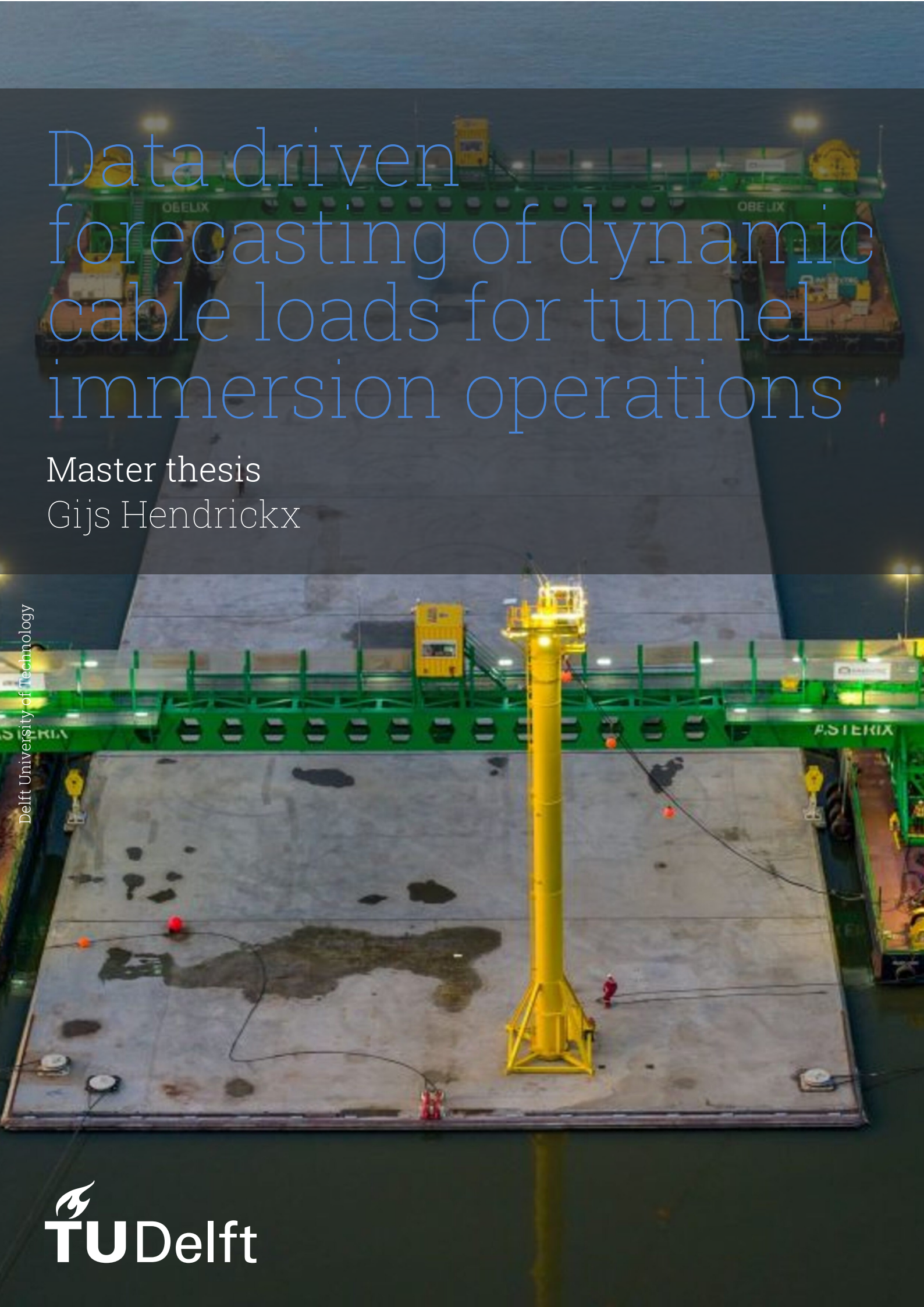




The background image is an aerial night photograph of a large-scale construction operation. A massive, rectangular concrete segment, likely for a tunnel, is being hoisted by a tall yellow crane mounted on a green barge. The barge is labeled 'OBELIX' in two locations. The concrete segment has some dark stains on its surface. Several red safety lights are visible on the segment and the crane. The scene is illuminated by artificial lights, creating a high-contrast night scene.

Data driven forecasting of dynamic cable loads for tunnel immersion operations

Master thesis

Gijs Hendrickx

Data driven forecasting of dynamic cable loads for tunnel immersion operations

by

Gijs Hendrickx

Supervisor TU Delft:	Prof. Dr. ir. W.S.J. Uijtewaal
Supervisor TU Delft:	Dr. ing. J.A. Antolínez
Supervisor DEME:	ir. E. Van Putten
Supervisor DEME:	ir. W. Haring
Project Duration:	February, 2026 - July, 2026
Faculty:	Civil Engineering and Geosciences

Preface

This thesis is the final part of the masters track: Hydraulic and Offshore Structures, within the masters programme Civil Engineering at TU Delft. For the last six months I have been working on this research, bridging the gap between software and civil engineering. Over the past seven years of my education I have developed both in the civil engineering and software engineering field, and combining the two in this final work completes the journey.

Several experts helped me along the way, and I would like to express my sincere thanks to all of them! I would like to thank José Antolinez for being the chair of my committee and my daily supervisor at the TU Delft. Our shared passion for sailing made the meetings very productive! I would also like to thank Wim Uijtewaal for his experience and time to help me with my complex hydraulic problems. I would like to thank Eelco van Putten from DEME for being my daily supervisor, your experience on immersion projects have been really helpful and has given me new insights. Finally I would like to thank Wouter Haring for bringing this subject to my attention after our meeting at the Waterbouw symposium.

I would like to give a big thanks to my family and friends who have supported me throughout these seven years of education and helped me getting my final degree. Their support and their time for a chat have been very helpful!

*Gijs Hendrickx
Delft, July 2026*

Figures statement: All visuals, renders, and diagrams are original work by the author unless explicitly referenced otherwise.

AI statement: The use of artificial intelligence in the form of the large language model ChatGPT or Claude has been used on several occasions. Firstly, it has been used to aid in the modelling process of the machine learning, with the help of trouble shooting bugs. Secondly, it was used to refine paragraphs to increase reading flow of the report and to check for spelling and grammar mistakes. Lastly, it was applied to create BibTex codes for references.

Abstract

The immersion of the tunnel elements is a critical operation in the construction of an immersed tunnel. During this operation, the tunnel element is lowered to the seabed, guided by vertical cables, whose loads vary continuously as a result of the interaction with environmental and operational inputs, such as water density changes and cable pay out events. Predicting these loads accurately would allow the operation to be optimized, enhancing both the safety and the efficiency of the lowering process.

In current practice, cable loads are estimated using methods of increasing fidelity. Engineering hand calculations (low-fidelity) are quick to compute but rely on simplifying assumptions that neglect hydrodynamic forces, limiting their accuracy. Mid-fidelity models such as OrcaFlex estimate these hydrodynamic forces using potential flow theory and Morison-type force equations, which improves accuracy but introduces calibration coefficients that must be estimated. High-fidelity methods such as Computational Fluid Dynamics (CFD) resolve the Navier–Stokes equations and can capture the fluid structure interaction, but at a high computational cost, which makes them impractical for operational use. Furthermore, none of these methods can adapt to cable loads measured during previous immersion operations. This research investigates to what extent machine learning models, trained on operational monitoring data, can improve the accuracy and generalizability of cable load estimation compared to these traditional engineering methods.

The machine learning models are benchmarked against the engineering estimates: the DEME immersion sheet for the static loads and a two-degree-of-freedom (2DOF) analytical model for the dynamic loads. The monitoring data used in this study comes from the Oosterweel tunnel in Antwerp, from which six immersion sequences were retrieved, each containing operational and environmental variables. Quality control was applied to remove sensor faults, after which a data analysis was performed to characterise the stationarity of the data and the signal was filtered to retain the structural behaviour of the system. The target data were then split into static and dynamic cable loads. For the static loads, a multivariate regression (MVR) and a multilayer perceptron (MLP) were selected: the MVR captures the linear correlation between the input forces, while the MLP additionally captures the non-linear behaviour. For the dynamic loads, a long short-term memory (LSTM) and Fourier neural operator (FNO) were developed because these models both account for sequential inductive bias and the FNO also works with spectral inductive bias. For the MVR, MLP, and LSTM, a weighted mean squared error (MSE) loss function was used, and for the FNO, a Sobolev loss function. The models were evaluated by their coefficient of determination (R^2) and root mean squared error ($RMSE$) against the evaluation set, and for the dynamic models, the period distribution was additionally compared.

The data analysis revealed a two-regime structure in the monitoring data. The boundary between these regimes is the moment the element passes through the waterline. Besides this, the analysis indicated that the oscillation period decreases as the element descends and increases again near the seabed. This contradicts the available literature on immersed tunnels in wave environments. This effect is most likely caused by the depth-dependent added mass.

The machine learning models outperformed the engineering estimates in both regimes. For the static loads, the MLP reached an average of $R^2 = 0.92$ and $RMSE = 5.7$ t, against $R^2 = 0.33$ and $RMSE = 16.1$ t, for the immersion sheet. For the dynamic loads, the FNO and LSTM achieved positive R^2 values (0.44 and 0.42 respectively), where the 2DOF estimate scored negative. Both models reproduced the non-constant oscillation period. However, the peak amplitudes remained underestimated. A convergence study showed the number of training sequences required to outperform the engineering estimates (static $n = 2$, dynamic $n = 5$).

This study indicates that operational monitoring data can be used to train machine learning models that estimate cable loads more accurately than the engineering methods currently in use. Although the dynamic models still underestimate peak amplitudes, limiting their direct use for optimizing the cable payout rate, the modelling can be transferred to future immersion projects.

Contents

Preface	i
Abstract	ii
1 Introduction	1
1.1 Cause	1
1.2 Problem Statement	2
1.3 Objective	2
1.4 Research Questions	2
1.5 Scope	3
1.6 Methodology overview	3
1.7 Thesis outline	5
2 Theoretical background	6
2.1 Environmental variables	6
2.1.1 Current	6
2.1.2 Waves	8
2.1.3 Water Density	10
2.1.4 Summary	11
2.2 Structural dynamic systems	11
2.2.1 Properties	11
2.2.2 Damped mass spring system	12
2.2.3 Summary	14
2.3 Hydrodynamic forcing	14
2.3.1 Morison equation	14
2.3.2 Vortex induced vibrations	15
2.3.3 Seafloor effects	16
2.3.4 Buoyancy	17
2.3.5 Damping	17
2.3.6 Summary	18
2.4 Calculation methods	18
2.4.1 Numerical	18
2.4.2 Computational Fluid Dynamics	19
2.4.3 Machine learning	19
2.4.4 Summary	20
2.5 Immersed tunnel definitions	20
2.5.1 Element shapes	21
2.5.2 Immersion configurations	21
2.5.3 Lowering procedure	21
2.6 Reference research	21
2.6.1 Research gaps	23
2.7 Summary	23
3 Case study and monitoring data	25
3.1 Oosterweel tunnel project	25
3.1.1 Project overview	26
3.1.2 Environmental conditions	26
3.2 Immersion system	28
3.2.1 Tunnel elements	29
3.2.2 Immersion pontoons	30

3.2.3	Cable configuration	30
3.2.4	Ballast system	30
3.2.5	Operational windows	31
3.3	Immersion principles	32
3.3.1	Initial state	32
3.3.2	Ballasting	32
3.3.3	Lowering	32
3.4	Monitoring system	32
3.4.1	Measured signals	32
3.4.2	Sampling and resolution	33
3.5	Dataset overview	33
4	Data analysis	35
4.1	Analysis method	35
4.2	Cleaning method	36
4.2.1	Operational variables	36
4.2.2	Environmental variables	37
4.3	Data walk through	37
4.3.1	Cable loads	38
4.3.2	Cable lengths	38
4.3.3	Ballast weight	38
4.3.4	Current velocity	38
4.3.5	Water density	38
4.3.6	Summary	40
4.4	Data characterisation	40
4.4.1	Time domain	40
4.4.2	Frequency domain	42
4.4.3	Cut off validation	44
4.4.4	Data smoothing	47
4.4.5	Summary	48
4.5	Correlations	49
4.5.1	Tank weight	49
4.5.2	Cable length	50
4.5.3	Water density	50
4.6	Conclusion	50
5	Static modelling approaches	52
5.1	Methodology	52
5.1.1	Regime split	52
5.1.2	Input and target features	52
5.1.3	Normalisation	52
5.1.4	Validation	52
5.1.5	Evaluation	53
5.2	Static estimate	53
5.2.1	Initial state	53
5.2.2	Calculation timeline	54
5.2.3	After regime	56
5.3	Machine learning architectures	56
5.3.1	Linear Regression	56
5.3.2	Multivariate regression	57
5.3.3	Multi layer perceptron	58
5.3.4	Training	59
5.4	Results	60
5.4.1	Convergence analysis	60
5.4.2	Predictions	61
6	Dynamic modelling approaches	64
6.1	Methodology	64

6.1.1	Regime	64
6.1.2	Inputs and targets	64
6.1.3	Normalisation	65
6.1.4	Training and Validation	65
6.1.5	Evaluation	65
6.2	Engineer method	65
6.2.1	1DOF	66
6.2.2	2DOF	67
6.3	Machine learning architectures	68
6.3.1	Long short term memory	69
6.3.2	Fourier neural operator	71
6.4	Results	72
6.4.1	Convergence analysis	72
6.4.2	Period and amplitude comparison	74
6.4.3	Dynamic cable load prediction	75
7	Discussion and conclusion	77
7.1	Discussion	77
7.2	Conclusions and recommendations	78
7.2.1	Improving machine learning models	80
7.2.2	Further research	81
	References	82
A	Data analysis	85
A.1	Frequency analysis	85
A.2	Element correlations	86
A.3	Full calculation cut off validation	89
A.3.1	Input data	89
A.3.2	Cut off validation extended	92
A.3.3	Results	92
B	2DOF System derivation	95
B.1	2DOF system derivation	95

Introduction

1.1. Cause

An immersed tunnel is a type of tunnel used to cross a stretch of water. Where a conventional tunnel is bored as a continuous structure, an immersed tunnel consists of multiple prefabricated elements. These elements are constructed in a dry dock, and once completed they are towed towards the construction site. The assembly of the tunnel is governed by Archimedes principle (Archimedes, 2002). The elements contain water tanks which can be filled to make the element heavier. When the weight of the element exceeds its buoyancy, it begins to sink. This process is called the immersion operation, and is guided by four vertical cables (Molenaar, 1993), allowing for a controlled descent to the bottom of the sea or river.

The moving water at the construction site results in a response of the tunnel element. According to Newtons second law, these accelerations cause additional dynamic loads on the element (Clough & Penzien, 1995). These loads are also affected by the weight of the element, which increases overtime. The connected vertical cables have to carry these loads. Since the cable acts as a spring the resulting force is linearly correlated with the oscillatory motion of the element. This interplay between static and dynamic loading causes the cable loads to change continuously throughout the operation. Being able to anticipate these loads before the operation begins would allow the ballast and the cable pay out strategy to be optimised so that cables stay within their safe working range. This would improve both safety and the efficiency of the operation.

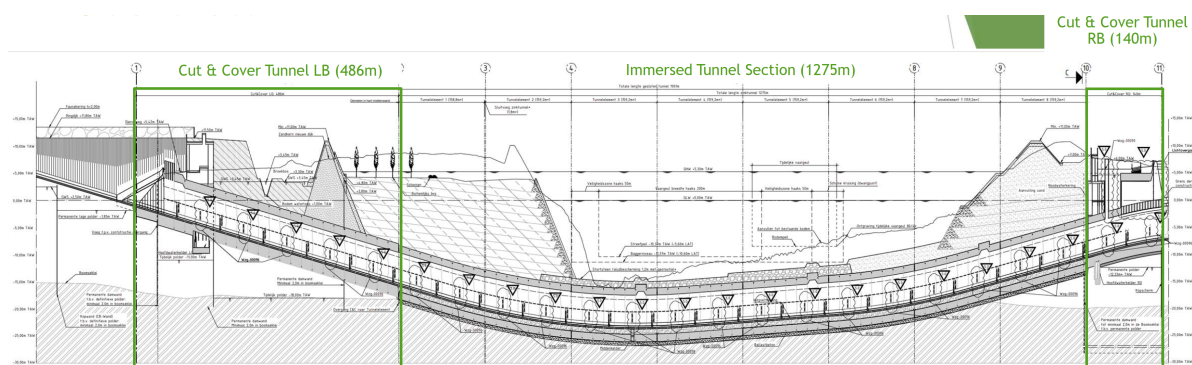


Figure 1.1: Cross-section of the Oosterweel connection (van der A, 2025)

The latest immersed tunnel constructed by DEME is the Oosterweel tunnel in Antwerp. This tunnel consists of eight tunnel elements, as shown in Figure 1.1, and crosses the Scheldt river. This river has a tidal range of approximately five meters and an average current velocity of 1 m/s . To anticipate the loads during immersion, DEME conducted several studies, including OrcaFlex (Vink & Reijm, 2023)

and CFD (Cornu & Rohit, 2024) simulations. Nevertheless, the immersion operation had to be stopped multiple times to stop the vibrations of the element (van Putten, 2025a), causing operational delays and doubts in the strength of the immersion structure. In other recently finished projects by DEME, like the Blankenburg connection in Rotterdam, hydrodynamic effects caused by a sudden change in water density resulted in a broken mooring cable, postponing the tunnel immersion operation (Haring et al., 2023). These events show that the used modelling techniques still are not able to capture all the hydrodynamic and operational effects. These incidents show that the cable loads during the immersion operation cannot yet be reliably anticipated, with the modelling techniques currently used in practice.

1.2. Problem Statement

Anticipating the cable loads requires a model that can predict them from the environmental and operational variables of the operation. The hydrodynamic response of the element is affected by environmental variables, such as the water level, current velocity, waves, and water density (Yang et al., 2017). Operational variables like cable pay out rates and amount of ballast water also affects the response (van Putten, 2025a).

In current practice, the cable loads are estimated using methods of increasing fidelity, each with its own limitation. Engineering hand calculations like the immersion sheet (low-fidelity) are quick, but rely on simplifying assumptions that neglect hydrodynamic forces, limiting their accuracy. Mid-fidelity models, such as OrcaFlex, estimate these forces using the potential flow theory and Morison type equations. These improve the accuracy, but require estimated calibration coefficients. High-fidelity models, like Computational Fluid Dynamics (CFD) resolves the Navier–Stokes equations and capture the fluid structure interaction, but at a computational cost that makes them infeasible during a live operation. Furthermore, these three approaches are defined before the operation and cannot learn from the cable loads measured during previous operations. While calibration to project specific conditions is possible, the computational demand of the high-fidelity methods makes it unfeasible in practice.

Machine learning models offer an alternative approach: rather than approximating the underlying physics, they capture relationships directly from measured data (Goodfellow et al., 2016). Recent developments in physics informed machine learning (Miyanawala et al., 2024), (Sundar et al., 2024) have shown promising results in hydrodynamic applications, but have not yet been applied to tunnel immersion operations. It remains unclear whether such data-driven model outperform the traditional engineering tools currently used in practice. A systematic comparison between machine learning approaches and established modelling techniques, ranging from engineering hand calculations to hydrodynamic simulations, has not yet been conducted for this application.

1.3. Objective

The objective of this research is to develop machine learning models that predict the cable loads during the vertical lowering phase of a tunnel element, and to evaluate them against the engineering methods currently used. The models predict the cable loads from the operational and environmental inputs of the operation because these are known ahead of the operation, which would allow for optimizing the lowering sequence. The models are developed with the dataset of the Oosterweel project in Antwerp. Both static and dynamic cable loads are modelled using the traditional methods; engineering hand calculations in the form of the immersion sheet (van der A, 2025) supported with CFD simulations (Cornu & Rohit, 2024) and an analytical 2DOF model, and data-driven methods: regression, neural networks for the static load and deep learning networks in the form of LSTM and FNO for the dynamic loads. Model performance is quantified by comparing predicted loads of the data driven models against the traditional methods.

1.4. Research Questions

Main Question

To what extent can machine learning models improve the accuracy and generalizability of vertical cable load estimation during tunnel element immersion operations, compared to traditional engineering approaches?

Sub-questions

1. Which operational and environmental variables have the strongest influence on cable load variation during immersion?
2. How do machine learning approaches (regression and neural networks) compare to traditional (quasi) static estimation methods (engineering hand calculations and CFD)?
3. How do machine learning models (LSTM and Fourier neural operators) compare to engineering estimates for dynamic behaviour in capturing dynamic cable load behaviour?
4. How does the prediction accuracy of machine learning models evolve with increasing training data and at what point do they match or exceed the traditional approaches?
5. Can machine learning models reliably identify peak loads and threshold exceedances compared to traditional methods?

1.5. Scope

This research develops and evaluates machine learning models for predicting the vertical cable loads during tunnel immersion operations, using the monitoring data from the Oosterweel project. A number of boundaries have been set to define the research area.

- **Process phase:** Only the lowering process during the vertical positioning of the tunnel element is considered. Horizontal positioning, and final seabed placement are excluded, but to be considered in future studies.
- **Loads:** The static and dynamic loads in the vertical cables are modelled. Loads in other systems, like the pontoons and horizontal mooring lines, are excluded.
- **Data:** The data is limited to the recently completed Oosterweel immersed tunnel project. The machine learning models are therefore calibrated to the conditions of this site.
- **Traditional models:** The traditional methods used for comparison are the CFD and OrcaFlex simulations performed during this project, together with the immersion sheet and an analytical two degree of freedom model. The CFD and OrcaFlex results are taken from existing project reports, whereas the immersion sheet was adapted from the DEME calculation and the 2DOF model was developed for this research.
- **Validation:** The machine learning models are evaluated on an immersion sequence that is excluded from the training set.

1.6. Methodology overview

To answer the research questions, a case study is used: The Oosterweel project in Antwerp, from which the monitoring data is taken. The approach for this research is schematized in Figure 1.2, and is divided into four parts.

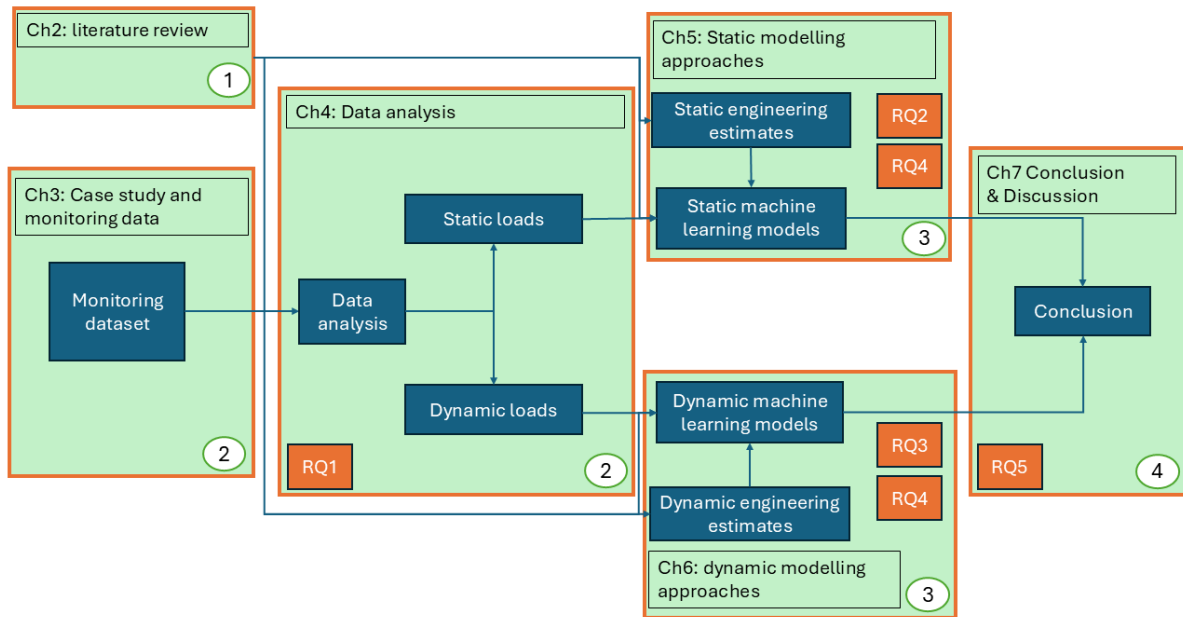


Figure 1.2: Schematic overview of the methodology, showing the research questions (orange), the modelling and data processing (blue), the chapters (green) and the parts (white)

First, a literature study is conducted to identify the governing physical principles and the state of the art in both traditional modelling and machine learning methods for fluid structure interaction problems (Chapter 2). From this study, the research gaps are identified.

The second part introduces the monitoring dataset from the case study (Chapter 3). The filtered dataset, with outliers removed, is then analysed in Chapter 4. The data analysis characterises the statistical and spectral properties of the cable load data. Furthermore, the analysis aims to identify the correlations between input variables and the target variable: the cable load. From this analysis, modelling architectures are motivated for the next part, and the input and target data are generated.

In the third part, the models are trained and compared against the traditional methods. For this comparison, the models are separated into two groups based on their target data. The first model will predict the static cable load, whereas the second model predicts the dynamic cable load. For the static model, the two approaches are compared: the traditional immersion sheet developed by DEME, which consists of hand calculations and CFD estimations, and machine learning networks in the form of multivariate regression and a multilayer perceptron. The traditional methods represent the current engineering solution, with the immersion sheet, a time series estimate can be made for the expected individual cable loads. Although simplified, it can convert ballast levels and draft changes into cable loads. The CFD analysis provides an expected force range resulting from the current velocity and element orientation. The machine learning models, on the other hand, are trained to predict the static individual cable load as a continuous time series from the operational and environmental input variables. The methods are compared using the root mean squared error ($RMSE$) and the coefficient of determination (R^2).

For the dynamic load, two approaches are compared, a two degree of freedom system model and a machine learning approach in the form of a long short term memory (LSTM) network and a Fourier neural operator (FNO). DEME performed an OrcaFlex simulation to estimate the maximum cable load. However, this did not produce a time series estimate of the dynamic load, so the 2DOF model was developed. The machine learning models are trained to predict the dynamic cable loads as time series. Besides using $RMSE$ and R^2 , the predictions are also compared by their period and amplitude distributions.

For the regression, MLP and LSTM model, the monitoring dataset is split using Kfold cross validation. This breaks the training dataset in little chunks, splitting the data randomly over the entire set. Each

training set has than a different chunk as validation. One element is left out the training set and used as evaluation. For all models, a convergence analysis is performed to see how performance improves with increasing training data.

In the final part the results are discussed, and the conclusions are drawn.

1.7. Thesis outline

This thesis consists of seven chapters:

1. **Chapter 1 Introduction:** provides the scope, objective, and the research questions.
2. **Chapter 2 Literature background:** provides theoretical background on immersed tunnel construction, hydrodynamic loading and machine learning, and ends with the research gaps.
3. **Chapter 3 Case study:** introduces the case study and the monitoring dataset.
4. **Chapter 4 Data analysis:** performs a data analysis to identify the behaviour of the data and determine which machine learning approaches might be useful.
5. **Chapter 5 Static modelling approaches:** presents the machine learning models developed for the static cable load behaviour and compares them to traditional approaches.
6. **Chapter 6 Dynamic modelling approaches:** presents the machine learning models developed for the dynamic cable load behaviour and compares them to traditional approaches.
7. **Chapter 7 Conclusion and discussion:** evaluates the results, discusses the findings and provides recommendations for future work.

2

Theoretical background

This chapter provides an overview of the theoretical background applicable to tunnel immersion operations. To understand the behaviour of the model and assess its validity, it is necessary to identify which physical relationships it captures. To derive the dynamic cable loads acting during tunnel immersion operations, the causes, the external variables acting on the structure need to be identified, followed by the relationships governing fluid structure interaction. First these environmental variables: current, waves, water density and wind will be explained. Then, the relationship between these external variables and the forces acting on the structure causing the dynamic behaviour will be explained. Furthermore multiple approaches are presented to derive the response of these forces over time. In the last part, the general principles of tunnel immersion operations is given as well as how their design affects their dynamic behaviour. At the end of every subsection a brief overview is given what points can be taken, and what lessons can be learned. The chapter concludes with a summary covering the findings.

2.1. Environmental variables

Depending on the construction site of an immersed tunnel, various environmental conditions will affect its dynamic behaviour. This section will introduce those variables, and explain when they have to be taken into account and how they affect the dynamic response of a element during a lowering sequence. There are four environmental variables considered: current, waves, water density and wind.

2.1.1. Current

The movement of water at the construction site of immersed tunnels causes additional stress on the structure, and the immersion cables. Since the tunnel elements typically range from 150 to 220 m in length with a height of approximately 10 m , this results in a minimum frontal area of 1500 m^2 . This area can increase further when the orientation relative to the current changes. Due to this size even a small current will result in significant forces. This shows why the current cannot be neglected. Current can be separated into three regimes: tidal current, discharge current and wind induced current.

Tidal current

Tidal currents are caused by the gravitational pull of the moon and sun (university, 1999). These currents are periodic and naturally change direction four times every 24 hours, this type of current is referred to as a semidiurnal tidal regime, and applies for example to the North Sea. Diurnal tides change direction twice per day, and occur for example in the South China Sea. The strength of these currents depends on the local water depth and the location, deeper water is generally associated with higher current velocities. Tidal currents mostly occur in the open sea as well as in inland rivers. The spring and neap tides in tidally driven currents occur twice every month. Spring tides occur during the full and new moon while neap tides occur during the first and third quarter of the moon. For the construction of immersed tunnels the neap tide is favourable since lower current velocities relate to lower stresses. In the North Sea, tidally induced current varies between the 0.1 m/s and 2 m/s depending on the location

(Vindenes et al., 2018).

Discharge current

Discharge driven currents are caused by the downstream movement of water, related to gravity. These types of currents occur in rivers. Compared to tidal currents, they are not periodic and depend on the discharge upstream of the river. Normally, rivers have peak discharges during early spring due to snow melt, but also in the summer period peak velocities can be caused by intense rainfall causing a spike in flow velocities. The flow velocity distribution in these rivers is governed by the conservation of energy along a streamline. Applying Bernoulli's principle between two cross-sections of the river, the relationship between pressure, velocity and elevation can be expressed as (Munson et al., 2012):

$$\frac{p_1}{\rho g} + \frac{u_1^2}{2g} + z_1 = \frac{p_2}{\rho g} + \frac{u_2^2}{2g} + z_2 \quad (2.1)$$

$$Q = A_1 u_1 = A_2 u_2 \quad (2.2)$$

When assuming conservation mass and energy, and therefore neglecting the loss due to friction, Equation (2.1) can be solved, resulting in the flow velocity. The relation between the cross-section of the river A and the flow velocity u is given in equation (2.2).

Wind induced current

The wind induced current is caused by the shear friction between the water particles on the surface and the wind particles. This interaction accelerates or slows down the movement of the top layer. The behaviour of this current is illustrated in the Figure 2.1:

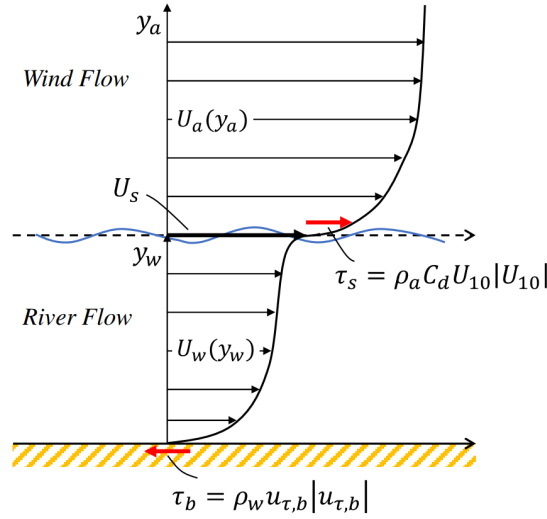


Figure 2.1: Wind induced current velocity profile over the water depth, showing the decay of surface shear stress with depth (Yoshimura et al., 2024)

The change in velocity due to wind is nonlinear across the depth profile. The friction of the wind with the water surface and the resulting velocity profile over the water depth can be described with the following equation. This effect is also schematized in Figure 2.1.

$$\tau_s = \rho_a C_d U_{10}^2 \quad (2.3)$$

$$U_w(y_w) = \frac{u_{\tau,b}}{k} \ln\left(\frac{y_w + y_b}{y_b}\right) \quad (2.4)$$

Where ρ_a is the air density, U_{10} the wind velocity at 10 meters above the surface. $u_{\tau,b}$ is the bed friction velocity and k the von Kármán constant. The friction coefficient C_d is a dimensionless number that depends on the wind velocity and given (Yoshimura et al., 2024):

$$C_d = (1.2 + 0.025 U_{10}) * 10^{-3} \quad (2.5)$$

In open water conditions the current velocity reaches a maximum of 3 to 4 percent of the wind velocity U_{10} (Yoshimura et al., 2024). Also the effect of the wind increases when the bed friction coefficient is

small relative to the wind friction. For wind velocities higher than 10m/s the water velocity near the bed is affected as well (Yoshimura et al., 2024). These effects are more important for river areas. Due to the size of the elements these effects cannot be neglected.

2.1.2. Waves

The general behaviour of waves can be described with the linear wave theory (Airy, 1845). This theory is applicable to gravitational waves. The theory is based on the Navier stokes equations describing the continuity and the momentum balance. Starting from the momentum balance equation and assuming there is no viscosity and the fluid is incompressible results in the Euler equations. Solving these equations can be done but at great computational cost (Airy, 1845). To simplify, irrotational flow can be assumed. This is justified for flow regimes where viscous effects are negligible and the flow can be described by its velocity potential, allowing the pressure to be governed purely by gravity and inertia. For irrotational flow the earlier derived continuity equation can be rewritten to Equation (2.6). Where ϕ stands for the velocity potential of the water, given in Equation (2.7).

$$\frac{\partial^2 \Phi}{\partial x^2} + \frac{\partial^2 \Phi}{\partial z^2} = 0 \quad (2.6)$$

$$\Phi = \frac{\omega \alpha}{k} \frac{\cosh[k(d+z)]}{\sinh(kd)} \cos(\omega t - kx) \quad (2.7)$$

Taking the first order derivative of the velocity potential with respect to the flow direction results in the flow velocity of an individual particle,

$$\hat{u}_x(z) = \omega \alpha \frac{\cosh[k(d+z)]}{\sinh(kd)} \sin(\omega t - kx) \quad (2.8) \quad \hat{u}_z(z) = \omega \alpha \frac{\sinh[k(d+z)]}{\sinh(kd)} \cos(\omega t - kx) \quad (2.9)$$

In these equations the velocity amplitude is described by the first term and the last term describes the phase of the particle. The wave number is represented in the equation by k , which follows from the dispersion relation:

$$\omega^2 = gk \tanh(kd) \quad (2.10)$$

$$L = \frac{gT^2}{2\pi} \tanh\left(\frac{2\pi d}{L}\right) \quad (2.11)$$

Depending on the wave number and the water depth d the velocity profile of the water can be determined

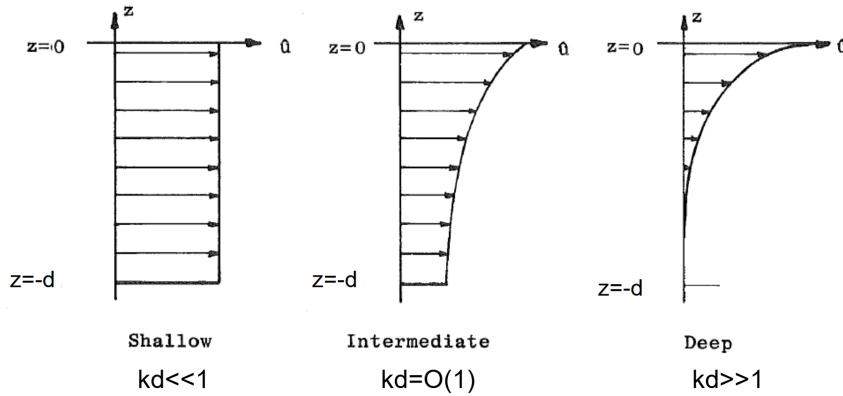


Figure 2.2: Wave induced water particles velocity profiles for deep, intermediate and shallow water conditions, showing the decay of orbital motion with depth (Airy, 1845)

Besides resulting in an equation which describes the velocity of an individual particle also the pressure gradient can be derived from Equation (2.6). Inserting the irrotational assumption and the velocity potential into Equation (2.6) results in the Bernoulli equation, and if the regime of the waves is considered small $H/L \ll 1$. The equation can be simplified to the linearized Bernoulli equation:

$$\frac{\partial \phi}{\partial t} + \frac{p}{\rho} + gz = 0 \quad (2.12)$$

Rearranging this equation so p can be derived, and inserting the definition of the velocity potential the pressure over the depth can be described by a hydrostatic term and a wave induced term. In this equation the $z = 0$ at the water surface and becomes negative towards the seabed.

$$p = -\rho g z + \rho g \frac{\cosh(k(z+d))}{\cosh(kd)} \alpha \sin(\omega t - kx) \quad (2.13)$$

To apply the wave theory, the wave period T and the water depth d need to come from measurements. These measurements can be taken from a deployed weather buoy or from historical data. In this data the effect of wind driven waves is accounted for. The one aspect that is neglected by this theory is the potential of waves to grow over time due to friction between wind and the water particles.

