Master's thesis

NTNU
Norwegian University of Science and Technology
Faculty of Engineering
Department of Structural Engineering

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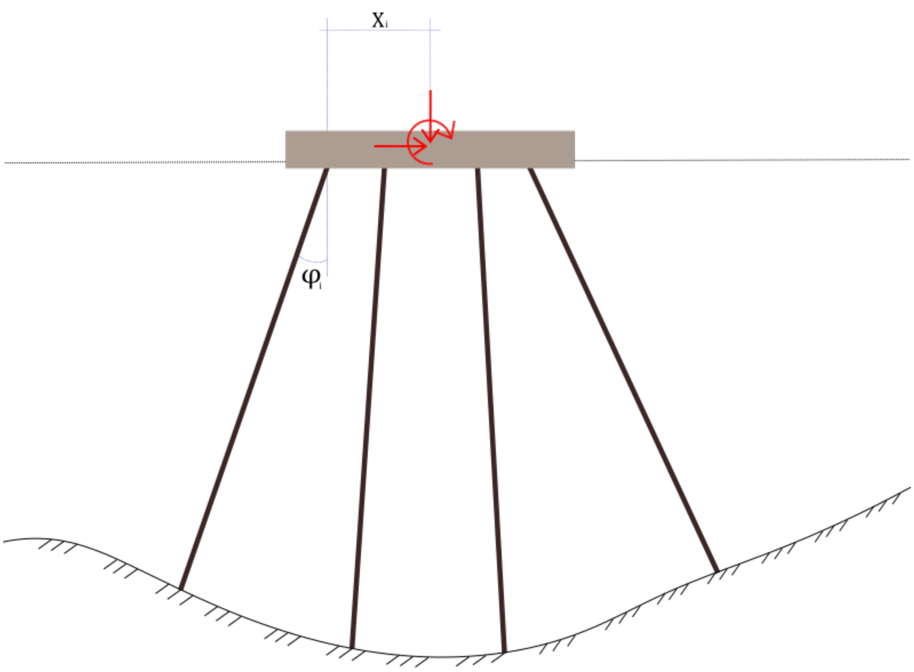
Structural Optimization of Pile Foundation with the use of Generative Design and Machine Learning.

Master's thesis in Civil and Environmental Engineering

Supervisor: Nils Erik Anders Rønnquist

June 2020



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Structural Optimization of Pile Foundation with the use of Generative Design and Machine Learning.

Optimalisering av pelegruppe ved bruk av generativ design og maskinlæring.

BY:

Martin Wilhelmsen

SUMMARY:
The goal of this thesis has been to define and quantify what is regarded as an optimal design of a point bearing pile foundation, how it could be achieved and how ML can make the design process more efficient as well as contribute to better designs. The work of this master thesis is based on a combination of qualitative and quantitative research methodology. It starts with an overview on how to design pile foundations, followed by Structural Optimization and ML.

The results indicate that an optimal design of a pile foundation can be characterised with an antisymmetric, fan like, formation of the piles with an as small as possible diameter. This thesis found the Adaptive Genetic Algorithm to be superior in speed compared to other methods, with a moderately loss of accuracy. With the Random Forest Regressor showing a marginal superiority, a ML model with an acceptable level of accuracy has not been possible to achieve in this thesis. How Norconsult can obtain a functional ML model in the future is therefore presented in the end of this thesis.

RESPONSIBLE TEACHER: Nils Erik Anders Rønnquist

SUPERVISOR(S): Jan Roar Steinnes

CARRIED OUT AT: Department of Structural Engineering, NTNU, Trondheim and Bridge Department at Norconsult AS, Sandvika.

Preface

This master thesis was written as a final part of my Master of Science Degree at the Norwegian University of Science and Technology (NTNU), department of structural engineering. The work has been carried out from January to June 2020.

During my years at NTNU I particularly grew an interest in the courses regarding structural engineering, such as structural mechanic, dynamic and the Finite Element Method courses. During a summer intern at Norconsult I was introduced to parametric modelling and was quickly fascinated by this type of design method. This made me indecisive in the choice between computational mechanic or conceptual structural design as my main study, so I decided to do both. In the conceptual structural design course, I was introduced to Artificial Intelligence in the construction industry by a lecture, held by Nathalie Labonnote, and decided that is was something I would like to learn more about. With this, and the introduced issue from Norconsult, the choice to write about Structural Optimization and Machine Learning fell naturally.

I would like to express my sincere gratitude to my supervisor Professor Nils Erik Anders Rønnquist and all staff of the Conceptual Structural Design Group at NTNU. Thank you, Marcin Luczkowski and Nathalie Labonnote for interesting and educational lectures during last semester. Thank you, Nils Erik Anders Rønnquist, for interesting discussion and all your inspiration during this semester.

Finally, a sincere gratitude to the people (soon colleagues) at the bridge department at Norconsult AS. Without your helpful discussions, friendly coffee breaks and lifting spirit the work on this thesis would not be the same. A special thank you to Henrik Skyvulstad, Jan Roar Steinnes, Anders Ørmen and Tor Martin Lystad.

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Abstract

This master thesis deals with structural optimization of a pile foundation with the use of a Generative Design (GD) approach and Machine Learning (ML). The goal of this thesis has been to define and quantify what is regarded as an optimal design of a point bearing pile foundation, how it could be achieved and how ML can make the design process more efficient as well as contribute to better designs.

The work of this master thesis is based on a combination of qualitative and quantitative research methodology, with an overview on how to design pile foundations, followed by Structural Optimization and ML. The work is limited to theoretical analyses carried out in OpenSeesPy with substantial use of Python programming. The design process was performed according to the criteria given in the Eurocodes and from the Norwegian Public Roads Administration manuals, as well as the Norwegian committee on piles guidance.

The results indicate that an optimal design of a pile foundation can be characterised with an antisymmetric, fan like, formation of the piles with an as small as possible diameter.

Numerous different optimization methods has been tried out, trying to decrease the computational time for the problem at hand. This thesis found the Adaptive Genetic Algorithm to be superior in speed compared to other methods, with a moderately loss of accuracy.

Various type of ML models and extensively tweaking of parameters where tried out, trying to create a well functional ML model. With the Random Forest Regressor showing a marginal superiority, an acceptable level of accuracy has not been possible to achieve in this thesis. Proving the huge amount of available, high quality, Training Data (TD) needed for ML. How Norconsult can obtain a functional ML model in the future is therefore presented in the end of this thesis.

Sammendrag

Denne masteroppgaven handler om optimalisering av pelegruppe ved bruk av generativ design og maskinlæring. Formålet med denne oppgaven har vært å definere og kvantifisere hva et optimalt design av en spissbærende pelegruppe er, hvordan dette kan oppnås og hvordan maskinlæring kan effektivisere design prosessen og i tillegg bidra til bedre design.

Arbeidet med denne masteroppgaven baserer seg på en kombinasjon av kvalitative og kvantitativ metode, med en oversikt over hvordan man dimensjonerer pelegrupper, etterfulgt av optimalisering og maskinlæring. Arbeidet er begrenset til teoretiske analyser i OpenSeesPy og utlagt bruk av Python programmering. Dimensjoneringen er utført i henhold til designkriteriene gitt i Eurokodene og fra Statens vegvesens manualer, samt den norske pelekomites veileder.

Resultatene indikerer at et optimalt design av en pelegruppe kan karakteriseres ved en antisymmetrisk, vifteformasjon av pelene, med en så liten diameter som mulig.

En rekke forskjellige optimaliseringsmetoder har vært prøvd ut, i et forsøk på å redusere beregningstiden for problemet. Denne oppgaven har funnet adaptive genetiske algoritmer til å ha overlegen hastighet i forhold til de andre metodene, med et moderat tap av nøyaktighet.

Forskjellige typer maskinlæringsmodeller og omfattende justering av parametere har blitt testet, i et forsøk på å lage en velfungerende maskinlæringsmodell. Med Random Forest Regressor modellens marginale overlegenhet, har ett akseptabelt nivå av nøyaktighet ikke vært mulig å oppnå i denne oppgaven. Dette bevisstgjør den enorme mengden av tilgjengelig, høykvalitets, treningsdata som er nødvendig til maskinlæring. Hvordan Norconsult kan oppnå en velfungerende maskinlæringsmodell i fremtiden er derfor presentert i slutten av denne oppgaven.

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Abbreviations

Symbol	Description
FEA	Finite Element Analysis.
FEM	Finite Element method.
AEC	Architecture, Engineering and construction industry.
DOF	Degrees of Freedom.
AI	Artificial Intelligence.
ML	Machine Learning.
TD	Training Data.
GD	Generative Design.
GA	Genetic Algorithm.
AGA	Adaptive Genetic Algorithm.
CR	Crossover Rate.
MR	Mutation Rate.

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1 Introduction

1.1 Background

Structural engineering has stood the time from the pyramids to the modern ages. The first structural engineer dates to 2700 B.C.E. [1] when the step pyramid for Pharaoh Djoser was built. Throughout the ancient and medieval history, architectural design and construction was carried out by skill craft workers such as stone masons and carpenters. No theory of structures existed and understanding of how structures worked and managed to stand was extremely limited. It was almost solely based on empirical evidence of what had worked before. Structures were repetitive and increases in scale was incremental. In Figure 1 we see the pyramids of Pharaoh Djoser (left) and the pyramids of Giza (right), which showcase how structures was scaled. A pyramid is inherently stable and can almost be infinitely scaled, as opposed to most other structures which cannot be linearly increased in size proportion to increased loads.

Figure 1-1: Pyramid of Pharaoh Djoser (left) [49] and Pyramids of Giza (right) [50].

The physical sciences underlying structural engineering first began to be understood in the Renaissance and has been developing ever since. The first real theoretical understanding of the behaviour of structural material and the strength of structural members was carried out by Galileo Galilei in the 17-century [2]. His work "Dialogues Relating to Two New Sciences" from 1638 marks the beginning of structural analysis. Later significant work includes:

- Hooke's Law by Robert Hook in 1676
- "Philosophiae Naturalis Principia Mathematica" by Sir Isaac Newton in 1687
- Euler-Bernoulli beam equation by Leonhard Euler and David Bernoulli in 1750
- The mathematically formulation of general theory of elasticity by Claude-Louise Navier in 1821.

In the 19-century new material like reinforced concrete, steel and prestressed concrete pushed the boundary of what was possible. As time progressed the structures got thinner, curvier and more complex. The demands on the structural engineer increased and lead to the need for more accurate calculations. With this, and the rise of the computer, a new way of calculating structures began to rise. Figure 1-2 shows the Sydney Opera House. Its curvy roof created the need for complex and accurate calculations.

Figure 1-2: The Sydney Opera House with its curvy roof [3].

Finite Element Method (FEM)

In 1956 the paper "Stiffness and Deflection of Complex Structures" was published. It introduced the name "Finite Element Method" (FEM) which is still regarded at the first comprehensive treatment of the method today. The development of Finite Element Analysis (FEA) programs enabled structural engineers to predict the stresses in complex structures accurately. Figure 1-3 shows the results of a FEA where the stresses is plotted as a colour plot.

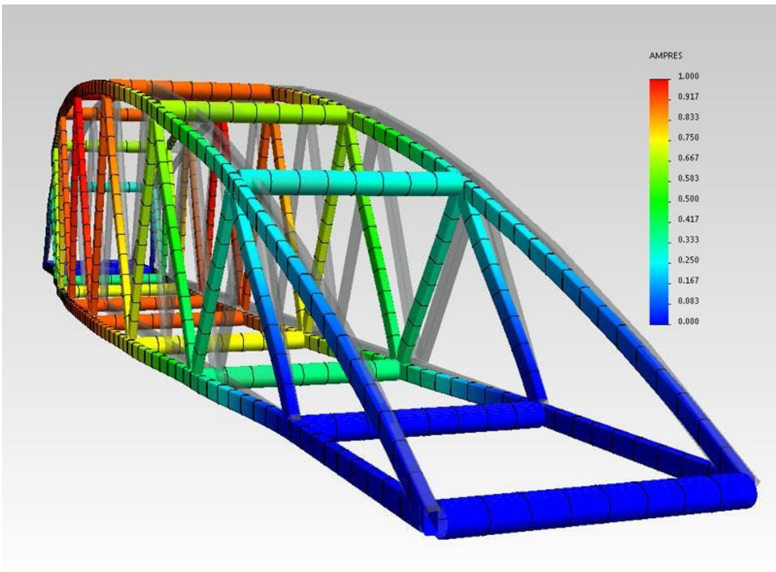

Figure 1-3: FEA result of a bridge [4].

While the FEM only predict the stresses in the structures accurately, it does not define if the design of the structure is good or not. The geometrical configuration of the structure greatly affects its structural properties. Traditionally the geometry is decided by the architect, and the structural engineer is left with the job of making the design work. Since the two aspect of the structure greatly affect each other, it cannot be separated from each other. By setting the geometry early, it leaves no room for the architect and engineer to play around with the form and shape together. To ensure an early collaboration, common and iterative modelling tools was developed.

Parametric Design

The idea of parametric design is to ensure an early collaboration between architects and engineers, with the ability to feed information directly into production machines like 3D printers and computer numerical controlled (CNC) machines. Parametric design is referred to design obtained with the use of some varying parameters optimising the structural expression, structural integrity and performance. In parametric design and modelling the variables will serve a hierarchy of mathematical and geometric relations which will immediately obtain possibly complex results in addition to enable multiple design option. An example where the synergy between shape and structural integrity are showcased is parametric shells. For a thin shell to be structurally sound and to minimise lateral forces on the footings, it generally must be doble curved. In order to obtain these shapes a form finding method must be used. Figure 1-4 shows an ultra-thin concrete shell where form finding algorithms was used to get the shape. The shell was created with a knitted formwork weighing just 55 kg and was developed at ETH Zürich [5].

Figure 1-4: KnittCandela, an ultra-thin concrete shell by researchers at ETH Zürich [5].

A form finding method or an optimization routine in order to minimize bending forces can be tidies and computer power demanding. In an era when our resources get scarce, an optimization routine gets more and more common. We are then left with a big dataset which can be used to increase our knowledge about structures and to make better prediction on the initial design.

Artificial intelligent (AI) in structural analysis

In order to speed up the process of optimization and to benefit from the dataset, AI could be used. AI is a computational method attempting to simulate human cognition capability through symbol manipulation and symbolically structured knowledge [6]. There has been a growing interest in the use of AI in engineering the recent years. Many AI branches has been used in structural engineering, such as: machine learning (ML), pattern recognition, neural networks, fuzzy logic, evolutionary computation, deep learning, expert systems probability theory, discriminant analysis, swarm optimization, metaheuristic optimization and decision trees. These has been used for the purpose of structural health monitoring (SHM)/damage detection, optimization, performance evaluation, structural reliability and structural parameter identification [6]. AI also make it possible to save time in otherwise time-consuming tasks. ML has been used to automate the steel connections detailing in a BIM model. The machine designed over 70% of the connections successfully without human intervention [7]. Figure 1-5 shows an overview of the process.

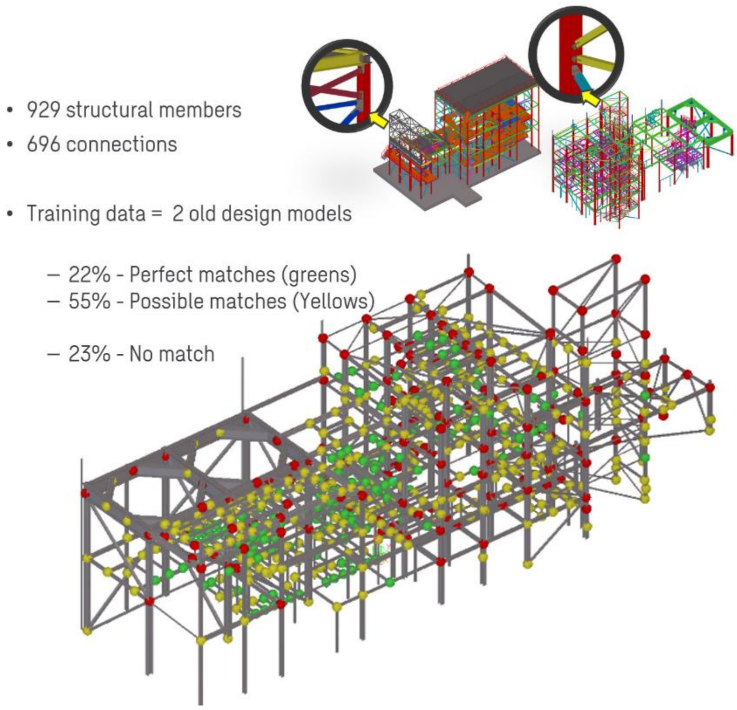

Figure 1-5: Structure where ML was used for steel connection design [8].

For a structure of this size and complexity, almost 50% of the time goes to design of connections [9]. Automation reduces this time significantly, and eventually, get rid of it altogether. AI-powered tools can provide better quality, be more productive and profitable, and do thing that were not possible in the past.

The productivity of the 10-trillion-dollar Architecture, Engineering and Construction (AEC) industry has not increase noticeably over the last 20 years [9]. With the large possibility of increased efficiency and the emerging trend of BIM models, making it possible to use the digital information for quantitative research and providing more accessible and structured data, AI could be the solution to untangle the lag AEC industry is facing.

1.2 Goal of this thesis

The goal of this thesis is to learn what an optimal solution of a pile foundation is, which variables regarding this are of most importance and how ML can be used to make the design process more efficient and contribute to better designs. To do this a case study of a pile foundation was chosen. The case study was introduced, to the writer, by a Norwegian consultancy firm, Norconsult AS. For further description of the case-study see chapter *1.2.1 Case-study: Råna bridge,* below.

A pile foundation provides a multi variable problem, as many other structures are. This makes a pile foundation a good test object and will make transferable results. Norconsult design hundreds of pile foundations in their projects every year. Usually, the design that is chosen is the first that satisfies the design requirements from N400, with moderately adjustment in order to try to optimize the design. The reason for this is because a pile foundation, and how every parameters are affecting each other, is difficult to predict and interpret.

The primary aim of this thesis is then to learn more about design of pile foundation and to see how ML can serve as a design tool in order to come up with better and more optimal design. The goal is to end up with a digital helper that learn from optimal designs and can help engineers in the future to better design pile foundations. The aim for this thesis is therefore to answer the following research questions:

Research questions:

- What characterises an optimal design of pile foundation?
- How can optimal design of pile foundations be achieved?
- How can ML help engineers in making better designs of pile foundation and to make the design process more efficient?

Norconsult would like to see how their process on designing pile foundation could be improved with the use of ML. A collected view on the research question and the issue from Norconsult could be preserved in the following main issue for this thesis:

- *How to ensure an optimal solution of a pile foundation, regarding structural properties, economic and buildability, with the use of machine learning.*

The research questions try to break down and emphasize the main issue that Norconsult has for this thesis.

1.2.1 Case-study: Råna bridge

In order to answer the questions addressed in the previous chapter and to make the result of this thesis useful for Norconsult, a case study on a previously project by Norconsult was chosen. This will serve as the calculation model in order to preserve the results in something real.

The case study is a pile foundation of a bridge. Specifically, the pile foundation of a prestressed beam bridge situation near Arendal in the project E18 Tvedestrand – Arendal, "Råna bru". The pile foundation in axis 3 will serve as a model in the optimization part and will be altered to serve as training data for the ML part. The figures bellow shows an overview of the bridge.

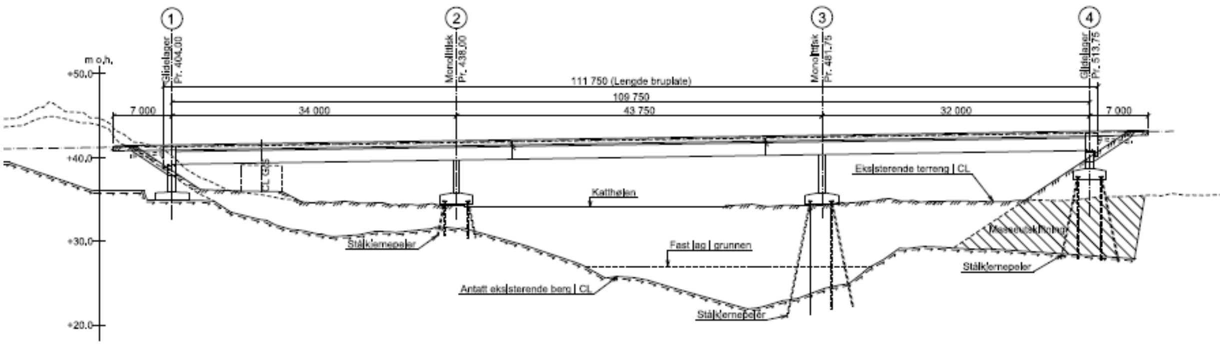

Figure 1-6: Elevation of Råna bridge.

