
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<td>MLER</td>
<td>Most Likely Extreme Response</td>
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<tr>
<td>MSE</td>
<td>Mean Squared Error</td>
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<tr>
<td>NN</td>
<td>Neural Network</td>
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<tr>
<td>NOTC</td>
<td>National Ocean Technology Centre</td>
</tr>
<tr>
<td>PCA</td>
<td>Principal Component Analysis</td>
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<tr>
<td>PDF</td>
<td>Probability Density Function</td>
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<tr>
<td>PINN</td>
<td>Physics-informed Neural Network</td>
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<tr>
<td>POT</td>
<td>Peaks-over-threshold</td>
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<tr>
<td>PReLU</td>
<td>Parametric Rectified Linear Unit</td>
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<tr>
<td>PTO</td>
<td>Power Take-off</td>
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<tr>
<td>RAO</td>
<td>Response Amplitude Operator</td>
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<tr>
<td>ReLU</td>
<td>Rectified Linear Unit</td>
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<tr>
<td>ResNet</td>
<td>Residual Neural Networks</td>
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<tr>
<td>RL</td>
<td>Reinforcement Learning</td>
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<tr>
<td>SLS</td>
<td>Serviceability Limit State</td>
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<tr>
<td>TPL</td>
<td>Technology Performance Level</td>
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<tr>
<td>TRL</td>
<td>Technological Readiness Level</td>
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<tr>
<td>ULS</td>
<td>Ultimate Limit State</td>
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<tr>
<td>UPPMAX</td>
<td>Uppsala Multidisciplinary Center for Advanced Computational Science</td>
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<tr>
<td>WAMIT</td>
<td>WaveAnalysisMIT</td>
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<tr>
<td>WDRT</td>
<td>WEC Design Response Toolbox</td>
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<tr>
<td>WEC</td>
<td>Wave Energy Converter</td>
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<tr>
<td>WEC-Sim</td>
<td>Wave Energy Converter SIMulator</td>
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1. Introduction

Fossil fuels contribute to over 60% of electricity generation worldwide with coal followed by gas being the largest contributors. Low-carbon sources (nuclear and renewables) however supply only about one-third of global electricity with hydro- and nuclear power making the most substantial contributions [1]. These statistics may vary depending on the region. In Europe, fossil fuels account for 40% of electricity generation, with natural gas being responsible for approximately half of that share. Meanwhile, renewable energies contribute to only around one-third, and nuclear power accounts for approximately one-quarter of the overall electricity production. Renewable energy sources still heavily depend on fossil fuels to maintain energy balance, particularly during periods of high demand. For example, the 2022 drought in Europe caused a significant decline in power generation from hydropower and nuclear sources, leading to a reliance on fossil fuels to compensate for the shortfall [2]. Furthermore, excessive greenhouse gas emissions have led to a pressing environmental crisis that requires immediate action. To address the aforementioned issues, a significantly larger proportion of the total electricity generation and its balancing system will need to be constituted from various renewable sources.

Oceans contain tremendous amounts of energy that may be harnessed through wave energy converters (WECs), offering the possibility of supplying up to 10% of global electricity consumption [3]. The reliability and economic viability of WECs are still subject to ongoing disputes, despite notable advancements in their technical maturity over the past few decades. The commercialization of WECs involves ongoing developments in two key areas. The first area includes maximizing power absorption, which has shown significant progress through the introduction of various control strategies [4]. The second area involves enhancing the reliability and survivability of these devices, aiming to avoid oversized structural design and consequently reduce their levelized cost of energy (LCOE). Besides LCOE, technological readiness level (TRL) and technology performance level (TPL) are other two merits that are employed in the assessment of the techno-economic progress of WECs. It is advised to prioritize the advancement of TPL while the TRL is at a low price until a satisfactory level of confidence is attained from both an economic and commercial standpoint [5]. The long-term economic potential can be realized by ensuring the survivability, reliability, and maintenance of WECs, as well as optimizing their overall power performance, scalability, and environmental aspects [6]. Hence, there yet exist numerous challenges to be addressed using novel approaches before the deployment of WECs in oceans.
1.1 Aim of the thesis
The main goal of this thesis is to first examine the dependency of the prediction horizon length on dissipative losses, aiming to maximize the power absorption for WECs; next, to evaluate the effect of extreme loads aroused from the extreme wave conditions on the motion and dynamic of a point absorber wave energy converter; then, to assess the reliability of a point absorber WEC through the computation of the ultimate limit state (ULS) and fatigue limit state (FLS) from the experimental wave tank and numerical data; subsequently, to propose a survivability control, utilizing the neural network (NN) architectures, to adjust the system damping, aiming to minimize the line (mooring) force.

1.2 Thesis overview and outline
To address the aforementioned goals, this thesis is divided into the following parts;

Part I discusses the non-causal optimal control law for wave energy conversion, which necessitates predicting waves and wave forces over a future horizon. Upon delving deeper into the details, the question arises regarding how far into the future this knowledge (namely, the prediction horizon) is required and how dissipative losses influence this factor. What are the other elements that need to be considered when determining this prediction horizon? To address these questions, Part I emphasizes how the length of the prediction horizon, required to achieve the maximum power output, is computed and influenced by the dissipative losses in the conversion chain through the computation of velocity reference trajectories for different generic body shapes and oscillation modes. The discussion encompasses sensitivity to noise and the utilization of filtering techniques to enhance performance in cases where the prediction horizon is limited or predictions are not entirely accurate. Additionally, considerations are given to factors such as amplitude constraints and other real-world effects encountered in actual systems.

Hence, Part I outlines: first, a background and summary of real-time control, including the requirements for the prediction horizon, are presented in section 2.1. Next, the theory behind the computation of optimal velocity and useful power as a function of the available prediction horizon and loss coefficient is explained in section 2.2. Generic wave energy concepts and control variables are elaborated upon in section 2.3. The discussion on sensitivity to different parameters in the evaluation of the prediction horizon is found in section 2.4. Finally, the conclusion of this part is drawn in section 2.5.

Part II delves into a comprehensive exploration of the motion and dynamics of a point absorber under the impact of extreme loads resulting from ex-
treme wave conditions. For this purpose, a wave tank experiment at a scale of 1:30 was conducted in the Ocean and Coastal Engineering Laboratory of Aalborg University. This experimental setup provides a foundational understanding of the system’s behavior and the forces it encounters. Part II begins with an in-depth analysis of the experimental results, delving into the effects of various parameters. These parameters include i) power take-off (PTO) damping parameters, ii) different wave type representations (i.e. regular, irregular, and focused waves) of the same state, and iii) nonlinear phenomena like wave breaking, wave breaking slamming, and overtopping on mooring force.

To transcend the limitations of experimental data and extend the comprehension to broader environmental conditions, the integration of numerical models becomes indispensable. Ensuring the reliability of these numerical models mandates calibration with real-measured data derived from the wave tank experiments. Hence, a numerical WEC-Sim (Wave Energy Converter SIMulator) model is meticulously developed and calibrated based on the wave tank experimental data. This calibrated model serves as a crucial tool for further enhancing the system’s response in reliability and survivability analyses.

The outline of Part II is structured as follows: section 3.1 provides an overview and synthesis of extreme waves and their impact on WECs, considering both experimental and numerical perspectives. Following this, section 3.2 and section 3.3 delineate the methodologies for the wave tank experimental setup and numerical modeling of the point absorber wave energy converter under extreme waves, respectively. The analysis of line force data acquired from the wave tank experiment is extensively addressed, covering aspects such as damping effects, wave type representation, and more, as presented in section 3.4. Moreover, the performance of the WEC-Sim model is presented and discussed in section 3.4. Consequently, the findings of the results are summarized in section 3.5.

**Part III** delves into an in-depth investigation of the reliable operation over the lifetime of a point absorber WEC, achieved through the computation of limit states. These states signify conditions where the structure and its components can no longer meet their intended design specifications. Part III emphasizes the examination of two primary failure modes: instantaneous failure due to high loads and fatigue failure resulting from gradual structural damage accumulated over years of operation. Addressing these failure modes involves a thorough study of the ultimate limit state (ULS), corresponding to the maximum capacity of the load-carrying device and its subsystems, and the fatigue limit state (FLS), associated with system failure due to cyclic loading.

The approach to determining the environmental design load (DL) for the line force of a point-absorber WEC is described, considering a 50-year environmental contour for the Dowsing site in the North Sea, within the framework of ULS. To augment the data for this analysis, a numerical model using WEC-Sim simulates the response of the WEC under extreme conditions.
Following the fatigue analysis for sea states inside and around the 50-year environmental contour, the partial damage within each 1-hour sea state sample is determined using rainflow counting and the Palmgren-Miner rule. Thus, by taking into account the joint probability density function of the sea states, the equivalent two-million cycle load is calculated, considering the accumulated damage over a 50-year operational period. Lastly, through a comparison of FLS and ULS, the governing limit state in the design of the WEC system at hand is identified.

Part III is organized as follows: section 4.1 specifies the significance of both ULS and FLS in evaluating the reliability of wave energy converters, along with the associated challenges and scientific gaps. section 4.2 extensively explores the determination of environmental design load by examining the short-term and long-term response of the device. Additionally, section 4.3 details the fatigue analysis methodology, utilizing the Palmgren-Miner rule and rainflow counting method to compute the fatigue life for the shackle component connecting the buoy to the mooring line. Subsequently, section 4.4 presents the findings and discussions stemming from these studies. Lastly, section 4.5 conducts a comparison between the ULS and FLS safety factors, aiming to identify the predominant factor influencing the design process for a point absorber, similar to the one under study.

Part IV introduces innovative survivability control strategies employing neural network (NN) models aimed at minimizing line forces through adaptive system damping.

Understanding the theoretical dynamics of a system under extreme wave conditions is inherently challenging. Consequently, numerical modeling for such systems is either encumbered by uncertainties or demands extensive computational resources. Machine learning applications emerge as a promising alternative to address these challenges. Part IV comprehensively elucidates various neural network architectures serving as survivability control systems for WECs. Additionally, it delves into the impact of uncertainties in predicting future knowledge on the performance of neural network control systems.

Part IV is arranged as follows: section 5.1 delves into the application of neural networks in designing survivability strategies for wave energy converters, providing insights into the advantages and challenges they present. In section 5.2, three distinct neural networks are introduced to predict the optimal required damping for minimizing peak line forces. section 5.3 thoroughly examines the accuracy, limitations of each approach, and the sensitivity of the resultant optimal damping to uncertainties within each neural network. Finally, section 5.4 summarizes the conclusions drawn from each approach and assesses the feasibility of implementing these strategies in actual wave energy converters.
Note that some of the texts in this thesis are taken directly from the licentiate thesis [7].
2. Part I: Prediction horizon in power maximization control

2.1 Background

To achieve energy efficiency over a large range of wave conditions, a control system can be used to tune the oscillator dynamics with incoming waves. The early stage of the control approach for wave energy converters (WECs) reveals the usage of the frequency domain relationships in the regulation of the system dynamics for different incoming wave spectra to obtain maximum power absorption. The real-time control is not generally applicable with the frequency domain technique due to the appearance of strong non-causality when converting the frequency domain relation to the time domain. Therefore, the optimal power absorption cannot be acquired unless the future knowledge of wave excitation force or motion is well known [8–11].

Many authors tried to address the question of the required prediction horizon for future knowledge, and some of the works are summarized as follows: Falnes [8] emphasized the role of memory kernel, i.e. inverse Fourier of the radiation impedance in the prediction horizon requirement. Fusco and Ringwood [12] presented the prediction horizon required for different cylinder and sphere sizes of floating devices working in heave motion. Merigaud [13] discussed how an optimal controller can be applied for a combination of local and remote monitoring through a review of stochastic representations of ocean waves.

Part I investigates how much the prediction horizon length depends on the dissipative losses in order to capture the maximum power absorption through the calculation of the velocity reference trajectory using generic body shapes and modes. The study also considers the influence of various factors, such as noise, filtering of the transfer function, amplitude constraints, and other wave parameters encountered in a real system, on the required prediction length for power maximization purposes.

2.2 Theory

2.2.1 Time and frequency domain model

The equation of motion for a single-degree-of-freedom (SDOF) wave energy converter in the time domain can be described as [8]:

\[(M + M_\infty)\ddot{v}(t) + \int_0^t v(\tau)k(t - \tau)d\tau + R_\beta v(t) + S_b \eta(t) = F_{exec}(t) + F_{PTO}(t)\]  \hspace{1cm} (2.1)
where $\eta(t)$ and $v(t)$ are the position and velocity of the floater, respectively. The excitation force is represented by $F_{\text{exc}}(t)$, while the power take-off force excluding the machinery loss is $F_{\text{PTO}}(t)$. The total loss term, which includes hydrodynamic drag, machinery friction, and flow losses, is indicated by the dissipative loss coefficient, $R_l$. Note that in this study, this term is linearised and thereby it is proportional to the velocity. Moreover, $M$ is the mass of the wave-absorbing body, and $M_\infty$ is the added mass at infinite frequency. Lastly, $S_b$ is the hydrostatic stiffness coefficient.

For a wave energy device with a rotational mode of motion, the same equation is applied with rotation angle $\eta(t) = \theta(t)$ and angular velocity $\nu(t) = \dot{\theta}(t)$. Further, the forces are replaced by corresponding torques as $\tau_{\text{exc}}(t)$ and $\tau_{\text{PTO}}(t)$. Consequently, angular stiffness $S_\theta$, angular damping $R_\theta$, and moment of inertia $I_\theta$ are substituted for stiffness, damping, and mass. Note that $\theta$ is considered small, i.e. $-30^\circ < \theta < +30^\circ$, for the following two reasons [14]:

- The buoyancy restoring coefficient is considered constant.
- Hydrodynamic coefficient, e.g. radiation resistance and added inertia are unrelated to angular position, due to the wave torque decoupling effect.

In the frequency domain, the equation of motion can be written as:

$$
\left( j \omega M + Z_r(\omega) + \frac{S_b}{j \omega} \right) \nu'(\omega) + R_l \nu'(\omega) = F_{\text{exc}}(\omega) + F_{\text{PTO}}(\omega)
$$

(2.2)

where radiation impedance, $Z_r(\omega)$, owing to the body’s motion radiated waves is:

$$
Z_r(\omega) = R_r(\omega) + j \omega M_r(\omega) = R_r(\omega) + j \omega [M_a(\omega) + M_\infty]
$$

(2.3)

where $R_r(\omega)$ is the radiation resistance which is real and even in the frequency domain. Further, $M_r(\omega)$ is the total added mass in which $M_a(\omega)$ is the added mass at frequencies $\omega < \infty$ and $M_\infty$ the added mass at infinite frequency. The compact form of the equation of motion can be written as [11]:

$$
\nu'(\omega) = \frac{1}{Z_i(\omega)} (F_{\text{PTO}}(\omega) + F_{\text{exc}}(\omega)),
$$

(2.4)

where the intrinsic impedance $Z_i(\omega)$ is identified as:

$$
Z_i(\omega) = R_r(\omega) + R_l + j \left( \omega (M + M_r(\omega)) - \frac{S_b}{\omega} \right).
$$

(2.5)
The optimal velocity for the maximum power absorption can be derived following cf. [11]:

\[ V_{\text{opt}}(\omega) = \frac{1}{Z_i(\omega) + Z_i^*(\omega)} F_{\text{exc}}(\omega) \]  
\[ = \frac{1}{2R_r(\omega) + 2R_i} F_{\text{exc}}(\omega) \]  
\[ = H_{\text{opt}}(\omega) F_{\text{exc}}(\omega) \]  

where \( H_{\text{opt}} \) is called the frequency response. Note that with the optimal velocity strategy, only half of the average wave excitation power will be absorbed and the other half is either partly re-radiated or partly dissipated due to losses.

### 2.2.2 Non-causality of the real-time control system in the time domain

The optimal velocity in the time domain can be written as:

\[ V_{\text{opt}}(t) = \int_{-\infty}^{\infty} h_{\text{opt}}(\tau) f_{\text{exc}}(t - \tau) d\tau. \]  

One of the challenges in the control of wave energy converters is the non-causality of optimal velocity in the time domain. Simply put, both past and future knowledge of the excitation force is required to compute the optimal velocity at time \( t \). To mathematically deal with this non-causality, first the impulse response using inverse Fourier transform can be written as:

\[ h_{\text{opt}}(t) = \frac{1}{2R_l} \delta(t) + k_{\text{opt}}(t) \]  
\[ k_{\text{opt}}(t) = \mathcal{F}^{-1} \left\{ H_{\text{opt}}(\omega) - \frac{1}{2R_l} \right\} \]

where \( \delta(t) \) is the Dirac delta function. Here, the mathematical definition of \( k_{\text{opt}}(t) \) is introduced in order for Equation 2.10 to be well-defined since \( H_{\text{opt}}(\omega) \) tends to a constant value as \( \omega \to \infty \), [11].

Now by truncating the convolution integral shown in Equation 2.9, the suboptimal finite-horizon velocity can be achieved as:

\[ V_{\text{opt}}^{T_h}(t) = \frac{1}{2R_l} f_{\text{exc}}(t) + \int_{-T_h}^{T_h} k_{\text{opt}}(\tau) f_{\text{exc}}(t - \tau) d\tau. \]  

The above equation is referred to as single truncation. Subsequently, if the integration limits are considered as \([-T_h, +T_h]\), Equation 2.12 indicates double truncation of the convolution integral.
Goodness-of-fit (GOF) measures the deviation of the sub-optimal from optimal velocity as:

\[
\text{GOF}(T_h) = 1 - \sqrt{\frac{\sum (v_{\text{opt}} - v_{T_h})^2}{\sum v_{\text{opt}}^2}}.
\] (2.13)

2.2.3 Useful power

The useful power is computed based on the excitation power \( P_e \), radiation power \( P_r \), and loss power \( P_l \) as [8]:

\[
P_u = P_e - P_r - P_l.
\] (2.14)

Hence,

\[
P_e(t) = F_{\text{exc}}(t) \nu(t)
\] (2.15)

\[
P_r(t) = F_r(t) \nu(t) = \nu(t) \int_{-\infty}^{+\infty} r_r(\tau) \nu(t - \tau) d\tau
\] (2.16)

\[
P_l(t) = F_l(t) \nu(t) = R_l \nu^2(t)
\] (2.17)

where the radiation and loss forces are \( F_r(t) \), and \( F_l(t) \), respectively, and the impulse response of the radiation resistance \( R_r(\omega) \) is \( r_r(t) \).

The useful energy can be defined as, \( E_u = \int_0^{T_f} P_u dt \), in which \( T_f \) is the full length of the time series.

2.3 Method

2.3.1 Generic WEC concepts

Three different WEC concepts are considered in the study of the prediction horizon: a floating sphere that oscillates in surge or heave, a submerged sphere that oscillates in surge or heave, and a bottom-hinged flap that oscillates about a mean position of \( 0^\circ \) or \(-30^\circ \), see Table 2.1 and Figure 2.1 for further details.

2.3.2 Hydrodynamic coefficients

The potential flow solver WAMIT (WaveAnalysisMIT) [15] is used to derive the hydrodynamic coefficients, which are radiation resistance, added mass, and excitation force coefficients, see Figure 2.2. The geometry of both floating and submerged spheres are defined analytically in WAMIT, while the bottom-hinged flap is modeled by AeroHydro’s MultiSurf software [16]. Note that the irregular frequencies removal function [15] is not activated in the WAMIT setup which leads to the singularities seen in some of the curves.
Figure 2.1. Generic concepts illustration with notional power take-off, retrieved from Paper I.
Table 2.1. *Generic concepts properties, retrieved from Paper I.*

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td><strong>Floating sphere</strong></td>
<td></td>
</tr>
<tr>
<td>$r$</td>
<td>Radius</td>
<td>5 m</td>
</tr>
<tr>
<td>$d$</td>
<td>Equilibrium draft</td>
<td>5 m</td>
</tr>
<tr>
<td>$h$</td>
<td>Water depth</td>
<td>Deep water</td>
</tr>
<tr>
<td>$\tau_{\text{float},1}$</td>
<td>Time constant, surge</td>
<td>0.44 s</td>
</tr>
<tr>
<td>$\tau_{\text{float},3}$</td>
<td>Time constant, heave</td>
<td>0.93 s</td>
</tr>
<tr>
<td></td>
<td><strong>Submerged sphere</strong></td>
<td></td>
</tr>
<tr>
<td>$r$</td>
<td>Radius</td>
<td>5 m</td>
</tr>
<tr>
<td>$s$</td>
<td>Equilibrium submergence</td>
<td>5 m</td>
</tr>
<tr>
<td>$h$</td>
<td>Water depth</td>
<td>Deep water</td>
</tr>
<tr>
<td>$\tau_{\text{sub},1}$</td>
<td>Time constant, surge</td>
<td>1.17 s</td>
</tr>
<tr>
<td>$\tau_{\text{sub},3}$</td>
<td>Time constant, heave</td>
<td>1.17 s</td>
</tr>
<tr>
<td></td>
<td><strong>Bottom-hinged flap</strong></td>
<td></td>
</tr>
<tr>
<td>$W \times L \times H$</td>
<td>Width x Thickness x Height</td>
<td>18 m x 1.8 m x 12 m</td>
</tr>
<tr>
<td>$z_h$</td>
<td>Vertical hinge position</td>
<td>-10.5 m</td>
</tr>
<tr>
<td>$h$</td>
<td>Water depth</td>
<td>11 m</td>
</tr>
<tr>
<td>$\theta_0$</td>
<td>Equilibrium angle</td>
<td>0 and $-30^\circ$</td>
</tr>
<tr>
<td>$\tau_{0,0^\circ}$</td>
<td>Time constant, upright</td>
<td>0.58 s</td>
</tr>
<tr>
<td>$\tau_{0,30^\circ}$</td>
<td>Time constant, inclined</td>
<td>0.77 s</td>
</tr>
</tbody>
</table>

(a) Added mass.
(b) Radiation resistance.

(c) Excitation force and excitation torque coefficients.

Figure 2.2. Hydrodynamic coefficients, retrieved from Paper I: a submerged sphere; b floating sphere; c bottom-hinged flap.
2.3.3 Wave spectrum and excitation force
The excitation force and torque are computed based on the wave elevation, derived from the assumption of the JONSWAP spectrum [17]:

\[
S_J(\omega) = A_\gamma S_{PM}(\omega) \exp\left(-0.5 \left(\frac{\omega - \omega_p}{\sigma_p}\right)^2\right)
\]  

(2.18)

where \( \sigma \) is the spectral width parameter defined as \( \sigma_a = 0.07 \) for \( \omega \leq \omega_p \), and \( \sigma_b = 0.09 \) for \( \omega > \omega_p \). Moreover, \( \gamma \) is a non-dimensional shape parameter. Additionally, \( A_\gamma = 1 - 0.287 \ln(\gamma) \) is a normalizing factor, and \( S_{PM} \) is the Pierson-Moskowitz spectrum:

\[
S_{PM}(\omega) = \frac{5}{16} H_s^2 \omega_p^4 \omega^5 \exp\left(-\frac{5}{4} \frac{\omega}{\omega_p}\right).
\]  

(2.19)

Here, \( H_s \) and \( T_p \) are the significant wave height and peak period, respectively. The peak angular frequency is defined as \( \omega_p \).

Then, through the superposition of the frequency components \( \omega_i \), the excitation force (or corresponding torque) is computed as:

\[
F_{exc}(t) = \sum_i a_i \cos(\omega_i t + \angle f(\omega_i) + \phi_{i,\text{rand}})
\]  

(2.20)

\[
a_i = |f_{exc}(\omega_i)| \sqrt{2S_J(\omega_i) d\omega}
\]  

(2.21)

where the phase \( \phi_{i,\text{rand}} \) is considered as evenly distributed random data over \([0, 2\pi]\). The complex excitation force coefficient is represented by \( f_{exc}(\omega_i) \). Furthermore, \( a_i \) is the amplitude corresponding to each component of the excitation spectrum \( S_{exc}(\omega_i) = |f_{exc}(\omega_i)|^2 S_J(\omega_i) \).

2.3.4 Main variables
The information flow in the computation of the power output as a function of the prediction horizon is shown in Figure 2.3. Further, the effect of loss damping, JONSWAP shape factor, energy period, noise, constraint, and filtering are studied, see Table 2.2.

To find the characteristics of generic concepts studied here, a prediction horizon ranging from 0.0 to 15 s is considered to be sufficient. The range of loss damping is selected through educated guesses since the details of machinery conversion are not considered here. Thereby, this range has been chosen based on the hydrodynamic drag as a lower limit for the minimum expected total loss. The optimal power is obtained for the infinite range of the prediction horizon which is here considered as the maximum available time of the impulse response.

The frequency response of the optimal transfer function in Equation 2.9 with an optional filtering cf. [11, 21] by the aim of reducing the prediction
Note that some of the parameters such as estimated excitation force, $\hat{F}_{\text{exc}}(t)$ and the corresponding spectrum $\hat{S}_{\text{exc}}(\omega)$ are assumed to be known here through estimation methods such as Kalman filtering, see [18–20]. Also, careful consideration is required when adding the filtering to avoid distorting the phase of the signal.

**Figure 2.3.** Information flow depicting the course of computation in this study, retrieved from Paper I.

**Table 2.2.** Parameter studies, retrieved from Paper I.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Concept</th>
<th>Range</th>
<th>Sea state $H_s$</th>
<th>$T_e$</th>
<th>$\gamma$</th>
<th>Loss damping</th>
</tr>
</thead>
<tbody>
<tr>
<td>Loss damping</td>
<td>Floating &amp; submerged sphere</td>
<td>[5, 100] kN/m</td>
<td>2.5 m</td>
<td>6.5, 9.5, 12.5 s</td>
<td>3.3</td>
<td>-</td>
</tr>
<tr>
<td>Bottom-hinged flap</td>
<td>[2, 100] MNsm</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Shape factor</td>
<td>Floating &amp; submerged sphere</td>
<td>[1, 5], steps = 0.1</td>
<td>2.5 m</td>
<td>6.5, 9.5, 12.5 s</td>
<td>-</td>
<td>25 kN/m</td>
</tr>
<tr>
<td>Bottom-hinged flap</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>10 MNsm</td>
</tr>
<tr>
<td>Energy period</td>
<td>Floating &amp; submerged sphere</td>
<td>[3.5, 15.5], steps = 0.5 s</td>
<td>2.5 m</td>
<td>-</td>
<td>3.3</td>
<td>25 kN/m</td>
</tr>
<tr>
<td>Bottom-hinged flap</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>10 MNsm</td>
</tr>
<tr>
<td>Noise</td>
<td>Floating &amp; submerged sphere</td>
<td>5, 15, 30, 45%</td>
<td>2.5 m</td>
<td>6.5, 9.5, 12.5 s</td>
<td>3.3</td>
<td>25, 45, 65 kN/m</td>
</tr>
<tr>
<td>Bottom-hinged flap</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>10, 30, 90 MNsm</td>
</tr>
<tr>
<td>Constraint</td>
<td>Floating &amp; submerged sphere</td>
<td>±3 m</td>
<td>[0.5, 12.5], steps = 0.5 m</td>
<td>6.5, 9.5, 12.5 s</td>
<td>3.3</td>
<td>25 kN/m</td>
</tr>
<tr>
<td>Bottom-hinged flap</td>
<td>±15°</td>
<td>-</td>
<td></td>
<td></td>
<td></td>
<td>10 MNsm</td>
</tr>
<tr>
<td>Filtering</td>
<td>Floating &amp; submerged sphere</td>
<td>5, 10, 20, 30, 40, 50%</td>
<td>2.5 m</td>
<td>6.5, 9.5, 12.5 s</td>
<td>3.3</td>
<td>25 kN/m</td>
</tr>
<tr>
<td>Bottom-hinged flap</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>10 MNsm</td>
</tr>
</tbody>
</table>

The sensitivity to oscillation amplitude constraints is investigated in a simplified, sub-optimal manner. In this methodology, lower and upper amplitude requirements and non-causality of the optimal transfer function is shown in Figure 2.4. The optimal impulse response function is illustrated in Figure 2.5 which shows a faster decay to zero when increasing the damping loss.