These derivations describe the natural behaviour of waves in both deep and shallow water. They also present an equation to describe the water pressure over the water depth. Although it often looks like the water is only moving at the surface as a result of waves, the derivations show that the movement can also cause an additional increase in the water pressure over the depth. These effect cannot be neglected for deriving the dynamic response of the tunnel. Additionally waves also induce motion in the topside structure of the immersion configuration. These additional movements can temporarily increase the distance between the pontoons and the immersed element, increasing the cable loads

Wind waves

The linear wave theory presented above describes the propagation of waves with known height and period. However this theory does not explain how those waves originate. The construction site of the Oosterweel tunnel is located in a river. Here the waves are predominantly generated by local wind. Wind blowing over a water surface causes shear stress on the surface layer. This friction energy can cause small waves. The resulting wave height depends on three variables: the wind speed U_{10} , the fetch length F and the duration of the wind t_d

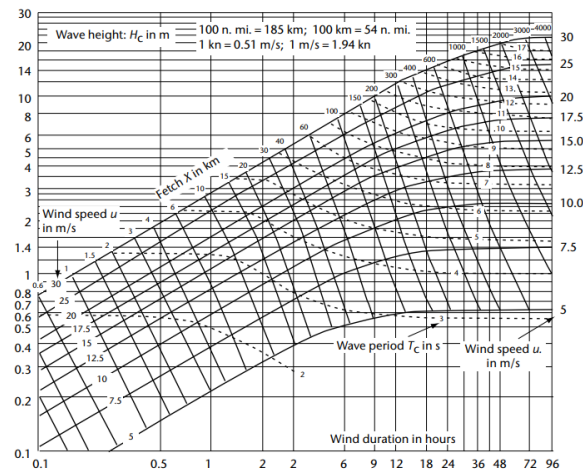


Figure 2.3: Nomogram for wind induced waves (Groen & Dorrestein, 1976)

With the nomogram for wind induced waves by (Groen & Dorrestein, 1976). The wave height can be calculated. In river environments often the fetch length is the limiting factor due to the curves in the river.

Since the generated wave field is no longer linear a different metric is used. The wave is classified with the help of the significant wave height. Which is equal to the average of the highest one third of measured greatest waves (Holthuijsen, 2007).

$$H_s = \frac{1}{N} \sum H_m \quad (2.14)$$

2.1.3. Water Density

Salinity

The density of water directly affects the buoyancy force acting on a submerged body as described by Archimedes principle Equation (2.40). In freshwater, the density is 1000 kg/m^3 , while seawater has a density of 1025 kg/m^3 . The density increases linearly with the salinity of the water and decreases with the temperature, although temperature variations during an immersion operation (typically 4-8 hours) are negligible. Salinity, on the other hand can vary significantly on tidal timescales, making it an important factor during immersion operations. Salinity is defined as the total concentration of dissolved salts in water, typically expressed in practical salinity units (PSU)

The rate at which water density changes over time depends on the environmental conditions at the construction site.

Estuarine classification

Construction sites for immersed tunnels located in estuaries, regions where freshwater river discharge mixes with saltwater from the sea, are subjected to varying water density. The mixing behaviour of an estuary can be characterised using the classification framework of Hansen and Rattray (Hansen & Rattray, 1966), which categorises estuaries based on two parameters: the vertical stratification (the ratio of the top to bottom salinity difference to the depth average salinity $\Delta S/S_0 < 0.1$) and the strength of the estuarine circulation (the ratio of surface velocity to freshwater velocity u_s/u_f). This classification method distinguishes four types:

- Type 1a-1b (well mixed): Weak stratification $\Delta S/S_0 < 0.1$, and horizontal diffusion dominates the salt transport. Tidal mixing is sufficiently energetic to homogenise the water column vertically
- Type 2a-2b (partially mixed): Moderate stratification exists, with both gravitational circulation and tidal mixing contributing to the salt balance.
- Type 3 (fjord-type): Deep strongly stratified estuaries where a sill restricts bottom exchange
- Type 4 (salt wedge): Highly stratified estuaries dominated by river discharge, with a sharp interface between fresh and salt water

The stability of the stratification can be assessed locally using the gradient Richardson number:

$$Ri = \frac{N^2}{S^2} = \frac{-\frac{g}{\rho} \frac{\delta \rho}{\delta z}}{(\frac{\delta u}{\delta z})^2} \quad (2.15)$$

This dimensionless number describes the ratio between the stabilising effect of the buoyancy (the density gradient) and the destabilising effect of the velocity shear. When $Ri > 0.25$, the stratification is stable and layers of different density remain separated. When $Ri < 0.25$, turbulent mixing dominates and the water column tends towards a well mixed state.

Another classification for an estuary is the intrusion length. It describes how far landward saltwater penetrates into the estuary. This length is primarily governed by the river discharge and channel depth, and is modulated by tidal range and estuarine geometry (Hendrickx et al., 2023). For tunnel immersion operations, it is important to determine the salinity stratification regime via the Hansen and Rattray framework but furthermore also whether the construction site is within the intrusion length. The application of this classification framework to the specific case of the Scheldt estuary is presented in Section 3.1

Pycnocline effects

In partially mixed and temporarily stratified estuaries, a pycnocline, a sharp vertical gradient in water density, can develop. When a pycnocline is present, the water velocity profile becomes non-uniform: the less dense upper layer flows faster than the denser lower layer. This creates a nonlinear velocity distribution over the water depth.

For tunnel immersion operations, the presence of a pycnocline has two consequences. First the buoyancy force on the tunnel element depends on the density of the water it displaces. A sudden change in water density can increase the buoyancy of the element causing a sudden reduction in the cable loads. Secondly the nonlinear velocity profile affects the drag forces over the element height, affecting the cable loads as well.

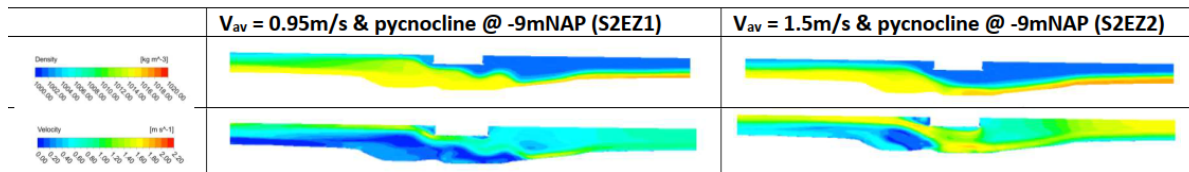


Figure 2.4: Illustration of the pycnocline effect on the velocity profile in a stratified estuary showing the accelerated upper layer and reduced lower layer velocity (Haring et al., 2023)

An example of this is shown in Figure 2.4, the pycnocline is not mixing with the top layer resulting in a velocity increase of the top layer. The effect of this was recently shown during the construction of an immersed tunnel in the Netherlands. The effect was so strong that it caused a mooring cable to break

2.1.4. Summary

The governing environmental variables have been discussed as well as how their behaviour can be described. Secondly a short overview is given of the locations where they come into play and when they should be taken into account

Table 2.1: Summary of environmental variables, their governing equations and the construction site conditions where they are relevant

Variable	Governing equations / principles	Construction locations
Current	Bernoulli's theorem Equation (2.1)	Rivers, high tidal areas like the North Sea
Waves	Linear wave theory (Airy) Equation (2.7)	Open sea, lakes, rivers
Water density	Hansen Rattray type and pycnocline	River deltas in high tidal areas
Wind	Kármán equation Equation (2.4)	Open sea, rivers

2.2. Structural dynamic systems

The immersion system can be schematized as a damped mass spring system. Where the element (mass), the immersion cables (springs), and the water (damper) can be directly correlated. In this section the basic response of these systems will be explained when they are in a natural position without time dependent external loading. The systems are explained with examples drawn from tunnel immersion operations, to put them into perspective.

2.2.1. Properties

The response of a system is governed by the degrees of freedom of a system. The degrees of freedom represent the minimum number of independent displacements, comprising translations and rotations. Normally each object starts with six degrees of freedom, for each axis X, Y, Z the object can both translate and rotate. Each degree of freedom has its own natural frequency and eigenvector. This follows from the undamped equation of motion:

$$m\ddot{x} + kx = 0 \quad (2.16) \quad x = \phi e^{i\omega t} \quad (2.17)$$

For systems with multiple degrees of freedom, a direct solution in physical coordinates is not possible, the equations must therefore be transformed into modal coordinates where each mode can be solved independently. The summation of these modes results in the total response of the system. Assuming that the response of the system is harmonic, Equation (2.17) can be substituted into Equation (2.16). Setting the determinant to zero yields the eigenfrequencies ω substituting these back into the equation and solving for ϕ yields the eigenvector. A natural frequency, ω is the rate at which each degree of freedom oscillates freely when it is excited by an external force (Clough & Penzien, 1995). The eigenvector quantifies the relative amplitude and phase of every other degree of freedom at this natural frequency. The natural frequency together with its eigenvector is called a mode. Each system with N degrees of freedom has N modes. Each mode is orthogonal to the other modes with respect to both the stiffness matrix and the mass matrix, enabling the derivation of the individual response since the system is decoupled. The total response of the system is a superposition of the response of the individual modes following:

$$u(t) = \sum_{i=1}^n \phi_i q_i(t) = \phi_1 q_1(t) + \phi_2 q_2(t) + \cdots + \phi_n q_n(t) \quad (2.18)$$

The natural frequencies also explain the behaviour of the system, a low natural frequency describes a flexible structure whereas a high natural frequency describes a stiff structure. The response of the system is dependent on the frequency of the excitation force. The excitation force will excite modes with the same frequency, so stiffer modes are less susceptible to low frequency forces. From the mathematical derivation of the eigenfrequency, an increase in mass causes lower natural frequencies, whereas an increase in stiffness results in higher natural frequencies.

2.2.2. Damped mass spring system

An often used schematization for a dynamic system is a damped mass spring system. The system can have multiple degrees of freedom and can be damped in multiple directions as well. The system described in Figure 2.5 has only translational movement, the spring k and the damper c .

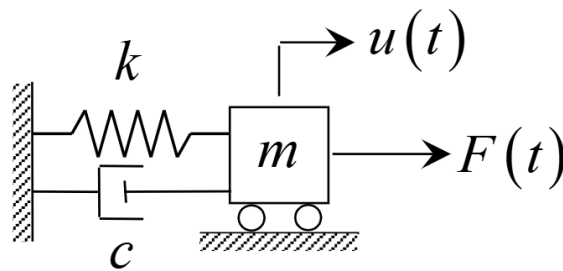


Figure 2.5: Schematic of a single degree of freedom damped mass spring system with mass m spring stiffness k and viscous damping c and excitation force $F(t)$ (Clough & Penzien, 1995)

Applying Newton's second law, which states that the acceleration of an object depends upon two factors, the acting force and the mass of the object. The equation of motion is given in Equation (2.19) and its canonical form in Equation (2.20), which is a simplified version.

$$m\ddot{u} + c\dot{u} + ku = F(t) \quad (2.19) \quad \ddot{u} + 2\zeta\omega_0\dot{u} + \omega_0^2 u = F(t) \quad (2.20)$$

The response of the system when an external force is applied, has two parts, a particular solution matching the frequency of the input, and a steady state response assuming the force is zero. Combining these results in the response of the system. The damping of this system can be derived from the damping ratio ζ . By dividing the damping c by c_{crit} , where c_{crit} follows from $2\sqrt{km}$. There are three different damping ratios. For $\zeta > 1$ the system is overdamped: this results in two real negative roots, and the system returns to its original equilibrium without oscillating. For $\zeta = 1$ the system is critically damped, again the roots are both real and negative. This is the fastest return to the original equilibrium state without oscillation. For $0 < \zeta < 1$ the system solutions are complex resulting in a subcritically damped system, the system will oscillate with exponentially decaying amplitude (Clough & Penzien, 1995). For deriving the steady state response for a system with one degree of freedom two initial conditions are required:

$$u(t) = \sum U_n \exp(s_n t) \quad (2.21) \quad s_{1,2} = \omega_0(-\zeta \pm \sqrt{\zeta^2 - 1}) \quad (2.22)$$

Assuming an oscillating motion, the steady state solution can be derived from substituting Equation (2.21) into Equation (2.20) yielding in two roots given by Equation (2.22). The particular solution for a excitation force which is constant over time is equal to F/k and should be added to the steady solution. As mentioned earlier, for multiple degree of freedom systems the frequency of the acting force activates the corresponding modes at those frequencies, one risk, however, is that the excitation frequency coincides with one of the natural frequencies resulting in resonance. When an object is resonating it significantly increases the amplitude of the response.

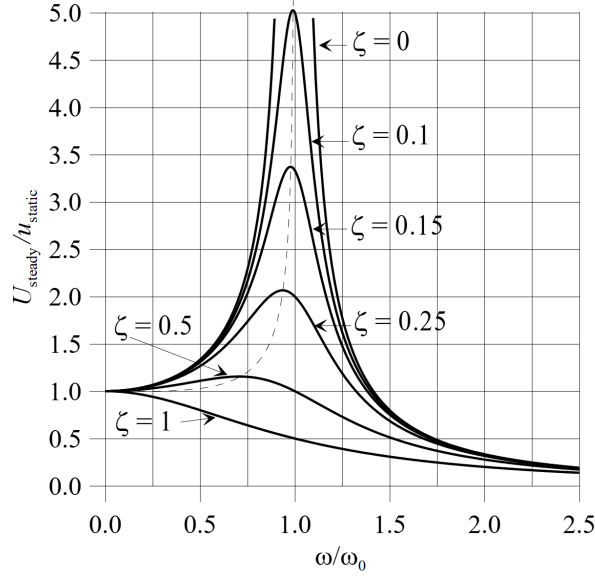


Figure 2.6: Dynamic amplification factor as a function of the frequency ratio ω/ω_0 for various damping ratios ζ , showing the resonance peak at $\omega/\omega_0 = 1$ (Clough & Penzien, 1995)

The amplitude of the system response when resonance occurs is given in figure 2.6, where the response amplitude is compared with the static behaviour of the system. The lower the damping ratio the higher the amplitude for a resonating force. In Figure 2.6 the dynamic amplification factor is shown as a function of ω/ω_0 , when equal to 1, resonance occurs. With the decrease of the damping ratio ζ the peak amplitude at resonance increases, resulting in an unbounded response for an undamped system. For tunnel immersion structures the damping is caused by structural damping (from the cables) and hydrodynamic damping (from the surrounding water. Studies on similar structures, like submerged floating tunnels, have shown damping regimes between 2% and 10% of critical damping (Rahman & Gupta, 2020). Following from Figure 2.6, this results in a system that has relatively high dynamic loads. Because of these high resulting forces resonance needs to be prevented, therefore the harmonic exciting forces like fluid-induced vibrations need to be analysed, this is explained in the following section.

For a coupled immersion system, containing both hydrodynamic springs (the floaters) and the structural springs (the cables) the stiffness can be derived in the following manner. The hydrodynamic stiffness of the floaters is equal to:

$$K_{floater} = \rho_w \cdot g \cdot A_w \quad (2.23) \quad A_w = b_{floater} \cdot L_{floater} \quad (2.24)$$

The cable stiffness for a cable with multiple loops through pulleys is equal to:

$$K_{cable} = \frac{n_{pullies} \cdot E \cdot A}{L} \quad (2.25)$$

For the cable stiffness this equation is valid for the assumption the all parts of the cable contributed evenly to the damping of the system. Therefore, there is zero frictions loss in the disk of the system. This is conservative with respect to the resonance risk of the system. By accounting for the friction in disks the system the cables do not act like parrell springs anymore and therefore the stiffness reduces. Lower stiffness resulst in a lower natural frequency with is further away from the excitation frequency of the cables therefore this assumption is conservative from this perspective

The floaters and cables act as a spring in series, the cables are directly attached to the element, so a movement of the element first causes a response of cables. These cables pull the floaters more underwater and cause a response accordingly. Therefore this system is in serie.

To calculated the combined stiffness of this serie system. The following equation can be used:

$$K_{tot} = \frac{1}{\frac{1}{n_{hp} \cdot k_{cable}} + \frac{1}{n_{fl} \cdot k_{fl}}} \quad (2.26)$$

$$K_{tot} = \frac{1}{\frac{1}{n_{hp} \cdot k_{cable}} + \frac{1}{n_{fl} \cdot k_{fl}}} \cdot d^2 \quad (2.27)$$

For cases where the element is not yet fully submerged the hydraulic stiffness of the element it self has to be accounted for. Since this directly damps the motion this acts in parrel with the cable / floater system.

2.2.3. Summary

The dynamic principles mentioned in this section are summarized in the following table. For each principle the governing equation is given and the resulting effect is mentioned

Table 2.2: Summary of structural dynamic principles, their governing equations, and the system behaviour they determine

Dynamic principle	Given by	Determines
Natural frequency	Equation (2.16)	Resonance risk
Modal superposition	Equation (2.18)	Total response
Damping regime	Equation (2.20)	Oscillation behaviour
Resonance amplification	Figure 2.6	Resonance oscillation magnitude

2.3. Hydrodynamic forcing

Calculating the loads on a submerged structure interacting with water is a complex process. There are various ways to calculate these forces. This process becomes even more complex when the object it self is moving as well. The movement of the structure also influences the relative velocity profile between the body and the fluid. In this section the relevant methods will be shown and a summary will be provided at the end.

2.3.1. Morison equation

Describing the interaction between a submerged structure and a fluid was formalised by J.E. Morison. His objective was to predict wave forces on an exposed vertical pile, stretching from the seafloor to the water surface. The forces acting on the pile can be described with the following equation (Morison et al., 1950):

$$F = F_I + F_D = \rho C_m V \dot{u} + \frac{1}{2} \rho C_d u |u| \quad (2.28)$$

In Equation (2.28) the C_m and C_d are two dimensionless constants for the added mass, where C_m is the dimensionless added mass coefficient and C_d is the drag coefficient. The Morison equation is only applicable to structures where the relative dimension of the cross-section is small relative to the incoming wavelength, so-called slender structures. In those cases it can be assumed that the structure does not cause diffraction of the incoming wave field, and undisturbed flow kinematics can be used directly. Here, u represents the relative velocity between the incoming fluid particle and the structure. If the structure is moving and a water current comes is present, the equation can be modified to:

$$F = F_I + F_D = \rho C_m V (\dot{u} + \dot{u}_{cur} - \dot{u}_{seg}) + \frac{1}{2} \rho C_d (u + u_{cur} - u_{seg}) |u + u_{cur} - u_{seg}| \quad (2.29)$$

The Morison equation consists of two parts a F_I describes the flow inertia and F_D describes the drag on the element. The inertia term follows from potential flow theory Equation (2.7), stating that the force acting on the structure is equal to the integral of the pressure gradient over the structures surface. This can be divided into two parts, the Froude Krylov force, following from this pressure gradient and the added mass which is caused by the acceleration of the surrounding fluid due to the movement of a body:

$$F_{fk} = \rho V \dot{u} \quad (2.30)$$

$$F_a = C_a \rho V \dot{u} \quad (2.31)$$

The total inertia coefficient C_m can therefore by written as $C_m = 1 + C_a$ combining the Froude Krylov and the added mass contributions. The ratio between the added mass and the drag forces can be

characterised by the Keulegan Carpenter number, which describes the relationship between oscillatory movement of the structure and the incoming current

$$KC = \frac{U_m T}{L} \quad (2.32)$$

For low KC numbers ($\ll 3$) the inertia force dominates and therefore the drag can be neglected, in these case the flow is barely disturbed by the structure (Keulegan & Carpenter, 1958). Up to a KC number of 15 the drag can be linearized. Beyond $KC = 15$, the full Morison equation is required and the drag cannot be reduced further (Journée & Massie, 2001). For structures of this type the flow is disturbed for a length equivalent to the scale of structure dimension.

The added mass coefficient quantifies how much water is affected by the presence of the structure. For an added mass coefficient of 1 the added mass equals the fluid displaced by the body, however for added mass coefficient above 1 the movement of a greater volume of surrounding fluid is affected by the presence of the object. In this case the drag is dominant.

The added mass coefficient C_a follows from DNV-RP-H103. The added mass coefficient depends on the ratio between the length and width of the tunnel element. Also for multiple degrees of freedom systems, if the object is not symmetric in all axes the coefficients vary between the different flow directions. The C_a can be derived from (Veritas, 2025):

$$C_a = -\frac{f_{inertia}}{\rho A \dot{v}} \quad (2.33)$$

$$C_D = \frac{f_{drag}}{\frac{1}{2} \rho D v^2} \quad (2.34)$$

2.3.2. Vortex induced vibrations

The presence of a submerged object into the flow field can result in the separation of the boundary layer, also called vortex shedding. This can result in a pressure difference between the top and the bottom layer of the structure. This pressure gradient can result in additional forcing acting on the structure. The pressure differences will result in additional lift on the structure and furthermore can cause oscillatory forces. Vortex shedding can be characterized by the Strouhal number. Vortex shedding is not solely driven by bluff-body geometry, flow viscosity can also trigger separation of the boundary layer, represented by the Reynolds number Equation (2.36). The Reynolds number is a dimensionless number expressing the ratio of inertial to viscous forces. A high Reynolds number indicates that inertial effects dominate, and the flow is prone to boundary layer separation.

$$S_t = \frac{f_s D}{U} \quad (2.35)$$

$$Re = U D / \nu \quad (2.36)$$

In Equation (2.35), f_s : Shedding frequency, D : Cylinder diameter, U current velocity. Typically a shape has a certain S_t number depending on the geometry and the Reynolds number. With that, the shedding frequency f_s can be derived. A high Reynolds number can result in Vortex shedding as well. The interplay of these two numbers describes the behaviour of fluid around a submerged structure.

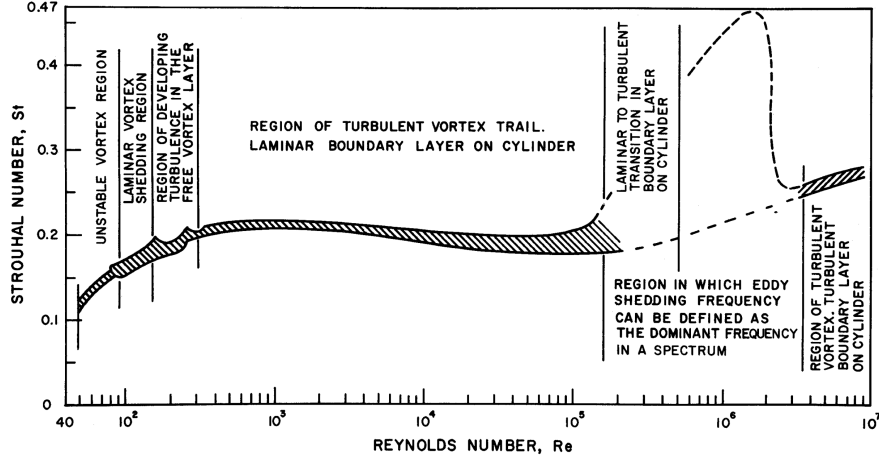


Figure 2.7: Strouhal number as a function of Reynolds number for circular cylinders, showing the transition between flow regimes and the onset of vortex shedding (Lienhard, 1966)

If the vortex shedding results in oscillatory flow and synchronizes with one of the structural natural frequencies, resonance occurs. This resonance causes the displacement amplitude of the structure to increase. This process is called Vortex induced vibrations (VIV) (P. X. Zou et al., 2022). Another phenomenon related to VIV is the "lock-in" principle. This process is characterised by the locking of the vortex shedding frequency onto the structural natural frequency (P. X. Zou et al., 2022).

The resulting oscillating forces on the structure can be decomposed into a lift force and a drag force, given by (Veritas, 2025). The drag force acts in the same direction as the current whereas the lift force acts perpendicular to the current

$$F_L(t) = \frac{1}{2} \rho C_L(t) D U^2 \quad (2.37)$$

$$F_D(t) = \frac{1}{2} \rho C_D(t) D U^2 \quad (2.38)$$

Besides the additional drag and lift on the element the VIV also results in additional damping and added mass in the direction perpendicular to the flow velocity. Assuming that the lifting force is harmonic and the resulting motion of the structure is harmonic as well. The added damping and added mass can be added to the general equation of motion, following Equation (2.16). This results in (Journée & Massie, 2001):

$$\left(m + \frac{F_{L,0}}{y_0 \omega^2} \cos(\psi)\right) \ddot{y} + \left(c - \frac{F_{L,0}}{y_0 \omega} \sin(\psi)\right) \dot{y} + ky = 0 \quad (2.39)$$

2.3.3. Seafloor effects

When a large object is being submerged and is approaching its final location on the seabed, some additional effects come into play. In the final stage of the lowering the water is being "trapped" between the object and the seafloor. The available flow paths are very narrow resulting in a temporary increase in pressure. The research on this effect remains limited. However it can be concluded from recent projects (Busan, Macau) that when the lowering speed is too high the pressure below the element increases rapidly causing additional buoyancy and preventing accurate landing (van Putten, 2025b).

Recent research however, tried to quantify this effect (Song, Chen, & Zhang, 2021). They investigated the near-seabed immersion stage of a submerged tunnel element while suspended. A numerical model was developed based on potential flow theory and validated with experimental tests. The numerical model allowed full 6 DOF motion of the tunnel element while being suspended. The relative clearance of the tunnel element is defined as δ/d where δ represents the distance between the underside of the tunnel element and the seabed and d the height of the tunnel element. For a relative clearance ratio of $\delta/d < 0.26$ the ground effect is significant and causes significant nonlinear motion characteristics, including roll resonance, it also affects the asymmetric offset in surge, pitch and yaw of the tunnel.

However this paper does not quantify the near-ground effect as an upward force. It can only characterise the shift in the natural response of the system with respect to the natural frequencies and eigenvectors (Song, Chen, & Zhang, 2021).

2.3.4. Buoyancy

The density of the water affects the buoyancy force on an immersed object. The buoyancy follows from the law of Archimedes which states that the upward buoyancy force acting on a submerged body equals the weight of the fluid displaced by that body (Archimedes, 2002). Secondly as shown in Equation (2.13) the water density is also linearly correlated with the hydrostatic pressure.

$$F_B = \rho g V \quad (2.40)$$

The density of water is linearly correlated with the upward force F_B . This correlation shows that salt water provides more buoyancy. Water densities vary between 1000 kg/m^3 for fresh water and 1025 kg/m^3 for salt water. The water temperature also affects the density of the water, a lower water temperature results in a higher density, causing greater buoyancy. However during the immersion process it can be assumed that the temperature remains constant.

2.3.5. Damping

Damping describes the dissipation of energy from an oscillating system, causing a reduction in the amplitude of motion over time. During the immersion of a tunnel element, the damping results from multiple physical mechanisms, that act simultaneously on the structure. As mentioned in Section 2.2, the damping acting on a damped mass spring system, following Equation (2.19), is given with c . The damping contributions can be divided into three parts: structural, hydrodynamic and radiation damping.

Structural damping is a result of the mechanical properties of the system. The damping is a result from friction within the material or the connections. For immersion operations, the damping comes mostly from the steel cables, which run through pulleys, introducing additional friction damping. A common way to describe this structural damping is via Rayleigh damping (P. Zou, 2022). The damping is expressed as a linear combination of the mass and stiffness matrices.

$$\mathbf{C} = \alpha \mathbf{M} + \beta \mathbf{K} \quad (2.41)$$

Here, α and β are the Rayleigh damping coefficients. For comparable structures like submerged floating tunnels, coefficients ranging between $\alpha = 0.946$ and $\beta = 0.00022$ with a damping ratio of $0.01 < \zeta < 0.05$ (Rahman & Gupta, 2020), and $\alpha = 0.286$ and $\beta = 0.007$ with a damping ratio of $\zeta = 0.025$ (P. Zou, 2022) have been found. According to the DNV, the structural the damping ratio should be between 1–3% (Veritas, 2025)

The hydrodynamic damping follows from the interaction between the moving structure and the surrounding fluid. This velocity dependent damping was already introduced in Section 2.3.1 and Section 2.3.2. The hydrodynamic damping can be divided into the drag on the structure and the lift forces of the structure resulting from the fluid structure interaction. The drag part follows from Equation (2.28) and adding into Equation (2.19) accounts for the first part of the hydrodynamic damping.

The vortex induced vibrations cause additional hydrodynamic damping. As mentioned in Equation (2.39), the lift force as a resulting from the fluid structure interaction introduces an additional damping component in the direction perpendicular to the current. Depending on the phase difference this effect can either increase or decrease the effective damping. For $\sin(\psi) > 0$ the lift force opposes the motion and adds damping, while for $\sin(\psi) < 0$ the lift force amplifies the motion reducing the total damping. This is the second part of the hydrodynamic damping.

The radiation damping characterises the relationship between outgoing waves that are generated by the motion of the element and the energy carried away from the system. In the initial stages of the immersion operation, when the element is close to the surface, this effect comes into play. As the immersion depth increases the wave generating capacity of the structure decrease and this effect can be neglected (Yang et al., 2017).

The combined effect of these damping mechanisms, in combination with the stiffness and mass matrices, determines the damping ratio ζ of the system. The damping ratios can vary between $0.02 < \zeta < 0.10$ as mentioned in Section 2.2.2. For low damping ratios the amplitude of the motion is significant even for small exciting forces (see Figure 2.6). These forces correspond to with the frequencies of the hydrodynamic such as those described by the Morison equation Equation (2.28) and VIV Equation (2.37)

2.3.6. Summary

The hydrodynamic forces in this section, which act on a tunnel element during immersion, have been summarised in Table 2.3. For each force, the causing external variables have been mentioned as well as the resulting damping associated with it.

Table 2.3: Summary of the hydrodynamic forces acting on a tunnel element during immersion, their causing external variables, and associated damping contributions

Force	Causing external variables	Additional damping
Morison drag	Current and waves	Drag
Morison Inertia	Current and waves	-
Vortex induced vibration	Current	Lift damping
Seafloor effects	Water density, current velocity	Yes (Quantified in literature)
Buoyancy effects	Water density	-

Also the structural damping has been highlighted as a result of the structural properties of the immersion system. This is can be approximated with Rayleigh damping.

2.4. Calculation methods

Damped mass spring systems following Equation (2.16) can be solved with the help of conventional numerical methods or with machine learning methods. Since the system is time dependent, the computation is demanding when the time horizon increases. Furthermore when the system is excited by a fluid and the system is not restricted in any of its degrees of freedom the behaviour can be highly non linear. The response can be obtained by numerically solving the ODE, by applying computational fluid dynamics or by fitting a data-driven model using machine learning.

2.4.1. Numerical

Solving Equation (2.19) can be done analytically however when the time periods become too long a numerical method can be preferred. There are various ways of solving an ODE numerically. The most common ways are the Euler method and the RK4 method. A brief overview of each of method is given below.

The Euler method evaluates the ODE at a fixed interval Δt . At each step, the derivate is evaluated at the current state and used as a constant slope to extrapolate to the next point in time. This is referred to as the forward Euler method, given in Equation (2.42). The backward Euler method Equation (2.43) method evaluates the derivative at the next time step t_{n+1} , making the scheme unconditionally stable, regardless of the magnitude of Δt

$$x_{n+1} = x_n + \Delta t \cdot f(x_n, t_n) \quad (2.42) \quad x_{n+1} = x_n + \Delta t \cdot f(x_{n+1}, t_{n+1}) \quad (2.43)$$

The timestep Δt needs to be small enough to capture all the dynamics, a large Δt will cause the solution to diverge Equation (2.19). A general rule of thumb to prevent this from happening is $\Delta t < \frac{2}{\omega_n}$.

Another method for evaluating an ODE numerically is the RK4 method. This method evaluates the derivatives at multiple points within the interval $[t_n, t_n + h]$ and combines them in a weighted average

slope.

$$\begin{cases} k_1 = hf(t_n, y_n) \\ k_2 = hf\left(t_n + \frac{h}{2}, y_n + \frac{k_1}{2}\right) \\ k_3 = hf\left(t_n + \frac{h}{2}, y_n + \frac{k_2}{2}\right) \\ k_4 = hf(t_n + h, y_n + k_3) \end{cases} \quad (2.44)$$

k_1 and k_4 are evaluated at the start and end of the interval, while k_2 and k_3 are intermediate evaluations.

$$y_{n+1} = y_n + \frac{1}{6}(k_1 + 2k_2 + 2k_3 + k_4) \quad (2.45)$$

Compared to the First Order method, the error of Rk4 is fourth order, and therefore more accurate and better suited for this case.

2.4.2. Computational Fluid Dynamics

Computational Fluid Dynamics (CFD) is a numerical method to approximate fluid flow problems. A CFD model can numerically determine forces acting on a structure due to fluid structure interaction by computing the flow velocity and pressure field around it. The governing equations of CFD are the Navier Stokes equations, which describe the conservation of mass and momentum for a viscous fluid. The fluid can be assumed incompressible, which simplifies the continuity equation (Versteeg & Malalasekera, 2007).

Accounting for all turbulent scales in the flow field is computationally too expensive for practical analysis. Therefore the Reynolds-averaged Navier Stokes equations are used (RANS). In this approach, the flow variables are divided into a time-averaged component and a fluctuating component. This simplifies the problem but keeps track of the mean flow and turbulent fluctuations. This decomposition however introduces unknown terms, the Reynolds stresses, which require a turbulence closure model, such as the $k - \omega$ SST turbulence model (Menter, 1993).

The governing equations are discretised over a mesh of control volumes using the Finite Volume Method (FVM), ensuring conservation of mass and momentum across each cell. The simulation accuracy depends on the resolution of the mesh, a finer mesh better resolves the gradients in the flow, but significantly increases the computational cost. Therefore the mesh is coarser at locations where the flow is undisturbed and finer near the surface of the structure a finer mesh is applied.

2.4.3. Machine learning

A machine learning model can be used to approach complex problems. The challenge is to ensure the model captures the physically relevant relationships in the data. For engineering applications, the model needs to have explainable behaviour. The main goal of machine learning is to identify a certain relationship which results in a mapping from input data to output data. This results in two types of models, generative models, which learn the joint distribution of inputs and outputs $p(x, y)$, allowing for uncertainty quantification in the predictions, and discriminative models which learn the conditional mapping $p(y|x)$, optimising predictive accuracy without modelling the input distribution. A machine learning model is always constructed from the same components: The architecture, the hyperparameters, the loss function and the evaluation metrics.

Before diving into the different machine learning architectures the curse of dimensionality has to be explained. This concept motivates the modelling architecture discussed below. The curse of dimensionality refers to the fact that the amount of data needed to estimate a function increases exponentially with the number of input variables (Bellman, 1961). For example when estimating a function with one variable, sampling 20% of its range covers 20% of the entire input space. However, when there are two variables and 20% is sampled from, this only covers 4% of the input space. To overcome this issue some assumptions can be made to reduce the required amount of data. These built-in assumptions reduce the hypothesis space. An accurate inductive bias can help the model to learn efficiently from limited samples and converge faster (Goodfellow et al., 2016). A few of these inductive biases will be discussed.

Spatial inductive bias is the assumption of locality and translation invariance. It assumes that features (like an edge in an image) are meaningful regardless of where they appear and that nearby pixels are more related than distant ones. Convolutional neural networks are based on this principle. Sequential inductive bias assumes that the order of data points is as important as the data point themselves; it implies a causal or temporal relationship where a current state depends on previous states. Recurrent neural networks and transformers are based on these principles. Physics-based inductive bias forces the model to respect a mathematical relationship such as the conservation of energy and mass instead of just learning from data; this inductive bias can be included in the loss function rather than in the architecture (Goodfellow et al., 2016).

Another type of model architecture is statistically driven models (Bishop, 2006). In these types of models, it is assumed that the data is statistically correlated. As introduced above, these can be categorised into two categories: discriminative and generative models. Examples of discriminative models include logistic regression models and supported vector machines (SVM). Examples of generative models include variational Auto encoders and large language models such as ChatGPT.

The hyperparameters of the model are the settings applied to the architecture to optimize its behaviour. These "settings" include the learning rate, batch size of training data, number of layers and number of hidden neurons for an MLP network. For Bayesian models, the hyperparameters include the type of kernels used. The type of optimizer can also be considered a hyperparameter.

The loss function quantifies the discrepancy between the model prediction and the target data. The outcome of the model is compared to the target data. Generally speaking the difference between those values is the loss. The most commonly used loss functions are the Mean Squared Error (MSE) and the Maximum Likelihood Estimation (MLE). The loss function is what the model optimizes; it will always try to minimize the loss.

The evaluation metrics are measures used to assess the model performance on new data. When the model is applied to new input data to output the evaluation metrics evaluate how closely the outputs match the desired outcome.

Before assembling a machine learning model the data must be analysed. Data can be classified in two ways: stationary or non stationary. Stationary data has constant mean and variance over time. For stationary data often regression models and MLPs work fine. For more complex data, Non stationary data, deeper and more complex architectures are required. Non stationary data exhibits a non constant mean and variance over time.

2.4.4. Summary

Three approaches for deriving the dynamic response of the cable-tunnel system have been discussed. Each method has different strengths regarding computational cost as well as the ability to capture unknown relationships. The methods have been summarized in the following table:

Table 2.4: Comparison of calculation methods for deriving the dynamic response of the immersion system

Method	Physical basis	Computational cost	Data-adaptive
Numerical	Explicit ODE	Low	No
CFD	Full Navier-Stokes	Very high	No
Machine learning	Implicit (learned)	Medium	Yes

2.5. Immersed tunnel definitions

An immersed tunnel consists of several prefabricated tunnel elements. These elements are floated to the construction site and then installed one by one. Underwater these elements are connected to each other. Often an immersed tunnel is installed in a trench that has been dredged on the seabed (Molenaar, 1993). Compared to bored tunnels, immersed tunnels have a number of advantages; the construction can be faster, and it is often cheaper (Molenaar, 1993).

Depending on the environmental conditions at the construction site various design choices can be made. These choices can be grouped into two categories, the element shapes and the immersion

configuration. Often these tunnels are placed in rivers, however immersed tunnels also have been constructed at sea, like the Busan Geoje link (Immontec, 2010) and the Fehmarnbelt project (Femern A/S, 2025). In these environments the wave height becomes a design parameter because it will cause oscillatory movement of the immersion pontoons.