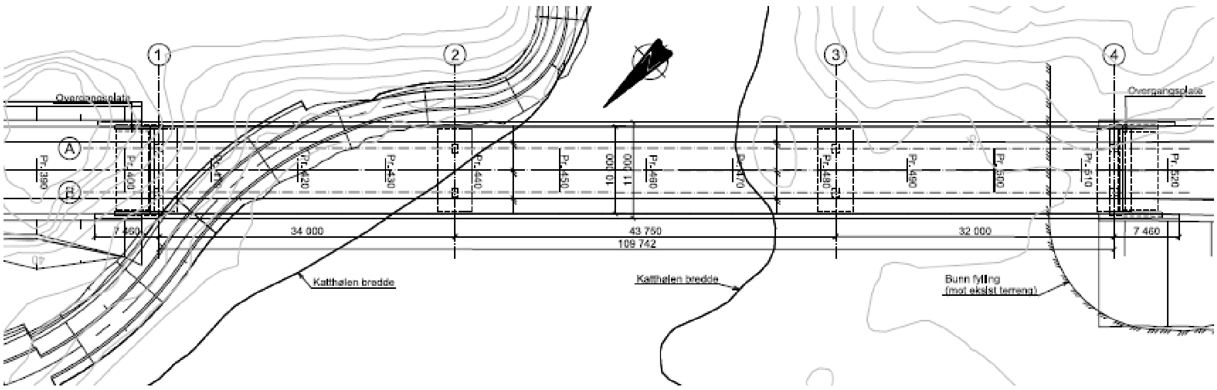

Figure 1-7: Plan view of Råna bridge.

The pile foundation will be designed according to the Norwegian design criteria for bridges given in handbook N400 – bruprosjektering [10]. The loads will be taken from the global analysis model for Råna bridge and are in accordance with N400. The loads will later be change in order to build the data set for the ML. A detailed description of the model is given in chapter *5.1 Modell.*

1.2.2 Limitations

To be able to answer the research question in the available time, the following limitations has been adopted:

- The model is limited to a 2D model.
- Only steel core point bearing piles is considered.
- Only one soil type is considered: loose sand.
- Buckling is neglected.
- Only linear springs is considered, second order effects are neglected.
- Design of pile cap is neglected.
- Contribution from downdrag and driving is neglected.

It is assumed that driving and mounting is done according to the applicable rules and that the piles attain satisfactory properties after mounting.

1.2.3 Outline of this thesis

In order to learn more about piles and pile foundations a review on how piles and pile foundations are designed is presented in the beginning of this thesis. This forms the basis for the definition of the structural optimization of pile foundation. When all this is defined the numerical model as well as the initial results are presented. In this part of the thesis it is focused on a single load case rather than a load combination. In order to not complicate the analysis too much in the beginning and to better asses the algorithms more efficiently. When different solution methods are presented in chapter 6, the analysis move more over to include load combinations. In the end, different ML models has been built based on the results from the previous chapters. Results from this can be found in chapter 7, before discussion, conclusion and further work ties it all together and makes the end of this master thesis.

2 Methodology

The goal of this thesis is to get a better understanding of what characterise an optimal pile foundation and to see how ML can help in the process of achieving an optimal solution. This is achieved by combining a qualitative and quantitative research methodology. The calculations are done based on quantitative data, where some of the data are made quantitative by a group of engineers collected qualitative knowledge. The choice of methodology is based on opportunities and available resources. Time limitations and the lack of available testing facility makes it difficult to obtain new empirical data, this limits the thesis to pure theoretical calculations. Accuracy in the calculations is emphasise, but since some of the quantitative data is based on qualitative knowledge, the quality of the calculation will be affected by this.

2.1 Method

Because of the authors limited experience in design of piles and pile foundations the thesis starts with an overview on how to design such structures. Acquired knowledge from this stage will also later be essential in order to be able to define what is thought to be an optimal pile configuration. “Hard data” related to piles is also systematically collected in this stage, for later to be used in the calculations. The Norwegian committee on piles guidance “Peleveiledningen” [11] gives guidance when designing piles as well as illuminating challenges and considerations. Based on this, N400 [10], Eurocode 7 [12], handbook V220: Geoteknikk i veibygging [13] and other research papers makes chapter 3 *Design of piles and pile foundations* the basis for the analyse and optimization chapters. As well as serving as training data for the ML part, this also provides the basis for results and discussion, from which later a conclusion is drawn.

The analyze and optimization methods chapters is based on a numerical model and FEA. By using an ordinary pile foundation as a test object, one acquires insight and understanding about the design process. The optimization methods chapter introduces different methods of optimization and contributes to a large extent how the design process can be more efficient and enable search for optimal solutions. This chapter contributes to understanding on how different parameters affect the overall assessment of the solution, as well as each parameters importance. The ML chapter explains how AI can be used in order to make the design procedure more efficient, by utilize collected knowledge from the previously chapters.

2.1.1 Materials and software

The calculation is based on the design rules given in Eurocode 7 and N400. All the numerical analysis is done in Python with the use of opensource library OpenSeesPy [14]. OpenSees was chosen for its speed benefits compared to other commercially available programs, which was critical for this thesis. Other Python packages that has been used for visualisation and calculation includes: NumPy, matplotlib, h5py, math, and SciPy optimize. Python has been used throughout the entire thesis. For the ML part the opensource library Scikit-learn [15] was chosen.

OpenSeesPy

OpenSeesPy is a Python 3 interpreter of OpenSees, which enable the use of the FEM directly in Python. OpenSees has been developed as the computational platform for research in performance-based earthquake engineering at the Pacific Earthquake Engineering Research Center. It has advanced capabilities for modelling and analysing, with a wide range of material models, elements and solution algorithms. It is design for parallel computing to allow scalable simulations on high-end computers or for parameter studies.

Scikit-learn

Scikit-learn is a free ML library for Python and features various classification, regression and clustering algorithm. The Scikit-learn project initially started as a Google Summer of Code project by David Cournapeau but was later rewritten by other developers from the French Institute for Research in Computer Science and Automation. It was first publicly realised in February 2010. Scikit-Learn is one of the most popular ML libraries on GitHub.

2.1.2 Procedure and implementation

After acquiring the knowledge that forms the basis for the calculation, the focus is mainly on the design and analysis of a pile foundation. A test model of a common pile foundation for a bridge facilitates good, up to date and transferable observation and gives the assumptions needed for the analysis. Later, different optimization methods are used in order to speed up the process and to see which variables that plays an important role in the assessment of the feasible solutions. This knowledge is then used as training data for the ML model. How the ML is performing is then checked against the acquired results from the optimization methods. Based on the collocated knowledge, key features to obtain an optimal pile foundation and how ML can help to obtain this are considered.

2.2 Reflection and quality assurance

2.2.1 Validity

This thesis gives an indication on what characterise an optimal configuration of a pile foundation, and how to obtain it efficiently. However, an optimal pile foundation will vary dependent on project specifically features as well as national costume. The results is only relevant in the sense that there are agreement with the points given in chapter 4.2 *Cost Function*. All the points from this chapter are consultant with an expert group from Norconsult and prices are collected from "Norsk Prisbok" [16]. This makes the results primarily relevant for the firm as well as the Norwegian AEC industry.

The optimal configuration that the model obtain will greatly depend on the forces it is subjected to. To ensure that the prediction by the ML model is accurate for as many load combinations as possible, and therefore its validity, a good spread in the loads when creating the training data is emphasised.

2.2.2 Reliability

Because the calculation is based on Eurocode 7 and N400 the reliability concerning the calculation can be comparable with the Eurocode and N400. Since all the calculations has been done in a non-commercial program, the program has been tested and compared with ABAQUS in order to check the accuracy of the program and to ensure reliable results. The optimization and ML part extensively use available libraries for Python. In order to ensure reliable results in these phases, well known and documented libraries has been chosen.

2.2.3 Generalisability

By using a common and general pile foundation as the test object, we can obtain more general results then a very specific and complex pile foundation would give. The pile foundation at hand has been chosen specifically for this manner. The variables of the calculation model that are kept free, enables varied types of foundations to form. This substantiates the generalisability of the model and then the results.

The results from the calculation is tied up to a chosen depth to the bedrock and the lateral soil stiffness. The values for the soil stiffness are chosen conservatively within the given limitations of the thesis. Literature find the depth to bedrock to be of insignificant importance with the thesis limitations. This makes the result transferable for other values of the fixed variables as well.

3 Design of piles and pile foundations

This chapter will describe more closely what a pile is and how it is designed, manufactured and constructed.

3.1 Design of piles

Based on the load transfer mechanism, a pile is classified either as a point bearing pile or as friction pile [17]. A point bearing pile reaches all the way down to the bedrock. It transfers all the applied load to the tip as axial loads and behaves as an ordinary column. The surrounding soil offers no additional load carrying capacity, but even weak soil does prevent lateral displacement and therefor prevent buckling [18]. Friction piles is not hammered down to bedrock and transfer the loads to the ground through skin friction. In Figure 3-1 a representation of the different classification is shown.

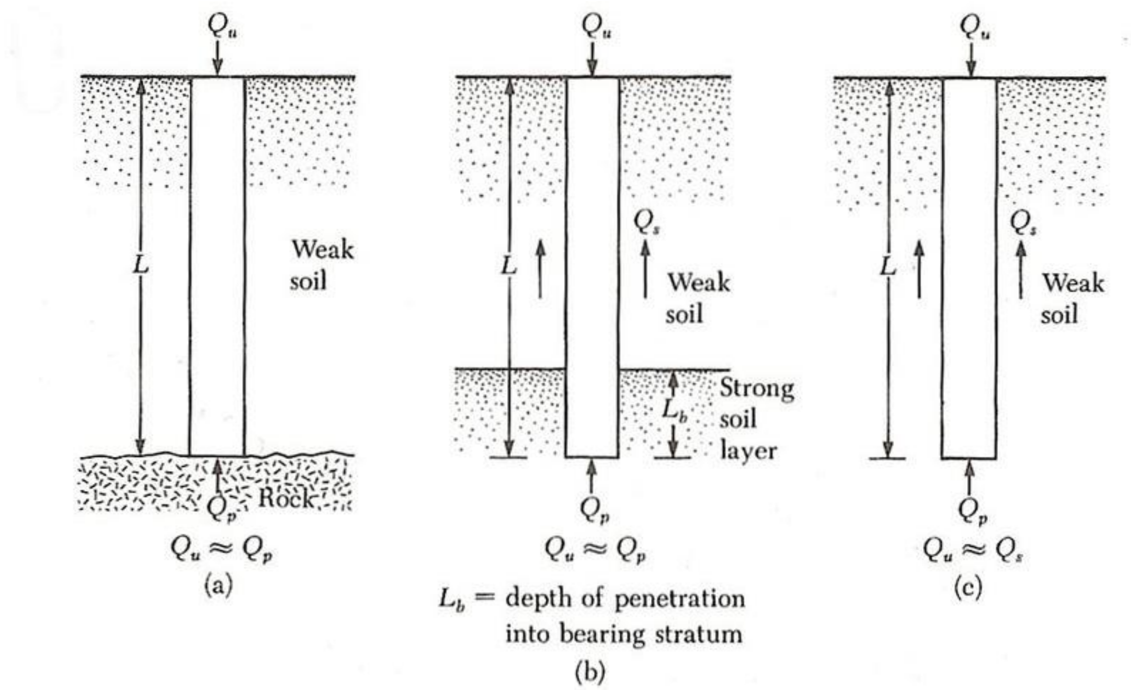

Figure 3-1: Different load carrying categories; point bearing pile (a), combination of point bearing and friction pile (b) and friction pile (c) [19].

The total load carrying capacity (Q_U) is given as the sum of the contribution from skin friction (Q_S) and point bearing resistance (Q_P). The contribution to each category will vary dependent on the soil type.

$$Q_U = Q_P + Q_S \tag{3-1}$$

3.2 Friction piles

Design of friction piles is separated into two different types of analysis:

- S_U – analysis: short term analysis for piles in clay.
- $\alpha\varphi$ – analysis: short- and long-term analysis for piles in sand and clay

The friction force along the pile is dependent on the shear forces along the pile. In S_U analysis the shear forces are dependent on the shear resistance of the soil, while in $\alpha\varphi$ it is dependent on the normal stresses and the roughness of the pile [17].

3.2.1 S_U - analysis

The carrying capacity for S_U- analysis is given as:

$$Q_U = Q_S + Q_P - G_P' \tag{3-2}$$

Where:

Q_S is the skin friction resistance.

Q_P is the point bearing resistance.

G_P' is the weight of the pile, optionally reduces for buoyancy.

The skin friction resistance is calculated as:

$$Q_S = f_r * \frac{s_{um}}{\gamma_m} * A_s \tag{3-3}$$

Where:

A_s is the surface area of the pile.

s_{um} is the average undrained unstirred shear strength.

γ_m is a material coefficient.

f_r is a reconsolidation factor which express the relationship between the shear resistance along the pile shaft after ramming and the original shear resistance in the soil. f_r depends on soil type, pile material and shape. It can be taken from Figure 3-2.

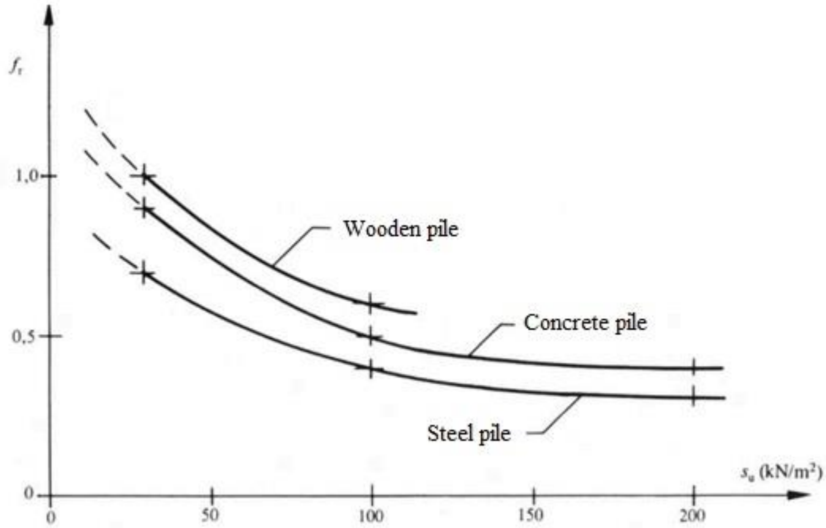

Figure 3-2: Reconsolidation factor as a function of shear resistance and pile type [17].

The point bearing resistance is calculated as:

$$Q_P = \bar{\sigma}_v * A_p \tag{3-4}$$

$$Q_P = (N_c * \frac{s_{up}}{\gamma_m} + \bar{\gamma}' * D) * A_p \tag{3-5}$$

Where:

- N_c is a load carrying factor. Equal to 9 for a small deep foundation (pile).
- s_{up} is the shear strength at the pile tip.
- $\bar{\gamma}'$ is the density of the suppressed soil.
- D is the depth of the pile.
- A_p is the area of the pile tip.

3.2.2 $\alpha\varphi$ - analysis

The carrying capacity for $\alpha\varphi$ - analysis is given as:

$$Q_U = Q_S + Q_P - G_P' \tag{3-6}$$

The skin friction resistance is calculated as:

$$Q_S = \bar{\tau}_s * A_s = (\sigma_A' + a)r * \tan(\rho) * A_S = S_A(\sigma_A' + a) * A_S \tag{3-7}$$

Where:

- $\bar{\tau}_s$ is the shear stress along the pile shaft.
- σ_A' is the average vertical stress along the pile shaft. i.e. at the depth D/2.
- a is the average attraction for the same area.

S_A is a shear stress coefficient. It is dependent on mobilised friction, $\tan\rho = \frac{\tan\varphi}{\gamma_m}$, and absolute roughness $|r|$. S_A can be taken from Figure 3-3.

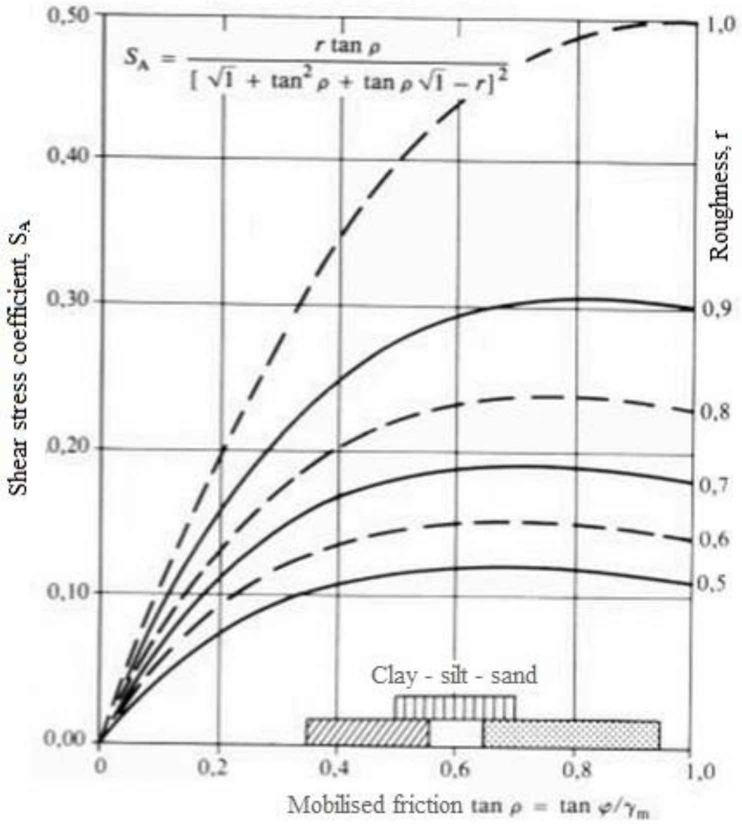

Figure 3-3: Shear stress coefficient as a function of roughness and mobilised friction [17].

The point bearing resistance is calculated as:

$$Q_P = \bar{\sigma}_v' * A_p \tag{3-8}$$

$$Q_P = (\frac{1}{2} * N_\gamma * \bar{\gamma}' * B_0 + N_q * p' + (N_q - 1) * a) * A_p \tag{3-9}$$

By neglecting the first term, because of small width (B_0), and setting the weight of the pile to the same as the suppressed soil, we get:

$$Q_P = (N_q - 1)(p' + a) * A_p = \bar{\sigma}_{vn}' * A_p \tag{3-10}$$

Where:

p' is the shear stress along the pile shaft.

N_q is a load carrying factor and can be taken from Figure 3-4.

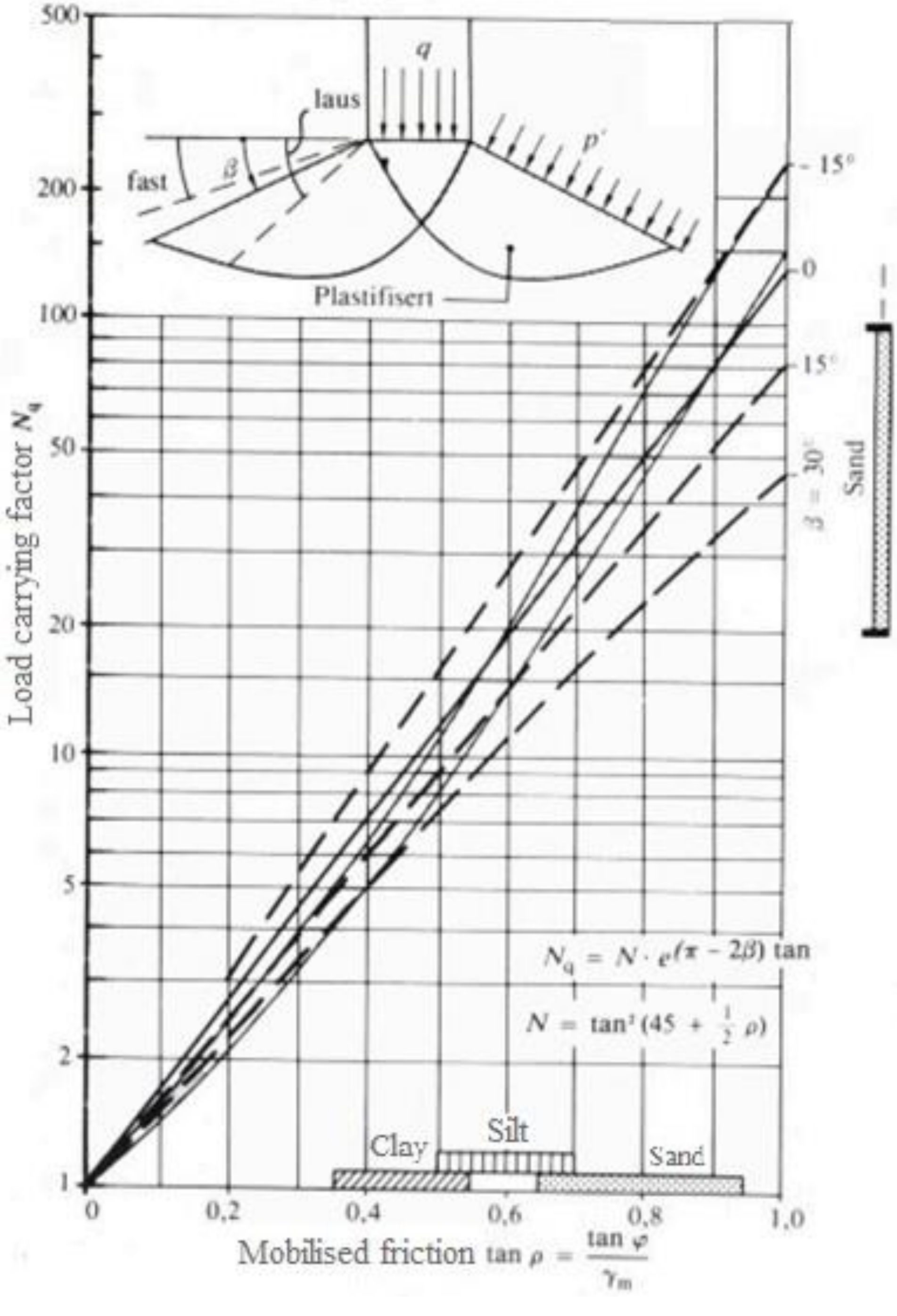

Figure 3-4: Load carrying factor [17].