### 2.3.5 Other variations

The sensitivity to the prediction accuracy is examined by defining a noise signal added to the excitation force. The noise signal is introduced similarly to the wave spectrum with a standard deviation of $\sigma_n/\sigma_f$ ranging from 0 to 1 with steps 0.05. The significant wave height is computed as $H_{s,n} = 4\sigma_n$ in the generation of the noise signal, while the parameters such as shape factor and energy period are kept constant.

The sensitivity to oscillation amplitude constraints is investigated in a simplified, sub-optimal manner. In this methodology, lower and upper amplitude
Figure 2.4. Sub-figures a, b, c are representing the submerged sphere, floating sphere, and bottom-hinged flap, respectively, retrieved from Paper I. The optimal transfer function between the optimal velocity and the excitation force is shown for the damping value of 25 kNs/m for the floating and submerged sphere and 10 MNms for the bottom-hinged flap. The optional filtering based on the excitation spectrum for the energy period of 6.5 s is applied. Here, the filtering limit is set to 5%. The spikes in the curves are owing to singularities in the numerical solution.
Figure 2.5. Sub-figures a, b, c are representing the submerged sphere, floating sphere, and bottom-hinged flap, respectively, retrieved from Paper I. The impulse response for the surging sphere and the upright flap for different damping is depicted. The dots represent the impulse response at time zero.
constraints of $\pm 3$ m are considered for the floating and submerged sphere, and $\pm 15^\circ$ for the bottom-hinged flap. When the position response exceeds these constraints, the velocity signal will be set to zero:

\[
V_{\text{constr}}(t) = \begin{cases} 
   V_{\text{opt}}^{T_h}(t) & |\eta_{\text{opt}}^{T_h}(t)| \leq \eta_{\text{max}} \\
   0 & \text{otherwise} 
\end{cases} 
\]

(2.22)

where $\eta_{\text{opt}}^{T_h}(t) = \int_0^t V_{\text{opt}}^{T_h}(t) dt$. This gives a similar response to an infinitely strong and rapid optimal machinery control system.

The sensitivity of the prediction requirement to the filtering of the transfer function is studied by defining a cut-off frequency for the optimal transfer function. The cut-off frequency is chosen based on cutting a percentage of the peak value of the excitation spectrum, which is called the filtering limit and varies over [5, 50]%. This technique defines the upper and lower filtering frequencies and the optimal transfer function is truncated at the largest function value between the two filtering frequencies.

Lastly, the no-prediction useful power is computed as a reference based on a constant transfer function for all generic concepts. In the computation of the transfer function, the radiation resistance is considered constant and equal to the value at which the no-prediction power is maximum.

2.3.6 Normalization

To keep the study general and easy to compare among the different generic concepts, the prediction horizon, damping losses, and useful power are normalized. The prediction horizon is normalized based on the first zero crossing of the function $K_{\text{opt}}(t)$ as $N_T = T_h/\tau_0$. Loss damping is normalized by the radiation resistance and its value at the energy period of each sea state, as $N_R = R_l/R_r(\omega_e) = R_l/R_r(2\pi/T_e)$. And, the sub-optimal power is normalized with the optimal power, as $N_P = P_u^{\text{opt}}/P^{\text{opt}}_u$, in which $P^{\text{opt}}_u$ is the optimal useful power, that is defined as $P^{\text{opt}}_u = \lim_{T_h \to \infty} P_u$.

Varying the size of the device can be seen as varying the sea state parameters which may be easier to interpret by making both sea states and hydrodynamic parameters non-dimensional. However, these parameters are kept dimensional and representative of realistic cases to ease the comprehension of the results for the sea states and bodies.

2.4 Results and discussion

2.4.1 Sensitivity of prediction horizon to loss damping

The maximum average power with ideal prediction and no-prediction is shown in Figure 2.6 for different damping levels normalized as $r_d = R_l/R_r(\omega_e)$. The
results evidence that the bottom-hinged flap shows the slowest convergence to the optimal solution in comparison with the submerged and floating sphere. The reason that the maximum power output reduces in high energy periods is the dissipative losses. Since the radiation resistance has a descending pattern in high energy periods, the relative damping \( \frac{R_l}{R_r(\omega_e)} \) increases and subsequently reduces the optimal power. The average optimal power follows a descending pattern as the relative damping increases, see Figure 2.6. An increase in the losses implies both that a large part of the absorbed power is dissipated and also the power capture itself decreases due to a reduction in optimal velocity.

Figure 2.7 illustrates the contour of the relative power for different relative damping and prediction horizons for the submerged and floating sphere, and bottom-hinged flap cases. It is shown that increasing the damping reduces the requirement for a long prediction horizon to achieve maximum power absorption. In other words, there is no advantage in predicting the incoming waves if the dissipative losses are high. Looking back to Equation 2.7, when the damping term, i.e. both radiation resistance and loss damping, is being dominated by the radiation resistance, the prediction is highly influenced by the memory effect in wave radiation, implying strong non-causality. Now, if the damping loss increases and becomes a dominant factor, the problem goes from being strongly non-causal to predominately causal. As Figure 2.7 indicates, small relative damping and short prediction horizon lead to low relative power. At high relative damping, i.e. relative damping \( \gg 1 \), the transfer function tends to a constant value, thus leading the control problem from being strongly non-causal to causal.

### 2.4.2 Sensitivity of prediction horizon to energy period

Figure 2.8 shows the sensitivity of the prediction requirement to the energy period. For all generic concepts presented here (see Figure 2.1), the relative power is low at a small energy period and a short prediction horizon. This position corresponds to the frequency range of each optimal transfer function where the radiation resistance is equal or larger than the loss damping, see Figure 2.2, and implies the importance of prediction for the sea states with a small energy period.

Furthermore, for all generic concepts, the maximum optimal power is achieved in the energy period range of [5.5, 13.5] s except the floating sphere in heave motion. In this case, the excitation magnitude reaches its maximum for long waves, also it has a slower decline of the radiation resistance in comparison with other concepts which indicates the ascending pattern of optimal power seen in Figure 2.8. It will however experience the same decline in the optimal power as other concepts but for much higher wave periods.
Figure 2.6. Maximum average power computed based on both ideal prediction and no-prediction for different damping levels for all generic concepts (see Figure 2.1), where relative damping is defined as $r_d = \frac{R_l}{R_r} (\omega_e)$, retrieved from Paper I. a-c represent the submerged sphere in surge motion, and d-f depict its heave motion. For the floating sphere, g-i show surge motion, while j-l illustrate heave motion. The bottom-hinged flap, with a zero pitch angle, is shown in m-o, and p-r represent the same flap with a -30° pitch angle. For each generic concept, each row corresponds to different energy periods: $T_e = [6.5, 9.5, 12.5]$ s, respectively.
Figure 2.7. Relative power for different prediction horizon and damping where relative damping is \( r_d = R_l/R_r(\omega_e) \), retrieved from Paper I.

a,b,c Submerged sphere in surge motion for \( T_e = [6.5, 9.5, 12.5] \) s, respectively.
d,e,f Submerged sphere in heave motion for \( T_e = [6.5, 9.5, 12.5] \) s, respectively.
g,h,i Floating sphere in surge motion for \( T_e = [6.5, 9.5, 12.5] \) s, respectively.
j,k,l Floating sphere in heave motion for \( T_e = [6.5, 9.5, 12.5] \) s, respectively.
m,n,o Bottom-hinged flap with zero pitch angle for \( T_e = [6.5, 9.5, 12.5] \) s, respectively.
p,q,r Bottom-hinged flap with -30° pitch angle for \( T_e = [6.5, 9.5, 12.5] \) s, respectively.
Figure 2.8. Sensitivity to energy period through contour plot of relative power for different lengths of prediction horizon and energy period for all concepts. Below each contour plot, a curve plot of optimal power versus energy period is shown, retrieved from Paper I. Submerge sphere for damping of 25 kNs/m for surge motion in a,b and for heave motion in c,d. Floating sphere for damping of 25 kNs/m for surge motion in e,f and for heave motion in g,h. Bottom-hinged flap with zero mean pitch angle in i,j, and bottom-hinged flap with a mean angle of -30° in k,l, for damping of 10 MNsm.
2.4.3 Sensitivity of prediction horizon to JONSWAP spectrum shape factor

The effect of different JONSWAP shape factors (i.e., a non-dimensional peak shape parameter) in the range [1, 5] is studied. No significant changes are observed in the requirement for prediction horizon for any of the generic concepts.

2.4.4 Sensitivity of prediction horizon to noise

The investigation of the effect of noisy prediction is shown in Figure 2.9. Both no-prediction and predicted relative power are reduced by increasing the noise level. Interestingly, the required prediction horizon to achieve a close-to-optimal power remains fairly constant. Note that the relative power is normalized with the predicted power with no noise. The results suggest that a noise level of up to 20% is allowed for which the optimal predicted power will not be lost for more than 10%. In a realistic situation, it is expected to have a more accurate prediction for earlier parts of the horizon which is not considered here. However, the results can be reviewed as the worst-case scenario for the uncertainty level evaluated at the end of the prediction horizon.

2.4.5 Sensitivity of prediction horizon to constraints

The sensitivity of the prediction horizon to amplitude constraint is shown in Figure 2.10 where the WEC amplitude is limited to ±3 m for the submerged and floating sphere and ±15° for the bottom-hinged flap. As it is expected, the relative power is reduced by increasing the significant wave height after the constraint is engaged, hence, the prediction horizon has less influence. Moreover, it is shown that in the longer waves, the WEC oscillation is larger, and thereby, constraints kick in for smaller wave heights. The amplitude response can be seen as the product of both the excitation spectrum and optimal transfer function. Note that the relative power is normalized with the unconstrained optimal power. The amplitude constraint studied here implies that when the constraint is engaged, the controller has to cease the motion and then release it at the right time (similar to latching-like behavior). Therefore, depending on the controller and machinery system, it might be required to predict the waves about one-half cycle ahead.

2.4.6 Sensitivity of prediction horizon to filtering

Filtering the transfer function may be one way to reduce the prediction requirement. The sensitivity of the prediction horizon requirement to the filtering limit is shown in Figure 2.11. Two main factors contribute to the sensitivity of
Figure 2.9. The effect of different noise levels is illustrated on the plot of relative power versus prediction horizon for all generic concepts. The no-prediction power is shown by circles corresponding to each noise level, retrieved from Paper I.

a,b,c Submerged sphere in surge for 25 kNs/m damping and $T_e = [6.5, 9.5, 12.5]$ s, respectively. d,e,f Submerged sphere in heave for 25 kNs/m damping and $T_e = [6.5, 9.5, 12.5]$ s, respectively. g,h,i Floating sphere in surge for 25 kNs/m damping and $T_e = [6.5, 9.5, 12.5]$ s, respectively. j,k,l Floating sphere in heave for 25 kNs/m damping and $T_e = [6.5, 9.5, 12.5]$ s, respectively. m,n,o Bottom-hinged flap with zero pitch angle for 10 MNsm damping and $T_e = [6.5, 9.5, 12.5]$ s, respectively. p,q,r Bottom-hinged flap with -30° pitch angle for 10 MNsm damping and $T_e = [6.5, 9.5, 12.5]$ s, respectively.
Figure 2.10. Contour plot of amplitude constraint is shown through relative power as a function of prediction horizon and significant wave height when amplitude constraints are applied, retrieved from Paper I.

a,b,c Submerged sphere in surge for damping of 25 kNs/m and $T_e = [6.5, 9.5, 12.5]$ s, respectively.

d,e,f Submerged sphere in heave for damping of 25 kNs/m and $T_e = [6.5, 9.5, 12.5]$ s, respectively.

g,h,i Floating sphere in surge for damping of 25 kNs/m and $T_e = [6.5, 9.5, 12.5]$ s, respectively.

j,k,l Floating sphere in heave for damping of 25 kNs/m and $T_e = [6.5, 9.5, 12.5]$ s, respectively.

m,n,o Bottom-hinged flap with zero pitch angle for damping of 10 MNsm and $T_e = [6.5, 9.5, 12.5]$ s, respectively.

p,q,r Bottom-hinged flap with -30 pitch angle for damping of 10 MNsm and $T_e = [6.5, 9.5, 12.5]$ s, respectively.
the prediction horizon to the filtering limit: First, the position of cut-off frequencies on optimal transfer function, and second, the shape of the excitation spectrum. When the cut-off frequencies are located on the slope of the transfer function, high sensitivity can be seen. For instance, for submerged spheres both in heave and surge motion and for $T_e = 12.5$ s, these cut-off frequencies are placed on the non-steep beginning of the optimal transfer function which leads to insensitivity to the filtering limit. When the spectrum is steep, the cut-off frequencies change insignificantly for different filtering limits, and therefore the filtering has a small contribution. This effect may be seen in the bottom-hinged flap in high wave periods. Note that the relative power is normalized based on the optimal power with an unfiltered transfer function. Filtering of the transfer function shows promising results in improving the performance for some of the wave conditions when the prediction horizon is limited and the excitation spectrum is centered around the sloping frequency of the optimal transfer function. However, solely filtering cannot warrant the performance being close to the maximum absorption. Interesting to note that filtering of the transfer function and increased level of dissipative losses have a similar effect and both reduce the prediction requirement by reducing the variation of the transfer function.

2.4.7 Implementation in a real WEC system

In non-causality of the optimal velocity, the first frequency characteristic is a dominant factor, as also is discussed in [12]. In other words, to achieve a certain level of power output in different sea states, almost the same prediction horizon is required. The first frequency characteristic corresponds to the first zero-crossing of the impulse response. A small frequency characteristic leads to $k_{opt}(t)$ slowly approaching zero, and thereby, puts more demanding requirements on the prediction horizon to obtain the same relative power. Furthermore, if the prediction horizon is larger than the first zero-crossing of the impulse response in the time domain, the extra predicted information is not being used since the function value in Equation 2.9 will be nearly zero.

Dissipative losses push the maximum power down the curve as shown in Figure 2.6, even if optimum control and unconstrained motion are considered. Although this work suggests a modest prediction horizon is sufficient overall, the maximum achievable power is considerably smaller than what is usually quoted as the maximum power for a wave energy converter. Hence, it is essential to accurately identify the dissipative losses to assess the expected power output for a wave energy converter realistically.

In this study, the analysis focuses on idealized cases of WEC operation in one degree of freedom. Although realistic situations involve multiple degrees of freedom, the obtained results remain valid for each rigid-body mode. The
Figure 2.11. The effect of filtering of the transfer function for the range 5% to 50% is shown for relative power versus prediction horizon plots, retrieved from Paper I. 
a,b,c Submerged sphere in surge for damping of 25 kN/m and \( T_e = [6.5, 9.5, 12.5] \) s, respectively. 
d,e,f Submerged sphere in heave for damping of 25 kN/m and \( T_e = [6.5, 9.5, 12.5] \) s, respectively. 
g,h,i Floating sphere in surge for damping of 25 kN/m and \( T_e = [6.5, 9.5, 12.5] \) s, respectively. 
j,k,l Floating sphere in heave for damping of 25 kN/m and \( T_e = [6.5, 9.5, 12.5] \) s, respectively. 
m,n,o Bottom-hinged flap with zero pitch angle for damping of 10 MNsm and \( T_e = [6.5, 9.5, 12.5] \) s, respectively. 
p,q,r Bottom-hinged flap with -30° pitch angle for damping of 10 MNsm and \( T_e = [6.5, 9.5, 12.5] \) s, respectively.
controller system effectively combines excitation and radiation in both modes, accounting for dissipative losses to address the problem comprehensively.

Here, the system is fully linearised, while a real system may have some important non-linearities. This may lead to the requirement for longer prediction over the next half a wave cycle or so to obtain the optimal power.

The prediction requirement might be influenced by other control objectives such as load mitigation, minimized power fluctuations, or production-on-demand. The prediction requirement is still expected to be, at maximum, close to half a wave cycle. The machinery control system may use the computation performed here as an input with a reference-following approach, as shown in [12].

2.5 Summary of the results

The maximum power output from wave energy converters versus prediction horizon is investigated for different levels of dissipative losses as well as other parameters such as spectrum shape, energy period, prediction accuracy, amplitude constraint, and filtering of the transfer function for optimal velocity. Three different generic concepts and modes of motion are considered as: a submerged and a floating sphere oscillating in surge and heave motion, and a bottom-hinged flap oscillating about a mean position of 0 or -30°. Throughout this work, the assumption of linear behavior is taken.

The results indicate that a high level of dissipative losses, such as machinery losses and hydrodynamic drag, will minimize the need for prediction. Through realistic assumptions of dissipative losses and under no amplitude constraints, the prediction of a few seconds to half a wave period is rather sufficient to reach the maximum power output. When a limited prediction horizon is available, filtering of the transfer function significantly improves the power conversion for most of the sea states as suggested also in [12]. The noise sensitivity study shows that only 10% power output reduction is seen for about 20% noise level of the wave excitation force. The prediction of the excitation force is less advantageous as the system is more constrained, or the larger the significant wave height is.

The presented results here are still expected to be qualitatively valid for real systems with more control objectives, non-linear losses, and various constraints. Therefore, it is anticipated that wave forces should be predicted about half a wave cycle ahead considering the complexity of real systems. The results show that the prediction horizon required for maximal power output is much shorter than what is usually assumed, which can be of great importance for wave energy development.
3. Part II: Extreme load analysis

3.1 Background
To minimize the destructive impact on wave energy converters during extreme wave conditions, comprehending the dynamics and forces of the system is of significant importance. Extreme waves often involve strong nonlinearities, such as wave breaking [22], overtopping [23], and slamming [24], which pose challenges to describe them mathematically.

The effect of extreme waves has been investigated by several researchers using experimental and numerical analyses. For instance, Göteman et al [25] and Sjökvist et al [26] found that increasing damping leads to a reduction in peak line forces. Hann et al [27] studied the influence of wave steepness using non-breaking focused waves and the location of wave breaking on the mooring. Their conclusion was that mooring loads are primarily affected by the location of wave breaking rather than wave steepness. In a different context, Ropero-Giralda et al [28] deduced that submerging the device during extreme events alleviates loads on the structure. Additionally, Katsidoniotaki et al [29] delved into the impact of extreme sea states with a 50-year return period on a point-absorbing device. They assessed the effects of wave breaking, slamming, and wave steepness for focused waves through numerical simulations. Their findings underscored the substantial influence of high waves on generating elevated forces.

Part II delves into the response of the point absorber wave energy converter (WEC) under extreme sea states with a 50-year return period. For this purpose, a carefully designed 1:30 scaled wave tank experiment is conducted. The following sections outline the wave tank’s experimental setup, covering aspects from buoy design, power take-off (PTO), and measurement systems to the selection of sea states. Subsequently, the experimental data is utilized to calibrate the numerical WEC-Sim (Wave Energy Converter SIMulator) model, further enhancing the dataset for subsequent assessment of system reliability and survivability. As such, the construction of the numerical model is also explained in detail.

3.2 Wave tank experiment methodology
To evaluate the dynamics of a point absorber WEC during extreme wave conditions, a 1:30 scaled wave tank experiment is conducted in the Ocean and Coastal Engineering Laboratory of Aalborg University. The scaled experimental setup is modeled after the full-scale Uppsala University WEC [30].
Utilizing the Froude-scaling law, the scaled parameters are established. The choice of a 1:30 scale reflects a compromise, seeking a size large enough to replicate a realistic system while remaining small enough to generate extreme waves typical of the North Sea wave climate within the limitations of the wave tank. The wave tank experiment setup comprises a linear friction power take-off (PTO), an aluminum buoy with a cylindrical shape featuring an ellipsoidal bottom, and three pulleys. These pulleys connect the buoy in the wave tank to the PTO on the gantry using a 3 mm Dyneema rope, see Figure 3.1. The water depth of $0.73 \pm 0.02$ m is considered.

![Figure 3.1. Schematic of wave tank experiment, retrieved from Paper VII.](image)

### 3.2.1 Power take-off

For the purpose of this experiment, three different power take-off systems are designed, out of which two are based on eddy current braking damping and the last one has friction-based damping, see Figure 3.2.

The eddy current-based linear PTO consists of a steel rod that moves vertically between two electromagnets, while the eddy current-based rotary PTO consists of an aluminum disc that rotates in a magnetic field. The electromagnets are controlled by varying the coil current ranging from 0.2-1.4 A, where the maximum range of 800 and 1200 turns are considered for the linear and the rotary eddy current-based PTOs, respectively. Taking the eddy current-based rotary PTO as an example, the rotating disk creates eddy currents on the disk which leads to a repulsive (Lorentz) force between the disk and the coil [31]. According to the Lorentz force, the eddy currents on the disk are proportional to the magnetic field’s tangential velocity and magnitude. It must be noted that due to the ferromagnetic properties of the steel rod in the eddy current-based linear PTO, a temporal magnet is formed between the rod and one pole of the coil which resulted in pure friction in the movement of the rod instead.
To assess the appropriateness of the eddy current-based PTOs, a set of dry testing experiments is performed in which the attached weight connected to each PTO varies, as shown in Figure 3.3. Again, considering the eddy current-based rotary PTO as an example, heavier attached weight in the presence of a near-constant eddy current braking force has a greater speed of drop, while lighter attached weights imply the domination of the friction force in the bearings in comparison to the gravity. Increasing the number of magnet pairs can be one way to increase this value. Analysis of the B-H curve indicates that increasing the number of windings on coil cores is unlikely to have a significant impact on eddy current in both linear and rotary PTOs, as magnetic saturation points are reached. Furthermore, studying the B-H curve for different alloy types suggests that altering the alloy type does not substantially shift the saturation point, affecting the desired damping effect. While larger coils may slightly delay saturation, it is noteworthy that magnetic saturation remains independent of the geometry [32].

To investigate the effect of damping across the entire range from zero to infinity, the linear friction damping PTO shown in Figure 3.2 (c) is designed and utilized to fulfill the aim of this experiment. This PTO consists of a Teflon block rubbing against an aluminum rod and a pretension spring module for applying constant friction damping. To achieve smooth and robust movement with minimal vibration, the aluminum rod is connected to a linear guide.

Various configurations of PTO damping are examined including three constant sliding-friction damping forces: $F_{D_0} \approx 0 \text{ N}$, $F_{D_1} \approx 7.4 \text{ N}$, and $F_{D_2} \approx 18.9 \text{ N}$. These cases are referred to as $D_0$, $D_1$, and $D_2$ damping configurations, respectively. The fourth configuration involved an infinite damping coefficient case. For zero and infinite damping configurations, the linear guide is removed and substituted by a rod and attached weight equal to the mass of the PTO. Then, the infinite damping coefficient case is obtained by locking the rod at
(a) The friction force versus the coil current for the eddy current linear PTO.

(b) The friction force versus the mass of attached weight for the eddy current linear PTO.
(c) The damping coefficient versus the coil current for the eddy current rotary PTO.

(d) The damping coefficient versus the mass of attached weight for the eddy current rotary PTO.  
*Figure 3.3.* The results of the dry testing for the 1:30 scaled eddy current PTOs, retrieved from Paper III, are shown.
the equilibrium position (here is also referred to as locked PTO case), while in
the zero damping case free movement of the rod is allowed. Note that the zero
damping configuration refers to the PTO’s zero damping while all other friction
sources such as pulleys are inherent in the system. The PTO mass is 2.138 ± 0.001 kg including the load cell, loop, and turnbuckle.

Only the upper end-stop is considered as a constraint for translator motion, and there is no lower end-stop. The end-stop spring is characterized by a spring coefficient of 5.9 N/mm, with uncompressed and compressed lengths of 60 mm and 28 mm, respectively. A stroke length of 220 mm is chosen to assess the effect of end-stop spring compression.

3.2.2 Buoy

An aluminum cylindrical buoy with an ellipsoidal bottom and a scale of 1:30 is designed with a diameter and height of 330 mm and 380 mm, respectively, see Figure 3.4. The buoy’s draft is 230 mm with a mass of 15.73 ± 0.001 kg. The center of gravity with respect to the origin located at the bottom center of the buoy with the z-axis pointing in the upright direction, and measured from SolidWorks is: \((x_{CG}, y_{CG}, z_{CG}) = (0, 0, 118.6)\) mm. The moment of inertia with respect to the coordinate system with the same orientation but placed at CG, measured from SolidWorks is: \((I_{xx}, I_{yy}, I_{zz}) = (0.3537, 0.3536, 0.2918)\) kgm\(^2\). Out of three pulleys that connect the buoy to the gantry, two are at the wave basin and one is at the gantry.

Figure 3.4. The buoy in scale 1:30 where 3D and section views are shown in (a) and (b), respectively, retrieved from Paper V.
3.2.3 Measurement systems

A draw wire position sensor is used to measure the position of the PTO translator, while the Qualisys system [33] tracks the buoy motion in six degrees of freedom using four cameras. Two load cells with a mass of 150 g collect the force data at the buoy and PTO side. Eight wave gauges are installed to measure the surface elevation, see Figure 3.5. The load cell data and position sensor readings are logged using two seven-gram SG-Link-200-OEM units communicating via radio frequency, in conjunction with a LORD sensing WSDA gateway that ensures 50 μs node synchronization.

![Figure 3.5](image)

Figure 3.5. Illustrates the dimensions of the wave tank and the configuration of wave gauges (in millimeters) during the wave calibration in the empty tank, excluding the PTO and buoy. Subsequently, the buoy is situated at the location of wave gauge 8 after calibration. A strategic location for the buoy is determined, taking into account the wave tank dimensions, with a focus on both wave development and minimizing the impact of wall reflections on the buoy’s dynamics, retrieved from Paper IV.

Measurement system uncertainties

To calculate the PTO friction damping forces of 7.4 N and 18.9 N, a two-step process involving double differentiation of displacement is employed to obtain acceleration, which is then used to compute the friction force. However, this process introduces noise and uncertainty due to the derivation and subsequent low-pass filtering of the data. The same filtering uncertainties are observed in the line force data collected by the load cell. While the nature of these uncertainties is understood, accurately quantifying them is challenging due to their dependence on both filtering characteristics and measurement errors.
Note that the Qualisys system may have missing data points lasting a few milliseconds, and the cause of these data gaps could be attributed to either waves overtopping the buoy or deficiencies in the Qualisys camera.

