

Load testing of a quay wall

Evaluating the use of load testing by application of Bayesian updating

N. den Adel



*Cover picture: drone image taken during final construction phase of the quay in the port of Rotterdam.
(Image of MUC; Alain Timmermans)*

Load testing of a Quay Wall

Evaluating the use of load testing by an application of
Bayesian updating

By

N. den Adel

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Chairman thesis committee	prof.dr.ir. S.N. Jonkman	(TU Delft, Hydraulic engineering)
Daily supervisor	dr.ir. J.G. de Gijt	(TU Delft, Hydraulic engineering)
Additional members	ir. A.A. Roubos	(TU Delft, Hydraulic engineering)
	dr. ir. T. Schweckendiek	(TU Delft, Hydraulic engineering)
	dr. ir. R.B.J. Brinkgreve	(TU Delft, Geo engineering)
	ir. H.J. Wolters	(Iv-Infra)

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Preface

This Master of Science thesis is the final part of my educational period at the Delft University of Technology (DUT). This thesis is written to obtain the Master of Science in Civil Engineering title. The selected Master's track is Hydraulic Engineering with specialization Hydraulic Structures. With this thesis a period of five years of studying at the DUT ends. I have very much enjoyed the challenges and insights the study has given me.

The master thesis shows an efficient method of using monitoring data to increase the accuracy of a probabilistic model. The current design practice is developing towards probabilistic calculations and an increased use of sensors to monitor structures. As the thesis uses the one to enhance the other, possibly the method can in the future be used on a broader scale in Civil Engineering.

This thesis has been written on behalf of Iv-Infra bv. Iv-Infra bv is a part of the Iv-Groep holding. The thesis is written at the Hydraulic Structures department of Iv-Infra. I would like to thank Iv-Infra for providing me with the opportunity and the facilities. Furthermore, I would also like to thank the colleagues of the Hydraulic Structures department for their support and giving me a pleasant stay.

Another contribution towards finishing this thesis was made by the graduation committee. I would like to thank all members of the graduation committee for their advices and forcing me to think critically about my own work. The committee consisted of:

- prof.dr.ir. S.N. Jonkman (TU Delft, Hydraulic engineering)
- dr.ir. J.G. de Gijt (TU Delft, Hydraulic engineering)
- ir. A.A. Roubos (TU Delft, Hydraulic engineering)
- dr. ir. T. Schweckendiek (TU Delft, Hydraulic engineering)
- dr. ir. R.B.J. Brinkgreve (TU Delft, Geo engineering)
- ir. H.J. Wolters (Iv-Infra)

The last, but definitely not the least, word of thanks is for the support provided by my girlfriend and family. Their advice and support have been of great importance for the entire duration of my study.

Nick den Adel

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Summary

During the lifetime of quays, it is likely that the desire arises for a quay to be used in a different condition than it was initially designed for. Examples are: a higher surcharge loading on the quay in order to increase the storage capacity or a higher retaining height due to the wish for larger ships to arrive at the quay. If the loading conditions change, the reliability of the quay needs to be reassessed. Reassessment of the quays proves to be difficult. The main problem is the large uncertainty in for example soil parameters, soil behaviour and the current state of the structural elements. To cope with this uncertainty, the structural- and soil parameters are estimated. As estimates are used, it is uncertain how 'well' the model predicts the real behaviour.

In this thesis a possible solution to reduce this uncertainty is reviewed. This option is to use monitoring data obtained from a controlled loading situation to enhance the probabilistic model. The technique of Bayesian updating is used for this. Bayesian updating uses monitoring data to probabilistically update the included stochastic variables. Bayesian updating changes the means and standard deviations of the variables. These changes result in the most likely combination of the variables. This most likely combination is based on the measurement and the prior distributions of the variables. The result of a Bayesian update is thus a changed set of stochastic variables.

In general, the process for performing the update is the following. A prior prediction of the quay's behaviour based on the prior distributions of the variables is made. These prior variables are based on the soil investigations and the design documents. Then the measurements are used to determine the posterior distributions of the variables and a posterior prediction is made.

The reference case used in the thesis is a combi-wall anchored by two grout anchors at each tubular pile. The quay is modelled with Blum and PLAXIS.

For the Bayesian update, it is assumed that the maximum deflection of the wall and the strain in the top anchor tube is measured. For the research fictitious measurements cases are defined. Several fictitious cases are used to show the effect of Bayesian updating.

Based on the results found with the different update cases it can be concluded that Bayesian updating increases the accuracy of the probabilistic model. The standard deviations of the included variables reduce and if variables are chosen too conservative or too optimistic the mean will be changed accordingly. This change in the variables is the largest for the variables with a large influence on the failure probability.

The result of Bayesian updating is the most likely combination of the variables. It is more efficient and more accurate to use this most likely combination, instead of fitting the model prediction to the measurements. In that case it will be hard to prove that the fitted combination of parameters is the combination which will occur as usually many variables are included and thus many combinations are possible.

By performing a Bayesian update the reliability of the quay can be determined more accurately. If the measurement shows that the prior prediction is too optimistic the reliability decreases. It is then possible to prove that reinforcing is required and also the effect of reinforcing can be determined with more certainty by using the updated model.

For the other cases, a too conservative prior prediction or a prediction equal to the measurements, an increase of reliability is found. It can then be determined if this increase proves the quay to be sufficiently safe and if an increase of retaining height or an increase of surcharge load is possible.

The results show how the obtained data from a test loading can be used. For a full evaluation of test loading, more research into the procedure and the costs of test loading is required.

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List of Symbols

Geotechnical symbols		
K_a	Coefficient of active earth pressure	[-]
K_p	Coefficient of passive earth pressure	[-]
γ_d	Dry volumetric weight	[kN/m ³]
γ_{sat}	Wet volumetric weight	[kN/m ³]
φ	Friction angle	[°]
c	Cohesion	[kN/m ²]
δ	Delta friction angle	[°]
ψ	Dilatancy angle	[°]
E_{50}^{ref}	Secant soil stiffness obtained from drained triaxial test	[kN/m ²]
E_{oed}^{ref}	Tangent soil stiffness obtained from oedometer loading	[kN/m ²]
E_{ur}^{ref}	Unloading/reloading soil stiffness	[kN/m ²]
R_{int}	Ratio for the interface's shear strength	[-]
$\gamma_{0,7}$	Strain at which the small strain stiffness is decreased to 70% of its original value	[-]
G_0	Shear strain modules at very small strains	[kN/m ²]
m	Power for stiffness dependent on stress-level	[-]
ρ_x	Specific density of material x	[kg/m ³]
v	Void ratio	[-]
Reliability symbols		
P_f	Probability of failure	[-]
μ_z	Mean value of variable or function : z	[-]
σ_z	Standard deviation of variable or function z	[-]
β	Reliability index	[-]
γ	Safety factor	[-]
α	Sensitivity factor	[-]
p_0	Conditional acceptance probability in Subset Simulation	[-]
General material symbols		
$f_{y;d}$	Design yield strength	[N/mm ²]
E	Young's Modulus	[N/mm ²]
I	Moment of Inertia	[m ⁴]
A	Area	[m ²]
ε	Strain	[-]
L	Length	[m]
F	Force	[kN]
ϕ	Diameter	[m]
Abbreviations		
SuS	Subset Simulation	
BUS	Bayesian Updating with Structural reliability methods	
MCS	Monte Carlo Simulation	
MCMCS	Markov Chain Monte Carlo Simulation	
FORM	First Order Reliability Method	
HS	Hardening Soil, PLAXIS material model	
HS-SS	Hardening Soil Small Strain, PLAXIS material model	

1 Introduction

The main functions of quay walls are to provide a safe place for ships to berth and to allow safe unloading and reloading of ships. Therefore, the developments of quay walls throughout the years are closely related to the developments in the shipping industry. Figure 1 shows the development of ship dimensions in time. The graph shows that, starting from approximately the 1960's, the draught of ships has increased considerably. As the draught of the ships increases also the retaining height of the quay walls must be increased. Accompanied with this increase of draught the amount of cargo has significantly increased. Requiring more and larger cranes to unload ships, these cranes impose considerable loads on the quay.

A recent example (2018) of a large dredging operation in the Port of Rotterdam, is the deepening of the Nieuwe Waterweg and Botlek harbour. The Botlek area is an older port expansion and is realized in 1960. In the recent dredging operation, the depth of the harbour basins is increased from NAP -14,50 to NAP -15,90. This provides access for ships with a draught up to 15 m. Prior to this dredging operation, the safety of the quays in the Botlek area need to be reassessed.

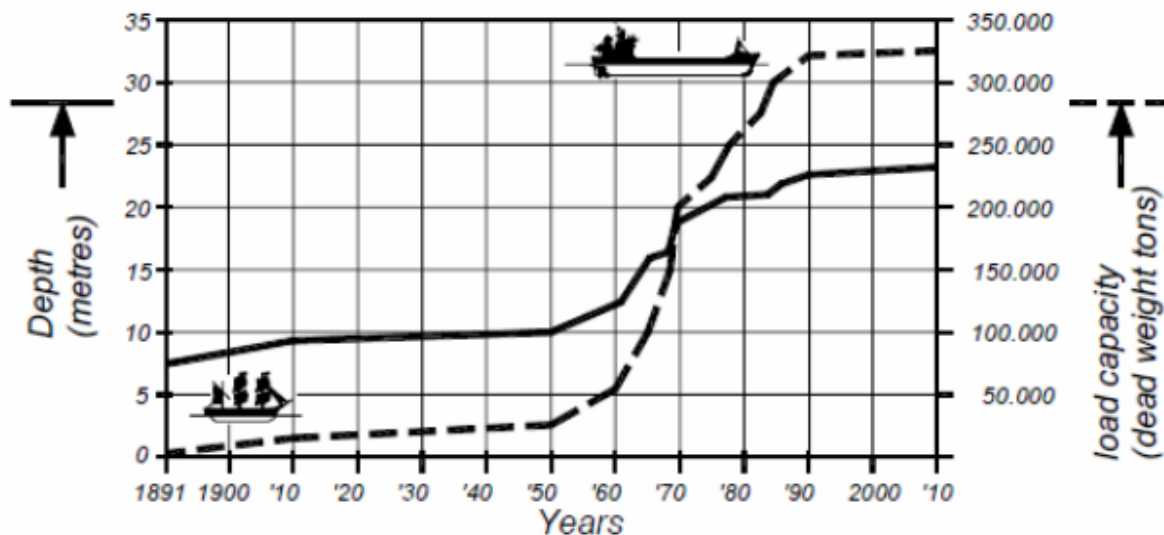


Figure 1 Development of ship dimensions in time (van Tol & de Gijt, 1999)

In addition to the increasing draught also the type of cargo which is being loaded on quay walls is changing. Starting with the first ships, which were classified as general cargo ships, carrying all sorts of cargo, to the development of specialized ships nowadays. Starting from the 1950's ships are becoming more dedicated to one type of cargo such as containers, bulk, oil or LNG. These shifts in cargo types also introduced a change in the loads acting on the quay.

Another aspect is the development of the port itself. Ports can grow, expand or relocate certain areas. This leaves the old quay walls without function. In order to make these quay walls functional again, by for example increasing the retaining height, it must be verified that this new usage is possible.

Furthermore, companies that use a quay can change over time. So, another important factor which could lead to reassessment of a quay wall is the development of ports.

The previous examples illustrate that the loads on quay walls are changing throughout the years. Usually quay walls are designed for a life time of 50 years. Looking at the graph in Figure 1, in 50 years the ships draught and carrying capacity have significantly increased and so are the loads on the quays. Due to the complicated nature of quays it is not easily verified that a quay is able to withstand these larger loads.

Experience has shown that quay walls in the Rotterdam Harbour are already adapted after 15-20 years of service time. This is indicated in Figure 2. The vertical axis shows the lifetime in years and the horizontal axis indicates the year in which the quay is constructed. A special case is the quays for the chemical industry, indicated by the yellow bar on the bottom of the graph; they are already adapted after 5 years of service life.