3.3 Point bearing piles

The characteristic load carrying capacity of a point bearing pile will either be decided by the strength of the pile material or tip, or the strength of the rock type its rammed into [11]. Point bearing piles is usually used when the bedrock is hard, so the pile capacity is therefore limited by the strength of the material and/or buckling. The capacity is therefore calculated as an ordinary column with lateral springs, see Figure 3-5.

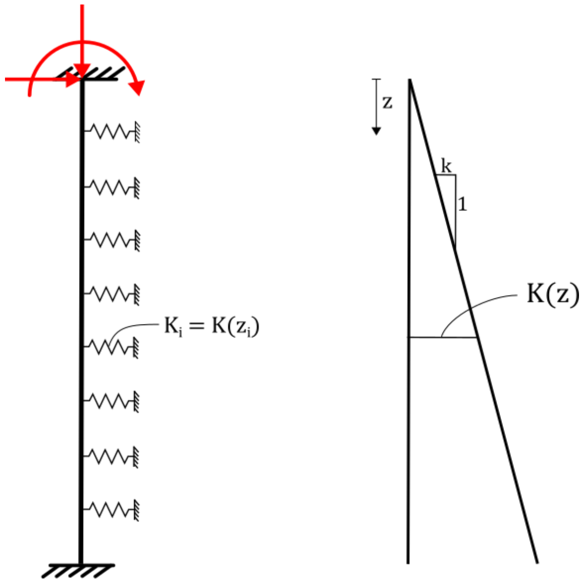

Figure 3-5: Calculation model of a pile, with lateral springs.

3.3.1 Lateral springs

The lateral springs represents the support from the surrounding soil. As the soil is pushed by the pile a pressure between the pile and soil is mobilised. The lateral spring stiffness increases with the depth and is given as:

$$K(z) = k * d * z \tag{3-11}$$

Where:

- k is the slope of the soil's reaction modules.
- d is the diameter of the pile.
- z is the depth.

There are great uncertainties around the soil's characteristics, so the spring stiffness should always be chosen conservatively. Typical values for the slope of the soil's reaction modules can be taken from Table 3-1.

Table 3-1: Values for the slope of soil's reaction modules, k [13].

Soil type	k (KN/m³)	
	Above groundwater	Below groundwater
Loose sand	5 000	4 500
Middle firm sand	22 000	15 000
Firm sand	60 000	34 000

3.3.2 Buckling

Buckling is primary an issue that needs to be checked for all piles through water or air, and for slender steel piles or steel core piles in soft clays or other soils with low strength and stiffness [11]. For a straight homogenous pile, the theoretical buckling load is given as:

$$N_{Buckling} = \frac{(\pi^2 * E * I)}{L_k^2} + \frac{C * L_k^2}{\pi^2} \tag{3-12}$$

Where:

I is the pile's moment of inertia.

L_k is the buckling length.

C is the soil's reaction module.

The first term is the Euler buckling load for a pile in air, and the second term is the contribution from the soils lateral support.

3.3.3 Capacity

For piles in moderately firm clay or loose sand, buckling is commonly not an issue. The capacity of the pile can then be taken directly from a stress check of the section. This yield:

$$N_{Rd} = f_a * A * \frac{f_y}{\gamma_m} \tag{3-13}$$

Where:

A is the area of the section of the pile.

f_y is the characteristic yield strength of the pile.

f_a is a reduction factor that accommodate the different between piles and other structural elements, as well as including specific conditions for the pile-work. Recommended values can be taken from Table 3-3

If the pile is subjected to a combination of moments and axial forces the resultant stress must be checked against the resistance of the section:

$$\frac{N_{Ed}}{A} \pm \frac{M_{Ed}}{W} \leq \frac{f_y * f_a}{\gamma_m} = f_{yd} \tag{3-14}$$

Where:

N_{Ed} is the axial force in the pile.

M_{Ed} is the moment in the pile.

W is the modulus of the pile.

f_{yd} is the design yield strength of the pile.

3.3.4 Reduction factor f_a

An assembly of condition that's effect the reduction factor can be found in Table 3-2. The corresponding values of the reduction factor can be taken from Table 3-3.

Table 3-2: Assembly of conditions that affects choice of f_a.

	Favourable	**Unfavourable**
Soil conditions	Homogenous and rock free soil. Increasing strength with depth. Even and well bedrock	Corrosion harsh soil. Rocks and block in soil. Skew, uneven and hard bedrock
Site investigation	Comprehensive site investigation	Inadequate site investigation.
Number of piles in a group	More than 5 piles. Small variation of pile lengths.	Less than 3 piles. Great variation of pile lengths.
Ramming equipment and execution	Adequate weight of hammer and god driving cap. Vertical piles. Experience contractor.	inadequate weight of hammer. Driving from raft. Unexperienced contractor.
Installation method	Drilling, casting and grouting.	Ramming/driving.
Control of pile work.	God control of piles and ramming. Implementation of complete protocols.	Little or lacking protocol.

Table 3-3: Recommended reduction factors [12].

Conditions	f_a
Favourable	0.9
Mean	0.75
Unfavourable	0.6

3.4 Pile types

Piles are usually made of concrete, timber or steel. Concrete is used for precast concrete piles, cast in place and prestressed concrete piles, while steel piles are used for permanent or temporary works. When wood is available at an economical price, timber can be used for temporary piles [18].

3.4.1 Timber piles

Timber piles was frequently used as friction piles in the older days, but are not much used in later years. Some countries still use timber piles for permanent work today. It is most suitable for long cohesion piling and piling beneath embankments. The timber needs to be in good condition and without insects.

Keeping the timber below groundwater level protects the timber against decay and putrefaction. To protect and strengthen the tip of the pile, timber piles can be provided with toe cover. The usual method of protecting timber is with pressure creosoting. It is essential that the timber is driven in the right direction and should not be driven into firm ground, as this can easily damage the pile [20].

In Table 3-4, advantages and disadvantages of timber piles can be found.

Table 3-4: Advantages and disadvantages of timber piles

Advantages	Disadvantages
The piles are easy to handle.	Piles will rot above ground water level and have a limited bearing capacity.
Relatively inexpensive where timber is plentiful.	Can easily be damaged during driving by stones and boulders.
Section can be joined, and excess length is easily removed.	The piles are difficult to splice and are attacked by marine bores in saltwater.

3.4.2 Concrete piles

Concrete piles can be either precast or casted in place.

3.4.2.1 Precast concrete piles

Rammed concrete piles is widely used for ordinary foundation work. They are most used as point bearing piles, but are also used as friction piles in sand, gravel and solid clay.

Precast concrete piles are made of high-quality concrete and reinforcement. The section is usually square, triangle, circle or octagonal. They are produced in length of 3 to 13 meters and can easily be connected in order to reach required length. In Figure 3-6 a section of a concrete pile with reinforcement and the spigot/socket joint is shown.

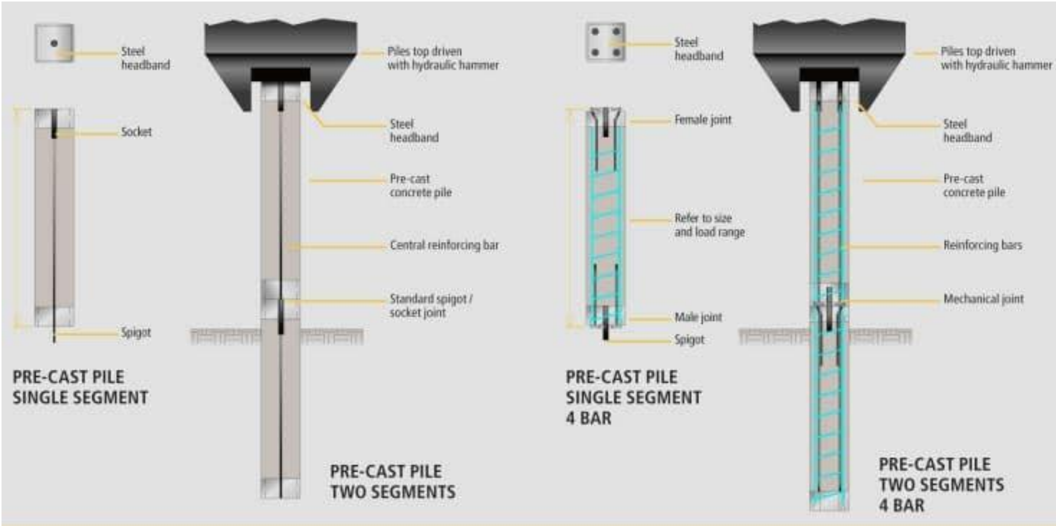

Figure 3-6: Precast concrete pile with detailing [21].

Advantages and disadvantaged of precast concrete piles can be found in Table 3-5.

Table 3-5: Advantages and disadvantages of precast concrete piles.

Advantages	Disadvantages
Can be driven in long lengths.	Displacement, heave and disturbance of soil during driving.
Can increase the relative density of granular founding stratum.	Can be damage during driving. Replacement piles may be required.
Are easy to splice and relatively inexpensive.	Cannot be driven with very large diameters or in condition of limited headroom.
Stable in squeezing ground; soft clays and silts.	

This make precast concrete piles ideal when we have:

- Moderately loads
- Moderately depth
- Non challenging rock conditions
- Non rough rock substance
- Piling from land
- Non stability problems

3.4.2.2 Cast in place concrete piles or pillars

Cast in place concrete piles, or pillars, are rough concrete piles formed by pouring concrete into a hole. The hole can be established by turning steel tubes into the ground and at the same time excavating the soil on the inside. The pile is reinforced and casted while the tube is pulled up.

Cast in place concrete piles can be friction or point bearing piles. For friction piles the tip is expanded in order to increase the load carrying capacity. The piles can range from 900 to 1500mm in diameter and have a large load carrying capacity [11].

Advantages and disadvantaged of cast in place concrete piles can be found in Table 3-6.

Table 3-6: Advantages and disadvantaged of cast in place concrete piles.

Advantages	Disadvantages
Length can be readily varied to suit varying ground conditions.	Concrete not placed under ideal conditions and cannot be subsequently inspected.
Can be installed in very large diameters.	Water under artesian pressure may pipe up pile shaft and wash out cement.
End enlargement up to two or three diameters are possible in clays.	Cannot be readily extended above ground level especially in river and marine structures.
Material of piles is not dependent on handling or driving conditions.	Boring methods may loosen sandy or gravely soils, requiring base grouting to achieve economic base resistance.
Can be installed in very long lengths.	

This make cast in place concrete piles ideal when we have:

- Big concentrated loads
- Big depths
- Stability issues
- Need for little noise and vibrations during construction

3.4.3 Steel piles

Steel piles can be rammed or drilled into the ground. They are made of H, X, hollow pipes or solid pipes sections. The hollow pipes may be filled with concrete or even reinforced to add strength. Steel piles are suitable for handling and driving in long lengths. Their relatively small cross-section combined with their high strength makes penetration easier in firm soil.

Steel piles can easily be cut off or joined by welding. When driven into soil with low pH value the piles may corrode. Coating or cathodic protection may be employed, but it is common to allow for an amount of corrosion in design by simply over dimensioning.

Advantages and disadvantaged of steel piles can be found in Table 3-7.

Table 3-7: Advantages and disadvantaged of steel piles.

Advantages	Disadvantages
The piles are easy to handle and can easily be cut to desired length.	The piles will corrode.
Can be driven through dense layers and into inclined and difficult rock.	Will deviate relatively easy during driving.
Can be driven hard and in very long lengths.	Are relatively expensive.
Can carry heavy loads	

3.5 Selection of piles

What kind of pile that is best suited for a project is dependent on many factors. It is not possible to determine an absolute and unambiguously recommendation. The statics, geotechnical, construction and environment all need to interact in order to have an optimal technical and economical solution [11]. Some aspects that need to be considered when choosing a pile type are found in Table 3-8.

Table 3-8: Selection aspects for piles.

Category	Aspect
Loads	- How big are the loads? - Only vertical loads or combination of horizontal loads? - Is it tension forces?
Soil conditions	- How are the soil conditions? - How is the stability in the area? - Is it difficult to drive the pile through the soil? - Is the bedrock skewed? - Is the soil touchy for erosion during drilling? - Are there environmental impact demands?
Neighbourly relations	- Restriction of ramming because of noise and shaking? - Can piling cause stability issues or settlement for neighbouring site?

	- Can mud be released?
Construction	- Big or small site? Is it room for the piling machine? - Should it be piled from the terrain or in the pit? - Piling from raft? - Piling near and simultaneously with other construction activities? - Restrictions regarding road, train or high-voltage cables?
Marked	- Price on piles - Which pile type is uncomplicated to install in the area?

The main reason for choosing a pile type is that it can carry all the applied forces. Therefore, a summary of typical capacities for different piles are displayed in Table 3-9.

Table 3-9: Typical characteristic capacities and lengths for the most common piles [11].

Pile type	Sectional design capacity without moments [KN]	Lengths [m]
Pre casted concrete piles	1 500 – 3 000	8 – 50
Casted in place concrete piles	5 000 – 25 000	5 – 50
Steel piles	2 000 – 7 000	20 – 70
Rammed steel pipe piles	4 000 – 16 000	20 – 70
Drilled steel pipe piles	8 000 – 25 000	10 – 50
Steel core piles	1 000 – 5 700	5 - 70

3.6 Piles in group

So far, we have only dealt with single piles. In order to obtain enough capacity and stability two or more piles are placed together to form a pile foundation. A group of piles can carry more loads than a single pile can carry alone. It can be made of many vertical or skewed piles with complex geometry. Figure 3-7 shows a representation of a typical pile foundation.

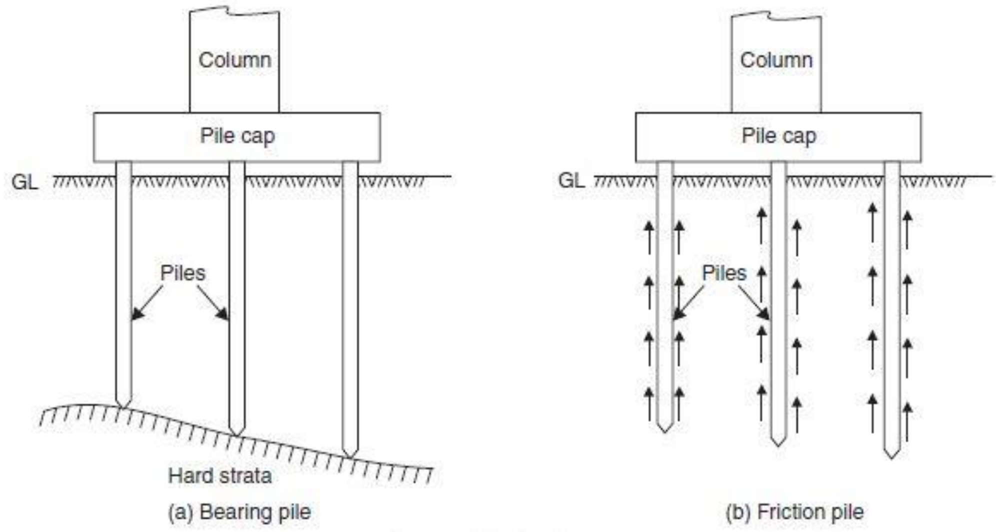

Figure 3-7: Pile foundation with the two different carrying methods.

For simple pile foundations only subjected to pure vertical loads, the loads can be distributed to the necessary amount of single piles. No analysis of the group is necessary, and the loads are carried as axial loads in each pile. When subjected to a combination of moment, vertical- and horizontal forces, the pile foundation acts as a space frame. The moments will only lead to a redistribution of the vertical loads compared to the situation of only vertical and horizontal forces [11]. In principal there three different ways a pile foundation can carry forces:

- as axial load in piles
- from the lateral carrying capacity for each pile
- from the lateral support of the foundation

Axial loads in piles

Compression forces in piles is the ideal load carrying situation [11]. By placing piles in different direction, a stable system in which horizontal forces can be carried as axial forces may be obtained. The horizontal capacity is therefore limited by the inclination of the piles. An inclination of 4:1 will for example only have the ability to carry a quarter of the axial capacity as horizontal force. Figure 3-8 shows how the forces are distributed as axial loads in the piles.

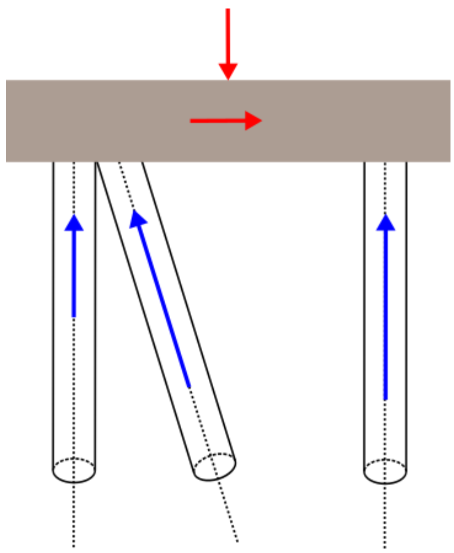

Figure 3-8: Illustration on how loads are carried as axial loads in piles.

Lateral carrying capacity

The relative displacement between the pile and the surrounding soil enable passive pressure to form. This pressure enables lateral carrying capacity, but the deformation that enables this pressure is not necessarily possible in practise, due to demand of compatibility between forces and deformation. The influence of piles standing to close to each other is also something that needs to be considered. There are desirable that the horizontal forces are transferred as axial load in piles, rather than lateral forces to the soil, but it is common to check against shear and bending. See Figure 3-9.

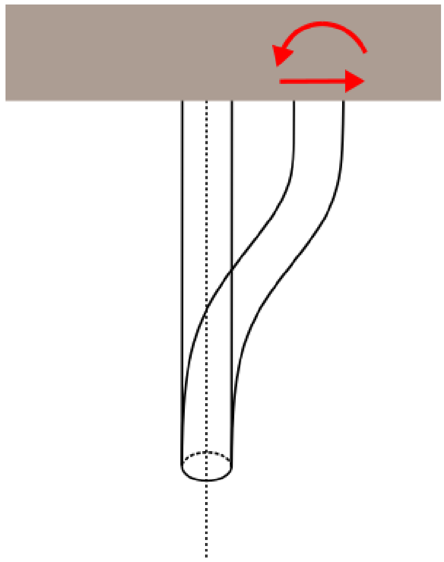

Figure 3-9: Illustration on the lateral carrying capacity of a pile.

Lateral support from foundation

This is not a direct part of the piles carrying capacity, but it is common to have a backfilling around the foundation in which the pile heads are encased. Horizontal movements of the foundation will activate passive pressure and enable horizontal forces to be carried, see Figure 3-10. If this capacity should be included, it must be certain that the backfilling is not later removed. It is therefore not usual to include this in the capacity of the pile foundation.

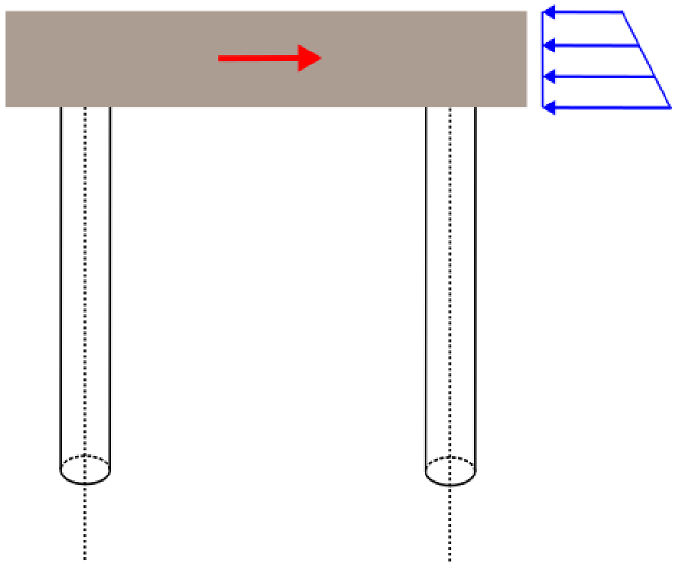

Figure 3-10: Illustration on the lateral carrying capacity from the slab.

3.6.1 Static stability

If the piles axis intersects each other in one point the group will only be stable if the force attacks in this point. If the pile foundation is subjected to other exterior forces or moments, the piles should be placed such that their axis does not intersect in just one point. Figure 3-11 shows an unstable configuration (A) and a stable configuration (B).