The design choices governing the element shapes and immersion configurations will be further explained in this section

2.5.1. Element shapes

For the design of the element shapes first the number of traffic lines needs to be determined. Often the tunnels contain multiple car lanes, but also rail lanes and walkways for pedestrians. The tunnels are often constructed out of reinforced concrete, with prestressed steel. The concrete elements must be able to float with all temporary equipment installed. However the aim is to keep the freeboard at a minimum so that the required ballast to overcome the buoyancy is minimised. This additional ballast is often added in temporary ballast tanks. The size of these tanks is determined by the over buoyancy of the element and the maximum water density difference. The length of these element depends on the construction site (Molenaar, 1993).

The shapes of the elements are often rectangular shapes, because this maximises the interior space, however the also circular cross section are also popular. These are mostly used for the construction of metro tunnels. Also if the tunnel element is made out of steel rather than concrete, the majority are often made with a circular shape.

2.5.2. Immersion configurations

The immersion configuration consists of 2 parts. First of all the immersion pontoons. These floating platforms control the immersion operation. On top of the these platforms the horizontal and vertical winches are positioned. These pontoons often consists of 2 floaters and a connecting bridge. Sometimes it is chosen to use only one pontoon with holes for the cables. This is decided based on the available space and the environmental conditions

The winches positioned on these pontoons control the operation. The horizontal winches position the element above the trench. These cables are often connected to anchors or points on the shore. Connecting the pontoons and the element is a complex task, often the tunnel is pushed with the help of tugboats towards the final location and their the tugboats are disconnected one by one and replaced by the cables. The vertical cables are connected to the element and lower it to its final position. These winches are manually controlled by the immersion commander.

2.5.3. Lowering procedure

Before the lowering procedure can start the buoyancy has to be overcome. Depending on the winch capacity, ballast is added until a minimum load in the cables is reached. This load is required to provide a minimum tension in the cables and create some buffer so the element does not float back to the surface (van der A, 2025). Once this minimum load is reached, the cables are being eased out. Increasing the cable length causes a dynamic response of the system following Equation (2.19). Therefore this process is done very slowly. If during the immersion process the water density changes, the water ballast has to be adjusted accordingly to maintain the correct weight

2.6. Reference research

Recent studies governing tunnel immersion operations and the use of machine learning for fluid structure interaction are presented below. For each of the mentioned papers a short summary is provided on what they investigated and what their findings were, and why they are useful for this research.

"Hydrodynamic response of a submerged tunnel element suspended from a twin-barge under random waves" (Yang et al., 2017) This research investigated the motion characteristics and dynamic responses of an immersed tunnel element during the installation process in an open sea environment. The tunnel was connected to a twin barge immersion system. The coupled dynamic response was investigated with a numerical model and validated with experimental tests. The damping properties of the system were obtained from the experiments. The numerical model was based on the potential flow

theory and simulated with the help of OrcaFlex, to simulate the movements of the element. Their main findings were the effect of the immersion depth on the total response of the system. When the element is closer to the surface the response increases significantly because of wave interaction. Secondly it was concluded that the system must be considered fully coupled, since the motion of the tunnel element is amplified by the movements of the pontoons. The findings of this research about the behaviour of a tunnel are relevant to this study, it demonstrates the importance of modelling the system as fully coupled and shows how to retrieve the damping coefficients from experiments. Secondly the paper quantifies how a system should respond when excited by waves.

"Physics informed neural networks modelling for system with moving immersed obundaris: application to unsteady flow past a plunging foil". (Sundar et al., 2024) This research investigated the unsteady flows past moving boundaries by simulating the flow around a foil. A PINN was used to simulate the behaviour, the Navier Stokes equations were incorporated in the PINN. They were able to produce a high resolution reconstruction of the flow behaviour around the moving foil. With that they were able to recover the pressure gradients. Also the primary vortices were recovered behind the structure. This demonstrates that physics can be embedded in neural network models for fluid-structure problems.

"Coupled motion characteristics of a large scale tunnel element suspended by immersion rigs in the vicinity of seabed". (Song, Chen, & Zhang, 2021) This research investigated the ground effect in the last stage of the immersion operation. With the help of a numerical model which was validated with a physical test the tried to characterise this effect. They concluded that the effect was significant once the relative distance between the seafloor and the underside of the tunnel element decreased to $\delta/d < 0.26$ (Section 2.3.3). The effect is strongly coupled to the tunnel's roll motion as well. The study quantifies the ground effect in the final lowering stage and demonstrates the coupling between near-seabed hydrodynamis and roll resonance

"Effect of immersion depth on the coupled dynamics of a tunnel-rig system in irregular waves" (Song, Qu, et al., 2021) In this paper the suspension line tension was measured as a response to the 6 DOF motions of the tunnel element. Using a physical scale model, the wave-induced motions of the tunnel element were shown to generate additional loads in the suspension lines. No numerical model was used to validate these loads. Secondly, they found that deeper immersion, with corresponding longer cables, results in lower natural frequencies across all modes. For this research this papelr is mostly relevant for validation. Since the study does not use real operational inputs, the general patterns of and the governing frequencies of the response can be compared.

"Response of a submerged floating tunnel subject to flow induced vibrations" (P. X. Zou et al., 2022) This research investigated the dynamic response of a submerged floating tunnel to VIV. They also translated this response to the structural properties of the tunnel. They found that the flow induced vibration is predominantly governed by wave-dominated conditions rather than unsteady current. Also the shape of the cross-section plays a dominant role in the VIV of the element. For this research this study is useful to explain and quantify the possible consequences of VIV and how shapes can be selected to mitigate this effect. However this research was based on way fluid interaction, meaning structural feedback on the flow was not accounted for. For a tunnel immersion operation where the tunnel has significant motion, the structural feedback to the flow field cannot be neglected.

"Time-domain response of immersing tunnel element under wave actions" (Chen et al., 2009) This research investigated the time domain response of a tunnel element to waves, during its immersion process. The effect of diffraction caused by the tunnel element on the incoming waves was accounted for. The tunnel element was modelled in 3 degrees of freedom: sway, heave and roll motions. They calculated the forces in as a result of this motion. Their main findings were that the response decreases when the immersion depth increases, however the response appears to be more linear in deeper stages. Furthermore they found that the element behaves non linearly in shallow waters and exhibits asymmetric roll motions. This research is useful to describe the motion of the tunnel element alone. However the movement of the barges was neglected in this paper.

Real-time prediction of hydrodynamic forces and dynamic responses of a generic jack-up platform using learning (Miyawala et al., 2024) This research investigated the real-time prediction of hydrodynamic forces and the structural dynamic response of a jack-up platform subjected to waves. The

aim was to reduce the calculation time of the simulation. An LSTM model was trained on a database of CFD models. The LSTM takes as input a wave field time series, and returns the bending moments and displacements as outputs. The model achieved an accuracy of up to 94% and reduced the calculation time from several weeks to seconds. This research shows the potential of using data-driven models to forecast the motion of floating structures, as well as predicting the resulting forces.

2.6.1. Research gaps

The referenced studies yield several findings that are relevant for this research. Furthermore they position the gap this research addresses.

The studies of Yang et al. (2017) and Chen et al. (2009) show that the dynamic response of the tunnel element is depth dependent. They stated that the amplitude of the motion decreases with increasing element depth. This is caused by the decay of fluid particle velocity, which was accelerated initially by surface waves. Secondly it was shown that the immersion system cannot be treated as a decoupled system by Yang et al. (2017) and Chen et al. (2009). Both the motion of the pontoon and the motion of the element affect the cable loads. Also the dynamic behaviour of the element becomes highly non-linear in shallow waters. From Song, Chen, and Zhang (2021), it can be found that additional dynamic effects start in the last stage of the immersion process, when the element is near the seabed. This contradicts the studies of Yang et al. (2017) and Chen et al. (2009). Showing the need for additional research.

The papers of Sundar et al. (2024) and Miyanawala et al. (2024) showed a potential solution through applying machine learning to these types of problems. Sundar et al. (2024) showed that pressure field can be retrieved with a PINN, but the resulting forces remain unsolved. The paper of Miyanawala et al. (2024) showed that both the structural response and the dynamic response of a vessel can be obtained with the help of an LSTM model trained on a CFD dataset.

A gap that remains unresolved in these studies is the coupling between element motions and structural response to cable pay out events. Furthermore none of these studies are capable of handling both fluid structure phenomena and operational immersion inputs. This gap can be filled by designing a machine learning network that identifies these underlying relationships from the data, and allows for predicting these cable loads.

2.7. Summary

This chapter established the theoretical background required to understand and to model dynamic cable loads during tunnel immersion operations. The governing physical principles have been outlined as well as relevant research supporting this topic. A short overview is provided with the aim of motivating the research gap for a data-driven approach.

The governing environmental variables causing the dynamic response are identified as the current, waves, water density and wind at the project location. The relative impact of these forces depends on the construction site. The response in tidal rivers is predominantly caused by water density and current oscillations, where as the response in open seas is more affected by waves and currents. The structural section showed that the immersion configuration cable must be modelled as a multi degree of freedom damped mass spring system. With damping ratios varying between 2 and 10% of the critical damping. This shows that the structure will have a high dynamic response when it starts oscillating as a result of harmonic excitation forcing. Secondly the dynamic response is most significant when the element is positioned near the water surface. The main forces acting on the structure during the immersion operation can be described with the Morison equation, vortex induced vibrations and the law of Archimedes. The combination of these forces results in a non-linear force acting on the structure. It has to be highlighted that the vortex induced vibrations can cause resonance in the structural response, secondly the correlated damping, when in phase, can amplify the motion even further. To solve the resulting ODE various methods have been discussed. It was stated that conventional calculation methods require long calculation times, making them inefficient for modelling entire immersion sequences. However a data-driven approaches could be promising.

From the recent research the absence of a model capable of predicting vertical cable loads directly from operational and environmental monitoring data during a tunnel immersion operation was shown.

The theoretical background established in this chapter provides the physical understanding needed to design and validate such a model: the input variables should contain the environmental variables as well as the operational variables. The architecture should be able to identify the underlying physical relationships described in Section 2.3 and the output of the model should show similar behaviour to that described in the recent studies.

Case study and monitoring data

This chapter introduces the case study used to address the research questions: the Oosterweel immersed tunnel in Antwerp, Belgium. This project was selected because it represents one of the most recent immersed tunnel projects. The tunnel was constructed in an estuarine environment, characterized by strong tidal currents and salinity stratification (Doorme, 2019). Furthermore, the immersion system was equipped with a monitoring system, providing the operational and environmental data required for a surrogate modelling approach.

This chapter is structured as follows: Section 3.1 introduces the project scope and the environmental conditions at the construction site. Section 3.2 describes the system used to lower the tunnel elements, covering the element properties, pontoon configuration, cable system and the ballasting system. Section 3.4 introduces the monitoring system, detailing the measured signals and their sampling resolution. Section 3.5 provides an overview of the available dataset for each tunnel element, including the missing data. These sections establish an understanding of the data required for the analysis in the following chapter.

3.1. Oosterweel tunnel project

This study takes the Scheldt tunnel as its case study. This tunnel is part of the Oosterweel connection, which is a major infrastructure project with the aim of completing the northern section of the Antwerp ring road. The project consists of three components: a cut and cover tunnel through the harbour area in the North of Antwerp, the Oosterweel interchange and the Schelde tunnel, which serves as the case study. The location of these individual parts is shown in Figure 3.1.

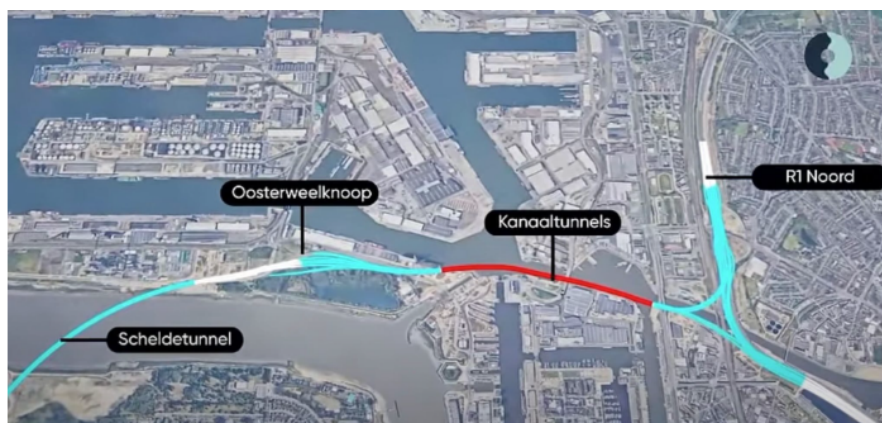


Figure 3.1: Overview of the Oosterweel connection project, showing the three main components: the cut and cover tunnel, the Oosterweel interchange and the Scheldt immersed tunnel (Sweet, 2024)

During the early design phase, two alternatives to an immersed tunnel were considered: a bridge and a bored tunnel. A bridge was deemed infeasible due to the intensive shipping traffic in the port of Antwerp, which would require a very high bridge. A bored tunnel was also rejected due to space constraints on both sides, as a result of the harbour activities. An immersed tunnel was therefore selected as the most suitable solution, despite the challenging construction conditions caused by the Schelde river: current velocities up to 1.7 m/s, a tidal range of approximately five meters and a salinity stratification due to the mixing of seawater and river discharge (Doorme, 2019).

The construction of the Oosterweel tunnel was carried out by TM COTU, a consortium including DEME Group, Jan De Nul, Besix and Stadsbader (contractors). The preparations for the construction work started in 2021 and the project is expected to be finished in early 2030.

3.1.1. Project overview

The Scheldt tunnel is an immersed tunnel connecting the northern and southern river banks. The connection accommodates three traffic lanes in each direction and a separate cycling lane. The total tunnel length is 1900 meters, divided into three sections: from the North part of the river the first 140 meters is a cut and cover tunnel; the next 1275 meters is an immersed tunnel containing 8 elements and on the South side there is again a cut and cover tunnel of 486 meters, as also shown in Figure 1.1. The elements are numbered TE1 to TE8, with TE1 being located at the southern end.



Figure 3.2: (a) Transport route of the tunnel elements from the dry dock in Zeebrugge via the North Sea and Schelde river to the construction side in Antwerp. (b) Longitudinal cross section of the Schelde tunnel showing the vertical alignment of the eight immersed elements. (van der A, 2025)

The tunnel elements were constructed in a temporary dry dock in Zeebrugge, Belgium. After construction, each element was made watertight and floated, then towed across the North Sea and up the Schelde river, with an intermediate tidal stop in Terneuzen, to their parking location in the Doeldok near Antwerp. There, the final modifications were carried out to prepare each element for immersion. From there the elements were towed to the construction site in the Scheldt river and lowered to their final location on the river bed.

3.1.2. Environmental conditions

The environmental conditions at the Oosterweel construction site have been characterised in a study by (Doorme, 2019), based on ten years of monitoring data from measurement buoys in the Schelde river. This subsection summarises the governing conditions relevant to immersion operations: water level, water density and current velocity and direction. For each of these variables the operational range and the extreme design values (100 year return period) are reported.

Water level The water level at the construction site is primarily governed by the semi-diurnal tidal regime of the North Sea, resulting in a tidal range of approximately 5.5 m under normal conditions. Secondary water level variations occur during periods of elevated river discharge. The extreme design water level corresponding to a 100 year return period is 7.5 m TAW Table 3.1.

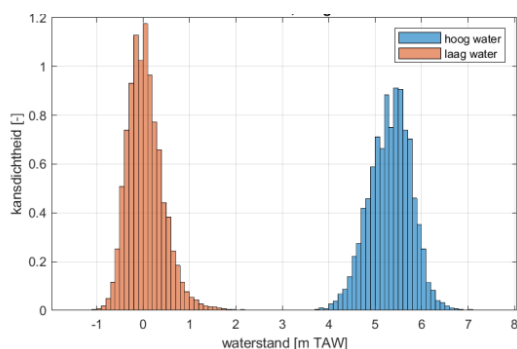


Figure 3.3: Probability density function of low and high water at Oosterweel for the period 1987 to 2013, supplemented to 2018 (Doorme, 2019).

terugkeerperiode [jaar]	hoogwater [m TAW]		laagwater [m TAW]	
	Antwerpen	Oosterweel	Antwerpen	Oosterweel
1	6.4	6.5	-0.4	-0.3
2	6.8	6.8	-0.8	-0.8
5	7.0	7.0	-1.1	-1.1
10	7.2	7.2	-1.2	-1.2
50	7.5	7.5	-1.5	-1.4
100	7.6	7.7	-1.6	-1.5
200	7.8	7.8	-1.7	-1.6

Table 3.1: Extreme value analysis of environmental conditions at the construction site, showing the 100 year return period design values (Doorme, 2019).

This value governs the structural design of the tunnel. The tidal amplitude is important during the construction phase. When the operation is started at high tide the element will move closer to the riverbed as water level decreases, reducing the amount of cable paid out and thereby, reducing the dynamic forces.

Water density The Schelde river at the construction site is a macro tidal estuary where the North Sea saltwater mixes with freshwater river discharge. Following the Hansen Rattray classification (Hansen & Rattray, 1966), the Schelde is categorised as a well-mixed, tide dominated estuary. This classification is based on the tidally averaged salinity measurements from the permanent monitoring station, therefore the effect of a pycnocline can be neglected (Doorme, 2019). The report also shows that the construction site is well within the intrusion length. The average tidal salinity amplitude is 5.59 PSU, which at a temperature of 10 degrees corresponds to a density increase of 5.6 kg/m^3 in water density.

Current velocity and direction The current velocity in the Schelde river is predominantly tidally driven. with the flow direction reversing approximately every six hours. The velocity during upcoming tide is slightly lower because the river discharge is reducing the current (Figure 3.4).

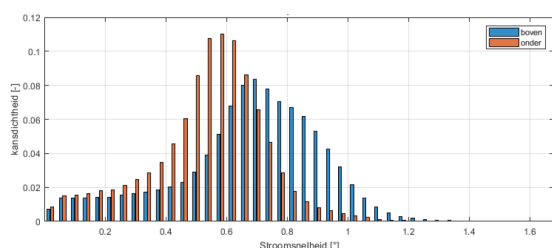


Figure 3.4: Empirical probability density function of the current velocity in the Western Schelde at the Oosterweel location, for both upper (blue) and lower (red) measurement setup (Doorme, 2019).

Terugkeerperiode [jaar]	maximale vloedsnelheid [m/s]	maximale ebsnelheid [m/s]
1		
2		
5	1.45	1.26
10	1.56	1.32
50	1.71	1.42
100	1.76	1.46
200	1.81	1.48

Table 3.2: Extreme value analysis of current velocities at the construction site, showing the 100-year return period design velocity of 1.71 m/s (Doorme, 2019).

The depth averaged current velocity under normal conditions ranges from 0.6 to 0.8 m/s while the design current velocity (100 years return period) is 1.71 m/s (Table 3.2). The current velocity varies over the water depth as a result of the river's bathymetry and bed friction, with higher velocities near the surface. This depth dependent velocity profile is relevant because the hydrodynamic forces on the tunnel element depend on this velocity.

The reference current velocity is measured at the position of element four, located close to the south bank of the river where the flow velocity is the highest. At the other element locations, the current velocity is lower due to the river's cross sectional geometry. Relative to the middle river prediction.

Elements 1 and 2 experience 60% of the current velocity, elements 3 through 5 the full 100%, element 6 only 80%. and elements 7 and 8 also 60% (Doorme, 2019). In this manner the predicted flow velocity can be converted towards the expected flow velocity at a specific element location.

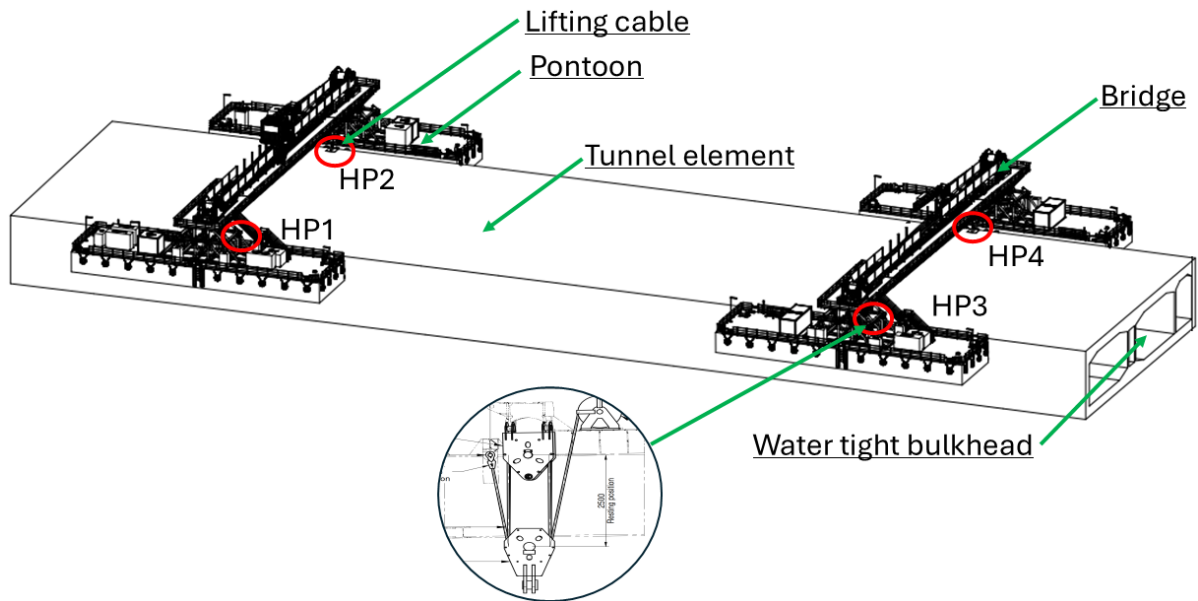
Conclusion The governing environmental design conditions for the Oosterweel tunnel are summarised in Table 3.3

Table 3.3: Summary of environmental design conditions for the Oosterweel tunnel, including normal operating ranges and extreme values corresponding to a 100 year return period

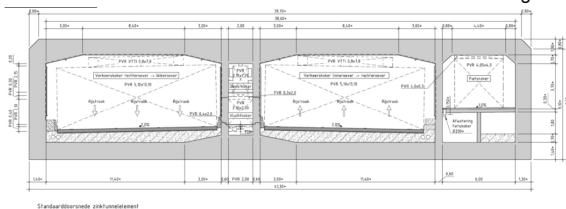
Parameter	Unit	Normal Range	Extreme Condition	Return Period
Water density	<i>PSU</i>	1.58 – 7.17	8.42 – 16.93	1/100 years
Water level	<i>m</i>	0 – 5.5	+7.6	1/100 years
current velocity	<i>m/s</i>	0.6 – 0.8	1.71	1/100 years
current direction	<i>degree</i>	90 – 270 (high or low tide)		1/100 years

3.2. Immersion system

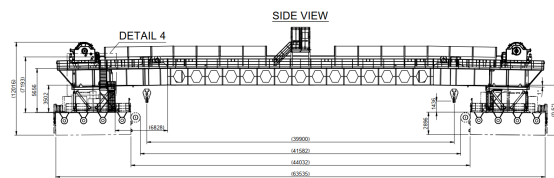
Each tunnel element was lowered to the riverbed using the same immersion system. The process begins with positioning the element between the two immersion pontoons. The coupled system is then towed to the construction site and moored in place. Once moored, the ballast tanks inside the element are filled with water, increasing the system's weight until it exceeds its buoyancy force. After, the vertical cables connecting the element to the pontoons are paid out to lower the element to its final position on the riverbed. This immersion system can be separated into four components: the tunnel elements, the immersion pontoons, the immersion cables and the ballasting system. The layout of this system is shown in Figure 3.5, which shows the configuration with the two pontoons, the connections points and a detail drawing of the cable configuration in Figure 3.5a, the cross section of the element in Figure 3.5b and the cross section of the pontoons in Figure 3.5c. In the following subsections, these individual parts will be described. During the immersion process, the movement of the pontoons is restricted horizontally, by mooring lines connected to the shore or to anchor piles on the riverbed. These horizontal mooring lines are outside the scope of this research as only the vertical cable loads are considered in the forecasting model.



(a) System overview, showing the lifting points (red), the tunnel element, the pontoons, the connecting bridges and the watertight bulkhead. The detail drawing shows the cable configuration



(b) Technical drawing of the cross section of the tunnel element.



(c) Technical drawing of the cross section of the immersion pontoon, where the width of the tunnel element is 41.25 m.

Figure 3.5: Immersion system with a) the system configuration, b) the cross section of the tunnel and c) the cross section of the immersed tunnel

3.2.1. Tunnel elements

The tunnel consists of eight elements, each with a length of 159.7 meters, a width of 41.3 meters and a height of 9.9 meters. The height however is not uniform across all elements: elements 1, 3, 5 and 7 have an additional ventilation unit on their roof increasing the total height. This difference in height increases the total submerged volume, and therefore requires more ballast water to overcome the buoyancy. The cross section of the tunnel consists of two car tubes and one bicycle lane (Figure 3.5b).

Furthermore, the tunnel elements are not geometrically straight. The curvature both horizontally and vertically is depending on the position of the elements across the tunnel trajectory (Figure 3.2b). Horizontally the tunnel follows a curve, this curve affects the horizontal cross-section that is exposed to the current. Although the effect of this is expected to be small in comparison with a straight cross section. The vertical profile is not straight either. Depending on the location of the element the left, right or middle part of the element is lower. This translates to an uneven buoyancy distribution along the waterline. Therefore the individual cable lengths differ to maintain symmetric cable forces.

Before immersion, the element weight is managed such that it has a free floating draft of approximately 20 cm in freshwater, at a water density of 1000 kg/m^3 . This ensures that the element stays above the waterline, and it reduces the cable loads compared to a under buoyant element. To trim this free floating draft, and to ensure zero trim and heel, additional concrete ballast is placed inside each element at the temporary storage location in the Doeldok(Figure 3.2a). The resulting total weight of each element is approximately 63300 tonnes, which includes the element weight as well as temporary immersion equipment such as the access shaft, the watertight bulkheads and the temporary water ballast tanks.

The deck of the tunnel elements contains multiple cable connections points and bollards, for horizontal

mooring lines used during positioning. In addition, four lifting points are installed on the elements, which connect to the lowering winches on the immersion pontoons. These four lifting points, referred to as HP1, HP2, HP3 and HP4 are the main load bearing connections during the lowering phase. The cables which are connected to these point are the main focus of this research. The four lifting points are arranged in two pairs (Figure 3.5a): the port pair (HP1, HP2) and starboard pair (HP3, HP4) control the pitch, while the leading pair (HP1, HP3) and trailing pair (HP2, HP4) control the roll.

3.2.2. Immersion pontoons

Each tunnel element is lowered using a pair of immersion pontoons with a catamaran configuration (Figure 3.5b). The pontoons consists of two floaters connected by a steel bridge. These floaters are constructed from twelve 40-foot freight containers, resulting in a combined dimension of 36.9 m in length and a width of 9.6 m. The distance between the pontoons is 44 meters (Figure 3.5c). However some additional fenders are positioned on the inside of the pontoons leaving a clearance of 16 cm at both sides when the element is in place. The total mass of each pontoon including the winches, bridge structure, and operating units is 789 tons.

3.2.3. Cable configuration

The tunnel element is connected via four lifting points, (HP1 to HP4, shown in Figure 3.5a). The corresponding immersion winches are mounted inside the catamaran bridge structure. To reduce the cable diameter and winch size, each cable passes through a system of pulleys with a total of eight falls per lifting point, the detail drawing is shown in Figure 3.5a. The load at a lifting point is therefore shared across eight strands, so the tension in each strand is one eighth of the total load at that point. The load sensors described in Section 3.4 measure the resultant load per lifting point, not the individual strand tension. The lifting points are designed for a maximum load (ULS) of 411 tonnes per lifting point. The cables used on the lowering winches are 400m, 46mm Powerlift 6 6X36 WS + IWRC MBL 1491 KN, with a modulus of elasticity $E = 105000 \text{ N/mm}^2$, and a fill percentage of 0.46[–]. The modulus and fill factor are the properties that determine the cable stiffness, which governs the dynamic cable response, calculated in Section 4.4.3

Due to the number of delays and the minimum clearance between the element and the pontoon, the minimum amount of cable for zero freeboards is 54.8m. In The starting case the cables have a minimum length of 49.6m. This is due to the design of the system and the size of pulley system

The winches are manually operated. To limit dynamic excitation of the system during cable payout, the winches are equipped with a ramp-up and ramp-down system. This allows the winches to gradually increase speed over a period of 40 seconds instead of instantaneously speeding up. The maximum cable payout velocity is 2.5 m/min. This controlled payout is important because sudden accelerations of the element would result in dynamic cable loads, this phenomenon is analysed further in Chapter 6.

3.2.4. Ballast system

To temporarily increase the weight of the element, so that it overcomes its buoyancy, ballast tanks are placed inside both car tubes of the tunnel. A total of five tanks have been installed as shown in Figure 3.6. The tanks have different sizes and different filling rates. The rates of P1 and S1 are the largest with a volume of 1088 m³ the other three tanks, P2, M and S2 have a volume of 342 m³. The positioning of the tanks gives the operators the ability to control the trim and heel angle during the immersion. The total ballast weight that can be used is 4348 ton. The weight of the ballast water is equal to that of the water in the Schelde river at the moment it is being pumped in.

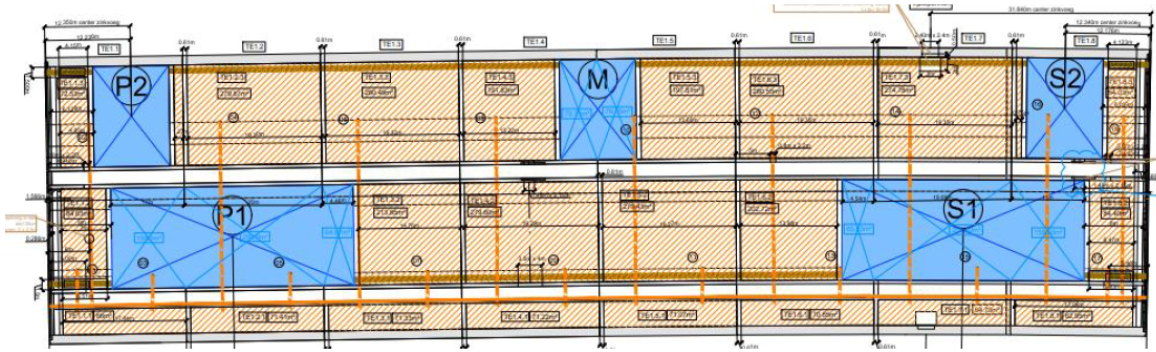


Figure 3.6: Plan view of the ballast tank layout inside the tunnel element, showing the five tanks (P1, P2, M, S1, S2) and their positions within the traffic tubes (van der A, 2025)

The tanks are filled via a piping system, with a governing fill time of 75 minutes for tank S2. The tanks can also be emptied to raise the element back to the surface in the event of an operational failure or when approaching the SLS load limit. Which tanks are filled first and at what rate, directly controls the descent rate and the trim of the element during immersion.

3.2.5. Operational windows

The immersion operation can only proceed when the environmental conditions and structural loads remain within predefined limits. These limits ensure that the cable loads at each lifting point stay within the design envelope throughout the lowering sequence. The governing operational limits are summarised in Table 3.4

Table 3.4: Operational limits for immersion operations, defining the allowable environmental conditions, tidal constraints, and cable load

Category	Parameter	Limit	Unit
Environmental	Wave height	≤ 0.22	m
	Wind speed	≤ 13.8	m/s
	Current velocity (ebb)	≤ 1.20	m/s
	Current velocity (flood)	≤ 1.47	m/s
	Water density	≤ 1021	kg/m ³
Tidal	Spring tide	not permitted	
	Preferred tidal phase	slack water / early ebb	
Structural	Maximum cable load (ULS)	≤ 411	t / HP
	Minimum cable load	≥ 50	t / HP

The environmental limits are set to minimise the dynamic loads acting on the immersion system. The wave height and wind speed limits constrain the wave induced excitation of the pontoons, thereby reducing dynamic cable loads. The current velocity limit constrains the hydrodynamic drag on the tunnel element. The maximum allowable current velocity differs between ebb (1.20 m/s) and flood (1.47 m/s). The reason is that the immersion operation starts with low tide, in this phase the immersion pontoon has to be connected to the horizontal mooring lines. This process is more complex due to the movement of the tugboats. Once the mooring lines are connected the operation continues into high tide. The water density limit of 1021 kg/m³ constrains the buoyancy force to ensure there is enough ballast capacity to overcome it. Immersion is not permitted during spring tide, when both current velocities and water level variations are at their highest. The structural limits define the allowable cable load range. The upper limit of 411 tonnes per lifting point corresponds to the ultimate limit state (ULS) capacity of the winch and cable system. The lower limit of 50 tonnes prevents cable slack, which would risk losing control of the system. Together these constraints define the operational windows within

which immersion can proceed safely. Maintaining these limits during an operation lasting several hours, while the environment is continuously changing with the tidal cycle, requires real-time monitoring of all relevant variables.

3.3. Immersion principles

The previous section described the components of the immersion system and the relevant environmental variables. This section will go into how these components interact with the environmental variables and affect the load on the vertical cables during the immersion operation. The cable load is defined as the difference between the weight of the element (including ballast) and its buoyancy.

3.3.1. Initial state

The start of the operation is considered to be the moment in time the element is positioned above the tunnel trench and is connected to the horizontal cables. In this stage the cables are preloaded with 50 tonnes of pre tension. This is achieved by slightly lifting the element out of the water (3 cm), and simultaneously drawing the pontoons down by 13 cm (Equation (2.40)). The difference in draft change is due to the difference in the waterplane area between the element and the pontoon. During this stage the element is still over buoyant.

3.3.2. Ballasting

Water ballast is then added to the tanks inside the element to overcome its buoyancy. Because the element is still above the waterline the relationship between added ballast and cable load is not one to one. Adding ballast increases the draft of both the pontoons and the element since they are connected by the immersion cables. Therefore the additional ballast is absorbed by the total hydrostatic stiffness of the system. For example for every 100 tons of added ballast water, the cable load increases by 18 tons. In this stage, the cable load is very sensitive to cable payout. Paying out cable lowers the element through the waterline, which increases its submerged volume and therefore its buoyancy, this reduces the overweight and with it the cable load. For reference paying out 50 cm of cable at every lifting point reduces the individual load with 50 tons.

3.3.3. Lowering

Once the element is fully below the waterline, the lowering phase starts. In this stage cable is paid out to lower the element to its final position. During the lowering stage, ballast has to be added depending on the water density gradient. If the water density of the river is increasing, buoyancy increases and therefore reducing the overweight. To maintain the minimum cable load of 50 tonnes ballast has to be added. In this stage the element has its maximum submerged volume. So adding 100 tonnes ballast translates into 100 tonnes of cable load.

3.4. Monitoring system

The immersion system is equipped with a monitoring system that records both environmental and operational variables, throughout each lowering sequence. The primary purpose of this system is to verify that the immersion operation remains within the defined operational limits (Table 3.4) and to provide real-time information for go/no-go decision process. For this research, the monitoring data serves an additional purpose: it provides the input and target variables for the data-driven forecasting model developed in Chapter 5 and Chapter 6. This section describes the measured variables and their resolutions and concludes with an overview of the available data.

3.4.1. Measured signals

The monitoring system captures two types of variables, environmental and operational. The environmental variables are measured by two instrumented buoys positioned upstream and downstream of the construction site. The upstream buoy is used as the reference for the undisturbed flow conditions, as it measures the current velocity, direction and water density before interaction with the tunnel element and pontoons. Each buoy measures the depth profile of water velocity, the flow direction, and the water density profile over the river depth. In addition to these real-time measurements, a prediction system provides forecasts of the environmental conditions, which are used to support the go/no go decision

prior to each immersion operation.

The following operations variables are measured:

- **Cable lengths:** Measured via a running line monitoring system on each winch, recording the paid out cable length at each of the four lifting points (HP1 - HP4)
- **Cable loads:** Measured with two methods: directly via load cells connected directly to the cables, and an indirectly based on the measured pontoon draft, from which the cable load is calculated using hydrostatic equilibrium.
- **Ballast tank levels** Measured via water level sensors in each of the five ballast tanks (P1, S1, P2, S2, M)
- **Hydrostatic pressure** Measured on the watertight bulkheads at both ends of the element

3.4.2. Sampling and resolution

The sampling rate of the environmental variables is once every 10 minutes, 0.00167 Hz. The prediction model used for the expected water density and current velocity produces a new prediction every 12 hours, these predictions have a sampling rate once every 30 seconds, 0.0333 Hz (Chu & Breugem, 2025). The operational variables on the otherhand all have the same sampling frequency of once every second, or 1 Hz.

The resolution of the environmental measurements is approximately 0.31 PSU for salinity and for the current velocity the measurement error is 0.11 m/s for the out going tide and 0.14 m/s for the upcoming tide (van der A, 2025). The error in the operational sensors is negligible compared to the magnitude of the forces.

3.5. Dataset overview

Table 3.5: Overview of available monitoring data per tunnel element, showing the completeness of environmental and operational variables for each immersion sequence. Bold entries indicate elements with complete datasets used in this research

ID	Environmental Variables			Operational Variables			Time Variables	
	Water Density	Current Velocity	Current Direction	Cable Lengths	Ballast Level	Cable Loads	Start of Operation	Duration
Element 1	✓	✓	✓	✓	✓	✓	4-6-2025	06:03
Element 2	✓	✓	✓	✓	✓	✓	21-7-2025	12:11
Element 3	✓	✓	✓	✗	✓	✓	4-8-2025	06:42
Element 4	✓	✓	✓	✗	✗	✗	20-8-2025	06:33
Element 4bis	✓	✓	✓	✓	✓	✓	16-9-2025	04:32
Element 5	✓	✓	✓	✓	✓	✓	31-10-2025	04:15
Element 6	✓	✓	✓	✗	✗	✗	14-11-2025	03:45
Element 7	✓	✓	✓	✓	✓	✓	14-12-2025	05:53
Element 8	✓	✓	✓	✓	✓	✓	29-11-2025	04:35

Table 3.5 summarises the available monitoring data per element. Element 3, 4 and 6 lack operational data: in these cases the data files were corrupted and no operational data could be retrieved. The TE4bis refers to the second immersion attempt of the fourth element. During the first attempt, too much sand had accumulated in the trench in the river bed. Therefore the element could not be placed at the correct location and had to be raised again. TE2 is an outlier in terms of duration (12 hours vs. 4 - 6 hours for other elements) due to an electrical failure in the starting phase. The extended duration means that the element loads follow a different pattern than the other elements. Despite this, TE2 is kept in the dataset since it provides a test for model robustness. The available input variables for the models of Chapter 5 and Chapter 6 are listed in Table 3.6.