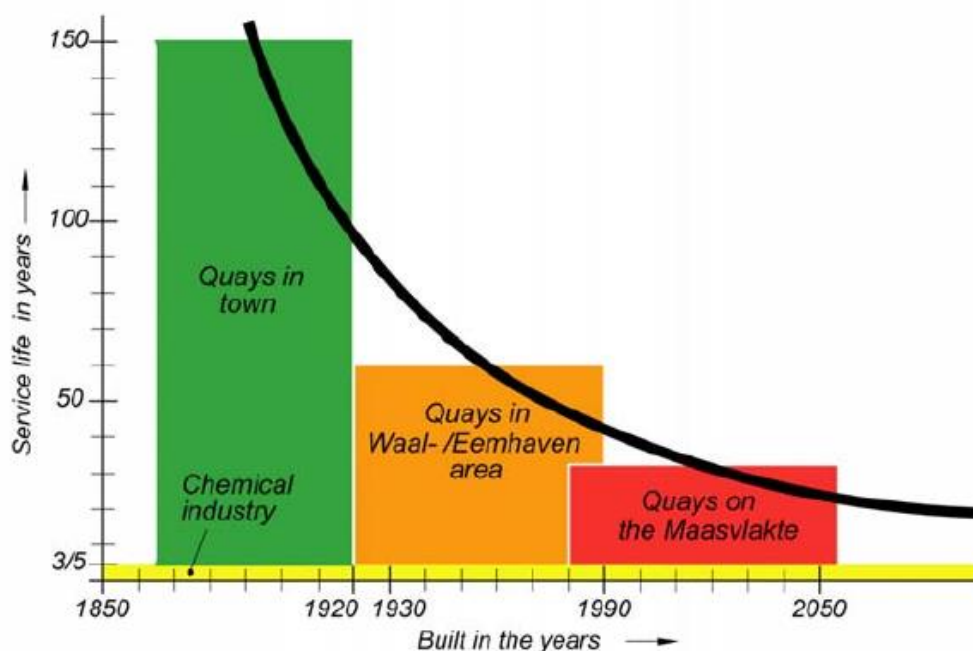


Figure 2 Service life of quay walls in Rotterdam (van der Toorn & de Gijt, 2009)

1.1 Problem description

As introduced in the first part of this chapter it is likely that during the lifetime of a quay the desire arises for a change in the loading conditions. This changed load could be due to an increase of the ships draught or to a changed function of the quay. Whenever the load exceeds the design load, the reliability of the quay wall needs to be reassessed.

Also when a quay is approaching the end of its lifetime, it is necessary to reassess the quay. It might be possible that the lifetime can be extended for a couple of years.

In the reassessment of quays there are a lot of uncertainties, for example: the state of the structure. A quay wall is for the most part submerged and embedded in the subsoil, which makes it difficult to inspect the structure. Next to the uncertainty in the structure itself, there is in many cases a large uncertainty in the behaviour of the soil.

In addition to these uncertainties the design requirements for quay walls are changing in time. Especially for older quays the design calculations made, do not comply with the current safety standards.

To summarize, proving that a quay wall is suitable for a new function is no easy task. The large uncertainties lead to estimates of the soil- and structural parameters. A risk inherent to these estimates is that a too conservative approach is used. This in turn leads to expensive reinforcement measures or an entire replacement of the quay. Due to these conservative estimates it might be possible that these measures are not necessary. However, it is also possible that a too optimistic approach is adopted and thus the reliability of the quay is over estimated. Proving that an approach is too optimistic, too conservative or realistic is however not yet possible.

1.2 Research objective

Based on the problem description there is a need for a method which can more accurately predict the actual strength of a quay wall. One of the methods, which is currently under consideration, to do so is test loading quay walls. How to perform a test load is not part of the scope of this research. A possible option for test loading could be, loading the quay by stacking containers behind the quay.

Using the containers, the loads on the quay can be stepwise increased. Another option is increasing the retaining height by slowly dredging in front of the quay. Both of these options increase the load on the quay in a controlled manner. If the quay is monitored during the test, one can use the obtained data to determine the level up to which it is safe to load the quay. More options can be thought of, this will however not be part of the research. This thesis focusses on using the data obtained from a test loading.

The main advantage of test loading is that the real strength of the quay can be determined. The main disadvantage of the method is the risk of permanent damage to the quay. As quays have numerous different failure mechanisms and some of those mechanisms occur without warning, it can be difficult to predict which mechanism is governing. So, to safely execute a test load, one needs model predictions to verify that sudden failures do not occur and monitoring to prevent failures that do give warning signals. Also monitoring is used to verify that the behaviour of the quay is within predefined boundaries and to determine when the loading should be stopped.

Although model predictions and monitoring are in many ways available in engineering practice, they are often used as separate items. For the test load to be useful the obtained data during the test load must be used to enhance the model predictions. Therefore, this research will focus on using the obtained data in the model predictions. One method in particular is useful for this problem: Bayesian updating.

A Bayesian update uses evidence to probabilistically update a prediction. Evidence can be either measurements or the knowledge that a structure has survived a certain load. Some examples of studies which have applied Bayesian updating are (Schweckendiek, 2010) and (van der Meijs, 2015). Schweckendiek has used survived load data, the knowledge that a flood defence has survived a certain high-water event, to increase the reliability of a flood defence. Van der Meijs has applied Bayesian updating to increase the accuracy of settlement predictions based on settlement plate measurements.

For a quay to be safe, the failure probability needs to be sufficiently low. As written in the problem statement, there is a large uncertainty in the prediction of the failure probability of a quay wall. By using monitoring data, for example strain or displacement measurements, Bayesian updating can help in reducing this uncertainty. Based on the above the objective of the research is defined as:

developing a Bayesian updating method which improves the prediction of the failure probability of a quay wall.

The problem description and research objective can be translated into the following research question:

How to use Bayesian updating to improve the prediction of the failure probability of a quay wall?

Sub questions have been defined to aid in answering the main research question. The following sub questions are defined:

What improvements to the probabilistic model can be obtained through performing a Bayesian update?

How are the results of the Bayesian update influenced by a different measurement quantity?

1.3 Thesis structure and strategy

After introducing the problem and the thesis' objectives, the thesis starts in chapter 2 with explaining the theory required. An overview of the calculation methods for quay walls and the concept of structural reliability, including Bayesian updating, is explained. Based on this literature study a research method is defined, which is also explained in this chapter.

In chapter 3 Bayesian updating is applied to an analytical model of a cantilever beam. This example allows to gain insight into the process of Bayesian updating.

The case which is investigated is introduced in chapter 4. The structural details and soil profile are provided. In this chapter also, the starting points for the Bayesian update are listed.

In chapter 5 Bayesian updating is applied to the first calculation model, the model of Blum. After investigating the results obtained from Blum, a finite element model is applied.

Chapter 6 contains the explanation and the input of the finite element model. Bayesian updating is then applied to the finite element model.

The obtained results from the Bayesian updates are used in chapter 7 to determine if the loads on the quay can be increased. As this calculated increase is determined based on fictitious measurements, a global strategy is provided to obtain the measurements in practice and to perform a Bayesian update based on real measurements.

Answers to the research question and the sub questions are given in chapter 8. Chapter 8 also lists recommendations. The thesis ends with an evaluation of the results and possible further research subjects in chapter 9.

2 Theoretical Background

The theory required to answer the research question can be divided into two main categories, these categories are: calculation methods for quay walls and the concept of structural reliability. Each of these categories are treated separately in this chapter.

2.1 Quay wall calculation models

For designing quay walls there are three main calculation models available. These are:

- Model of Blum
- Spring model
- Finite Element Model

These models are shortly explained in this section.

2.1.1 Blum

The model of Blum is a relatively simple calculation method. The simplicity of the method allows to make hand calculations. The method of Blum assumes that the soil behaves either fully active or fully passive. This assumption can be visualized in Figure 3. The red line indicating the assumption by Blum so either passive or active, while in reality soil behaves more like the black curve.

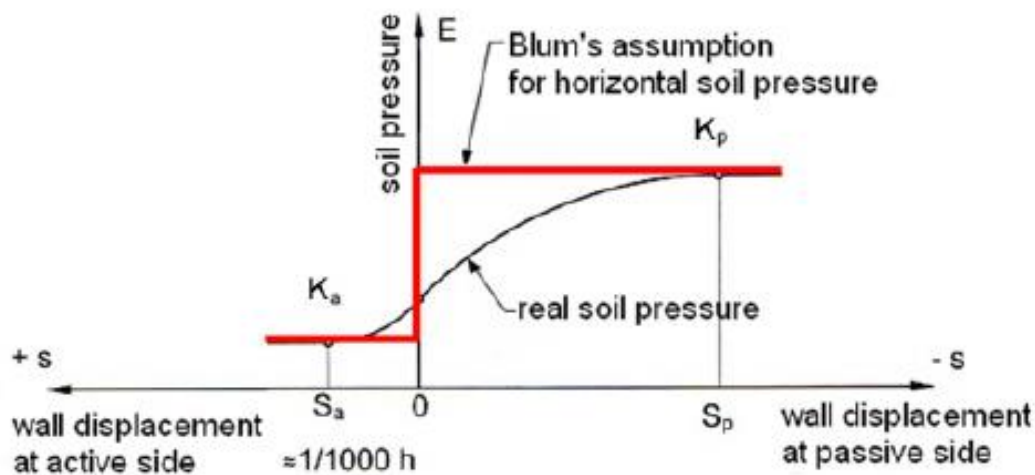


Figure 3 Stress-Strain relation as assumed by Blum (Molenaar & Voorendt, 2017)

Furthermore, Blum assumes that somewhere in the soil the sheet pile is fully clamped and at this clamped point the moments are equal to zero. This assumption allows a quick calculation of the required embedded depth of the sheet pile. Blum has proven effective as a first approximation. However, the deformations are poorly predicted and a staged construction cannot be modelled. Therefore, for design purposes usually a spring- or finite element model is applied.

2.1.2 Spring model

A more advanced model is the spring model. It schematizes the soil as a set of elasto-plastic springs. This schematization is a more accurate prediction of the real stress-strain behaviour. However, it is still a simplified approach as the non-linear stress-strain relation of soils, the black parabolic line in Figure 3, is approximated by linear line segments. This model is shown in Figure 4a. The pile schematization is shown, in which the soil is represented in multiple springs. This process is based on uncoupled springs and is therefore unable to include arching effects in the ground.

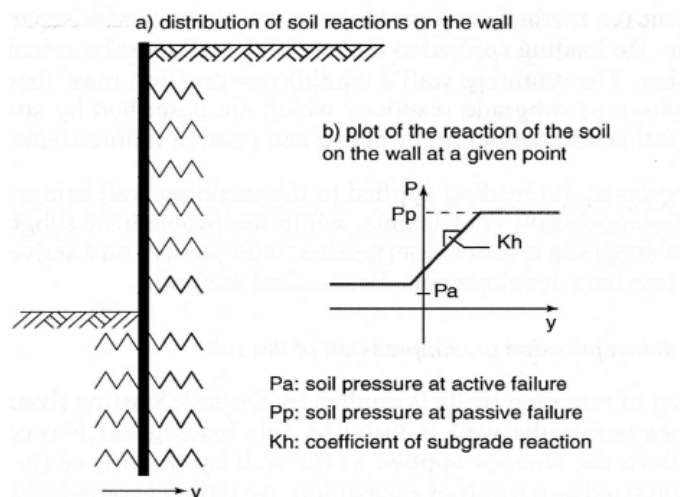


Figure 4 Representation of spring model and stress strain relation (de Gijt, 2010)

The stress-strain relationship used in the spring model is shown in Figure 4b. In this figure a bi-linear stress strain relationship is shown, it is also possible to use multiple linear line segments in order to approximate the non-linear relation.

The main arguments for using a spring model in design calculations are that it is a simple, fast, and user-friendly method. These benefits do come at a cost. The disadvantage of the spring model is that in the soil stiffness simplifications are made. These have as result that the displacements are not accurately predicted.

To determine the forces on the wall, a choice must be made in applying a method based on straight slip surfaces or on curved slip surfaces. In principle applying straight slip surfaces is only valid when the sheet pile is smooth and no friction occurs between soil and pile. In reality this is never true, so a curved slip surface is present. For determining the active pressures, the difference between the methods is rather small, except for high friction angles. In the case of high friction angles, methods based on straight slip surfaces tend to overestimate the resistance. So, for larger friction angles, a method based on curved slip surfaces is usually applied (Deltares, 2016).

In the cases of a non-horizontal ground level or discontinuity in the surcharge load straight slip surfaces need to be used, as neither can be modelled when applying curved slip surfaces.