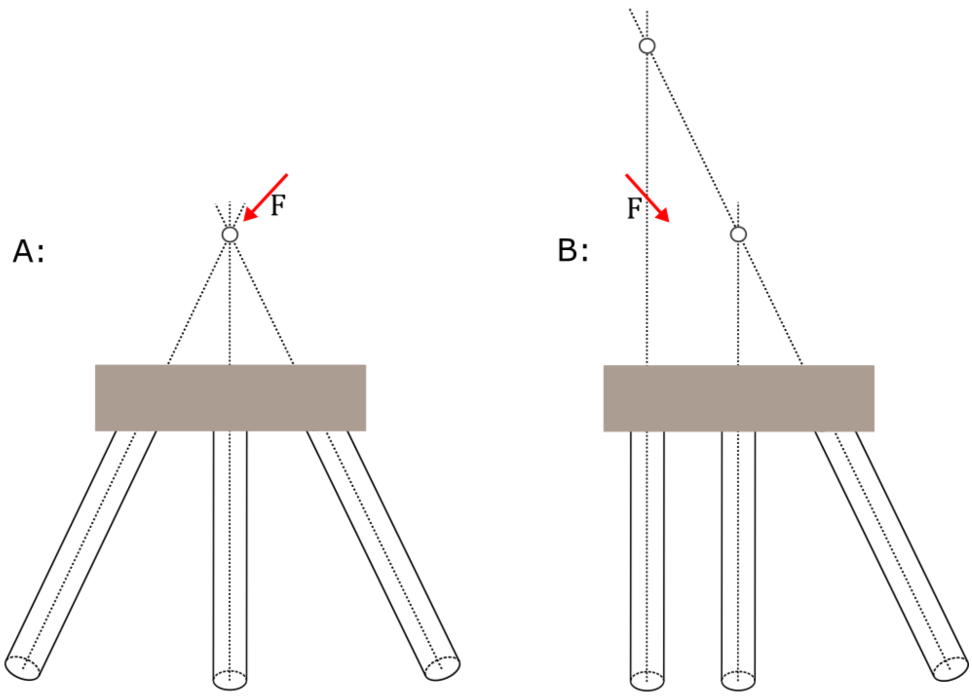

Figure 3-11: Example of an unstable (A) and stable (B) configuration.

3.6.2 Geometrical formation of piles in group

There are several aspects that decides the shape and size of the foundation. It will be a combined assessment of loads, stiffness, interaction with the overlying structure and pile type. The size of the foundation will for example be significantly smaller for drilled piles, compared to regular precast concrete piles [11].

When driving piles in sand, the surrounding soil will compress. The piles should therefore not be too close to each other, which may cause difficulties with driving. In clays the driving may cause stirring of the surrounding soil and increase earth pressure. These can cause the pile to draw against previously driven piles. Therefore, it is recommended to have a minimum spacing between piles. Recommended distance can be found in Table 3-10. The pile sequence should also be considered in order to limit these effects. For example, the direction of a skew pile is more important than a vertical one and should therefore be driven first in order to limit the dragging effect.

Table 3-10: Recommended minimum distance between vertical rammed piles.

Pile length [m]	Friction piles		Point bearing piles
	In sand	In clay	
< 12	3d	4d	3d
12 – 24	4d	5d	4d
> 24	5d	6d	5d
d = Pile diameter or biggest section measure.			

For drilled piles, the distance between piles will depend on execution method and direction requirement. The dragging effect for vertical rammed point bearing piles is also not consider to be a structural problem. For incidents like this the distance between piles may be less than the values given in Table 3-10.

In order to maintain a good force transfer in the foundation, the edge distance for the outer pile needs to be limited. These distances are defined in design rules given in: N400 and "JD 525, Regler for prosjektering av bruer". This minimum distance is 400mm according to N400.

3.6.3 Analyses of piled structures

Structures on pile foundation is statically undetermined. For structures like this, the analysis needs to account for interaction between the overlaying structure and the foundation. This is because the reactions from the foundation to the structure depends on the pile foundations displacements [11].

The load distribution on the pile foundation and different parts of the structure is dependent on the relative stiffness of the whole structure. A rigid foundation will attract more forces than a flexible one. Example of factors that will influence the foundation stiffness are:

- variation of soil condition
- depth to bedrock
- number of piles
- pile type
- placement of piles

This implies that the pile foundations stiffnesses needs to be taken into consideration when analysing the overlaying structure.

A piled structure can be separated into the overlaying structure and a given amount of pile foundations, in order to analyse this separately. The connections between the pile foundation and the overlaying structure is represented by nodes with 6 degrees of freedom (DOF), supported by springs. In the system analysis of the overlaying structure, the nodes are represented as spring supports, while in the pile foundation analysis they are considered as displaceable points applied with the support loads from the system analysis, see Figure 3-12.

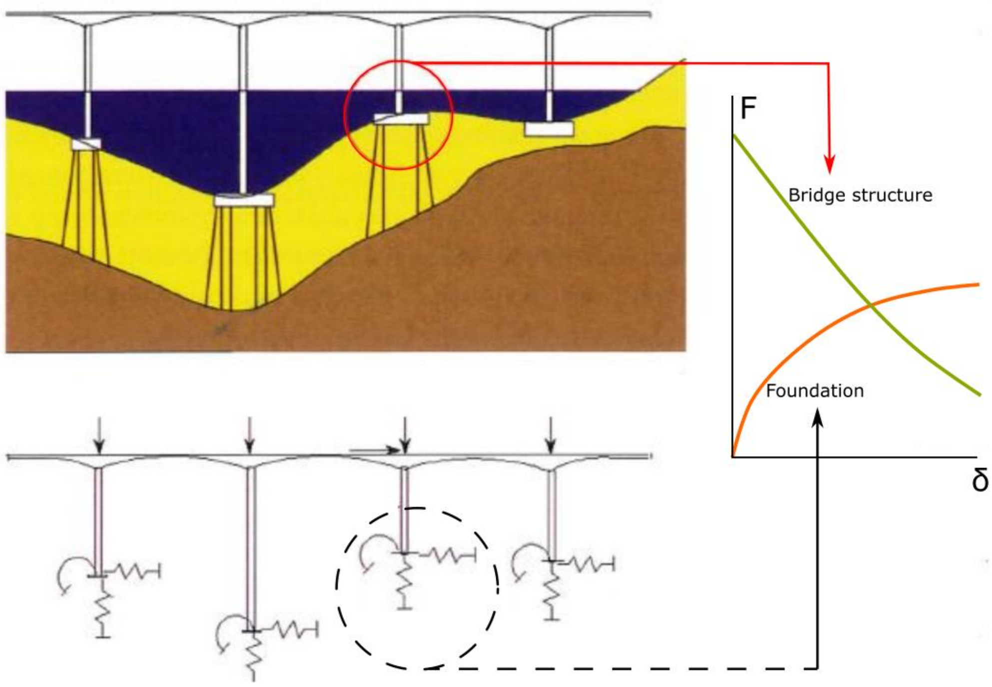

Figure 3-12: Illustration of the system model for piled bridges subjected to static forces [11].

With the use of separate system analysis and pile foundation analysis, it is important to ensure that the displacements of the supports in the system analysis corresponds to the displacement of the support points from the pile foundation analysis. This can be done by specifying a condensed stiffness matrix for the overlaying structure in every pile foundation analysis, or by representing the stiffness matrix for each pile foundation in the system analysis. The latter being the most common one. The stiffness matrix for the pile foundations can be generated by successively applying unit displacement in each of the 6 DOF's for each foundation. The stiffness matrix will be symmetrical and be on the form:

$$K_{foundation} = \begin{bmatrix} K_{xx} & K_{xy} & K_{xz} & K_{x\phi_x} & K_{x\phi_y} & K_{x\phi_z} \\ \vdots & K_{yy} & K_{yz} & K_{y\phi_x} & K_{y\phi_y} & K_{y\phi_z} \\ \vdots & \vdots & K_{zz} & K_{z\phi_x} & K_{z\phi_y} & K_{z\phi_z} \\ \vdots & \vdots & \vdots & K_{\phi_x\phi_x} & K_{\phi_x\phi_y} & K_{\phi_x\phi_z} \\ \vdots & \vdots & \vdots & \vdots & K_{\phi_y\phi_y} & K_{\phi_y\phi_z} \\ \vdots & \vdots & \vdots & \vdots & \vdots & K_{\phi_z\phi_z} \end{bmatrix} \tag{3-15}$$

The solution method will be an iterative method in order to ensure compatibility between the displacement from the system analysis and the foundation analysis.

4 Structural optimization of pile foundation

In order to find out what characterise a good solution of a pile foundation, a discussion with people in the industry and search in the literature has been carried out. This chapter describe these findings and investigate how different variables affect the overall evaluation of the design, and how an optimal design can be obtained.

4.1 Optimal design of pile foundation

An optimal design of a pile foundation is not one specific thing, and its characteristics will vary within the industry and across countries. Depending on who you are asking you will almost get a different answer every time, but there is some resemblance.

A pile foundation consists of multiple variables that describes its strength, stress distribution and stiffness. The ability of quantifying, as well as evaluating, a design solution can therefore be challenging. The need for the ability to choose the best design solution from a set of available alternatives makes it to an optimization problem. Optimization of a structure can be with respect to many things. Structural optimization is commonly performed with a goal to minimize stresses, weight or deflection. In general, the idea of optimization is to select the best element from some set of available alternatives [22] and can be represented in the following way:

> **Given**: a function $f: A \rightarrow \mathbb{R}$ from some set A to the real numbers.
> **Sought**: an element $\mathbf{x_0} \in \mathrm{A}$ such that $\mathrm{f}(\mathbf{x_0}) \leq \mathrm{f}(\mathbf{x})$ for all $\mathbf{x} \in \mathrm{A}$ (minimization) or such that $\mathrm{f}(\mathbf{x_0}) \geq \mathrm{f}(\mathbf{x})$ for all $\mathbf{x} \in \mathrm{A}$ (maximization).

Here A is some subset of the Eucludian space $\mathbb{R}^{\mathrm{n}}$, often specified by a set of constraints that the members of A must satisfy. The domain A of f is called the search space or the choice set, while the elements of A are called candidate solutions or feasible solutions [22]. The function f is called, variously, a penalty function or cost function, a utility or fitness function. A feasible solution that minimize (or maximize) the cost function is called an optimal solution.

This cost function can therefore be adopted to quantify the evaluation of a design. The feasible design solution can then be evaluated with a score or a cost to that design. This makes it easy to evaluate two different design solutions, and to choose the solution with the highest score (lowest cost). The score of the design will be given by the cost function and constructing this right, so it represents what is known (or though) to be a good design, is key in order to succeed.

4.2 Cost Function

The cost function should include all aspects that characterize a good design and then be able to separate a good design from a bad design. The relative weight or penalty for each variable then needs to be of appropriate size. The following variables has been found to be important for a good design, and has therefore been adopted into the cost function:

4.2.1 Length and diameter of the pile

The length of the pile is directly related to the construction cost of a pile. A long pile costs more than a short pile and will therefore lead to an overall more costly design. An expensive design is not regarded as a good design and the length of the piles should therefore give a penalty to the overall design. In this thesis the cost per meter of a pile is collected from the price database given in "Norsk Prisbok" [16]. The prices are presented in Table 4-1 below.

Table 4-1: Prices for steel core piles.

Name	Unit	Unit price
Steel core pile Ø = 100mm	m	3 517, -
Steel core pile Ø = 130mm	m	3 829, -
Steel core pile Ø = 150mm	m	4 350, -
Steel core pile Ø = 180mm	m	5 897, -
Steel core pile Ø = 200mm	m	6 711, -

Dependent on project size, location, order volume and firm agreements the cost per meter of a pile will vary greatly across projects. In order to obtain correct results for a specific project the actual cost per meter of the piles should be used. This is not publicly available information, so the prices from "Norsk Prisbok" has therefore been adopted in this thesis.

As Table 4-1 shows, the price increases with increasing diameter. This is a result from the increased manufacturing cost associated with the volume increase caused by the change in diameter. The contribution from the length and diameter of the pile, to the overall cost for a pile, has been set by a curve fitting through the points taken from Table 4-1. This yield:

$$C^{i}_{pile}(A) = \left(284200 * \left(Diameter^{i}_{A}\right)^{2} - 51890 * Diameter^{i}_{A} + 5820\right) * Length^{i}_{A} \qquad (4\text{-}1)$$

Where both the diameter and length are given in meters. Figure 4-1 shows a graphical representation.

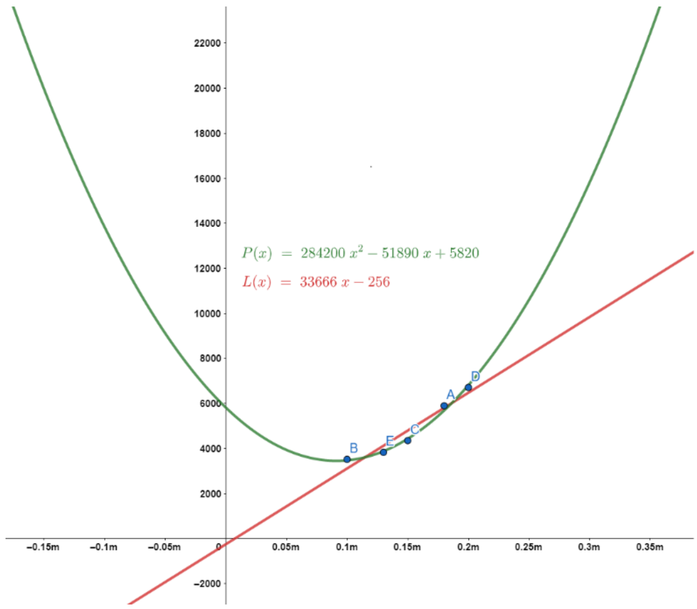

Figure 4-1: Cost development dependent on diameter

4.2.2 Necessary foundation slab size

In order to maintain a good load transfer between piles and columns, the size of the foundation need to be of satisfactory dimensions. All piles need to fit inside the foundation and there should be a minimum distance between the outmost pile and the edge of the foundation.

The thickness of the foundation should be such that loads are transferred efficient and without large curvature of the foundation slab. The angle of the outermost strut in a strut and tie model [23] is therefore limited, and the thickness is varied in order to obtain this limit, see Figure 4-2.

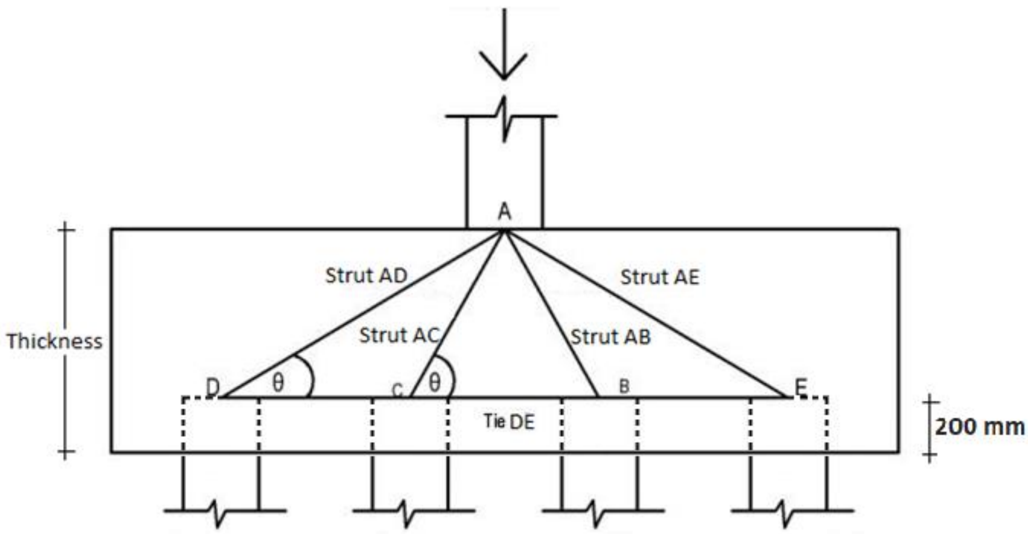

Figure 4-2: Strut and tie model of pile foundation.

Far spread piles will lead to a thick foundation slab and increased manufacturing cost of the foundation. This effects the design badly. The contribution to the cost function has been set to:

$$C_{slab}(A) = Width_A * Thickness_A * 4800 \tag{4-2}$$

The price of concrete/m^3 is taken from "Norsk Prisbok" and includes concrete and reinforcement. A reinforcement amount of 130 kg/m^3 is assumed.

4.2.3 Tension in piles

According to N400 there should be no tension in piles when designing bridges. The cost for achieving tension in piles should therefore be so high it eliminates the candidate solution completely. There is also a desire to give a penalty if the axial force is approaching tension, in order to increase the robustness of the design. The contribution to the cost function is therefore given as:

$$C^i_{Axial\ force}(A) = \begin{cases} 10^9, & N^i_A \leq 0 \\ N^i_A + 0.05 * N^i_{Rd}, & -0.05 * N^i_{Rd} < N^i_A < 0 \\ 0, & N^i_A \leq -0.05 * N^i_{Rd} \end{cases} \tag{4-3}$$

Where:

N^i_A is the axial load in the pile, i, for the candidate solution A.

N^i_{Rd} is the axial capacity of the pile, i, for the candidate solution A.

4.2.4 Yield in piles

Yielding in piles is not wanted when designing pile foundations. The structure has some degree of redundancy, so to allow for yielding could have enable increased utilization of the structure, but at a cost of safety. It would also lead to a change in the system and decrease the overall stiffness of the pile foundation. This could lead to increased forces in the overlaying structure, caused by the increased displacement. If yielding occurs the cost is set to 10^9. This should eliminate any designs where yielding occurs.

$$if\ yielding \rightarrow f(A) = 10^9 \tag{4-4}$$

4.2.5 Displacement

Displacement is a very difficult variable to assign a cost to. Some displacement should be allowed, in order to reduce enforced forces in the overlaying structure, but should be limited to ensure sufficient stiffness and rigidity. N400 do not give clear limits of displacement, but recommends the following:

- The horizontal displacement in the bridge end should be smaller than 50 mm.
- Grout and lamellae in the transverse direction of the bridge should be less than 80 mm and bigger than 50 mm.
- The difference in vertical displacement in grouts should be less than 10 mm.

Based on these recommendations a limitation of the displacement on 50 mm in the longitudinal and transversal direction and 10 mm in the vertical direction has been adopted. Up to this limits the cost is linearly increasing and jumps up to a high value when the limit values are reached. The contribution is given as:

$$C_{U_x}(A) = \begin{cases} 0, & U_x \leq 10 \\ (U_x * 1000 - 10\,000), & 10 < U_x < 50 \\ 10^9, & U_x \geq 50 \end{cases} \tag{4-5}$$

$$C_{U_z}(A) = \begin{cases} U_z * 1000, & U_z < 10 \\ 10^9, & U_z \geq 10 \end{cases} \tag{4-6}$$

Where:

U_x is the absolute value of the horizontal displacement.

U_z is the absolute value of the vertical displacement.

There is not any clear recommendation on the limits of the rotation of the foundations. The cost of rotation is also set to be linearly increasing up to a limit value of 2 degrees.

$$C_{\phi}(A) = \begin{cases} 0, & \phi \leq 1 \\ (\phi * 40\,00 - 40\,000), & 1 < \phi < 2 \\ 10^9, & \phi \geq 2 \end{cases} \tag{4-7}$$

Where:

ϕ is the absolute value of the rotation.

4.2.6 Total cost

The total sum for the whole configuration, and the cost for the candidate solutions, is then the sum of each contribution to the cost function and can be taken as:

$$\begin{aligned} f(A) = & \left(\sum_{i=1}^{\#\,Piles} C^i_{pile}(A) + C^i_{Axial\,force}(A) + C^i_{Yield}(A) \right) \\ & + C_{slab}(A) + C_{U_x}(A) + C_{U_z}(A) + C_{\phi}(A) \end{aligned} \tag{4-8}$$

4.3 Parameter study

In order to get a better understanding on how the cost function is working and to see how the different variables are affecting the overall evaluation of the design, a parameter study has been conducted. The cost function is plotted for two varying variables while all other variables are held constant. This will emphasise how each variable effects the overall quality of the design.

4.3.1 Diameter and length of pile

Figure 4-3 shows how the cost varies dependent on the diameter and length of the pile.

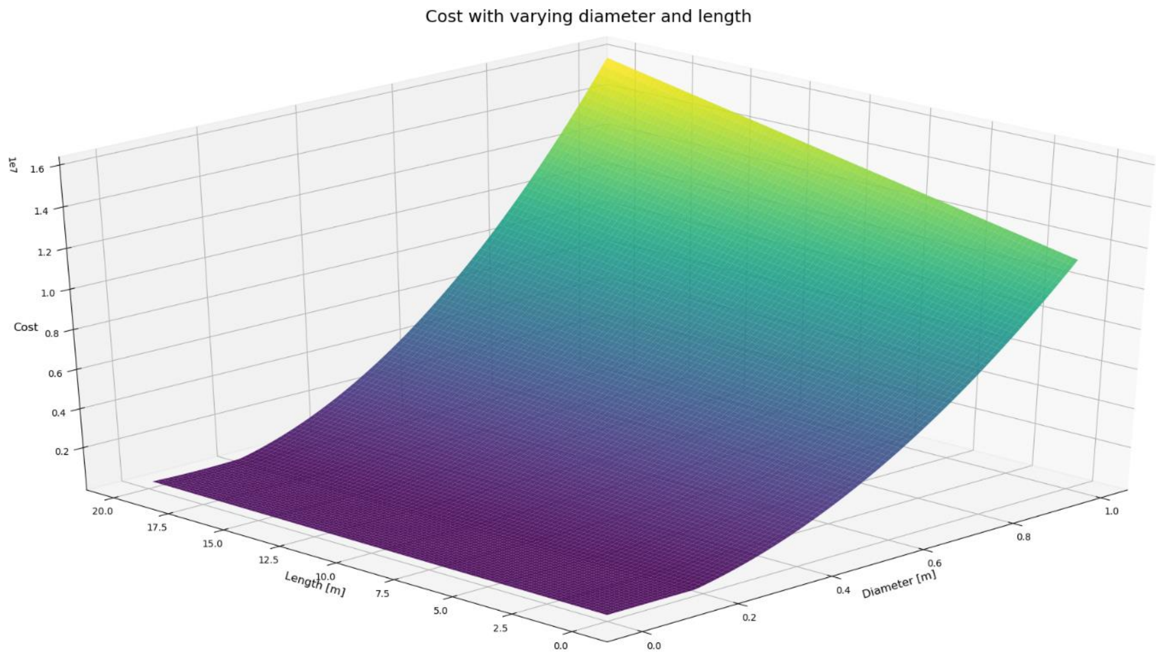

Figure 4-3: Cost with varying diameter and length

The cost varies linearly in the length direction and quadratically in the diameter direction. In the diameter direction it has a local minimum at diameter = 0.09. This can also be shown in Figure 4-1. The pitch in the length direction is increasing with increasing diameter. In order to minimize the cost, the length should also be minimized, and the diameter should have a value of 90mm.