Table 3.6: Overview of possible input and target variables for machine learning models

variable	Input/output	Sampling	Physical interpretation
Cable lengths (HP1 – HP4)	Input	1 Hz	element depth
Ballast tank levels (P1, P2, M, S1, S2)	Input	1 Hz	element weight
Water density	Input	0.0017 Hz	Buoyancy
Current velocity	Input	0.0017 Hz	Drag force
Cable loads (HP1 – HP4)	Target	1 Hz	Immersion loads

From this table additional inputs can be derived, for example the velocity and the acceleration of the element can be described by taking the first or second order derivate of the cable length. Selecting the best set of input variables for the different models is motivated in Chapter 5 and Chapter 6

4

Data analysis

This chapter presents the analysis of the monitoring data introduced in Chapter 3. The dataset contains six immersion sequences (TE1, TE2, TE4bis, TE5, TE7 and TE8). The data consists of multivariate time series of four lifting points, ballast tank levels, cable lengths and environmental measurements. This analysis serves two purposes: understanding the behaviour of the dataset and its correlations and secondly preparing the data for the data driven model.

The chapter is structured as follows: first the methodology of this analysis is described in Section 4.1, after which the data outliers and faulty measurements are filtered in Section 4.2. Then the data is visually analysed using a representative element sequence in Section 4.3. The signal properties are then analysed in Section 4.4. The following chapters will use this analysed dataset. In Chapter 5 and Chapter 6 the static and dynamic signal will be predicted and validated against the traditional methods.

4.1. Analysis method

The monitoring data contains raw measurements of cable loads, cable lengths, ballast levels, current velocities, current direction and water salinity across six tunnel immersions. Before any conclusions can be drawn from this data, several modifications have to be made. The time series are sampled out of phase and contain outliers from sensor malfunctions. An analysis method is therefore required to transform the raw data into a dataset that is suitable for both physical interpretation and machine learning. This analysis is separated into three parts.

The first part is data cleaning: identifying and removing outliers, assessing signal quality per variable and synchronizing the sampling intervals. This step is necessary for all subsequent analyses because spectral methods and smoothing filters assume continuous, consistently sampled data. Without this step, a leftover spike will have a dominant effect on the entire frequency spectrum, and irregular time steps may cause aliasing in any Fourier-based analysis.

The second stage is a visual inspection of the data. Here the aim is to identify the main characteristics of the data: is it oscillating? If so what are the main oscillations? What are the load outliers? Does the immersion sequence contain different phases? At the end of this subsection a reasoning will be given for the selected analysis methods in the following subsection so the stationarity of the data can be assessed.

The third stage is signal analysis. The first objective will be to quantify the stationarity of the data: to what extent is the behaviour explainable? How do the mean, variance and standard deviation evolve over time? Following this, a frequency analysis is conducted to characterize the signal's periodic components. To expand this analysis further also a Fourier analysis is performed to identify the dominant oscillation periods. After this analysis the data can be smoothed so it is ready to be used for the machine learning model.

4.2. Cleaning method

The dataset contains measurements from faulty sensors, or spikes that are not explainable by the physical behaviour. These outliers must be removed before any analysis can be performed. Secondly the timing of the data needs to be synchronized. The resulting product is a dataset with a continuous timeline for each immersion sequence.

To perform this data cleaning a peak over threshold (POT) method is applied. For each variable an upper threshold, τ_{upper} and lower threshold τ_{lower} are defined based on the physically plausible range of a variable, for example a cable cannot have a negative length. A data point x_i is classified as outlier if it exceeds either bound:

$$x_i \notin [\tau_{lower}, \tau_{upper}] \implies x_i = outlier \quad (4.1)$$

An alternative method for this would be block maxima. In this method the highest value within an interval will always be identified as the threshold. This works well for seasonal data where the outlier is always at the same point, however in this case it would result in only identifying the highest block outlier and missing out the others.

Once the outliers have been identified the missing data points are replaced through linear interpolation between the last valid point before the outlier and the first valid point following it. Marking the last valid index as a and the first valid index after as b , each point to be restored at index i ($a < i < b$) is computed as:

$$x_i = x_a + \frac{x_b - x_a}{t_b - t_a} \cdot (t_i - t_a) \quad (4.2)$$

One boundary case remains, if the first data point is flagged as an outlier, there is no preceding valid value to interpolate from. In this case, the first subsequent valid value is copied to fill the gap. The same logic applies at the end of the time series.

After the outliers are removed, each variable still has its own original timeline, with small offsets and irregular intervals. To merge these variables into a single dataset the time series are synchronised using the *resample* function from *Pandas* implement in Python. This function operates by first defining a new time index at the desired frequency, in this case 1 Hz. For all of the elements the reference time frame is the time series of the first lifting point. After this time series is resampled to 1 Hz, the other variables are interpolated on this grid with *resample*. This function groups all data points falling within each one-second bin and replaces them with the mean of those points. For time series with a higher frequency than 1 Hz, this acts as downsampling, for variables with lower frequencies, resampling would produce NaN values at timestamps where no data was available. These points are filled with linear interpolation.

It should be noted that, given the high sampling frequency of the data (1 Hz), replacing individual outlier points through interpolation represents a negligible loss in resolution. The interpolated parts are only a few seconds long, which is short compared to the timescales of the physical processes governing the cable loads and environmental conditions. This cleaning is separated into two subsections, the operational variables and the environmental variables. Each of the subsections concludes with a table reporting, for every tunnel element and for every variable, the percentage of data points that were identified as outliers and had to be removed.

4.2.1. Operational variables

The operational variables have been analysed following the peak over threshold method described above. First, the reasoning for the thresholds is discussed. Then, the results will be analysed, and their effect on the reliability of the data.

The lower threshold for the cable length is set at -10 m. Although a negative cable length is physically impossible, the cable length sensors can register negative values when the cable is retracted beyond the sensor's calibration zero point. Rather than discarding these readings, they are preserved because the entire cable length signal is later shifted upward to account for this offset. This is done because a negative length would have no physical meaning and would interfere with the calculations. If these initial values were removed, the subsequent correction would shorten the effective cable length. The outliers in this time series are extreme misreads like -999 m, which are well below the - 10 m threshold

and therefore reliably captured. The upper threshold is set at 400 m, this is the total amount of cable spooled on the winches (van der A, 2025).

The ballast level sensors are positioned slightly above the tank floor. When the water level drops below a sensor, it returns a negative reading. As with the cable length, these values are retained because the zero level of each tank is later added to the time series to ensure consistent ballast weight computation across all tanks. The upper threshold is set at 645 [cm], since this is the maximum water level inside the ballast tanks (van der A, 2025).

The lower threshold for the cable load is set at 8 tonnes. During immersion sequence 2, the cable loads at the front hoisting points (HP1 and HP2) decreased sharply during the last stage of the operation because the front of the element had already been placed on its foundation, while the rear was still hanging in the cables. This caused the front cable loads to drop below the minimum of 50 tonnes. The upper threshold was set at 477 tonnes, corresponding to the ULS load.

Table 4.1: Data cleaning results for operational variables, showing the fraction of data points identified as outliers for each variable and tunnel element.

Variable	TE1	TE2	TE4bis	TE5	TE7	TE8	Lower Threshold	Upper Threshold
Cable Lengths	0.08%	0.9%	0.07%	27.5%	0.09%	2.0%	-10 [m]	400 [m]
Ballast Levels	0%	0%	0%	0%	0%	0%	-1 [cm]	400 [cm]
Cable load	0.01%	0%	0%	0.02%	0%	0%	8 [ton]	477 [ton]

Table 4.1 shows that the ballast levels and the cable loads contain a low number of outliers, indicating that these sensors operated reliably throughout the immersion sequences. It has to be noted that for all variables there are multiple sensors, the system has a total of 5 ballast tanks and 4 cables. The percentage mentioned in the table corresponds to the sensor with the highest outlier fraction. From data observations it was noted that the timing of the misreads is identical. So, for example for the cable lengths, the error happens at the same time for all four sensors, suggesting some kind of power cut.

One error stands out, element 5, where 27.5% of the cable length data was flagged as outliers. These errors all occur at the beginning of the sequence, during the ballast filling phase in which the cable length remains constant. Therefore the marked values can be replaced by the last valid reading without any loss of resolution. The remaining immersion sequences show outlier rates below 2%, confirming that the cable length data is reliable for the phases in which cable payout is actively occurring.

4.2.2. Environmental variables

The environmental variables, water salinity, current velocity and current direction are recorded from the same measurement buoys, at a sampling interval of 10 minutes, resulting in a lower amount of data than the operational variables, which are sampled at 1 Hz. Thresholds for the POT were defined as follows: water density bounds were set to a minimum of 999.7 kg/m^3 , which is the minimum water density recorded in the last 10 years following (Doorme, 2019) and a maximum was set at 1021 kg/m^3 which is the upper limit for a no go decision, since the immersion sequences proceeded, this limit was never exceeded. The current direction has a minimum of -0.1, since one cannot have negative degrees and a maximum of 360 degrees, because after that it goes back to zero again. With these thresholds no outliers were flagged in any of the six immersion sequences, therefore no table was provided.

One consideration applies however for the current direction. Because the direction is expressed in degrees, standard linear interpolation cannot be applied. For example interpolation between 350 and 10 would give an intermediate value of 180, rather than the correct value of 0. To avoid this, the current direction is interpolated using circular interpolation, which represents each angle as a unit vector.

4.3. Data walk through

This section provides a visual walkthrough of the cleaned time series for a representative immersion sequence. The sequences can be categorized into two groups based on the water density gradient. If the water density increases over time, the cable loads tend to decrease. The example sequence has a decreasing water density behavior, which relates to an increasing load pattern. The purpose of this

walkthrough is to become familiar with the data and motivate why a frequency analysis is necessary in the following section. The data shown is unfiltered, but with removed outliers, the smoothed average of the cable loads is added to mark the global trend. The data time series is shown in Figure 4.1, with a) cable loads, b) cable lengths, c) ballast weight, d) current velocity, and e) water density.

4.3.1. Cable loads

The cable load time series (Figure 4.1a) shows two characteristics. First, the variance of individual cable loads increase substantially as the operation progresses. During the start of the operation the average cable load rises approximately linearly, correlating with the filling of the ballast tanks, this part of the signal has a relatively low variance. Secondly, when the cables begin to pay out the character of the signal changes: the mean force continues to increase but more gently than before. However, dynamic oscillations start to dominate the data. These oscillations are correlated with the payout of cable. This difference in behaviour suggests that the governing physical mechanism shifts from a static system where the loads are mostly caused by the ballast weight to a system where the loads are mostly a consequence of hydrodynamic and operational effects.

Another observation from the time series is that the rear lifting points (HP3 and HP4) carry a consistently higher load in the later part of the immersion. This asymmetry correlates with the operational procedure, in which the element is lowered under a slight horizontal angle in the later stage of the immersion. This is done because the final position of the element is also at a slight angle. This angle puts more load on the rear cables.

Furthermore, from the data it can be seen that the amplitude of the oscillations is the largest at the beginning of the lowering phase and gradually decreases over time.

4.3.2. Cable lengths

The cable lengths, shown in Figure 4.1b, remain constant during the first part of the sequence, in this part the element sinks due to the increasing weight of the system. One exception to this is at $T = 23:50$, when the cables pay out, which decreases the load in the system because the buoyancy of the element increases. Once the element has overcome its buoyancy the cable payout starts. The cable lengths do not increase continuously but rather in a stepwise manner. This start-stop pattern is intentional: by interrupting the payout, the dynamic oscillations are given time to damp out. Additionally, the rear cables (HP3 and HP4) are longer than the front cables, producing the inclined element orientation.

4.3.3. Ballast weight

The ballast weight, shown in Figure 4.1c, is distributed over multiple tanks, of which the primary tanks (S1 and P1) receive the largest share of ballast. These tanks have the greatest volume and are positioned close to the centre of gravity of the element Figure 3.6. Filling these tanks evenly is necessary to keep an equal force distribution over the lifting points. The profile of the total ballast weight is characterised by a rapid increase during the starting phase followed by a stable stage. This reflects the fact that first the element has to overcome its buoyancy and afterwards it can be lowered to its final position. Once sufficient negative buoyancy is established, further lowering is achieved by paying out cables rather than by adding more ballast.

4.3.4. Current velocity

Figure 4.1d shows the current velocity. The current velocity measured during the TE1 sequence varies between 0 and 0.29 m/s . High tide occurs during the ballast filling stage of the operation, in which the current velocity drops to zero before increasing again. Although the current velocity primarily affects the horizontal mooring cables (which are outside the scope of this study), it influences the vertical force distribution through the drag force acting on the submerged element. The low current velocities measured in this sequence suggest that the associated loads are less significant compared to the buoyancy and inertia effects described above.

4.3.5. Water density

The water density, shown in Figure 4.1e, is showing a gradual decrease during the second stage of the operation, correlating with the increasing average cable load in this stage. This correlation comes

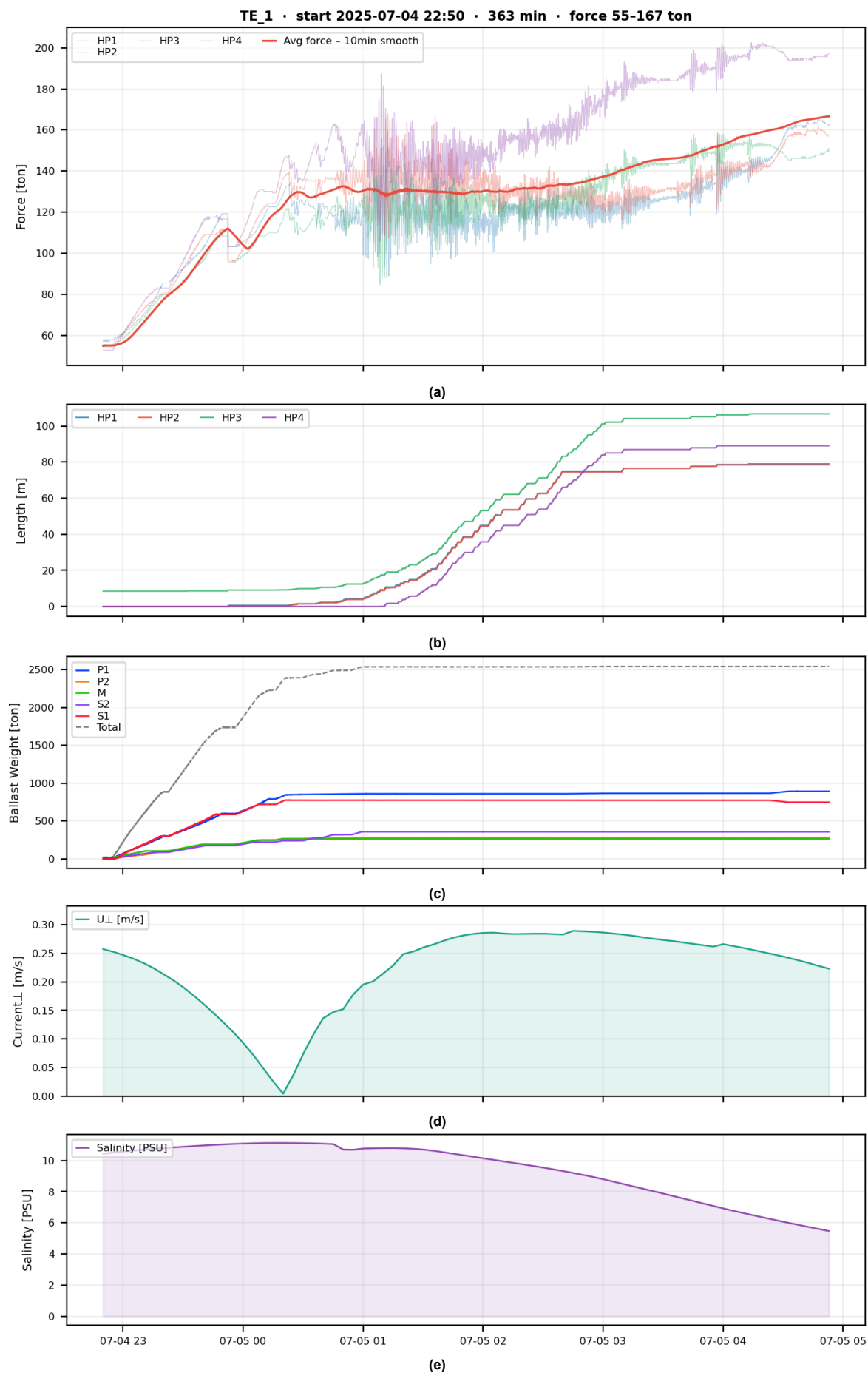


Figure 4.1: Overview of the cleaned monitoring data, for immersion sequence TE1, showing a) cable loads for four lifting points with smoothed average, b) individual cable lengths, c) ballast weight per tank and total tank weight, d) current velocity and e) water density. The figures have a shared yaxis presenting the time

from the fact that a decrease in water density reduces the buoyancy of the submerged element and therefore increases the cable load. Another observation is that the density starts to decrease slightly after the current shifts direction, which is consistent with the findings of (Doorme, 2019).

4.3.6. Summary

The data walk through shows that the cable load response is non stationary and that the dominant driving variables shift over the course of the operation. In the starting phase, the cable load increases as a result of adding ballast weight. Here the variance is low and the behaviour is predictable following from the static equilibrium. In the lowering stage, the mean cable load increases mostly due to the decreasing water density, while the oscillations are triggered by the cable payout.

Another finding is that these oscillations are not directly shown in any of the input variables. Although they are initiated by the cable payout, their amplitude and frequency differ from this variable, indicating the properties of the system shapes this oscillatory behaviour. This brings implications for the modelling: the trend may be captured by a static equilibrium model, whereas the oscillatory components require an understanding of the system's dynamic properties.

These findings motivate the follow-up analysis, both in the time domain to show the behaviour of the mean and the variance over time and secondly in the frequency domain, showing how the frequencies change over time.

4.4. Data characterisation

Before using the dataset for model training, the statistical and spectral properties of the signals must be understood. This is necessary for two reasons: first machine learning models like neural networks (Section 2.4.3), which rely on gradient based optimisation, assume that the input features have stable statistical properties, meaning that the model has difficulties to generalise with unstable data. Secondly, sensor data from an industrial environment contains measurement noise, which reduces the predictive accuracy and increases the risk of overfitting.

To characterise the data, two analyses have been performed. In the time domain the behaviour of the average and variance of the dataset is analysed, with the help of a sliding window. This approach is a test for stationarity: if the windowed mean and variance remain constant over the duration of an immersion, the data can be seen as stationary, within that element. If not, the non stationarity must be accounted for, for example by applying principal component analysis (PCA) to search for a stationary dimension in the data or by choosing a more complex machine learning network like an LSTM network (section 2.4.3), which can deal with this type of data. In the second analysis the data is analysed in the frequency domain to identify dominant frequencies in the signal and also to identify a potential cut off frequency. This cut off frequency can then be used to filter the data by separating the noise from the dynamic oscillations.

At the end of this section the data will be smoothed, with the aim of keeping the physical characteristics but removing the noise. In the end a conclusion will be given whether the data is stationary or not.

4.4.1. Time domain

To assess whether the cable load data are stationary, two time domain analyses are performed: a rolling window analysis of the mean and variance and an autocorrelation analysis (ACF). The rolling mean and variance are computed on the average cable load, whereas the autocorrelation plot is computed for the individual cable loads. The interval duration between equal mean, variance and the lag duration of the ACF can be used for the selection of a window size in Chapter 6

For the rolling mean and variance a centred rolling window of width equal to 5% of the total signal duration is applied to the average cable load of each sequence. The resulting mean and variance are plotted against the normalised time (0 - 100%) of the immersion duration, so that sequences of different lengths can be compared to one single axis. The results are shown in Figure 4.2.

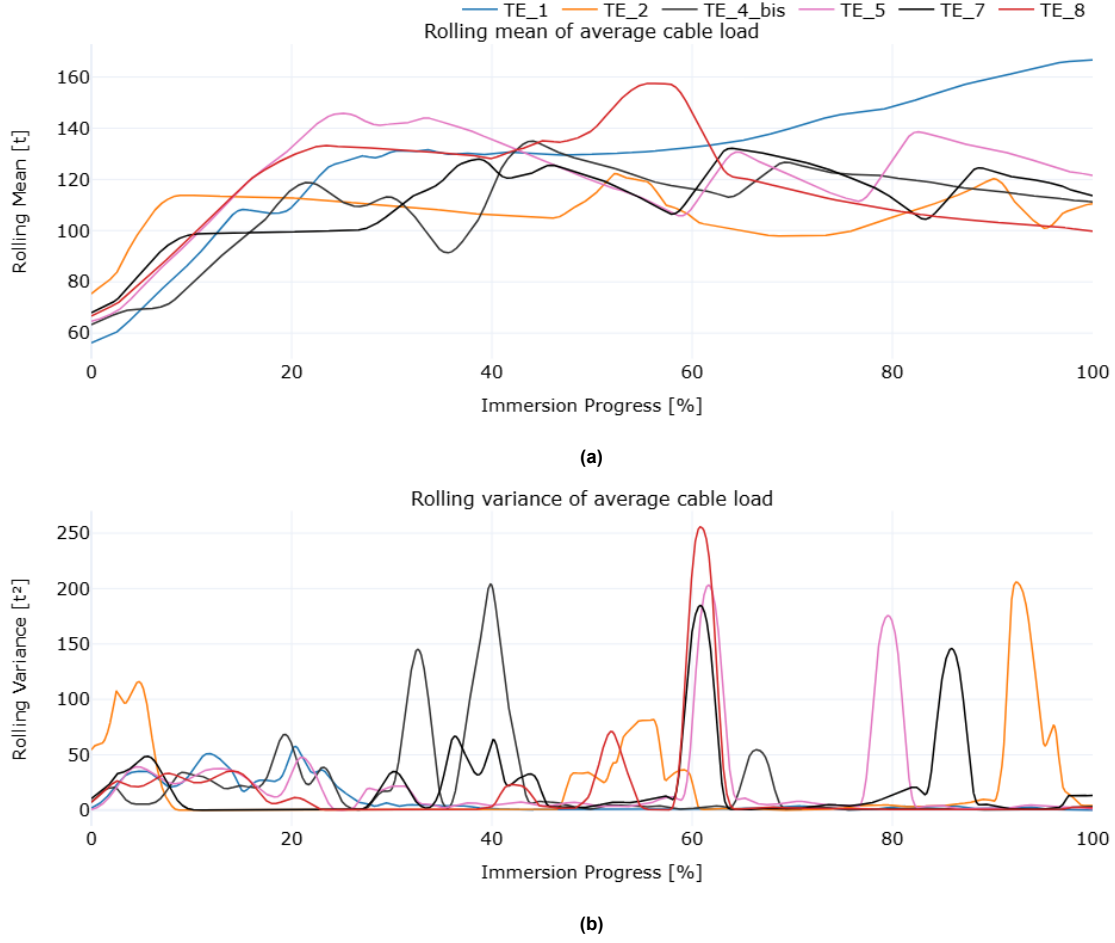


Figure 4.2: a) Rolling mean and b) variance of the average cable load for all immersion sequences, computed with a centred window of 5% of the signal duration and plotted against normalised time with a shared y axis.

The rolling mean (Figure 4.2a) supports the two regime structure identified in the previous section. During the first 20 to 30% of the timeline the mean increases steadily across all sequences, this is mostly a consequence of the increasing ballast weight. Afterwards, the individual means diverge: sequences with a decreasing water density (TE1 and TE2) show an increasing mean load, whereas sequences with an increasing water density (TE4bis, TE5, TE7 and TE8) show a decreasing mean load. There is no shared trend across all elements, which confirms that the mean is non stationary and element dependent. The rolling variance (Figure 4.2b), supports this. The variance is low during the first 20 to 30% of the timeline where the ballast is being filled. The highest variance tends to occur during 30 to 60% of the timeline. This phase corresponds to the part where the element is moving through the waterline, where the added mass is the highest. In several sequences, additional variance spikes appear at later stages. These spikes occur in the sequences with an increasing water density trend: as the buoyancy increases, the cable loads decrease towards the operational minimum of 50 tonnes, which requires additional ballast causing these variance spikes.

The autocorrelation function (ACF) was used to investigate if there are periodic components in the data. The ACF quantifies the linear correlation between the signal and a lagged copy of itself. For a discrete time series x_t of length N with mean μ , the autocorrelation at lag τ is defined as:

$$R(\tau) = \frac{\sum_{t=1}^{N-\tau} (x_t - \bar{x})(x_{t+\tau} - \bar{x})}{\sum_{t=1}^N (x_t - \bar{x})^2} \quad (4.3)$$

The numerator computes the covariance between the original data and the lagged copy. The denominator normalises this by the total variance. So that $-1 \leq R(\tau) \leq 1$. A value of R close to zero indicates no

correlation. A positive value indicates a positive correlation. The results of this analysis are shown for the first and fourth element. From these sequence, only the third cable correlations are represented. These sequences were selected to show the differences in correlation between an increasing and decreasing water density. The blue shaded area shows the confidence interval of this correlation.

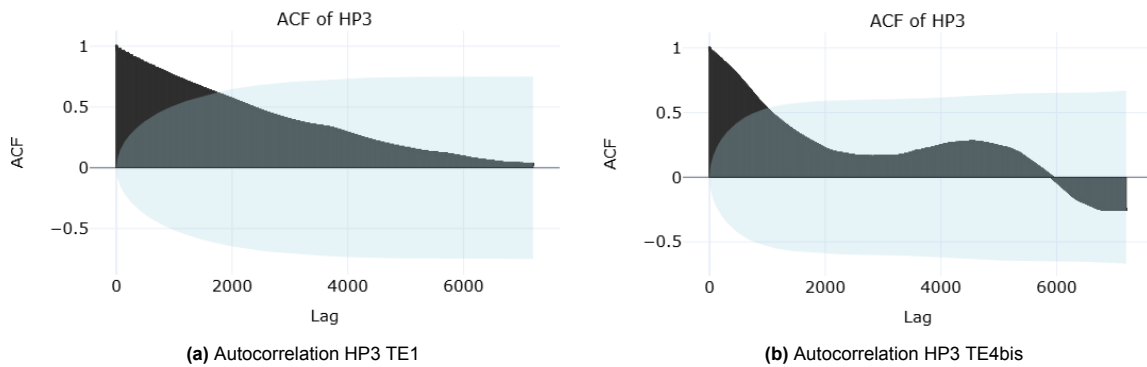


Figure 4.3: Autocorrelation function of the third cable (HP3) load, where shaded areas indicate the 95% confidence intervals. a) Results for TE1. b) Results for TE4bis.

For TE1 (Figure 4.3a) the autocorrelation decreases with increasing lag for the cable. This decay indicates that the signal has no dominant repeating pattern. However for TE4bis (Figure 4.3b), the observation is that the correlation of the cable appear to increase again after 4000 seconds (roughly 66 minutes). This period corresponds to the interval between successive ballast additions observed during that sequence. These ballast additions were a result of the increasing water density. The behaviour in correlation is shared between element one, two and eight, as well as element four, five and seven. The both groups share the same water density gradient regime, the first negative and the second positive

4.4.2. Frequency domain

In the frequency domain also two analyses have been performed. The main oscillating periods and potential cut off frequency for the data smoothing are derived with the help of power spectral density (PSD) analyses. Subsequently, the frequency content is analysed over time to identify in which phase the oscillations appear, since the time domain analysis showed that the oscillations are not constant over the duration of the operation.

The power spectral density is estimated using Welch's method (Welch, 1967). This method improves upon the standard periodogram by reducing the variance of the spectral estimate. The method works as follows: first, the time series is divided into overlapping segments, the length of each part is 1024 samples. This length is long enough to capture the longer oscillations periods, but can still focus on the natural frequencies. The overlap between the segments is 50%, which is standard setting. The overlap is included to maintain the data accuracy at the edges. Subsequently, each segment is multiplied by a windowing function, which tapers the signal toward zero at the edges. This is necessary because a finite length segment implicitly assumes that the signal is zero outside the observation window. Without this tapering function, the abrupt transition from zero to the first sample introduces self made high frequency content, this is also known as spectral leakage. Once finished, a discrete Fourier transform is applied to each segment to transform it from the time domain to the frequency domain. The resulting power spectrum quantifies the energy content per frequency. Finally the spectra of all segments are averaged, which reduces the total noise. The PSD is computed for the average cable loads. The results are shown in Figure 4.4

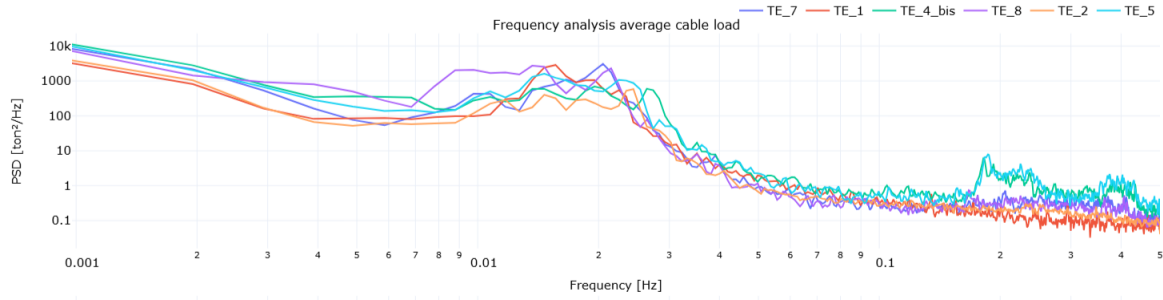


Figure 4.4: Power spectral density of the average cable load for all immersion sequences, estimated using Welch's method with a segment length of 1024 samples, with shared axis: frequency (hz)

The spectra of the six immersion sequences share a common shape: the spectral energy is concentrated in the range below 0.005 Hz (periods longer than 200 seconds). These frequencies correspond to slow trends, for example the trends driven by ballast filling or water density changes. A secondary energy concentration is visible between 0.01 and 0.03 Hz (periods of 33 to 100 seconds). These periods correspond to the dynamic oscillations observed during the cable payout phase. Above 0.03 Hz the energy decreases, and the signal is dominated by noise.

Although the spectral shape is consistent across all elements, a few differences can be seen. First the intensity of the 0.01 - 0.03 Hz peak varies between sequences. TE1 exhibits the highest energy in this band, which is consistent with the operational notes reporting a strong dynamic response during that immersion, this was also the first operation, where ramp up and ramp down was disabled. Second the noise distribution is not equal. TE4bis and TE5 contain more energy in this frequency region. This energy has to do with the sloshing of the water inside the ballast tank.

A spectrogram analysis shows the distribution of the spectral energy over the duration of the immersion. The spectrogram applies the same Welch PSD estimation to each successive time window, producing a time frequency map of the spectral energy. The results are shown in Figure 4.5, the red line in the figure marks the moment in time that the element moves through the waterline.

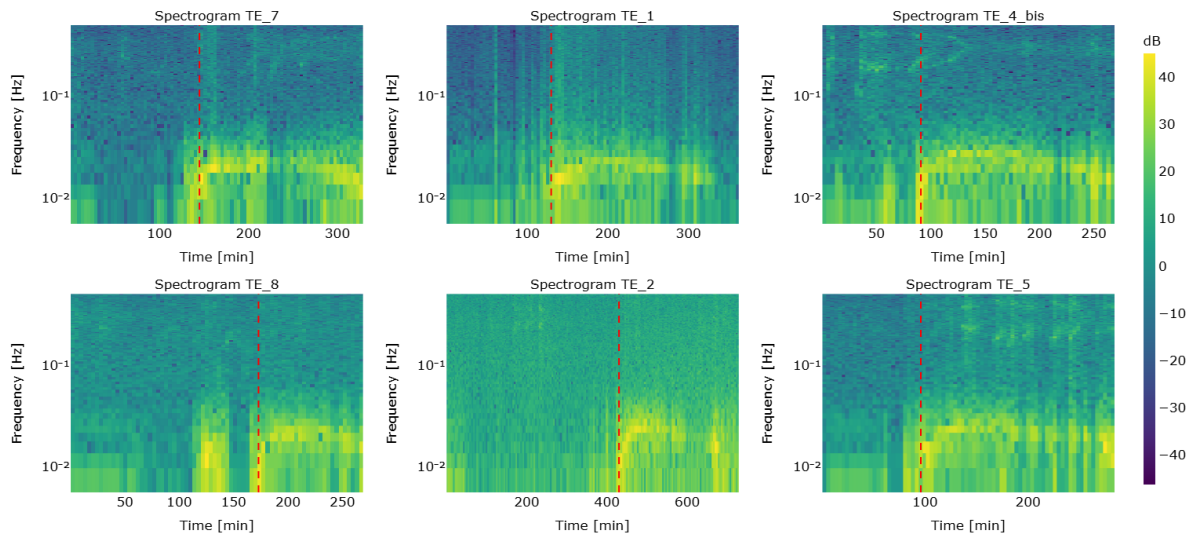


Figure 4.5: Spectrogram of the average cable load for all immersion sequences. The red line marks the moment the element crosses the waterline. The frequency is presented on the y axis with a log scale, the x axis presents the timeline

The spectrograms confirm that the dynamic energy in the 0.01 to 0.03 Hz band is not uniformly distributed over the duration of the operation. The low frequency content (below 0.01 Hz) is present throughout the entire sequence, reflecting the slowly varying mean load. The energy in the 0.01 - 0.03

Hz band however, appears predominantly after the start of the cable payout, which supporting the regime transition identified in the time domain analysis.

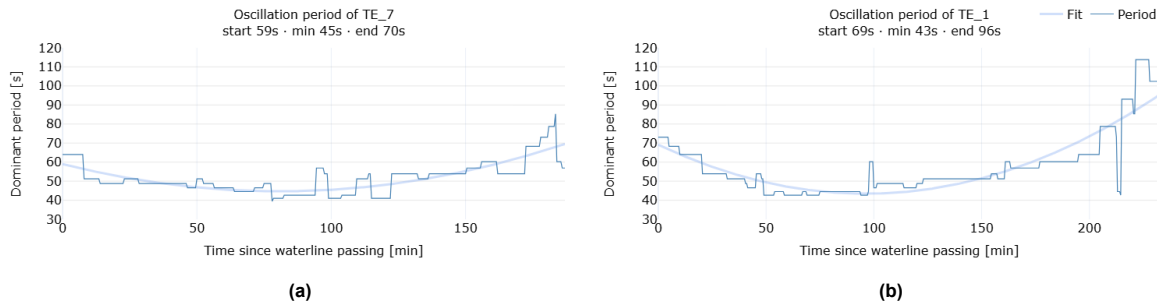


Figure 4.6: Dominant oscillation period of the average cable load during immersion operations for sequences a) TE7, b) TE1

The after regime is further evaluated to examine how the dominant oscillation period evolves over time. The results of this analysis are shown in Figure 4.6. For this analysis, a Fourier transform was applied to the average cable load, the function used the same segment length as described previously: 1024 samples. From The resulting power spectrum, the dominant frequency and corresponding oscillation period were extracted. To show the general trend in the data a second order polynomial was fitted. From Figure 4.6, it appears that another variable is changing over time once the element is submerged, which affects the oscillation period. This effect is further investigated in Chapter 6.

From this analysis it can be concluded that a cut off frequency of 0.07 Hz would be sufficient for filtering out the noise. A cut off frequency of 0.03 Hz would impose the risk of filtering out the structural response of the system, therefore 0.07 Hz is chosen. In the following section this filter is applied to remove the noise in the signal and to decompose the signal into a static (low frequency) and dynamic (high frequency component)

4.4.3. Cut off validation

Following from the frequency analysis a cut off frequency of 0.07 Hz has been chosen. With this cut off frequency, a number of structural behaviours are filtered out. The aim of this subsection is to identify which behaviours are filtered out, and to argue why their removal does not affect the scope of this research. For example, the sloshing of water inside the ballast tanks is expected to occur well above 0.07 Hz, but the resulting forces are small compared to the cable loads and cannot push the cable loads beyond their ULS limit, so filtering this phenomenon out is acceptable

Four phenomena are investigated. The general natural frequencies of the system (heave, pitch and roll) are derived first, because they describe the response of the coupled system to any vertical or rotational excitation and are therefore most likely to appear in the measured cable loads. Second, vortex induced vibrations on both the cables and the submerged element are analysed. Third, the sloshing frequency of the water inside the ballast tanks is analysed. Lastly the excitation frequency caused by cable payout is considered.

For each element, the frequencies were calculated for four situations: the element partially submerged with 0.1 m of remaining freeboard, the element at 1/3 of its final depth, the element at 2/3 of the final depth, and the element at its final depth. In the last case it is assumed the element is still not touching the bottom. For the calculation the system is simplified to a linear, undamped, single degree of freedom mass spring system, with each natural frequency (heave, pitch and roll) calculated independently. The added mass is also assumed to be constant over time, rather than varying with the depth of the element. This way the frequencies are overestimated to be sure that they are captured with the cut off frequency. The hydrostatic stiffness of the element is only included for the freeboard 0.1 m case, in the other three cases the element is fully submerged and this stiffness drops out.