If straight slip surfaces are applied the delta friction angle (a parameter describing the friction between the soil and the sheet pile) must be reduced. When curved slip surfaces are applied this reduction is not necessary. (CUR, 2012).

In general, independent of applying straight or curved slip surfaces, D-Sheet Piling is unable to realistically model quays with relief platforms. D-Sheet piling is a one-dimensional software program. This implies that any combination of a sheet pile and other structural elements cannot be realistically modelled.

For determining the forces on the sheet pile, three methods are available in D-Sheet Piling. These are (Deltares, 2016):

- Culmann

The method of Culmann is especially useful if the soil profile behind the sheet pile is not horizontal or if a surcharge load is present. The method can be described according to Figure 5. The method is based on straight slip surfaces. Along each slip surface equilibrium is calculated between the surcharge B , the soil weight W , the force from the sheet pile Q , the normal force N and the shear force T . The program searches for the slip surface along which the maximum active- and minimum passive pressures are present.

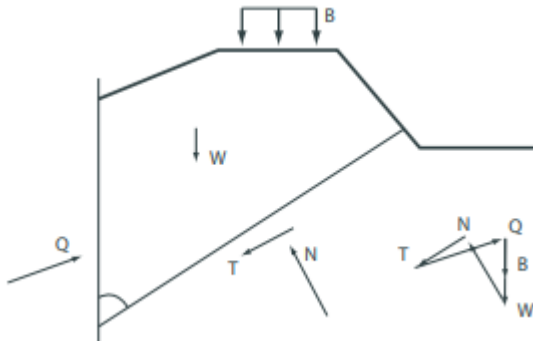


Figure 5 Method Culmann (Deltares, 2016)

- Müller-Breslau

A second solution based on straight slip surfaces are the formulas defined by Müller-Breslau. The formulas assume a straight slip surface with an angle of $\frac{\pi}{4} \pm \frac{\varphi}{2}$. If a vertical sheet pile is applied and a horizontal ground surface is present the formulas can be written as:

$$K_a = \frac{\cos^2(\varphi)}{\left(1 + \sqrt{\frac{\sin(\varphi) \sin(\varphi + \delta)}{\cos(\delta)}}\right)^2}$$

$$K_p = \frac{\cos^2(\varphi)}{\left(1 - \sqrt{\frac{\sin(\varphi) \sin(\varphi + \delta)}{\cos(\delta)}}\right)^2}$$

The above equations for K_a and K_p are valid under the following conditions:

- $\varphi \leq 30^\circ$ for rough steel sheet pilings and comparable walls
- $\varphi \leq 35^\circ$ for rough concrete pilings

- Kötter

Another possibility are the formulas of Kötter. These formulas describe a curved slip surface. The following assumptions are made when using the equations:

- The surface is horizontal and unloaded.
- The soil is homogeneous with volumetric weight of zero.
- The slip plane consists of a logarithmic spiral and a straight part.

The above three statements are assumptions and one should keep this in mind when using the method of Kötter.

Kötter defines the following active pressure coefficient:

$$K_a = \frac{1 - \sin(\varphi) \sin(2\alpha + \varphi)}{1 + \sin(\varphi)} e^{((-0,5\pi + \varphi + 2\alpha)\tan(\varphi))}$$

With α : $\cos(2\alpha + \varphi - \delta) = \frac{\sin(\delta)}{\sin(\varphi)}$

For the passive pressure coefficient:

$$K_p = \frac{1 - \sin(\varphi) \sin(2\alpha' + \varphi)}{1 + \sin(\varphi)} e^{((-0,5\pi + \varphi + 2\alpha')\tan(\varphi))}$$

With α' : $\cos(2\alpha' - \varphi + \delta) = \frac{\sin(\delta)}{\sin(\varphi)}$

2.1.3 Finite Element model

The final and most powerful model is to employ a finite element analysis. Using a finite element analysis, a fundamental approach can be applied which reduces the number of simplifications. It reliably predicts both forces and deformations. Finite element models can take into account two or three-dimensional structures. It is thus possible to take into account interaction between different structural elements for example the effect of a relief platform and interaction between foundation piles and the sheet pile. Applying a finite element method however, requires more input parameters and has in general a calculation time which is significantly longer than using software based on the spring model.

The accuracy of the finite element calculation is dependent on the soil model which is used. For quay walls the following four models are generally applied:

- Linear Elastic Model

The simplest of the available models is the linear elastic model. It is based on Hooke's law and assumes a linear relation between stress and strain. It requires as input the Young's modulus and the Poisson's ratio. Soils in general do not behave linear elastic and therefore this model is only useful for very stiff and strong soils, for example rock formations and in some cases when concrete is modelled.

- Mohr-Coulomb Model

The Mohr-Coulomb Model includes plastic behaviour of soils and is an improvement compared to the linear elastic model. Mohr-Coulomb assumes a linear elastic perfectly plastic material. This is shown in Figure 6. The first, linear elastic, part of Figure 6 is described by Hooke's law. The second, plastic, part is the failure criterion as defined by Mohr-Coulomb. Not included in the model of Mohr-Coulomb is dependency of the stiffness on the stress level, the stress path and the strain level. Only the depth dependent stiffness can be included. The approximated stress-strain relationship as used in the Mohr-Coulomb model represents soil behaviour close to failure quite well. In non-failure conditions the Mohr-Coulomb model tends to deviate from the real behaviour.

The soil behaviour of Mohr-Coulomb model has the benefit of a method called c, φ reduction. The described strength reduction is also possible with the advanced soil behaviour models. However, the advanced features of these models will be lost and thus the behaviour during such a strength reduction is equal to the Mohr-Coulomb model.

The c, φ reduction method can calculate safety factors. By stepwise reduction of the friction angle and the cohesion, the method determines the point of failure. The safety factor can then be defined as:

$$\text{Safety Factor} = \sum MSF = \frac{\tan(\varphi) \text{ prior}}{\tan(\varphi) \text{ reduced}} = \frac{c \text{ prior}}{c \text{ reduced}}$$

In which $c, \varphi \text{ prior}$ are the friction angle and cohesion values of the soil. The $c, \varphi \text{ reduced}$ are the friction angles and cohesion values at global failure.



Figure 6 Stress-Strain relationship of a linear elastic perfectly plastic material (left) and the Mohr Coulomb yield surface in principal stress space (right) (Plaxis bv, 2017)

- Hardening Soil Model

Based on Quay Walls (2013) the Hardening Soil model is the most suitable model for designing retaining structures. The Hardening Soil model describes the soil strength based on the Mohr-Coulomb failure criterion. However, the Hardening Soil model can more realistically describe the soil stiffness. Mohr-Coulomb using a linear-elastic perfectly plastic description, while the Hardening Soil model uses a hyperbolic stress-strain relation, shown in Figure 7.

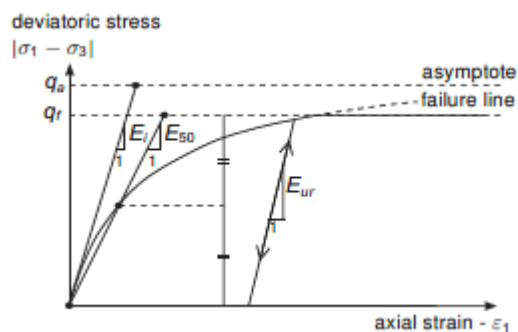


Figure 7 Hyperbolic stress-strain relation in primary loading for a standard drained triaxial test (Plaxis bv, 2017)

Key feature of the Hardening Soil model, is the fact that the yield surface can expand in the principle stress state, shown in Figure 8. In the Mohr-Coulomb model this yield surface is fixed, shown in Figure 6. The expansion of the yield surface is caused by plastic strains and is called hardening, hence the name Hardening Soil model.

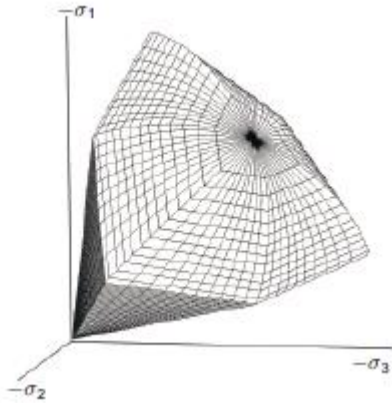


Figure 8 Representation of total yield contour of the Hardening Soil model in principal stress space for cohesionless soil (Plaxis bv, 2017)

To predict deformations even more accurate, an adapted version of the Hardening Soil model can be used. This is called: Hardening Soil Small Strain model. This model includes the effect that soil behaves stiffer in small strain conditions.

- Soft Soil Creep Model

In case the structure is placed in soft soils, with a dominant time-dependent behaviour, the soft soil creep model can describe the viscous behaviour of soft soil. The model is also based on the Mohr-Coulomb failure criterion, but it allows modelling of the following aspects: stress-dependent stiffness moduli, pre-consolidation stress and unload/reload behaviour. In particular for soft soils this model is more accurate than the hardening soil model. The model will not be used in this research and thus only a brief overview is provided.

2.2 Structural Reliability

The goal of designing structures is ensuring that the structure will be safe. A safe structure is in general defined as a structure with a sufficiently low probability of failure. To determine the 'safety' of a structure, a reliability analysis is performed. The concept of this analysis is explained in this chapter.

2.2.1 General concept

A structural reliability problem can be written in the following equation or limit state function.

$$Z = R - S$$

In this equation R is the resistance and S represents the load (solicitation). The structure will not fail as long as $Z > 0$, which means that $R > S$. Traditionally this problem was solved using a deterministic approach. A certain nominal or expected value of the structural resistance and the expected loads are used. Usually an overall safety factor is applied, in equation form this results in:

$$Z = R_{nom} - \gamma S_{nom}$$

In which γ is the overall safety factor. In the above approach, it is assumed that the load and the resistance can be calculated with reasonable accuracy. This is however not always the case, as there is uncertainty on both the load and the resistance side. To take these uncertainties into account probabilistic methods have been developed. These methods aim to calculate the probability of failure. The probability of failure equals:

$$P_f = P(Z < 0) = P(S > R)$$

For structures a maximum allowable failure probability is defined. For quay walls this maximum depends on the consequences of failure. Three different consequence classes are defined; the classes are presented in Table 1. In this table the reliability index β is defined. β is related to the probability of failure, in case the limit state function is normally distributed, by:

$$P(Z < 0) = \Phi\left(\frac{0 - \mu_z}{\sigma_z}\right) = \Phi\left(-\frac{\mu_z}{\sigma_z}\right) = \Phi(-\beta)$$

Table 1 Reliability classes according to NEN-EN 1990 (Broeken & de Gijt, 2013)

Description of reliability classes	Reliability index β	Design life in years	Examples
RC 1/CC 1 Low consequence for loss of human life and economic, social or environmental consequences small or negligible	$\beta = 3,3$	50	Quay walls and port infrastructure that are part of a terminal or port with functional redundancy and limited number of people at risk
RC 2/CC 2 Medium consequence for loss of human life and economic, social or environmental consequences considerable	$\beta = 3,8$	50	Unique port infrastructure of vital economic importance without functional redundancy; Quay walls that are a part of another system, such as chemical or power plants, but for which failure would not lead to failure of other structures, such as hazardous installations Urban quay walls, located in fairly crowded locations Soil-retaining walls that are part of secondary flood defence systems or dams Quay walls needed for recovery after earthquake damage or tsunamis; Quay walls facilitating cruise vessels
RC 3/CC 3 High consequence for loss of human life and economic, social or environmental consequences very great	$\beta = 4,3$	50	Soil-retaining walls that are part of a primary flood defence system or major dam Soil-retaining walls the failure of which would lead to the inaccessibility or unavailability of main commercial waterways Quay walls the failure of which would lead to the failure of other hazardous structures, such as hazardous installations of chemical or power plants.

To calculate the probability of failure, three levels of probabilistic methods can be defined:

- Level I semi-probabilistic approach
- Level II full probabilistic approach with approximations
- Level III full probabilistic approach

The difference between the levels is explained in detail in the next sections.