4.3.2 Foundation volume and axial force

Figure 4-4 shows the cost variation dependent on the volume of the foundation and the axial force in the pile.

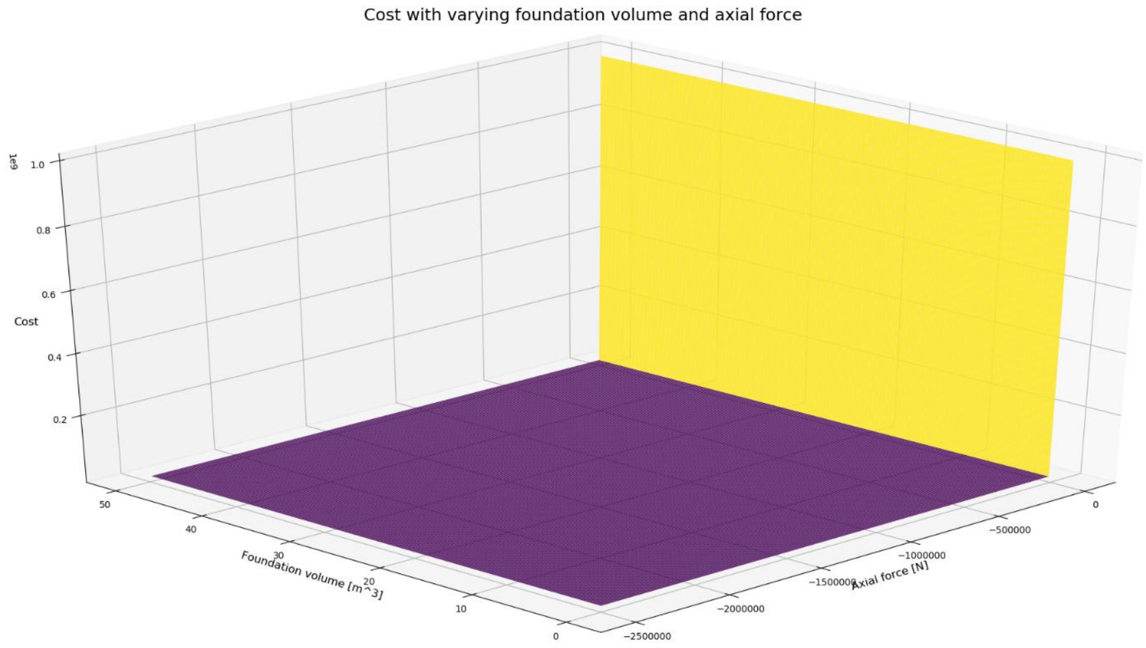

Figure 4-4: Cost with varying foundation volume and axial force.

The figure gives little information on how the cost is varying and blows up when the axial force in the pile is positive, i.e. when tension occurs. The cost function almost looks like a Dirac delta function [24] and work almost like a switch when tension occurs. This is exactly what was desired, and the plot confirm this.

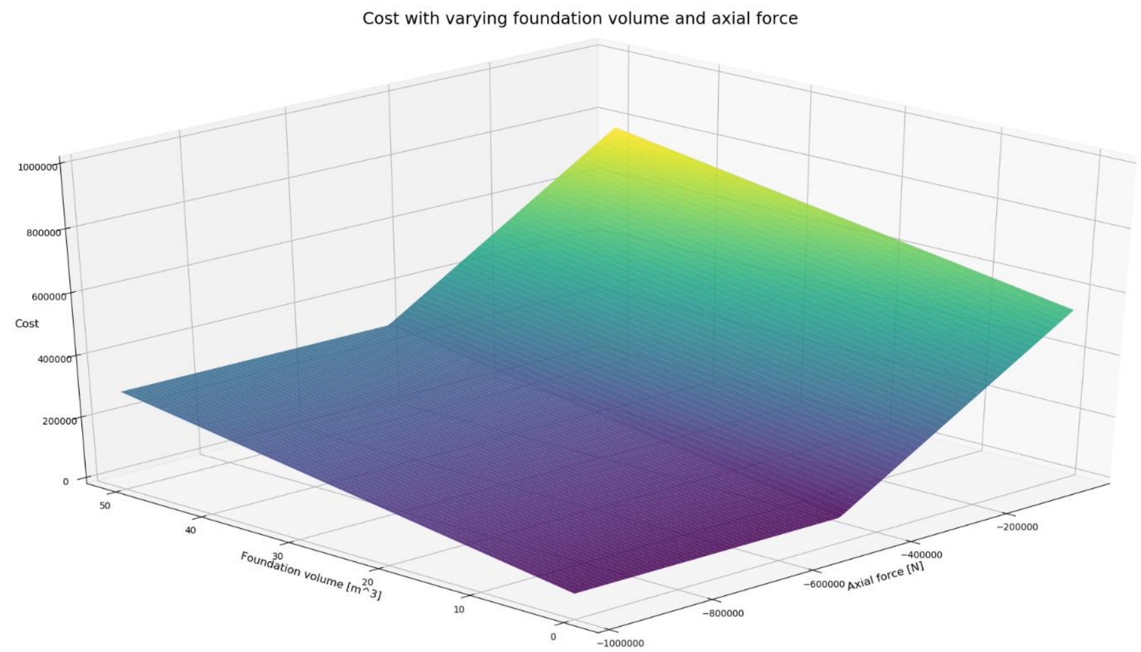

Figure 4-5: Closeup on how cost varies dependent on foundation volume and axial force.

A more closeup look on the function, revels how the cost is varying dependent on the foundation volume and the axial force, see Figure 4-5. The cost is varying linearly in the foundation volume direction and remains constant in the axial force direction, when the compression in the pile is bigger than 5% of the axial capacity. When the compression is less than 5% of the axial capacity, it varies linearly. This linearly increasement is due to the desire of robustness in the design. An optimal design is achieved when the foundation volume is minimized, and compression is kept above the 5% limit of the axial capacity.

4.3.3 Displacement in Z- and X-direction

Figure 4-6 shows the cost variation dependent on displacement in the horizontal and vertical direction.

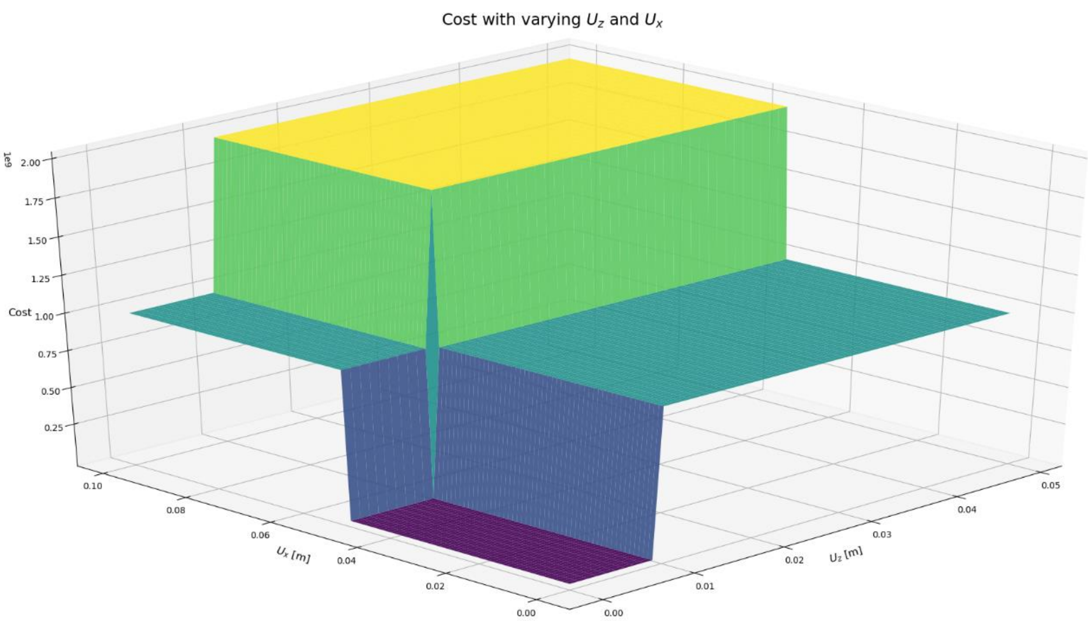

Figure 4-6: Cost with varying displacement in z- and x-direction.

The cost is extremely big when the limits for the displacements is exceeded and even bigger when both are exceeded. In the domain where neither of the limits are exceeded, Figure 4-7 shows the cost variation.

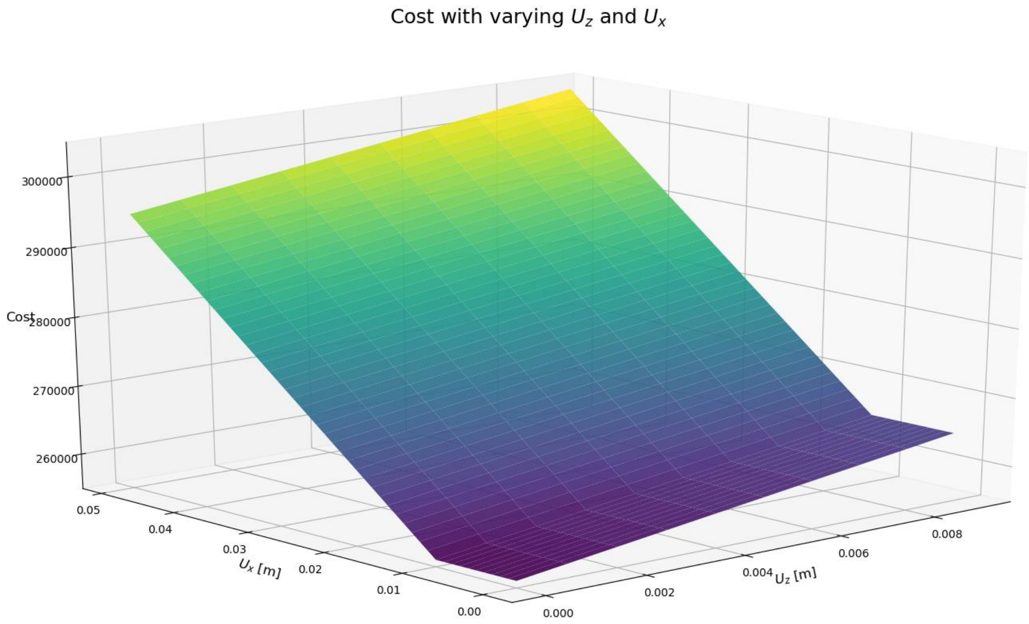

Figure 4-7: Cost variation within displacement limits.

The optimal solution is then obtained when the displacement in the x-direction is held below 10mm and when the displacement in the z-direction is minimized.

4.3.4 Rotation

Figure 4-8 shows how the cost varies dependent on the rotation of the pile foundation. It is zero when the rotation is below a limit value of 1 degree and increases linearly up to a threshold value of 2 degrees. Over this, the cost is set to a high value in order to prevent greater angles than this. An optimal solution regarding rotation is then obtained when the angle is below 2 degrees.

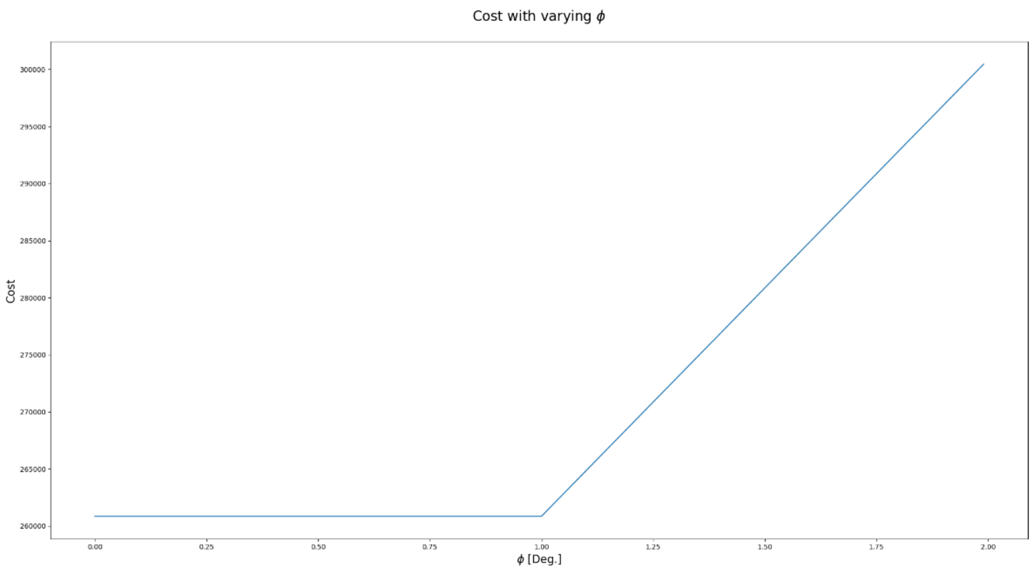

Figure 4-8: Cost with varying rotation.

4.3.5 Summary

The above plots substantiate the performance of the cost function to be as wanted, regarding the criteria described in: *4.2 Cost Function*. By looking on the variables isolated we can obtain an idea on how each variable is affecting the cost, but this will not give the complete picture. How the different variables are weighed compared to each other, and how changing one variable affects the cost contribution from other variables, are of high importance. How the piles are placed in the group will also affect the distribution of the forces and stresses in the piles. This may change the cost for the different configurations greatly. A small change in the configuration could lead to tension in one or more pile(s). This will make the cost suddenly jump up and eliminated the candidate solution. The cost function should therefore not be investigated in an isolated manner. A plot of the cost function with respect to all the 7 variables, would also not be possible to produce.

5 Numerical model and initial analysis

This chapter gives a description of the numerical model with all its variables and constrains. The model is only subjected to a single load case in order to get an overview on how the model is performing. The result from the analysis, by a brute force method, are also presented.

5.1 Modell

As described in chapter 1.2.1 *Case-study: Råna bridge,* the numerical model of the pile foundation is limited to a 2D model. The model has 3 degrees of freedom (DOF) per node, two translation and one rotation. An illustration of the model is shown in Figure 5-1.

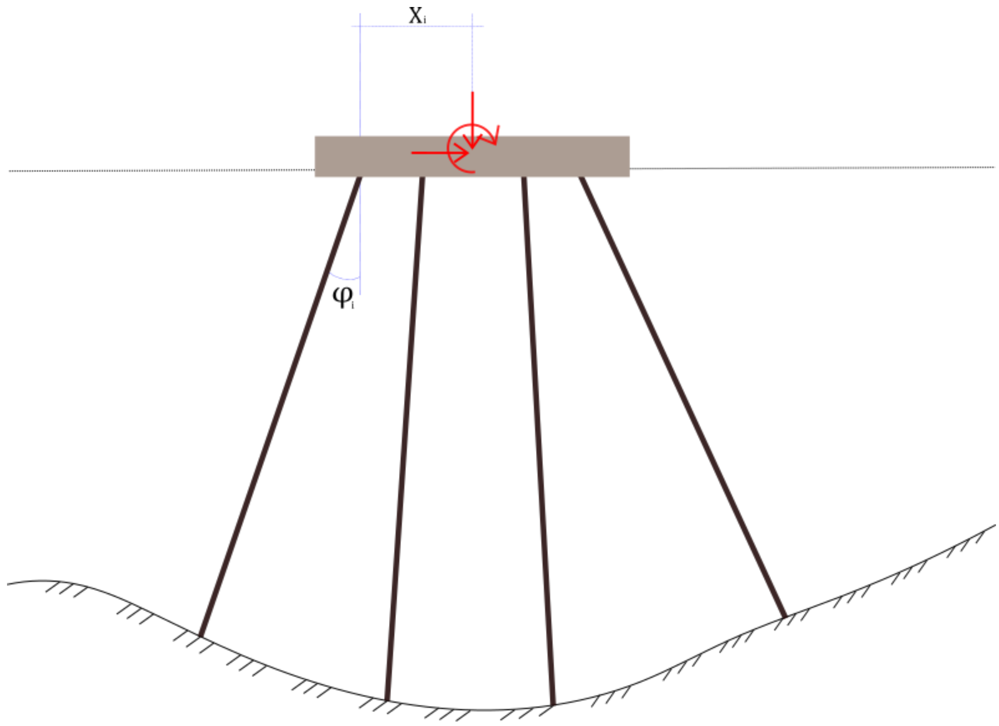

Figure 5-1: Analytical model.

A pile foundation is a multivariable problem, where its configuration describes its structural properties and response. The model has been chosen to have a fixed amount of piles. This results in 9 different variables that describes the entire solution space, $\mathbb{R}^9$, and are the following:

- Diameter of the piles.
- X_i^{top} – Position of the top of the pile. Where i = 1,2,3,4.
- ϕ_i – Angle of the pile. Where i = 1,2,3,4.

In order to confine the solution space and to enable finding optimal solutions, the variables need to be discretised. The discretisation was chosen to be the following:

- Diameter $\in$ $\{0.09, 0.1, 0.11, 0.12, 0.13, 0.15, 0.18, 0.19, 0.2, 0.21, 0.22, 0.23\}$
- X_i^{top} $\in$ $\{ -5 , -4.5 , -4.0 \ldots 5 \}$
- ϕ_i $\in$ $\{ -30 , -25 , -20 \ldots 30\}$

This results in a solution space, $\mathbb{R}^9$, that contains 66 654 862 092 possible combinations. The discretisation of the diameter is chosen according to available sizes. The position is discretised with agreement with the recommended minimum distance between piles, described in chapter 3.6.2 *Geometrical formation of piles in* group.

Discretising the analytical model and making a numerical model was done in OpenSees. The model in OpenSees, for a given configuration, is shown in Figure 5-2 below.

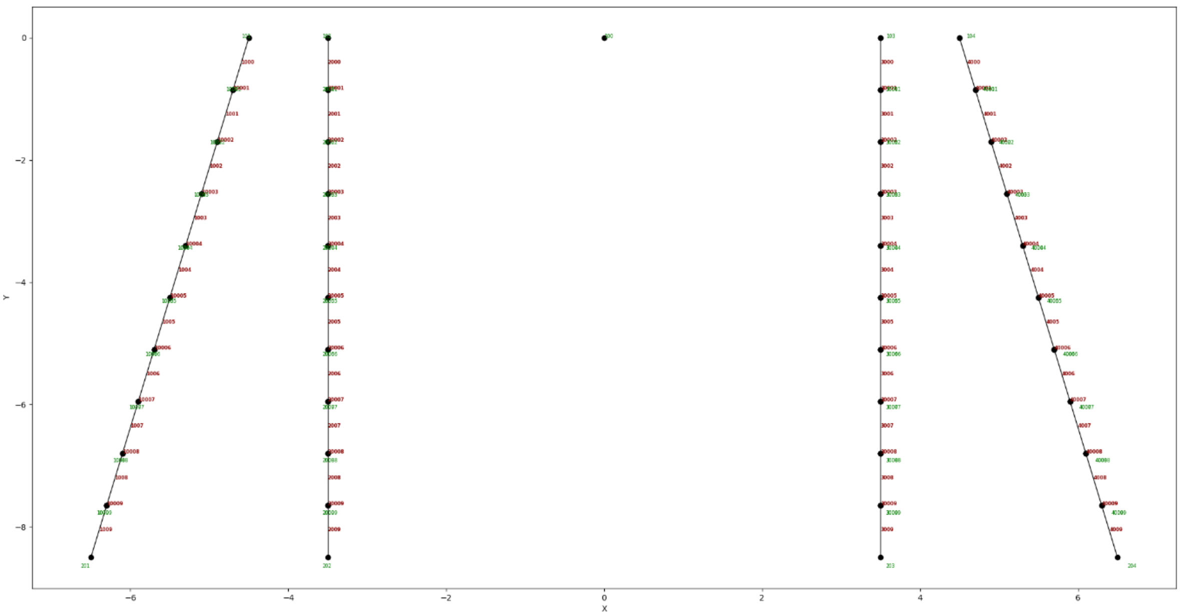

Figure 5-2: Numerical model in OpenSees.

Each pile is discretised into 10 elastic beam elements. The bottom node for each pile is fixed and the top nodes are connected to the “master” node in the middle by rigid links. All loads are applied to the “master” node, which is located in the centroid of the foundation slab. Each node along the piles is connected to a fixed node at the same location by a zero-length element. These zero-length elements, made of multiple uniaxial material, represents the lateral support from the surround soil as springs. The spring stiffnesses are according to the description in *3.3.1 Lateral springs* with the slope of the soil’s reaction modules (k) sett to 4500 KN/m³.