The equations and data used in this section are introduced in Chapter 2 and Chapter 3. This subsection presents the calculation for element 5 at 2/3 depth. The full analysis and results are shown in Section A.3. At the end of this subsection an overview table is provided with the expected frequency

ranges

Natural frequency

The heave frequency of the system for the four cases is calculated as follows. First, the cable spring stiffness is calculated using Equation (2.25). For the case of 2/3 depth it comes to:

$$K_{cable} = \frac{n_{pullies} \cdot E \cdot A}{L} = \frac{8[-] \cdot 105000[N/mm^2] \cdot \frac{0.46[-] \cdot \pi \cdot 46[mm]^2}{4}}{146.55[m]} = 4381.81[kN/m] \quad (4.4)$$

Here A is the cross section of the cable, computed using the fill factor of 0.46[-] and the cable diameter of 46 [mm]

The second spring in the system is the hydrostatic stiffness of the floaters. According to Equation (2.23), this stiffness is equal to:

$$K_{floater} = \rho_w \cdot g \cdot A_w = 1001[kg/m^3] \cdot 9.81[m/s^2] \cdot 36.9[m] \cdot 9.6[m] = 3478[kN/m] \quad (4.5)$$

The two floaters are connected with a bridge in between, this bridge bends when the element is being lowered, this can also be approximated as a spring which is in serie with the cables and the floaters. The spring stiffness of the bridge is approximated as follows:

$$K_b = \frac{F_b}{u} = \frac{278[ton] \cdot 9.81[m/s^2]}{0.23[m]} = 11857.3[kN/m] \quad (4.6)$$

The 23 [cm] bending at the 278 t load follows from (Vuyk, 2025) The resulting stiffness of the system following Equation (2.27) is then equal to:

$$K_{tot} = \frac{1}{\frac{1}{n_{hp} \cdot K_{cable}} + \frac{1}{n_{fl} \cdot K_{fl}} + \frac{1}{n_b \cdot K_b}} = \frac{1}{\frac{1}{4 \cdot 4381.81[kN/m]} + \frac{1}{4 \cdot 3478[kN/m]} + \frac{1}{2 \cdot 11857}} = 5845[kN/m] \quad (4.7)$$

The total mass for this case is equal to:

$$M_{tot} = n_{pon} \cdot M_{pon} + M_{el} + M_{ballast} + C_a \cdot V_{sub} = 2 \cdot 782[ton] + 63209.8[ton] + 2365[ton] + 2[-] \cdot 9.8[m] \cdot 159.9[m] \cdot 40[m] = 193779[ton] \quad (4.8)$$

The weight of the cables is included in the pontoon weight. The added mass coefficient for tunnel element is take from (Eysink et al., 1995) and the additional added mass on the cable is neglected. This leads to a natural frequency of:

$$f_n = \frac{1}{2\pi} \sqrt{\frac{k}{m}} = \frac{1}{2\pi} \sqrt{\frac{5845[kN/m]}{193779[ton]}} = 0.029[Hz] \quad (4.9)$$

For the pitch calculation, the cable stiffness expression is unchanged. However, the hydrostatic stiffness changes by a factor of two. When the element rotates, only 2 floaters contributes to the equilibrium of the system. This contribution can be expressed as the rotational water plane stiffness.

Additionally, the total stiffness of the system changes: the springs no longer act in translation but in rotation, so each contribution is multiplied by the square of it's lever arm. For the pitch movement the rotational arm is equal to 50 meters for all lifting points

$$K_{tot} = \frac{1}{\frac{1}{n_{hp} \cdot K_{cable}} + \frac{1}{n_{fl} \cdot K_{fl}}} \cdot d^2 = \frac{1}{\frac{1}{4 \cdot 4381.81[kN/m]} + \frac{1}{4 \cdot 3478[kN/m]}} \cdot 50^2[m] = 1.94 \cdot 10^7[kNm/rad] \quad (4.10)$$

For the rotational motion the mass is replaced by the mass moment of inertia about the rotation axis, including the contribution of added inertia. Following (Vugts, 1968) the added inertia coefficient in pitch is equal to 0.045 [-]. The lyy of the tunnel element follows from (van der A, 2025). This results in a total moment of inertia of:

$$I_{yy,tot} = I_{yy,el} + I_{yy,add} = 1.16 \cdot 10^8[tonm^2] + 4.55 \cdot 10^7[tonm^2] = 1.61 \cdot 10^8[tonm^2] \quad (4.11)$$

Following Equation (4.9) the natural frequency is then equal to 0.055 [Hz].

For the roll motion, the calculation is the same compared to that of the pitch. However the lever arm D is shorter since the element is smaller in this direction. The lever arm is equal to 20 meter. According to (Vugts, 1968) the corresponding added inertia coefficient is equal to 0.025. With a resulting eigen frequency of 0.066 [Hz]

From this analysis it becomes apparent that the general behaviour of the system is covered by the current cut off frequency of 0.07 Hz. The frequency analysis however shows that the dominate frequencies of the system are in the range of 0.01 and 0.03. The differences is most likely due to an overestimation of the cable stiffness and a under estimations of the added inertia and mass.

Vortex induced vibrations

The second phenomenon investigated is vortex induced vibrations. For this case two scenarios are considered: the VIV acting on the cables, compared with the natural frequency of the cables to check for lock in, and the VIV acting on the tunnel element, compared with the heave frequency of the system.

For the VIV on the cables, the natural frequency of the cable is first calculated using:

$$f_n = \frac{n}{2L} \sqrt{\frac{F}{M}} \quad (4.12)$$

Here n is the mode number, L the cable length, F the force in the cable and M the mass per meter cable. Because the free cable length between two adjacent pulleys is in the range of 10 to 27 m, the cables are relatively flexible. This makes oscillations in higher modes are also realistic. For element 5 the first mode is considered. The other mode frequencies can be found in the Section A.3.2

For element 5, the first mode of the cable frequency is equal to

$$f_n = \frac{n}{2L} \sqrt{\frac{F}{M}} = \frac{1}{2 \cdot 18.32[m]} \sqrt{\frac{17.13 \cdot 1000 \cdot 9.81[kN]}{9.37[kg/m]}} = 3,65[Hz] \quad (4.13)$$

The weight per meter of cable is the structural weight of 7.71 [kg/m] (van der A, 2025) plus an added mass contribution equivalent to the displaced water around the cable, giving a 9.37 [kg/m] total.

The expected VIV frequency of the cable is equal to:

$$f_s = \frac{St \cdot U}{D} = \frac{0.2 \cdot 0.4[m/s]}{46[mm]} = 1,74[hz] \quad (4.14)$$

The strouhal number is equal to 0.2 [-] follows from (Veritas, 2011)

Because the cable eigen frequency in the first mode is higher than the cable shedding frequency, lock in on the cable is not expected and this phenomenon being filtered out is therefore not an issue. Furthermore, this effect cannot even be measured with the 1 Hz sampling frequency of the monitoring system.

For the element itself the characteristic dimension is the element height 9.9 m. following Equation (2.35) the resulting f_s is

$$f_s = \frac{St \cdot U}{D} = \frac{0.13 \cdot 0.40[m/s]}{9.9[m]} = 0.005[hz] \quad (4.15)$$

This frequency is well below the natural heave frequency of the system (0.0037 - 0.046 Hz), so lock in on the element is also not expected.

Sloshing ballast tanks The third phenomenon considered is the sloshing of water in the ballast tanks. To estimate the sloshing frequency, the tanks are divided into two categories. The large tanks (P1 and S1) have a length of 34.5 meter and the small tanks (P2, S2, M) have a length of 11 m Figure 3.6. The tank is treated as a rectangular basin and the wave number of the lowest sloshing mode is computed as:

$$k = \frac{n\pi}{L_{tank}} \Rightarrow k_{small} = \frac{\pi}{11} = 0.286 \text{ [m}^{-1}\text{]}, \quad k_{large} = \frac{\pi}{34.5} = 0.091 \text{ [m}^{-1}\text{]} \quad (4.16)$$

The frequency of the lowest sloshing mode in a basin follows from the linear dispersion relation Equation (2.10). Because the water depth in tank does not exceed the threshold for intermediate depth Figure 2.2. The dispersion relation can be reduced to its shallow water form:

$$\omega = k\sqrt{gh} \quad (4.17)$$

where h is the water depth in the tank. The lowest frequency occurs at the minimum ballast level of 110 cm. This results in a sloshing frequency of $f_{slosh,small} = 0.14 \text{ [Hz]}$ and for the larger tank in $f_{slosh,small} = 0.047 \text{ [Hz]}$

Excitation by cable payout

The effective excitation frequency caused by stepwise payout of cable is approximated by computing the frequency of the interval between the start stop events. This range normally lies between 20 and 60 seconds Figure 4.1. Corresponding to frequencies $1/20 = 0.05 \text{ Hz}$ and $1/60 = 0.017 \text{ Hz}$. These frequencies fall within the band of filtered signal and close to the heave frequency of the system.

Summary

Table 4.2 shows the frequency ranges of the four phenomena across the six elements for the four states. The natural frequency of the system in heave, roll and pitch are maintained with the cut off frequency of 0.07 Hz. The movement of the element during its initial state (freeboard 0.1) and the cable VIV is filtered out, as well as the sloshing modes of the water.

Its expected that the cable stiffness is overestimated since zero friction is assumed, reducing this stiffness will result in lower natural frequencies and therefore the cut off frequency is sufficient.

Table 4.2: Summary of the physical phenomena investigated in the cut-off validation, with their estimated frequency ranges across the six elements and four submerge states, and the resulting filtering status by the 0.07 Hz filter used in the smoothing of the data component.

Phenomenon	Frequency range [Hz]	Treatment
Heave (freeboard ≈ 0.1 m)	0.127	Filtered out
Heave (submerged, 1/3–final)	0.027–0.03	Retained
Pitch (freeboard 0.1 m)	0.154	Filtered out
Pitch (submerged, 1/3–final)	0.042–0.048	Retained
Roll (freeboard 0.1 m)	0.104	Filtered out
Roll (submerged, 1/3–final)	0.048–0.054	Retained
Cable VIV (shedding, f_s)	0.44–3.3	Filtered out
Cable natural frequency	2.13–10.27	Filtered out
Element VIV (shedding)	0.001–0.009	Retained
Sloshing, large tanks (lowest mode)	0.4–0.57	Filtered out
Sloshing, small tanks (lowest mode)	1.49–1.95	Filtered out
Cable-payout excitation	0.017–0.05	Retained

4.4.4. Data smoothing

Based on the frequency analysis in the previous section, the cable load signal is processed into two components: a static component representing the slowly varying mean load and a dynamic component capturing the oscillatory behaviour. Each component is derived independently from the original signal using a different filtering approach, because the static signal must maintain the sharp load transitions caused by ballast additions, whereas the dynamic signal must preserve the oscillatory content while removing measurement noise. The filter is applied to all cable loads, for every immersion sequence, an example of this filter is shown in Figure 4.7

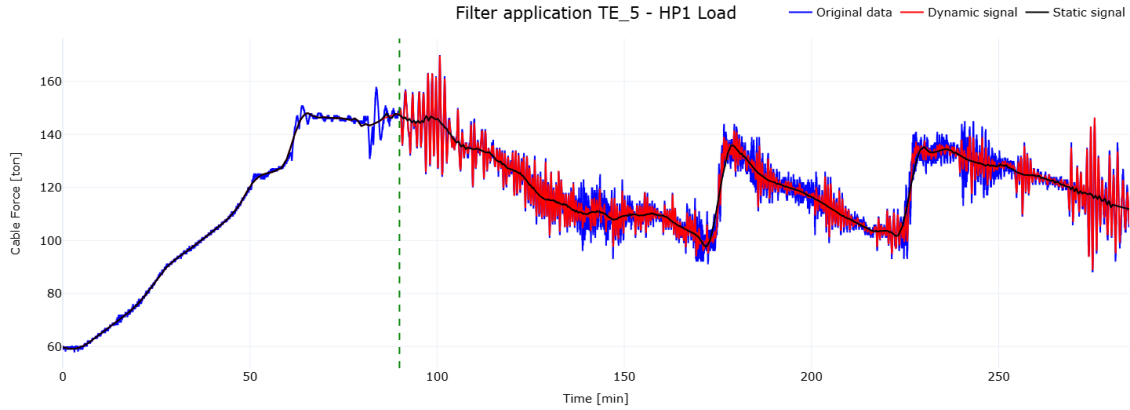


Figure 4.7: Data smoothing applied to HP1 of TE5. The original data (blue), static component (Savitzky-Golay filter) and dynamic component (Savitzky-Golay and Butterworth filter) are shown. The dashed line marks the transition through the waterline.

The static signal was derived with the help of a Savitzky-Golay filter from SciPy. This filter operates by fitting a low degree polynomial to the data points within a sliding window using least squares. The fitted polynomial value at the centre of the window replaces the original data point. Because the filter fits a polynomial rather than computing a weighted average it preserves the sharp features. The filter is defined by two parameters, the window length set to 551, and the polynomial order which is set to 2. The large window ensures that longer periods of oscillations are suppressed, so that only the static trend remains. A Butterworth filter was not used for the static component because it would smooth out the steep gradients which can be caused by additional ballast, resulting in a signal that deviates too much from the actual static behaviour.

For the dynamic signal, two filter configurations are applied depending on the phase of the operation. Before the element crosses the waterline, the same Savitzky-Golay filter is used in the same configuration as for the static. In this phase the cable loads are dominated by the static ballast filling process, and the measured signal contains high frequency measurement noise of the order ± 1 tonne. This does not reflect actual load variations and is pure noise. After the element passes through the waterline another filter is used with a cut-off frequency of 0.02 Hz. This frequency is based on the frequency analysis (figure 4.4), which showed that the dominant dynamic energy is concentrated below 0.07 Hz and that the content above this frequency is predominately noise. An order of 3 has been applied to provide a smooth transition between noise and dynamic oscillations.

4.4.5. Summary

The analyses presented in this section characterise the statistical and spectral properties of the cable load data. From these analyses three conclusions can be drawn.

First, the cable load time series is non stationary. Both the rolling mean and rolling variance change over the duration of each immersion sequence, and their trajectories differ between elements depending on the water density gradient. Secondly, the autocorrelation analysis shows that the cable load signal does not contain a shared periodic pattern across all elements. However, sequences with an increasing water density do show a minor long period correlation corresponding to the corrective ballasting cycle. The last finding is that the spectral content of the signal is not constant over time. The spectrogram analysis shows that the low frequency energy associated with the static behaviour is present throughout the entire operation, whereas the dynamic energy in the 0.01-0.03 Hz band appears predominantly after the element crosses the waterline. This confirms that there is a regime transition.

Based on these findings a modelling architecture can be motivated for the static and dynamic loads. The static load is determined by the equilibrium of the current state of the system and is not affected by its previous state. Therefore a machine learning architecture without memory is sufficient. A multivariate regression (MVR) and a multilayer perceptron (MLP) operates without a memory state and can

predict this equilibrium by summing the input variables. For the dynamic load the previous system state does matter. The response of the system is damped, the load in each state depends on the previous motion. Therefore a long short term memory network is used, since this model takes the previous state into account. Because of the oscillatory behaviour of the system also a Fourier neural operator has been trained. This type of network works with the pre assumption that the target can be described by fourier composition of the input variables.

4.5. Correlations

The previous section analysed the dataset in the time and frequency domain. This section focuses on the correlations between the operational and environmental variables and the cable loads. The operational variables considered are the average tank weight and the average cable length. Water density is included as the environmental variable. From the data walk through no major effect could be seen of the current velocity therefore, it is left out of this analysis. The target variable against which all correlations are computed is the average cable load.

The correlation between these variables and the target variable is quantified with the help of three correlation coefficients: Pearson, Spearman and the squared Pearson R^2 . The Pearson coefficient r measures the linear association between two variables. A value of $r = 1$ or $r = -1$ indicates a perfect positive or negative linear relationship. While $r = 0$ indicates no linear correlation. The Pearson coefficient is sensitive to outliers and assumes that the relationship must be linear. Therefore it can underestimate curved relationships. The Spearman correlation coefficient ρ addresses this limitation by analysing the rank of the data, measuring whether two variables consistently increase or decrease together, regardless of the functional form. A Spearman coefficient of 1 corresponds to a positive correlation and -1 to a negative one, but compared to Pearson, these correlations do not have to be linear. The R^2 value shows what part of the variance in the cable load is explained by the linear component of each input variable. An R^2 of 0.9 means that 90 % of the load variance can be attributed to the linear trend.

All these correlations are computed for each individual element and then averaged over all elements. Since from the time domain analysis in Section 4.4 it became apparent that the mean and variance change over time (Figure 4.2) the correlation coefficients are calculated both for the full duration and for pre and post waterline phases. The correlations are shown in Table 4.3

Table 4.3: Mean correlation statistics between input variables and average cable load, averaged across all six tunnel elements. For each variable the full sequence, pre-immersion and post-immersion phases are reported.

Variable	Phase	Pearson r	Spearman ρ	R^2
Average tank weight [Ton]	Full	0.692	0.499	0.541
	Pre	0.960	0.872	0.924
	Post	0.439	0.452	0.292
Average cable length [m]	Full	0.226	0.278	0.208
	Pre	0.438	0.704	0.225
	Post	-0.006	-0.015	0.265
Water density [kg/m ³]	Full	0.118	-0.044	0.201
	Pre	0.265	0.172	0.515
	Post	-0.405	-0.471	0.322

4.5.1. Tank weight

The average tank weight shows the strongest overall correlation with the cable load $r = 0.692$. However, the phase split analyses shows that this correlation is not constant over time. During the pre immersion stage the correlation is stronger than in the period after, ($0.960 > 0.439$). This is mostly due to the fact that the majority of the ballast is added before the submersion, after the tank levels remain mostly constant.

After the waterline is crossed the mean correlation drops to $r = 0.439$. From the individual results there

is a difference here as well the elements with a positive water density gradient (TE5, and TE7) have the lowest correlations, $r = 0.12$ and $r = 0.16$. In these cases the load decreases over time with a constant and sudden ballast additions, this correlation is not captured. These results are shown in Section A.2.

In addition to the average tank weight correlation, the Pearson correlation between each individual ballast tank and each lifting point is also calculated. The rear lifting points HP3 and HP4 consistently show stronger correlations $r = 0.69 - 0.76$ than the front lifting points. This is due to the fact that the element is lowered under an angle and that therefore these correlations are higher, because as a result the water inside the tanks is moving to one side.

Table 4.4: Pearson correlation between individual ballast tank weight and individual lifting point loads, averaged across all tunnel elements.

Variable	HP1	HP2	HP3	HP4
P1	0.57	0.57	0.76	0.69
P2	0.54	0.60	0.73	0.72
M	0.53	0.59	0.73	0.73
S1	0.53	0.56	0.74	0.69
S2	0.48	0.58	0.70	0.71

4.5.2. Cable length

The average cable length shows a weak overall linear correlation $r = 0.226$ but the spearman coefficient does show there is a correlation although non linear. This mostly occurs during the- pre immersion stage, where the spearman coefficient is at $p = 0.704$. Once the element is fully submerged it is difficult to determine correlations because the cable lengths mostly cause dynamic effects. These effects are not captured in the analysis of the mean cable load. But from the frequency analysis Figure 4.5 it was shown that these occur right after cable was being paid out. Another interesting observation is that during the pre immersion stage a negative correlation was expected, since payout cable increases the submerged depth of the element, which increases the hydrostatic pressure on the element and reduces the net upward force in the cables. However in this phase the weight of the element is also increased due to ballast filling. Which hides this effect in the correlation analysis

4.5.3. Water density

The correlation with water density changes the most between the two immersion phases. According to the physics the water density should have a negative correlation with cable loads, if the water density increases the cable loads decrease due to the increasing buoyancy of the element. From the phase split, it becomes apparent that this effect is overruled by the ballast intake in the starting stage, since it has a positive correlation $r = 0.118$. However from the post analysis it becomes clear that this correlation is negative in the end. In the post stage, the ballast levels stay mostly constant and therefore the water density effect is shown

4.6. Conclusion

This chapter presents the method and results of a data analysis performed on the monitoring dataset, containing six immersion sequences. From the analysis, performed both in the time and frequency domain and the derived correlation coefficients, three findings can be concluded.

First, the data quality is sufficient for a machine learning model. The peak over threshold method identified outliers rates below 2% for most sequences and variables. The only exception is the cable length data of TE5, where 27.5% of the data was removed. However since these errors occurred during the starting phase of the sequence, where the cable lengths remain constant, the removal of data had no effect on the data quality.

Secondly the behaviour of the cable load is non stationary. The rolling mean and variance change over the duration of each immersion. Furthermore their trajectories differ between elements, depending on the prevailing water density gradient. This non stationary behaviour can be used for model architecture

selection, it suggests that a deep network like an LSTM would be necessary to capture the underlying effects.

Third the analysis shows a two regime structure in the immersion process, with a boundary at the moment the element is fully submerged. This moment is recorded in the operational logbooks for each immersion sequences. The two phases differ both in which inputs affect the static loads as well as frequency domain of the signal. Before the waterline crossing, the static load is governed by the increasing ballast weight, validated by the linear correlation of $r = 0.96$ (Table 4.3). During this stage also the variance of the signal is low.

Once the element passes the water line the governing variable is less clear. The ballast correlation reduce to $r = 0.44$ and the water density effect is correctly correlated $r = -0.40$ (Before $r = 0.265$). Also in this phase the cable loads shown an oscillatory behaviour Figure 4.5.

5

Static modelling approaches

This chapter investigates whether machine learning methods can outperform an engineering approach for predicting static cable loads during tunnel immersion operations. Two machine learning architectures are evaluated: multivariate regression and a multilayer perceptron (MLP). A linear regression model is also trained as a diagnostic tool, to understand the importance of each input. The engineering method used for comparison is the immersion sheet developed by DEME, supported by additional CFD simulations. This sheet is used to estimate the cable loads during the lowering phase.

This chapter is structured as follows. First, the methodology is described, covering the regime split, and the normalization, training, validation and evaluation strategy (Section 5.1). Next, the static estimate is described, including the governing equations (Section 5.2). The machine learning methods are then explained, covering the model architectures, input selection and hyperparameter tuning (Section 5.3). Finally, the results are presented for both the cable load predictions and the convergence analysis of the models (Section 5.4).

5.1. Methodology

5.1.1. Regime split

From the data analysis it became clear that variable dependencies change over the course of the immersion operation. This is also motivated physically in Section 3.3. Therefore, two separate models are trained, one for the before regime and one for the after regime.

5.1.2. Input and target features

For all the models the following input variables can be selected: ballast weight, the cable lengths, the water density and the current velocity and direction. These variables describe the physical behaviour of the immersion.

The target variable for the static model is the low frequency component of the cable load at each lifting point (HP1 - HP4). This static component is isolated by applying a Savgol filter to measured cable loads, as described in Chapter 4.

5.1.3. Normalisation

For every training cycle, both input and target are normalized using a standard scaler which removes the mean and rescales to unit variance. The training set is normalized independently of the evaluation and validation sets. The fitted normalizer is then used to normalize these sets.

5.1.4. Validation

For each model, one immersion sequence is held out for evaluation. The remaining five sequences form the training set. The training dataset is divided into 80% training and 20% validation. However, for the regression models no validation set was used since the models have a closed form least squares

solution, and therefore no iterative training. For the MLP, K-fold cross validation is used. With this approach, several models are trained with a different 20% slice held out for validation each training cycle. Each model makes a prediction on the evaluation set. The final result is the average of those predictions.

This makes the model less sensitive to outliers. The before dataset contains 58134 training samples and 5857 evaluation samples and the after dataset 60121 training samples and 11337 evaluation samples. Early stopping is used for the MLP, meaning that the training is halted once the validation loss has not decreased for 10 consecutive epochs.

5.1.5. Evaluation

The performance of the models is evaluated on the immersion sequence held out from the training and validation. Each model's prediction is then compared with the static estimate on the evaluation element, using the coefficient of determination R^2 (Equation (5.1)) and $RMSE$ (Equation (5.2)).

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2} \quad (5.1)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad (5.2)$$

Where:

- y : target value
- $\hat{y}_i$: predicted value
- $\bar{y}$: mean of the targets values
- n : number of samples

5.2. Static estimate

The engineering benchmark used for comparison is the static estimate. It is derived from the immersion sheet, an Excel tool developed by DEME during the Oosterweel project that converts ballast weight or water displacement into cable loads. Because the tool was not designed for time series estimates, it was modified in Python. This Python version, referred to hereafter as static estimate, also account for water density changes, the hydrostatic coupling between element and pontoons, cable payout and the drag force from the current. The drag force is estimated based on a report by IMDC (Cornu & Rohit, 2024).

The calculation is split into two regimes, one for the period before the element passes through the waterline and one for the period after. This split is necessary because the calculation is very sensitive to the moment of waterline crossing: a small error in the predicted draft at the crossing causes a large error in the predicted cable load after, since this mistake is carried throughout the calculation. By computing the two regimes independently, errors from the first stage do not affect the second stage.

5.2.1. Initial state

The start of the operation is the moment the pontoons are connected to the horizontal mooring lines and the vertical cables are preloaded to the operational minimum of 50 tonnes per lifting point. The free floating draft of the pontoon and the element is calculated independently and equals:

$$H_{freefloating} = \frac{W_{element}}{LB\rho_w} \quad (5.3)$$

Then the overweight of the element is calculated. The overweight is the difference between the buoyancy of the element and the elements weight. This is equal to:

$$F_{overweight} = W_{element} - \rho_w BLH_{draft} \quad (5.4)$$

Then this overweight is distributed across the individual cables via the moment balance of the element and ballast weight around the lifting points. The location of $e_{ballast,(x,y)}$ is shown in Figure 5.1

$$e_{ballast,(x,y)} = -HP_{cog,(x,y)} - W_{ballast,cog,(x,y)} \quad (5.5)$$

Where HP_{cog} is the position of the geometric center of the four lifting points and $W_{ballast}$ is the CoG of the ballast water relative to the center of gravity of the element.

$$M_{ballast,x,y} = e_{ballast,(x,y)} \cdot F_{overweight} \quad (5.6)$$

$$\Delta F_{x,y} = \frac{2M_{ballast,(x,y)}}{HP_{separating(x,y)}} \quad (5.7)$$

Where $HP_{separating}$ is the distance between the lifting points in both axes.

$$HP_i = \frac{F_{overweight}}{4} \pm \Delta F_x \pm \Delta F_y \quad (5.8)$$

Equation (5.8) uses sign combinations (+, -), (+, +), (-, -), (-, +) for HP1 to HP4. The same distribution is applied at every timestep.

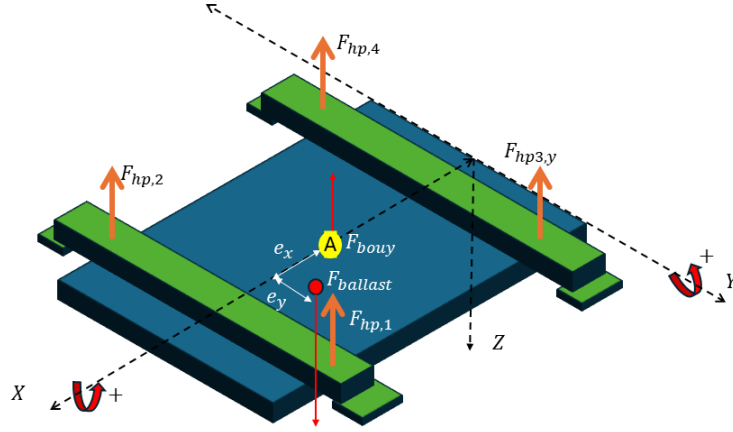


Figure 5.1: Schematization of lifting forces ($F_{hp,i}$), ballast force and location $F_{ballast}$, e_y , e_x and center of buoyancy.

To prevent the cables from going slack a minimum cable load of 50 tonnes is applied (200 tonnes total). Therefore, the element is slightly lifted out of the water, reducing its buoyancy and thus increasing the overweight. The element has to be lifted 3 cm out of the water to reach the 50 tonnes of pre tension.

5.2.2. Calculation timeline

The steps of the Python model can be described chronologically. The model first calculates the added ballast compared to the previous timestep, then it calculates the position of this added ballast and the resulting shift in CoG. Then it calculates the change in draft as a result. If cable is paid out during this timestep, the resulting draft change is also computed. Then the model checks whether the element is fully submerged and recalculates the cable loads. These steps are now briefly described. As support two schematic diagrams Figure 5.2a and Figure 5.2b have been added. To maintain numerical stability the system is evaluated at 10 second intervals.

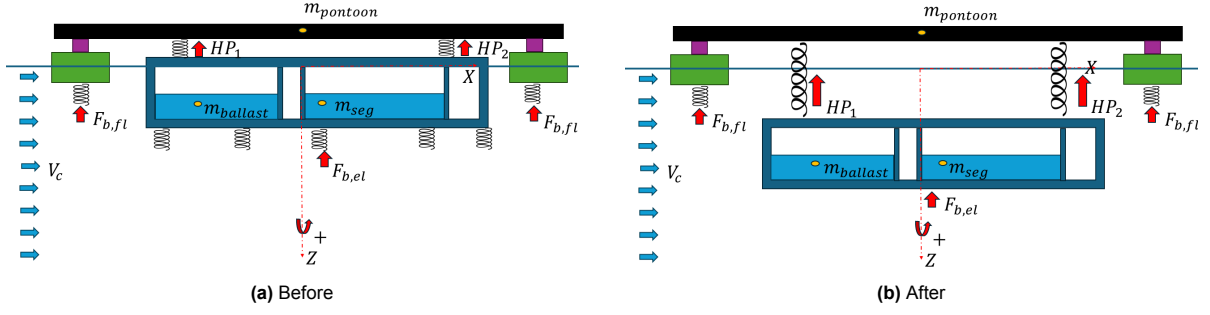


Figure 5.2: a) Schematization of the before regime, including the current velocity V_c , the hydrostatic stiffness of the element $F_{b,el}$, the stiffness of the floaters $F_{b,fl}$ and the cable loads HP_i b) Schematization of the after regime, including the current velocity V_c , the buoyancy of the element $F_{b,el}$, the stiffness of the floaters $F_{b,fl}$ and the cable loads HP_i

The change in ballast is calculated relative to the previous timestep. This ballast increment is then multiplied by the CoG position of the tank and the contributions are summed across all five tanks. The sum is then divided by the total ballast weight to obtain the ballast CoG. The resulting draft change is then calculated assuming the element is still above the waterline:

$$\Delta H = \frac{W_{ballast}}{F_{hydro,element} + F_{hydro,pontoon}} \quad (5.9)$$

When cable is paid out, two scenarios are possible. In the first case (Figure 5.2a) the element is still above the waterline. When cable is being paid out the pontoons rise slightly and the element descends. However since the water plane area of the element is 4.5 times that of the two pontoons combined, for every eight meter of cable paid out, the element descends by 0.17 m, accounting for the pulley system. This calculation is still done with the assumption that the element is partially above the waterline.

The new draft is then calculated. If the change in draft caused by the ballast and the cable payout exceeds the element height, the element is fully submerged and the calculation switches to the after regime (Figure 5.2b). Then again the overweight is calculated and the force distribution follows the same approach as in Equation (5.5) to Equation (5.8). During the overweight calculation (Equation (5.4)) the changing water density is taken into account.

The fluid structure interaction force is also added to each cable load. For the Oosterweel project, an extensive CFD simulation was performed (Cornu & Rohit, 2024). From this analysis the resulting lift forces (Table 5.1) are taken.

Table 5.1: Vertical force F_Z as a results of fluid structure interaction, where negative values act downwards. From the CFD simulations (Cornu & Rohit, 2024)

Element	CFD case	Flow direction [°]	F_z [kN]
TE_4_bis	TE4V (flood)	80 – 120	−1359
	TE4E (ebb)	270 – 320	49
TE_5	TE5V (flood)	80 – 120	−769
	TE5E (ebb)	270 – 320	69
TE_7	TE7V (flood)	80 – 120	205
	TE7E (ebb)	270 – 320	48

These forces correspond to a reference current velocity with an average of 1 m/s. It is assumed that the current velocity is uniform over the water depth, which results in an overestimation of the force, because the flow decelerates exponentially near bed due to friction Figure 2.2. The forces are neglected for TE1, TE2 and TE8, because they are located outside the current (Figure 3.2b)

The force is scaled quadratically with the measured current velocity (Equation (2.28)). The force is then divided by four and added to the individual cable loads. It has to be noted that the direction of the Z

axis in CFD simulation was opposite: a negative F_z acts downward and therefore increases the cable load.

5.2.3. After regime

In the after regime each tonne of added ballast translates directly into a tonne of cable load, and the majority of the load changes is caused by the water density. An increase in water density raises the buoyancy of the submerged element and reduces the cable load. The initial state of the after regime simulation is the overweight of the element at that time, rather than the free floating draft.

5.3. Machine learning architectures

This section describes the mathematical form of each of the three models introduced in the methodology, together with the input selection that follows from inspecting the model outputs.

5.3.1. Linear Regression

A linear regression model is used to find a linear relationship in the data. It assumes the target data can be estimated by a linear combination of the input variables. This is done by assigning weights to the individual inputs. Regression models also train an intercept value to capture the offset in the data. The only modelling choice for a linear regression model is the set of input parameters.

$$\hat{y} = w_0 + \sum_{i=1}^n w_i x_i \quad (5.10)$$

$$\mathbf{w} = (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T \mathbf{y} \quad (5.11)$$

Equation (5.10) shows the mathematical form the model, where $\hat{y}$ is the predicted value, w_0 is the intercept, w_i the variable weights, and x_i the input variables. The aim is to find the optimal weight vector $\mathbf{w}$ that minimizes the sum of squared errors. This can be done with using linear algebra shown in Equation (5.11). Where $\mathbf{X}$ is the input matrix (with a column of ones added for the intercept), $\mathbf{X}^T$ is its transpose, and $\mathbf{y}$ is the vector of actual target values.

The linear regression model is trained to predict the average cable load. To assess input importance, multiple models were trained, each evaluated on a different held out element and trained on the remaining five.

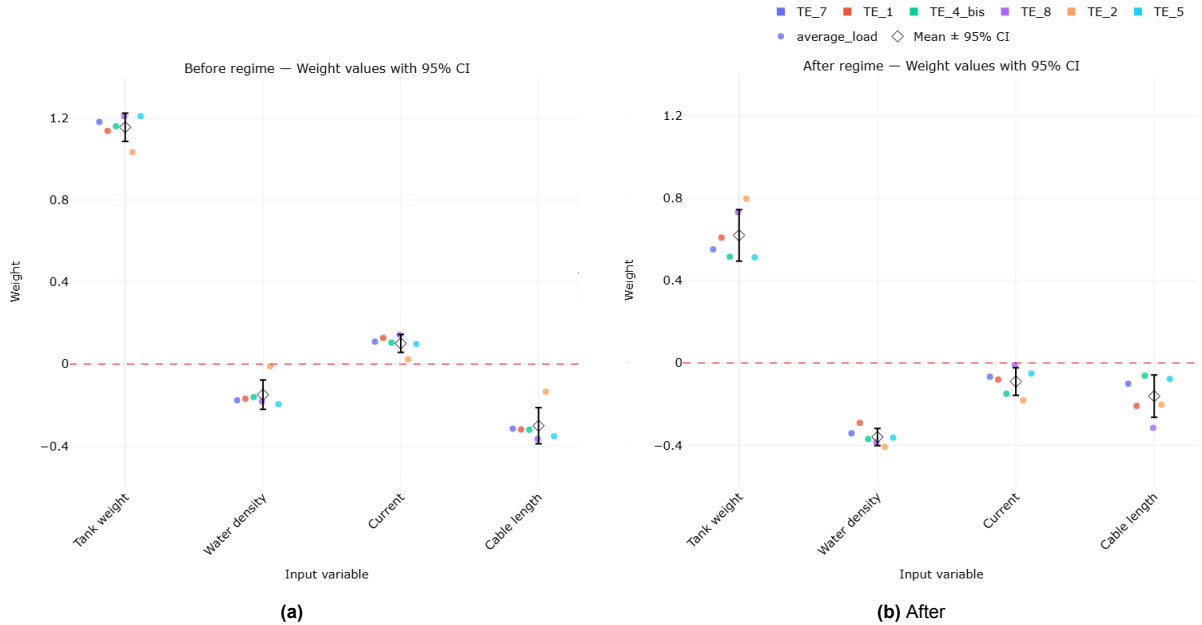


Figure 5.3: a) Linear regression weights for the before regime model, bars show the mean weight across leave one element out simulations with $\pm 1\sigma$ b) Linear regression weights for the after regime model

From a physics perspective the following variables describes the immersion operation: average ballast weight, the water density, the average cable length and the current velocity. These are also the inputs used by static estimate, so they form a reasonable starting point. Figure 5.3a and Figure 5.3b show the weight for these factors for the two phases (before and after the waterline). From this analysis it can be seen that the model assigns almost zero weight to the water density and the current velocity in the before regime and in the after regime, current velocity is assigned near zero weight. This is in line with the correlation found in Chapter 4. Therefore these variables were not used for the final model since it would only add noise to the prediction.

5.3.2. Multivariate regression

The multivariate regression model predicts the four cable loads simultaneously, instead of their average. This allows the model to capture the differences in behaviour between lifting points. Multivariate regression assigns a weight vector to the inputs, with an independent weight for each output (Equation (5.12)). The weights are still optimized to minimise the error with the target, this is done using Equation (5.13).

$$\hat{y}_j = w_{0,j} + \sum_{i=1}^n w_{i,j} x_i \quad (5.12)$$

$$\mathbf{W} = (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T \mathbf{Y} \quad (5.13)$$

From the linear regression it was understood that the current velocity and the water density did not contribute to the prediction, so both were excluded, in the after regime only the current velocity was excluded. The final set of input parameters for the before regime is the individual cable length and the average tank weight, and for the after regime it is individual tank weight, the water density and the average cable length.