A summary of the experimental setup features and measurement properties is given in Table 3.1.

Table 3.1. Experimental setup properties, retrieved from Paper IV.

<table>
<thead>
<tr>
<th>Description</th>
<th>Value</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>PTO</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mass</td>
<td>2.138 ± 0.001</td>
<td>kg</td>
</tr>
<tr>
<td>Stroke length</td>
<td>220</td>
<td>mm</td>
</tr>
<tr>
<td>End-stop spring coefficient</td>
<td>5.9</td>
<td>N/mm</td>
</tr>
<tr>
<td>End-stop spring uncompressed</td>
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<td>mm</td>
</tr>
<tr>
<td>End-stop spring compressed</td>
<td>28</td>
<td>mm</td>
</tr>
<tr>
<td><strong>Buoy</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mass</td>
<td>15.73 ± 0.001</td>
<td>kg</td>
</tr>
<tr>
<td>Diameter</td>
<td>330</td>
<td>mm</td>
</tr>
<tr>
<td>Height</td>
<td>380</td>
<td>mm</td>
</tr>
<tr>
<td>Draft</td>
<td>230</td>
<td>mm</td>
</tr>
<tr>
<td>Center of gravity ((x_{CG}, y_{CG}, z_{CG}))</td>
<td>(0 \times 0 \times 118.6)</td>
<td>mm</td>
</tr>
<tr>
<td>Moment of inertia ((I_{xx}, I_{yy}, I_{zz}))</td>
<td>(0.3537 \times 0.3536 \times 0.2918)</td>
<td>kgm²</td>
</tr>
<tr>
<td><strong>Wave tank</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Dimension(^a)</td>
<td>13 × 8 × 1.5</td>
<td>m</td>
</tr>
<tr>
<td>Buoy’s position from wave maker</td>
<td>4.819</td>
<td>m</td>
</tr>
<tr>
<td>Buoy’s position from side walls</td>
<td>6.477, 6.54</td>
<td>m</td>
</tr>
<tr>
<td>Water depth</td>
<td>0.73 ± 0.02</td>
<td>m</td>
</tr>
<tr>
<td><strong>Sensors</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Position sensor measurement range</td>
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<td>mm</td>
</tr>
<tr>
<td>Load cell capacity</td>
<td>2000</td>
<td>N</td>
</tr>
<tr>
<td>Qualisys(^b)</td>
<td>4 cameras</td>
<td>-</td>
</tr>
<tr>
<td>Wave gauges(^c)</td>
<td>8 probes</td>
<td>-</td>
</tr>
</tbody>
</table>

\(^a\) Dimension of active test area: length × width × depth
\(^b\) Qualisys has a sampling rate of 300 Hz.
\(^c\) Wave gauges and data acquisition have a sampling rate of 256 Hz.

3.2.4 Environmental contour and sea states

Sea states are selected from an environmental contour constructed using the I-FORM hybrid method, featuring a 50-year return period for the Dowsing site located 56 km from the east coast of the United Kingdom in the North Sea (refer to Figure 3.6).

The summarized overview of the I-FORM hybrid method, as previously detailed in [34], can be outlined as follows: Assuming the short-term extreme sea conditions, characterized by the significant wave height \((H_s)\) and peak period \((T_p)\), are known, a joint probability density function (PDF) can be employed to infer the long-term extreme sea conditions [36–39]:

\[
p_{H_s,T_p}(h_s,t_p) = p_{H_s}(h_s)p_{T_p|H_s}(t_p|h_s)
\]  

(3.1)
Observations: Dowsing

Figure 3.6. The 50-year environmental contour for the Dowsing site in the North Sea, based on the I-FORM hybrid method [34] is depicted for a full-scale system. The experimental setup includes seven circles that symbolize the chosen sea states for this study. The axes of the graph display the peak period ($T_p$) and significant wave height ($H_s$), adapted from [35].

Here, $h_s$ and $t_p$ denote specific values of $H_s$ and $T_p$ respectively. It is worth noting that within Equation 3.1, the inclusion of either the zero-crossing period ($T_z$), energy period ($T_e$), or peak period ($T_p$) is permissible. The process of calculating Equation 3.1 can be deconstructed into the subsequent stages:

i. Compute the marginal probability density function of $H_s$ using the hybrid model as [36]:

$$p_{H_s}(h_s) = \begin{cases} \frac{1}{\sqrt{2\pi h_s}b} \exp\left\{ -\frac{(\ln h_s - \hat{a})^2}{2b^2} \right\}, & \text{for } h_s \leq \eta \\ \frac{\hat{d}}{\hat{c}} \left( \frac{h_s}{\hat{c}} \right)^{d-1} \exp\left\{ -\left( \frac{h_s}{\hat{c}} \right)^d \right\}, & \text{for } h_s > \eta \end{cases}$$ (3.2)

where $\eta$ is referred to as the threshold or transition point. Initially, a log-normal distribution is employed to model all observations of $H_s$ where $h_s \leq \eta$. The parameters $\hat{a}$ and $\hat{b}$ correspond to the mean and variance of the variable $\ln h_s$, respectively. Subsequently, the shape parameter $\hat{d}$ and the scale parameter $\hat{c}$ of the Weibull tail distribution are determined in such a way that they ensure the hybrid model maintains continuity in both density and distribution functions at $h_s = \eta$. Attaining a suitable fit for the most extreme $H_s$ values is of significance. To address this, [34] considered solely the upper 10% of the $H_s$ data to establish the threshold $\eta$. They indicated that the Cramér–von Mises goodness-of-fit (GOF) metric was utilized to determine the value of $\eta$ by examining only this upper 10% segment of the $H_s$ data.
ii. Derive the conditional marginal probability density function of $T_p$ given $H_s$ using a log-normal model, expressed as [37, 39]:

$$p_{T_p|H_s}(t_p|h_s) = \frac{1}{\sqrt{2\pi}\sigma(h_s)t_p} \exp\left\{ -\frac{(\ln t_p - \mu(h_s))^2}{2\sigma(h_s)^2} \right\}$$  \hspace{1cm} (3.3)

where $\sigma(h_s)$ and $\mu(h_s)$ represent the conditional standard deviation and mean of the variable $\ln t_p$ given $h_s$, respectively. To extrapolate the data beyond the observed range, a smoothed function is applied to the parameters $\sigma(h_s)$ and $\mu(h_s)$, analogous to the approach detailed in equations (7) and (8) in [37]:

$$\mu(h_s) = a_0 + a_1 h_s^2$$  \hspace{1cm} (3.4)

$$\sigma(h_s)^2 = b_0 + b_1 \exp\{-b_2 h_s\}.$$  

An approach to determine the values of $a_0, a_1, a_2, b_0, b_1, b_2$ involves segmenting the $H_s$ data into bins, fitting a log-normal distribution to the $T_p$ data within each bin to acquire $\mu(h_s)$ and $\sigma(h_s)$, and subsequently estimating these parameters by employing curve fitting with the computed $\mu(h_s)$ and $\sigma(h_s)$ values across different $h_s$ values.

iii. Utilize the Rosenblatt transformation scheme [40, 41] to convert the cumulative distribution functions (CDF) into a u-space defined by uncorrelated standard Gaussian variables, denoted as $U_1$ and $U_2$:

$$P_{H_s}(h_s) = \Phi(u_1)$$

$$P_{T_p|H_s}(t_p|h_s) = \Phi(u_2)$$

where $\Phi(\cdot)$ stands for the standard Gaussian cumulative distribution function. Following this transformation, the correlation between $H_s$ and $T_p$ is removed.

iv. Define the 50-year contour line within the u-space by tracing the circumference of the circle described by $\beta = \sqrt{U_1^2 + U_2^2}$, where $\beta$ signifies the circle’s radius, and it can be computed as [39]:

$$\beta = \Phi^{-1}\left(1 - \frac{T_{ss}}{8760 T_r}\right)$$  \hspace{1cm} (3.6)

where $T_r$ and $T_{ss}$ are the return period and sea state duration, respectively. The sea state duration ($T_{ss}$) of one hour is considered to construct the environmental contour here. To achieve a satisfactory environmental contour, a common practice involved inflating the circle, with the aim of compensating for the approximation of the true stochastic response using its median value, as detailed in [39]: $\beta^* = \beta / \sqrt{1 - \alpha^2}$. Here, the value of $\alpha^2$ typically falls within the range of 0.1 to 0.2. In pursuit of more accurate environmental contours, different alternatives can now be
employed, including the adjustment of median response or the consideration of a higher percentile of $H_s$ data to establish the threshold value, as demonstrated in the case of the hybrid model outlined by [34] and detailed in Equation 3.2. As a result, the hybrid model introduced by [34] and applied here does not involve any inflation rate.

v. Transfer the standard Gaussian variables, $U_1$ and $U_2$, to their corresponding $H_s$ and $T_p$ values in order to construct the 50-year environmental contour using the original coordinates:

\begin{align*}
    h_s &= P_{H_s}^{-1}(\Phi(u_1)) \\
    t_p &= P_{T_p|H_s}^{-1}(\Phi(u_2)|H_s = h_s).
\end{align*}

The dataset for plotting the environmental contour is drawn from 15.4 years of observations spanning from 2003 to 2019, utilizing a network of wave buoy measurements (WaveNet [42]) positioned along the UK coastline [34]. It is worth noting that a 15.4-year observational dataset might be relatively brief for constructing a 50-year environmental contour. In extreme value analysis, such as fitting a generalized extreme value model (GEV) using annual maxima, it is more common to derive return levels based on roughly twice the length of the available data. However, very few observational sites have around 25 years of data, and wave-modeled datasets often fall short of replicating all aspects of observations accurately enough to serve as a substitute for direct observations.

**Wave type representation**

The input to the wavemaker is three wave-type representations (i.e. regular, irregular, and focused waves) of sea states shown by red circles in Figure 3.6.

The irregular waves are generated based on the JONSWAP spectrum, as described previously in Equation 2.18 on the basis of the Pierson-Moskowitz spectrum as outlined in Equation 2.19.

The equivalent regular waves is determined as $T = T_z$ and $H = 1.9H_s$ in which $T$ and $T_z$ are the wave and zero-up crossing periods and $H$ is the wave height. The value 1.9 comes from the presumption that the wave height follows Rayleigh distribution during extreme wave conditions [17, 29, 43].

The equivalent focused waves are generated based on the Gaussian wave packet [44] as:

\[ \eta_G(x,t) = \int_{-\infty}^{\infty} S_G(k) \exp(i(kx - \omega t))dk \]  

where $k$ is the wavenumber. The focusing time and focusing position are represented as $x$ and $t$, respectively, and $S_G(k)$ is the Gaussian shape amplitude spectrum defined as:

\[ S_G(k) = \frac{A_0}{\epsilon \sqrt{2\pi}} \exp[-(k - k_0)^2/2\epsilon^2]. \]
The amplitude crest, \( A_0 = \sqrt{2m_0 \ln(n)} \), is computed based on the largest amplitude expected in \( n = 1000 \) waves in a 3-hour sea state [27, 29, 35]. The standard deviation of the Gaussian amplitude spectrum, \( \varepsilon \), is also referred to as the bandwidth parameter or form factor.

The wave steepness for irregular, focused, and regular waves is presented as \( k_p H_s/2, k_p A_0 \), and \( H/L \), respectively where \( k_p \) is the wavenumber at the peak frequency and \( L \) is the wavelength. Note that identifying the irregular wave’s steepness is somewhat difficult. Hence, \( k_p H_s/2 \) is introduced as an indicative parameter for the steepness of the irregular waves similar to [45].

The sea state information for all three wave-type representations is summarized in Table 3.2.

### Table 3.2. Summary of sea state information, retrieved from Paper IV.

<table>
<thead>
<tr>
<th>Sea state</th>
<th>( H_s ) [m]</th>
<th>( T_p ) [s]</th>
<th>( k_p H_s/2 ) [-]</th>
<th>( A_0 ) [m]</th>
<th>( k_p A_0 ) [-]</th>
<th>( \varepsilon ) [1/m]</th>
<th>( H ) [m]</th>
<th>( T ) [s]</th>
<th>( H/L ) [-]</th>
</tr>
</thead>
<tbody>
<tr>
<td>S5a</td>
<td>0.18</td>
<td>1.64</td>
<td>0.1572</td>
<td>0.1700</td>
<td>0.2969</td>
<td>0.720</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>S5b</td>
<td>0.12</td>
<td>1.64</td>
<td>0.1048</td>
<td>0.1150</td>
<td>0.2009</td>
<td>0.700</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>S5c</td>
<td>0.07</td>
<td>1.64</td>
<td>0.0611</td>
<td>0.0682</td>
<td>0.1191</td>
<td>0.700</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>S6</td>
<td>0.22</td>
<td>2.10</td>
<td>0.1382</td>
<td>0.1700</td>
<td>0.2135</td>
<td>0.530</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>S8</td>
<td>0.18</td>
<td>2.56</td>
<td>0.0891</td>
<td>0.1500</td>
<td>0.1485</td>
<td>0.400</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>S9</td>
<td>0.12</td>
<td>3.20</td>
<td>0.0461</td>
<td>0.1150</td>
<td>0.0885</td>
<td>0.327</td>
<td>0.2223</td>
<td>1.52</td>
<td>0.0691</td>
</tr>
<tr>
<td>S10</td>
<td>0.07</td>
<td>4.29</td>
<td>0.0196</td>
<td>0.0682</td>
<td>0.0383</td>
<td>0.230</td>
<td>0.1143</td>
<td>1.52</td>
<td>0.0356</td>
</tr>
</tbody>
</table>

### Wave calibration

The runtime for focused, regular, and irregular waves is 1.0, 3.0, and 10 minutes, respectively. The wave calibration for all three wave representations is shown in Figure 3.7 and Figure 3.8. The discrepancies observed at the trough between analytical and experimental data for regular waves, as depicted in Figure 3.7 (b), can be attributed to factors such as wave steepness, wave tank dimensions, and the influence of intermediate water depth (\( h \)). Intermediate waves are characterized by a water depth-to-wavelength ratio falling within the range of \( 1/20 < h/L < 1/2 \), where \( L \) represents wavelength and \( h \) denotes water depth. Specifically, intermediate waves are affected by the wave tank bed. Consequently, wave celerity depends on both water depth and wavelength [46]. It is noteworthy that for irregular and focused waves, the wavelength estimation can be determined based on the peak period and designated as \( L_p \). In Figure 3.8, a simple comparison is made between the generation of focused waves with both the Gaussian wave packet, i.e. used in this experiment, and the NewWave theory [47]. The focused waves of sea states S5a, S5b, S5c, and 10 show similarity when synthesized from the Gaussian wave packet compared to the generated ones from the NewWave theory. To allow full development of the waves in the wave tank, the first 50 seconds of all data for regular and irregular waves are disregarded.
Figure 3.7. Comparison of the experimental and analytical data. In (a), the comparison of $H_s$ and $T_p$ for the experimental and analytical data is shown. In (b), the comparison of the regular waves for sea states 9 and 10 is presented through $a$ and $b$, respectively. Both (a) and (b) are retrieved from Paper IV.
3.2.5 Extreme nonlinear phenomena

Throughout the experiment, several nonlinear phenomena were observed, including wave breaking, wave breaking slamming, and overtopping. The dominance of one phenomenon over another depended on the damping configuration of the system. For instance, overtopping was more prominent when the movement of the WEC was more restricted due to larger damping. Conversely, wave-breaking slamming was more frequently observed with lower damping, resulting in frequent compression of the end-stop spring. The following explains the nonlinear phenomena encountered during the wave tanks experiment:

Wave breaking occurs when the water particles’ velocity at the wave crest exceeds a limit that is determined by the most energetic waves in a specific water depth and wavelength [48]. Wave breaking is a highly nonlinear phenomenon that contains large turbulent kinetic energy, thereby inducing massive loads on marine devices. Breaking criteria [49–53] may be used to identify whether waves in a particular sea state break.

Overtopping is a nonlinear phenomenon that depends on both wave height and wave period [23]. Typically, it occurs when a wave with a substantial
height exceeds the top surface of the device, inducing high loads on the structure as a result.

Slamming (water impact) is another nonlinear phenomenon that is caused by sudden high water pressure on the device within a short time interval (ms). Bottom slamming and wave-breaking slamming are the two main categories in studying this nonlinear phenomenon for point-absorbing devices. Bottom slamming \cite{54–56} occurs when a device is subjected to a high water impact at the bottom due to dropping after being lifted above the water surface. The horizontal impact of the bulk of water with a high relative velocity between the body and wave crest results in wave-breaking slamming. For a floating slender body, the horizontal force due to the wave breaking has the main contribution from a combination of drag, inertia, and slamming forces. For non-slender bodies, i.e. the diameter of the floater is significant in comparison to the wavelength, the wave radiation damping and diffraction forces should be considered for a more accurate assessment of the wave impact \cite{57}. The contribution of each force can be given as: drag and slamming have quadratic relation with the relative velocity between the body and wave crest, and inertia is proportional to the relative acceleration between water and the body. The Morison equation \cite{58} is usually used to quantify the quasi-static forces, i.e. inertia and drag, and slamming force is typically derived from Wagner’s theory \cite{59}. Only wave braking (horizontal) slamming is observed during the wave tank experiment.

### 3.3 Numerical WEC-Sim model methodology

The WEC-Sim model \cite{60} comprises a buoy that is meshed using Rhino software \cite{61} and incorporates a series of three interconnected one-degree-of-freedom (1-DoF) WEC-Sim power take-offs to replicate the movement of the buoy in heave, surge, and pitch. Note that the physical PTO in the experimental setup is a linear friction-damping PTO that solely moves vertically (1-DoF). Conversely, the WEC-Sim model’s three PTOs are virtual simulation components designed not only to constrain the buoy’s motion across all three degrees of freedom but also to provide feedback and actuation forces, see Figure 3.9.

#### 3.3.1 Weakly nonlinear effects

To capture weakly nonlinear buoy dynamics, nlHydro = 2 is used in the WEC-Sim input file. This setting considers nonlinear buoyancy and Froude–Krylov forces \cite{62} and integrates pressure resulting from the instantaneous wave elevation and the buoy’s position. This approach improves the equation of motion’s accuracy by discarding the constant buoyancy assumption.
Figure 3.9. The WEC-Sim model illustrates the buoy and the interconnected series of three WEC-Sim PTOs, retrieved from Paper V.
3.3.2 Drag coefficients and force

The drag coefficient in heave is calculated by curve fitting the experimental decay test to the numerical results from WEC-Sim using the least squares method. To obtain the surge drag coefficient, the response amplitude operator (RAO) computed from WEC-Sim is tuned to align with the experimental RAO. For the pitch drag coefficient, the calibration process involves adjusting the buoy motion simulated in WEC-Sim using the least square methods where the experimental data captured by the Qualisys camera in regular waves serves as a benchmark for this process.

3.3.3 WEC-Sim line force

The line force in WEC-Sim is derived from the equation of motion in vector form by looking at the PTO from the buoy side:

\[ m_{PTO} \ddot{z}_{PTO} = F_{\text{line}} + F_{\text{endstop}} + F_{f_{PTO}} + F_{f_{p}} + m_{PTO} g \]  \hspace{1cm} (3.10)

where the total translator mass including its attachment is denoted as \( m_{PTO} \). The PTO, end-stop spring, and pulley friction forces are nominated as \( F_{f_{PTO}} \), \( F_{\text{endstop}} \), and \( F_{f_{p}} \), respectively. Moreover, the gravitational and PTO accelerations are \( \ddot{z}_{PTO} \) and \( g \), respectively. The WEC-Sim PTO blocks’ force actuation is determined by \( F_{\text{line}} \) and the instantaneous position of the buoy, as illustrated in Figure 3.10.

Subsequently, in accordance with the representation in Figure 3.10, the calculations for surge force \( (F_{\text{surf}}) \), heave force \( (F_{\text{heave}}) \), and pitch moment \( (M_{\text{pitch}}) \) are performed using the following formulae:

\[ F_{\text{surf}} = -F_{\text{line}} \sin(\theta + \phi) \]  \hspace{1cm} (3.11)
\[ F_{\text{heave}} = -F_{\text{line}} \cos(\theta + \phi) \]
\[ M_{\text{pitch}} = -F_{\text{surf}}L_0 \cos(h_5) + F_{\text{heave}}L_0 \sin(h_5) \]

where \( h_5 \) is the pitch angle, and \( \theta \), \( \phi \), and \( R_2 \) that are shown in Figure 3.10 are obtained as:

\[ \theta = \tan^{-1}\left(\frac{h_1}{L_1 + h_3}\right) \]  \hspace{1cm} (3.12)
\[ \phi = \sin^{-1}\left(\frac{L_0 \sin(\theta - h_5)}{R_2}\right) \]
\[ R_2^2 = L_2^2 + L_0^2 - 2L_0L_2 \cos(\theta - h_5) \]

3.3.4 WEC-Sim PTO friction model

The WEC-Sim PTO friction force as described in Equation 3.10, is simulated by incorporating static friction components including Strubeck and Coulomb...
forces, both dependent on the relative velocity \([63]\):

\[
F_{fPTO} = \sqrt{2e} (F_{brk} - F_{CPTO}) \exp \left( - \frac{\dot{z}_{PTO}}{v_{St}} \right) \frac{\dot{z}_{PTO}}{v_{St}}^2 + F_{CPTO} \tanh \left( \frac{\dot{z}_{PTO}}{v_{Coul}} \right)
\]  

(3.13)

where the breakaway friction and Coulomb forces are \(F_{brk}\) and \(F_{CPTO}\), respectively. Furthermore, the Stribeck velocity is \(v_{St} = v_{brk} \sqrt{2}\), and the Coulomb velocity threshold is \(v_{Coul} = v_{brk}/10\) in which \(v_{brk}\) is the breakaway friction velocity. Moreover, the relative velocity is \(\dot{z}_{PTO}\), and \(e\) is the Euler’s number. Since the contact surface between Teflon and Aluminum is dry, the viscous friction is considered zero. Figure 3.11 demonstrates each frictional component that constitutes the friction model used here. Stribeck and Coulomb frictions combine at zero velocity to form the breakaway friction. Coulomb friction opposes motion consistently, while Stribeck friction shows a negative slope at low velocities.

3.3.5 WEC-Sim pulley friction model

The pulley friction is represented solely by the Coulomb component, which is dependent on the relative velocity:

\[
F_{fp} = F_{C_p} \tanh \left( \frac{\dot{z}_{PTO}}{v_{Coul}} \right)
\]  

(3.14)

here, \(F_{C_p} = \mu_p F_{line}\) represents the Coulomb force, with \(\mu_p\) denoting the pulley friction coefficient. This coefficient was determined through a series of simple experiments involving manually moving the translator downward at nearly zero velocity. During this process, load cells on both the buoy and PTO sides
recorded the forces. Subsequently, the pulley friction force was calculated by subtracting the logged forces from these two sides. Ultimately, the pulley friction coefficient was derived through the proportionality between the pulley friction force and the line force measured by the load cell connected to the buoy.

3.3.6 WEC-Sim end-stop module

The end-stop is simulated as an elastic end-stop:

\[
F_{\text{endstop}} = \begin{cases} 
    k_{\text{es}} (l_0 - l_c) + k_{\text{st}} \left( z - \frac{l_s}{2} \right) + c_{\text{st}} \dot{z}, & (i) \\
    k_{\text{es}} (l_0 - l_c) + k_{\text{st}} \left( z - \frac{l_s}{2} \right), & (ii) \\
    k_{\text{es}} \left( z - \left( \frac{l_s}{2} - (l_0 - l_c) \right) \right), & (iii) 
\end{cases}
\]  

(3.15)

This breakdown applies: \( (i) \) when \( z > \frac{l_s}{2} \) and \( \dot{z} > 0 \), \( (ii) \) when \( z > \frac{l_s}{2} \) and \( \dot{z} \leq 0 \), and \( (iii) \) when \( \frac{l_s}{2} - (l_0 - l_c) < z \leq \frac{l_s}{2} \). Further, \( k_{\text{es}} \) is the spring coefficient of the end-stop, while \( k_{\text{st}} \) denotes the equivalent spring coefficient of the structure. Additionally, \( l_s \) represents the length of the stroke, and \( l_0 \) and \( l_c \) stand for the initial and compressed lengths of the end-stop spring, respectively. Moreover, the energy dissipation after complete spring compression is similarly represented through a viscous damper with the coefficient \( c_{\text{st}} \) for \( \dot{z} > 0 \).
3.4 Results and discussion

3.4.1 Effect of different wave-type representations

The effect of different wave type representations is shown in Figure 3.12. A large deviation is seen for sea states 6, 8, and 10 between different wave types for most of the damping cases. Deriving the equivalent waves (irregular, regular, and focused waves) is not straightforward, especially for focused waves for which the choice of the bandwidth parameter of the Gaussian wave packet is quite important. Hence, not all the focused waves may be simply translated to their corresponding irregular waves. Looking back to Figure 3.8, even though sea state 10 shows a similarity between focused waves generated from Gaussian wave packet and NewWave theory, a large discrepancy is seen between different wave type representations. Therefore, it can be concluded that different wave-type representations of the same sea state do not give the same maximum line force. Comparing the irregular with regular waves is another evidence of this fact. It is noteworthy to observe that sea states 5a, 5b, and 5c demonstrate the same magnitude of the peak line force for both irregular and focused waves and all damping cases, see Figure 3.12. It is of great interest to experimentally compare the peak forces obtained from irregular waves with the focused waves generated based on the NewWave theory. The results here suggest that the irregular waves are a more conservative choice in survivability assessment as they showed higher peak line forces among different wave type representations.

3.4.2 Effect of significant wave height and peak period

The effect of significant wave height and peak period on the maximum line force is shown in Figure 3.13. Starting from irregular waves, Figure 3.13 (a), sea state 6 shows the highest peak line force in all damping configurations. Furthermore, sea states with the same $H_s$ but higher $T_p$ show higher maximum line force, for instance in comparing sea states 5c and 10 ($H_s = 0.07$ m) or sea states 5b and 9 ($H_s = 0.12$ m). One exception is seen when comparing sea states 5a and 8 ($H_s = 0.18$ m) with peak periods of 1.64 s and 2.56 s, respectively. In this case, sea state 5a shows a higher peak line force even though it has lower $T_p$. It is important to mention that in the second repetition of sea state 8 with $D_1$, the data is missing for a few seconds that is the same interval in which repetition one has its maximum value. This may explain the slightly different peak forces obtained in the two repetitions of this sea state in $D_1$. As aforementioned, the first 50 seconds of the data are disregarded for irregular waves and regular waves to allow full development of the waves in the wave tank, and we intend to keep this practice the same for all the sea states. Again for sea state 8 and damping $D_0$, the maximum line force is fairly similar to sea state 5a in the first 22 s of the data, which may be considered when analyzing this data. Moreover, clear wave breaking is seen for sea state
Figure 3.12. Maximum line force for all sea states and all damping cases where $a$ is for $D_0$; $b$ for $D_1$; $c$ for $D_2$; and $d$ for $D_\infty$, retrieved from Paper IV.
Figure 3.13. Maximum line force for all damping configurations and all sea states where a and b show irregular and focused waves results, respectively, retrieved from Paper IV.