5.2 First analysis and results

Fixing the diameter to 0.15 m, effectively reducing the number of combinations to 5.5 billion, and running the analysis for each possible configuration, it took too long time to finish. Introducing a coarser discretization made it possible to execute, with a runtime on three days. This was performed on a computer with a 2,7 GHz intel core i7 processor. Collecting the feasible solutions with lowest cost gave the following configurations, see Figure 5-3 below.

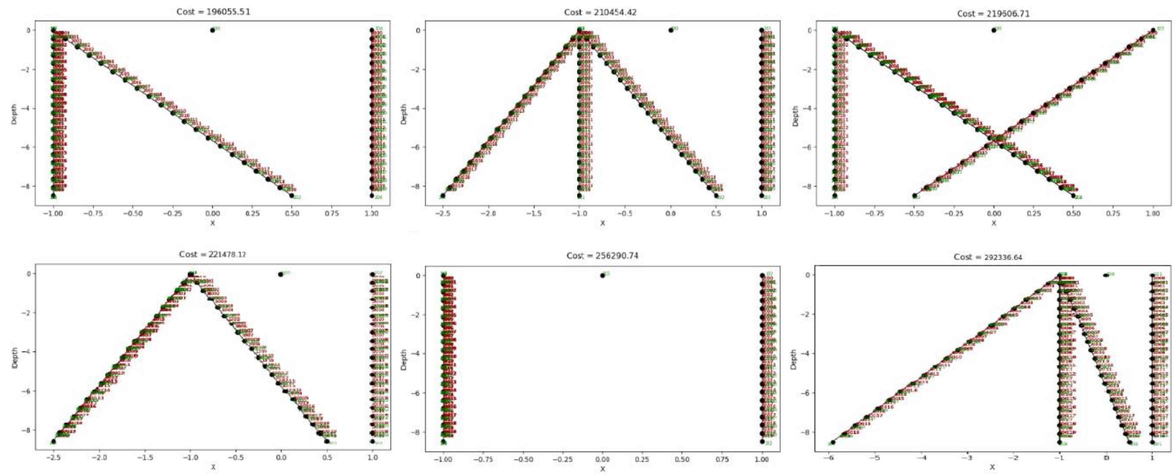

Figure 5-3: low cost solutions from first analysis.

For many of these configurations the piles are crossing each other. This is not wanted because it would cause problems during construction. By looping over all the variables in this way, it would also lead to calculation of equal configurations with new numbering. This is just wasting computation time and is not wanted. Some constrains to prevent this should therefore be implemented.

5.3 Second analysis and results

In order to avoid crossing piles and equal configurations with new numbering, the following constrains was introduced:

- $X_j^{top} \geq X_i^{top}$, $where: \ i = 1,2,3 \ and \ j = 2,3,4$
- $\phi_j \geq \phi_i$, $where: \ i = 1,2,3 \ \ and \ \ j = 2,3,4$

This reduces the number of combinations by a factor of 287 and reduces the solution space to a magnitude of 19 339 320 possibilities. This made the algorithm much faster and enabled completion with the initial discretization. The runtime reduced to around 13.5 hours. The 6 configurations with the lowest cost are shown in Figure 5-4. Now none of the piles is crossing each other, but it allows for piles in the same location.

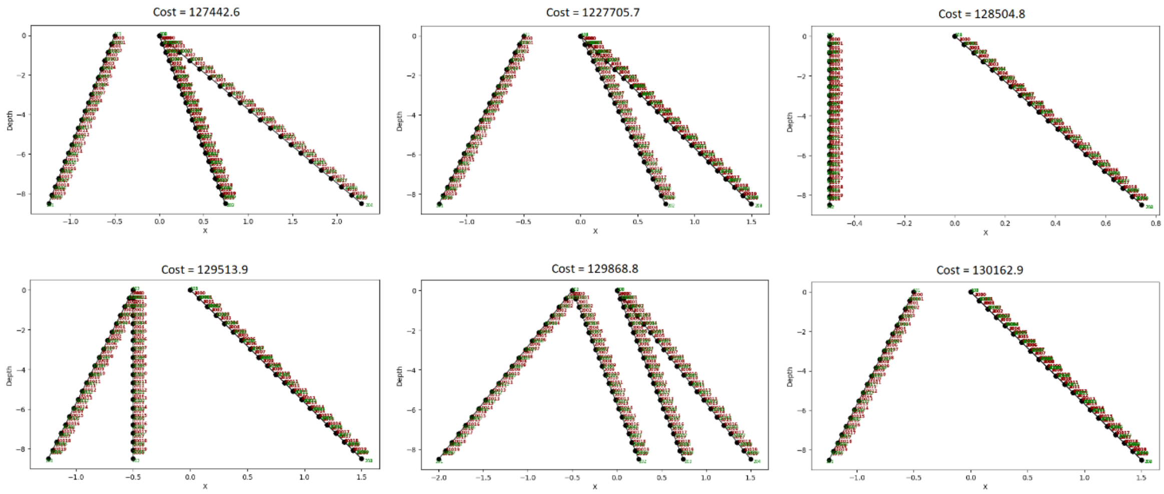

Figure 5-4: low cost solutions from second analysis (with constrains).

5.4 Discussion

The above runtimes have only dealt with one fixed diameter and therefore reduced the problem to 8 variables instead of 9. Including varying diameter will lead to almost 12 times the computation time. This could be reduced by utilization parallelization [25], but it would still take a lot of time. The solution method of using a brute force algorithm is shown not to be feasible.

All these analyses have only dealt with a single load case, and not a load combination consisting of multiple load cases. Including this would lead to a massive increase in computation time. In a common global analysis of a bridge, there are 12 different load cases from a 3D model and 6 for a 2D model. It would have been too time consuming to approach this with the same “Brute force” method as previously. This creates the need for a different design approach and a method with significantly better performance.

6 Optimization methods

Previously chapters find the computational time to be too big in order to find an optimal solution in a sensible amount of time. This chapter describe different optimization methods that has been used in this thesis, in order to improve efficiency and save computation time.

6.1 Use of unit load method

Since all the analysis is linear, the principal of superposition is valid and therefore the unit load method may be used. The unit load method is a technique that utilize the concept of virtual work and makes it possible to calculate the effect of many forces in an efficiently manner. By calculating the effect of a unit load applied sequentially in each DOF, the combined action of an arbitrary load may be obtained by scaling and combining each response from the unit loads. Figure 6-1 gives a brief explanation on the method.

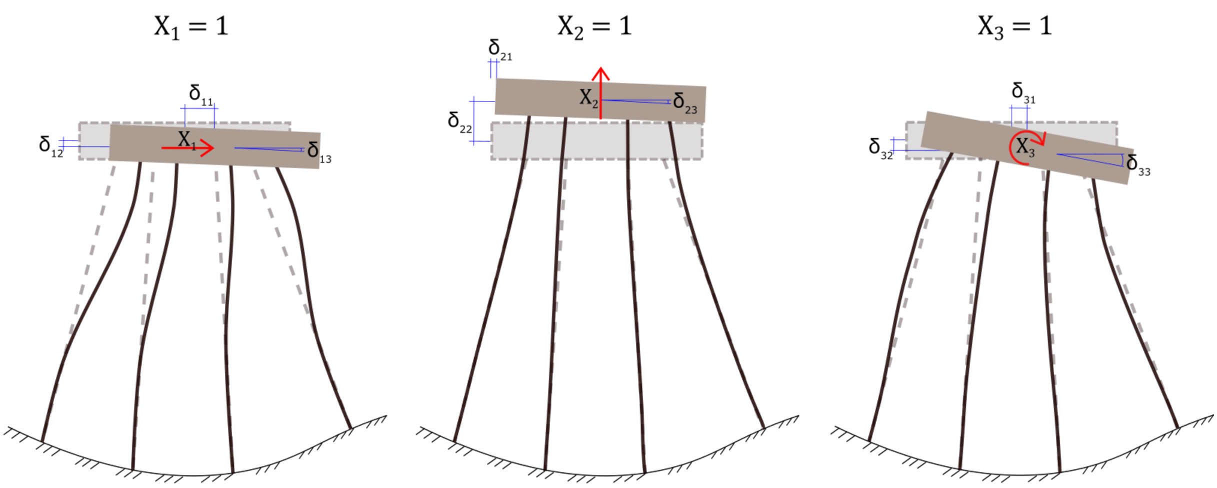

Figure 6-1: Explanation of the unit load method.

The resulting action for an arbitrary load is then given as:

$$\delta_j = \sum_{i=1}^{3} X_i * \delta_{ij} \tag{6-1}$$

Where X_i represents the load in DOF i. The combined action is represented in Figure 6-2 below.

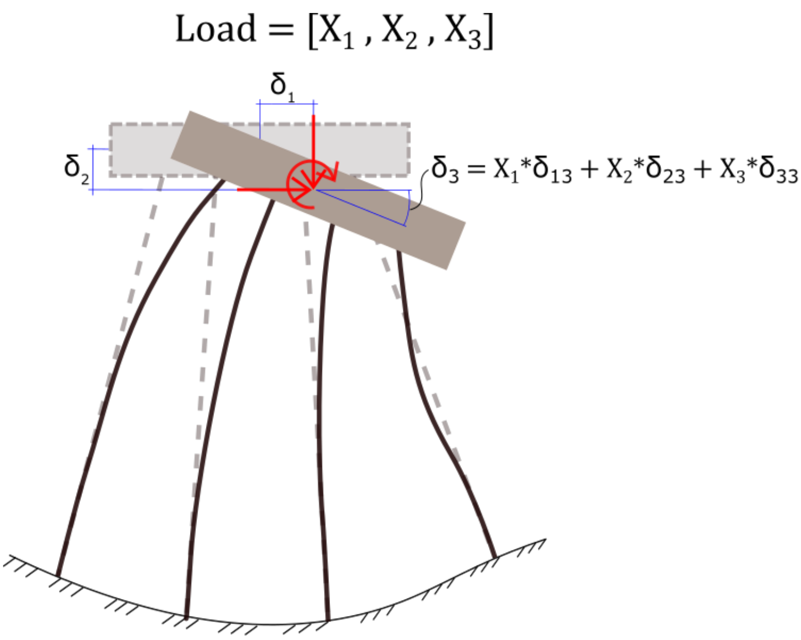

Figure 6-2: Combined action from an arbitrary load.

In order to do this, one must first calculate the response from each unit load and store this information in order to use it later for scaling and combination. When doing this for the pile foundation in Figure 5-1 it created 55 GB of information and took a week to generate.

An optimal solution subjected to a single load case can now be obtained by scaling the responses and combining them instead of calculating each configuration. However, the cost cannot be scaled in the same manner and need to be recalculated. This method reduced the computational time to 2 hours in comparison with the previously 13.5 hours.

When employing the unit load method on a load combination of six load cases, it still cannot find an optimal solution in a sensible amount of time. Other optimization method is therefore investigated, and the unit load method is used as a benchmark when testing other methods. The unit load method solves the optimization in an exact manner, by using “brute force”, and guarantees a global minimum, which may not be the case for other methods.

6.2 Generative design (GD) approach

Generative design is a design procedure in which the designer collaborates with artificial intelligence algorithms to generate and evaluate hundreds of potential designs [26]. It employs Genetic algorithms (GA) in order to search a space of potential solution to find one (or several) which solves the problem [27]. The design procedure goes through the stages presented in Figure 6-3 below.

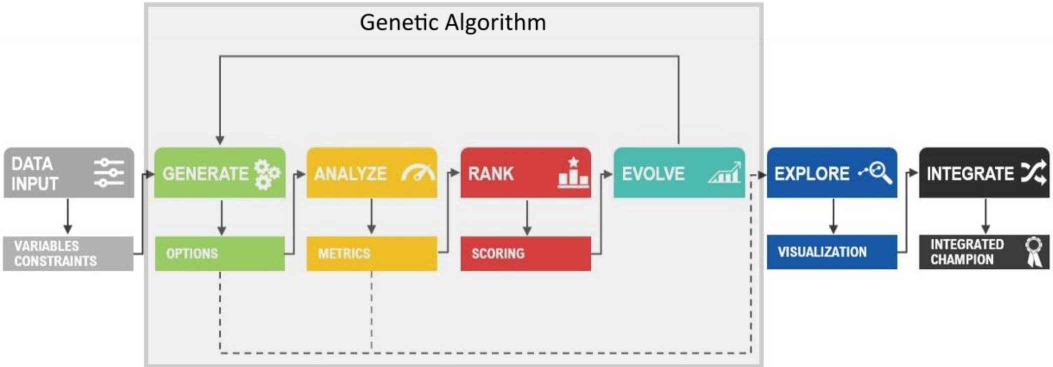

Figure 6-3: GD approach with the GA part highlighted in grey.

It starts by defining the variables and constrains of the problem. Then by using GA it goes through an evolvement phase which ends with an amount of high scoring feasible solutions that satisfies the constrains.

6.2.1 Genetic Algorithm (GA)

GA is stochastic search algorithms that are based on Charles Darwin's theory on natural selection, the process that drives biological evolution [28]. The GA repeatedly modifies a population of individual solutions. At each step, the GA selects individuals from the current population to be parents and uses them to produce offspring for the new generation. Over successive generations, the populations evolve toward an optimal solution. Figure 6-4 describes the typical process of a GA.

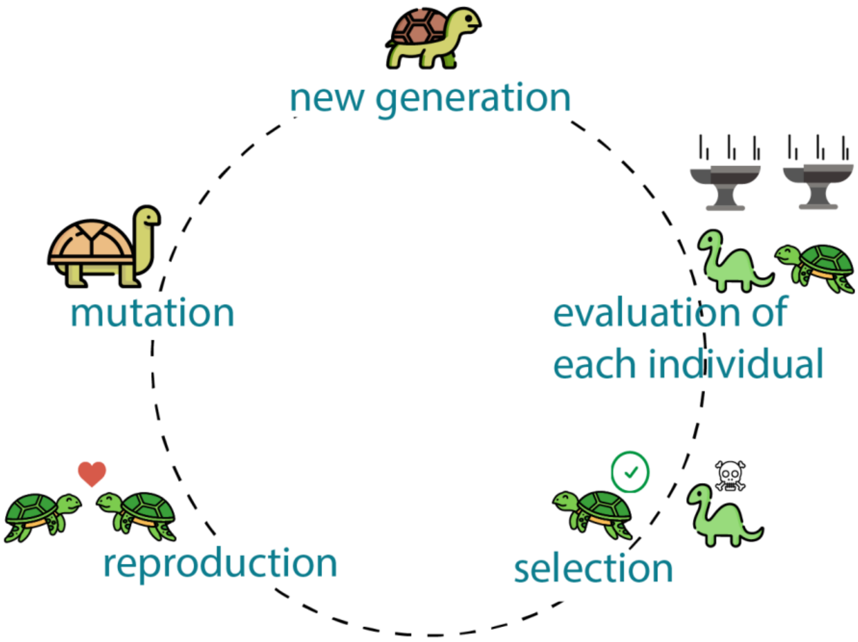

Figure 6-4: Typical genetic algorithm phases [29].

6.2.1.1 Evaluation

How the evaluation of each individual is done will vary greatly dependent on the optimization problem at hand. In order to obtain good results from the GA, it is essential that the evaluation is done right. The evaluation is done with an objective function, which will measure the solutions against each other, to decide which is best. Therefore, it is crucial that the objective function is quantifiable and enables maximization or minimization [30].

In this thesis the cost function described in chapter *4.2 Cost Function* has been used as the objective function and to evaluated each individual.

6.2.1.2 Selection

Selection is the process of selecting parents for reproduction. The purpose of selection is to emphasize fitter individuals in the population so that the offspring hence produced has higher fitness. Selection, however, must be balanced with variation from crossover and mutation. Very strong selection will lead to highly fit individuals taking over the population, thus reducing the diversity needed for change and progress. On the other hand, very weak selection may result in too slow evolution [30].

The most used selection methods include Roulette Wheel Selection, Rank Selection, Tournament Selection and Boltzmann Selection. In this thesis the Roulette Wheel Selection was adopted.

6.2.1.3 Reproduction

In the reproduction stage the selected parents produce offspring. In this part, recombination and mutation operators are used.

Crossover

Crossover is a genetic operator used to combine the genetic information of two parents to generate new offspring [31]. There are different methods of crossover and includes single point crossover, N-point crossover, uniform crossover, three parent crossover, arithmetic crossover, partially mapped crossover, crossover ORDER and cycle crossover [32]. The first three being the simplest ones. Figure 6-5 explains how the simples forms of crossover are performed.

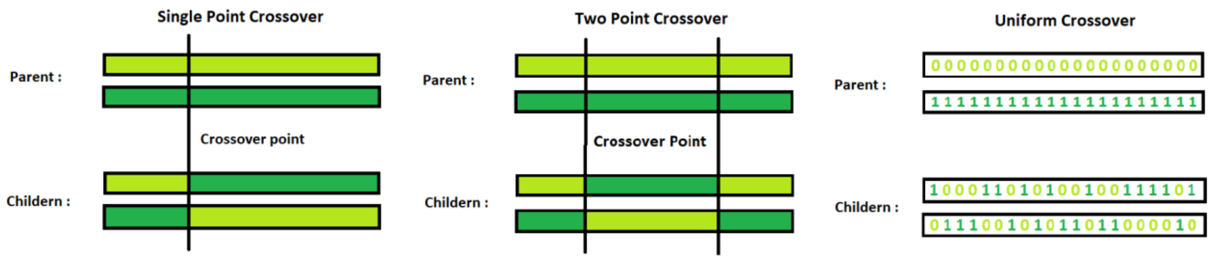

Figure 6-5: Single point, two point and uniform crossover method.

In this thesis uniform crossover was chosen.

Mutation

Mutation is a genetic operator used to maintain genetic diversity from one generation to the next. It alters one or more gene in a chromosome from its initial state. Mutation occurs according to a user-defined mutation probability and should be set low in order to avoid the search to turn into a primitive random search. Mutation is used to avoid local minima by preventing too similar chromosomes in the population, thus slowing or even stopping convergence to the global optimum [33].

Different types of mutation include bit string, flip bit, boundary, non-uniform, uniform, gaussian and shrink. In this thesis a uniform mutation type was chosen.

6.2.1.4 New generation

When the reproduction is done a new generation is form by the offspring. In order to improve GA's performance, the best individuals must always participate in reproduction. Such individual may be lost if they are destroyed by crossover or mutation. To avoid this "Elitism" may be adopted into the algorithm.

Elitism

Elitism is a process of making sure that the fittest individuals are not destroyed. The first or the few best chromosomes from a population are copied to the new generation. This will eliminate the possibility of losing the fittest individuals. This can have dramatic impact on performance by ensuring that the GA does not waste time re-discovering previously discarded partial solutions [34]. Elitism has been implemented in this thesis.

6.2.1.5 Results from the GA

Since the value of the mutation rate and the crossover rate is key in order to get good results, varying values for each parameter has been tried out. The number of generations is fixed to a value of 50 and the number of parents is initially set to 10. This is later changed in order to check the influence. Figure 6-6 and Figure 6-7 shows the variation of the fittest individual for different values of crossover rate (CR) and mutation rate (MR).

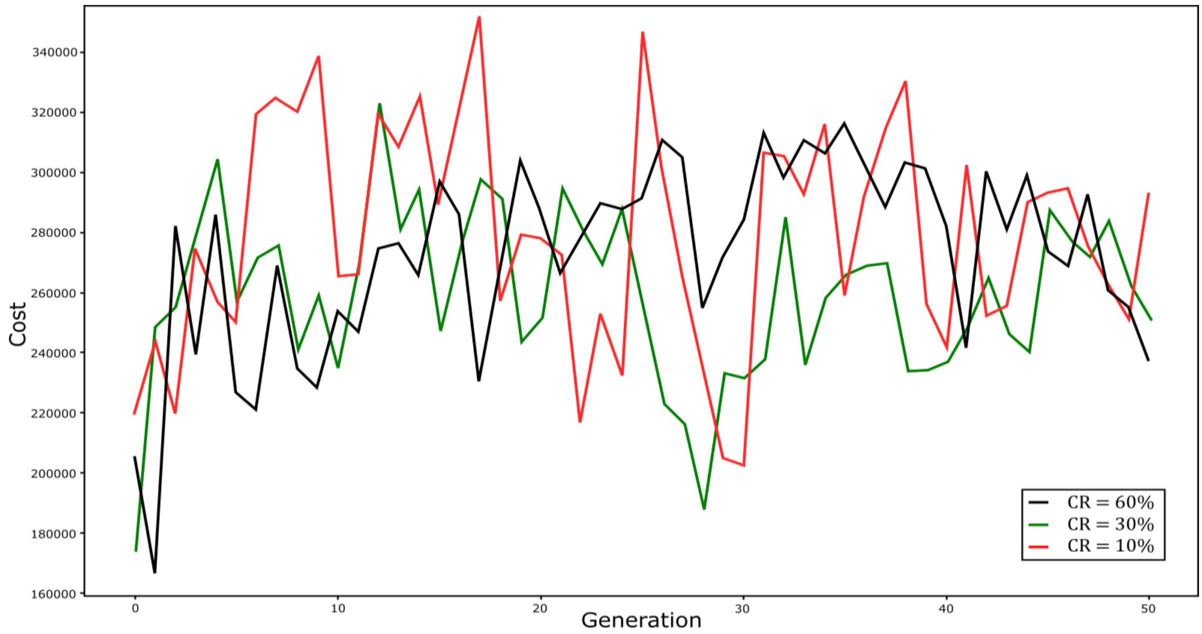

Figure 6-6: Cost development with constant MR (=0.05) and varying CR.