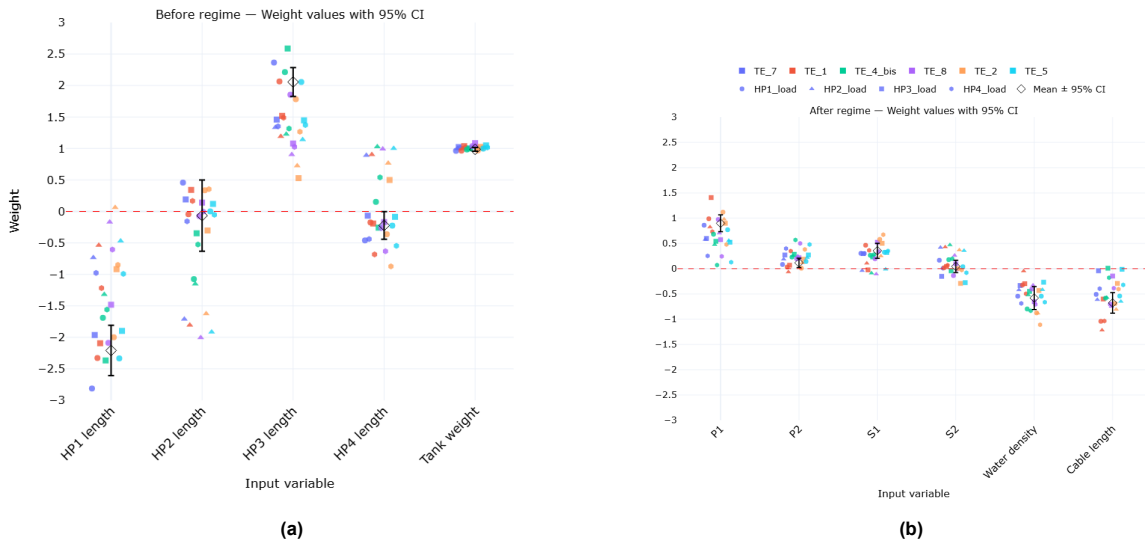


Figure 5.4: a) Multivariate regression weights for the before regime model, bars show the mean weight across leave one element out simulations with $\pm 1\sigma$ b) Multivariate regression weights for the after regime model

From this analysis it can be seen that there is a much broader variance in the input weights. Figure 5.4a shows that the HP2 length is almost zero but with a wide spread. This reflects the fact that the cable is not always paid out during the before phase. For example the strong negative correlation between HP1 length and the cable loads shows that the model can captures this relationship. Because cable payout lowers the element through the waterline, increasing its submerged volume and thereby its buoyancy. Furthermore, it becomes apparent that all the models assign a weight of approximately 1.0 to the average tank weight. This indicates the model couples ballast directly to cable load, without accounting for the part of ballast absorbed by the hydrostatic stiffness of the system. Another observation is that the weights in the after regime (Figure 5.4b) show more narrow confidence intervals, meaning the model is

more certain about the variables. In this case the model assigns higher weights to larger tanks (P1 and S1) than the smaller ones (P2 and S2), this is because the larger tanks sit further away from the center of gravity and therefore their weight produces larger moment and load shifts. It makes physical sense that the after regime shows narrower confidence intervals: in the before regime the element transitions from partially above to fully submerged, and the interplay between inputs is more complex than in the fully submerged after regime.

5.3.3. Multi layer perceptron

The MLP is a non linear regression model that maps the same input features used by the MVR onto the same four cable loads, but allows the relationship between inputs and outputs to be non linear via hidden layers and activation functions (Figure 5.5). The same regime split is applied: one MLP is trained for the before regime and a second one for the after.

Information is processed through the MLP layer by layer. The layers are fully connected, with a trainable weight for every neuron to neuron link. Each neuron in a hidden layer computes a weighted sum of the outputs of the previous layers plus a trainable bias, and then applies a non linear activation function.

$$z_j^{[l]} = b_j^{[l]} + \sum_{i=1}^{D^{[l-1]}} w_{ji}^{[l]} a_i^{[l-1]} \quad (5.14)$$

$$a_j^{[l]} = \sigma(z_j^{[l]}) \quad (5.15)$$

Where:

- $z_j^{[l]}$ is the output of the layer
- $b_j^{[l]}$ is the bias of the j -th neuron in layer l .
- $w_{ji}^{[l]}$ is the weight connecting the i -th neuron of layer $l - 1$ to the j -th neuron of layer l .
- $D^{[l-1]}$ is the number of neurons in the previous layer (equals the input dimension for $l = 1$, and M for subsequent hidden layers).
- σ is the non-linear activation function.

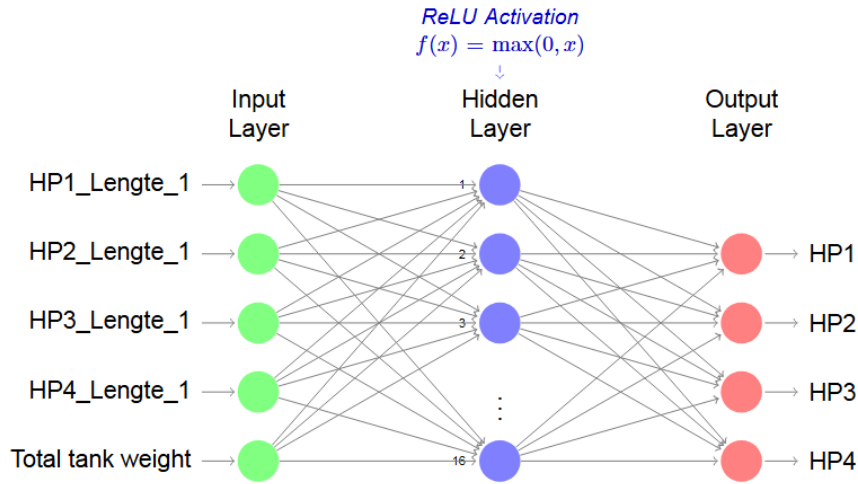


Figure 5.5: Architecture of the multilayer perceptron used for static cable load prediction, showing the input layer (green), hidden layer (purple) and output layer (red) and the connections (grey lines)

The loss function is a weighted mean squared error across the four cable loads:

$$\mathcal{L} = \sum_{i=1}^4 \lambda_i \cdot \text{MSE}_i, \quad \sum_{i=1}^4 \lambda_i = 1 \quad (5.16)$$

Where λ_i is the weight assigned to cable i and MSE_i is the mean squared error on that cable. Without per cable weighting, the gradient of the loss would be dominated by the cable with the largest absolute error. The weighting allows the model to pay more attention to cables it currently predicts poorly. This weight is dynamic and updated during the training

The architecture and training hyperparameters are given in Table 5.2. The single hidden layer with 16 neurons was chosen manually. It was chosen to use a small model since the dataset is limited. Dropout is applied to the hidden layer with a rate of 0.3 to reduce overfitting. This dropout randomly disables 30% of the hidden neurons at each training step, preventing the model from relying on individual neurons.

Table 5.2: Multi-Layer Perceptron (MLP) Configuration

Hidden Layers	Hidden Neurons	Activation Function	Trainable Params	Learning Rate	Dropout
1	16	ReLU	163	0.001	0.3

5.3.4. Training

The goal of training is to find the weight values that minimise the loss. This is done iteratively: at each training step the network makes a prediction. The loss is computed, and the weights are adjusted in the direction that reduces the loss. The adjustment requires knowing how much each weight contributed to the error, which is computed by backpropagation

Backpropagation applies the chain rule to propagate the error signal backwards through the network, from the output layer to the input layer. The gradient of the loss with respect to a weight in a layer l is:

$$\frac{\partial \mathcal{L}}{\partial w_{ji}^{[l]}} = \delta_j^{[l]} \cdot a_i^{[l-1]} \quad (5.17)$$

Where $\delta_j^{[l]}$ is the error signal of a neuron, and a the output of the activation function, is propagated backwards from the output as:

$$\delta_j^{[l]} = \sigma'(z_j^{[l]}) \sum_k w_{kj}^{[l+1]} \cdot \delta_k^{[l+1]} \quad (5.18)$$

This shows that the error signal at each layer depends on the error signal of all neurons in the previous layer, weighted by the connecting weights and scaled by the derivative of the activation function. Once the gradients are known, the weights are updated by an optimiser

An optimiser is an algorithm that uses the computed gradients to update the network weights. The simplest optimiser is gradient descent, which updates every weight by a fixed step in the direction of the negative gradient.

$$w_{t+1} = w_t - \eta \cdot \frac{\partial \mathcal{L}}{\partial w_t} \quad (5.19)$$

Where η is the learning rate. The limitation of gradient descent is that it applies the same learning rate to every parameter, regardless of the history of its gradients. For variables with large gradients this results in the fact they constantly overshoot the predictions, causing a zig zag pattern.

An optimizer addressing this issue is the Adaptive moment estimation (Adam) optimizer. This optimizer maintains a running estimate of the first moment (mean) and second moment (variance) of the gradients for each parameter.

$$m_t = \beta_1 m_{t-1} + (1 - \beta_1) g_t \quad (5.20) \quad v_t = \beta_2 v_{t-1} + (1 - \beta_2) g_t^2 \quad (5.21)$$

Where $g_t = \frac{\partial \mathcal{L}}{\partial w_{t-1}}$ is the gradient at step t . Since both moments are starting at zero, additional bias is added to prevent underestimation in the early training steps:

$$\hat{m}_t = \frac{m_t}{1 - \beta_1^t} \quad (5.22) \quad \hat{v}_t = \frac{v_t}{1 - \beta_2^t} \quad (5.23)$$

The resulting weight update is then:

$$w_{t+1} = w_t - \frac{\eta}{\sqrt{\hat{v}_t} + \epsilon} \cdot \hat{m}_t \quad (5.24)$$

Where η is the learning $\beta_1 = 0.9$, $\beta_2 = 0.999$ and $\epsilon = 10^{-8}$ to prevent division by zero. The denominator $\sqrt{\hat{v}_t}$ scales the weight update inversely with the magnitude of the past gradient: parameters with large gradient receive smaller updates, while parameters with small or noisy gradient receive relatively larger updates. This adaptive scaling makes Adam suited for problems where gradients magnitudes vary across parameters, which is the case in this dataset as shown in Figure 5.4a and Figure 5.4b.

5.4. Results

This section presents the performance of the MVR and MLP models for static load prediction. The section is structured in two parts. First, a convergence analysis is performed to determine how model accuracy evolves as the training set grows. The optimal dataset from this analysis is then used for the final predictions, which are compared against the static estimate

5.4.1. Convergence analysis

To assess how much training data is required for the machine learning models to outperform the static estimate, both models were trained on growing datasets. The dataset order was fixed as: TE7, TE1, TE4bis, TE2 and TE8, with one element added per training cycle. For each increment the model was retrained from scratch and evaluated on the held out evaluation element (TE5) using *RMSE* and *R²*. The convergence results for the MVR model are shown in Figure 5.6 and for the MLP in Figure 5.7.

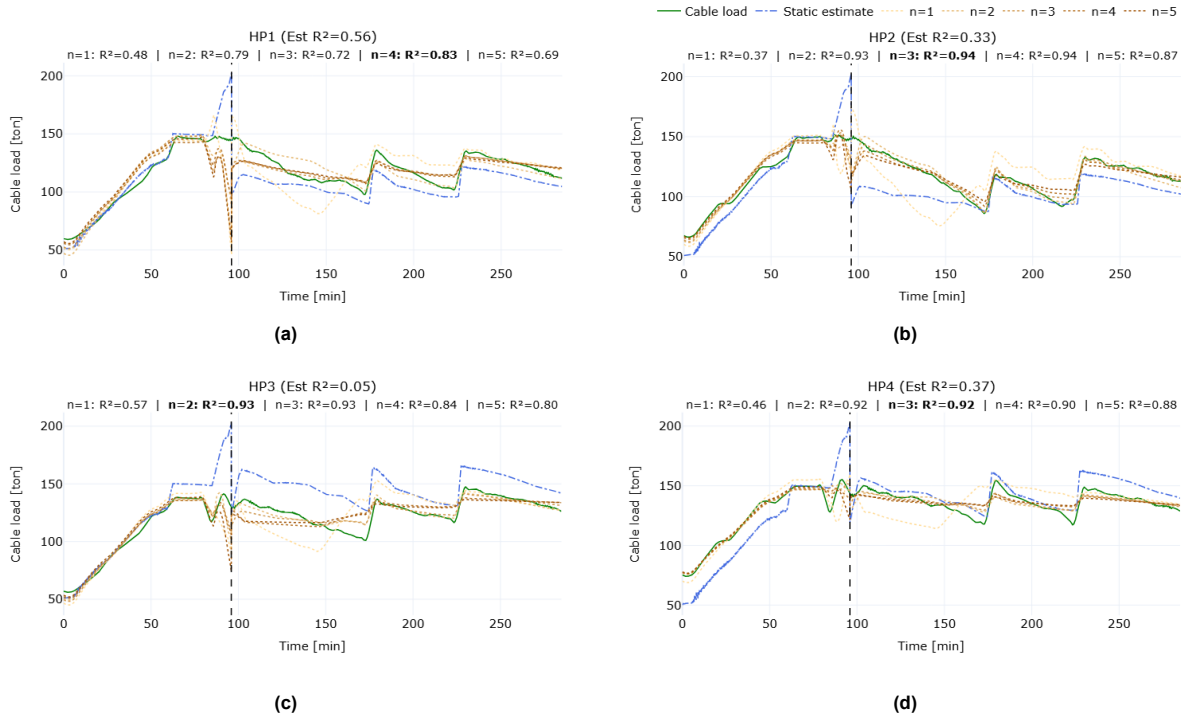


Figure 5.6: Multivariate convergence analysis: predicted cable load for the evaluation element as a function of training set size. Each line represents a training set size, darker shades indicate more training data

A thing that stands out from the Figure 5.6 is that all predictions have a sharp drop in load at the end of the before regime. This is a consequence of the increasing cable length at the end of this regime, which is negatively correlated with cable load (Figure 5.3a). This interpretation is correct however, this effect is not constant over time, as soon as the element is fully submerged the cable length does not affect the load anymore.

Accuracy on the prediction of the evaluation element does not improve monotonically as elements are added: both models reach their best performance on the first two elements (TE7 and TE1) and degrade thereafter. This is a result of the variation in the training elements: TE2 was immersed over a duration of 12 hours as a results of an electrical failure, and TE8 lies outside the main current stream (Figure 3.2b), so by adding them, widens the input distribution, reducing the accuracy of the prediction.

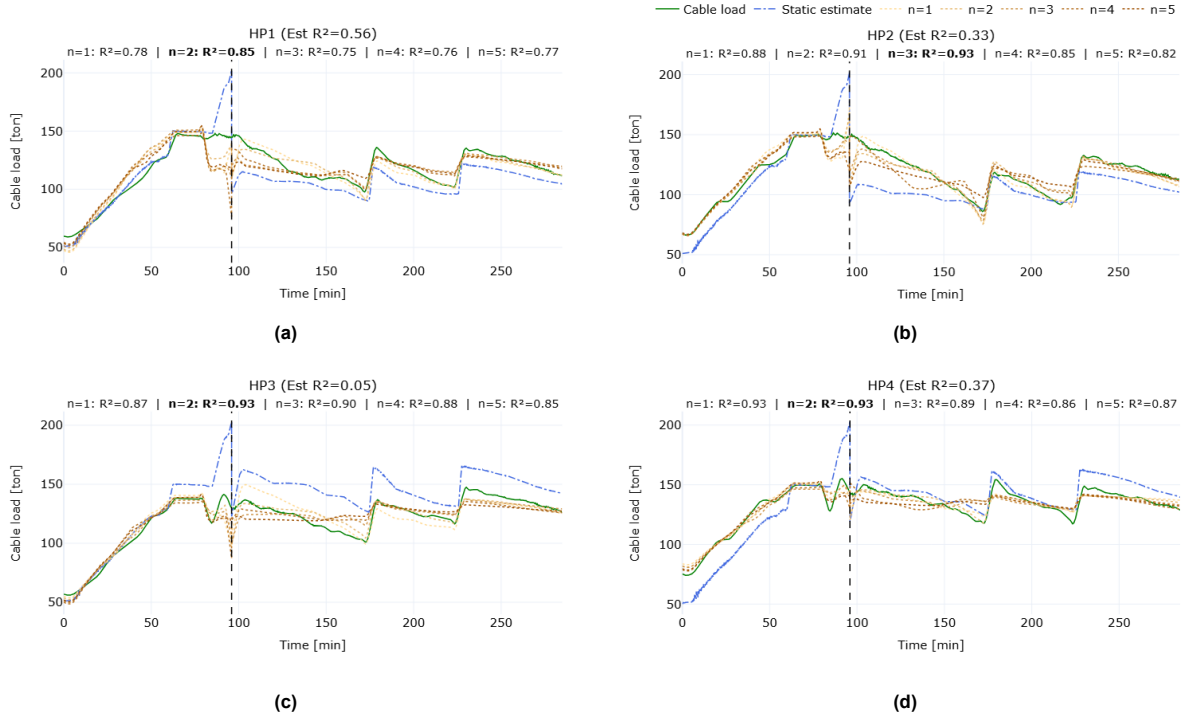


Figure 5.7: Multilayer perceptron analysis: predicted cable load for the evaluation element as a function of training set size. Each line representing the dataset uses, darker gradients means more data

A pattern in the MLP predictions is that the model captures the load behaviour well at HP1 and HP2, but underestimates the load increase associated with ballast additions at HP3 and HP4. This effects remains regardless of the training setsize, suggesting its a limitation of the model rather than a lack of data. This load asymmetry is probably caused by the effect of lowering under an angle.

5.4.2. Predictions

The final predictions of the MVR and MLP models are shown in Figure 5.8, compared to the static estimate. Both models are trained on a dataset with the elements TE7 and TE1, as a result from the convergence analysis.

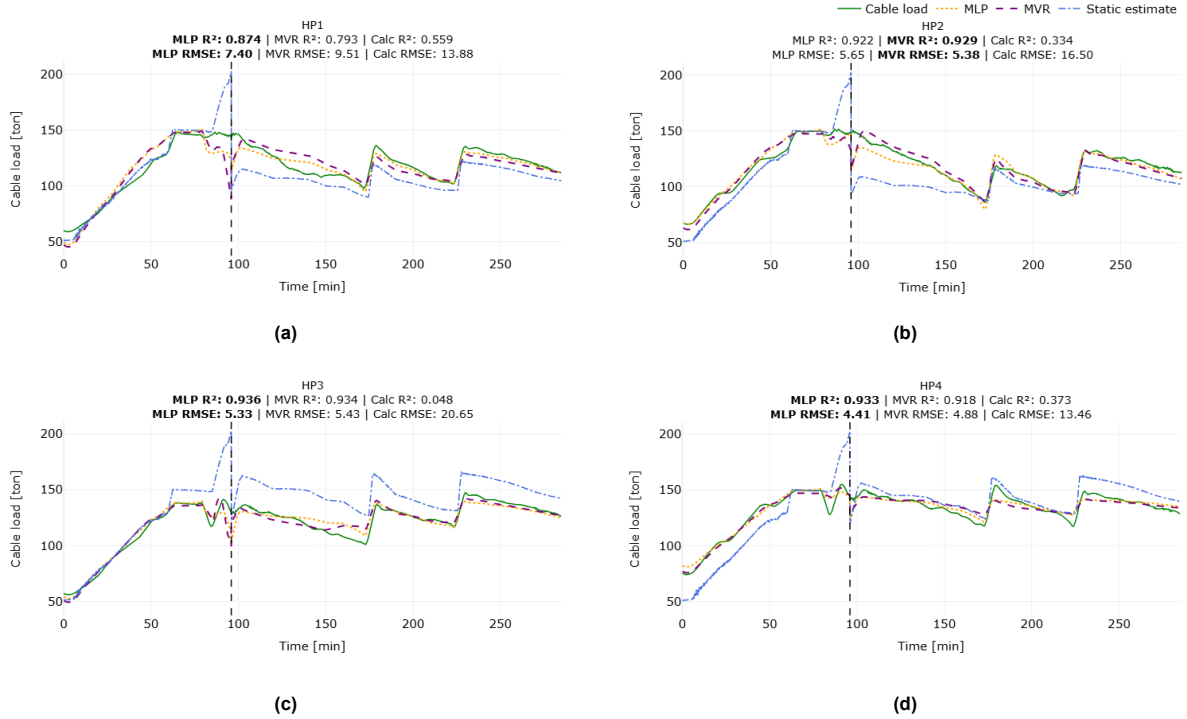


Figure 5.8: Predictions regression and MLP network compared to the static estimate, representing target (green), MLP (yellow dotted), regression (purple dotted) and static estimate (blue dotted)

Compared to the MVR model the MLP does not overestimate the negative effect of the cable length over time. Both models outperform the static estimate based on their R^2 and $RMSE$ values (Table 5.3). However, the static estimate appears to better estimate the sharp increase in load correlated to ballast intake.

To further analyse the prediction errors, a scatter plot of predicted loads versus the target loads is shown in Figure 5.9.

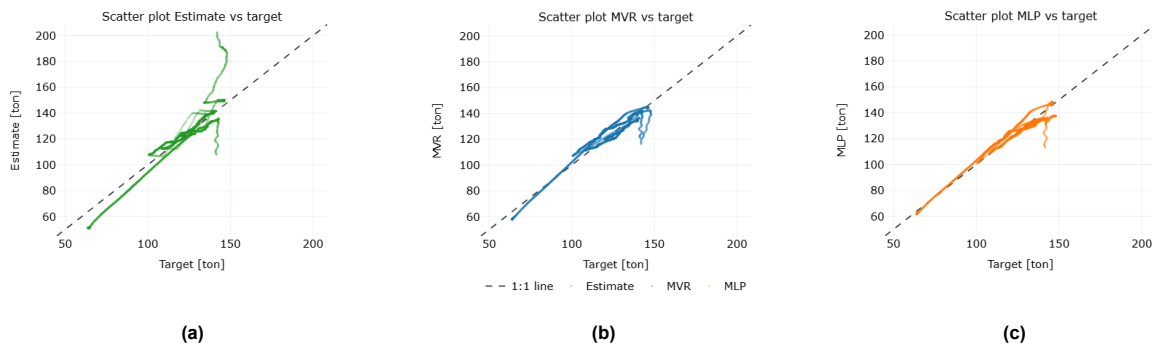


Figure 5.9: Scatter plot of the predictions versus the target data: a) the static estimate, b) the MVR and c) the MLP

The scatter plot shows that the majority of the predictions sit around the 1:1 line, suggesting that both models capture the overall pattern in the data correctly. The largest offsets occur at higher loads, where both models shown a more noisy behaviour.

Table 5.3: R^2 and RMSE of the static estimate, MVR, and MLP evaluated on TE5.

Cable	Static estimate		MVR		MLP	
	R^2	RMSE [t]	R^2	RMSE [t]	R^2	RMSE [t]
HP1	0.559	13.88	0.793	9.51	0.874	7.40
HP2	0.334	16.50	0.929	5.38	0.922	5.65
HP3	0.048	20.65	0.934	5.43	0.936	5.33
HP4	0.373	13.46	0.918	4.88	0.933	4.41
Average	0.329	16.13	0.894	6.3	0.916	5.70

6

Dynamic modelling approaches

This chapter investigates whether machine learning models can outperform a traditional engineering calculation for predicting dynamic cable loads during tunnel immersion operations. The dynamic response of the system is predominantly a consequence of cable payout, which excites the coupled pontoon element system and causes it to oscillate. An additional excitation is produced by the interaction of the water with the element during immersion.

The aim is to simulate this oscillatory behaviour. For this simulation, two machine learning networks were developed: a long short term memory (LSTM) and a Fourier neural operator (FNO). The engineering method used for comparison is a coupled 2DOF, solved using an analytical solution. This model estimates the dynamic cable loads over time using the physical properties of the system.

This chapter is structured as follows. First, the methodology is introduced, covering the training data, normalisation, training, validation and evaluation strategy (Section 6.1). Next, the 2DOF engineering model is described, including its governing equations and the assumptions required to produce a time series estimate of the dynamic cable loads (Section 6.2). Then, the two machine learning methods are explained, covering their architecture, input selection and hyperparameter tuning (Section 6.3). Finally the results are presented for both the cable load prediction and the convergence analysis (Section 6.4).

6.1. Methodology

The dynamic modelling approach follows the same pattern as the static modelling approach. It relies on the findings of the data analysis, which supports a regime split. For the dynamic modelling approach, only the dynamic part of the operation is simulated.

6.1.1. Regime

The data analysis showed (Figure 4.5) that the dynamic behaviour starts after the element has passed through the waterline. Therefore, the modelling in this chapter focuses on the fully submerged phase of the immersion operation. This transition moment is logged in the logbooks of the operation, and is also equal to the regime split used in Chapter 5.

This separation is also physically motivated. Once the cable is paid out, the system is excited by the resulting impulsive force, causing the coupled pontoon element system to oscillate. Prior to the waterline crossing, the element's waterplane area contributes to the hydrostatic stiffness of the system. This waterplane stiffness vanishes as the element becomes fully submerged, reducing the total stiffness.

6.1.2. Inputs and targets

The target variable for both of the machine learning models is the dynamic residual of the cable load at each lifting point. This signal is obtained by subtracting the static component from the filtered cable load. The resulting signal has zero mean and captures the oscillatory behaviour of the system.

The input set consists of the same variables used in the static model: ballast tank weight, cable length,

water density, and current velocity and direction. In addition, cable velocity and cable acceleration are included as inputs. These were derived by taking the derivative of the cable length with respect to time with the use of the finite difference method.

For the FNO, the input set is extended with the heave motion of the tunnel element and the total weight including the added mass. These result from the 2DOF. These variables describe the dynamic behaviour of the system. Since the FNO operates through spectral convolutions in the frequency domain, it is able to learn the coupling between the element motion and the cable load. The LSTM, by contrast, processes the signal sequentially in the time domain and learns dependencies step by step. The spectral coupling between element motion and cable load is therefore not captured by the LSTM architecture, and including the heave and added mass did not improve its performance.

6.1.3. Normalisation

The normalisation strategy follows the same approach as for the static modelling (Chapter 5). Both the input features and target are normalised for the entire training dataset. The training normaliser is then used for normalizing the evaluation and validation sets.

6.1.4. Training and Validation

Both the LSTM and FNO operate on sequential windows of input data. The window length is based on the dominant oscillation period of the system and the interval between cable pay out moments, resulting in a window length of 120 seconds for the LSTM, and 180 seconds for the FNO model.

For both models, one tunnel element is held out as the evaluation set. The remaining elements form the training and validation dataset. Of this set, 80% is used for training and 20% is used for validation. For the LSTM K-fold cross validation was applied, rotating the validation 20% over the dataset. It was not applied on the FNO because it maps functions to functions rather than sequences to points.

The two models process sequential input data rather than a single data point. The LSTM uses the past 120 seconds of input data to predict the next timestep. The FNO takes a full 180 second input window and predicts the corresponding 180 second target sequence. Because the FNO predicts a full 180 seconds, a stride of 30 seconds is applied when sampling the data. The stride reduces the overlap in the data. The resulting dataset is 59526 training samples for the LSTM and 1977 samples sequences for the FNO.

Early stopping is applied to both models to prevent overfitting, stopping training when the validation loss has not decreased for 10 consecutive epochs. Dropout is applied to the LSTM but not to the FNO, the reasoning behind this is discussed in the architecture sections.

6.1.5. Evaluation

The models are evaluated in both the time domain and frequency domain. In the time domain, the R^2 coefficient and $RMSE$ are used to compare the prediction against the evaluation dataset. In the frequency domain, the results are compared by their oscillation period and amplitude, which are retrieved with the help of a Hilbert transformation (Hilbert, 1953). This second comparison is included because the R^2 and $RMSE$ are sensitive to phase shifts in the prediction: a model that correctly reproduces the frequency and amplitude of the oscillation, but with a phase offset will produce a low R^2 and $RMSE$ score despite capturing the physically relevant behaviour.

The models are also evaluated through a convergence analysis, assessing how many immersion sequences are required for the machine learning models to outperform the 2DOF estimate in terms of R^2 and $RMSE$ on the evaluation set.

6.2. Engineer method

The dynamic behaviour of immersed tunnel elements has been studied previously. Nagel (2011) presented the immersion system as a coupled multi degree of freedom mass spring model in three degrees of freedom (sway, heave and roll). His system was a representation of the Busan Geoje link. That model is driven by wave loading, which governs the response in open water immersions. The Oosterwreel immersion, by contrast, is constructed in a river where the waves are limited to 0.22 m (Table 3.4) and

therefore the excitation is minor. For the Oosterweel system the dominant dynamic excitation is the impulsive force as a result of cable payout. The 2DOF model retains only the two heave degrees of freedom coupled through the cables, but uses the cable pay out acceleration as excitation instead of the waves.

For the Oosterweel tunnel no simulation was performed to estimate the cable loads during the immersion operations. However a test was performed to determine the dynamic load in the case of an emergency stop. This was done to establish at what speeds the winches can be safely operated without the risk of failure, the results of this analysis are shown in Figure 6.1.

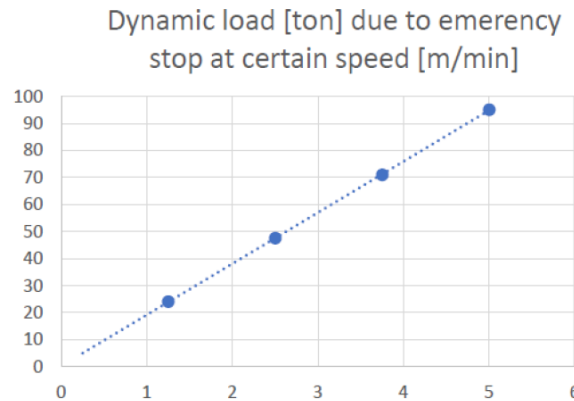


Figure 6.1: Dynamic load [ton] per cable, as a result of an emergency stop at a given speed [m/min], (Vink & Reijm, 2023)

This analysis was performed with a constant added mass of 50%. From the analysis it was concluded that the ramp up and ramp down speed of the system has to be 40 seconds when operating under normal conditions, and the winch could have a maximum velocity of 2.5 m/min. The dynamic amplification factor of this system is 1.15, which is well within the safety factors.

However this analysis is not usable for making a time series estimate of the cable load to compare with the machine learning models. Secondly, the added mass is underestimated. According to (Eysink et al., 1995), the added mass coefficient is equal to 2 for a rectangular tunnel element. In that reference, the element has dimensions of 140 x 45.25 x 8.5 m. As shown in Figure 4.6, the oscillation period is non constant over time. Because the measured period is the system response to the excitation force rather than its natural frequency, it cannot be coupled directly to the system properties. However, it suggests that the added mass is not constant over time. Near the seabed and the surface the added mass coefficient is higher, as a result of the reduced freedom of the surrounding water. Veritas (2011) describes this effect, the added mass increase as the clearance between the element and the boundary decreases. For simplicity it is assumed that the added mass coefficient is four at the surface and the seafloor, and two in-between. The decrease and increase of the added mass coefficient follows from an engineering judgement. The added mass is included in the equation motion in Equation (6.1) and Equation (6.4).

First the basic one degree of freedom system is explained, after which the heave motion of the pontoon is added. In both cases the effect of drag and current induced vibrations are neglected.

6.2.1. 1DOF

The immersion system can be simulated as a damped mass spring system. In this case the hydrostatic stiffness of the pontoon is neglected (Figure 6.2). The stiffness of the spring, the immersion cable, decreases with an increasing cable length. When the cable is being extended, the pontoon moves with $z = c + \delta$ Where c is the cable length and δ the deformation of the cable. When cable is paid out the system responds with a delay.

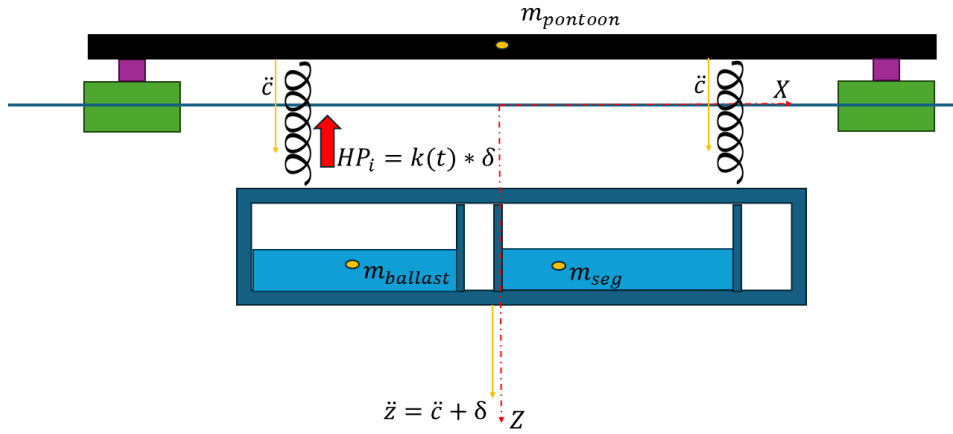


Figure 6.2: 1DOF system schematization, neglecting the hydrostatic stiffness of the pontoons, with HP_i representing the cable loads, $\ddot{c}$ the cable acceleration, δ the deformation of the cable

The equation of motion of this system is:

$$m\ddot{\delta} + c\dot{\delta} + k(t)\delta = W - m\ddot{c} \quad (6.1)$$

Where m is the mass of the element, k the spring stiffness and W the overweight of the element, since only the dynamic force is modelled, this is set to 0.

This system can be converted to its canonical form:

$$\ddot{u} + 2\zeta\omega_0\dot{u} + \omega_0^2u = FF = -\frac{m\ddot{c}}{k} \quad (6.2)$$

The solution to this equation has two parts: a general solution and a particular solution. The general solution is of the form:

$$\delta_{gen} = \exp(-\zeta\omega_0 t)(A\cos(\omega_1 t) + B\sin(\omega_1 t)) \quad (6.3)$$

And since the excitation force over the timestamp $dt = 1$ s is constant, the particular solution is equal to $-\frac{m\ddot{c}}{k}$

For the unknowns A and B in the general solution the initial conditions of each timestamp need to be known. At each timestep it can be stated that the displacement is equal to the displacement of the last time step. For the starting conditions it is assumed that the system is at rest $\delta = \dot{\delta} = 0$. The dynamic amplification factor of the system can be derived by taking the maximum amplitude and calculating u_{steady}/u_{static} .

6.2.2. 2DOF

The additional degree of freedom is the displacement of the pontoon, with x_1 the heave of the element and x_2 the heave of the pontoons (Figure 6.3). First, the equation of motion is derived for both degrees of freedom, after which the system is solved for the payout excitation force $F = ma$.

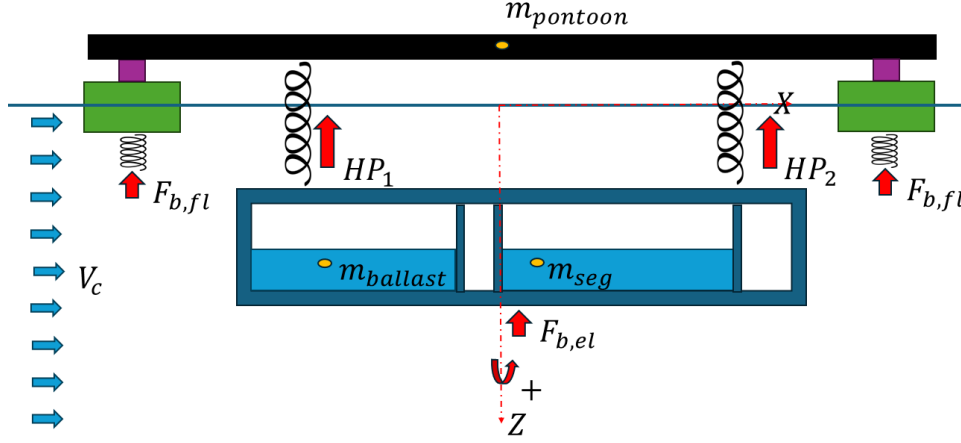


Figure 6.3: Schematization of the coupled 2DOF element pontoon system, accounting for the hydrostatic stiffness of the pontoons $F_{b,fl}$, the buoyancy of the element $F_{b,el}$, and the resulting cable loads HP_i

The equation of motion of the element pontoon system is given as:

$$\begin{bmatrix} m_e + m_a & 0 \\ 0 & m_p \end{bmatrix} \begin{Bmatrix} \ddot{x}_1 \\ \ddot{x}_2 \end{Bmatrix} + C \begin{Bmatrix} \dot{x}_1 \\ \dot{x}_2 \end{Bmatrix} + \begin{bmatrix} k_{cable} & -k_{cable} \\ -k_{cable} & k_{cable} + k_w \end{bmatrix} \begin{Bmatrix} x_1 \\ x_2 \end{Bmatrix} = \begin{Bmatrix} -m_e \ddot{\delta} \\ 0 \end{Bmatrix} \quad (6.4)$$

This set of equations follows from the movement of the pontoon being equal to the deformation of the cable x_1 plus the extended cable length a . Following (P. Zou, 2022) the damping of submerged floating structures can be estimated with Rayleigh damping, using the lowest frequencies of the system and a damping ratio 0.02. The full derivation of the systems response can be found in Chapter B.