2.2.2 Level I analysis

The semi probabilistic approach aims to be a practical, not too complicated approach to a probabilistic design. The method can be described as follows: first characteristic values of both the load and the strength are defined. For a load parameter a characteristic value is a high representative value. It is commonly defined as a value which has a probability of exceedance of 5%. For resistance parameter a low characteristic value is used. For a low characteristic value holds that the probability of obtaining a lower value is 5%.

The characteristic values are then multiplied or divided by a safety factor, to obtain design values. It should then still be the case that the strength should be higher than the loads. The above can be written in a formula, as shown here:

$$\frac{R_k}{\gamma_R} > \gamma_S S_k$$

- R_k Characteristic value for resistance
- γ_R Partial safety factor on resistance
- S_k Characteristic value of load (solicitation)
- γ_S Partial safety factor on load

The formula and the approach with characteristic and design values can also be visualized in the graph in Figure 9. In red the distribution of the load is shown and in green the distribution of the resistance. Furthermore, the characteristic values (R_k, S_k) and the design values (R_d, S_d) are shown.

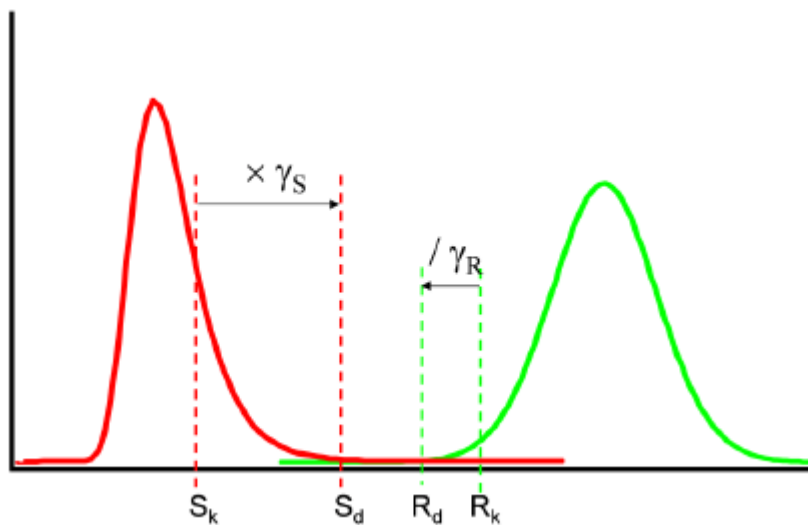


Figure 9 Level 1 approach (Jonkman et al, 2017)

The factors used to determine the design values are called partial safety factors. In general, for normally distributed variables the partial safety factors can be calculated with:

$$\gamma_m = \frac{R_k}{r^*} = \frac{R_k}{\mu_r - \alpha_s \beta \sigma_r}$$

The γ_m represents, in this case, a partial factor on a resistance parameter. As is indicated by the subscript 'r' in the inequality.

The partial safety factor is higher in case:

- the influence coefficient α is higher;
- the target reliability index β is higher;
- the standard deviation σ is higher.

The partial factors used in level 1 methods are usually not determined by the formula but prescribed in guidelines. The exact failure probability is not calculated. The safety is included in the definition of the partial safety factors. The predefined partial factors in the guidelines are derived from the more advanced level II and level III analyses.

2.2.3 Level II analysis

A level II probabilistic calculation employs a fully probabilistic approach with approximations. In a fully probabilistic approach no partial factors are included. All variables and their uncertainty can be included into the limit state function. However, in the evaluation of the limit state function approximations are made to reduce the computational effort. The most commonly applied level II method is the First Order Reliability Method (FORM). Several other methods are available, but only FORM is treated here.

FORM approximates the failure probability by linearizing the limit state function. For a linear limit state function this provides the exact failure probability. However, most limit state functions are non-linear. FORM is based on the principle introduced by Hasofer and Lind (1974), which is:

The reliability index β is equal to the shortest distance from the origin to the surface described by $g(\underline{U})=0$ in the space of normalized basic variables

This principle can be seen in Figure 10.

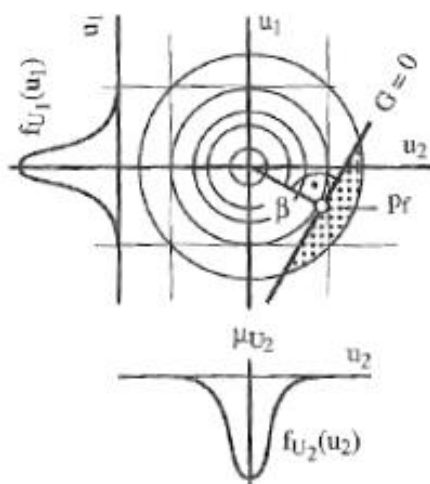


Figure 10 Reliability index as introduced by Hasofer and Lind (Jonkman et al, 2017)

The principle makes the application of FORM suitable to any kind of limit state function. The linearization which is applied in FORM reduces the accuracy of the calculation but also reduces the computational effort. The accuracy of the linearization is dependent on the chosen linearization point. Most effective is linearizing the function in the design point. The design point is defined as the point on the failure plane which has the largest contribution to the actual probability of failure. As this point is usually not known on beforehand, FORM iteratively converges to this design point.

In addition to finding the design point, FORM shows the sensitivity factors of the variables involved. This provides useful information into which variables are dominating the failure probability.

The steps required to perform FORM are the following:

1. Choose starting values

$$\beta = \frac{\mu_z}{\sigma_z}$$

2. Linearize function in starting values, substitute β in:

$$Z = g(\bar{U}) \approx g(\bar{U}_0) + \sum_{i=1}^n \frac{\delta g}{\delta u_i}(\bar{U}_0)(\bar{U}_i - \bar{U}_{0i})$$

$$\alpha_i = \frac{\frac{\delta}{\delta X_i} g(X^*) \sigma_{X_i}}{\sqrt{\sum_{i=1}^n \frac{\delta}{\delta X_i} g(X^*) \sigma_{X_i}^2}} = \frac{\frac{\delta}{\delta X_i} g(X^*) \sigma_{X_i}}{\sigma_z}$$

3. Use the determined β and α values to determine new design point

$$X_i^* = \mu - \alpha_i \beta \sigma_{X_i}$$

4. Repeat steps 1 to 3 until convergence is reached

2.2.4 Level III analysis

The most accurate solution for a probabilistic analysis is a level III method. A level III method is a fully probabilistic approach without approximations or linearization. The most well-known level III method is a Monte Carlo simulation. Other methods are numerical integration or solving the limit state function analytically. The last two methods are rarely used due to fact that usually many variables are included, resulting in complicated limit state functions. For the analytical solution this means that the formula is not easily solved and for numerical integration the number of calculations required increases with an exponent equal to two times the number of variables. Numerical integration puts, due to this exponential relation, a high demand on CPU-power. It is therefore, only applicable for low dimensional problems. A Monte Carlo can always and relatively easily be applied. As Monte Carlo simulation and other probabilistic methods based on a Monte Carlo Simulation are used in this thesis, the process of a Monte Carlo simulation is explained in this section.

A Monte Carlo simulation is a very simple solution to determine the failure probability. Once the limit state function and the distributions of the included variables are defined, the simulation can start. The Monte Carlo simulation takes random draws from the probability distribution functions of the variables and then evaluates the limit state function.

The probability of failure is then simply defined as:

$$P_f = \frac{N_f}{N}$$

In which:

- N_f is the number of evaluations in which the structure fails.
- N is the total number of evaluations done.

A huge disadvantage of this method is that for low failure probabilities a large amount of simulations must be done to accurately determine this failure probability. This effect can be seen in the graph in Figure 11. This figure shows that for a $\beta = 4$ over 20000 calculations have been done and still, some spread is present in the calculated reliability index.

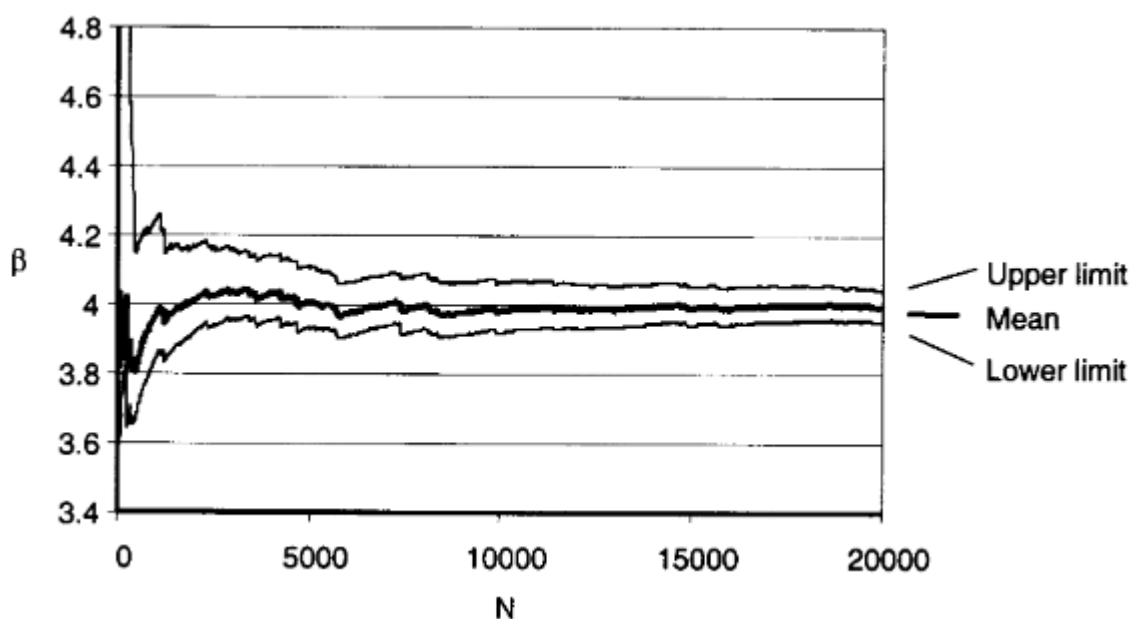


Figure 11 Number of Monte Carlo simulations required (Jonkman et al, 2017)

To reduce the number of calculations required, several techniques have been developed which significantly improve the efficiency of the simulation. Two of those techniques are treated here: Importance Sampling and Directional Sampling.

Both of these techniques rely on the fact that taking samples from the original distribution is not efficient for low probabilities of failure. The chance that a “bad draw” is taken from the sampling distribution is too low. In order to reduce the number of calculations required the chance of obtaining a bad draw must be increased.

Importance sampling solves this problem by taking samples from a different sampling distribution and relating them through the following function:

$$P_f = \frac{\sum_{i=1}^n I(Z_i) \frac{f_{R,S}(r_i, s_i)}{h_{R,S}(r_i, s_i)}}{n}$$

In which:

- $f_{R,S}$ is the original distribution.
- $h_{R,S}$ is the sampling distribution.

The larger the probability of obtaining a “bad draw” the more effective importance sampling is. The method of importance sampling is most effective if the sampling distribution is close or in the design point. So, to achieve an optimum efficiency it requires knowledge of the failure plane which is usually not present on beforehand.

Directional sampling solves both the efficiency problem and knowledge about the failure plane is not required. Directional Sampling searches for the design point without requiring information on the failure plane on beforehand. Directional Sampling follows an iterative procedure much like FORM, in which the design point is determined in the iterative process. Instead of FORM it is not based on the linearized approximation. As directional sampling is a sampling method, the accuracy of the solution is dependent on the number of directions or calculations which are evaluated.

The principle of Directional Sampling can be explained with the help of Figure 12. In the standard normal space in each direction a line is evaluated. Along this line it is checked when a change in sign occurs, in other words when failure occurs. For each found direction, for which failure occurs, the reliability analysis will be performed by one dimensional integration.