In order to have a good converting algorithm, the cost of the population should go down as new generations is formed. By looking at Figure 6-6, we can see that the average slope for a CR of 60% is slightly positive and for a CR of 30% and 10% it is slightly negative. This may indicate that a CR below 30% should be used. Therefore, a CR on 20% has been adopted in this thesis.

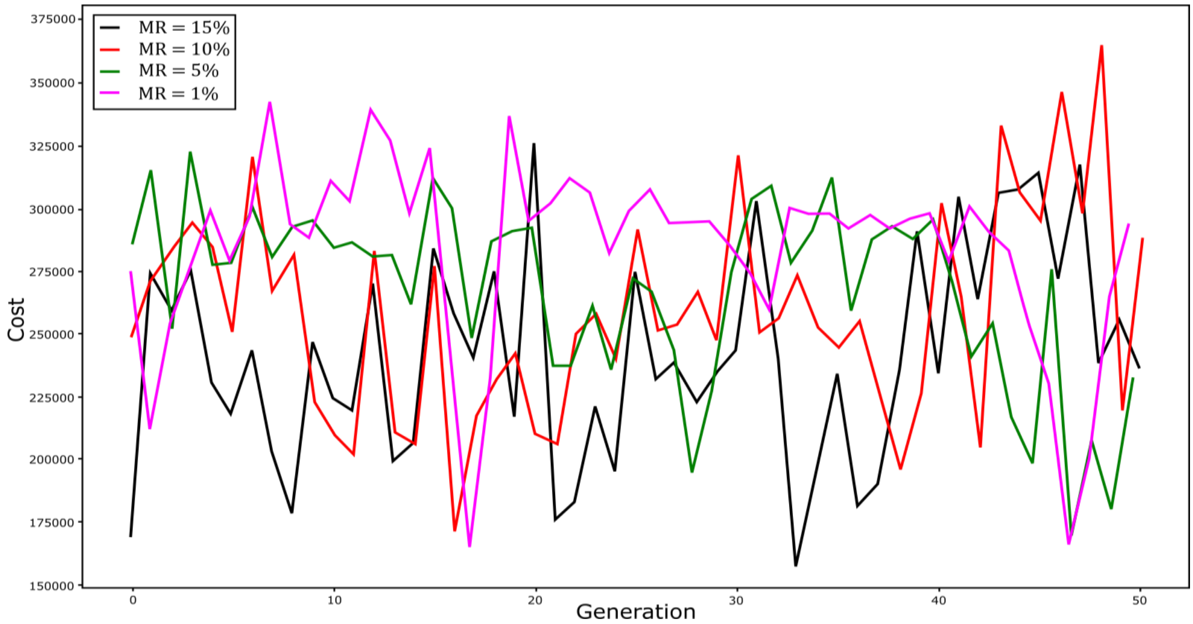

Figure 6-7: Cost development with constant CR (=0.2) and varying MR.

Varying the mutation rate shows that low mutation rate gives lower average slope of the cost. This corresponds to the advice given in [33]. In Figure 6-7 we see that a MR of 15% and 10% has a slightly positive average slope and with a MR of 5% the slope is slightly negative. Based on this, the mutation rate is set to 5% in this thesis.

Figure 6-8 shows the variation of the fittest individual for different number of parents.

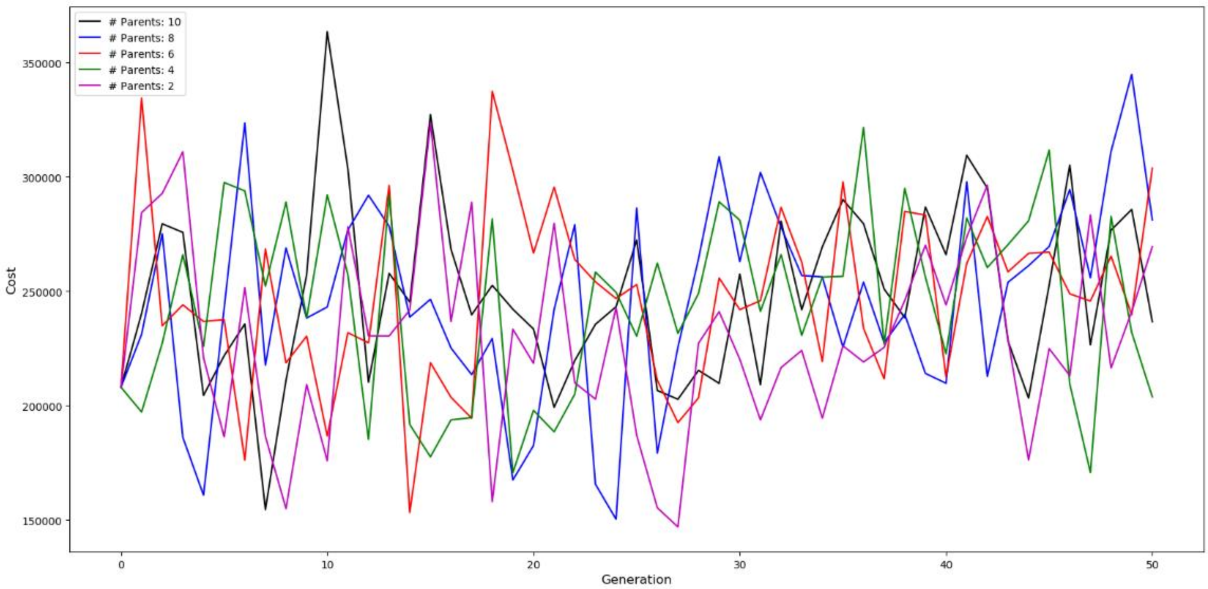

Figure 6-8 Cost development with different number of parents.

The figure gives no inclusive evidence on whether certain number of parents is better than another. The development compared to one another look somewhat more random. The same analysis has been run multiple times with the same inconclusive result. The number of parents is therefore considered not to be import regarding convergence.

After tweaking the parameters, the algorithm still exhibits convergence problems. The algorithm quickly jumps to another local minima point and starts the procedure of finding the minima again. This can indicate that the solution space is highly nonlinear. In order to avoid this jumping between local minima areas, adjusting the mutation and crossover rate may prohibit the search engine to alter between local minima points. This will decrease the randomness in the algorithm. Another way to restrict the randomness is to completely avoid it, by changing to another optimization method before the GA jumps to another local minima. To increase refinement and to obtain a better local optimum, the use of Adaptive Genetic Algorithm (AGA) may be used.

6.2.2 Adaptive Genetic Algorithm (AGA)

The chosen value for the crossover and mutation rate greatly determine the accuracy and the convergence speed of the GA. Instead of using fix valued of CR and MR, AGAs utilize the population information in each generation. It then adaptively adjusts the CR and MR in order to maintain the population diversity as well as to sustain the convergence capacity.

In addition to adjusting CR and MR it can be quite effective to combine GA with other optimization methods. GA tends to be quite good at finding generally good global solution, but fairly inefficient at finding the absolute global optimum. Other techniques, such as simple hill climbing, are very effective at finding absolute optimum in a limited region [34]. Combining GA with hill climbing may dramatically improve the efficiency of the GA, while overcoming the lack of robustness of hill climbing.

In this thesis the GA was combined with the trust-constr optimization method, from the SciPy optimize library, in order to create an AGA that can handle constrains. The trust-constr method uses the trust-region interior point method when inequality constrains are imposed. For description of the method see [35].

6.2.2.1 Results from the AGA

By employing AGA, the algorithm does not longer have convergency issues. The accuracy as well as the computation time shows dramatically improvement. Figure 6-9 Shows how AGA has improved the results from a previously GA run.

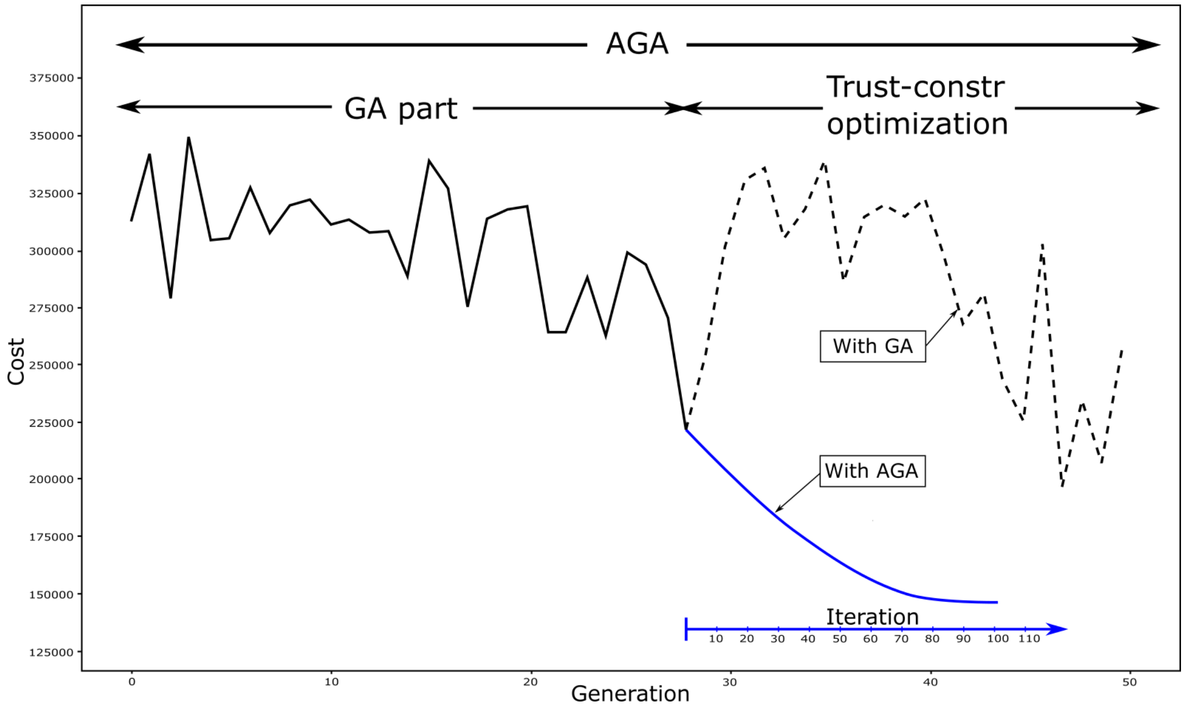

Figure 6-9: Cost development of AGA compared with GA.

When to stop the GA and go over to the trust-constr optimization is up to the user to choose. Should it be after a certain amount of generations, begin from the best generation for a certain amount or just right after the initial generation is formed? This will not have a big effect on the final cost for the fittest individual, if the limitation of iteration is not set to be too small. In this thesis the trust-constr optimization is set to start after the initial generation. This is done to make the algorithm as efficient as possible. The maximum number of iterations is then set to a conservatively high number in order to prevent premature termination. This will lead the algorithm to function almost like a swarm optimization algorithm. An explanation of this is found in Figure 6-10.

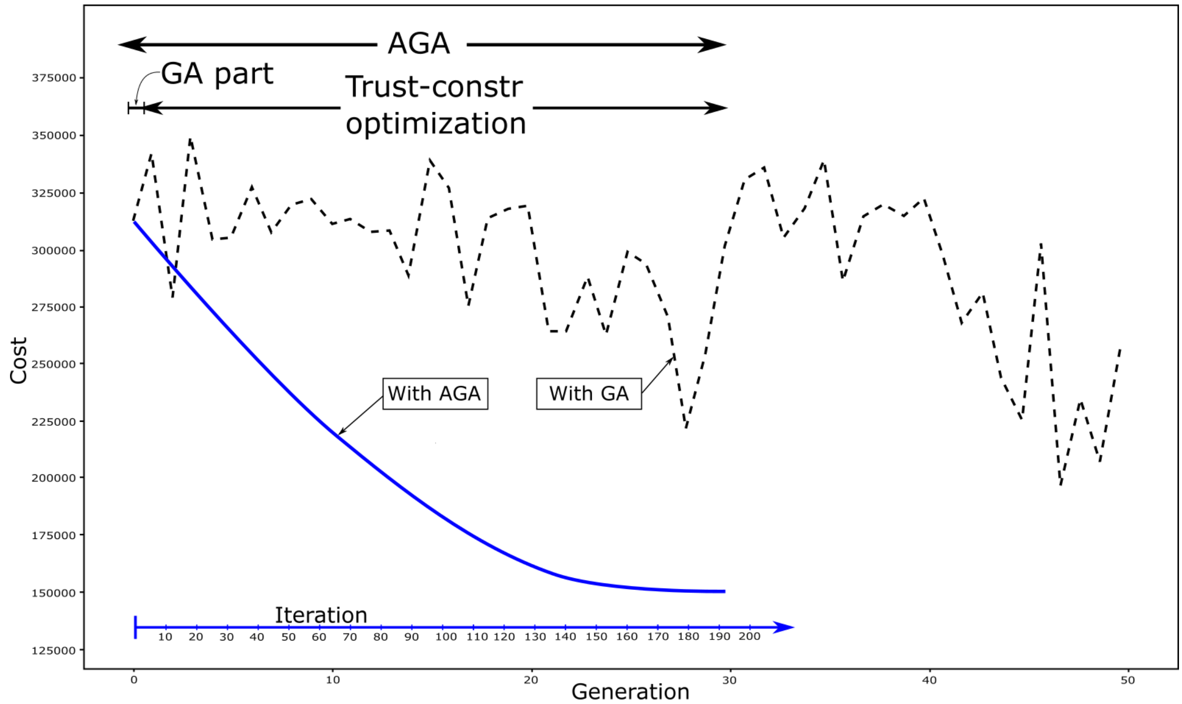

Figure 6-10: Cost development of AGA with immediately trust-constr optimization.

All the previously shown results are for a single load case and not for a given load combination. Employing the same AGA on a load combination of six loads will give the configuration that has the lowest cost subjected to six different load cases as the optimum. The optimum is then the highest cost the optimal configuration achieves when subjected to six different load cases. This cause the optimal cost to increase because the algorithm now must search for an intermediate solution. For results regarding AGA for load combination see chapter 6.3 *Comparison between optimization methods.*

6.3 Comparison between optimization methods

The presented method of finding an optimum all has their ups and downs. The unit load method of being exact, but with the large drawback on computational time. The efficiency of the genetic algorithms, but only giving the optima in an approximated manner. The quality of the approximation from the GA's is greatly dependent on algorithmic parameters chosen by the user. In order to get a good spread in the initial population and to avoid premature converge, a large enough size of the initial population should be chosen. This value has been found to be 50 000 or larger. Employing the different methods on a pile foundation, subjected to a single load case and a load combination, gives the following results.

Table 6-1: Optimal cost for different methods.

	Unit load	GA	AGA
Single load case	146 865	149 000	141 913
Load combination	165 644	230 781	198 902

Subjected to a single load case the GA only gives a marginal increase in cost, compared to the exact unit load method. The cost is only increased with 1.5%. The AGA gives a lower price than the unit load method. This is because the AGA represents the variables as continuous rather than discrete. The AGA can then fine-tune the variables in between the discretization that the unit load method and GA has. The AGA gives the best results, but its deduction in cost may results in a solution that is more difficult to build.

Subjected to a load combination, the cost from each method has increased compared to the single load case. The lowest cost is now the highest cost the optimal configuration achieves when subjected to six different load cases. This favour the more robust solutions which can achieve a low cost for a variety of loads. This increase of robustness comes with an additional cost and therefore increases the cost of the global optima.

The unit load method gives the lowest cost for the load combination. The GA and the AGA have an increased cost of 39.3% and 20% respectively. A change to one size bigger diameter results in a 20% increase of cost, so the GA and the AGA does not give a significant increase in cost. With the AGA being 20 time faster it proves to be an effective and accurate algorithm.

7 Machine Learning (ML)

The optimized configurations from chapter 6 have been used to train a machine learning algorithm. This chapter will briefly explain what ML is, different methods of creating a ML model and their accuracy for the problem at hand.

7.1 What is Machine Learning?

Machine learning is a technique used to perform specific task without using explicit instructions, relying on patterns and inference instead [36]. It is seen as a subset of AI. ML algorithms build a mathematical model based on sample data, known as "training data", in order to make prediction on new data. It can be implemented by a multitude of algorithms. Machine learning techniques use supervised or unsupervised learning strategies. Supervised learning uses input data (features) that is labelled and then the algorithms try to find rules to map inputs into outputs (labels). Classification and regression are both types of supervised learning. Classification is used when output is restricted to a limited set of values, while regression is used when the output is continuous. In unsupervised learning, the goal is to discover hidden patterns in the data [37].

7.2 Training data

For the ML algorithm to be able to make predictions, it needs training data. The training data is used to build the ML model and is a key factor in order to make reliable and accurate ML models.

The problem at hand for this thesis is to create a ML model that can predict an optimal configuration (output) from a set of forces (input). For this we need output/input pair, linking the configuration wanted subjected to a given load combination, in order to train the model. Such data has not been available for this thesis and has therefore been created synthetically. The first step is to create many load combinations. This could be taken from previously projects that Norconsult has done, but this mean looking through thousands of reports and manually structuring the data. To save time the load combinations was created by picking random values from a confined region, inspired by the load combinations from previous projects.

When creating a ML model there is always a question on how much Training Data (TD) is needed. The answer for this question is that no one knows. The amount of TD needed will vary greatly depended on:

- the complexity of the problem
- the complexity of the learning algorithm

In this thesis the TD consist of 4000 samples and are limited by time limitations. The optimal configurations for each load combination has been created using the AGA explained in chapter 6.2.2 *Adaptive Genetic Algorithm (AGA).* It took over 200 hours to make with 8 parallel cores running simultaneously. The input/output pairs, consisting of load combination and optimal configuration, makes up the TD.

Some learning algorithms are so called "closed-form solvers", meaning it will not be able to make predictions on data that are outside the bounds of the TD. For such learning algorithms to give good prediction, a good spread in the TD, such that it covers as much of the solution space as possible, should be emphasised. This is also something that can help any solver increase it robustness, and to prevent the model from only being accurate for a confined space in the solution space. In general, we want a ML model that can generalize as accurately as possible [38]. Figure 7-1 below tries to explain this concept.

Figure 7-1: Illustration of well spread TD (left) and confined TD (right).

7.3 Models

When the TD is created, one can fit the ML model to the TD. Different ML models are best suited for different problems, therefore, variously ML models has been tested. The accuracy, before and after adjusting algorithmic parameters, as well as a short description for each method, is presented in the following chapters.

The TD is split into a training set (75%) and a test set (25%). The test set is used to assess the accuracy of the model on new data and will reveal if the model generalizes well or not. This is measured with the coefficient of determination R^2 of the prediction. This is defined as $(1 - \frac{u}{v})$, where u is the residual sum of squares and v is the total sum of squares. The best possible score is 1.0 and it can be negative (arbitrary worse), meaning the model fits the data worse than a horizontal hyperplane (constant guess) [38].

Since the prediction is continuous-valued attributes, the different models are regression supervised learning algorithm. The scheme of the ML procedure of this thesis is shown in Figure 7-2 below.

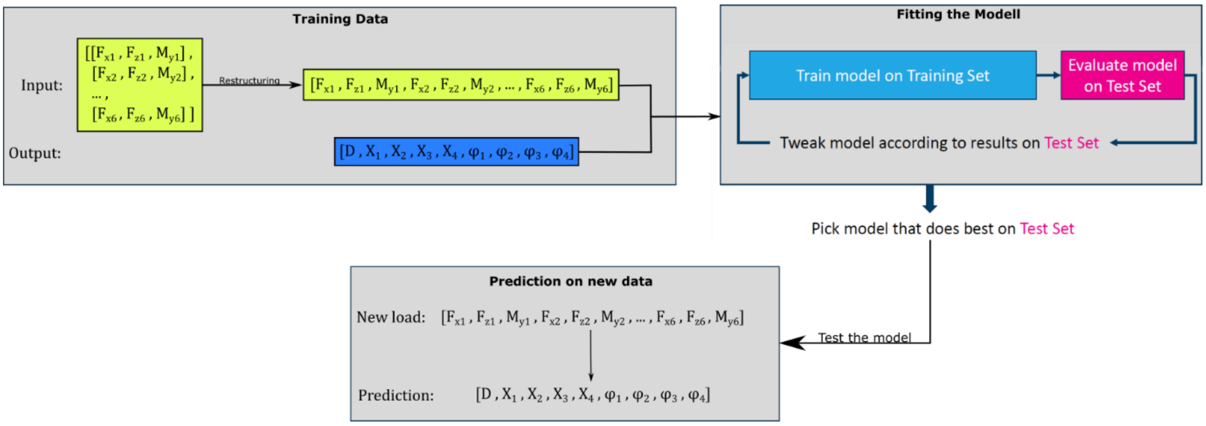

Figure 7-2: ML procedure scheme.

7.3.1 K-nearest neighbours (KNN)

Description

KNN is a non-parametric method used for classification or regression. The input consists of the k closest training examples in the feature space. For KNN regression the output value is the average of the values of k nearest neighbours, where k is specified by the user. By assigning different weights to the contribution of the neighbours the average becomes a weighted average. Weights can assign based on distance or a user defined function [39] [40].

Accuracy

The accuracy of the KNN model, with uniform weights and 5 neighbours (default), is:

- Training set score: 24%
- Test set score: -16%

The model has a poor fit on the training set and a negative score on the test set. The model does not generalize well and has poor accuracy. It will not predict well.