5a which also has higher steepness compared to sea state 8, the effect of which should not be ignored. For focused waves, Figure 3.13 (b), sea state 5a shows the highest maximum force that is different from irregular waves where sea state 6 induces the highest line force on the buoy. This may be due to the effect of the Gaussian bandwidth parameter and the uncertainty in the accuracy of translation to equivalent focused waves. Regardless, the same observation as irregular waves can be seen when comparing sea states 5c and 10 ($H_s = 0.07$ m) or sea states 5b and 9 ($H_s = 0.12$ m) for which the sea states with higher $T_p$ show higher peak line forces. This may be further understood by comparing Figure 3.14 and Figure 3.15 where the amplitude of the surge motion in sea state 9 is considerably larger than in sea state 5b. This implies that the PTO translator is mainly influenced by the surge motion. The maximum line force that is seen far after the focusing time, i.e. $29.7 \pm 0.05$ s, for sea state 9 and damping $D_0$ is also due to the large amplitude of surge motion between 31 and 32 s.
Figure 3.14. Line force and buoy motions in focused waves for sea state 5b where a, b, c, d, and e represent damping $D_0$; f, g, h, i, and j show $D_1$; k, l, m, n, and o illustrate $D_2$; p, q, r, s, and t depict $D_\infty$. Also, $\eta$ is the surface elevation. The solid and dashed lines depict the two repetitions, with the exception of the lines representing the end-stop springs, retrieved from Paper IV.
Figure 3.15. Line force and buoy motions in focused waves for sea state 9 where a, b, c, d, and e represent damping $D_0$; f, g, h, i, and j show $D_1$; k, l, m, n, and o illustrate $D_2$; p, q, r, s, and t depict $D_{\infty}$. Also, \( \eta \) is the surface elevation. The solid and dashed lines depict the two repetitions, with the exception of the lines representing the end-stop springs, retrieved from Paper IV.
### 3.4.3 Effect of damping

Looking again at Figure 3.13, for both irregular and focused waves, results show that **there is an optimum value of damping for which the peak line force is minimum**. For most of the cases, damping $D_0$ and $D_\infty$ represent the highest force values. The zero damping case is associated with greater involvement of the end-stop spring, while the locked damping case corresponds to the higher relative velocity between the buoy and waves, and hence, higher forces are achieved in these cases. Note that in the locked damping case, since the translator is locked, the position sensor shows a constant zero value as shown for instance in Figure 3.15. In this case, the buoy has only negative heave motion with small fluctuations. Moreover, increasing the damping leads to a delay in the heave motion peaks. In sea state 6 in focused waves, see Figure 3.13, this delay results in almost simultaneous surge and heave motion peaks, and consequently higher line force. Another interesting observation is that the surge amplitude is insensitive to damping which is due to waves always pushing the buoy forward, while in heave changing the damping may introduce lag or lead in the buoy’s motion with respect to the surface elevation.

---

### 3.4.4 Effect of end-stop

Figure 3.16 shows the influence of the end-stop in irregular waves for damping cases $D_0$, $D_1$, and $D_2$. Sea state 6 shows the highest number of end-stop engagements, while sea state 5a shows the highest intensity of the end-stop spring compression. A direct correlation can be seen between the number of end-stop compressions and the root-mean-square of forces.

Looking back at Figure 3.15, the double peak observed around the focused time, in sea state 9 for damping $D_0$, is primarily attributed to the compression of the end-stop spring. The initial peak primarily arises due to the heave amplitude, while the subsequent peak is predominantly a result of significant surge motion. Comparing Figure 3.14 and Figure 3.15, the end-stop is more compressed in sea state 9 due to the higher amplitude of the surge motion. Hence, it can be seen that the end-stop compression contributes to the sudden peak forces which are followed by line slacking.

Again looking at Figure 3.12, sea state 9 shows a significantly larger peak line force compared to sea state 10 since the end-stop is constantly compressed due to the larger value of $H_s$ in sea state 9 leading to a large difference between these two sea states.

Out of seven sea states tested in this experiment, only sea state 5c did not compress the end-stop spring. Having a larger peak period in sea state 10 leads to a larger surge motion of the buoy and a higher displacement amplitude of the PTO translator and more compression of the end-stop spring when compared with sea state 5c with the same $H_s$.  

---
Figure 3.16. The effect of end-stop for irregular waves for three PTO damping of 0, 7.4, and 18.9 N for the time interval of 50 to 600 s where a and d show the number of end-stop spring compression for repetitions one and two, respectively, b and e illustrate the RMS of end-stop spring compression (in millimeters), and in c and f the RMS of line force (in Newtons) after the engagement of end-stop spring is shown. Sea states 5c and 10 were not tested for zero PTO damping configuration, retrieved from Paper IV.

3.4.5 Effect of overtopping and wave breaking slamming

Here, the overtopping phenomenon is assessed by tracking two trajectory points A and B on the top surface of the buoy through the following equations: $z_A = z_{CG} + r \sin(\theta + \phi)$ and $z_B = z_{CG} + r \sin(\theta - \phi)$ where $z_A$ and $z_B$ are the heave trajectory of points A and B, $r$ is the distance from point A to the center of gravity, and $\theta$ and $\phi$ are the pitch angle and the angle between $r$ and x-y plane, respectively, see Figure 3.17. Overtopping leads to a reduction in the line force since the water pressure on the buoy’s top surface due to overtopping and the line force act in the same downward direction, see Figure 3.18 for damping case $D_2$. In the locked damping case, the influence of nonlinearities is more dominant and its analysis is more complex. As shown in Figure 3.18 for damping case $D_\infty$, the two repetitions do not replicate each other at all times. Further, the missing data relates to the Qualisys marker being fully shadowed by water due to overtopping in this case. Furthermore, it is anticipated that the depicted high line force has been reduced due to the occurrence of overtopping. It is worth noting that while the line force may be leveled out
as a consequence of these events, other parts of the device such as the buoy hull are subject to the high forces due to the overtopping phenomenon. This implies the importance of a profound analysis of the overtopping effect especially for the point-absorbing devices containing the PTO or other important mechanical and electrical sub-systems inside the buoy.

In this experiment, clear wave breaking is observed for sea states 5a and 6, which results in the wave-breaking slamming phenomenon. The wave-breaking slamming leads to high line forces which are short in time and quickly drop to zero after the wave impact. The effect of wave-breaking slamming is similar to the line force dynamics seen for the infinite damping coefficient case where the influence of line slap and slack leading to the frequent fluctuation of the line force is quite apparent.

It should come as no surprise that the wave-breaking slamming can be followed by the overtopping phenomenon. In this case, the downward water pressure counteracts heave forces and results in the reduction of the line force
component in the heave. Therefore, although the wave-breaking slamming (surge force) leads to an increase in the line force, the overtopping phenomenon reduces its heave component, and the total line force may become smaller.

3.4.6 Effect of natural frequency

Here, the effect of natural frequency ($\omega_n$, it may be also referred to as undamped natural frequency) is investigated for $D_0$, $D_1$, and $D_2$ excluding the infinite damping coefficient. From the decay test, the natural frequency of the system in heave is calculated as 6.05 rad/s, refer to Paper IV. Hence, sea states 5a, 5b, and 5c are regarded as the nearest to the natural frequency of the system. As Figure 3.19 also indicates, the response amplitude in heave motion for sea states 5a, 5b, and 5c is the highest for $D_0$ and $D_1$ cases, and as the damping increases, i.e. in $D_2$, the amplification of buoy’s motion at natural frequency becomes harder to capture. On the contrary, the response amplitude in surge motion shows an enhancing trend as $T_p$ increases. Keeping the significant wave height constant and changing the peak period means changing the wavelength, thus, influencing the surge motion, and consequently, the PTO translator. This explains the higher line force that is achieved for sea states with higher $T_p$ while having the same significant wave height, for instance when comparing sea states 5b and 9 and sea states 5c and 10.

The RAO is computed as the maximum motion amplitude in each respective degree of freedom (heave, surge, and pitch) divided by the maximum surface elevation.

3.4.7 Numerical WEC-Sim model Performance

In order to assess the performance of WEC-Sim, the empirical cumulative distribution function (ECDF) of peak line forces obtained from both the WEC-Sim simulations and the experimental data for sea state 8 and $D_0$, $D_1$, and $D_2$ damping configurations is depicted in Figure 3.20. The WEC-Sim simulation is conducted for 20 different seeds (phases) of 0.18 hours for damping configurations of $D_0$, $D_1$, and $D_2$ for the 1:30 scaled model. The locked PTO case was not analyzed here due to the WEC-Sim model’s inability to accurately simulate the system response for this damping configuration. The WEC-Sim model faced challenges in replicating this complex scenario, where the significant influence of nonlinear phenomena, such as excessive overtopping and frequent slack in the line rope, was observed during the experimental campaign. Another example of the WEC-Sim performance is illustrated in Figure 3.21 for sea states 5a, 6, and 8 in the $D_1$ case. The maximum line force response obtained from the numerical WEC-Sim simulations is illustrated concerning $H_s$ and $T_p$ in Figure 3.22. Furthermore, Figure 3.22 shows the maximum line
Figure 3.19. RAO is shown for focused waves and for all damping cases in heave, surge, and pitch motion, retrieved from Paper IV. a, d, g, and j show RAO in heave for damping cases of $D_0$, $D_1$, $D_2$, and $D_\infty$, respectively. b, e, h, and k show RAO in surge for damping cases of $D_0$, $D_1$, $D_2$, and $D_\infty$, respectively. c, f, i, and l show RAO in pitch for damping cases of $D_0$, $D_1$, $D_2$, and $D_\infty$, respectively.

force response obtained from numerical WEC-Sim simulations with respect to $H_s$ and $T_p$. The line force peak consistently increases with higher significant wave heights. However, concerning the peak period, it tends to peak closer to the system’s natural frequency. The WEC-Sim simulations were executed on a high-performance computing (HPC) cluster provided by the Uppsala Multi-disciplinary Center for Advanced Computational Science (UPPMAX).
Figure 3.20. The empirical cumulative distribution functions (ECDFs) illustrating the peak line forces from WEC-Sim and experimental data for sea state 8 are presented in (a), (b), and (c) for the three damping configurations: $D_0$, $D_1$, and $D_2$, respectively.
(a) For sea state 5a and $D_1$ damping configuration.

(b) For sea state 6 and $D_1$ damping configuration.

(c) For sea state 8 and $D_1$ damping configuration.

Figure 3.21. Comparison of WEC-Sim and experimental force peaks’ ECDF for sea states 5a, 6, and 8 in the $D_1$ case, adopted from Paper VI.

Figure 3.22. The maximum line force observed in the simulated sea states using WEC-Sim is presented, illustrating the variation with respect to significant wave height ($H_s$) and peak period ($T_p$) in (a) and (b), respectively. These observations are derived from the 1:30 scaled model, adopted from Paper VII.
3.5 Summary of the results

The result of a wave tank experiment with a scale of 1:30 is studied in intermediate water depth consisting of a frictional linear PTO and a cylindrical buoy with an ellipsoidal bottom subjected to extreme sea states with 50 years return period from the Dowsing site in the North Sea. The experimental results are presented for the four friction-damping values of zero, 7.4 N, 18.9 N, and infinity damping coefficient (that is locked PTO case).

Considering the line force in the system, it is concluded that the same peak force is not necessarily achieved in different wave-type representations of one sea state. The irregular waves are more conservative cases when evaluating or designing for extreme sea states as they achieve the highest peak line force.

Changing the damping may be considered a strategy to minimize the maximum line force of a point-absorbing device during extreme wave conditions. The experimental results here depict that there is an optimum value for which the peak forces are minimized. **The high forces seen for the zero PTO damping case are owing to the impact of the end-stop, whereas the high forces in the locked damping case are due to the influence of high relative velocity between the buoy and waves. This leads to the bathtub effect** seen in Figure 3.13 (a). For the focused waves that are short in time, the effect of the nonlinearities such as overtopping and wave breaking slamming is more dominant, and hence, the same bathtub shape may not be clearly seen for some of the sea states seen in Figure 3.13 (b). Note that the presented results here confirm the earlier studies in [25] and [26] that an increase in PTO damping leads to a reduction in the maximum line force. However, here the study is extended for the whole PTO damping range from zero to infinity.

Overtopping and wave breaking are two nonlinear phenomena seen in extreme conditions. When the waves break on the device, high horizontal (surge) force is induced which can lead to high line forces. Overtopping however reduces the line force by lowering the vertical component (heave) of the force.

In the comparison of the sea states with the same significant wave height, longer waves with larger wave periods produce higher surge amplitude in the device resulting in higher line forces. On the other hand, with the same $T_p$, a higher maximum line force is seen for the sea states with larger $H_s$.

The end-stop engages more often in lower damping cases in which the peaks of the line force are the consequence of the compression of the end-stop spring.

Finally, the PTO model in WEC-Sim is simulated using a static friction model that incorporates Stribeck, Coulomb, and viscous components. Additionally, the pulley friction in WEC-Sim is represented solely by the Coulomb component. While the PTO force resulting from the WEC-Sim model is adequate given the experimental data, accurately modeling and calibrating friction-based systems can be complex, especially in cases where significant nonlinearities are not present.
4. Part III: Reliability analysis

4.1 Background

To be considered reliable, a wave energy converter must effectively address both fatigue and instantaneous failure modes throughout its lifespan.

The analysis of instantaneous failure is often followed by the identification of the environmental design load case (DLC) to evaluate the ability of marine structures to withstand anticipated loads that may lead to failures. Subsequently, various international standards for marine structures [64–66] outline optimal methodologies for determining these design load cases. These standards recommend establishing the design load for each load type—such as hydrostatic, hydrodynamic, and aerodynamic loads—as well as for different environmental load conditions, including normal, survival under extreme, and abnormal environmental conditions.

Among several considerations in specifying the design load, the International Electrotechnical Commission (IEC) recommends utilizing 50-year sea states defined by significant wave height ($H_s$) and peak period ($T_p$) to simulate extreme wave conditions and the response of wave energy converters (WECs) [67]. A good example of applying this advice can be seen in the work by Edwards and Coe (2019) [68], where they evaluated and compared five methods in calculating environmental contours, such as principal component analysis (PCA), Rosenblatt, Gaussian, Gumbel, and Clayton, for the two-body floater RM3 WEC. Based on the available dataset, their findings indicated that the PCA method projected higher significant wave heights for extended energy periods. The authors emphasized the significance of this finding, particularly its impact on design considerations such as evaluating low-frequency phenomena like mooring tension. However, the quest to find the best platform for determining the design load case has persisted. For example, to calculate the design load for a two-body point absorber (RM3), Van Rij et al. [69] considered three different computational fidelities such as a potential flow boundary-element method, WAMIT (WaveAnalysisMIT), in the frequency domain; a modified version of the linear-based WEC-Sim model in the time domain; and a computational fluid dynamics (CFD) model coupled with the finite element (FEM) method in the time domain for both focused and regular waves. By comparing the computed design load from the numerical and experimental data, the authors inferred that the WAMIT failed to represent the nonlinear mooring force accurately. Additionally, the WEC-Sim model underestimated the three-dimensional structural moments, while the CFD combined with FEM yielded high nonlinear responses, enabling the prediction of the most likely extreme response (MLER) design load for focused waves. Vanem [70] investigated the uncertainty associated with estimating extreme values for three
datasets from the North Atlantic Ocean. The study summarized the estimated 20-year and 100-year return values using various methods such as generalized extreme value (GEV), Gumbel, Weibull, Frechet, generalized Pareto distribution (GPD), and the average conditional exceedance rate (ACER) method. Considerable variation was observed across these methods in conducting extreme value analysis. The author concluded that selecting a single preferred method or approach for this type of analysis is not straightforward. Coe et al. (2018b) [71] examined the optimal method for predicting the design load of a spheroid floater WEC. They investigated the necessary number of sea states to determine the design load using the “full sea state approach” (explained in detail in subsection 4.2.2). Their findings indicated that employing 50 sea states within the environmental contour gives stable results for the specific WEC under consideration. Moreover, while increasing the number of sea states did not significantly alter the predicted response level, it did aid in reducing uncertainty in the response.

The common practice for predicting fatigue failure involves combining rainflow counting, which breaks down the load history into a series of constant amplitude loads [72], with the linear cumulative damage assumption following the Palmgren-Miner rule.

A few studies have delved into fatigue analysis concerning various components of wave energy converters. Kolios et al. (2018) [73] developed a reliability assessment framework that constructed a parametric finite element model for point-absorber WECs, incorporating stochastic parameters like wave loads and material properties. Their assessment of the NOTC (National Ocean Technology Centre) 10 kW multi-point WECs revealed a likelihood of fatigue failure approximately 4.1 years into operation based on this framework. Yang et al. (2020) [74] specifically examined the fatigue life of fiber mooring lines using rainflow counting and the Palmgren-Miner rule. Their findings indicated that in simulations of a 10-WEC array, hydrodynamic interactions can significantly influence predicted fatigue damage which can vary by over tenfold depending on the incident load direction. Zurkinden et al. (2013) [75] investigated accumulated fatigue damage and annual power production, considering a control load that is either constant or variable based on the peak period. Their observations showed that the variable control load increased power production by about 21%, simultaneously raising accumulated fatigue damage by 63% compared to the scenario with a constant control load.

Part III investigates the computation of the design load case (related to ultimate limit state (ULS) analysis), as well as the partial damage in hourly sea states, and the equivalent two-million cycle load (associated with fatigue limit state (FLS) analysis). Subsequently, it conducts a comparison between the ULS and FLS safety factors to determine the prevailing limit state in the design of the point-absorber WEC.
4.2 Theory and method: environmental design load

The design load case refers to design situations – specific combinations of loads, forces, and conditions – that are considered during the design and analysis of a structure or system. These design situations encompass a range of scenarios: power production, start-up, normal shutdown, emergency shutdown, parked or idling states, as well as transportation, maintenance, and repair activities. This study focuses on determining the environmental design load (DL) for the line (mooring) force of a point-absorber WEC, following the procedure outlined below:

1. Environmental conditions are acquired based on a 50-year environmental contour for the Dowsing site, as detailed in subsection 3.2.4.
2. A physical 1:30 scaled wave tank experiment is conducted, as explained in section 3.2. Sea states are selected following the aforementioned 50-year environmental contour.
3. A numerical dynamic model of the WEC using WEC-Sim is constructed and validated against experimental data to enhance the dataset. The simulations are conducted over a 1-hour duration with 20 seeds, similar to the recommendation by [76].
4. Short-term extreme responses for the 1-hour simulations are estimated using statistical methods.
5. Long-term extreme responses for the point-absorber WEC under consideration are determined for the Dowsing site in the North Sea.
6. Finally, the environmental design load for the mooring line is derived.

Furthermore, a limit state indicates a condition where the structure and its components no longer meet their intended design criteria, as specified by [76]. These limit states can be categorized into several groups: (1) The ultimate limit state (ULS) corresponds to the maximum capacity (resistance) of the load-carrying device and its subsystems; (2) The fatigue limit state (FLS) pertains to system failure resulting from cyclic loading; (3) The accidental limit state (ALS) is associated with survival conditions following damage or non-linear environmental conditions; (4) The serviceability limit state (SLS) relates to tolerance criteria for design usage purposes, as defined by [76]. The selection of appropriate limit states depends on operational conditions, with consideration for factors such as ultimate, fatigue, accidental, and serviceability conditions. These states further encompass different load categories, including permanent loads, variable functional loads, environmental loads, and deformation loads. In the context of this study, the focus lies on the ultimate limit state. The aim is to determine the design load for the line force based on environmental loads.

Note that the calculations for both short-term and long-term extreme response analyses are carried out using the 1:30 scaled system. Thus, when taking into account 20 simulation runs of 1-hour duration for a full-scale model,
this corresponds to 20 simulations of 0.18 hours for a 1:30 scaled model. The Froude scaling law is employed within this study to convert parameters between the full-scale and 1:30-scaled models.

### 4.2.1 Short-term extreme response analysis

The short-term extreme response provides insight into the maximum response of the device (such as bending moment or mooring line force) when the device operates within a specific sea state for a defined period, usually equivalent to a storm duration lasting from 1 to 3 hours. This assessment assumes that the spectral density of the sea state is constant during this period [71, 77].

One key challenge in designing WECs revolves around reliably identifying the characteristic extreme value with limited data [77, 78]. Various methods address this challenge for non-Gaussian data, including the Weibull tail-fit, Winterstein’s method [79, 80], and the average conditional exceedance rate (ACER) [81]. These methods accommodate situations with insufficient data but introduce statistical uncertainties, especially concerning simulation length [82]. To address this, Sagrilo proposed a straightforward approach considering a single short-time simulation, adjusting a safety factor for each extreme value method [78].

This section delves into the explanation of the short-term extreme response analysis employing peaks-over-threshold. For a comprehensive overview of alternative short-term extreme response analysis methods and a comparative study among these approaches, Paper VI provides detailed insights.

### Peaks-over-threshold distribution

The peaks-over-threshold (POT) method [83] examines the upper tail of the line force distribution. This method involves setting a specific threshold and then fitting a generalized Pareto distribution (GPD) model to the exceedances, which are data points exceeding the chosen threshold \( u \): \( z = x - u \) for \( x > u \) [83]. The cumulative distribution function (CDF) of the GPD fitted to the exceedances is expressed as:

\[
P_{\text{GPD}}(z) = \begin{cases} 
1 - (1 + \frac{kz}{\alpha})^{-\frac{1}{k}}, & k \neq 0, 1 + \frac{kz}{\alpha} > 0 \\
1 - \exp\left(-\frac{z}{\alpha}\right), & k = 0, z > 0 
\end{cases} \tag{4.1}
\]

here, the scale and shape parameters are denoted as \( \alpha \) and \( k \), respectively. In the case of \( k = 0 \), the distribution reduces to the exponential distribution (ED). For \( k < 0 \), there is an upper bound of \( u - \alpha/k \) for the exceedance distribution, while for \( k > 0 \), the distribution has no upper limit [83].

The methodology of this approach is summarized in the following steps:

1. Choose the line force peaks by identifying the zero up-crossings of the surface elevation. Essentially, select the force peaks within the period
bounded by two consecutive zero up-crossings of the surface elevation, see Figure 4.1. The PDF histogram in Figure 4.2 showcases the force data distribution for sea state 7. Predominantly, the data depicts forces below 39 N, marked by two prominent peaks indicating the distinct frictional behavior of the PTO during both downward and upward motions of the translator.

2. Determine an appropriate threshold for each sea state by examining the mean residual life plot and stability plots of shape and scale parameters, see Figure 4.3. A standard technique involves assessing the mean residual plot from right to left, selecting the first point (threshold) where the mean residual curve exhibits an approximately linear trend. Subsequently, ensure that within the chosen threshold vicinity, the shape parameter remains relatively constant, and the scale parameter exhibits linearity [83]. The selected threshold for the sea states 5a, 6, 7, 8, 9, and 10 are presented in Table 4.1. In Figure 4.3, dashed lines indicate the 95% confidence interval ($\mu_{\text{exc}} \pm 1.96 \sigma_{\text{exc}}$) for the mean residual life plot, where $\mu_{\text{exc}}$ and $\sigma_{\text{exc}}$ represent the mean and standard deviation of the exceedances. Error bars illustrate the standard deviations of the shape and scale parameters. These intervals and errors assist in determining an appropriate threshold for the POT method. Higher thresholds cause fewer exceedances, leading to increased data variance. This behavior is observed in both the confidence interval lines of the mean residual life plot and the error bars of parameters (shape, scale) computed from ‘the observed information matrix’ using the maximum likelihood estimates (MLE) method. Details are in [83], section 2.6.4. The POT method, evaluated through diagnostic plots in Figure 4.4, effectively models high-force data points, aligning well with the probability and quantile plots. The probability plots highlight the CDF of force peaks above the threshold, where all the data points cluster near the end of the diagonal line, indicating high-force peaks above the threshold, with CDF values almost reaching one.

The strategy explained here is reliable for a limited number of sea states, such as the contour approach analysis. However, it becomes inefficient and time-consuming for a larger set of sea states, like the full sea state approach analysis. To address this issue, we propose a threshold selection as: $\mu_{\text{xp}} + 1.4\sigma_{\text{xp}}$, where $\mu_{\text{xp}}$ and $\sigma_{\text{xp}}$ represent the mean and standard deviation of peak forces. We require over 20 exceedances and a negative shape parameter to set this threshold. If these conditions are not met, we iteratively lower the threshold. Though less meticulous than the contour approach, we have performed an extensive study to validate our model’s appropriateness, showing good to reasonable fits for the selected sea states.

3. Fit the generalized Pareto distribution (described in Equation 4.1) to the exceedances of the line force peaks: $z_p = x_p - u$ for $x_p > u$. 

86
Figure 4.1. Force data extracted from the WEC-Sim model for sea state 7, characterized by $H_s = 0.24$ m and $T_p = 2.42$ s from the environmental contour shown in Figure 3.6, is depicted in (a). Zoomed-in data between 490 s to 510 s highlighting the selected peaks, denoted as red circles, is presented in (b). Additionally, the surface elevation with zero up-crossings is illustrated in (c). Note that sea state 7 was not tested during the experimental campaign due to limitations in the wave tank’s capability to generate waves as steep as sea state 7. Hence, the response of this sea state was derived from the WEC-Sim numerical model, retrieved from Paper VI.

Figure 4.2. The probability density function (PDF) histogram depicting the line force data derived from the WEC-Sim model for sea state 7, retrieved from Paper VI.
Figure 4.3. Mean residual life plots along with stability plots for shape and scale parameters, which are employed in selecting thresholds for the peaks-over-threshold method. The dashed lines in mean residual life plots represent the 95% confidence interval, and the error bars in the shape and scale stability plots indicate the standard deviation for each parameter, retrieved from Paper VI.
Figure 4.4. Plots assessing the goodness-of-fit for the peaks-over-threshold method, retrieved from Paper VI.
Table 4.1. Threshold selection for the POT method in different sea states, retrieved from Paper VI.

<table>
<thead>
<tr>
<th>Sea state</th>
<th>5a</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
</tr>
</thead>
<tbody>
<tr>
<td>Threshold</td>
<td>168</td>
<td>200</td>
<td>234</td>
<td>165</td>
<td>54</td>
<td>48</td>
</tr>
</tbody>
</table>

4. Calculate the cumulative distribution of peaks based on the cumulative distribution of exceedances using [77, 84, 85]:

\[
P_{P_GPD}(z_P + u) = 1 - \left( \frac{N_{pot}}{N_t} \left( 1 - P_{GPD}(z_P) \right) \right) \tag{4.2}
\]

where \(N_{pot}\) represents the number of peaks above the threshold, and \(N_t\) is the total number of peaks.