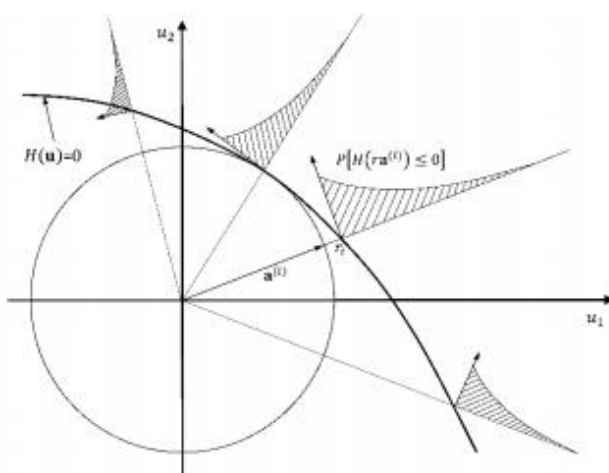


Figure 12 Principle of Directional Sampling (Schweckendiek, 2006)

2.2.5 Uncertainty

A main topic of this research is to reduce the uncertainty in the prediction. There is uncertainty in for example the soil parameters, soil behaviour, harbour bottom depth, surcharge load and in the structures response. In order to reduce the uncertainty, it is first required to define the different types of uncertainty and which of those types can actually be reduced. Van Gelder (2010) defines the two following types of uncertainty: inherent uncertainty and epistemic uncertainty. Inherent uncertainty is defined as the randomness or variation in nature; it is not possible to reduce this type of uncertainty. An example of inherent uncertainty is the fact that it is not possible to predict, with absolute certainty, the maximum water level which will occur next year; even if we would have collected the water levels over an infinite amount of years.

The other type of uncertainty, epistemic, is related to a lack of knowledge or an insufficient amount of data. Epistemic uncertainty can be reduced by collecting more data or doing more research into the phenomena. Van Gelder (2010) further divides the two types into five uncertainty categories shown in Figure 13.

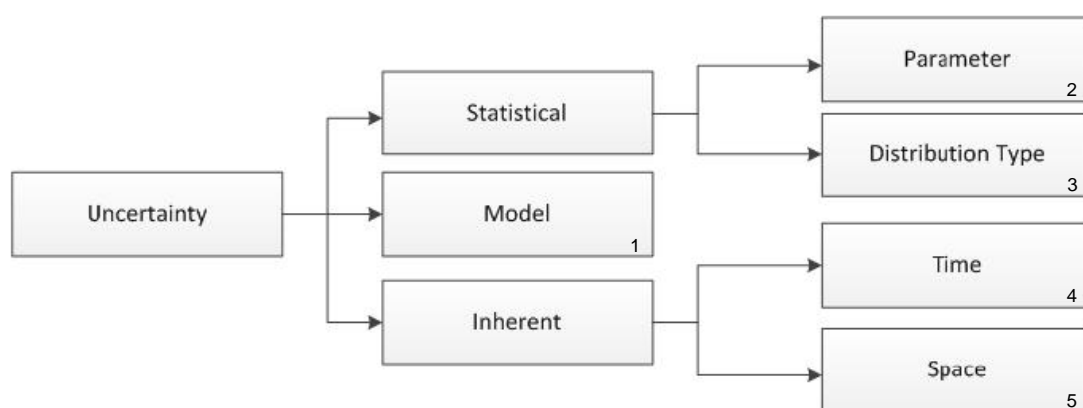


Figure 13 Types of uncertainty (van Gelder, 2010)

The statistical types of uncertainty are related to the amount of data which is available. In the case of soil parameters, there is an uncertainty due to the fact that usually a limited amount of investigations is done and this limited amount must represent the whole area. This uncertainty can be reduced by doing more investigations to obtain a better estimate for the parameters and their distributions.

Model uncertainty is for example dependent on how the soil behaviour is schematized in the calculation model. Using the spring model for calculation generally results in a larger model uncertainty than using a finite element hardening soil model.

Inherent uncertainty can be divided into uncertainty in time and space. The uncertainty in time is related to predicting future events, which is of course not possible. Uncertainty in space can theoretically be reduced. This is however a problem of costs. It is usually considered to be too expensive to do site investigations at a close enough distance to fully reduce the spatial uncertainty.

In view of this research the main focus will be on reducing the statistical uncertainty. The goal is to make a better prediction of the parameters and their distributions. This will be done using a Bayesian update technique which is treated in the next paragraph.

2.2.6 Bayesian updating

As shortly introduced, Bayesian updating will be used to update model predictions according to measurements on site. A Bayesian update is a tool to improve the accuracy of a predictions based on evidence. In general evidence can be any property, measured quantity or observation. The evidence, in this case, are measurements.

Bayesian updating is based on the conditional statistics theory developed by Bayes. This theorem is defined as

(Dekking, Kraaikamp, Meester, & Lopuhaä, 2005):

$$P(A|B) = \frac{P(B|A) * P(A)}{P(B)}$$

In which:

- $P(A)$ is the probability that event A occurs.
- $P(B)$ is the probability that event B occurs.
- $P(A|B)$ the conditional probability that A occurs when event B is true.
- $P(B|A)$ the conditional probability that B occurs when event A is true.

The Bayes formula can be written in a slightly different form, so it allows updating predictions to the measurements. For this, a distinction is made between the prior probability of failure and the posterior probability of failure. The prior probability of failure is the prediction made based on the site investigations and the prior beliefs, this would then represent the prediction as done for a reassessment of the quay. It is the prediction before using the measurements. The prior failure probability can be calculated by making assumptions on the soil and structure characteristics.

The posterior probability of failure is the prediction which is updated using the measurement data. This is the probability of failure one would obtain after performing a test loading or any other method of obtaining the required monitoring data.

A limit state Z can be defined and the prior probability of failure can be written as:

$$P(Z(X < 0))$$

To introduce the measurements, an observation limit state can be defined $g(X)$. Failure can be defined if the measurements exceed a certain threshold, for example a larger deformation than 0,10 m is defined as failure. The observation limit state is then written as:

$$g(X) = 0,10 - x_{measured}$$

- $x_{measured}$ is the measured deformation

For this observation limit state also holds that failure occurs when $g(X) < 0$.

The prior probability of failure and the observation limit state can be applied into Bayes Theorem. Resulting in the posterior probability of failure $P(F|g)$ (Schweckendiek, 2010):

$$P(F|g) = \frac{P(Z(X) < 0 \cap g(X) < 0)}{P(g(X) < 0)}$$

- $P(F|g)$ is the posterior failure probability based on the measurements.
- $P(Z(X) < 0)$ is the prior probability of failure.
- $P(g(X) < 0)$ is the probability that the observation limit state function is smaller than zero.
- $P(Z(X) < 0 \cap g(X) < 0)$ is the probability that the limit state function and the observation limit state function are smaller than zero.

The required steps for applying a Bayesian update to the model are visualized in the flowchart in Figure 14. A Bayesian update can be done 'direct' or 'indirect'. The indirect procedure will first update all the parameters and then calculate the new probability of failure. This has the advantage that it gives insight into the changes in parameter values. However, this method requires two probabilistic calculations, resulting in a larger computational effort. The direct approach gives the updated probability of failure immediately.

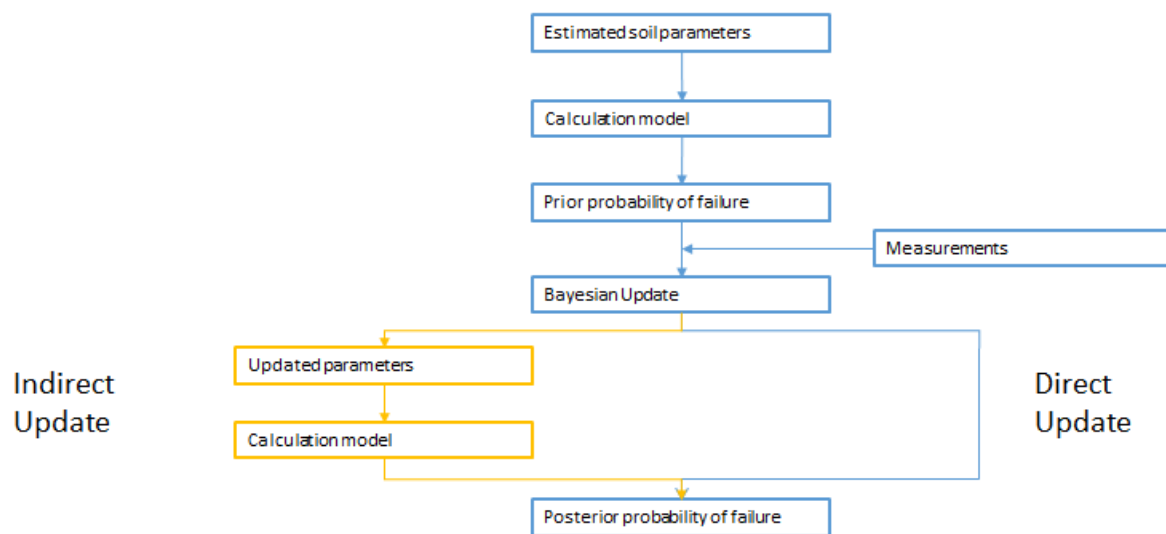


Figure 14 Flowchart Bayesian Update

To determine the analytical solution for a Bayesian updating problem with a large number of variables is difficult. In order to solve the formula, it must be integrated over all included variables. The result is a multi-dimensional integral which in general cannot be solved easily.

Therefore, a different approach is required. A commonly applied method to solve the equation is by using sampling methods. The most well-known are the Markov Chain Monte Carlo (MCMC) methods, which are usually based on the Metropolis Hastings Algorithm.

This method searches for the posterior distribution of the variables. It compares the likelihood of each sample with the previous sample and either accepts or rejects the sample. By this procedure the

method reaches, after a number of samples, a stationary distribution which is equal to the posterior distribution.

The disadvantage of using a MCMC method is that it can take a large number of samples before this stationary distribution is reached. In addition to the problem of actually reaching a stationary distribution, the samples are correlated. To obtain sufficiently uncorrelated posterior samples a large number of samples is required.

In order to overcome the disadvantages of a MCMC method, the Bayesian Update with Structural reliability methods (BUS) is investigated. BUS rewrites the formula of Bayes into a Limit State format. This rewritten equation can then be solved by applying the standard reliability methods. The advantage of this approach is that it can be applied relatively simple and gives flexibility, as theoretically every already available structural reliability method can be applied.

Out of the three given methods, only BUS is treated here. Obtaining samples from the posterior distribution is according to (Papaioannou, Betz, & Straub, 2013) equivalent to solving the Limit State function below:

$$h(x, \mu_0) = \mu_0 - cL(x)$$

In which:

- μ_0 is a standard uniform random variable.
- c is a constant to ensure that $cL(x) < 1$, the optimum choice is $c = [\max(L(x))]^{-1}$.
- $L(x)$ is the likelihood function and is a probability density function defined as.
 - $L(x) = f_{y_i|x}(y_i|x)$
 - y contains the measurements

If a sample is obtained for which holds that:

$$h(x, \mu_0) < 0$$

Then this sample falls in the posterior distribution. The most straight forward way to obtain these samples would be crude Monte Carlo simulation. For multi-dimensional problems and if the probability that $h(x, \mu_0) < 0$ is low, this will be inefficient. Applying techniques such as FORM, Importance Sampling or Directional Sampling will improve the efficiency. However, after obtaining the samples for which holds that $h(x, \mu_0) < 0$, additional steps must be taken to transform these samples to the 'real' distributions.

The above holds in case all variables are transformed to independent standard normal variables and under the condition that the measurement data is of the equality type.

In general, a distinction can be made between equality- and inequality information. Inequality information implies that the measurement is greater or less than a function of random variables. Examples of inequality information are survived loads or incomplete load test data. The evidence ϵ can be written as (Straub D. , 2011) :

$$\epsilon \equiv \{h(x < 0)\} \quad \vee \quad \epsilon \equiv \{h(x > 0)\}$$

Equality information is commonly obtained when measuring certain quantities, displacements for example. Equality evidence can be written as:

$$\epsilon \equiv \{h(x = 0)\}$$

2.3 Research methodology

An overview of theory regarding quay walls, probabilistic design and Bayesian updating is described in previous paragraphs. The use of this theory to answer the research and sub question is explained in this section.

2.3.1 Bayesian update

The objective of the thesis is to apply Bayesian updating to a quay wall calculation model. In section 2.2.6 three methods have been explained for Bayesian updating. These are: solving Bayes formula analytically, Markov Chain Monte Carlo method and Bayesian updating with structural reliability methods (BUS). From these options, BUS seems to be the most suitable method for applying to this research topic. It provides more flexibility in the used evaluation method and it should therefore give more control on the convergence and calculation time compared to a Markov Chain Monte Carlo approach. These benefits make BUS the better choice. As BUS can potentially be combined with any structural reliability method, further study is required to determine the most suitable method. In chapter 3, a choice is made which reliability method will be used.