The resulting equation is solved with a linear solver in Python. For the hydrostatic stiffness of the pontoon the bending of the pontoon is incorporated:

$$k_{w,tot} = \frac{1}{\frac{1}{k_w} + \frac{1}{k_p}} \quad (6.5)$$

6.3. Machine learning architectures

Standard machine learning models such as regression and multilayer perceptrons treat each input independently and cannot capture relationships between data points over time. By implementing a sequential inductive bias, the network can retain information from previous time steps and learn temporal dependencies. The most common implementation of this concept is the recurrent neural network (RNN), in which the hidden state at each time step is updated as:

$$h_t = f(U^T x^t + W^T h^{t-1} + b) \quad (6.6) \quad o^{(t)} = g(V^T h^{(t)} + b_o) \quad (6.7)$$

Where h_t is the hidden state at time t , x_t is the input and W_h , W_x and b are the learned parameters. f and g represent the activation functions. The output of the final step is given by Equation (6.7). Although this formulation allows information to propagate through time, training the network requires deriving the loss gradient through the chain of hidden states. This computation is known as backpropagation through time (BPTT). The gradient of the loss with respect to the weights, $\mathbf{W}$ is:

$$\frac{\partial L}{\partial \mathbf{W}} = \frac{\partial L(y^{(\tau)}, o^{(\tau)})}{\partial o^{(\tau)}} \frac{\partial o^{(\tau)}}{\partial \mathbf{h}^{(\tau)}} \sum_{t=1}^{\tau} \left(\prod_{j=t+1}^{\tau} \frac{\partial \mathbf{h}^{(j)}}{\partial \mathbf{h}^{(j-1)}} \right) \frac{\partial \mathbf{h}^{(t)}}{\partial \mathbf{W}} \quad (6.8)$$

This equation shows how the gradient of the loss flows through the network. The chain rule accumulates the loss, causing gradients to explode or vanish. This prevents the network from learning long range dependencies. For the window lengths of 120 and 180 seconds, this reduces the performance of the model.

The two architectures presented in this section address this problem differently. The LSTM network uses a gating mechanism that controls the flow of information and gradients through time, allowing the network to learn over longer sequences without vanishing gradients. The FNO decomposes the input into the frequency domain and learns the system response through spectral convolutions, avoiding the BPTT.

6.3.1. Long short term memory

An LSTM network is a form of RNN that uses a gating mechanism to process information throughout the network. An LSTM can operate as a sequence to sequence operator (mapping 10 seconds of inputs to 10 seconds of outputs) or as a sequence to one operator, converting an input sequence to a single output. The sequence to one version is used in this case to maximise the number of available training samples.

Architecture

The LSTM processes information through a system of three gates and a cell state as shown in Figure 6.4. The cell state can be seen as a highway of information that runs through the entire sequence, allowing gradients to flow backwards through time without being multiplied through a chain of weights. The gates act as the entry and exit points of this highway, controlling what information is added, removed or passed to the output of each timestep.

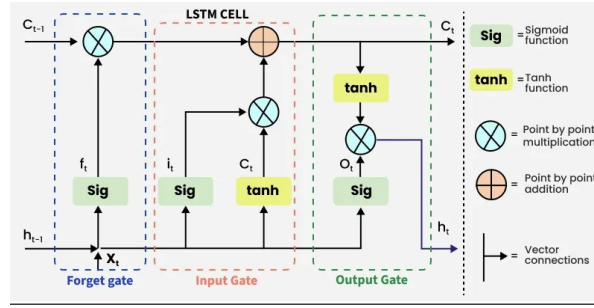


Figure 6.4: LSTM schematization with forget gate (blue), input gate (orange) and output gate (green) (GeeksforGeeks, 2022)

The first gate is the forget gate, which decides what fraction of the previous cell state should be discarded

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \quad (6.9)$$

Where σ is the sigmoid function, which returns a value between zero and one. A value of zero means that the previous cell state is completely forgotten, a value of one means it stays untouched. W_f and b_f are the learnable weight and bias of the forget gate, and $[h_{t-1}, x]$ concatenates the previous hidden state and the current input.

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \quad (6.10) \quad c_t = \tanh(W_c \cdot [h_{t-1}, x_t] + b_c) \quad (6.11)$$

The input gate decides what new information is added to the cell state. It consists of two parts: a sigmoid that controls how much new information is allowed in Equation (6.10), and a $\tanh$ that convert the new information into a vector Equation (6.11).

The cell state is then updated by combining the forget gate and the input gate:

$$c_t = f_t \cdot c_{t-1} + i_t \tilde{c}_t \quad (6.12)$$

This structure of the cell state allows for BPTT, since the gradient of the loss with respect to an earlier cell state flows back through summations rather than through a chain of multiplications.

The last gate decides what part of the updated cell state is passed forward as the next hidden state:

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \quad (6.13) \quad h_t = o_t \odot \tanh(c_t) \quad (6.14)$$

Where $\tanh$ maps the updated cell state c_t to values between -1 and 1 and the sigmoid (σ) scales the incoming hidden state h_{t-1} . The next step then uses the updated cell state and hidden state.

The designed architecture has three stacked layers, each with a hidden size of 16. Dropout randomly drops 30% of the hidden state before passing it to the next layer. This prevents the network from relying on any single hidden unit and reduces overfitting. The last layer converts the hidden state features to four cable load predictions.

Input and sequence processing

The LSTM takes a window length of 120 seconds as input and processes it through three stacked LSTM layers to produce a single output. This window length, according to Figure 4.6, presents all the oscillations periods and leaves some room for damping. The nine input features are the cable accelerations and velocities at each lifting point (HP1 - HP4) and the average cable length. The data flow through the network is shown in Figure 6.5.

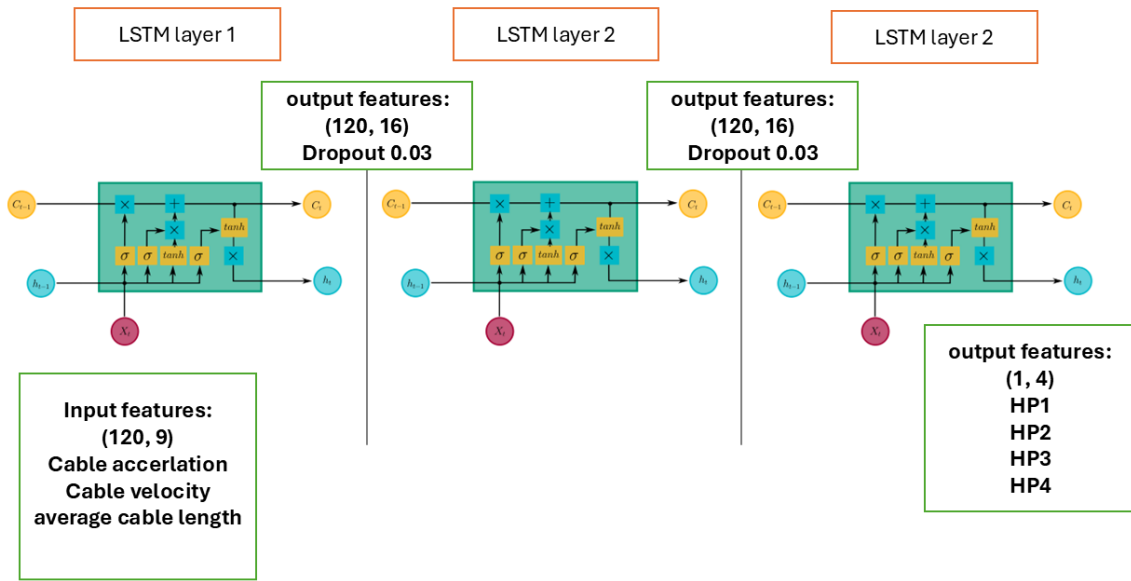


Figure 6.5: LSTM configuration, with 3 LSTM layers, 9 input features and a hiddenstate of 16, and a non linear output layer

At each timestep the nine input features are mapped to 16 hidden states by the first LSTM layer. The hidden state sequence is then passed through the second and third layer, which learns higher level patterns in the data. After the third layer only the hidden state at the final timestep is used, which is projected to four cable loads with a final linear output layer. The sliding window takes 120 seconds as input (from $t = 0$ to $t = 120$) the next input is $t = 1$ to $t = 121$, and so on. The prediction is the dynamic residual at $t=121$, which is not included in the input.

Training

The loss function is the same weighted MSE used for the MLP in Chapter 5, multiplying the per cable MSE with higher weights for higher errors. The Adam optimiser is used to update the network weights. The network is trained with a batch size of 256, meaning the gradient is computed over 256 windows before each weight update. Early stopping is applied with a patience of 10 epochs. The final architecture is given in Table 6.1.

Table 6.1: Long short term memory configuration

Stacked Layers	Hidden Neurons	Trainable Parameters	Learning Rate	Dropout	Samples
3	16	6516	0.001	0.3	59526

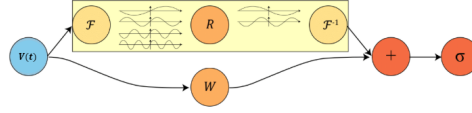


Figure 6.6: Fourier neural operator schematization, with spectral convolutions (top layer) and local bypass (w) (Li, 2020)

6.3.2. Fourier neural operator

Multilayer perceptrons map finite dimensional vectors to vectors and are restricted to the input and output dimensions on which they were trained. A recent development in deep learning is the neural operator, which maps functions to functions rather than vectors to vectors.

$$u = (K_l \odot \sigma_l \cdots \odot \sigma_0 \odot K_0)v \quad (6.15)$$

$$v'(x) = \int k(x, y)v(y)dy + Wv(x) \quad (6.16)$$

Equation (6.15) shows the mathematical structure of a standard neural network, where σ represents the activation functions and K the linear layers and u and v the output and input vectors. The neural operator in Equation (6.16) replaces the linear layers with kernel integral operators that map the input function v to the output function v' . As a result the neural operators are resolution invariant. The kernel integrations allows to take into account every pre considered point, and to reduce the complexity of the calculation, it uses convolutions weighting the distance between x and y .

A neural network trained on data sampled at a resolution of 100x100 grid points cannot be applied to data at a finer resolution of 200X200, because the input dimension has changed. However a neural operator learns the underlying relationship and can be evaluated at any resolution, since it operates on the function itself rather than on a fixed discretisation of it. The most popular operator based architecture is the Fourier neural Operator (FNO), which operates in the frequency domain.

Architecture

The Fourier neural operator performs the kernel integral operation in the frequency domain using spectral convolutions. The architecture of a single FNO layer is shown in Figure 6.6.

The input sequence is first lifted from the original feature dimension to a higher-dimensional channel space by a linear layer. This lifted representation is then passed through a series of Fourier layers. In each layer, the input v is transformed to the frequency domain using a fast Fourier transform (FFT).

Only the lowest k Fourier modes are kept, discarding all high frequency components. For this application $k = 5$ modes are used. This selection has two effects: it focuses the network on the low frequency oscillatory content that dominates the dynamic cable load, and it acts as a regularisation by preventing the network from overfitting to left over high frequency noise, therefore dropout was not applied any more to this network. With a down length of 180, the longest period that can be covered is 90 seconds. Which is within the measured periods Figure 4.6.

The *FFT* decomposes the input into phase and amplitude, which are complex. As a result learnable complex weights R_ϕ are applied to resulting frequency modes.

The result of this transformation is then transformed back to the physical domain using an inverse *FFT*. In parallel a local linear transformation W is applied directly to the input in the physical domain and added to the spectral convolution output:

$$v_{l+1}(x) = \sigma(\mathcal{F}^{-\infty}(R_l(k)\hat{v}_l(k)))(x) + W_l v_l(x) + b \quad (6.17)$$

Where σ is the non linear activation function. The local bypass W preserves information about local features in the signal that may be lost when removing the high frequency modes. For this application three layers are stacked, each operating in 16 hidden channels. After the final layer, a linear projection maps the hidden representation back to the targets. The configuration is summarised in Table 6.2.

Table 6.2: Fourier neural operator network configuration

hidden channels	modes	layers	Trainable Parameters	Learning rate	Samples
16	5	3	5564	0.001	1977

Input and sequence processing

The Fourier neural operator takes a time sequences as input and predicts the corresponding output sequence of equal length. For this application a sequence length of 180 seconds is used. This period covers multiple oscillation cycles and therefore allows the model to learn the underlying amplitude and damping behaviour. Longer windows reduce the number of available training samples, so 180 seconds was selected as compromise between frequency content and data quantity.

Training windows are extracted using a sliding windows with a stride of 30 seconds. The first window covers $t = 0$ to $t = 180$ s and predicts the target sequence of the same interval. The second window covers $t = 30$ to $t = 210$ and so on. Consecutive windows therefore overlap by 150 seconds. For the evaluation set, windows are selected sequentially with no overlap so that the predictions can be concatenated into a continuous time series without duplication.

The input dataset consists eleven features per timestep: the cable accelerations and velocities at each lifting point, the average cable length, the heave motion of the tunnel element as computed from the 2DOF estimate and the total weight, including the added mass. The heave motion is included as an additional input because the FNO operates through spectral convolutions in the frequency domain. Since the heave of the element is directly coupled to the oscillatory cable loads, providing the heave time series as an input allows the FNO to learn this coupling. The training dataset contains 1977 samples, each consisting of a sequence of length 180, with eleven input features

Training

The FNO is trained using the H^1 Sobolev loss, which measures the error between the predicted and target sequences in both the signal values and their first order time derivatives:

$$\mathcal{L}_{H^1} = \frac{1}{N} \sum_{i=1}^N \|u_i - \hat{u}_i\|_{L^2}^2 + \frac{1}{N} \sum_{i=1}^N \|\nabla u_i - \nabla \hat{u}_i\|_{L^2}^2 \quad (6.18)$$

Where u_i is the target sequence $\hat{u}$ is the predicted sequence and ∇u is the first order derivative along the time axis. The first term penalises pointwise amplitude error, the second term penalises the difference in the slope of the signal between consecutive timesteps.

The Adam optimiser is used to update the network weights, with a learning rate of 0.001.

6.4. Results

The performance of the models is evaluated in two ways: R^2 and $RMSE$ statistics for the time domain, and a comparison of the dominant oscillatory period and amplitude distribution in the frequency domain. First the convergence behaviour is analysed to determine how many training elements are required before the models outperform the 2DOF estimate.

6.4.1. Convergence analysis

For both models, convergence is assessed by adding tunnel elements to the training set one at a time, following the same order as the static analysis in Chapter 5: TE7, TE1, TE4bis, TE2, TE8. Performance is evaluated on the held out element TE5, at each training set size. The dominant period of the prediction is compared against the measured target. The performance is also compared with the R^2 and $RMSE$ metrics.

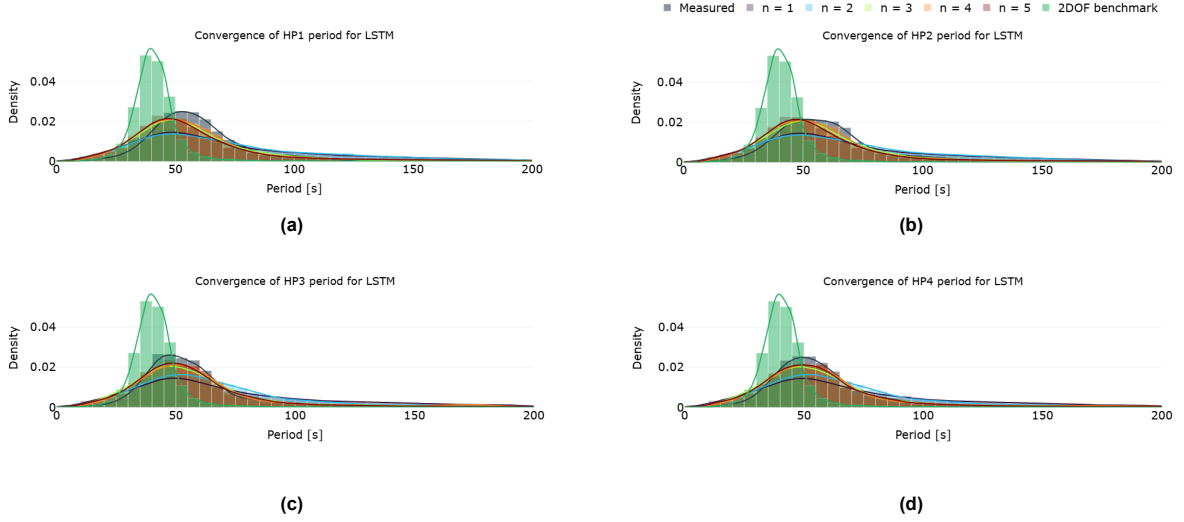


Figure 6.7: LSTM convergence analysis showing the probability density of the period per cable, as a function of training set size. The measured target distribution (grey), the 2DOF (green) estimate and the fitted Gaussian distributions (lines), are shown for reference.

The LSTM convergence results show that the model improves with each additional training element. Looking at the period distribution, the LSTM performs well even with a small training set, and consistently outperforms the 2DOF estimate. The 2DOF model underestimates the period, whereas the LSTM identifies it from the first training step. However, when evaluated on the R^2 and $RMSE$ metrics, the performance can be interpreted from a different perspective. The LSTM requires at least two training elements to match the 2DOF performance in terms of R^2 . In terms of $RMSE$ the model is better than the 2DOF estimate from the start with $n = 1$.

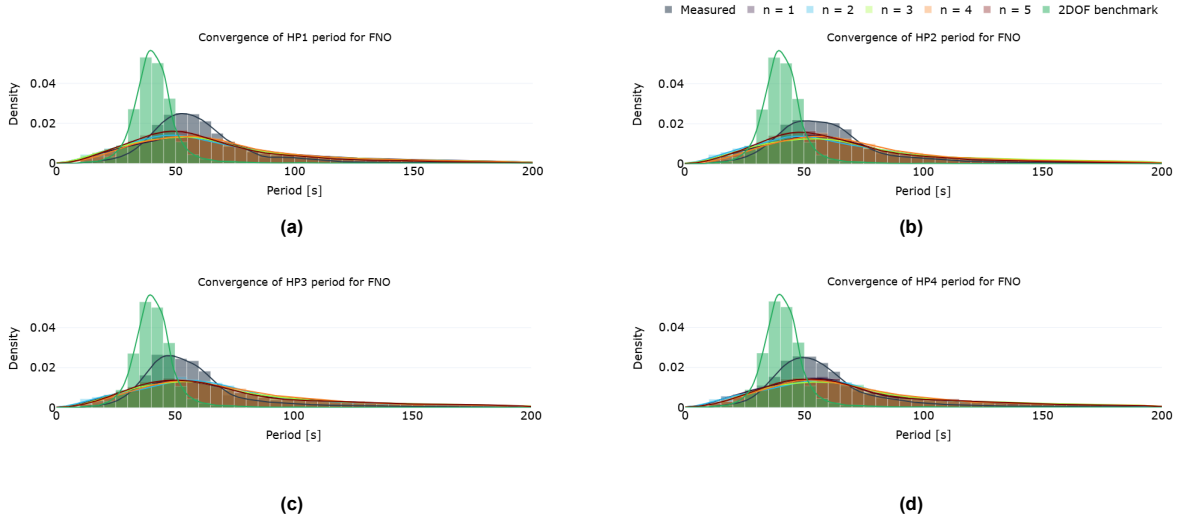


Figure 6.8: FNO convergence analysis showing the probability density distribution of the period per cable, as a function of training set size. The measured target distribution (grey), the 2DOF (green) estimate and the fitted Gaussian distributions (lines), are shown for reference.

The FNO convergence follows a similar trend to the LSTM, the period distribution improving consistently as more training elements are added. The FNO slightly overestimates higher periods. Figure 6.8 shows that its distribution is wider than the target distribution. In terms of R^2 , the FNO outperforms the 2DOF estimate from a dataset of $n = 1$. This is due to Fourier prior built into of the model.

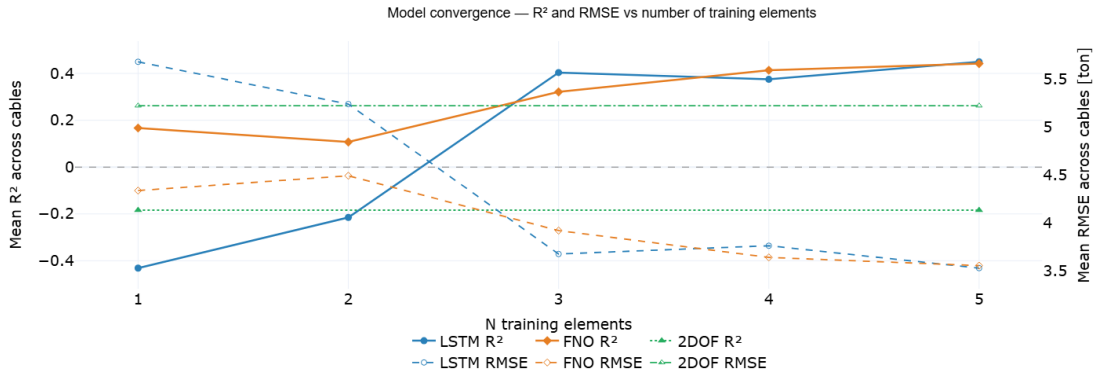


Figure 6.9: R^2 and RMSE of the LSTM and FNO models as a function of training set size evaluated on TE5, with the green lines representing the 2DOF estimate

Figure 6.9 shows the evolution of R^2 and $RMSE$ over the training set size for both models. The results show that the R^2 of both models increases after $n = 2$ and the $RMSE$ keeps decreasing, so the models keep benefitting from more training data. However, the gradient decreases as n increases, suggesting a maximum useful amount of data.

6.4.2. Period and amplitude comparison

Figure 6.10 shows the period distribution for each cable, comparing the 2DOF estimate, FNO, LSTM and target. The LSTM predicts the period better than the FNO model. Both machine learning models fail to capture the amplitude of the low frequency modes, which are the governing amplitudes for operational decisions.

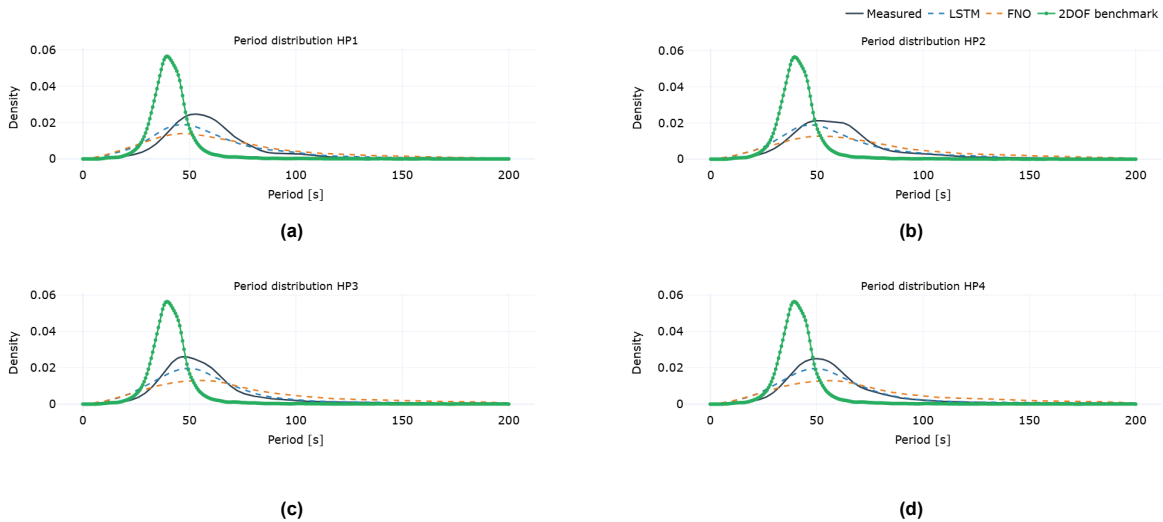


Figure 6.10: A histogram of the probability density distribution of the period per cable for the 2DOF estimate, LSTM, FNO and the measured target, evaluated on TE5, the lines show a fitted gaussian distribution

Figure 6.11 shows the distribution of the amplitudes of the predictions as well as the target. The amplitudes predicted by both machine learning models are consistently lower than those of the target variable, suggesting they consistently underestimate the force. The peak at zero amplitude also stands out. This comes from the fact that the machine learning models underestimate the damping behaviour of the system. In reality the load is always oscillating even when not excited due to the long damping period. The 2DOF estimate captures this damping behaviour more consistently.

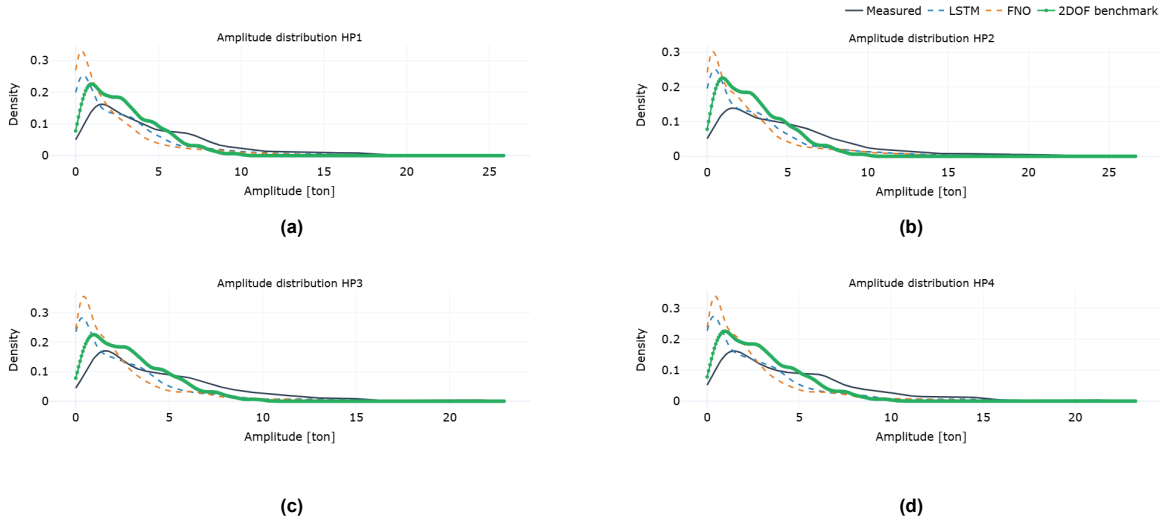


Figure 6.11: Distribution of the oscillation amplitudes per cable, for the 2DOF estimate, LSTM, FNO and the target variable, evaluated on TE5

6.4.3. Dynamic cable load prediction

The 2DOF estimate has a negative R^2 value of -0.184 on average (Table 6.3), meaning the model performs worse than predicting the mean of the data. This aligns with results following from the amplitude and oscillatory period. The 2DOF estimate is not able to capture the real period of the system, and the $RMSE$ is also the largest, showing the underestimation of the amplitude.

Table 6.3: R^2 and $RMSE$ of the 2DOF estimate, LSTM, and FNO evaluated on TE5.

Cable	2DOF		LSTM		FNO	
	R^2	$RMSE$ [t]	R^2	$RMSE$ [t]	R^2	$RMSE$ [t]
HP1	-0.238	5.39	0.415	3.71	0.441	3.62
HP2	-0.233	5.78	0.432	3.92	0.450	3.86
HP3	-0.124	4.79	0.406	3.48	0.427	3.42
HP4	-0.141	4.93	0.424	3.50	0.439	3.46
Average	-0.184	5.23	0.420	3.653	0.440	3.59

Both machine learning models outperform the 2DOF estimate when looking at the R^2 and $RMSE$. The FNO scores higher in these metrics compared to the amplitude and period comparison. This is because the FNO is better at capturing the phase of the target data. The performance of the model is consistent across the different cables, there are no major outliers.



Figure 6.12: QQ plot of 2DOF, FNO and LSTM prediction versus target, dotted line shows optimal prediction

Figure 6.12 shows the QQ plot of the predictions and the 2DOF estimate. It can be seen that the distribution of the 2DOF, FNO and the LSTM are less wide compared to the target. However the FNO and LSTM predictions are wider compared to the 2DOF, suggesting it is capturing the higher amplitudes better. This supports the findings of Figure 6.11 and Figure 6.10, that the model is underestimating the high amplitudes.

Discussion and conclusion

This chapter contains the final findings of this research, first the discussion points are given. After the conclusion of this research is described followed by the additional recommendations, for improving the models and for further research

7.1. Discussion

The engineering estimate used for evaluating the performance of the machine learning models is a simplified representation of the reality, ignoring the influences of hydrodynamic forces. Furthermore, the estimation of the added mass coefficient is also uncertain. The added mass coefficient from literature varies between 2 (Eysink et al., 1995) and 0.885 (Veritas, 2025). The data analysis (Figure 4.6) suggests that the added mass coefficient is not constant over the duration of the immersion. However since the measured frequency is the steady state response of the system and not the free vibration, it is not possible to re-engineer the added mass coefficient. A stronger evaluation estimate would likely have raised the R^2 and $RMSE$ of the engineering estimate, which would in turn require a larger dataset for the machine learning models to outperform it.

The frequency measured in the cable data is the final response of the system, presenting a superposition of the steady state modal response to excitation force F . F represents the combined force resulting from cable payout and the fluid structure interaction. As a result, the natural frequencies of the system cannot be retrieved, which limits the training data. The machine learning models can only identify the response to the excitation force. Because the input force is similar across the different sequences, the effect of this force cannot be isolated, which is a limiting factor. A dataset containing free vibrations of the element, would enable the model too learn the effect of the input force, and therefore improving the operational usage of the machine learning models.

The deep learning models, FNO and LSTM, are constrained by the limited size of the training dataset. A common rule of thumb for training deep learning networks is that the dataset should be at least ten times larger than the number of learnable parameters in the network. Table 6.1 shows the LSTM has 6516 trainable parameters against 59526 training samples, a ratio of approximately 1:9. Table 6.2 however, shows an imbalance for the FNO, with 5564 trainable parameters against 1977 samples, nearly three trainable parameters for every sample. This data scarcity affects the choice of the window length. A longer window would better capture the system's damping period, which according to the data analysis, exceeds ten minutes. However, lengthening the window would have reduced the number of training sequences further, decreasing the parameter to sample ratio. The chosen window lengths therefore reflect a compromise between capturing the full damping behaviour and the sample size

The generalizability of the models to other immersion projects is also difficult to evaluate. Depending on the location of the immersion process the layout of the system changes. For example, at construction sites with higher currents or deeper seafloors (the Blankenberg connection and the Busan connection) mooring lines are often attached to the tunnel element, to restrict its horizontal movement during the immersion process. These cables also limit the vertical movement, therefore decreasing the dynamic

loads. Secondly, for a longer immersed tunnel (the Fehmarnbelt) the tunnel element is underbuoyant before the operation starts, reducing the required amount of ballast water. A heavier object also has a lower natural frequency. This affects the hyperparameter settings of the FNO. Since lower natural frequencies would increase the minimum window size, and therefore also the number of modes needed to capture the oscillations.

All models are evaluated on TE5, which allows for direct comparison. However, TE5 may represent a favourable immersion operation. Evaluating on a single element results in a point estimate of model performance rather than a distribution, and provides no measure of how sensitive the result is to the choice of the evaluation sequence. The same limitation applies to the convergence tests, which used a fixed order: TE7, TE1, TE4bis, TE2 and TE8, rather than averaging over multiple possible orderings.

Although the data was filtered into static and dynamic components, some inherent noise remains that filtering cannot remove. In each ballast tank, only a single sensor measures the water level, which affects the accuracy of data when lowering under an angle. For example, if the element tilts to one side, the water inside that tank shifts towards that side, changing the local reading at the sensor even though the total volume of water in the tank has not changed. Secondly, the lifting load sensors were not calibrated at the start of each operation, therefore the possibility of systematic misreading in the cable loads can not be ruled out. Both effects introduce noise into the dataset that is uncorrelated with the actual state of the system. Because this noise is inherent in the data, the machine learning models have to learn this as well, reducing the generalizing performance of the models.

The regime split in the static estimate does affect the model performance, because the predicted loads do not align at the interface boundary, reducing the accuracy of the model. From an operational point of view this is the most critical part of the operation. Splitting this into two phases reduces the models capability of capturing these effects.

The models were trained with a weighted mean squared error loss function, which optimises the model to predict the expected value of the target given the input. This is only equivalent to the true signal when the target is fully described by what the model observes. For the dynamic cable loads however, the exact phase of the oscillation is not fully resolved within the window length, since the damping period of the system exceeds ten minutes. Consequently, training windows that appear similar to the model can correspond to oscillations at different, unresolved phases. In these cases, the loss minimising prediction is the average across these possible phases. This effect is strongest late in the damping, where the input window is furthest removed from the last clearly identifiable excitation event and phase uncertainty is largest, causing the loss optimal prediction to be zero. This mechanism explains the underestimation and the high peak in zero amplitude predictions shown in Figure 6.11 and Figure 6.10. For the FNO, the gradient loss (H^1), introduces an additional bias. This loss penalises the mismatch in prediction in time domain by looking at the time derivate. High amplitude and high frequency contribute the most to this loss term. Therefore the model is focused on capturing these and not on the lower gradient, damped loads. Both of these effects limit the models capability of predicting the actual load and the right amplitude.

7.2. Conclusions and recommendations

This research investigated whether machine learning models can improve the estimation of vertical cable loads during tunnel immersion operations, and to what extent these methods generalise to other projects. The central research question was:

To what extent can machine learning models improve the accuracy and generalizability of vertical cable load estimation during tunnel element immersion operations, compared to traditional engineering approaches?

Machine learning models outperform the traditional engineering estimate for static and dynamic forces. For the static forces, both the MVR and the MLP outperform the engineering estimate. With the MLP performing best, the MLP reduces the average $RMSE$ on the evaluation element TE5 from 16.1 t to 5.7 t, a reduction of 65%, and increases the R^2 from 0.33 to 0.92 (Table 5.3). For the dynamic forces, both the LSTM and FNO outperform the dynamic 2DOF estimate. The $RMSE$ drops from 5.2 t to 3.6 t, a reduction of 31%, and the R^2 raises from -0.18 to 0.44. However, the LSTM and FNO fail to capture

the higher amplitudes: in the 7 - 15 t amplitude band (Figure 6.11) the density of the prediction is half that of the target, suggesting they only capture 50% of these events.

The generalizability of the trained machine learning models to new projects depends on the immersion configuration and would require retraining. For the static models, retraining is only required if the immersion method differs. For the dynamic models, retraining is necessary because they learn the steady state response of the Oosterweel system. The methodological approach however, splitting the operation in a before and an after phase, can be used for new projects.

When looking back at the literature: Miyanawala et al. (2024) showed that an LSTM can be used to predict forces on a jack up vessel. This LSTM took the input from a numerical model which provides the movement of the structure. This research achieved lower accuracy, but without the numerical model, and therefore reducing the dataset. This shows that meaningful results can be computed at lower complexity.

The following sub questions are addressed:

1. *Which operational and environmental variables have the strongest influence on cable load variation during immersion?*

The data analysis in Chapter 4, showed that there are two governing physical regimes during the operation. The boundary between these regimes is the moment the element passes through the waterline. In the before regime load variations are a consequence of ballast intake ($r = 0.96$). Once the element moves through the waterline, the effect of the ballast is reduced to $r = 0.439$ and the loads are also affected by the water density $r = -0.405$.

For the dynamic force, the cable payout is the excitation force, causing it to oscillate near the excitation frequency. The added mass also affects the amplitude of the response. This added mass is not constant during the operation. The added mass is higher near the surface and close to the seafloor. This finding supports the findings of Song, Qu, et al. (2021), who saw an increase in amplitude due to near wall effect.

2. *How do machine learning approaches (regression and neural networks) compare to traditional (quasi) static estimation methods (engineering hand calculations and CFD)*

Both the MVR and MLP outperform the immersion sheet for continuous load prediction (Table 5.3). The weight analysis of the linear and multivariate regression models confirmed that the models correctly identify the physical relationships. The MLP also captures the non linear interactions between the inputs, removing the overestimation of the cable length that reduces the performance of the MVR.

3. *How do machine learning models (LSTM and fourier neural operators) compare to engineering estimates for dynamic behaviour in capturing dynamic cable load behaviour?*

Both the LSTM and FNO outperform the 2DOF engineering estimate as shown in Table 6.3. The 2DOF estimate, underestimates the oscillation period of the load. The LSTM and the FNO recover this oscillation period more accurately. However, compared to the 2DOF estimate, the machine learning models underestimate the damping. This is shown by a high peak in zero amplitude predictions. Both models also underestimate the high amplitudes that result from resonance and in phase movement of element heave and cable payout.

4. *How does the prediction accuracy of machine learning models evolve with increasing training data, at what point do they match or exceed the traditional approaches?*

The convergence analysis showed different behaviour between the static and dynamic models. For the static models, the best prediction is reached at a dataset of $n = 2$, after which accuracy decreases. For more complex architectures (the LSTM and FNO), the performance of the model keeps improving with each additional training element. The FNO shows a positive R^2 value from the first element ($n = 1$) reflecting the spectral inductive bias of the fourier transform.

5. *Can machine learning models reliably identify peak loads and threshold exceedances compared to traditional methods?*

The static machine learning models can estimate the peak loads, since the dynamic effects are ignored. The peak loads in this regime are a summation of the input forces and can therefore be estimated accurately. The dynamic models can not estimate these peak loads correctly, the models underestimate the high amplitudes that result from in phase movement of the element and the cable. Consequently, the models can not be used for optimising the cable pay out rate.

Besides the research questions, the data analysis showed another behaviour of the system which is not supported by literature. From Figure 4.6, it can be concluded that the dominant oscillation period of the cable load is decreasing as the element descends, and increases again as the element approaches the seafloor. This is contradicting with the findings of Yang et al. (2017), who found that the period increases throughout the descent as a result of the lengthening of the cables. The most likely explanation for the observed trend, which is also supported by Veritas (2011) is depth dependent added mass, which is the highest near the surface and the seafloor. As the element moves away from the surface the added mass reduces, which decreases the period. When the element is approaching the seafloor, the added mass increases and the period as well. This difference in behaviour can be explained by the construction conditions. The experiment of Yang et al. (2017) was conducted to investigate the effect of wave excitation on the element behaviour. When the element is descending the wave induced particle motion is decreasing and with it the excitation of the system. At the Oosterweel construction site, this effect could be neglected because of the absence of waves.