5. Compute the short-term extreme cumulative distribution function based on the cumulative distribution of the peaks as [77, 84, 85]:

\[
P_{st}(x) = P_P(x)^{N_{st}}. \tag{4.3}
\]

Here, the average number of peaks in each 1-hour short-term extreme simulation is \(N_{st} = N(\Delta t_{st}/\Delta t)\), where \(\Delta t_{st}\) represents the 1-hour short-term extreme simulation period, and \(\Delta t\) is the total 20 × 1 hours simulation length. For example, in Figure 4.5, the GPD model is applied to the upper tail distribution of force peaks for sea state 7 (\(H_s = 0.2362\) m and \(T_p = 2.42\) s) which is shown together with the extreme distribution for this sea state.

Figure 4.5. The PDF and CDF for peaks and extreme responses derived from the POT method applied to sea state 7, retrieved from Paper VI.
4.2.2 Long-term extreme response analysis

The assessment of long-term extreme responses provides insights into the design behavior of offshore systems under specific environmental conditions throughout their deployment life. This analysis can be conducted using two recognized techniques: the full sea state and contour approach, leading to the prediction of the design response.

**Full sea state approach**

The comprehensive long-term full sea state approach offers precise response predictions however demands extensive computational resources. This method encompasses a large number of sea states ($H_s$ and $T_p$) from within and around the environmental contour line to establish the long-term response distribution [64, 84, 86]. The long-term response distribution is derived as follows:

$$\bar{P}_{lt}(x) = \int_{H_s} \int_{T_p} \bar{P}_{st|H_s,T_p}(x|h_s,t_p) p_{H_s,T_p}(h_s,t_p) dh_s dt_p. \quad (4.4)$$

Here, $p_{H_s,T_p}$ represents the probability density of a specific sea state. Additionally, $\bar{P}_{st|H_s,T_p}$ denotes the short-term survival function (CCDF) of the response ($X$), formulated as:

$$\bar{P}_{st}(x) = p(X > x) = 1 - P_{st}(x) \quad (4.5)$$

where $P_{st}(x)$ signifies the short-term cumulative distribution function for 1-hour sea states. This analysis can account for various return periods (1, 25, 50, or 100 years) corresponding to different engineering design targets for diverse environmental load conditions.

Here, the full sea state approach is explored using 180, 360, and 720 sea state samples, aiming to evaluate result stability across different sample sizes. These samples are derived from the standard space (u-space) within various return periods (0.001, 0.01, 0.05, 0.1, 0.5, 1, 5, 10, and 50 years). In Figure 4.6 (a), the illustration displays the 180 sea states chosen within the u-space. The methodology involves dividing each return period into segments, and choosing a sea state within each segment randomly, aligning with the approach outlined in Coe et al. [2018] [71]. Subsequently, the sea states are transformed into the $T_p$ and $H_s$ space, as depicted in Figure 4.6 (b).
Figure 4.6. (a) displays the 180 sampled sea states in the u-space, and (b) illustrates their conversion into $H_s$ and $T_p$ space using the Rosenblatt transformation within the full-scale system, elucidating the x- and y-axis ranges, retrieved from Paper VI.

The joint probability distribution ($p_{H_s,T_p}$ in Equation 4.4) is computed by integrating the probability over each u-space section, shown in Figure 4.7. This figure demonstrates the joint probability density function in $T_p$ and $H_s$ space alongside contour lines representing different return periods.

Finally, the full long-term response is calculated using Equation 4.4, employing the short-term survival function or CCDF ($\bar{P}_t|H_s,T_p$) based on the GPD model for each short-term extreme distribution.

**Contour approach**

The contour approach [64, 71, 85] identifies sea states along the environmental contour contributing to maximum characteristic response. This method involves computing short-term extreme response distributions for these sea
states, determining the sea state with the largest response by finding the expected value (mean) across these distributions, and using a percentile of this distribution as the long-term extreme response.

Despite its faster analysis due to considering fewer sea states compared to the full sea state method, the contour approach has uncertainties and may underestimate response variability by overlooking various short-term realizations within the environmental contour [64]. To address this, a correction factor is sometimes applied. For example, studies like [86, 87] suggest using a correction factor of 1.3 derived from comparing responses between long-term full sea state and contour approaches. Another method involves considering a higher percentile from the selected short-term extreme distribution to compensate for this uncertainty [64, 71].

4.2.3 Analytical and numerical implementations

All analyses, except for the full sea state approach performed on Uppsala Multidisciplinary Center for Advanced Computational Science (UPPMAX), were conducted on a standard laptop. The buoy and PTO are designed using computer-aided design (CAD) software. The evaluation of the mechanical integrity and stresses on the device involves a simple finite element method (FEM) within the CAD software. WEC-Sim, executed in MATLAB, simulated the WEC’s surge, heave, and pitch motions. Hydrodynamic coefficients required for WEC-Sim were derived using the WAMIT software [15]. Rhino 3D [61] was employed for modeling the buoy’s outer surface in the WEC-Sim computations. The contour approach took a week of simulations, encompassing 120 sea state configurations (six sea states identified around the environmental contour, each simulated for 20 different seeds, resulting in 120 configurations). The full sea state approach utilized 20 cores on UPPMAX, with each sea state configuration requiring about 12 minutes. Statistical analysis was conducted using MATLAB and Python. The WEC Design Response Toolbox (WDRT) code, as presented in [85], is adapted to serve as the foundation to model short-term extreme responses.

4.3 Theory and method: fatigue analysis

The primary focus of this study lies in evaluating the equivalent fatigue load experienced by the shackle component, linking the buoy to the mooring rope (refer to Figure 3.1). In this investigation, the shackle is presumed to be constructed from high-strength steel, with a yield strength exceeding 500 MPa and surface roughness of \( R_a = 3.2 \) or superior [88]. A basic circular cross-section is adopted for the shackle geometry, with the diameter ranging from 0.05 to 0.2 meters. Stress concentration factors have not been considered to simplify the analysis.
The outline of this analysis is as follows:

1. The Palmgren-Miner rule is employed to conduct the fatigue life assessment for the shackle component. It follows a linear cumulative damage assumption and utilizes S-N fatigue data of the material [88].

2. Subsequently, the calibrated numerical WEC-Sim model computes the WEC response, specifically the line force, across 134 sea states. This response is then subject to the rainflow counting algorithm to dissect the load history into a sequence of unvarying amplitude loads [72]. The WEC-Sim simulations typically require around one week using a standard laptop computer.

3. Following this, the equivalent fatigue loads are determined by utilizing the joint probability density linked with each response.

4. Finally, the fatigue analysis is conducted utilizing the WDRT code [85]. This analysis incorporates a 50-year damage assessment to compute the equivalent constant amplitude forces for the 50-year duration. Additionally, the damage is assessed for $2 \times 10^6$ cycles, derived from simulations spanning one hour. For evaluating the fatigue behavior of the high-strength steel, the standard [88] proposes a design S-N curve: $\log N = 17.446 - 4.7 \log S$. This particular curve indicates a stress range of 235 MPa at $2 \times 10^6$ cycles. Notably, the recommended S-N curve, featuring a constant slope and excluding consideration of a fatigue limit, is specifically suggested for material exposed to seawater with cathodic protection, differing from its behavior when in contact with air. This rationale explains the choice of examining $2 \times 10^6$ cycles within our study.

It is essential to note that, as mentioned earlier, due to the system’s 1:30 scale, parameters undergo scaling using Froude scaling. Consequently, the 50-year and 1-hour durations correspond to approximately 9.13 years and 657.3 seconds, respectively. Furthermore, for the fatigue limit state, representing failure due to cyclic loading, a partial load safety factor of one is applied to the environmental loads [89].

4.3.1 Sea state’s probability density function

To assess the WEC response over a 50-year duration, encompassing sea states within and along the environmental contour, the area enclosed by the environmental contour is divided into a grid, as depicted in Figure 4.8. Assuming a uniform response within each grid module, the probability $(p_{jH_s,T_p})$ of each response is determined by integrating the joint probability density function across the area of each grid module:

$$
p_{jH_s,T_p}(h_s,t_p) = \int_{A_j} p_{H_s,T_p}(h_s,t_p) \, dt_p \, dh_s
$$

(4.6)
where \( A_j \) represents the area of each grid module. For grid modules without any sea state (circles in Figure 4.8), their probability is added to the closest grid module within the same \( H_s \) row. The joint probability density function, \( p_{H_s,T_p}(h_s,t_p) \), is computed using the I-FORM hybrid method, as formulated in [36–39, 90], and detailed in Equation 3.1. For further information, please refer to subsection 3.2.4.

4.3.2 Rainflow counting and equivalent load

The material laboratory tests to derive S-N curve data involve constant amplitude loading. In practical scenarios, however, structures undergo highly variable load amplitudes. Employing a cycle counting scheme like the rainflow counting method [72] breaks down the load history into a sequence of constant amplitude loads. By integrating this method with the linear cumulative damage assumption (Palmgren-Miner rule), one can determine the total damage and the corresponding equivalent constant amplitude load (hereafter referred to as equivalent load) from the variable load history. Utilizing the Palmgren-Miner rule, the damage for each sea state, \( D_s \), is formulated as:

\[
D_s = \sum \frac{n_i}{N_i}
\]  

where \( n_i \) represents the count of cycles with the constant amplitude stress \( (S_i) \). Additionally, \( N_i \) signifies the total cycles the material can endure under the stress amplitude \( S_i \) before failure, obtained from the S-N curve as:

\[
\log N_i = \log k - m \log S_i
\]  

where \( m \) denotes the fatigue exponent of the material. The slope and intercept of the S-N curve are \(-1/m\) and \( \log k/m \), respectively.
The rainflow counting algorithm, detailed in [72], can be summarized as follows: Begin by identifying all peaks and troughs within the load history, which is the line force data here. Next, create a list $E_1, \ldots, E_i$ comprising $i$ peaks or troughs under examination. This list is continuously updated through the following steps:

1. If $i < 3$, include another peak or trough.
2. Should $|E_i - E_{i-1}| < |E_{i-1} - E_{i-2}|$, return to step 1. Otherwise, proceed to step 3.
3. Record $|E_{i-1} - E_{i-2}|$ as a load range and remove the $E_{i-1}$ and $E_{i-2}$ data points. Then, revert to step 1.

The algorithm begins with the load history’s initial peak or trough and iterates until no further peaks or troughs remain for consideration in step 1. For a more detailed understanding, readers are advised to consult [72], particularly figures 4 to 16 contained within.

The total damages over 1 hour ($D_{1h}$) and 50 years ($D_{50y}$) on the structure are computed by:

$$
D_{1h} = \sum D_{sj} p_j H_s T_p
$$

(4.9)

$$
D_{50y} = D_{1h} n_h
$$

(4.10)

where $D_{sj}$ represents the damage in 1-hour of the $j^{th}$ sea state obtained from Equation 4.7. The duration of 50 years corresponds to $n_h = 50 \times 365 \times 24$ hours.

Finally, employing the Palmgren-Miner rule and the S-N curve, the constant amplitude stress equivalent to inducing specific damage $D$ on the structure is formulated as:

$$
S_{eq} = \left( \frac{kD_{neq}}{n_{eq}} \right)^{\frac{1}{m}}
$$

(4.11)

where $n_{eq}$ represents an arbitrary number of cycles for calculating the equivalent stress ($S_{eq}$). For example, the number of cycles in 50 years is computed as:

$$
n_{eq,50y} = \sum \left( 3600 \cdot \frac{n_h}{T_{avg,j}} \right) \cdot p_j H_s T_p
$$

(4.12)

where $T_{avg,j} = \frac{m_{0,j}}{m_{1,j}}$ denotes the average period of the $j^{th}$ sea state and is determined using the spectral moment equation $m_n = \int_0^\infty f^n \tilde{S}(f) df$, where $\tilde{S}$ is the wave spectrum.
4.4 Results and discussion

4.4.1 Environmental design load

Full sea state approach analysis

Figure 4.9 shows the full sea state survival function, indicating an expected long-term response of 497 N after 9.1 years in the 1:30 scaled system (equivalent to 50 years in the full-scale system).

The comparison of the full sea state survival function for varying sample sizes (180, 360, and 720) is shown in Figure 4.10. Coe et al. [2018] [71] investigated the full sea state approach’s sensitivity to sample sizes ranging from 50 to 400 sea states. Their findings indicated that higher sample sizes result in narrower confidence intervals, ensuring more accurate results. In our study, no significant difference is observed beyond 180 samples.

The full long-term responses corresponding to 1.8, 4.6, and 9.1-year return periods in the 1:30 scaled system (equivalent to 10, 25, and 50 years in the full-scale system) are used to determine the respective percentiles concerning the fitted model derived from the short-term extreme analysis of the most extreme sea state, referenced in Table 4.2. These percentiles will be utilized in the contour approach, as detailed in the following section.

![Figure 4.9](image)

*Figure 4.9.* The survival function for each sea state is illustrated by a red solid line, while the full sea state survival is depicted as the black line. Additionally, dashed lines indicate various time spans in the 1:30 scaled system, corresponding to 1, 5, 10, 25, and 50 years in the full-scale system, retrieved from Paper VI.

Contour approach analysis

The expected (mean) value of each sea state’s short-term extreme distribution is represented by black circles in Figure 4.11. Among all sea states, Sea state 7, characterized by the highest significant wave height, demonstrates the highest expected value. To determine the long-term extreme response and address
Figure 4.10. Comparison of the full sea state survival function for 180, 360, and 720 sea state samples, retrieved from Paper VI.

Table 4.2. The full long-term extreme responses (using the full sea state approach) and design loads for 1.8, 4.6, and 9.1 years are presented. The percentile of the short-term extreme method is determined from the cumulative distribution function (CDF) of the extreme distribution (e.g., shown in Figure 4.5). It’s essential to note that to calculate the design load, the full long-term extreme responses (440 N, 471 N, and 497 N) are multiplied by a load safety factor of 1.35, as outlined in Paper VI.

<table>
<thead>
<tr>
<th>Years return period</th>
<th>1.8 [years]</th>
<th>4.6 [years]</th>
<th>9.1 [years]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Full long-term response</td>
<td>440 [N]</td>
<td>471 [N]</td>
<td>497 [N]</td>
</tr>
<tr>
<td>Design load</td>
<td>594 [N]</td>
<td>635.85 [N]</td>
<td>670.95 [N]</td>
</tr>
<tr>
<td>Percentile for GPD model</td>
<td>95.49</td>
<td>99.55</td>
<td>99.99</td>
</tr>
</tbody>
</table>

Figure 4.11. The expected value of the short-term response for each sea state is represented as a black circle. Sea state 7 is specifically chosen due to its highest expected value to determine the long-term extreme responses of the device. Subsequently, the long-term extreme response of 497 N for the 9.1-year return period is derived from the cumulative distribution function (CDF) of the short-term extreme distribution, which corresponds to the 99.99th percentile, adopted from Paper VI.
uncertainties in the contour approach, a common practice involves selecting a higher percentile from the short-term extreme distribution. For instance, here, the design load for a 9.1-year return period (equivalent to a 50-year return period) is calculated as $497 \times 1.35 = 670.95$, representing the 99.99th percentile of the extreme distribution of sea state 7, seen in Figure 4.11. The designated load amounts to 670.95, equivalent to 18.11 MN in the full-scale system when multiplied by $30^3$. Note that the 99.99th percentile is selected from Table 4.2.

While the full sea state approach is laborious and time-consuming, it is an essential initial step to accurately establish required short-term extreme percentiles for any concept or technology. Subsequently, for similar technologies, these percentiles suffice for determining the environmental design load through the contour approach.

Other methods

There are various methods to determine the system’s short-term response. In Paper VI, several statistical methods such as Weibull tail-fit and Weibull two-parameters were outlined, emphasizing the applicability and performance of each method. One effective strategy to identify the most accurate methodology is utilizing the Bayesian theorem in conjunction with the Markov chain Monte Carlo (MCMC) algorithm. This approach provides a straightforward statistical assessment of the most suitable model based on available data, especially beneficial when working with limited datasets. To maintain the thesis’s focus, the explanation of the Bayesian approach coupled with the MCMC is not provided here. However, readers are encouraged to refer to Paper VI for a detailed insight into the implementation of this approach.

4.4.2 Fatigue

The damage in each sea state, denoted as $D_{s_j}$, is illustrated in Figure 4.12. The maximum equivalent force occurs approximately at the sea state with $H_s = 0.24$ m and $T_p = 2.4$ s. As the significant wave height rises, the equivalent force amplitude increases, indicating an expected rise in the damage. It’s important to note that the equivalent force is reliant on the chosen cycle count. In this context, the assessment involves two million cycles to compare the equivalent force and its corresponding stress value against the reported material stress limit of 235 MPa at the identical cycle count of $2 \times 10^6$ cycles, as documented in [88].

Utilizing Equation 4.11, the overall equivalent force for the 50-year environmental contour, from the 50-year structural damage ($D_{50y}$), is derived for two million cycles and $n_{eq, 50y}$ cycles, as reported in Table 4.3.

With an equivalent force of approximately 2.42 MN (or $89.5 \times 30^3$) for $2 \times 10^6$ cycles in the full-scale model, a circular cross-sectional area is assumed for a critical component experiencing the line force (specifically, the shackle). The fatigue equivalent stress in the material, expressed as $S_{eq} =$
Figure 4.12. A scatter plot displaying the fatigue equivalent force (in Newtons) for $2 \times 10^6$ cycles for each 657.3-second sea state for the 1:30 scaled model (equivalent to 1-hour sea state in full scale), indicated within each grid module, retrieved from Paper VII.

Table 4.3. The fatigue equivalent force for $2 \times 10^6$ and $n_{eq,50y}$ number of cycles for the 1:30 scaled model, retrieved from Paper VII.

<table>
<thead>
<tr>
<th></th>
<th>89.5 [N]</th>
<th>31.2 [N]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Equivalent force for $2 \times 10^6$ cycles</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Equivalent force for $n_{eq,50y}$ cycles</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

$F_{eq}/A_c$ with $A_c = \pi (d/2)^2$ denoting the cross-sectional area and $d$ representing the diameter, leads to the computation of the fatigue safety factor [41] as $\eta_f = S_{f,2M}/S_{eq}$. Here, $S_{f,2M} = 235$ MPa represents the fatigue stress amplitude for two million cycles. The relationship between the material stress and fatigue safety factor concerning the shackle diameter in the full-scale model is illustrated in Figure 4.13. To maintain the material stress below 235 MPa, a minimum diameter of approximately 0.114 m is necessary, corresponding to a fatigue safety factor of one.

The results detailed here are derived from sea states based on a single fixed seed (phase). It’s crucial to acknowledge that different seeds may yield distinct equivalent forces, particularly when assessing fatigue study results, which heavily rely on the time history. This variability is anticipated due to the presence of both narrow-banded and wide-banded spectrum sea states within the environmental contour. A narrower spectrum tends to result in less variability in the outcomes, while a wider spectrum produces more varied time histories, impacting equivalent forces differently based on the seed used. Figure 4.14 demonstrates the sensitivity of the equivalent force for the sea state 7 (i.e. featuring a significant wave height of 0.24 m and an energy period of 2.4 s), illustrating this variability. It is noteworthy that for this study, seed number 7
Figure 4.13. Variation of the fatigue safety factor and material stress concerning the cross-sectional diameter, depicted for the full-scale model, retrieved from Paper VII.

Figure 4.14. The impact of different seeds on the equivalent two-million-cycle force for the sea state 7, retrieved from Paper VII.

is considered for all sea states and simulations, generated by a random number generator for each seed number.

An intriguing finding emerges when comparing the peak force (review Figure 3.22) with the equivalent force among all sea states: a notably linear relationship exists between the maximum and equivalent forces, exhibiting a slope and intercept of 14.45 and 13.29, respectively, see Figure 4.15. This observation suggests that the maximum line force serves as a pivotal parameter for assessing the severity and anticipated damage across various sea states in WEC reliability studies. Paper IV has also leveraged this parameter, highlighting its significance. The graph in Figure 4.15 illustrates the relationship between $F_{\text{max}}$ and $F_{\text{eq}}$ for $2 \times 10^6$ cycles in the 1:30 scaled model.

4.4.3 ULS and FLS comparison

In assessing reliability, the design consideration between fatigue limit state (FLS) and ultimate limit state (ULS) prioritizes the one posing a higher struc-
The plot illustrates the correlation between the maximum force and the fatigue equivalent two-million cycle force observed from all sea states, accompanied by the best-fit line. The data represents results obtained from the 1:30 scaled model, retrieved from Paper VII.

Figure 4.15. The plot illustrates the correlation between the maximum force and the fatigue equivalent two-million cycle force observed from all sea states, accompanied by the best-fit line. The data represents results obtained from the 1:30 scaled model, retrieved from Paper VII.

4.5 Summary of the results

The environmental design load and fatigue of a point-absorber WEC system are investigated using a numerical WEC-Sim model calibrated with experimental data from extreme conditions in the North Sea’s Dowsing site.

The process of deriving the environmental design load is rigorously explored, resulting in an environmental design load of 670.95 N for the 1:30 scaled system over 9.1 years, corresponding to 18.11 MN in the full-scale system. In the fatigue analysis, a linear relation between fatigue equivalent force and maximum force per sea state is observed, indicating the latter’s potential for damage comparison. The total equivalent force for $2 \times 10^6$ cycles over 50 years stands at 2.42 MN in the full-scale model.

The comparison between fatigue and ultimate limit state safety factors illustrates that although the fatigue results slightly vary based on the simulation seed due to the load’s time dependency, the ultimate limit state governs the structural design of the system at hand.
5. Part IV: Survivability control

5.1 Background

To enhance the survivability of wave energy converters (WECs), it is crucial to avoid forces exceeding design thresholds and prevent over-designing the structure during challenging extreme wave conditions, ultimately reducing the Levelized Cost of Energy (LCOE). In the face of devastating extreme conditions, marine devices must adopt survival strategies to minimize damage to their structures. This includes addressing non-linear phenomena like wave breaking, wave breaking slamming, and overtopping, which pose complex challenges for WECs [22–24]. While model-based control strategies are sensitive to system models and parameters, data-driven control strategies prove advantageous. They are independent of internal models and their errors, making them particularly valuable in studying extreme waves where dynamic modeling is often infeasible due to complex dynamics and extensive computational costs [4].

In recent years, the drive for power maximization in Wave Energy Converters (WECs) has led to the exploration of various data-driven strategies. Anderlini et al. (2016) and their subsequent work in 2018 introduced online model-free reinforcement learning (RL) algorithms as resistive and reactive control strategies for point absorber WECs, respectively [91, 92]. Their findings underscored the challenges of algorithm convergence, especially in irregular waves, emphasizing the need for statistical reward functions [91]. Concurrently, advancements in extreme event forecasting by Ding et al. (2019) and Pickering et al. (2022) demonstrated neural architectures and model-agnostic frameworks for predicting extreme events, critical for survivability control systems [93, 94].

Our experimental results, as outlined in Paper IV, further emphasize the importance of optimal damping, leading to the proposal of a neural network (NN) algorithm to minimize line forces in a point absorber WEC during extreme conditions. These findings align with broader challenges identified in replicating system dynamics through wave tank experiments and numerical modeling [28, 95–100]. While wave tank experiments demand substantial resources, numerical modeling faces limitations in handling irregular waves and sensitivity to boundary conditions. To address these challenges, various control schemes have been proposed, often relying on linear assumptions and resulting in uncertainties [4, 91, 92, 101–104]. Machine learning approaches, such as neural networks, offer an alternative by liberating control systems from modeling errors and leveraging true and noisy data for robust predictions [101, 105].

Part IV focuses on enhancing the survivability of wave energy converters in extreme wave conditions. Three distinct approaches have been explored to
address survivability strategies from various angles. Each approach revolves around minimizing line forces using neural network algorithms to identify optimal damping during zero up-crossing episodes of surface elevation or within specified time intervals. The following provides details on each approach:

**Approach 1**
In this approach, the developed neural network focuses on providing rapid and accurate detection of optimal damping for survivability strategy. It delves into variations in optimal damping based on the system’s state.

**Approach 2**
This approach places emphasis on implementing a closed-loop control system in WEC-Sim. It utilizes a more advanced deep neural network (DNN) model to find and apply optimal damping. The approach introduces a DNN model to predict extreme event probability and peak line force, integrated into the control system of a numerical WEC-Sim model.

**Approach 3**
This approach provides a realistic estimation of the total uncertainties associated with predicting input parameters for the control strategy, such as surface elevation and system state, as well as the output parameters, i.e. the line force and the optimal damping desired for the survivability strategy. Additionally, it quantifies the sensitivity of the NN approach in determining line force to uncertainties present in different parameters of its input data.

Throughout the thesis, the neural network (NN) architecture in approach 1 is termed a deep neural network (DNN), while the NN architecture for approach 2 is referred to as an advanced DNN. This nomenclature aims to establish a clear distinction between these two models and prevent ambiguity.

### 5.2 Theory and method

The neural network architectures are developed in Python using Keras [106] as the application programming interface (API), operating on top of the TensorFlow machine learning library [107]. In the following, some of the terminologies and concepts that have been used are summarized:

**Generalization assessment**

The objective is to construct a neural network architecture capable of generalizing to unseen data. To evaluate this, the available dataset is shuffled and split into three subsets: the training set (70% of the data used for model training), the validation set (10% for fine-tuning hyperparameters), and the test set (20% for gauging overall performance and generalization ability).
Normalization
In neural networks, the process of normalization of input data involves adjusting its scale and distribution for improved model performance. Although each approach introduced here has implemented a slightly different normalization routine, they serve the same purpose, and the network has little to no sensitivity to these minor differences in normalization methods. The normalization techniques employed in each approach are detailed in their respective sections.

Forward and backward propagation
The fundamental concept underlying neural network learning encompasses forward and backward propagation. Forward propagation involves computing the output of each network layer by transmitting information from inputs to outputs. Let \(a^{[0]} = X\) represent the input vector, and the output of each layer \(z^{[l]}\) is defined as
\[
z^{[l]} = W^{[l]}a^{[l-1]} + b^{[l]} \tag{5.1}
\]
\[
a^{[l]} = g^{[l]}(z^{[l]}) \tag{5.2}
\]
where \(l = 1, 2, \ldots, N\) in a network with \(N\) layers. Here, \(W^{[l]}\) and \(b^{[l]}\) are weights and biases, and \(g^{[l]}\) denotes the activation function responsible for transforming one layer’s output into the subsequent layer’s input.