2.3.2 Case to be evaluated

In order to execute a Bayesian update, a suitable reference case is selected. For the focus to remain at the Bayesian update a relatively simple quay structure is chosen. For a quay, a simple case means an anchored sheet pile or anchored combi-wall. The selected reference case and the details of the structure and the soil is provided in chapter 4.

It should be noted that Bayesian updating can be applied to any type of retaining structure. This thesis shows that the finite element software PLAXIS can be used and thus also complicated structures can be evaluated.

To perform Bayesian updating measurements are required. In this thesis the measurement data is fictitious, the values used are assumed. It is chosen to use a more theoretical approach by assuming different measurement cases. This allows showing more general trends and thus different possible outcomes if one is to perform test loading. So, for this study it is chosen to use a real structure, but with fictitious measurements.

2.3.3 Calculation models

To evaluate the effectiveness of Bayesian updating, it is used in combination with the model of Blum and in combination with finite element software. The choice for Blum has the advantage of a fast calculation time results and as this model is relatively simple it allows to gain insight in to the process of Bayesian updating. The main reason for choosing Blum is that the results of the update can more easily be validated and possible bottlenecks can be identified. The disadvantage of Blum is the fact that the model is not sufficiently accurate and is in practice only used as a first estimation. Therefore once sufficient experience is gained with Blum, finite element software will be used to validate the results obtained from Blum. The finite element software used is PLAXIS 2D 2017.

3 Bayesian Updating with structural reliability methods

As introduced in chapter 2, Bayesian updating with structural reliability methods (BUS) will be applied. The key benefit of this method is that Bayesian updating can now be applied with any structural reliability method. This gives flexibility and provides control over the calculation process.

From the commonly available structural reliability methods, two are selected for applying BUS. These are: Monte Carlo Simulation and Subset Simulation. In this chapter the choice for these methods is explained, the principle of both methods is explained and the methods are applied on an example.

3.1 Selected structural reliability methods

Bayesian updating with structural reliability methods can be combined with all of the available structural reliability methods. As numerous methods are available, first a choice is made in which reliability methods will be used.

Three criteria are defined for the application of BUS in this research. These criteria are:

- The method should not require any knowledge of the posterior distribution.

BUS will be applied to fictitious monitoring data of a quay wall. The data are assumed to be obtained from a test loading. On beforehand the outcome of this test is unknown, the selected method should obtain reliable results independent of the test result.

- It should be possible to evaluate a large number of variables and correlation between variables.

The variables included for quay design are structural parameters, geotechnical parameters and geometrical parameters. Ideally all of these parameters and uncertainties need to be included. As geotechnical parameters can be correlated, this effect must also be included.

- It should be straightforward to obtain the posterior distributions of the variables.

This final criterion severely limits the possible reliability methods. It does however, make the application easier. If for example the well-known optimized reliability methods such as Directional Sampling or FORM are applied, the posterior distributions are difficult to determine. The reason for this is that, these methods apply optimization algorithms to determine the failure probability and thus the stochastic posterior distributions are not easily determined.

Based on the three listed criteria, Monte Carlo Simulation (MCS) and Subset Simulation (SuS) are selected for the application of BUS.

The application of MCS is relatively easy. All of the above criteria are met, no prior knowledge is required and also all variables and correlation can be included. Furthermore, one can directly obtain the samples which are in the posterior distribution and evaluating the stochastic distribution is thus relatively simple.

If the measurement is deviating from the prior prediction, MCS will be inefficient. As the probability of obtaining a posterior sample is then low.

To solve this problem another method, Subset Simulation, is investigated. Subset Simulation is based on a Monte Carlo approach but is much more efficient in sampling low probabilities. Furthermore, obtaining the posterior distributions remains relatively simple. Applying Subset Simulation is however more complex and requires all variables to be transformed to standard normal independent variables. To show the difference between the two methods, both Monte Carlo Simulation and Subset Simulation are applied to an example of a cantilever beam model. First some additional information about applying both methods is provided.

3.2 Monte Carlo Simulation

Applying BUS using a Monte Carlo Simulation is, as already introduced, a relatively straightforward method. The principle is based on a simple-rejection filter (Straub & Papaioannou, 2014). The samples are filtered based on their likelihood of occurring.

The measurements, including the measurement error, are written into a likelihood function. This likelihood function is a probability density function:

- $L(x) = f_{y_i|x}(y_i|x)$
- y contains the measurements, which can be a vector containing measured points or a certain measured mean value in combination with a measurement error.

The required steps to obtain samples from the posterior distribution are:

1. Generate sample X from prior distribution
2. Estimate a value for constant 'c'.
 c is a constant to ensure that $cL(x) < 1$, so the optimum choice is $c = [\max(L(x))]^{-1}$
 The purpose of the constant is to increase the number of samples which are in the posterior distribution. The optimum choice requires knowledge about the likelihood function.
3. Calculate probability $L(X)$
4. If $cL(X) > \mu_0$ X is a sample in posterior distribution
 If $cL(X) < \mu_0$ X is not a sample in posterior distribution
 μ_0 is a random draw from the standard uniform distribution
 c is a constant to ensure that $cL(x) < 1$, so the optimum choice is $c = [\max(L(x))]^{-1}$
5. Repeat until enough samples in posterior distribution are found

The above steps are written in a python code (Technical University of Munich, 2018), this code is shown in Appendix A.

In the above written steps, the constant c needs to be selected. In the cases used in this thesis the constant can exactly be determined. It should however be noted that this constant has a direct influence on the result of the update.

If a value of c is selected which causes $cL(x) > 1$, some samples will falsely be accepted. This will lead to an error in the estimate of the posterior distribution.

Selecting a value of c which causes $cL(x) \ll 1$, will lead to a very inefficient calculation. If a too low value of c is selected the acceptance rate will be low and thus a large number of calculations is required.

To summarize, the most efficient choice is thus $c = [\max(L(x))]^{-1}$.

3.3 Subset Simulation

As shortly introduced, Subset Simulation is a more efficient method to calculate samples with a low probability of occurrence. The principle for the simulation is to split the problem of small probability, into a series of problems with a higher probability. This is done by intermediate failure events. The ratio between the intermediate failure events is a constant conditional probability, p_0 . So instead of solving the initial problem which is assumed to have a low probability, a series of problems is solved. This series of problems proves much easier to solve. In mathematical formulation, the intermediate events are expressed as follows:

Failure is defined as $Z < 0$, the probability of failure $P_f(Z < 0)$

Subset Simulation calculates the probability of failure by M intermediate events:

$$P_f(Z < 0) = P_f(\cap_{i=1}^M Z_i) = \prod_{i=1}^M P_f(Z_i | Z_{i-1})$$

These M intermediate events are defined as:

$$Z < b_i, b \text{ ranges from } b_1 > b_2 \dots > b_m = 0$$

The values of b, are chosen adaptive such that the estimation of the conditional probability is equal to a value p_0 . This value is required as input and (Au & Beck, 2001) suggests that a value between [0,1-0,3] should be used.

The samples in the intermediate events, $b_1 > b_2 \dots > b_{m-1}$, are generated by Markov Chain Monte Carlo Simulation (MCMCS). This method compares the likelihood of each sample with the previous sample and either accepts or rejects the sample. By this procedure the method reaches, after a number of samples, a stationary distribution which is equal to the posterior distribution.

A common disadvantage of MCMCS is that it can require a large number of samples for the chain to converge. It is shown by (Papaioannou, Beck, Zwirgmaier, & Straub, 2014) that the Markov Chain used in Subset simulation does not suffer from this problem. The chain uses the samples from the previous event as a seed for the next event and as such the chain is already converged, so the samples are directly from the required distribution.

The samples conditional on $P_f(Z < 0)$, the final event, are generated by a Monte Carlo Simulation. Samples generated by MCMCS are dependent. To have uncorrelated posterior samples MCS is used for the final event.

Figure 15 further illustrates the explanation of Subset simulation. The figure shows a reliability calculation in standard normal space. The red parabola is the limit state function to be evaluated. The left figure indicates samples generated by MCS. It shows that only a few samples exceed the red limit state function. The right figure shows the procedure of Subset Simulation with one intermediate subset. The black parabola is used as an intermediate failure event. This intermediate failure plane is then used to evaluate the final failure event. This makes it more likely to have samples which exceed the red limit state function and thus to more efficiently calculate the failure probability.

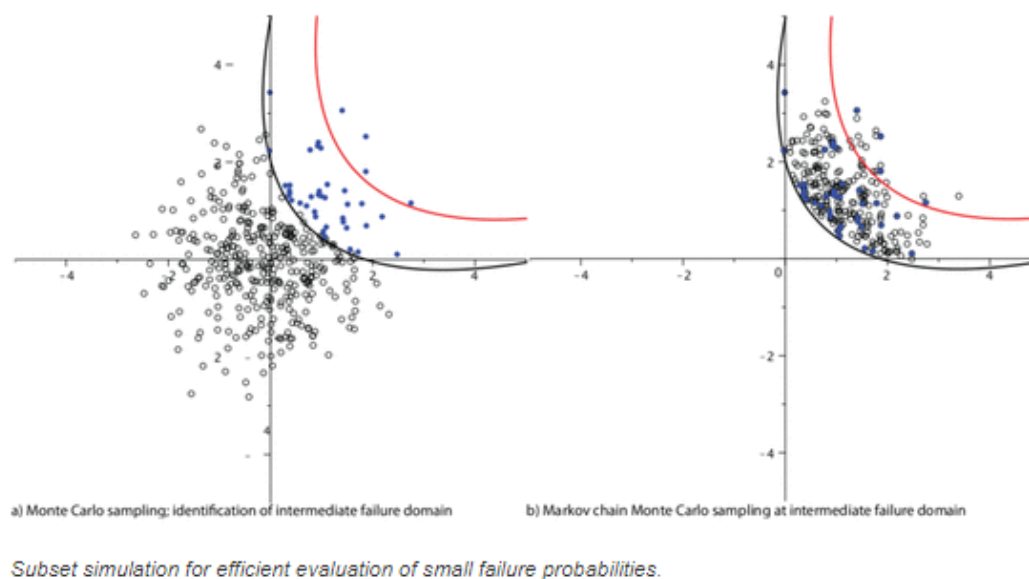


Figure 15 Principle of Subset Simulation (ERA group, 2018)

Applying Subset Simulation requires two choices: a choice in the conditional probability p_0 and a choice in how many samples of the intermediate events are taken. The number of samples should be chosen large enough to ensure that the conditional probability is accurately estimated.

To apply Subset Simulation in combination with BUS, one more step is required. From the obtained samples, it must be identified which of these samples are in the posterior distribution. This is done by applying the Likelihood filter (section 3.2) and generating a number of samples which are in this posterior distribution.

The above explained subset simulation procedure is applied with a matlab code. The code is based on (Straub & Papaioannou, 2014). It applies Subset simulation, as introduced by (Au & Beck, 2001). This original procedure is extended for applying BUS, so instead of failure probabilities the posterior distributions are determined. The used code is elaborated in Appendix B.

Furthermore, an 'adaptive approach' is used. This 'adaptive approach' eliminates the choice for the constant 'c', as shown by (Straub, Betz, & Papaioannou, 2014). Instead of estimating the coefficient before starting the simulation, the adaptive approach changes the coefficient during the simulation. Before generating the samples in each subset an estimate of the coefficient is made. After evaluating all samples in the subset, the coefficient is adapted and approaches the optimum choice.

An important final remark regarding the application of BUS with Subset Simulation, is that the input variables are transformed to standard normal independent variables. The matlab script uses the Nataf transformation (Lebrun & Dufloy, 2009). The Nataf transformation is based on a Gaussian Copula. This implies that the joint distribution of the variables will be normally distributed. So in principle, the marginal distributions must also be normally distributed. The Nataf transformation can take into account correlation between parameters, which is useful for modelling the soil parameters in the next chapters.

3.4 Example of Bayesian Updating

To compare the two methods, BUS with Monte Carlo simulation and BUS with Subset simulation, a model of a cantilever beam is used. The mechanical scheme is represented in Figure 16.



Figure 16 Cantilever beam with point load F

The deflection of the beam, w , can be calculated with the basic equation:

$$w = \frac{FL^3}{3EI}$$

Assume that the parameters are normally distributed according to Table 2. These parameters would represent a prismatic, rectangular, concrete beam with a width and height equal to 300 mm.