Manipulation

Changing the number of neighbours and changing to weights dependent on the distance may improve the model. Figure 7-3 shows how the accuracy change with increasing number of neighbours and changing weights.

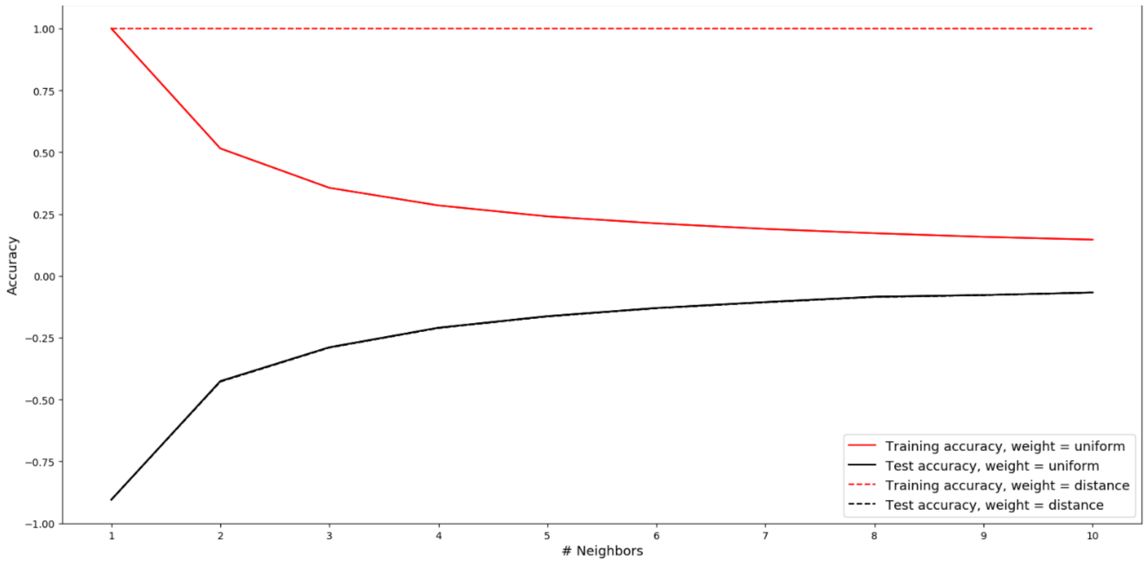

Figure 7-3: Accuracy as a function of number of neighbours.

Increasing the number of neighbours increases the accuracy on the test set, but it does not go over to the positive side. When using distance weight scheme, the accuracy on the training set is 100% for all neighbours, the model is highly overfitted. Manipulation of the model parameters does not give improved results.

7.3.2 Linear regression (least square)

Description

Linear regression fits a linear model with coefficients $w = (w_1, \dots, w_p)$ to minimize the residual sum of squares between the observed targets in the dataset, and the targets predicted by the linear approximation [41]. When multiple variables are predicted, rather than a single scalar, the process is called multiple linear regression [42].

Accuracy

The accuracy of the linear regression model is:

- Training set score: 7%
- Test set score: 6%

The model has a low fit on both the training and test sett. This indicates that the model underfits the training data. The model will not predict well.

Manipulation

The only manipulation available for the linear regression model is normalization of the TD and whether to use interception in the calculations. Changing this does not give any improvement of the model.

7.3.3 Lasso

Description

Lasso is a linear model that estimates sparse coefficients. It tends to prefer solutions with fewer non-zero coefficients, effectively reducing the number of features upon which the given solution is dependent. It consists of a linear model with added regularization term (α) [41].

Accuracy

The accuracy of the lasso model is:

- Training set score: 7%
- Test set score: 6%

The model has a low fit on both the training and test sett. This indicates that the model underfits the training data. The model will not predict well.

Manipulation

Available parameter for manipulation of the lasso model is the same as the linear model, with the additional regularization term. Changing the parameters does not give any improvement of the model.

7.3.4 Decision tree regressor

Description

Decision tree regressor is a non-parametric supervised learn method. The method predicts the value of a target variable by learning simple decision rules inferred from the data features. This could be a set of if-then-else decision rules. The deeper the tree, the more complex the decision rules and the fitter the model [43].

Accuracy

The accuracy of the decision tree regressor model is:

- Training set score: 100%
- Test set score: -83%

The model has a perfect fit on the training set and a negative score on the test set. The model does not generalize well and has poor accuracy. It is highly overfitted and will not predict well.

Manipulation

The decision tree regressor model is created by deciding on the function that measure the quality of the split, the strategy used to choose the split at each node and the maximum depth of the tree. Varying these parameters gives the following improved accuracy:

- Training set score: 6%
- Test set score: 2%

This was achieved by limiting the depth of the tree to 4. The accuracy is still poor, and the model will not predict well.

7.3.5 Random forest regressor

Description

Random forest is an ensemble learning method that operate by construction a multitude of decision trees at training and outputting the mean prediction of the individual trees. Random decision forest corrects the decision trees' habit of overfitting to their training set [44].

Accuracy

The accuracy of the random forest model is:

- Training set score: 81%
- Test set score: -1%

The model has a good fit on the training set and a slightly negative score on the test set. The model does not generalize well and has poor accuracy. It will not predict well.

Manipulation

The random forest model is created with the same decided parameters as decision tree regressor, with the additional number of trees in the forest that the average should be taken from. Varying these parameters gives the following improved accuracy:

- Training set score: 87%
- Test set score: 7%

This was achieved by setting the number of trees to 100. The accuracy on the training set is fairly good, but the model still don't generalize well.

7.3.6 Gradient Boosted Decision Tree (GBDT)

Description

GBDT produces a prediction model in the form of an ensemble of decision trees. It builds the model in a stage-wise fashion like other boosting methods do, and it generalizes them by allowing optimization of an arbitrary differentiable loss function. The algorithm iteratively chooses a function that point in the negative gradient direction, trying to correct the error of its predecessor [45]. It is one of the most popular ML models [38].

Accuracy

The accuracy of the GBDT model is:

- Training set score: 88%
- Test set score: -32%

The model has a good fit on the training set and a negative score on the test set. The model does not generalize well and has poor accuracy. It will not predict well.

Manipulation

Available parameters for the GBDT are the loss function to be optimized, learning rate (contribution of each tree), number of boosting stages to perform and the function to measure the quality of a split. Varying these parameters gives the following improved accuracy:

- Training set score: 94%
- Test set score: 2%

This was achieved by changing the function to measure quality of a split to the mean square error ('mse'), instead of the Friedman MSE, and the loss function to least absolute deviation ('lad'). The learning rate was set to 0.07 and number of estimators to 50. The accuracy is still poor, and the model will not predict well.

7.3.7 Multi-layer Perceptron (MLP) or Neural network

Description

MLP, or more commonly known as artificial neural network, is a supervised learning algorithm that learns a function $f(\cdot) : R^m \rightarrow R^o$ by training on a dataset, where m is the number of dimensions for input and o is the number of dimensions for output. The model consists of multiple layers and trains using backpropagation. The scheme of the model is shown in Figure 7-4 below.

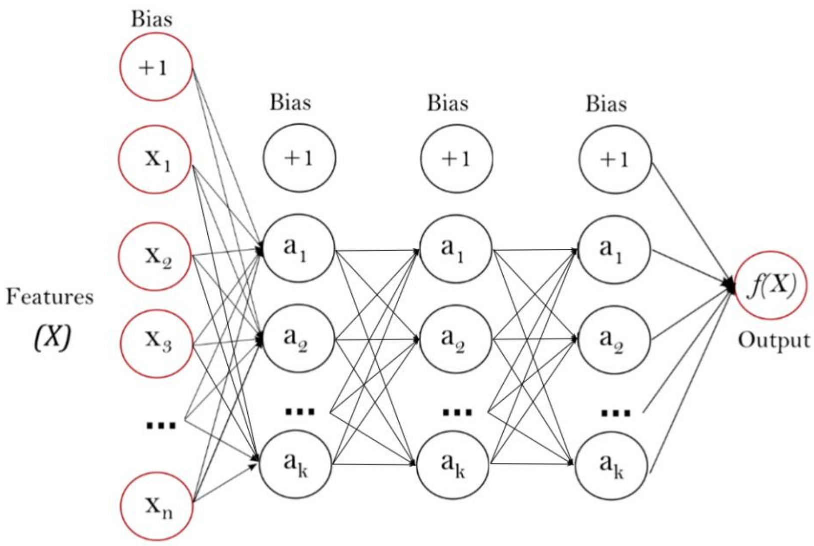

Figure 7-4: Neural network with 3 hidden layers of size k.

The first layer (input layer) consist of a set of neurons $\{x_i | x_1, x_2, \dots, x_m\}$ representing the input features $\boldsymbol{X} = x_1, x_2, \dots, x_m$. Each neuron in the hidden layer transform the values from the previous layer with a weighted linear summation, follow by a non-linear activation function. The output layer receives the values from the last hidden layer and transform them into output values. The number of hidden layers and the size of the layers will vary dependent of the problem at hand and must be chosen by the user.

Accuracy

The accuracy of the MLP model is:

- Training set score: -675240800%
- Test set score: -1110190000%

The accuracy of the MLP is completely rubbish and the model is not working at all. This is because MLP is highly sensitive to scaling of the data and to the choice of parameters [38]. The default parameters are not giving satisfactory results.

Manipulation

The MLP model needs a lot of tweaking in order to work. By rescaling the TD to have a mean of 0 and a variance of 1 the results is drastically improved. After normalization of the TD the accuracy is:

- Training set score: 14%
- Test set score: 2%

Further fine tuning of the size and the number of layers, as well as the activation function, solver for weight optimization, L2 penalty parameter (alpha), learning rate and the exponential decay rates, the accuracy is improved to:

- Training set score: 8%
- Test set score: 5 %

This was achieved by setting the layer size to 8, number of layer to 9, α to 0.4, the exponential decay rates to 0.6 (first moment vector) and 0.8 (second moment vector) and using a stochastic gradient-based optimizer as solver ('adam').

7.4 Evaluation

None of the presented models from the previous chapter have good accuracy. The best accuracy on the test set was achieved by the random forest model. While the accuracy score is only a measure on how well the prediction from the test set is equal to the given output from the test set, it will not premier solutions that are close to being equal. Since all the output labels are continuous a prediction of 3.2, when 3.15 is the correct value, will not contribute to increased accuracy. In the engineering world we do not care about which one of this value we get, we will most likely round this value (position of pile or angle) to an even nice number anyway. Let's then see what the models predict for the same load case used for the assessment of the optimization methods in chapter 6.3. See Table 7-1 below for the predictions and the cost of these predictions compared to the values given in Table 6-1.

Table 7-1: Predictions from the ML models.

ML models	Prediction	Cost
KNN	[0.18 , −2.11 , −0.03 , 1.95 , 2.50 , −24.98 , −4.98 , 19.03 , 26.00]	10e9
Linear regression	[0.19 , −2.20 , −0.49 , 1.63 , 2.86 , −23.28 , −1.00 , 18.73 , 25.88]	10e9
Lasso	[0.19 , −2.20 , −0.49 , 1.63 , 2.87 , −23.28 , −1.00 , 18.73 , 25.88]	10e9
Decision tree regressor	[0.19 , −2.49 , −0.25 , 1.33 , 2.55 , −23.63 , −10.56 , 13.66 , 24.34]	10e9
Random forest	[0.19 , −2.43 , −0.21 , 1.44 , 2.68 , −23.21 , −4.95 , 17.18 , 24.29]	10e9
GBDT	[0.18 , −2.21 , −0.35 , 1.39 , 2.82 , −23.31 , −3.68 , 20.48 , 23.72]	10e9
MLP / neural network	[0.19 , −2.04 , −0.69 , 1.68 , 2.92 , −23.80 , 2.11 , 20.51 , 25.38]	598 014
Values from Table 6-1		
Unit load	[0.13 , 0 , 0 , 0 , 0 , −10 , 5 , 5 , 5]	165 644
GA	[0.15 , −1.5 , −1.0 , 1.5 , 2.0 , −20 , 5 , 5 , 20]	230 781
AGA	[0.11 , −0.5 , −0.5 , −0.4 , 0.2 , −12.4 , −5.6 , 7.7 , 13.3]	198 902

In general, the ML model predicts a too big diameter and a wider position of the piles than the optimal solutions. The cost of the predicted configurations is all very high, except the one predicted by the MLP model. The high cost is caused by not satisfying the displacement criterions.

From all the different model the MLP models is predicting the best solution, in the sense that it gives the solution with the lowest cost. The predictions in themselves are not that different from each other, so the fact that the prediction by the MLP model has a much lower cost could be just by chance. The predicted configurations satisfy the displacement criterions and therefore gets a big reduction in the cost.

The performance of the models is not well. Apart from the MLP model, all the models predict invalid configurations.

7.5 Discussion

All the different models that have been tested gives inadequate accuracy score and is not able to generalize the TD well. The reason for this may be the relatively small amount of data used for training. The six load cases, consisting of three loads each and the large amount of possible values for each load, enables a huge amount of different combinations to form. From this, only 4000 samples were collected for training. If a larger set of TD had been available, the accuracy of the models may be greatly improved. Because of the lack of available TD and the tedious process of mining it, a larger TD set has not been possible to obtain for this thesis.

The collection of the TD is based on AGA and may not always give the best configuration. In this case the ML models are trained with unwanted solutions (costly solutions). Filtering out such input/output pair from the TD will improve the accuracy of the models. The improved accuracy of the model after employing this is shown in Table 7-2 below.

Table 7-2: Accuracy of ML models with filtered TD.

ML models	Training set score	Test set score	Cost of prediction
KNN	29 %	-10 %	10e9
Linear regression	12 %	10 %	447 769
Lasso	12 %	10 %	447 769
Decision tree regressor	11 %	2 %	10e9
Random forest	88 %	14 %	10e9
GBDT	77 %	1 %	10e9
MLP / neural network	18 %	7 %	888 841

The loads that goes into the AGA, and that are used to create the TD, is also synthetical. We cannot be sure if this data is representable for real load cases. The created force combinations also may tend to favour a certain diameter size for the optimal configurations. This will lead to an unwanted bias in the models. Bias in ML is defined as the phenomena of observing results that are systematically prejudiced due to faulty assumption [46]. Using real load combination from previous project may improve unwanted biases. This has not been available for this thesis, due to unfavourably storing structure and time limitations.

The initial accuracy of the model, prior to manipulation, was very low. This, and the discussed effects of the quality and size of the TD, shows the importance of tuning the models and collecting big amount of high-quality TD, in order to avoid unwanted biases.

8 Discussion

In the search for optimal solution in an optimization problem, the measurement of optima needs to be quantified. In this thesis, the measurement of optima is done with a cost function which includes several variables regarding pile foundation. The configurations that gives the lowest cost is then labeled as an optimal configuration. If these optimal configurations are in fact optimal or not is not explicitly given. The quantification of optimal pile foundation may be done differently dependent on available resources, cultural heritage, available technology, construction method and experience. By looking at the parameter study, a pile foundation with a diameter of 90mm that satisfies the yield and displacement criteria and have piles that are short and concentrated in the center, seems to be optimal. Here the variables are looked upon one by one. Because the cost itself is dependent on the displacement and stresses of the pile foundation, which again is dependent on the pile configuration and forces, makes the cost function a function of a function. This makes it more difficult to interpret each variable impact on the overall cost, hampering finding the minima point.

In the initial analysis of the numerical model, the diameter has a fixed value and the loads are limited to one single load case. Even with these simplifications the computational time has proven to be significant with the use of a "brute force" method. The implemented constrains dramatically reduces the computational time, but at the same time, the constrains is logical to implement and should always be implemented. It avoids calculation of equal combinations and prevent unbuildable solutions. So, by implementing these constrains we obtain a much more realistic initial solution space. It functions almost like an initial filtering of the solution space. From the optimal configurations from the second analysis, we see that all the pile foundations are slightly tilted to the left and the top of the piles are gathering in a common point. The clustering of the top of the piles leads to a small foundation slab, limiting the cost contribution from the necessary foundation slab size. The tilt to the left is caused by the desire for compression in the piles, and that the load case contains a horizontal component to the right. If the horizontal component had been to the left, the piles would have tilted to the right. This indicates that an optimal pile configuration tends to tilt in the direction opposite of the horizontal component.

Computational time has been a big issue for this thesis. Various method trying to decrease the computational time has been tried out. The use of unit load method brought the time down to 12 hours, when calculation for a given load combination. This is a massive decrease in computational time, compared to the initial brute force method who used 13.5 hours for just one load case. The GD approach brought the computational time down to under an hour, but at some expense of the accuracy. These solution methods rely on randomness and will be different for every run. You can be lucky and achieve good results or be unlucky and get bad results. In order to decrees this chance of being lucky or not, a big enough initial population should be chosen. This size has been found to be 50 000 for the problem at hand, only 0.26 % of the total solution space. For other problems, this number will differ and should always be investigated. For a pile foundation subjected to a load combination, instead of just one load case, the optimal configurations still have the clustering of the top of the piles, but the clear tilt of the pile foundation is now vaguer. The diameter has also increased. The vaguer tilt of the pile foundation may be due to the horizontal component of the load cases shifting between right and left, making none of the directions favorable over the other. The larger diameter is caused by the need for a more robust configuration, that can withstand a variation in the forces.

All the ML models fail to generalize well and to give good and reliably predictions. Varies type of models and extensively tweaking of parameters where tried out, but an acceptable level of accuracy has not been possible to achieve. This is because of the moderately size of the training data. In the later part of this thesis the amount of TD was almost doubled but lead to no improved accuracy of the models. This can indicate that we need a lot more TD for the models to generalize well. For this to happen the loads from previous project should be stored in a way that makes it easily accessible, removing the need for synthetical TD, and have enough time for mining the TD and to train the models. This has not been available for this thesis. The TD should also be mined with the unit load method to ensure high quality TD. Although it would take almost 20 times longer.

9 Conclusion

Every structure needs a good and solid foundation to stand on and are commonly achieved by using piles. This thesis has been about how this process of designing a pile foundation could be improved with the use of ML and how an optimal pile configuration may be attained. Throughout the work of this master thesis my knowledge about ML and pile foundation has grown. Based on this, an answer to the research questions may be presented:

- Based on the defined measurement of optima in chapter 4.2, an optimal design of pile foundation may be characterised with:
  - Diameter of piles should be kept as small as possible. This is usually between 0.11 m and 0.19 m. Piles with a diameter greater than 0.19 m should be avoided.
  - Fan like formation of piles, with top of piles clustered around a common point. Resembling the root system of a tree.
  - The pile foundation is antisymmetric. This contradict the recommendation from the Norwegian Pile Committee.

- An optimal design of a pile foundation may be achieved by numerous different methods. This thesis found the brute force method to be way tidies and recommends a vector optimization method, or an approximated generative design approach with the use of AGA.

- ML may help engineers in making better design of pile foundation in the sense that it can give design proposal fast and easy. Limiting the time-consuming process of trying different design in order to find an acceptable one. However, the quality of the prediction from the model is dependent on how the model is trained. The available TD for this thesis has not been enough to create an accurate model, proving the huge amount of TD needed for ML.

ML can definitely help Norconsult in order to ensure optimal solution of pile foundation regarding structural properties, economic and buildability. For this to happen the structure of storing data should be more accessible, removing the need for synthetical TD, and enough time and resources needs to be set aside for data mining. Working with ML is a time consuming and long-term commitment. If trained right, ML can serve as a collector of knowledge from the highly trained engineers, helping new engineers perform better, as well as transferring knowledge across departments and offices. ML and Optimization Algorithms may give a better understanding on how structures work and therefore not just only increase the artificial intelligent, but also our human intelligence.

10 Further work

The assessment of ML in this thesis has proven to be inconclusive due to the amount of available TD. In order to create an accurate ML model and to better investigate how ML can help in making better design of pile foundations, a larger amount of TD should be collected. Structuring and collecting real load combinations from previous projects, should also be executed in order to remove the need for synthetical TD.

To get a more realistic view on what an optimal pile foundation is, a 3D model of a pile foundation should be created. The finalist 3D model can then be used to create TD, in order to make the ML model able to make prediction in 3D and directly applicable into design of pile foundations. The model should also be able to vary the number of piles in the group.

The measurement of optima is also something that has been decide by an expert group in Norconsult. Other firms and people in the AEC industry may have additions and disagreements with the decided points. A survey on what is looked upon as an optimal solution of pile foundation may therefore be carried out.

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12 Appendices

The following appendices has been delivered digitally with this thesis. It can be made available by contacting the author or NTNU.

A – Calculate the cost for a given configuration.

B1 – Script to chapter 5.2.

B2 – Script to chapter 5.3.

C1 – Function: Calculate cost.

C2 – Function: Calculate max stress in pile.

C3 – Function: Make beam by start point endpoint.

D1 – Script to chapter 6.1. Unit load method, load case based.

D2 – Script to chapter 6.1. Unit load method, load combination based.

E1 – Script to chapter 6.2.1. GA, load case based.

E2 – Script to chapter 6.2.1. GA, load combination based.

F1 – Script to chapter 6.2.2. AGA, load case based.

F2 – Script to chapter 6.2.2. AGA, load combination based.

G1 – Script to chapter 7. Make load matrix for training.

G2 – Script to chapter 7. Make TD.

G3 – Script to chapter 7. Different ML models.

G4 – Script to chapter 7. Different ML models with excluding part of TD.

G5 – Script to chapter 7. Different ML models with excluding part of TD and larger TD.

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