Backward propagation involves updating weights and biases to minimize a predefined loss function. Further details regarding the loss function for each approach will be provided later. Here, for the sake of explanation, consider the loss function as a squared error between the network’s predicted output \(\hat{y}\) and the true experimental value \(y\), expressed as \(L(y, \hat{y}) = (y - \hat{y})^2\). The gradients of the loss with respect to every \(W^{[l]}\) and \(b^{[l]}\) are calculated through backpropagation as
\[
\nabla_{W^{[l]}} L(y, \hat{y}) = \delta^{[l]} a^{[l-1]T} \tag{5.3}
\]
\[
\nabla_{b^{[l]}} L(y, \hat{y}) = \delta^{[l]} \tag{5.4}
\]
where \(\delta^{[l]}\) signifies the gradient of the loss regarding the \(l^{th}\) layer output, computed iteratively for \(l = N - 1, N - 2, \ldots, 1\) and using element-wise derivatives \((g'(z^{[l]})\)) for the respective layers:
\[
\delta^{[l]} = \nabla_{z^{[l]}} L(y, \hat{y}) = (W^{[l+1]T} \delta^{[l+1]}) \circ g'(z^{[l]}) \tag{5.5}
\]
The element-wise product is represented by \(\circ\). In the case of the output layer \(N\), the expression for \(\delta^{[N]}\) is as follows:
\[
\delta^{[N]} = \nabla_{z^{[N]}} L(y, \hat{y}) = \nabla_{z} L(y, \hat{y}) \circ g'(z^{[N]}) \tag{5.6}
\]
Activation
The activation function in neural networks introduces non-linearities to enable the learning of complex patterns. Functions like sigmoid, tanh, ReLU (rectified linear unit), and softmax add nonlinear transformations to network outputs, enhancing their ability to capture intricate features and make accurate predictions. The activation function that is used in each approach is explained later.

Regularization
Weight decay or regularization commonly includes an extra term within the loss function. This addition penalizes hypotheses that may not generalize effectively, consequently minimizing the chances of over- or underfitting. The $L_2$ regularization is incorporated in all approaches as follows:

$$R_{L_2} = \frac{\alpha}{2} \sum_{ij} \theta_{ij}^2 \quad (5.7)$$

where $\theta_{ij}$ represents all parameters (weights and biases) in the network, and $\alpha$ is the weight cost, set as 0.0002. Consequently, the redefined loss function is:

$$L(Y, \hat{Y}) = \frac{1}{nb} \sum_{i=1}^{nb} (Y_i - \hat{Y}_i)^2 + R_{L_2} \quad (5.8)$$

with $Y$ and $\hat{Y}$ as vectors containing true and predicted values in a batch of size $nb$.

Optimization
Various optimization algorithms exist for determining optimal network parameters. For this study, Adam optimization \[110\] updates network parameters as follows:

$$\theta^{k+1} = \theta^k - \gamma \frac{\hat{M}_\theta^k}{\sqrt{\hat{V}_\theta^k} + \epsilon} \quad (5.9)$$

where $\theta^k$ denotes the weights and biases at the $k$th iteration, $\gamma$ is the learning rate, initially set to 0.0001, gradually reduced if no improvements occur during learning. The fixed $\epsilon = 10^{-8}$ is chosen. Further, the bias-corrected first and second moments of gradients, $\hat{M}_\theta^k$ and $\hat{V}_\theta^k$, are calculated as:

$$\hat{M}_\theta^k = \frac{M_\theta^k}{1 - \beta_1^k} \quad (5.10)$$

$$\hat{V}_\theta^k = \frac{V_\theta^k}{1 - \beta_2^k} \quad (5.11)$$
with decay rates $\beta_1 = 0.9$ and $\beta_2 = 0.99$. These moments ($M^k_\theta$ and $V^k_\theta$) are obtained from:

$$M^k_\theta = \beta_1 M^{k-1}_\theta + (1 - \beta_1) \nabla_\theta L(\theta^k) \quad (5.12)$$

$$V^k_\theta = \beta_2 V^{k-1}_\theta + (1 - \beta_2) (\nabla_\theta L(\theta^k))^2 \quad (5.13)$$

where $L(\theta) = L(Y, \hat{Y})$ represents the loss as a function of network parameters.

**Dropout**

Dropout involves randomly excluding a portion of neurons in a layer during training, eliminating their contributions in both forward and backward propagation. It aids in preventing overfitting and promotes the neural network’s learning of robust features, ultimately enhancing accuracy by improving the network’s ability to generalize from the data.

**Batch size and epochs**

Grouping data into batches is a common practice for applying the update rule based on the loss for each batch, as depicted in Equation 5.8. An epoch represents a complete pass through all the batches in the dataset.

**Early stopping**

During training, as the training error improves, the generalization error on the validation set might start to rise, indicating potential overfitting. Early stopping halts the training if no improvement in the validation error is observed after a set number of epochs. In this case, a patience value of 10 is used, signifying the optimizer stops after 10 epochs of no improvement.

**Correlation**

The network’s performance may be evaluated by computing the correlation between the true and predicted output vectors using the formula:

$$C_r = \frac{c_{12}}{\sqrt{c_{11}c_{22}}} \quad (5.14)$$

where $c_{ij}$ are elements of the covariance matrix.

**Grid search**

To identify the optimal network hyperparameters (nodes, layers, activation function, learning rate, regularization rate, optimization method, batch size, and dropout value), a grid search can be conducted to enhance the model’s performance.
5.2.1 Approach 1: deep neural network architecture

**Conceptualization and rationale in approach 1**

This approach outlines the utilization of a deep neural network (DNN) architecture to predict the peak line force, aiming to identify the optimal damping that minimizes the line force for each zero up-crossing episode of the surface elevation. The neural network is trained over the wave tank experimental data for all the sea states (i.e. sea states 5a, 5b, 5c, 6, 8, 9, 10) and all the damping configurations (i.e. $D_0$, $D_1$, $D_2$, and $D_\infty$). Figure 5.1 illustrates the schematic of the DNN architecture.

![Figure 5.1. Schematic of the fully connected DNN architecture. The dashed circles indicate dropout, retrieved from Paper VIII.](image)

**Inputs and output of the DNN model**

The neural network’s inputs include the sliding friction force, maximum wave amplitude, wave period for each zero up-crossing episode, and initial values of position, velocity, and acceleration at each zero up-crossing of the surface elevation. The peak line force in each zero-up crossing episode is the output of the network, see Figure 5.2.

**Normalization for DNN model**

The wave amplitude and period during each zero up-crossing event, along with the position, velocity, and acceleration at every zero up-crossing instance, are normalized within the range of [-1, 1]. This normalization is done using $(x_i - \mu)/\sigma$, where $\mu$ and $\sigma$ represent the mean and standard deviation of the respective feature $x_i$. Additionally, the damping and peak force data are adjusted to fall within [0, 1], and are scaled according to their maximum absolute values.

**Hyperparameters and DNN architecture**

Table 5.1 displays the optimal hyperparameters for the DNN model, consisting of 5 hidden layers with 128 nodes in each layer. The DNN architecture is shown in Figure 5.3. This architecture requires only a few minutes of training on a standard laptop.

The loss is determined by the mean squared error (MSE) between the predicted and actual line force peaks, and the accuracy is expressed as $1 - \sqrt{\text{MSE}}$. 108
Figure 5.2. The surface elevation and line force signals are shown for an arbitrary time window, where green circle markers indicate the commencement and conclusion of a zero up-crossing episode, while the black circle marker signifies the selected peak force within this interval, adapted from Paper IX (© 2023 IEEE).

Table 5.1. Hyperparameters for the DNN obtained after grid search. Note: the regularization rate is half the weight cost, $\alpha$, retrieved from Paper VIII.

<table>
<thead>
<tr>
<th>Hyperparameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of hidden layers</td>
<td>5</td>
</tr>
<tr>
<td>Number of nodes</td>
<td>128</td>
</tr>
<tr>
<td>Activation function</td>
<td>PReLU</td>
</tr>
<tr>
<td>Regularization</td>
<td>L2</td>
</tr>
<tr>
<td>Regularization rate</td>
<td>0.0001</td>
</tr>
<tr>
<td>Optimization method</td>
<td>Adam</td>
</tr>
<tr>
<td>Batch size</td>
<td>256</td>
</tr>
<tr>
<td>Dropout value</td>
<td>0.1</td>
</tr>
</tbody>
</table>

5.2.2 Approach 2: advanced deep neural network architecture

Conceptualization of control system in approach 2

To establish a closed-loop control system within the WEC-Sim numerical model, aiming to identify the optimal damping that minimizes the peak line force at each zero-up crossing of surface elevation, simulations are conducted using the WEC-Sim model. These simulations consider sea state 8 and three damping configurations of $D_0$, $D_1$, and $D_2$. Note that the locked power take-off (PTO) case is excluded from this study due to the WEC-Sim model’s inability to accurately replicate the system response under such complex conditions. Challenges in modeling this case arise from overtopping and the frequent slack observed in the line rope during the experimental campaign.

For the 1:30 scaled model, WEC-Sim is executed with 20 seeds for each damping configuration, each lasting 0.18 hours. This results in a cumulative system response duration of approximately 11 hours, constituting the dataset required for training the neural network model.
Figure 5.3. The DNN architecture for approach 1.
The controller utilizes the instantaneous values of the power take-off’s (PTO) position, velocity, and acceleration—eliminating the need for predicting system state. Additionally, it incorporates the current and future information on surface elevation as input of the model, see Figure 5.4. The optimization loop module provides a range of sliding friction-damping forces to the neural network model, facilitating the identification of the minimum peak line force and the corresponding optimal damping force. The obtained results showcase the controller’s performance under extreme sea conditions along the 50-year environmental contour.

Figure 5.4. Flowchart of the control system. The sliding friction force corresponds to the constant Coulomb friction damping force of the PTO, retrieved from Paper IX (© 2023 IEEE).

Inputs and output of the advanced DNN model
The input features consist of several components, including Coulomb force (i.e. sliding friction damping force), maximum wave amplitude, and wave period during each zero up-crossing episode of surface elevation. Additionally, the initial values of translator position, velocity, and acceleration are specified at the beginning of each zero up-crossing episode. Moreover, the input variables incorporate the wave steepness \( (H/\lambda) \), where \( H \) and \( \lambda \) denote the wave height and wavelength for every zero up-crossing episode of surface elevation. The initial and maximum values of the derivative of surface elevation with respect to time during each zero up-crossing episode are also used as the input to the model. The output of the model consists of the predicted value and the probability of the extremity of the peak line force.

Normalization for advanced DNN model
All input data used in the model is normalized by their maximum absolute value for each parameter, multiplied by a factor of 1.2 (e.g. \( \eta_n = \eta / (\max \{|\eta|\} \times 1.2) \)), except for the damping, which was normalized by the value 20, corre-
sponding to approximately the maximum damping. The measured peak line force data used to train the model is normalized as \( y_n = \frac{y}{\max\{|y|\}} \).

**Hyperparameters and advanced DNN architecture**

The hyperparameters, determined through grid search, are detailed in Table 5.2. The model architecture is illustrated in Figure 5.5. Initially, the model is trained to minimize the classification loss, specifically the binary cross-entropy (BCE). Subsequently, it endeavors to minimize the regression loss, measured as the mean squared error (MSE) between the predicted and actual values of the peak line force. The system’s accuracy is assessed by calculating the goodness-of-fit using the formula:

\[
GOF = 1 - \sqrt{\frac{(\hat{Y} - Y)^T (\hat{Y} - Y)}{Y^T Y}}
\]  

(5.15)

with \( Y \) and \( \hat{Y} \) as vectors containing true and predicted values of the peak line force.

**Table 5.2.** Hyperparameters used in the advanced DNN model after grid search, retrieved from Paper IX (© 2023 IEEE).

<table>
<thead>
<tr>
<th>Hyperparameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of nodes</td>
<td>64</td>
</tr>
<tr>
<td>Activation hidden layer</td>
<td>PReLU</td>
</tr>
<tr>
<td>Activation output layer classiication</td>
<td>Sigmoid</td>
</tr>
<tr>
<td>Activation output layer regression</td>
<td>ReLU</td>
</tr>
<tr>
<td>Regularization</td>
<td>L2</td>
</tr>
<tr>
<td>Optimization method</td>
<td>Adam</td>
</tr>
<tr>
<td>Batch size</td>
<td>256</td>
</tr>
</tbody>
</table>

**Hybrid Regression and Classification with Attention Mechanism**

The proposed network tackles both regression and classification tasks, with the latter aiding the regression by incorporating an attention mechanism for extreme forces surpassing a specified threshold. The inspiration for this attention mechanism is drawn from [93] and is adapted for the predictive context discussed here: \( \hat{y} = y_r + \zeta y_c \) where \( \hat{y} \) represents the predicted peak line force, \( y_r \) is the regression output of the network, and \( y_c \) signifies the predicted probability of extreme peak line forces exceeding a threshold of 80 N. This threshold is selected through an examination of the time history of the system response for the experimented damping configurations and denotes the lower limit for extreme forces. Additionally, \( \zeta \) acts as the attention factor for extreme events, serving as a trainable parameter within the network. The training algorithm of the model is outlined as follows:
Figure 5.5. The architecture of the advanced deep neural network, wherein "Output-R" and "Output-C" correspond to the regression and classification outputs of the DNN model, respectively, retrieved from Paper IX (© 2023 IEEE).
\begin{algorithm}
\textbf{Initialize:} parameters $\theta$, and $\zeta$
\begin{algorithmic}[1]
\FOR {each epoch}
\FOR {each training batch}
\STATE Minimize BCE loss function $L_{\text{BCE}}(\theta)$
\ENDFOR
\FOR {each training batch}
\STATE Calculate peak line force, $\hat{y} = y_r + \zeta y_c$ from network outputs $(y_r, y_c)$
\STATE Minimize MSE loss function $L_{\text{MSE}}(\theta, \zeta)$
\ENDFOR
\ENDFOR
\end{algorithmic}
\end{algorithm}

Algorithm 1: The algorithm for the training of the proposed DNN model.

Subsequently, the trained network is integrated into the control module of the WEC-Sim model. A range of Coulomb (sliding) friction-damping forces, spanning from 0.0 to 20 N with increments of 1.0 N, has been chosen for examination. Specifically, higher damping values are excluded to ensure the neural network’s accuracy within the bounds of its training dataset.

5.2.3 Approach 3: convolutional and deep neural network architecture

Conceptualization and rationale in approach 3

The data flow in predicting line forces using a series of neural networks is illustrated in Figure 5.6, depicting the integration of past and future knowledge of surface elevation and PTO translator position into the problem. At intervals of 0.36 s (equivalent to 2 s in full-scale WEC), computations are made for surface elevation, PTO translator position, and peak line forces across a range of damping values. Similar to other approaches, the damping value yielding the lowest peak force is identified as the optimal damping for survivability. The training times range from minutes to less than an hour on a standard laptop, except for the PTO translator position model, which utilized the Uppsala Multidisciplinary Center for Advanced Computational Science (UPPMAX) cluster for approximately two hours.

In this study, it is important to note that only the experimental data corresponding to sea state 6, characterized by $H_s = 0.22$ m and $T_p = 2.10$ s, along with damping configurations $D_0$, $D_1$, and $D_2$, are utilized to construct the training set for the neural network.

Normalization for convolutional and deep neural network

The parameters for both the convolutional neural network (CNN) and deep neural network (DNN) models developed in this approach are normalized uni-
formly across all models. The input and output data of the networks undergo normalization using a constant value derived from the maximum of each signal. It’s essential to note that the maximum value of each signal is rounded up to the nearest integer. Consequently, the normalized peak line force in each 0.36 s time interval is expressed as $F_{\text{line}_n} = F_{\text{line}}/400$. Similarly, the surface elevations at wave gauge (WG) 8 and 2 are normalized with $\eta_{n} = \eta/0.3$, while the PTO translator position and sliding friction damping forces are normalized as $z_{n} = z/0.2$ and $F_{Dn} = F_D/18.9$, respectively.

### Surface elevation DNN and hyperparameters
Exploring the experimental data further, Figure 5.7 illustrates the time series and spectrum of measured surface elevation for sea state 6 with $H_s = 0.22$ m and $T_p = 2.10$ s. Various damping configurations exhibit minimal variations in both spectrum and time series. The obtained data from wave tank experiments underscores that predicting surface elevation is robust, irrespective of WEC damping.

The deep neural network model predicts surface elevation approximately 0.36 s into the future (equivalent to 93 samples or 2 s in the full-scale system). This DNN model takes as input the historical surface elevation data from two wave gauges: i) at wave gauge 8, located in the closest vicinity of the buoy, and ii) at wave gauge 2, positioned upstream of the buoy. The historical signals from these two wave gauges are concatenated and fed into the network. The model’s output predicts the surface elevation at the position of wave gauge 8.

To determine the required historical data for accurate predictions, upper and lower bounds are established based on the auto-correlation function of the surface elevation at wave gauge 8 and the correlation function between signals from wave gauges 8 and 2. If the auto-correlation exceeds a predefined threshold, indicating a strong correlation, the signal is correlated with its delayed copy. The time corresponding to this threshold is known as the coherence time, marking the upper limit of the necessary history, [111] and [112]. Beyond this point, longer histories are expected to result in minimal improve-
Figure 5.7. The spectral density of surface elevation (a) and a segment of surface elevation time series (b) are presented based on experimental data for the 1:30 scaled system, retrieved from Paper XI.

Figure 5.8 visually represents a coherence time of approximately 15 seconds. Conversely, the lower bound is around 0.7 seconds, representing the time at which the correlation between the signals at wave gauge 2 and wave gauge 8 is maximal. For this model, a historical data window of 2.7 seconds is utilized to predict the next 0.36 seconds. The total dataset includes all possible 0.36-second windows of the signal. Table 5.3 summarizes the hyperparameters for this model.

**PTO translator position DNN and hyperparameters**

Examining the experimental data reveals a direct correlation between damping configurations and the PTO translator’s position. Higher damping limits amplitude, while lower damping induces larger movements, often engaging the end-stop. The impact is evident in Figure 5.9, where increasing damping narrows the position distribution.

In the sequential neural network to predict the PTO translator position, historical PTO translator position data and forthcoming information on surface elevation and damping force are utilized as inputs. The necessary past history for the PTO translator position is determined to be 2.7 seconds, equivalent to 15 seconds in the full-scale system. Future data on surface elevation and
Figure 5.8. Auto-correlation function for the signal at WG8 and the correlation function between signals from WG2 and WG8 are displayed for the 1:30 scaled experimental model, retrieved from Paper XI.

Table 5.3. The table presents the hyperparameters used in the neural network predicting the surface elevation. The learning rate for the Adam optimizer starts at 0.0001 and then undergoes a gradual decrease by a factor of 0.67 if the model fails to show improvement after ten epochs, reaching a lower bound of 0.00001.

<table>
<thead>
<tr>
<th>Hyperparameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of hidden layers</td>
<td>8</td>
</tr>
<tr>
<td>Number of nodes</td>
<td>128</td>
</tr>
<tr>
<td>Activation function</td>
<td>Hyperbolic tangent</td>
</tr>
<tr>
<td>Regularization</td>
<td>L2</td>
</tr>
<tr>
<td>Regularization rate</td>
<td>0.0001</td>
</tr>
<tr>
<td>Optimization method</td>
<td>Adam</td>
</tr>
<tr>
<td>Batch size</td>
<td>128</td>
</tr>
</tbody>
</table>

Figure 5.9. Box plot illustrating the PTO translator position in various damping configurations. The box represents the interquartile range (IQR), whiskers show the 5th and 95th percentiles, and the dashed line marks the mean. The figure shows the information for 1:30 scaled system, retrieved from Paper XI.
Table 5.4. This table provides an overview of the hyperparameters employed in the neural network for predicting the PTO translator position. The learning rate follows the same pattern as detailed in Table 5.3.

<table>
<thead>
<tr>
<th>Hyperparameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of hidden layers</td>
<td>8</td>
</tr>
<tr>
<td>Number of nodes</td>
<td>128</td>
</tr>
<tr>
<td>Activation function</td>
<td>Hyperbolic tangent</td>
</tr>
<tr>
<td>Regularization</td>
<td>$L_2$</td>
</tr>
<tr>
<td>Regularization rate</td>
<td>0.0001</td>
</tr>
<tr>
<td>Optimization method</td>
<td>Adam</td>
</tr>
<tr>
<td>Batch size</td>
<td>256</td>
</tr>
</tbody>
</table>

damping force is considered within a 0.36-second horizon. The network’s output then forecasts the upcoming details of the PTO translator position for a 0.36-second period, corresponding to 2 seconds in the full-scale WEC. The input and output datasets are generated by exploring all possible combinations of time series segments from PTO translator position, surface elevation, and damping force data for various damping configurations. The hyperparameters for this network are provided in Table 5.4.

**Peak line force CNN and hyperparameters**

The line force experimental data is segmented into non-overlapping blocks, each with a fixed duration of 0.36 seconds. The peak force data is then extracted, representing the maximum values within each block, as illustrated in Figure 5.10.

![Figure 5.10. Peak force for each 0.36-second block, depicted over a few seconds of the line force signal for the 1:30 scaled system, retrieved from Paper XI.](image)

The peak force is predicted using a convolutional neural network (CNN) with specific architecture details outlined in Table 5.5. The CNN comprises multiple convolutional layers with 250 filters and 10 kernels each, employing the Parametric Rectified Linear Unit (PReLU) activation function. The
Table 5.5. The convolutional neural network architecture to predict the peak line force in each 0.36-second interval, retrieved from Paper XI.

<table>
<thead>
<tr>
<th>Layer (type)</th>
<th>Output Shape</th>
<th>Number of Parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td>Conv1D</td>
<td>(None, 84, 250)</td>
<td>28,750</td>
</tr>
<tr>
<td>Conv1D</td>
<td>(None, 75, 250)</td>
<td>644,000</td>
</tr>
<tr>
<td>MaxPooling1D</td>
<td>(None, 37, 250)</td>
<td>0</td>
</tr>
<tr>
<td>Conv1D</td>
<td>(None, 28, 250)</td>
<td>632,250</td>
</tr>
<tr>
<td>Conv1D</td>
<td>(None, 28, 250)</td>
<td>69,750</td>
</tr>
<tr>
<td>GlobalAveragePooling1D</td>
<td>(None, 250)</td>
<td>0</td>
</tr>
<tr>
<td>Dropout</td>
<td>(None, 250)</td>
<td>0</td>
</tr>
<tr>
<td>Dense</td>
<td>(None, 1)</td>
<td>252</td>
</tr>
</tbody>
</table>

Total Parameters: 1,375,002 (Trainable: 1,375,002, Non-trainable: 0)

Table 5.6. This table presents a summary of the hyperparameters utilized in the neural network for predicting peak line force in approach 3. The learning rate adheres to the same pattern outlined in Table 5.3.

<table>
<thead>
<tr>
<th>Hyperparameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of hidden layers</td>
<td>4</td>
</tr>
<tr>
<td>Number of nodes</td>
<td>128</td>
</tr>
<tr>
<td>Activation function</td>
<td>PReLU</td>
</tr>
<tr>
<td>Regularization</td>
<td>L2</td>
</tr>
<tr>
<td>Regularization rate</td>
<td>0.0001</td>
</tr>
<tr>
<td>Optimization method</td>
<td>Adam</td>
</tr>
<tr>
<td>Batch size</td>
<td>32</td>
</tr>
</tbody>
</table>

Conv1D layer performs one-dimensional convolution between kernels and input layers, generating the corresponding output. Max pooling downsamples feature maps by computing the maximum value in each batch, while global average pooling averages over each feature map, reducing spatial dimensions to one. The input features for the CNN include future knowledge of surface elevation, PTO translator position, and PTO sliding friction damping force, with a prediction horizon of 0.36 seconds. The CNN’s output is the predicted peak line force within this future horizon. The hyperparameters are presented in Table 5.6.

Loss and accuracy assessment
The disparity between the network’s output and the actual (experimentally measured) data is evaluated using the following loss function:

\[
L(Y, \hat{Y}) = \sqrt{\frac{(\hat{Y} - Y)^T(\hat{Y} - Y)}{Y^TY}} + R_{L2}
\]  

(5.16)
where $Y$ and $\hat{Y}$ are column vectors representing the true and predicted values of the output, and $R_{L2}$ is the L2 regularization term. The system’s accuracy is then determined by its goodness-of-fit, as expressed in Equation 5.15.

**Sensitivity to the predicted future knowledge**

The model’s sensitivity to surface elevation and PTO translator position prediction accuracy is examined. The predicted surface elevation, with varying goodness-of-fit (GOF), is computed by assuming a noise spectrum similar to the wave spectrum. The noise ratio ($\sigma_n/\sigma_\eta$) is set as the ratio of standard deviations, ranging from 0.1 to 0.5 in increments of 0.1. As previously mentioned, the generation of irregular waves relies on the JONSWAP spectrum, detailed in Equation 2.18, with reference to the underlying Pierson-Moskowitz spectrum outlined in Equation 2.19.

To generate the noise spectrum, the significant wave height in Equation 2.19 is defined as $H_s = 4\sigma_n$, while maintaining the same peak angular frequency and shape factor as the wave spectrum without noise. Subsequently, the surface elevation noise is computed through the superposition of angular frequency components:

$$\eta_{\text{noise}}(t) = \sum_i a_i \cos(\omega_i t + \phi_{i,\text{rand}})$$

(5.17)

here, $a_i$ signifies the amplitude, and $\phi_{i,\text{rand}}$ denotes randomized phases distributed over $]0,2\pi[$. The resulting wave elevation noise is then combined with the actual surface elevation recorded by wave gauges during the experiment, providing an approximation of inaccurately predicted surface elevation under various GOF levels.

Similarly, the noise signal for the PTO translator position is derived by assuming a noise spectrum analogous to the PTO translator position spectrum through the Fourier transform. Given that the PTO translator position signal, $z(t)$, is defined within a finite interval $[-T/2, T/2]$, and considering its periodic nature [113], the Fourier series of the noise is expressed as:

$$z_{\text{noise}}(t) = \frac{1}{\text{SNR}} \sum_{n=-\infty}^{\infty} c_n e^{i\omega_n t}$$

(5.18)

here, SNR represents the signal-to-noise ratio, and $c_n$ denotes the complex amplitude computed from:

$$c_n = \frac{d\omega}{2\pi} \int_{-T/2}^{T/2} z(t) e^{-i\omega_n t} dt$$

(5.19)

where $\omega_n = nd\omega$ and the fundamental frequency is defined as $d\omega = \frac{2\pi}{T}$. The ratio $1/$SNR is defined as 0.001, 0.015, 0.05, 0.12, and 0.2. The various generated noisy signals for surface elevation and PTO translator position, along with their GOF, are depicted in Figure 5.11.
Figure 5.11. The signals of surface elevation ($\eta$) and PTO translator position ($z$) with different noise levels are displayed in (a) and (b), respectively, for the $D_0$ damping case, retrieved from Paper XI.
5.3 Results and discussion

5.3.1 Approach 1

Approach 1 has offered the simplest and fastest deep neural network model among all the introduced approaches. Here, the accuracy, loss, model performance, and implementation of this approach in the control system are discussed as follows.

**Loss and accuracy of the DNN model**

The illustration indicates that the DNN model converges around the 250th epoch, achieving approximately 95% accuracy for both the training and validation datasets. Importantly, the absence of significant deviations between the training and validation curves suggests that the DNN model exhibits robust generalization, mitigating concerns of over- or under-fitting. The convergence pattern and generalization characteristics are visually represented in Figure 5.12.