Table 2 Distribution of parameters cantilever beam

Parameter	Symbol		Mean μ	Standard deviation σ
Force	F	[N]	$1,00 \times 10^4$	$5,00 \times 10^2$
Length	L	[mm]	$5,00 \times 10^3$	$1,00 \times 10^2$
Young's modulus	E	[N/mm ²]	$3,00 \times 10^4$	$1,50 \times 10^3$
Moment of Inertia	I	[mm ⁴]	$6,75 \times 10^8$	$6,75 \times 10^6$

Using the parameters this results in the following prior distribution of the deflection, w .

- $\mu_w = 20,65$ mm
- $\sigma_w = 1,93$ mm

For comparison a failure definition is introduced. If the beam deflects more than 25 mm it is considered to be failed. This results in the prior reliability index of (calculated using a Monte Carlo Simulation with 100.000 samples):

- $\beta = 2,10$

Suppose that the displacement of the beam is measured. It is assumed that the measurements can be described by a normal distribution with a mean of 18 mm and standard deviation of 1 mm. The assumed standard deviation represents inaccuracies in the taken measurements by for example a deviation in the measurement equipment. The likelihood function, $L(x)$, can then be written as:

$$L(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$$

With:

- $\mu = 18$ mm
- $\sigma = 1$ mm
- x is the displacement as calculated using the basic equation for a cantilever beam

For the Monte Carlo simulation, the 'c' coefficient must be defined. As the likelihood function is known, the value of this constant is:

- $c = \max(L(x))^{-1}$
- $c = \sqrt{2\pi\sigma^2} = 2,51$

For both methods 100.000 samples are generated in the posterior distribution and for the Subset calculation a conditional probability $p_0 = 0,1$ is chosen. The results of the calculations for both methods are shown in Table 3.

Table 3 Calculation results deflection cantilever beam

Parameter	Posterior Monte Carlo simulation		Posterior Subset simulation	
	Mean μ	Standard deviation σ	Mean μ	Standard deviation σ
F [N]	$9,70 \times 10^3$	$4,53 \times 10^2$	$9,70 \times 10^3$	$4,41 \times 10^2$
L [mm]	$4,93 \times 10^3$	$9,63 \times 10^1$	$4,93 \times 10^3$	$8,35 \times 10^1$
E [N/mm ²]	$3,09 \times 10^4$	$1,37 \times 10^3$	$3,09 \times 10^4$	$1,34 \times 10^3$
I [mm ⁴]	$6,76 \times 10^8$	$7,06 \times 10^6$	$6,76 \times 10^8$	$6,71 \times 10^6$
w [mm]	$1,86 \times 10^1$	0,88	$1,86 \times 10^1$	0,86

In addition to Table 3 the relative changes obtained by both methods of Bayesian updating are shown in Figure 17 and Figure 18. In both graphs the change is expressed related to the prior values. So:

$$Change = \frac{Posterior}{Prior}$$

From the above formula it can be derived that if the bar height in the graph is below one, the posterior mean or standard deviation is lower than the prior one. If the bar height is more than one, the posterior mean or standard deviation is higher than the prior one

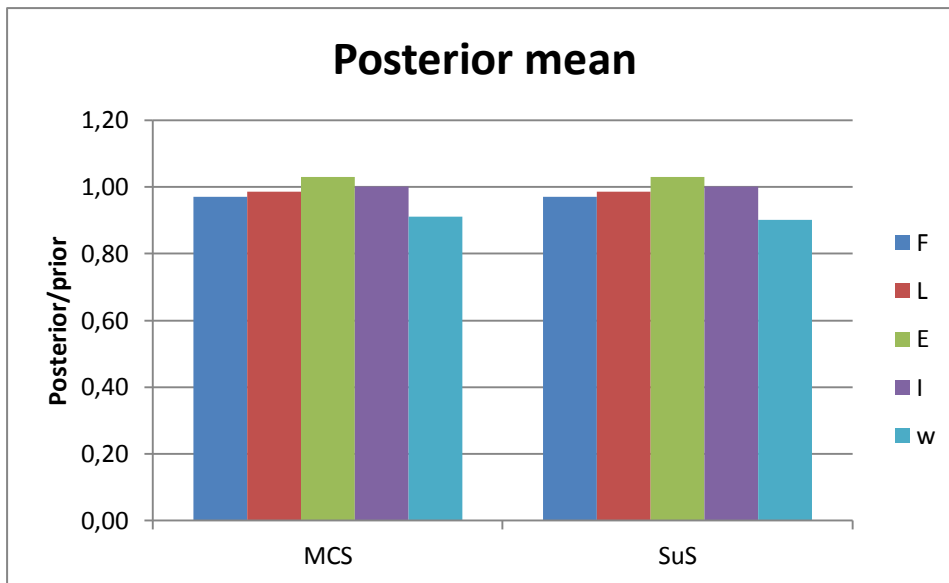


Figure 17 Relative change in mean

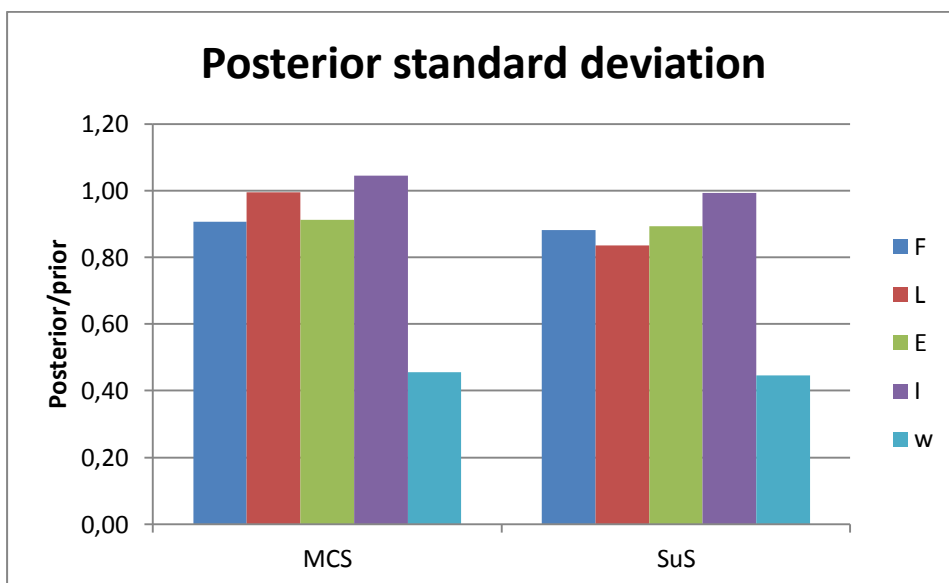


Figure 18 Relative change in standard deviation

The posterior reliability index can now be calculated (using a Monte Carlo Simulation with 100.000 samples):

- Posterior reliability Monte Carlo simulation
 - $\beta = 3,44$
- Posterior reliability Subset simulation
 - $\beta = 3,69$

By looking at Figure 17, the following can be observed. In the posterior distribution:

- the acting force, F , is reduced;
- the length, L , is reduced;
- the Young's Modulus, E , increases;
- the moment of inertia, I , remains more or less constant;
- the deflection, w , decreases.

The posterior distributions are obtained by Bayesian updating with a measurement which shows less deflection than initially predicted. So, the above listed observations make sense. Less deflection can be caused by a lower acting force, less beam length, an increased stiffness or a larger moment of inertia. The result of the Bayesian update is the most likely combination of the input parameters. The most likely combination is dependent on the prior distribution of the parameters and the provided measurements.

If, for example the length of the beam is measured before loading the beam and thus the length can be included with a much lower standard deviation, the resulting most likely combination will change. If the length is included with lower standard deviation it will be unlikely that the length will show a change and thus the remaining parameters will show a larger change.

The results from both methods are in general quite similar. Especially the obtained posterior means are almost the same value. The method of Subset simulation shows a slightly larger reduction in the estimated posterior standard deviations. This reduced standard deviation has the result that the predicted posterior reliability is higher with Subset simulation than with Monte Carlo simulation.

The final results for the displacement of the beam are visualized in Figure 19. The figure shows the probability density functions of the prior- (blue), the posterior distributions (red and black) and the measurement (green).

Bayesian updating according to the assumed measurement results in a much narrower distribution and a lower predicted deflection. The assumed measurement is a lower deflection and the measurement error is much lower than the deviation in the prior prediction. Thus, based on the assumed measurement the result is as expected. Furthermore, Figure 19 and Table 3 show that MCS and SuS give similar results. SuS results in a slightly narrower posterior distribution.

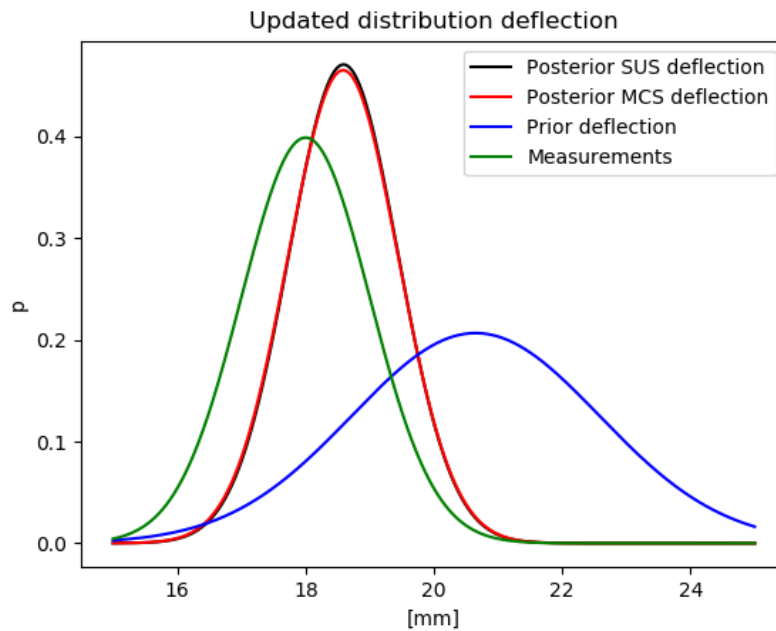


Figure 19 Probability density functions of prior and posterior distributions

As both methods provide almost similar results, another important aspect to compare is the efficiency of the methods. For the example treated in this chapter the calculation time is negligible, obtaining the results takes less than one minute. However once applied on more complicated models, the calculation time will be an important aspect. The time required for the simulations is related to the number of likelihood function calls. For each method the number of calls is:

- Number of likelihood function calls Monte Carlo Simulation 864.952
- Number of likelihood function calls Subset Simulation 300.000

In this example 100.000 samples were generated in the posterior distribution. The number of likelihood function calls in the SuS methods depends on the number of subsets, or intermediate failure events, required to solve the problem. In this example three subsets are required and thus 300.000 function calls are made.

In MCS the number of function calls is related to the acceptance rate. The chance of obtaining posterior samples is called the acceptance rate. As MCS is drawing random samples from the original distributions, the chance of obtaining a posterior sample is also random. The acceptance rate will decrease if the difference between the measurement distribution and the prior distribution is large.

In general SuS is more efficient and thus more suitable for the application of BUS.

4 Introduction to the case

This chapter provides information about the case which is used for the application of Bayesian updating. The chapter provides general information regarding the use of the quay wall, technical details regarding the structure, a representative soil profile and an overview of the starting points.

4.1 General case information

The used case is a quay wall located the port of Rotterdam. Specifically, the location of the quay is on the second Maasvlakte. The second Maasvlakte is a port expansion built on a land reclamation. The soil conditions at the second Maasvlakte are mostly sandy. The quay is realized in 2017. A satellite image of the second Maasvlakte is shown in Figure 20.



Figure 20 Second Maasvlakte [Google Maps]

4.2 Technical details

The quay has a retaining height of 14 m and the retaining element is a combined-wall. A combined-wall is a combination of tubular piles and sheet pile elements. This combination of piles and sheets has a much higher bending stiffness and bending moment capacity than standard sheet piles. A combined wall is therefore more suitable to resist larger retaining heights.