This research provides a comparison between data driven and traditional engineering methods for cable load estimation during tunnel immersion operations, using real operational monitoring data from the Oosterweel project. The results show that machine learning models trained on monitoring data can outperform the engineering estimates. The modelling framework used: data analysis, regime separation, static and dynamic prediction can be implemented for future immersion projects. The limitation of the model is the estimation of the high amplitude cable loads.

The research gap that this study aimed to fill was the coupling between environmental and operational inputs and cable loads with the help of machine learning, to understand the underlying relationship in the data. The developed machine learning model (MLP + FNO or LSTM) is able to connect these variables and to predict the cable loads better than the current used estimations methods.

7.2.1. Improving machine learning models

Following from the loss function limitations discussed above, it is recommended to develop a loss function that directly penalises amplitude error, rather than relying on pointwise (MSE) and gradient (H^1) terms. PyTorch has no built in loss function targeting amplitude offsets directly, but approaches exist in image reconstruction models, where gradient based penalties are used to maintain sharp reconstructions. Another improvement for the loss function, would be a loss function that penalises the phase difference between cables. The data analysis showed that the loads of HP1 and HP2 oscillate in phase as well do HP3 and HP4. This relation is a result of the fact that they are connected to the same pontoon. This structural relationship is not learned during training, so a loss term penalising the phase difference between paired cables could be added and tested to see whether model performance improves.

The limitations of the 2DOF estimate, the lack of validating monitoring data and the noise in the sensors can be tackled by developing a more complex numerical model. This model can set a better benchmark, provide more training data as well giving more optional input parameters. To achieve this the current 2DOF model should be expanded to 18 degrees of freedom, accounting for all six individual degrees of freedoms of three system parts: the two pontoons and the element. This system should also include the horizontal mooring lines, which are currently excluded. Validating such a model requires more data. To derive the natural frequency of the system as well as the added mass properties. Free vibrations tests of the structure should be conducted. Additionally two new measurements should be included as well: two GPS devices should be placed on both ends of the tunnel element to measure the actual movement over time. This way the heave, roll and pitch motion of the element can be validated. By also setting GPS devices on the pontoons, the motion of these parts can be validated as well. By placing two sensors in each of the ballast tanks, the ballast level can be more accurately measured, but secondly also the effect of the moving water can be accounted for in the model.

To improve the generalizability of the machine learning models, the evaluation methodology should be

changed. Instead of evaluating only at one element, the model should be evaluated against different elements and then the general performance should be optimized. This cross set up results in a more generalized set of input parameters which would improve the prediction capacity of the model.

7.2.2. Further research

This thesis shows the potential of using machine learning models to predict cable loads during immersion operations. However, to use these models for optimising the lowering procedure and reducing operational duration, the aim for this research, additional research is required to turn the developed models into operational tools. The following approach is suggested: first different lowering procedures have to be made: lowering with constant speed, faster ramp or ramp down time and lowering one side first for example. Then the constraints of this problem have to be set: what is the maximum cable load of the system, what is the maximum dynamic amplitude, what is the maximum cable pay out speed? Then these different cases can be simulated with the machine learning model, resulting in different lowering times and load amplitudes. With these simulations an optimal lowering sequence can be selected that allows for faster and safer operations.

Another way of using the machine learning models for operational decisions would be achieved by modifying the LSTM model, which predicts the cable load one second ahead, to predict further into the future, for example 30 seconds or a minute. This would require a different architecture capable of sequence to sequence prediction rather than sequence to one second ahead. A longer prediction would give the winch operator a warning in advance of an approaching high amplitude event, allowing to adjust the payout rate to anticipate. This tool would help optimizing the operation as described above, if during the operation the immersion plan has to be adjusted, the operators can still rely on the machine learning tools.

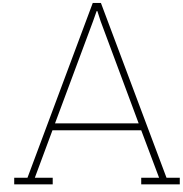
The model in this thesis is developed for the immersion dataset of the Oosterweel project. However, data is also available from other projects such as the Fehmarnbelt, the Blankenburg and Busan connection. Also, the developed models in this thesis still predict parts of the operation, and use a regime split to separate the operation. Ideally there is one model developed that can predict an entire operation, without the regime split, and can also deal with different immersion set ups. This more generalized approach can be achieved with an encoder transformer network. The encoder brings the input data to a higher dimensional space and flattens it, and the transformer, in the form of a Fourier neural operator, translates the high dimensional input space to predictions.

References

- Airy, G. B. (1845). Tides and waves. *Encyclopædia Metropolitana*.
- Archimedes. (2002). *On floating bodies* (T. L. Heath, Trans.) [Original work published ca. 250 BCE]. Dover Publications.
- Bellman, R. E. (1961). *Adaptive control processes: A guided tour*. Princeton University Press.
- Bishop, C. M. (2006). *Pattern recognition and machine learning*. Springer.
- Chen, Z.-j., Wang, Y.-x., Wang, G.-y., & Hou, Y. (2009). Time-domain responses of immersing tunnel element under wave actions. *Journal of Hydrodynamics, Ser. B*, 21(6), 739–749. [https://doi.org/10.1016/S1001-6058\(08\)60208-5](https://doi.org/10.1016/S1001-6058(08)60208-5)
- Chu, K., & Breugem, A. (2025, January). *Detailed telemac3d model as operational forecast model for the scheldetunnel* (I/RA/18080/24.257/KCH). IMDC. Van Immerseelstraat 66, 2018 Antwerpen, België.
- Clough, R. W., & Penzien, J. (1995). *Dynamics of structures* (3rd ed.). Computers & Structures, Inc.
- Cornu, T., & Rohit, K. (2024, June). *Current load otao additional cfd scenarios and assessment* (I/RA/18080/24.006/RKU/IMDC. Van Immerseelstraat 66, 2018 Antwerpen, België.
- Doorme, S. (2019, October). *Advies tenderfase oosterweeltunnel* (I/RA/18080/19.126/BDC/SDO). IMDC. Van Immerseelstraat 66, 2018 Antwerpen, België.
- Eysink, W. D., Luth, H. R., de Vroeg, J. H., & van Wijhe, H. J. (1995, April). *Tweede beneluxtunnel: Nautisch, hydraulisch en morfologisch onderzoek*. MHPoly.
- Femern A/S. (2025). *Fehmarnbelt tunnel*. Femern A/S. <https://femern.com/the-tunnel/fehmarbelt-tunnel/>
- GeeksforGeeks. (2022, September). Deep learning – Introduction to Long Short-Term Memory [Accessed: June 4, 2026]. <https://www.geeksforgeeks.org/deep-learning-introduction-to-long-short-term-memory/>
- Goodfellow, I., Bengio, Y., & Courville, A. (2016). *Deep learning* [<http://www.deeplearningbook.org>]. MIT Press.
- Groen, P., & Dorrestein, R. (1976). *Zeegolven [sea waves]* (Vol. 11) [KNMI Publication 111-11, 3rd edition]. Staatsdrukkerij.
- Hansen, D. V., & Rattray, M. (1966). New dimensions in estuary classification. *Limnology and Oceanography*, 11(3), 319–326. <https://doi.org/10.4319/lo.1966.11.3.0319>
- Haring, W., Kroeders, M., & Zaldivar, M. (2023). *Technical evaluation and improvements for tunnel immersion operation ten* [Internal company document].
- Hendrickx, G. G., Kranenburg, W. M., Antolínez, J. A. A., Huismans, Y., Aarninkhof, S. G. J., & Herman, P. M. J. (2023). Sensitivity of salt intrusion to estuary-scale changes. *Estuarine, Coastal and Shelf Science*, 295, 108564. <https://doi.org/10.1016/j.ecss.2023.108564>
- Hilbert, D. (1953). *Grundzüge einer allgemeinen theorie der linearen integralgleichungen [framework for a general theory of linear integral equations]* [(Original work published 1912)]. Chelsea Publishing Company.
- Holthuijsen, L. H. (2007). *Waves in oceanic and coastal waters* [p. 70]. Cambridge University Press. <https://doi.org/10.1017/CBO9780521860284>
- Immotec. (2010). *Project Busan-Geoje fixed link*. Immotec. Retrieved May 22, 2024, from <https://immotec.com/blog/artikel/busan-geoje-fixed-link/>
- Journée, J., & Massie, W. (2001). Hydromechanics.
- Keulegan, G. H., & Carpenter, L. H. (1958). Forces on cylinders and plates in an oscillating fluid. *Journal of Research of the National Bureau of Standards*, 60(5), 423–440. <https://doi.org/10.6028/jres.060.043>
- Li, Z. (2020, December 2). *Fourier neural operator*. Zongyi Li. Retrieved June 5, 2026, from <https://zongyi-li.github.io/blog/2020/fourier-pde/>

- Lienhard, J. H. (1966). *Synopsis of lift, drag, and vortex frequency data for rigid circular cylinders* (Bulletin No. 300). Washington State University, College of Engineering, Research Division. Pullman, Washington.
- Menter, F. (1993). *Zonal two equation k - ω turbulence models for aerodynamic flows*. American Institute of Aeronautics and Astronautics.
- Miyanawala, T., Li, Y., Law, Y., & Santo, H. (2024). Real-time prediction of hydrodynamic forces and dynamic responses of a generic jack-up platform using deep learning. *Ocean Engineering*, 306, 118003. <https://doi.org/10.1016/j.oceaneng.2024.118003>
- Molenaar, V. (1993). *Tunneling and underground space technology* (8th ed.). Pergamon Press Ltd, Great Britain.
- Morison, J. R., O'Brien, M. P., Johnson, J. W., & Schaaf, S. A. (1950). The force exerted by surface waves on piles. *Petroleum Transactions, AIME*, 189, 149–154.
- Munson, B. R., Young, D. F., Okiishi, T. H., & Huebsch, W. W. (2012). *Fundamentals of fluid mechanics* (7th ed.). John Wiley & Sons.
- Nagel, G. W. (2011). *Dynamic behaviour of tunnel elements during the immersion process* [Master's thesis]. Delft University of Technology.
- Rahman, M. H., & Gupta, C. (2020). Computation of rayleigh damping coefficient of a rectangular submerged floating tunnel (sft). *SN Applied Sciences*, 2(936). <https://doi.org/10.1007/s42452-020-2629-z>
- Song, Y., Chen, N.-Z., & Zhang, N. (2021). Coupled motion characteristics of a large-scale tunnel element suspended by immersion rigs in the vicinity of seabed. *Tunnelling and Underground Space Technology*, 110, 103804. <https://doi.org/10.1016/j.tust.2020.103804>
- Song, Y., Qu, Y., Chen, N.-Z., & Metrikine, A. V. (2021). Effect of immersion depth on the coupled dynamics of a tunnel-rigs system in irregular waves. *Tunnelling and Underground Space Technology*, 115, 104068. <https://doi.org/10.1016/j.tust.2021.104068>
- Sundar, R., Majumdar, D., Lucor, D., & Sarkar, S. (2024). Physics-informed neural networks modelling for systems with moving immersed boundaries: Application to an unsteady flow past a plunging foil. *Journal of Fluids and Structures*, 125, 104066. <https://doi.org/10.1016/j.jfluidstructs.2024.104066>
- Sweet, R. (2024, May). 'site of the century': Crews square up to antwerp's tunnel-under-a-canal.
- university, O. (1999). *Waves, tides and shallow water processes*. Butterworth-Heinemann, Oxford.
- van Putten, E. (2025a). *Evaualtie afzinkdata te1* [Internal company document].
- van Putten, E. (2025b). Thesis proposal.
- van der A, R. (2025). *Afzinkdraaiboek* (No. 3105-0034-09871-260) [Internal company document].
- Veritas, D. N. (2011). *Modelling and analysis of marine operations* (Recommended Practice No. DNV-RP-H103). DNV. Høvik, Norway.
- Veritas, D. N. (2025). *Dnv-rp-c205: Environmental conditions and environmental loads* [Recommended Practice, Edition April 2025].
- Versteeg, H., & Malalasekera, W. (2007). *An introduction to computational fluid dynamics: The finite volume method* (2nd). Pearson Education.
- Vindenes, H., Orvik, K. A., Sjøiland, H., & Wehde, H. (2018). Analysis of tidal currents in the north sea from shipboard acoustic doppler current profiler data. *Continental Shelf Research*, 162, 1–12. <https://doi.org/10.1016/j.csr.2018.04.001>
- Vink, N., & Reijm, M. (2023, November). *Oosterweel warping & immersion system static and dynamic analysis* (23160X1-ME01 v3.0). mhpoly. Peter Vineloolaan 46b, Bergen op Zoom, The Netherlands.
- Vugts, J. H. (1968). The hydrodynamic coefficients for swaying, heaving and rolling cylinders in a free surface. *International Shipbuilding Progress*, 15(167), 251–276.
- Vuyk. (2025, April). *Afzinkcatamarans, structurele analyse*. Immontec.
- Welch, P. D. (1967). The use of fast fourier transform for the estimation of power spectra: A method based on time averaging over short, modified periodograms. *IEEE Transactions on Audio and Electroacoustics*, 15(2), 70–73. <https://doi.org/10.1109/TAU.1967.1161901>
- Yang, C., Weller, S. D., Wang, Y.-x., Ning, D.-z., & Johanning, L. (2017). Hydrodynamic response of a submerged tunnel element suspended from a twin-barge under random waves. *Ocean Engineering*, 135, 63–75. <https://doi.org/10.1016/j.oceaneng.2017.03.001>

- Yoshimura, H., Omori, Y., & Fujita, I. (2024). Numerical investigation of wind stress on surface velocity and vertical velocity profile in an open-channel flow. *Journal of JSCE*, 12(2).
- Zou, P. X., Bricker, J. D., Chen, L. Z., Uijtewaal, W. S. J., & Ferreira, C. S. (2022). Response of a submerged floating tunnel subject to flow-induced vibration. *Engineering Structures*, 253, 113809. <https://doi.org/10.1016/j.engstruct.2021.113809>
- Zou, P. (2022, March). *Dynamic response of a submerged floating tunnel subject to hydraulic loading: Numerical modelling for engineering design* [Doctoral dissertation, Technische Universiteit Delft] [Proefschrift (Doctoral dissertation)]. <http://repository.tudelft.nl/>



Data analysis

A.1. Frequency analysis

This section provides additional frequency analysis to support the choice of the cut off frequency of 0.07 Hz.

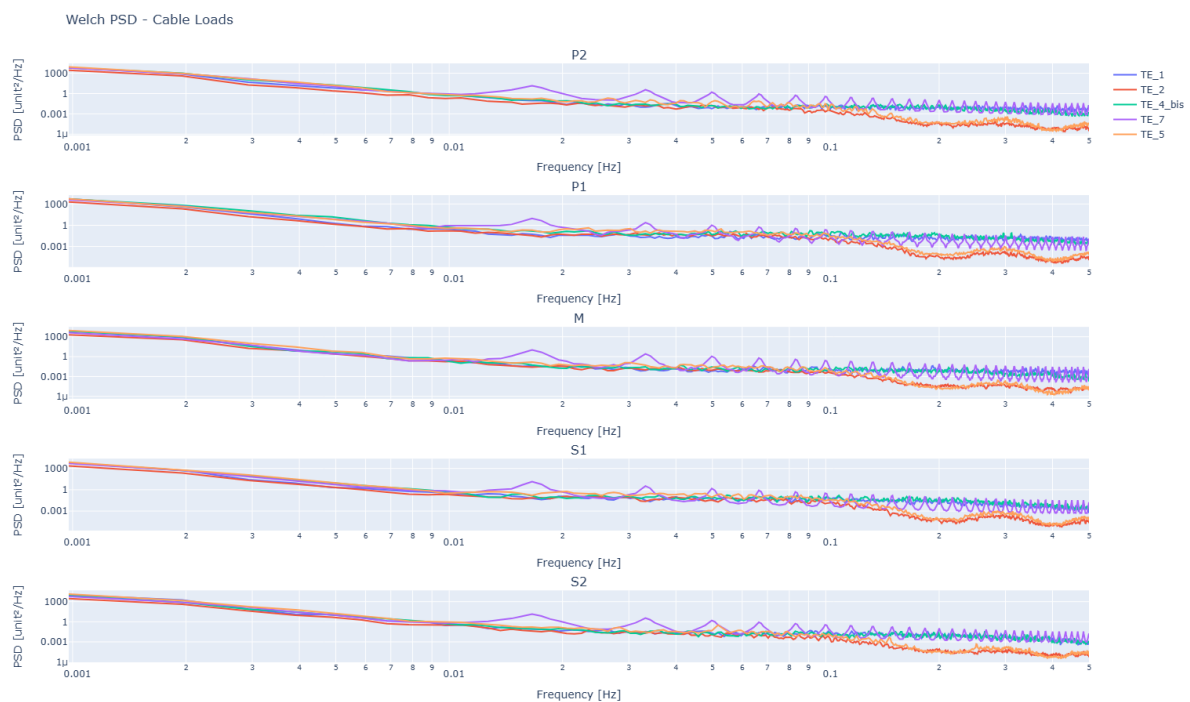


Figure A.1: Power spectral density of the individual tanklevels for all immersion sequences, estimated using Welch's method with a segment length of 1024 samples.

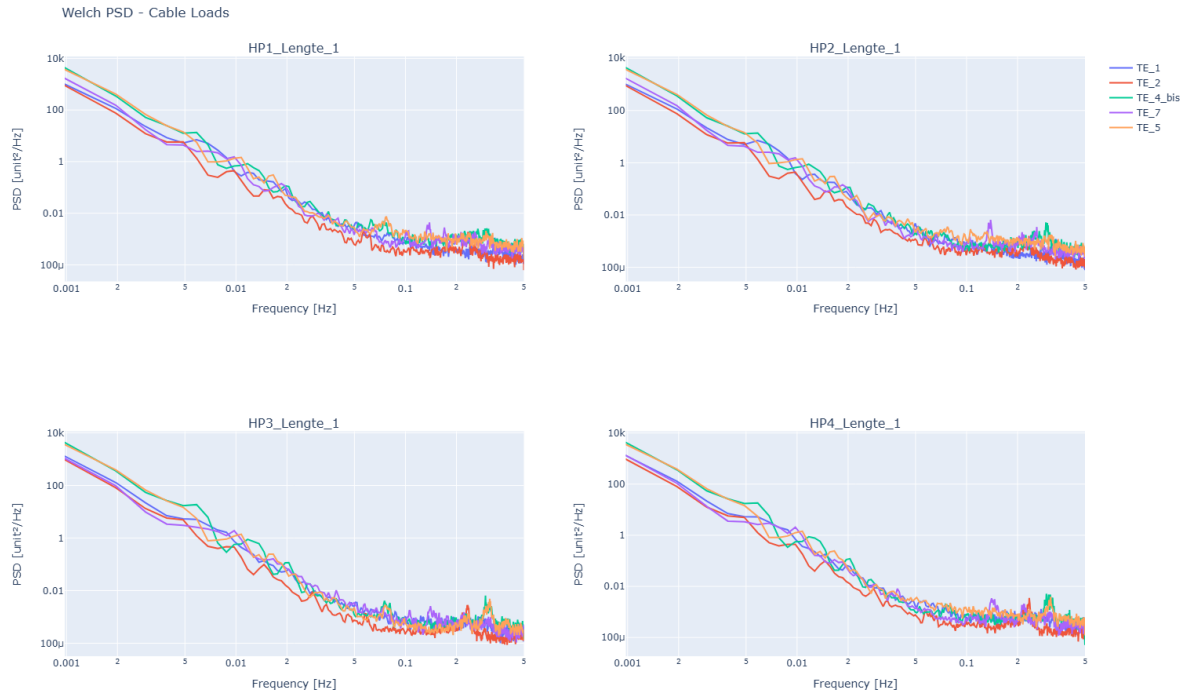


Figure A.2: Power spectral density of the individual cable lengths for all immersion sequences, estimated using Welch's method with a segment length of 1024 samples.

A.2. Element correlations

This section shows the element correlations for the individual input variables. The following variables are considered: total tank weight Table A.1, cable length Table A.2 and the water density Table A.3. Averaging the element correlation of Table A.1 would result in the table shown in Chapter 4.

Table A.1: Per-element correlation statistics between total tank weight and average cable load for the full sequence, pre-immersion and post-immersion phases.

Element	Phase	Pearson r	Spearman ρ	R^2
TE_1	Full	0.906	0.919	0.820
	Pre	0.992	0.968	0.984
	Post	0.876	0.832	0.768
TE_2	Full	0.182	-0.010	0.033
	Pre	0.842	0.745	0.709
	Post	0.132	0.463	0.017
TE_4_bis	Full	0.893	0.643	0.797
	Pre	0.965	0.901	0.931
	Post	0.583	0.219	0.340
TE_5	Full	0.722	0.298	0.521
	Pre	0.994	0.958	0.988
	Post	0.115	0.221	0.013
TE_8	Full	0.621	0.484	0.386
	Pre	0.996	0.818	0.993
	Post	0.765	0.939	0.585
TE_7	Full	0.831	0.662	0.690
	Pre	0.971	0.840	0.942
	Post	0.160	0.039	0.026
Mean	Full	0.692	0.499	0.541
	Pre	0.960	0.872	0.924
	Post	0.439	0.452	0.292

Table A.2: Per-element correlation statistics between average cable length and average cable load for the full sequence, pre-immersion and post-immersion phases.

Element	Phase	Pearson r	Spearman ρ	R^2
TE_1	Full	0.757	0.960	0.573
	Pre	0.667	0.931	0.445
	Post	0.764	0.965	0.584
TE_2	Full	-0.076	-0.065	0.006
	Pre	0.187	0.570	0.035
	Post	0.311	0.431	0.097
TE_4_bis	Full	0.531	0.499	0.282
	Pre	0.690	0.843	0.476
	Post	0.178	-0.170	0.032
TE_5	Full	0.140	0.063	0.020
	Pre	0.317	0.293	0.101
	Post	-0.265	-0.141	0.070
TE_8	Full	-0.427	-0.348	0.182
	Pre	0.420	0.881	0.177
	Post	-0.888	-0.988	0.788
TE_7	Full	0.430	0.558	0.185
	Pre	0.346	0.708	0.120
	Post	-0.137	-0.188	0.019
Mean	Full	0.226	0.278	0.208
	Pre	0.438	0.704	0.225
	Post	-0.006	-0.015	0.265

Table A.3: Per-element correlation statistics between water density and average cable load for the full sequence, pre-immersion and post-immersion phases.

Element	Phase	Pearson r	Spearman ρ	R^2
TE_1	Full	−0.719	−0.830	0.517
	Pre	0.744	0.620	0.554
	Post	−0.984	−0.969	0.969
TE_2	Full	0.015	−0.202	0.000
	Pre	0.246	−0.081	0.060
	Post	−0.465	−0.491	0.217
TE_4_bis	Full	0.707	0.504	0.500
	Pre	0.948	0.887	0.899
	Post	0.117	−0.165	0.014
TE_5	Full	0.158	0.004	0.025
	Pre	−0.517	−0.380	0.267
	Post	−0.102	−0.141	0.010
TE_8	Full	0.189	−0.117	0.036
	Pre	0.889	0.754	0.791
	Post	−0.833	−0.867	0.694
TE_7	Full	0.356	0.377	0.127
	Pre	−0.719	−0.769	0.517
	Post	−0.160	−0.191	0.026
Mean	Full	0.118	−0.044	0.201
	Pre	0.265	0.172	0.515
	Post	−0.405	−0.471	0.322

A.3. Full calculation cut off validation

This appendix supports the cut-off validation reported in Section 4.4. It first lists, for each tunnel element and each of the four submergence levels, the input data used in the calculation (Tables A.4 to A.10). It then summarises the equations used (Section A.3.2) and finally reports the resulting frequency ranges across all six elements and four depths (Tables A.11 to A.15, A.17 and A.18).

A.3.1. Input data

The system properties that are independent of element or depth are listed in Table A.4.

Table A.4: Constant system properties used in the cut-off validation.

Quantity	Symbol	Value
<i>Cable</i>		
Young's modulus	E	105 000 N/mm ²
diameter	D_{cable}	46 mm
Fill factor	μ	0.46
Initial length	L_0	49.62 m
Pulleys per HP	$n_{pulleys}$	8
Number of HP	n_{hp}	4
Mass per metre	m'_{cable}	8.5 kg/m
<i>Pontoon</i>		
Length	L_{pon}	36.9 m
Width	B_{pon}	9.6 m
Weight per catamaran	M_{pon}	782 ton
Number of pontoons	n_{pon}	4
<i>Element</i>		
Length	L_{el}	159.9 m
Width	W_{el}	40 m
Height	H_{el}	9.9 m
Empty weight	M_{el}	63209.7 ton
I_{yy} (pitch axis)	I_{yy}	1.16×10^8 ton m ²
I_{xx} (roll axis)	I_{xx}	1.49×10^7 ton m ²
Pitch lever arm	d_{pitch}	50 m
Roll lever arm	d_{roll}	20 m
Added-mass coeff. (heave)	$C_{a,heave}$	2.0 (Veritas, 2011)
Added-inertia coeff. (pitch)	$C_{a,pitch}$	0.025 (Vugts, 1968)
Added-inertia coeff. (roll)	$C_{a,roll}$	0.044 (Vugts, 1968)
<i>Ballast tanks (Figure 3.6)</i>		
Large tanks length	L_{large}	34.5 m
Small tanks length	L_{small}	11 m
Tank width	W_{tank}	14.5 m

The depth-dependent inputs are reported per element in Tables A.5 to A.10. The four depth levels are: freeboard 0.1 m , 1/3 of the final depth, 2/3 of the final depth and final position.

Table A.5: Total cable length L [m] per element and submergence level.

Element	freeboard 0.1	1/3	2/3	3/3
TE1	49.62	79.08	108.54	137.99
TE2	49.62	89.46	129.29	169.13
TE4bis	49.62	104.19	158.76	213.33
TE5	49.62	98.09	146.55	195.02
TE7	49.62	86.37	123.11	159.86
TE8	49.62	75.76	101.90	128.04

Table A.6: Total ballast mass $M_{ballast}$ [ton] per submergence level.

Element	freeboard 0.1	1/3	2/3	3/3
TE1	1912	2553	2552	2559
TE2	1656	2174	2174	2175
TE4bis	1810	2199	2196	2279
TE5	1482	2225	2365	2487
TE7	1698	2073	2203	2328
TE8	1639	2204	2204	2201

Table A.7: Water density ρ_w [kg/m³] at the element location per submergence level.

Element	freeboard 0.1	1/3	2/3	3/3
TE1	1005.7	1005.2	1004.6	1002.2
TE2	1006.3	1005.8	1005.7	1002.0
TE4bis	1003.1	1004.7	1005.4	1006.8
TE5	998.8	999.8	1001.1	1004.0
TE7	998.7	999.9	1002.3	1003.2
TE8	1000.7	1004.3	1004.6	1004.3

Table A.8: Current velocity U [m/s] at the element location per submergence level.

Element	freeboard 0.1	1/3	2/3	3/3
TE1	0.123	0.542	0.503	0.101
TE2	0.439	0.489	0.484	0.000
TE4bis	0.723	0.759	0.341	0.310
TE5	0.164	0.664	0.400	0.136
TE7	0.137	0.407	0.409	0.231
TE8	0.603	0.330	0.260	0.113

Table A.9: Cable load F [ton] per cable, per submergence level.

Element	freeboard 0.1	1/3	2/3	3/3
TE1	105.0	133.8	137.1	156.7
TE2	119.5	92.3	95.4	109.2
TE4bis	111.5	132.8	115.0	99.0
TE5	119.7	126.5	137.0	114.2
TE7	124.0	98.0	103.5	97.3
TE8	117.8	119.8	105.5	88.0

Table A.10: Ballast water depth in the small tanks (S) and large tanks (L) [cm] per submergence level.

Element	freeboard 0.1		1/3		2/3		3/3	
	S	L	S	L	S	L	S	L
TE1	130	126	190	160	189	160	189	161
TE2	119	106	151	142	151	142	141	146
TE4bis	127	117	136	151	134	152	139	158
TE5	110	93	163	141	167	153	175	161
TE7	120	109	130	141	140	150	149	158
TE8	118	105	152	144	152	144	152	144

A.3.2. Cut off validation extended

For each element and case the natural frequencies of the three degrees of freedom (heave, pitch roll) are computed under the same assumptions used in the worked example of Section 4.4: a linear, un-damped, single degree of freedom mass spring system, the added mass coefficient held constant with depth, and the hydrostatic stiffness of the element waterplane retained only in the freeboard configuration.

The cable spring stiffness for one HP follows from:

$$K_{cable} = \frac{n_{pulleys} \cdot E \cdot A}{L} \quad (A.1)$$

with L taken from Table A.5. The floater stiffness follows from

$$K_{floater} = \rho_w g A_{w,pon} \quad (A.2)$$

With ρ_w taken from Table A.7. For heave the total stiffness is the series combination of the four cables, the four floaters and the spring stiffness of the pontoon, in parallel with the element waterplane stiffness in the freeboard case only. For pitch and roll each spring contribution is multiplied by d^2 , where d is the lever arm from the rotation axis to the lifting point ($d_{pitch} = 50$ [m], $d_{roll} = 20$ [m], Table A.4).

The total mass for heave is equal to

$$M_{tot} = n_{pon} M_{pon} + M_{el} + M_{ballast} + C_a \rho_w V_{sub} \quad (A.3)$$

With $M_{ballast}$ from Table A.6 and V_{sub} the submerged volume of the element at the given depth, which constant for 1/3, 2/3 and final depth. For pitch and roll the mass is replaced by the moment of inertia I_{yy} or I_{xx} from Table A.4. The natural frequency of each mode then follows from

$$f_n = \frac{1}{2\pi} \sqrt{\frac{K_{tot}}{M_{tot}}} \quad (A.4)$$

The cable natural frequency is computed from:

$$f_{n,cable} = \frac{n}{2L} \sqrt{\frac{F}{m_{cable}}} \quad (A.5)$$

With F from Table A.9, the inter-pulley length L following from Table A.5 dividing by 8, n the mode number and m the cable weight per meter Table A.4. The viv frequency of the cable follows from

$$f_s = \frac{St \cdot U}{D_{cable}} \quad (A.6)$$

with $St = 0.2$ (Veritas, 2011); the shedding frequency of the element uses the same expression with the element height as the characteristic dimension and $St = 0.13$. The sloshing frequencies of the small and large ballast tanks follow from:

$$\omega = k\sqrt{gh} \quad (A.7)$$

with $k = \pi/L_{tank}$ and h the lowest ballast water level reached during the operation (Table A.10).

A.3.3. Results

Table A.11: Heave natural frequency $f_{n,heave}$ [Hz] per element and submergence level.

Element	freeboard 0.1	1/3	2/3	3/3
TE1	0.0751	0.0301	0.0289	0.0279
TE2	0.0751	0.0297	0.0282	0.0270
TE4bis	0.0750	0.0291	0.0273	0.0258
TE5	0.0749	0.0293	0.0276	0.0262
TE7	0.0748	0.0298	0.0284	0.0272
TE8	0.0749	0.0302	0.0292	0.0283

Table A.12: Pitch natural frequency $f_{n,pitch}$ [Hz] per element and submergence level.

Element	freeboard 0.1	1/3	2/3	3/3
TE1	0.1601	0.0622	0.0590	0.0562
TE2	0.1602	0.0610	0.0570	0.0536
TE4bis	0.1599	0.0594	0.0545	0.0506
TE5	0.1596	0.0600	0.0554	0.0518
TE7	0.1596	0.0612	0.0575	0.0544
TE8	0.1598	0.0626	0.0596	0.0571

Table A.13: Roll natural frequency $f_{n,roll}$ [Hz] per element and submergence level.

Element	freeboard 0.1	1/3	2/3	3/3
TE1	0.1047	0.0713	0.0676	0.0644
TE2	0.1047	0.0700	0.0654	0.0615
TE4bis	0.1046	0.0681	0.0625	0.0580
TE5	0.1044	0.0687	0.0635	0.0594
TE7	0.1043	0.0702	0.0659	0.0623
TE8	0.1044	0.0717	0.0684	0.0655

Table A.14: Cable shedding frequency $f_{s,cable} = StU/D_{cable}$ [Hz], with $St = 0.2$ and $D_{cable} = 46$ mm. Values track the current velocity (Table A.8); the value 0.00 at TE2 final corresponds to slack current.

Element	freeboard 0.1	1/3	2/3	3/3
TE1	0.53	2.36	2.19	0.44
TE2	1.91	2.13	2.10	0.00
TE4bis	3.14	3.30	1.48	1.35
TE5	0.71	2.89	1.74	0.59
TE7	0.60	1.77	1.78	1.00
TE8	2.62	1.43	1.13	0.49

Table A.15: Cable natural frequency $f_{n,cable}$ [Hz] in mode 1.

Element	freeboard 0.1	1/3	2/3	3/3
TE1	10.08	4.91	3.46	2.83
TE2	9.74	5.06	3.09	2.13
TE4bis	10.09	5.25	3.65	2.51
TE5	10.27	5.24	3.78	2.82
TE7	10.01	6.61	4.61	3.35
TE8	10.08	4.91	3.46	2.83

Table A.16: Cable natural frequency $f_{n,cable}$ [Hz] in mode 2.

Element	freeboard 0.1	1/3	2/3	3/3
TE1	18.89746	13.38445	9.872859	8.300512
TE2	20.16002	9.82515	6.912066	5.654964
TE4bis	19.47491	10.11974	6.18118	4.268086
TE5	20.1811	10.49314	7.308676	5.015559
TE7	20.53618	10.48895	7.562174	5.645263
TE8	20.01195	13.21828	9.224455	6.704378

Table A.17: Element shedding frequency $f_{s,element} = St U / H_{el}$ [Hz], with $St = 0.13$ and $H_{el} = 9.9$ m.

Element	freeboard 0.1	1/3	2/3	3/3
TE1	0.0016	0.0071	0.0066	0.0013
TE2	0.0058	0.0064	0.0064	0.0000
TE4bis	0.0095	0.0100	0.0045	0.0041
TE5	0.0022	0.0087	0.0053	0.0018
TE7	0.0018	0.0053	0.0054	0.0030
TE8	0.0079	0.0043	0.0034	0.0015

Table A.18: Lowest sloshing frequency f_{slosh} [Hz] for the small (S) and large (L) ballast tanks, computed from the shallow-water dispersion relation with h taken from Table A.10.

Element	freeboard 0.1		1/3		2/3		2/3	
	S	L	S	L	S	L	S	L
TE1	0.258	0.081	0.312	0.091	0.312	0.091	0.312	0.092
TE2	0.247	0.074	0.278	0.086	0.278	0.086	0.269	0.087
TE4bis	0.256	0.078	0.264	0.089	0.262	0.089	0.267	0.091
TE5	0.238	0.070	0.290	0.086	0.293	0.089	0.300	0.092
TE7	0.249	0.076	0.259	0.086	0.268	0.088	0.276	0.091
TE8	0.247	0.074	0.279	0.087	0.279	0.087	0.279	0.087

The ranges from these tables are reported in the summary table of Section 4.4 (Table 4.3).

B

2DOF System derivation

B.1. 2DOF system derivation

$$\begin{bmatrix} m_e + m_a & 0 \\ 0 & m_p m \end{bmatrix} \begin{Bmatrix} \ddot{x}_1 \\ \ddot{x}_2 \end{Bmatrix} + C \begin{Bmatrix} \dot{x}_1 \\ \dot{x}_2 \end{Bmatrix} + \begin{bmatrix} k_{tot} & -k_{tot} \\ -k_{tot} & k_{tot} + k_w \end{bmatrix} \begin{Bmatrix} x_1 \\ x_2 \end{Bmatrix} = \begin{Bmatrix} -m_e \ddot{a} \\ 0 \end{Bmatrix} \quad (\text{B.1})$$

Then the system has to be reduced in order, therefore the acceleration terms need to be isolated, everything will be multiplied with the inverse of the mass matrix:

$$\ddot{x} + M^{-1}C\dot{x} + M^{-1}kx = M^{-1}F \quad (\text{B.2})$$

rearranging brings:

$$\ddot{x} = -M^{-1}C\dot{x} - M^{-1}kx + M^{-1}F \quad (\text{B.3})$$

Now we define a state z that stacks velocity and this displacement

$$z = \begin{bmatrix} x \\ \dot{x} \end{bmatrix} = \begin{bmatrix} x_1 \\ x_2 \\ \dot{x}_1 \\ \dot{x}_2 \end{bmatrix} \quad (\text{B.4})$$

taking the first order derivative of this state vector results in:

$$\dot{z} = \begin{bmatrix} \dot{x} \\ \ddot{x} \end{bmatrix} = \begin{bmatrix} \dot{x}_1 \\ \dot{x}_2 \\ \ddot{x}_1 \\ \ddot{x}_2 \end{bmatrix} \quad (\text{B.5})$$

and now we can fill in $\ddot{x}$ from Equation (B.3). Resulting in:

$$\dot{z} = \begin{bmatrix} \dot{x} \\ -M^{-1}C\dot{x} - M^{-1}kx + M^{-1}F \end{bmatrix} \quad (\text{B.6})$$

Now want to find $\dot{z} = Az + b$ Resulting in:

$$\begin{bmatrix} \dot{x} \\ -M^{-1}C\dot{x} - M^{-1}kx + M^{-1}F \end{bmatrix} = \begin{bmatrix} 0 & I \\ -M^{-1}k & -M^{-1}C \end{bmatrix} \begin{bmatrix} x \\ \dot{x} \end{bmatrix} + \begin{bmatrix} 0 \\ M^{-1}F \end{bmatrix} \quad (\text{B.7})$$

The final matrix then for A :

$$A = \begin{bmatrix} 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \\ -k_{tot}/m & k_{tot}/m & C_{11}/m & C_{12}/m \\ k_{tot}/M_p & -(k_{tot} + K_h)/M_p & C_{21}/M_p & C_{22}/M_p \end{bmatrix}, \quad b = \begin{bmatrix} 0 \\ 0 \\ -a \\ 0 \end{bmatrix}. \quad (\text{B.8})$$