![Figure 5.12](image)

*Figure 5.12.* (a) Loss and (b) Accuracy of the DNN model for the validation and training datasets, retrieved from Paper VIII.
Correlation between DNN prediction and reality
The DNN’s performance is determined by evaluating the correlation, as outlined in Equation 5.14, which indicates an approximate 88% match between the predicted and actual outputs for the test dataset. This correlation is visualized with respect to two input features: maximum wave amplitude and period of each zero up-crossing episode. Figure 5.13 illustrates the peak forces for all zero up-crossing episodes in the test data, encompassing various damping configurations and experimental sea states. The results indicate a satisfactory correlation, with a clear pattern showing that higher maximum wave amplitudes lead to increased peak forces, effectively captured by the DNN model. Additionally, elevated peak forces are observed for wave periods of around 2.0 s, indicating proximity to the system’s natural frequency.

Figure 5.13. DNN model performance for the line peak force in respect to (a) maximum wave amplitude and (b) wave period of zero up-crossing episodes, retrieved from Paper VIII.

Figure 5.14 demonstrates the consistency in locality and spread of peak line forces between the predicted DNN output and true values. The boxplot dis-
The positioning and variability of peak line forces showcase the comparison between the predicted DNN output (cyan) and the actual experimental values (black) across different damping cases, retrieved from Paper VIII.

plays percentiles, quartiles, and medians for various damping configurations and sea states. Notably, the PTO-locked scenario exhibits the highest range of peak line force, aligning with previous findings. Moreover, on average, lower peak forces are experienced for specific damping configurations, while lower variability is expected for others. The distribution of peak forces for each damping configuration tends to skew towards lower values for all zero up-crossing episodes.

**Optimal damping configuration**

The variation in peak force for different damping values is presented in Figure 5.15 across two zero up-crossing episodes. Results indicate significant variability in the optimal PTO damping, which can be attributed to the initial state of the WEC (i.e. position, velocity, and acceleration) during the incident wave impact. The choice of damping depends on factors like buoy movement and wave extremity. For instance, if the buoy is rising with the incident wave, employing a higher damping configuration can prevent forceful compression of the upper end-stop, reducing line forces. Additionally, depending on wave extremity, an alternative optimal strategy may involve adjusting to zero PTO damping, allowing the buoy to surf along the wave and mitigating the impact of intense wave-breaking, slamming, and overtopping on the device.

For the studied point-absorber WEC without a lower end-stop, the slacked mooring line during downward buoy motion makes it insensitive to overtopping impacts. Nevertheless, the effect of overtopping in WEC survivability strategies should not be underestimated especially in the assessment of the buoy hall structure. Note that the proposed strategy fixes the damping force throughout each zero up-crossing episode.
Figure 5.15. Illustration of peak line forces for varied sliding friction damping forces in two random zero up-crossing episodes, retrieved from Paper VIII.

The probability density function (PDF) of optimal damping in the test dataset is depicted in Figure 5.16. The distribution reveals that zero damping is optimal in most zero up-crossing episodes, suggesting that the damping force should frequently be set to zero.

Figure 5.16. Probability density function for optimal PTO damping across all test datasets, retrieved from Paper VIII.
Practical implementation of DNN model in a WEC control system
To integrate a DNN model into the control system of the WEC, knowledge of surface elevation and PTO variables (position, velocity, and acceleration) at each zero up-crossing is crucial. Two strategies can be considered: either predicting these values a few cycles ahead or measuring them at each zero up-crossing instance. The challenge with the latter approach lies in the control system’s ability to swiftly calculate and apply optimal damping at each instance. Conversely, the former approach may be susceptible to modeling errors in predicting system states and surface elevation.

5.3.2 Approach 2
Approach 2 has introduced a more advanced deep neural network model compared to Approach 1. This model predicts the peak line forces by initially determining the probability of the extreme event occurring above the threshold of 80 N. It utilizes the information obtained from this classification to further predict the line forces through a regression task. Here, the model performance is discussed, along with its potential and limitations. Subsequently, the analysis is expanded by studying the influence of survivability control on the extreme peak force distribution of mooring force, which is an important factor in the derivation of the environmental design load.

Loss and accuracy of the advanced DNN
Figure 5.17 displays the accuracy and loss of the predicted peak line force values across the learning process. The figure indicates a negligible difference between the training and validation curves, affording the model’s well-generalized performance without noticeable overfitting or underfitting.

The advanced DNN performance evaluation
The evaluation of the network’s performance on the test dataset is illustrated in Figure 5.18 and Figure 5.19. Higher probabilities of extreme events are associated with increased peak line forces, demonstrating the effectiveness of the classification task in Figure 5.18. In Figure 5.19, the correlation between the predicted and true (WEC-Sim) peak line force data for the regression task is presented, achieving a goodness-of-fit of 80%. The attention mechanism integrated into this proposed DNN model ensures that peak line forces, even at larger values, closely align with the diagonal line, indicating consistent accuracy comparable to lower peak forces.
Figure 5.17. The accuracy (a) and loss (b) of the advanced DNN model in predicting the peak line force for both training and validation datasets in the regression task, retrieved from Paper IX (© 2023 IEEE).

Figure 5.18. The DNN model’s classification performance is illustrated by comparing the predicted probability of extreme line forces with the true peak line force data, retrieved from Paper IX (© 2023 IEEE).
Figure 5.19. Illustrating the regression task performance of the DNN model, the comparison between predicted and true peak line forces is presented. The color bar indicates the higher probability of extreme forces for larger peak line forces, retrieved from Paper IX (© 2023 IEEE).

WEC-Sim advanced DNN controller performance
Figure 5.20 illustrates the performance of the control system during a WEC-Sim runtime of 658 s or 0.18 h. The phase remains consistent in both scenarios, with and without the control system. The comparison involves the time history and the empirical cumulative distribution function (ECDF) of the line force with and without the control system. Analyzing the line force history reveals a consistent reduction in line force occurrences with the implemented control system. To specifically examine the tail of the line force data, the ECDF is computed for forces exceeding the 80 N threshold, focusing on $D_0$ and $D_1$ damping configurations. Conversely, while it may not be critical for survivability, the ECDF is plotted for the entire force data range in the case of $D_2$ to highlight the reduction in friction-dominated line force due to the controller frequently opting for lower damping configurations.

In comparison to the constant damping scenarios represented by $D_0$ and $D_1$, the ECDF curve for the controlled system exhibits an earlier convergence to the value one, as expected. This indicates a prompt reduction in peak forces, optimizing damping for each zero up-crossing episode of surface elevation. In the scenario involving $D_2$, the controller’s decision to use lower damping leads to a decrease in friction force. As a consequence, and being predominantly influenced by friction, the line force is correspondingly reduced. However, for higher line force values, the controller’s performance is somewhat inferior to a constant $D_2$ damping case. It is important to note that this does not necessarily advocate for the application of high damping during extreme events. The increased damping of the PTO restricts the system’s mobility, leading to more frequent wave-breaking slamming on the WEC structure and an elevated
Figure 5.20. The time domain evolution of line forces with and without the control module is depicted, along with the Empirical Cumulative Distribution Function (ECDF) of the force. Sub-figures (a), (b), and (c) provide a comparison for constant damping configurations $D_0$, $D_1$, and $D_2$, respectively. In the cases of $D_0$ and $D_1$, the ECDF illustrates forces above 80 N, relevant for survivability considerations. For $D_2$, the ECDF is presented for the entire force dataset, revealing intriguing trends in lower force values, retrieved from Paper IX (© 2023 IEEE).
likelihood of the over-topping phenomenon. However, as aforementioned, the survivability strategy in this context does not address the overtopping phenomenon. Another notable observation is the general reduction in peak line forces as damping increases from $D_0$ to $D_2$. Nevertheless, it would be incorrect to infer that an increase in damping would consistently lead to a reduction in peak forces. Our experimental data, which is presented in Paper IV, contradicts this assumption, revealing that the locked PTO case resulted in excessive peak forces. This highlights a limitation in the WEC-Sim model used in this study, which was unable to accurately replicate the system’s response in very high damping cases such as the locked PTO configuration. It is important to mention that in the controlled system, the damping remains constant during each zero up-crossing episode of surface elevation.

Exploring the potential and limitations of the controller system
While the controller aims to determine the optimal damping during each zero up-crossing episode of surface elevation, the system’s response is influenced by the historical record of selected damping values, which may negatively impact subsequent scenarios. An illustrative example of this phenomenon is presented in Figure 5.21. Despite the control system selecting zero damping as the optimal value, the system’s response deviates from what would be expected with a consistently zero damping. This deviation is evident when examining the PTO velocity signal immediately before the occurrence of the peak force. In the controlled case, the velocity signal is higher, influenced by the system’s response history. This introduces a unique situation where, despite the control strategy, the choice of damping may not consistently result in lower forces compared to the non-controlled system.

Alternatively, Figure 5.22 depicts the control system’s performance over a few seconds, where the line force response is significantly reduced by adjusting the damping.

The probability distribution function for the optimal damping in every zero up-crossing episode indicates the preference for lower damping configurations in most scenarios leading to reduced peak line forces (refer to Figure 5.23). In our prior experimental research presented in Paper IV, we asserted the existence of an optimal damping value for each sea state, typically situated in the higher range, resulting in minimized peak forces. It is crucial to emphasize that the findings in this study do not contradict our earlier experimental results in Paper IV. The earlier work concentrated on a specific damping configuration that minimized the peak line force across the entire sea state, whereas in this study, optimal damping is computed for each zero up-crossing episode of surface elevation, and its statistical distribution is explored.

Future work to enhancing DNN model accuracy
The future directions for improving the accuracy of the DNN model regarding predicted peak line force involve thorough investigations into various architec-
Figure 5.21. The figures depict the time history of the line force (a), optimal damping (b), PTO position (c), and PTO velocity (d), contrasting the controlled system with a constant $D_0$ scenario, retrieved from Paper IX (© 2023 IEEE).

Figure 5.22. Comparison of the line force data history under adaptive damping reducing force during each zero up-crossing episodes of surface elevation, (a), and with the constant $D_0$ damping, (b), retrieved from Paper IX (© 2023 IEEE).
tures. In the current study, a variety of architectures, such as residual neural networks (ResNet), have been evaluated; however, no significant improvement was observed. Furthermore, the exploration of a physics-informed neural network (PINN) model, incorporating initial system state values to derive the system’s equation of motion, did not yield improved accuracy. However, the PINN could potentially enhance force prediction if accurately predicting system states (e.g., position, velocity, and acceleration of the PTO translator) at the force’s peak moment is achieved, although achieving this can be challenging. Additionally, introducing a more sophisticated attention mechanism to further refine the accuracy of peak line force predictions can lead to a further increase in the accuracy of the prediction model.

The extreme peak mooring force distribution with and without survivability control system

To evaluate the impact of survivability control introduced in approach 2 on the environmental design load, crucial for the design and construction phase of these devices, both the long-term full sea state approach (considering 180 sea states in this study) and the contour approach are once again revisited. The results are briefly outlined here, comparing the system response with and without survivability. First, in Figure 5.24, the survival function for each individual sea state is displayed, along with the survival function for the full sea state shown by the black line, representing the weighted average of the CCDF for all sea states. It is important to note, as detailed in Chapter 4, that the generalized Pareto distribution (GPD) is employed to model the short-term distribution of each sea state above a certain threshold. Therefore, the full sea state survival function (CCDF) is presented above the maximum threshold of all sea states. Examining the 9.1-year return period, the return level is almost the same for damping configurations of $D_0$ and $D_1$, but notably lower for the
Figure 5.24. (a), (b), and (c) depict the survival functions for constant damping scenarios: $D_0$, $D_1$, and $D_2$, respectively. The blue lines showcase the complementary cumulative distribution function (CCDF) for 180 sea states, while the black line represents the overall sea state survival function. Dashed lines mark specific survival levels at 0.2, 0.9, 1.8, 4.6, and 9.1 years, corresponding to 1, 5, 10, 25, and 50 years, respectively, in the full-scale system, retrieved from Paper X.

$D_2$ case. This observation suggests that opting for lower damping configurations is a more conservative choice in the calculation of environmental design loads using a constant damping configuration.

As mentioned in Part III, the contour approach reduces the computation of system response to a few sea states along the environmental contour, identifying the most extreme sea state through the expected value of the short-term extreme distribution. Subsequently, an exploration of the expected value of the extreme peak force distribution for sea states 5a to 8 along the environmental contour was conducted using the GPD fit, as depicted in Figure 5.25. Lower damping cases showcase the highest expected value of the extreme distribution, aligning with observations in the full sea state approach where lower damping cases contribute to a larger long-term response. Moreover, in all con-
Figure 5.25. For each constant damping case ($D_0$, $D_1$, and $D_2$), sub-figures (a), (b), and (c) illustrate the expected value of the extreme peak force distribution for sea states 5a, 6, 7, and 8, retrieved from Paper X.

stant damping cases, sea state 7 exhibits the highest expected value, with the exception of the $D_0$ case where sea state 6 shows a similar expected value to sea state 7. Consequently, sea state 7 is identified as the most extreme sea state.

Exploring how a control system influences the reduction of expected forces in sea state 7, identified as the most extreme sea state, Figure 5.25 provides intriguing insights. As illustrated in Table 5.7, the control system shows a marginal decrease in the expected value compared to the constant damping cases of $D_0$ and $D_1$. However, in the constant damping case of $D_2$, the expected value is even lower than in the control case. This result does not necessarily support the adoption of larger damping values for survivability purposes. As previously mentioned, in larger damping configurations, the buoy’s
Table 5.7. The expected values of the extreme peak force distribution for sea state 7 under constant PTO damping scenarios of $D_0$, $D_1$, and $D_2$, along with the scenario involving the control system, retrieved from Paper X.

<table>
<thead>
<tr>
<th>Damping case</th>
<th>$D_0$</th>
<th>$D_1$</th>
<th>$D_2$</th>
<th>Control system</th>
</tr>
</thead>
<tbody>
<tr>
<td>Expected value of the extreme distribution</td>
<td>372.5 N</td>
<td>378.5 N</td>
<td>345.8 N</td>
<td>367.4 N</td>
</tr>
</tbody>
</table>

movement is more restrained, making it more susceptible to the overtopping phenomenon, leading to a reduction in mooring force. Paper IV has shown that, during the experiment, the peak line force was reduced when damping was increased up to a certain level. However, beyond that level, the peak force increased drastically due to the high relative velocity between the water and the buoy. Note that improving the performance of the advanced DNN model can reduce the expected value of the extreme distribution even more. The potential and limitations of the controller have been thoroughly explained in section 5.3.2.

5.3.3 Approach 3

**Surface elevation DNN prediction**

The surface elevation prediction model achieved convergence after 241 epochs, exhibiting 95% accuracy and a 0.05 loss for both the training and validation datasets. The predicted surface elevation aligns closely with the measured values, as depicted in Figure 5.26. To generate the complete predicted surface elevation signal, the length of the measured data is segmented into non-overlapping windows of 0.36 seconds. For each window, the surface elevation is predicted using the historical data from wave gauges 8 and 2. The overall predicted signal is then formed by concatenating all the predicted windows.

It is worth noting that while a long short-term memory (LSTM) network is commonly favored for predicting time series signals, the demonstrated performance of a well-established DNN here indicates comparable accuracy, achieved within a significantly shorter training time on the order of a few minutes.

**PTO translator position DNN prediction**

The network achieves a performance of 92% accuracy and a 0.08 loss for the training dataset and 87% accuracy with a 0.13 loss for the validation dataset after 322 epochs in predicting the PTO translator position signal. A comparison of the predicted PTO translator position with the true and predicted surface elevation, used as its input, is illustrated in Figure 5.27. The entire predicted PTO translator position signal is obtained similarly to the predicted surface elevation, as explained in section 5.3.3. Results indicate a decrease in network performance as damping increases. To address this, categorizing the damping range (e.g. low, average, high) and training separate models for each cate-
Figure 5.26. Predicted surface elevation in the $D_0$ damping case for the 1:30 scaled system using the DNN model is presented, where (a) displays the full-length surface elevation, and (b) shows a shorter time span for a closer look, retrieved from Paper XI.

gory may prevent a decline in prediction accuracy. However, this approach demands a more extensive training dataset and additional damping cases than those studied here. Generally, a larger training dataset contributes to improved accuracy in data-driven models.

**Peak force CNN prediction**
The training and validation accuracy for predicting peak force stand at 91% and 89%, respectively, accompanied by a loss of 0.09 and 0.11 after 106 epochs, as illustrated in Figure 5.28. A quantile plot in Figure 5.29 showcases the accuracy of 90.3% for the test dataset, where the predicted peak line force is calculated based on actual surface elevation and PTO translator position. The plot reveals a strong model performance, with data points closely aligned with the diagonal line.
Figure 5.27. The predicted PTO translator position for the three damping configurations of $D_0$, $D_1$, and $D_2$ from the DNN model is illustrated in (a), (b), and (c), respectively, for the 1:30 scaled system, retrieved from Paper XI.
Figure 5.28. Performance metrics, including loss and accuracy (Goodness-of-fit), of the CNN model in predicting peak forces for the 1:30 scaled system are shown in sub-figures (a) and (b), respectively, retrieved from Paper XI.

In Figure 5.30, the network’s performance is depicted when predicted surface elevation and PTO translator position are used as inputs. The accuracy of peak force prediction experiences a 7% decline for $D_0$ and $D_1$ damping cases compared to Figure 5.29, where true inputs were provided. Nevertheless, the model maintains a satisfactory correlation despite using predicted input signals. However, for the $D_2$ damping case, a more significant drop in performance is observed, with an accuracy of 75.6%. The anticipated drop in performance for the $D_2$ damping case, attributed to lower prediction accuracy, could potentially be alleviated by training the network with an expanded dataset. This would involve incorporating more experimental data, especially for larger damping cases, as elaborated in section 5.3.3. Furthermore, the correlation values (refer to Equation 5.14) for Figure 5.29 and Figure 5.30 (a), (b), and (c) are computed as 99%, 96.6%, 96.5%, and 89.2%, respectively.

To further assess the accuracy of the peak force prediction model, the predicted PTO translator position is filtered using a low-pass filter with a filter order of 4, a critical frequency of 3 rad/s, and a sampling frequency of 300 Hz. However, filtering the PTO translator position contributes only a minor 0.5% to less than 1.0% increase in the accuracy of predicted peak forces, rendering it ineffective in this context. It is important to note that the results presented here are based on unfiltered PTO translator position signals.
Figure 5.29. The quantile plot illustrates the correlation between the measured peak force in the experimental data, and the predicted one using the true surface elevation and PTO position, encompassing all damping configurations for the CNN model, retrieved from Paper XI.

Figure 5.30. The quantile plot compares the measured peak force with the predicted values based on the CNN model using the predicted surface elevation and PTO translator position. Sub-figures (a), (b), and (c) display the results for the damping cases $D_0$, $D_1$, and $D_2$, respectively, in the 1:30 scaled system, retrieved from Paper XI.
Sensitivity to uncertainties within the prediction of surface elevation and PTO translator position

The impact of different noise levels on the accuracy of the peak force prediction model is assessed in Figure 5.31. The study focuses on the separate effects of prediction accuracy in each input data, i.e. the surface elevation and the PTO translator position. The system is observed to be insensitive to variations in the prediction accuracy of surface elevation. In essence, uncertainties in wave elevation predictions do not negatively affect peak force predictions as long as the accuracy of translator position predictions remains intact.

It is important to note that the variation shown in the GOF for surface elevation among different damping cases is a result of generating noise signals based on random phase, as described in Equation 5.17.

In contrast, the network for prediction of peak forces exhibits sensitivity to the prediction accuracy of the PTO translator position. The figure illustrates that, with increasing damping, the force prediction model becomes less sensitive to the accuracy of PTO translator position predictions. Additionally, the lower damping cases of $D_0$ and $D_1$ show a linear trend concerning the prediction accuracy of the PTO translator position, while such a pattern is not observed for $D_2$. For instance, a prediction accuracy of around 60% and 70% for the PTO translator position resulted in a similar GOF for predicted peak forces in the $D_2$ configuration.

Sensitivity to prediction horizon for various NN models

The length of the prediction horizon is a crucial factor impacting the GOF for all predictive models. Opting for a 0.36 s horizon, equivalent to 2 s in the full-scale system, involves a trade-off between network accuracy and the permissible delay for the control system to adapt damping force. A shorter horizon enhances network prediction accuracy but escalates the control system’s demands. Conversely, extending the prediction horizon allows the WEC more time for damping adjustment, albeit at the cost of a less precise prediction of the optimal damping value.

In Figure 5.32, the sensitivity of accuracy (GOF) in surface elevation, PTO translator position, and peak force prediction models across different prediction horizons is examined. The range spans from 0.18 to 1.3 s, stepping at 0.36 s (equivalent to 1.0 to 7.0 s in the full-scale system with 2.0 s steps). The history time of 2.7 seconds is selected and remains constant for both the surface elevation and PTO translator position prediction models. The measured (true) data serves as input to all prediction models in Figure 5.32.

The outcomes underscore a substantial correlation between PTO translator position accuracy and the prediction horizon. With increasing prediction time, accuracy consistently diminishes. In contrast, the precision of surface elevation and peak line force prediction remains unaffected by variations in the prediction horizon length. This suggests that the peak line force prediction CNN model excels at predicting peak forces over a much longer horizon.
Figure 5.31. The impact of uncertainties in surface elevation and PTO translator positions on peak force prediction is depicted in (a), (b), and (c) for the damping cases $D_0$, $D_1$, and $D_2$, respectively, in the 1:30 scaled system, retrieved from Paper XI.
Figure 5.32. The accuracy of the surface elevation, PTO translator position, and peak force prediction models to varying prediction horizons is demonstrated in (a), (b), and (c), respectively, for the 1:30 scaled system using both the training and validation data sets, retrieved from Paper XI.

with minimal to no compromise in precision, given accurate PTO translator position predictions.

Sensitivity of the optimal damping to the uncertainties in the prediction of PTO translator position

By assigning different damping values to the peak force prediction model, the damping that results in the minimum peak force is identified for each window of 0.36 s in the line force signal. The distribution of optimal damping values, representing sliding friction force, is illustrated in Figure 5.33 for different prediction accuracies of the PTO translator position. Meanwhile, the surface elevation signal remains constant, and its prediction accuracy is detailed in section 5.3.3. When the predicted translator position signal becomes less accurate, the model tends to estimate higher damping values to minimize peak force. In the absence of errors in the predicted translator position, lower damping configurations, approaching zero, have a higher likelihood of yielding the minimum peak force. This aligns with our prior findings in Paper VIII, where optimal damping values were determined for a DNN model across seven sea states.
Figure 5.33. The probability density function representing optimal damping with varying prediction accuracy of the PTO translator position \( (z) \), retrieved from Paper XI.

It is important to note that sliding friction forces exceeding 18.9 N (corresponding to the \( D_2 \) damping configuration in the wave tank experiment) fall outside the training range of the network and may consequently be subject to inaccuracies.

**Implementation in a real WEC control system**

The proposed survivability model relies on future knowledge of incoming waves and the system state (PTO translator position) to predict peak line forces a few seconds ahead. While the CNN model shows high accuracy in predicting peak forces, its dependence on precise PTO translator position predictions may be considered a drawback. However, the accuracy of the PTO translator position network improves given sufficient training data for various damping values.
Prediction of highly nonlinear waves

Nonlinear coherent structures [114], such as breathers and solitons, can be studied using nonlinear Fourier analysis in the exploration of nonlinear wave terrains [115]. Identifying and predicting these nonlinear phenomena should also be considered for devising effective survivability strategies. Energetic waves, including solitons and breathers, can exert a significant impact on devices. In such cases, mere adaptation of damping may prove insufficient, necessitating the implementation of alternative survivability strategies, such as submerging or lifting the device from the water. Predicting these waves can be done by various methods, for instance, physics-informed neural networks, where the primary principle is based on predicting the waves according to Schrödinger equations. Ultimately, survivability strategies should be adapted based on understanding the nature of nonlinear waves and assessing the system dynamics through experimental campaigns.

5.4 Summary of the results

The survivability strategy for point absorber wave energy converters can be addressed by minimizing mooring forces through adjusting system parameters such as PTO damping. This may involve predicting system states and incoming wave information to enable the system for force (mooring) prediction. To substitute the computationally expensive numerical simulations required for this strategy, the application of data-driven methods has been studied. Three different neural network architectures are outlined to predict damping, aiming to minimize the mooring peak force. The first two models predict the peak force based solely on the current and future information of the surface elevation, as well as the instantaneous value of the system state (i.e., the position, velocity, and acceleration of the power take-off translator) at every zero up-crossing of the surface elevation, assuming that future information about surface elevation is well-known. However, in approach three, the survivability strategy and prediction of peak forces rely on predicting the system state and incoming wave. The third approach introduces and discusses in detail a neural network for predicting each input data.

The first model employs a relatively simple yet fast deep neural network that uses experimental data for its training and test data set, suggesting a constant optimal damping for each zero up-crossing episode of wave elevation. This approach achieves a correlation factor \( C_r = c_{12}/\sqrt{c_{11}c_{22}} \) of about 88% and an accuracy \( (1 - \sqrt{MSE}) \) of 95%. Furthermore, the results show that the optimal damping in each zero up-crossing episode differs, emphasizing the importance of predicting the mooring force during extreme events.

The second approach introduces the integration of a controller system designed for enhancing survivability within the numerical WEC-Sim model. This system has been fine-tuned using experimental data obtained from a
A more sophisticated and advanced version of the deep neural network, previously introduced in the first approach, is suggested. This network begins by identifying the probability of extreme events surpassing the 80 N threshold, leveraging this information to predict line forces through a regression task. The outcomes illustrate that the controller significantly reduces the line force experienced by the WEC. The survivability controller predominantly favors lower damping values as the optimal configuration for minimizing forces in most zero up-crossing episodes of surface elevation. Furthermore, the control system effectively diminishes line force, particularly when compared to the non-controlled system with constant PTO sliding friction force of zero Newton and 7.4 N corresponding to \(D_0\) and \(D_1\) cases, representing the lower and mid-range of PTO damping, respectively. Despite its effectiveness, there are instances where the controller fails to decrease line force. Potential reasons include: 1) incorrect damping selection due to the accuracy of predicted line force; 2) changes in the system response history compared to constant PTO damping cases, leading to higher force regardless of the selected damping or control strategy; 3) the network being trained over a limited damping range, neglecting higher damping ranges that could result in lower peak line force.

Additionally, in line with the neural network proposed in this approach, a reevaluation of the extreme peak force distribution explores how the control strategy affects the computation of environmental design load. This factor is identified as a crucial consideration in the design of wave energy converters as stated in Part III. Here, the analysis involves employing the full-state approach using the generalized Pareto distribution (GPD) to model short-term extreme peak force distribution and the survival function of the system response for 180 sea states within the environmental contour for constant PTO damping cases. The most extreme sea state (sea state 7) is then identified along the environmental contour, considering the highest expected value following the contour approach. For this most extreme sea state, the control strategy is implemented by adjusting the PTO damping through the deep neural network outlined in the second approach to minimize mooring forces. The results reveal that in the case of a no-control system, increasing constant damping reduces the full sea state survival function and expected value of extreme peak force distribution, indicating the sensitivity of the analysis to system damping. Moreover, the response of the system with the survivability control strategy is explored for the most extreme sea state (sea state 7) and demonstrates a reduction in the expected value of extreme peak force distribution when compared to the constant \(D_0\) and \(D_1\) cases. However, the control system fails to provide a lower expected value of the extreme peak force distribution than the \(D_2\) case.

The third approach explores the application of various neural networks for predicting incoming waves, system states, and mooring peak force. It argues that predicting future data introduces uncertainties within the computational process. However, these uncertainties may not necessarily lead to an inac-
urate optimal damping. The results are presented by explaining the neural network prediction models as follows: The DNN model for surface elevation prediction achieves a 95.5% goodness-of-fit for a prediction horizon of 0.36 s, equivalent to 2 s in the full-scale system. The PTO translator position prediction model attains accuracy rates of 93%, 92%, and 86% (GOF) for damping cases of $D_0$, $D_1$, and $D_2$, respectively, within the same prediction horizon as surface elevation, which is 0.36 s. The peak force prediction model achieves approximately 90% accuracy within the 0.36 s horizon when true (measured) data is provided as its input. This accuracy diminishes by around 7% when the predicted surface elevation and PTO translator position are given to the model for the damping cases of $D_0$ and $D_1$. The decrease in accuracy is more pronounced for the $D_2$ damping case. Subsequent sensitivity analysis reveals that the uncertainty in predicting wave elevation has an insignificant direct impact on predicting peak line forces. The convolutional neural network model for peak line force exhibits a significantly stronger dependence on PTO translator position as its input data. A sensitivity study of the peak force model to different noise levels in the input data demonstrates that the larger damping configuration of $D_2$ is less sensitive to uncertainties in PTO translator position prediction. Another sensitivity study on the prediction horizon shows that the GOF of the PTO translator position prediction monotonously decreases as the prediction horizon increases. Conversely, the peak line force and surface elevation prediction models are nearly insensitive to the prediction horizon. The results indicate that as the prediction accuracy of the PTO translator position drops, larger damping values are more frequently identified as the optimal damping, contrary to what a perfect translator position prediction suggests.

Finally, survivability strategies should also encompass the reduction of forces on the structure beyond mooring lines. For instance, mitigating excessive overtopping forces directed at the WEC hull, especially when it contains mechanical or electrical components, is crucial. This aspect remains unexplored in this study and serves as a potential subject for future research.
6. Conclusion

This doctoral thesis delves into the multifaceted domain of wave energy conversion, encompassing four distinct yet interrelated parts. The synthesis of findings across these segments not only advances the understanding of the intricate dynamics of wave energy converters (WECs) in extreme conditions but also sheds light on critical design considerations for increasing the reliability of these systems.

Part I: Prediction horizon in power maximization control
The initial part of the research focuses on maximizing power output in WECs, investigating the pivotal role of the prediction horizon. By considering dissipative losses, spectrum shape, and other parameters, the study provides insights into the optimal velocity governing optimal power absorption. The results underscore that a relatively short prediction horizon can suffice for achieving optimal power output, challenging conventional assumptions. Moreover, the incorporation of filtering techniques on the optimal transfer function between optimal velocity and excitation force enhances power conversion when a limited prediction horizon is available, offering a promising avenue for improving overall efficiency in wave energy harvesting systems. The noise sensitivity studies further contribute by showcasing the resilience of power output in the face of wave excitation force uncertainties.

Part II: Extreme load analysis through experimental validation
The second segment of the thesis translates insights into practical implications through a wave tank experiment. On a scale of 1:30, the experiment investigates peak forces and system responses in extreme conditions under various damping configurations. The findings emphasize the significance of damping in mitigating peak forces, offering valuable design considerations. The exploration of different wave representations highlights the conservative nature of irregular waves, crucial information for designing WECs to withstand extreme sea states. The study introduces an understanding of the impact of damping on system behavior, expanding the empirical knowledge base essential for robust WEC design.

Part III: Reliability through design load cases analysis
Part III tackles the critical aspects of environmental design load and fatigue analysis, providing fundamental guidelines in the design consideration of wave energy converters for reliable operations. Rigorous exploration leads to deriving the environmental design load, a key benchmark for designing WECs
capable of withstanding extreme conditions. The linear relation observed between fatigue equivalent constant amplitude force and maximum force per sea state introduces a valuable metric for comparing potential damage. By emphasizing the pivotal role of the ultimate limit state in structural design, the study underscores the importance of the ultimate limit state over the fatigue limit state, guiding engineering decisions.

**Part IV: Survivability control through data-driven approaches**

The final segment of the research introduces innovative survivability strategies for WECs, leveraging neural networks for predictive control of mooring forces. The study explores three distinct approaches to address the critical need for minimizing extreme forces during harsh environmental conditions. Using a deep neural network for predicting optimal damping in response to wave excitation introduces a data-driven paradigm for enhancing survivability. The integration of a controller system, fine-tuned using experimental data, demonstrates reductions in line forces, offering a practical mechanism for real-time force mitigation. The third approach, focusing on predicting incoming waves, system states, and mooring peak forces introduces a comprehensive neural network-based solution for survivability. This approach also delves into understanding the impact of uncertainties associated with predicting future information on the optimal damping of the survivability strategy. This multifaceted strategy presents a promising avenue for enhancing WEC survivability in extreme conditions.

In conclusion, this doctoral thesis contributes to practical solutions for improving the reliability and efficiency of WECs. The insights provided across the four parts of the research pave the way for a more robust and sustainable future for wave energy harvesting, and informing engineering practices in this field.
7. Future work

For future endeavors, evaluating the efficacy of the proposed survivability strategies in a wave tank experiment under extreme wave conditions is a pivotal undertaking. This evaluation should extend to diverse power take-off systems beyond friction-based mechanisms and encompass a spectrum of mooring configurations.

Additionally, there is a compelling need to delve into the lifespan of the device and its components within the context of survivability control, discerning the frequency of maintenance requirements.

Moving forward, the exploration of these strategies must extend to a collective setting, particularly within a wave energy converter park. Such an analysis should address the various factors such as wave energy converter (WEC) dynamics influenced by factors like shadowing, a critical consideration for point absorber wave energy converters park. Given their potential commercial viability, these converters often necessitate installation in groups to collectively meet energy demands. This facet, therefore, becomes paramount for their successful commercial deployment.
8. Summary of papers

**Paper I: Considerations on prediction horizon and dissipative losses for wave energy converters**

The paper investigates the non-causal optimal control law for wave energy converters, focusing on the prediction of waves and wave forces over a future horizon. By utilizing examples of generic body shapes and oscillation modes, the study explores the influence of dissipative losses in the conversion chain on the required prediction horizon for achieving maximum power output. The analysis includes considerations for sensitivity to noise, the use of filtering to enhance performance in cases of short prediction horizons or inaccurate predictions, and addresses challenges such as amplitude constraints and other real-world effects.

The results indicate that the prediction horizon needed to approach the maximum achievable power output for real systems ranges from a few seconds up to about half a wave period. This is notably shorter than previously reported horizon lengths. The study also considers factors such as energy period, spectrum shape factor, and the impact of amplitude constraints on the performance of wave energy converters. In conclusion, the paper highlights the investigation into the maximum power output from wave energy converters concerning the length of the prediction horizon and the level of dissipative losses. Generic converter concepts, combining various body shapes, submergence levels, and oscillation modes, were examined under the assumption of linear behavior. The study finds that single truncation of the convolution integral for optimal velocity, applying the finite prediction horizon only on the non-causal side, generally results in higher power output compared to double truncation. Dissipative losses like hydrodynamic drag and machinery friction were identified to reduce the need for longer prediction horizons. Additionally, the study suggests that, for most generic concepts, it is possible to reach at least 70% of the maximum absorbed power by selecting an appropriate transfer function in each sea state, eliminating the need for extensive prediction. The robustness of the results to noise in estimated and predicted excitation forces is demonstrated, emphasizing the practicality of the findings. Overall, the paper suggests that, with well-designed optimal controllers, achieving maximum power output for real systems may require much shorter prediction horizons than previously assumed.

The author was responsible for the formal analysis, visualization, coding and programming, and writing and editing of the paper. *The paper is published in the Journal of The Institution of Engineering and Technology (IET), Volume 15, October 2021.*
Paper II: Design and evaluation of linear and rotational generator scaled models for wave tank testing

The paper focuses on the significance of small-scale testing of wave energy converters (WECs) in controlled wave tank environments for technical, economic, risk, and reliability assessments before costly full-scale tests. For this purpose, two scaled (1:30) rotational and linear power take-off (PTO) systems for wave tank experiments are developed. The design addresses challenges related to mass, friction, and inertia in the PTO system, crucial factors in small-scale WEC models.

In conclusion, the study emphasizes the importance of small-scale experiments for assessing wave energy technologies comprehensively. The design challenges in the scale model’s power take-off system, including high friction, unwanted inertia, and cogging, are discussed. The paper presents the design and dry-testing experiment results for both rotational and linear PTO systems. The rotatory PTO, employing eddy current damping, exhibits promising characteristics due to the non-contact nature of damping. Damping increases with the applied current, independent of mass. Optimal power absorption would benefit from higher damping, achievable by increasing the number of magnet pairs (coils). On the other hand, the linear PTO, utilizing friction, demonstrates satisfactory results concerning braking force. The design is deemed simple and robust, making it suitable for scale experiments focused on studying risk and reliability rather than power maximization and control. The linear PTO, with its simple and robust design, is deemed suitable for experiments emphasizing risk and reliability assessment over power maximization. The study contributes to valuable insights into the design and evaluation of small-scale WEC models, highlighting the crucial role of controlled wave tank experiments in assessing the feasibility and reliability of wave energy technologies.

The author was responsible for conducting dry testing for PTOs, performing formal analysis, and writing and editing the paper. The paper is published in the proceeding of the 4th international conference on Renewable Energies Offshore (RENEW 2020) in Lisbon, Portugal, 12th-15th, October 2020. Book of Developments in Offshore Renewable Energies published by Taylor & Francis in October 2020.

Paper III: Wave energy converter power take-off system scaling and physical modeling

The paper addresses the challenge of harnessing wave power efficiently by developing and integrating reliable power take-off (PTO) mechanisms in wave energy devices. Emphasizing the importance of experimental testing at a small scale during device assessment, the paper explores solutions for replicating and evaluating PTO elements. Recommendations encompass enhancements in experimental setups, calibration practices, and error estimation methods,
aiming to ensure accurate scaling and evaluation of the PTO mechanism’s behavior. While acknowledging technology-dependent considerations, the paper identifies universally applicable practices.

In conclusion, the paper focuses on providing fundamental theory, practical guidelines, recommendations, and examples for planning PTO physical modeling. The overview suggests that to attain reliable experimental results, attention is drawn to adopting the correct experimental setup, calibration, and uncertainty analysis practices. The optimization of the experimental setup involves reducing mechanical friction between moving parts, followed by extended calibration work. The paper suggests implementing multiple methodologies for characterizing and calibrating PTO systems to enhance results. Case studies on different WECs exemplify the importance of customization and careful planning of experimental work. The methodology applied by other authors in previous experiments, as covered in the case studies, may be considered for future experiments. The paper emphasizes the importance of anticipating and documenting experimental work while underlining the need for a formal uncertainty analysis at various stages of progress. Overall, the guidance provided aims to enhance the reliability and accuracy of PTO physical modeling in small-scale experimental studies for WECs.

The author was responsible for conducting dry-testing experiments for PTOs, analyzing data for the Uppsala case study, and contributing to the writing of the paper. The paper is published in the Journal of Marine Science and Engineering (MDPI), Volume 8, August 2020.

Paper IV: Experimental investigation of a point-absorber wave energy converter response in different wave-type representations of extreme sea states

This paper presents the findings of a 1:30 scaled wave tank experiment investigating the behavior of a point-absorber in extreme sea states and intermediate water depth. The study focuses on the impact of the power take-off (PTO) damping parameter and various non-linear phenomena, including wave breaking and overtopping, with specific attention to the maximum line (mooring) force when an upper end-stop is present. The comparison of different wave representations—irregular, regular, and focused waves—reveals that they do not uniformly result in the same peak line force for the same sea state. Furthermore, an optimal damping value is identified for each sea state, leading to the smallest peak force. The paper also explores the effects of end-stop spring compression and wave-breaking slamming, which may be mitigated by overtopping water pressure. Notably, waves with longer wavelengths contribute to larger surge motion, potentially resulting in higher and more impactful line forces.

The study conducted wave tank experiments on a 1:30 scaled wave energy converter (WEC) in intermediate water depth. The experiments involved a
linear PTO with friction damping and a cylindrical buoy with an ellipsoidal bottom, exposed to extreme sea states with a 50-year return period. Different wave-type representations (irregular, regular, and focused waves) were examined under various PTO damping cases. The findings highlight that irregular waves, compared to focused waves, exhibit the highest peak force, making them the most conservative choice for assessing extreme waves. In conclusion, the results emphasize the existence of an optimum damping value to minimize the peak line force, supporting earlier studies suggesting that higher PTO damping can reduce peak line forces. However, the study extends previous research by exploring the entire PTO damping configuration range and revealing that increasing damping from zero can reduce the peak line force to a minimum before further damping increase leads to a higher peak force. The analysis also considers non-linear phenomena like wave breaking and overtopping, showing that breaking waves contribute to high line forces while overtopping aids in reducing the maximum line force.

The author was responsible for conducting the wave tank experiment, performing the formal analysis, and writing and editing the paper. The paper is published in the Journal of Ocean Engineering, ELSEVIER, Volume 248, March 2022.

**Paper V: Experimental results of force measurements from a scaled point absorbing wave energy converter subjected to extreme waves**

This paper introduces the implementation and setup of the WEC-Sim numerical model, designed to simulate the dynamics of the system numerically. To assess the accuracy of the numerical model, it is compared with experimental data derived from wave tank experiments. The wave tank experiment involved a 1:30 scaled friction damping linear power take-off (PTO) system coupled with a cylindrical buoy featuring an ellipsoidal bottom. The linear PTO includes a rod moving vertically against a Teflon block, introducing friction damping adjustable by changing the spring length. Two load cells measure line forces under the buoy and at the top of the PTO, while motion is tracked using a wire draw-line position sensor and a Qualisys system. Extreme wave conditions, modeled as regular, irregular, and focused waves with a 50-year return period at the Dowsing site in the North Sea, are tested during the experimental campaign. The experiment aims to analyze the impact of extreme wave loads on the WEC system, measuring buoy motion, translator displacement, and forces using a Qualisys system, wire draw-line position sensor, and load cell, respectively. Furthermore, the paper explains the implementation and setup of the WEC-Sim numerical model.

In conclusion, predicting system behavior under extreme wave loads is crucial for the development of wave energy technologies. While numerical modeling tools assist in designing systems for offshore conditions, validation with experimental data is necessary to reduce uncertainties. Key conclusions drawn
from both experimental and numerical results include the direct proportionality of increasing significant wave height ($H_S$) within the same peak period ($T_P$) to the maximum line force. Varying $T_P$ while maintaining the same $H_S$ can lead to significantly different maximum line forces. Additionally, different wave representations of the same sea state do not always result in identical buoy dynamics and line forces, emphasizing the need for careful consideration when translating results between wave types. Finally, the study shows a good agreement between experimental and numerical models. This underscores the reliability of the numerical model for conducting additional assessments related to the reliability and survivability of this point absorber wave energy converter.

The author was responsible for conducting the wave tank experiment, performing formal analysis, developing methodology, and writing and editing the paper. The paper is published in the proceedings of the 14th European Wave and Tidal Energy Conference in Plymouth, UK, 5-9th, September 2021.

**Paper VI: Environmental design load for the line force of a point-absorber wave energy converter**

This paper delves into the meticulous process of establishing the environmental design load for the line force of a 1:30 scaled point-absorber wave energy converter (WEC), specifically examining the site conditions at the Dowsing site in the North Sea with a 50-year return period. The methodology involves further developing and calibrating a numerical WEC-Sim model that has been introduced in Paper V based on experimental wave tank tests. The study primarily focuses on assessing short- and long-term extreme responses and employs various statistical approaches, alongside a probabilistic method, to gauge the probability of failure for critical components.

Emphasizing the importance of probabilistic methodologies and numerical modeling, the paper contributes significantly to the understanding of reliability and survivability aspects in WEC design. The conclusion underlines the obtained environmental design load for the line force, which amounts to 670.95 N for the 1:30 scaled system. When considering the ultimate limit state (ULS), this design load translates to 18.11 MN for a full-scale system, with a prudent application of a partial load safety factor of 1.35 to the full long-term extreme response. In essence, the paper showcases the intricate interplay between numerical simulations, statistical methodologies, and probabilistic assessments, providing crucial insights for designing WECs capable of withstanding extreme environmental conditions over extended operational periods.

The author was responsible for the conceptualization of most sections, and conducting the methodology, coding and programming, formal analysis, and writing of the paper. The paper is published in the Journal of Applied Ocean Research (ELSEVIER), Volume 128, November 2022.
Paper VII: Fatigue analysis of a point-absorber wave energy converter based on augmented data from a WEC-Sim model calibrated with experimental data

This paper addresses crucial aspects of reliability and survivability in the design of wave energy converters (WECs) to prevent over-design. One of the two primary failure modes is instantaneous failure caused by high instantaneous loads, and the other is fatigue failure resulting from accumulated structural damage over years of operation. The study focuses on fatigue failure through a fatigue analysis for a point-absorber WEC in sea states corresponding to a 50-year environmental contour from the Dowsing site, UK. The fatigue analysis utilizes data generated by a WEC-Sim model calibrated with a 1:30 scaled WEC from a wave tank experiment. Partial damage in each 1-hour sea state sample is calculated using rainflow counting and the Palmgren-Miner rule. By considering the joint probability density function of the sea states, the equivalent two-million cycle load is determined to be 2.42 MN for the full-scale system over 50 years of operation.

In conclusion, a linear relationship between the fatigue equivalent force and the maximum force in each sea state allows the use of the maximum force as a parameter for comparing damage between sea states. The comparison between the safety factors for the fatigue limit state (FLS) and ultimate limit state (ULS) reveals that the ULS governs the design of the WEC system under consideration. Additionally, the study highlights the potential variation in FLS results based on simulation seeds, as the fatigue equivalent load is highly dependent on the force data’s time history.

The author was responsible for the conceptualization, methodology, coding and programming, formal analysis, and writing of the paper. The paper is published in the proceedings of the 5th International Conference on Renewable Energies Offshore (RENEW 2022) in Lisbon, Portugal, 8–10, November 2022. Book of Trends in Renewable Energies Offshore published by Taylor & Francis in November 2022.

Paper VIII: A neural network approach to minimize line forces in the survivability of the point-absorber wave energy converter

This paper focuses on enhancing the survivability of wave energy converters (WECs) by minimizing extreme forces on the structure through an adaptive damping strategy. The approach involves developing a deep neural network (DNN) model capable of predicting peak line forces for a 1:30 scaled point-absorber WEC with a linear friction-damping power take-off (PTO). Leveraging wave tank experimental data, the DNN algorithm is trained to update system damping dynamically based on the system state (position, velocity, and acceleration) and incoming wave information during extreme sea states.

Results showcase the effectiveness of the DNN model, demonstrating a remarkable 88% correlation with true experimental data. The model’s training and validation accuracy is reported at about 95%, emphasizing its efficiency
in predicting peak line forces during extreme events. Furthermore, the DNN proves to be relatively fast, and capable of training within minutes, presenting a cost-effective and time-saving alternative to traditional numerical modeling. The key highlight of the paper lies in identifying the optimum damping for survivability, achieved by minimizing the peak line force. Importantly, the study reveals that the optimal damping value varies during each zero up-crossing episode, underlining the significance of predicting peak forces in extreme events. The findings propose a constant optimal damping strategy throughout each zero up-crossing episode, providing valuable insight for improving the survivability of WECs. In conclusion, the paper introduces a novel application of deep neural networks to predict optimal damping for WECs, offering an efficient and accurate alternative to computationally expensive numerical simulations. The potential implementation of this model in control systems holds promise for enhancing WEC survivability, ultimately contributing to the advancement of wave energy conversion technology.

The Author was responsible for the conceptualization, methodology, coding and programming, formal analysis, and writing of the paper. *The paper is published in the proceedings of the 42nd International Conference on Ocean, Offshore and Arctic Engineering (OMAE 2023) in Melbourne, Australia, June 2023.*

**Paper IX: Control of a point absorber wave energy converter in extreme wave conditions using a deep learning model in WEC-Sim**

The paper focuses on developing a more advanced survivability controller using a deep neural network model, building upon the one introduced in Paper VIII. The primary objective is to minimize the line (mooring) force on a 1:30 scaled wave energy converter (WEC) by dynamically adjusting the system damping. The advanced DNN model is trained on data from a 1:30 scaled wave tank experiment, simulating extreme sea states with a 50-year return period. This model is integrated into a control system module within a numerical WEC-Sim model, optimizing the power take-off (PTO) damping for each zero up-crossing episode of the surface elevation and reducing peak forces compared to constant PTO damping strategies.

The advanced DNN model begins by predicting the probability of extreme events and subsequently forecasts their peak line force values. Leveraging current and future information on surface elevation, along with instantaneous system state values (position, velocity, and acceleration), the model achieves an 80% accuracy in predicting peak line forces. In numerical simulations, the controller significantly minimizes the line force experienced by the WEC, displaying a preference for lower damping values to achieve force minimization. The paper concludes that the DNN model excels in accurately predicting peak line forces by assessing the probability of extreme events and leveraging this information for regression tasks. Despite its success, there are instances where the controller fails to reduce line force, attributed to factors like incor-
rect damping selection, changes in system response history, and limitations in the neural network’s training range. In summary, the paper introduces an effective survivability strategy for WECs through dynamic system damping adjustment using an advanced DNN-based control system. The approach exhibits promising results in minimizing line forces, highlighting its potential to enhance the reliability and performance of WECs in extreme sea conditions.

The author was responsible for the conceptualization, methodology, coding and programming, formal analysis, and writing of the paper. The paper is published at OCEANS Conference 2023, Limerick, Ireland, 2023.

Paper X: Investigation on the extreme peak mooring force distribution of a point absorber wave energy converter with and without a survivability control system

Following the survivability strategies developed in Paper IX, the analysis of the extreme peak mooring force distribution, crucial for determining the environmental design load, has been revisited to explore the influence of adaptive damping from the survivability control in reliability analysis. This paper extends the study conducted in Paper VI by broadening the analysis to include a range of power take-off (PTO) damping configurations, encompassing both constant damping cases and adaptive damping defined by survivability control strategies. The study utilizes a 1:30 scaled point absorber wave energy converter, with the mooring force response derived from a WEC-Sim model calibrated using wave tank experimental data. The selection of extreme sea states is based on a 50-year environmental contour. The analysis begins by obtaining the long-term extreme response using the full sea state approach for three constant damping cases of the PTO system. Subsequently, a contour approach is employed to compute the expected value of the extreme peak line force distribution for the sea states along the environmental contour. Additionally, for the most extreme sea state, a survivability control system, based on a deep neural network (DNN), adjusts the PTO damping to minimize the peak mooring force in each zero up-crossing episode of surface elevation.

The findings reveal that, in the absence of a control system, the zero PTO damping case is a conservative choice for analyzing the long-term response and determining the design load. The survivability control system slightly reduces the expected value of the extreme peak force distribution for the most extreme sea state along the environmental contour compared to lower constant PTO damping configurations. However, it falls short of surpassing specific constant damping configurations.

The Author was responsible for the conceptualization, methodology, coding and programming, formal analysis, and writing of the paper. The paper is published in proceeding The 15th European Wave and Tidal Energy Conference (EWTEC2023) in Bilbao, Spain, September 2023.
This paper addresses the challenging task of predicting future knowledge, essential for optimizing wave energy converter (WEC) survivability controller parameters such as damping to minimize line forces during extreme wave conditions. Traditional model-based control strategies often struggle with nonlinear system behaviors, prompting the adoption of data-driven approaches. The study utilizes a series of neural networks trained on experimental data to predict surface elevation, system state (power take-off (PTO) translator position), and peak line force for a 0.36-second prediction horizon.

The neural network models demonstrate impressive accuracy: 95.5% for surface elevation, 86-93% for PTO translator position across different damping cases, and approximately 90% for peak force when the system is subjected to extreme wave conditions. The research also emphasizes the impact of uncertainties on prediction accuracy and sensitivity to the prediction horizon. Notably, PTO translator position predictions significantly influence peak force predictions, especially for lower damping values. The sensitivity study shows that higher uncertainties within the prediction of the translator position lead to the suggestion of higher and unrealistic PTO damping by the survivability controller.

The Author was responsible for the conceptualization, methodology, coding and programming, formal analysis, and writing of the manuscript. *The manuscript is under review in the Journal of Renewable Energy (ELSEVIER), 2024.*
9. Svensk sammanfattning

Vågkraft, med fem gånger högre energitätet än vind och tio gånger högre energitätet än solenergi, erbjuder en övertygande lösning för koldioxidfri elektricitet. Trots sina fördelar omges den av pågående debatter om tillförlitlighet och ekonomisk genomförbarhet för vågkraftverk (wave energy converters (WECs)). För att tackla dessa utmaningar är denna doktorsavhandling uppdelad i fyra integrerade delar, fokuserande på att optimera prediktionshorisonten för effektoptimering, analysera extremvågs påverkan på systemdynamik, säkerställa tillförlitlighet och förbättra överlevnad i vågkraftverk.

Del I fördjupar sig i betydelsen av prediktionshorisonten för att uppnå maximal effektabsorption vid vågkraftomvandling. Genom att använda ett generiskt angreppssätt undersöker detta avsnitt dissipativa förluster, brus, filtrering, amplitudbegränsningar och verkliga vågparametrar. Målet är att fastställa den optimala prediktionslängden som är avgörande för att maximera effektuttaget. Resultaten antyder att en relativt kort prediktionshorisont kan vara tillräcklig för att uppnå optimalt effektuttag, vilket utmanar konventionella antaganden.


Del III utforskar tillförlitlighetsanalys för kritiska mekaniska komponenter av vågkraftverk. Säkerhetsfaktorer för ultimata gränstillstånd (ultimate limit state, ULS) jämförs med säkerhetsfaktorer för utmattning (fatigue limit state, FLS), och visar att det ultimata gränstillståndet har störst påverkan på tillförlitligheten för vågkraftverket, vilket illustrerar den övervägande påverkan av den ultimata gränstillståndet på punktabsorbator WEC-design.

Den sista delen, Del IV, fokuserar på att höja överlevnadsstrategier för vågkraftverk under extrema vågförhållanden. Tre tillvägagångssätt använder neurala nätverk för att minimera linkraften, strategiskt adressera optimal dämpning under nolluppkorsningsepisoder eller inom specificerade tidsintervall av våghöjd. Tydliga variationer framträder i varje tillvägagångssätt, från snabb detektion av optimal dämpning till integration av avancerade neurala nätverksarkitekter i reglersystem med återkoppling. Integrationen av ett kontrollsystem, finslipat med hjälp av experimentella data, visar minskningar av linkraften, vilket erbjuder en praktisk mekanism för kraftmildring i realtid.
Denna avhandling syftar till att unikt bidra till målet att främja teknologin för vågkraftsomvandling genom omfattande studier.
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