The combined wall is anchored with two grout anchors at each tubular pile. A cross-section of the structure is seen in Figure 38 in Appendix C. A summary of relevant characteristics is presented here, based on (Timmermans, 2015):

- Soil and water levels
 - Ground level NAP + 5,10 m
 - Harbor bottom level NAP - 8,90 m
 - Groundwater level NAP - 0,34 m
 - Harbor water level NAP - 0,84 m

- Applied anchors
 - Anchor Jetmix ϕ 101.6 mm x 22,2 mm
 - Area $A = 5.510 \text{ mm}^2$
 - Yield strength $f_{y;d} = 500 \text{ N/mm}^2$
 - Anchor angle 42,5 ° and 47,5 °
 - Anchor top level NAP +1,5 m and NAP +0,5 m
 - Top grouted part NAP - 24 m
 - Anchor center to center distance 2,941 m

- Applied retaining structure
 - Sheet piles 3 PU28
 - Top level NAP + 5,10 m
 - Toe level NAP - 12,5 m
 - Steel quality S355 $f_{y;d} = 477 \text{ N/mm}^2$
 - $E = 2,10 * 10^5 \text{ N/mm}^2$
 - $I = 0,36 * 10^5 \text{ mm}^4/m$

 - Tubular piles ϕ 1067-15 mm
 - Top level NAP + 5,10 m
 - Toe level NAP - 27,5 m
 - Steel quality X70 $f_{y;d} = 355 \text{ N/mm}^2$
 - $E = 2,10 * 10^5 \text{ N/mm}^2$
 - $I = 2,33 * 10^5 \text{ mm}^4/m$

 - System size combiwall 2,941 m
(Width of the three sheet piles and tubular pile)

A top view of the applied combi-wall including the dimensions is shown in Figure 21.

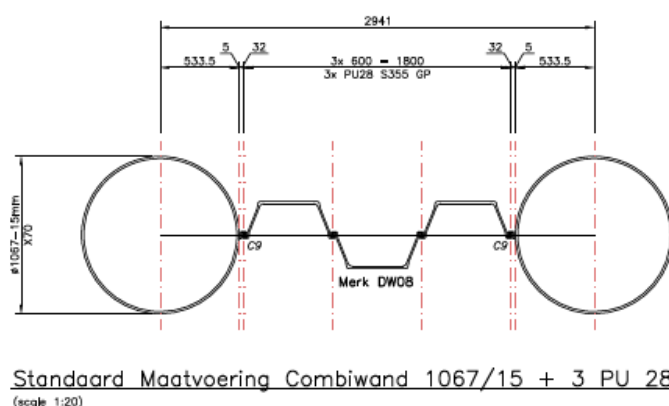


Figure 21 Applied combi-wall (Timmermans, 2015)

4.3 Soil profile

The second Maasvlakte is a large land reclamation and consists mainly of sandy soils. This sandy subsoil can be seen in the soil investigations which are done for the design of the wall. The soil profile present at the quay consists largely of sand with some small clay layers in between. Based on the soil investigations which are done during the design phase, one representative soil structure is defined. During the design phase the cone penetration tests (CPT's) and soil borings are performed.

Table 2b from NEN9997-1 is used to determine the strength parameters. The values obtained from this table are characteristic values.

The soil profile which is representative for the soil at the location of the quay is found in Table 4. The CPT which is used to derive these values is found in Appendix C.

Some CPT's show small deviations from this representative profile. These deviations are identified as local disturbances and it is assumed that the effect of these deviations is small on the behaviour of the wall. The profile as defined in Table 4 and the coefficient of variations listed below are used in the calculations in the following chapters.

Table 4 Soil profile based on DKM-124 (Timmermans, 2015)

Top level layer [m NAP]	Soil type	γ_d [kN/m ³]	γ_{sat} [kN/m ³]	φ [°]	c [kN/m ²]	E_{oed} [kN/m ²]
+5,1	Sand, clean, loose	17	19	30	0	15000
-4,0	Clay, slightly sandy, weak	15	15	22,5	0	1500
-5,5	Sand, clean, loose	17	19	30	0	15000
-10,0	Sand, slightly silty clayey	18	19	27	0	35000
-14,0	Sand, clean, loose	17	19	30	0	15000
-21,0	Clay, slightly sandy, weak	15	15	22,5	0	1500
-23,0	Sand, clean, solid	18	20	32,5	0	75000

Next to the representative soil parameters table 2b from NEN9997-1 provides coefficient of variation for each soil parameter. These are shown here:

- | | | |
|---------------------|-------------------------|---------------------------------|
| • Volumetric weight | γ_d/γ_{sat} | coefficient of variation = 0,05 |
| • Friction angle | φ | coefficient of variation = 0,10 |
| • Cohesion | c | coefficient of variation = 0,20 |
| • Stiffness | E_{oed} | coefficient of variation = 0,25 |

A schematic of the quay's cross-section indicating the different soil layers is shown in Figure 22.

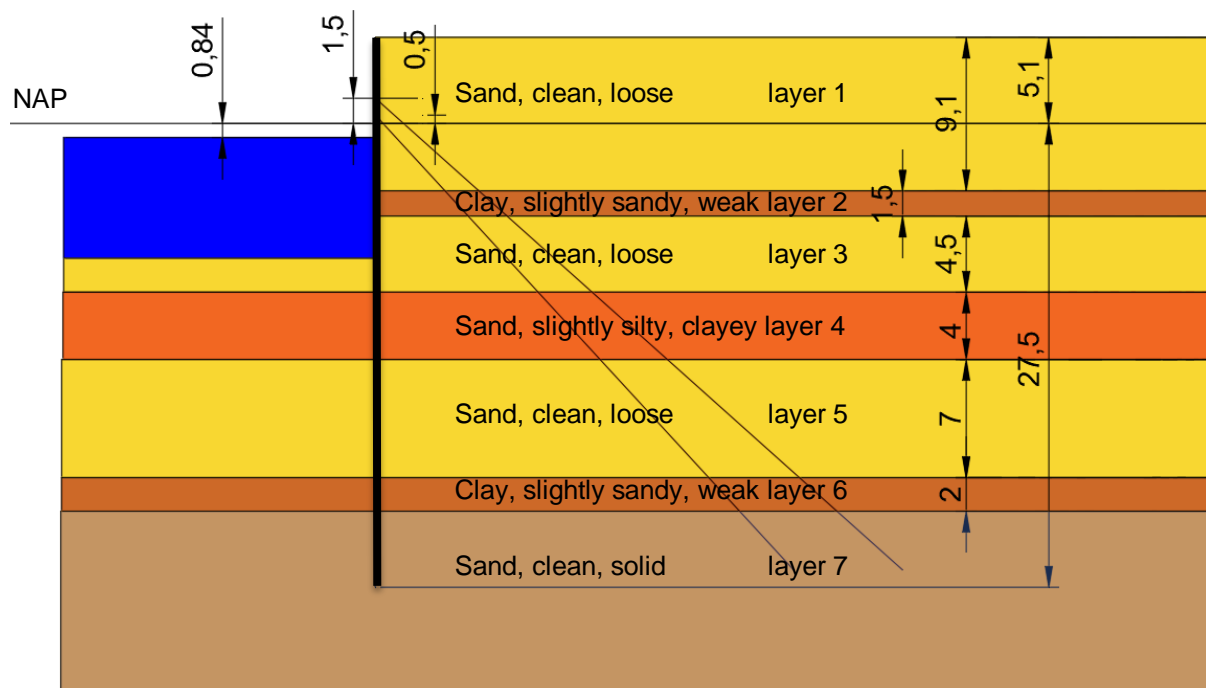


Figure 22 Schematic cross-section quay

4.4 Starting points

This section describes the general starting points for the calculations in the coming chapters. The specific model related starting points are described in the relevant chapters. The starting points are chosen to limit the scope of the calculations and to reduce the calculation efforts. The main starting points mentioned in this section are the selection of stochastic variables and the loading situation which is considered in the models.

For the design of quay walls, a significant amount of information is required. This can be seen while looking at the information which has been presented in the previous sections, 4.2 and 4.3. These sections describe structural parameters, geotechnical parameters and geometrical parameters. Theoretically there is in each presented value a certain amount of uncertainty. Including all of these uncertainties for all parameters will result in a large computational effort. Therefore, a selection of which parameters are treated as stochastic variables is made.

4.4.1 Structural parameters

One of the aims of applying Bayesian updating is to reduce the uncertainty in the variables by obtaining better estimates. This will be most interesting for the variables which are most uncertain. The structural parameters are in general less uncertain than soil parameters. For the case treated in this thesis, the structural parameters are well known. Using the design documents, it is determined which sheet, which tubular pile, the type of anchor and to which depth they are applied. Furthermore, due to the fact that the quay is only recently constructed, corrosion cannot have had a significant impact on the thicknesses of the structural parts. So, the update will be less interesting for these parameters as the prior estimates are already 'good' estimates. The structural parameters are treated deterministic with the characteristic values presented in section 4.2.

4.4.2 Geotechnical parameters

The reasoning in section 4.4.1 is not true for the geotechnical parameters. It will be interesting to see how the estimates for the geotechnical parameters change. Using the soil investigations and table 2b from NEN9997-1 one can obtain estimates for these parameters. For two reasons it is interesting to obtain better estimates for these parameters. First, guideline values are usually considered to be safe estimates. So, the real soil parameters might deviate from this and possibly be more favourable. The second reason is that performing a soil investigation is expensive and also has some remaining uncertainties caused by for example sample disturbance. Therefore, in the models the soil parameters are treated as stochastic variables.

For the model of Blum, the following parameters need to be included: volumetric weight, friction angle and cohesion. Table 4 shows that the soils have no cohesion and as such this parameter is treated deterministically with a value equal to zero. This leaves the volumetric weight and friction angle as stochastic variables. It is assumed that the parameters are distributed normally.

In PLAXIS the soil stiffness needs to be provided. This parameter is assumed to be lognormally distributed. The choices for these distributions are consistent with previous studies for example: (Schweckendiek, 2006), (Wolters, 2012), (Rippi, 2015) and (Janssen, 2016).

The variables presented in Table 4 are characteristic values. A characteristic value is defined as the value which has a probability of exceedance, in case of load parameters, of 5 %. For resistance parameters the probability of obtaining a lower value is 5 %. Using these values is common practice in deterministic and level 1 probabilistic calculations. In level 2 and level 3 probabilistic calculations, mean values should be used. If characteristic values are used, this leads to an underestimation of the failure probability. Therefore, mean values are used in the probabilistic calculations.

Based on the 95% confidence interval for normally distributed variables the characteristic values can be transformed to mean values by the following expression:

$$\mu_x = \frac{X_k}{1 - 1,64 * CoV}$$

In which:

- X_k Characteristic value as determined in Table 4.
- CoV Coefficient of Variation
- μ_x Resulting mean value of the variable

As the soil stiffness is lognormally distributed the above relation is not applicable to the soil stiffness parameters. The relation used to translate the characteristic stiffness to the mean value is based on the formula given in CUR166 (CUR, 2012):

$$\mu_{E_{soil}} = \frac{2}{1,3} * E_{k;low;soil}$$

The stochastic definition of the geotechnical parameters is presented in Table 5. In this table the following is presented: the characteristic value, mean and standard deviation. The mean value and the standard deviation are used in chapter 5 and chapter 6.

Table 5 Stochastic soil variables

Variable	Characteristic value	Mean μ	Standard deviation σ
Sand, clean, loose			
φ layer 1	30 ⁰	35,89 ⁰	3 ⁰
γ_{sat} layer 1	19 kN/m ³	20,69 kN/m ³	0,95 kN/m ³
γ_d layer 1	17 kN/m ³	18,52 kN/m ³	0,85 kN/m ³
E_{oed} layer 1 ¹	15000 kN/m ²	23076 kN/m ²	3750 kN/m ²
Clay, slightly sandy, weak			
φ layer 2	22,5 ⁰	26,91 ⁰	2,25 ⁰
γ_{sat} layer 2	15 kN/m ³	16,34 kN/m ³	0,75 kN/m ³
γ_d layer 2	15 kN/m ³	16,34 kN/m ³	0,75 kN/m ³
E_{oed} layer 2	1500 kN/m ²	2307 kN/m ²	375 kN/m ²
Sand, clean, loose			
φ layer 3	30 ⁰	35,89 ⁰	3 ⁰
γ_{sat} layer 3	19 kN/m ³	20,69 kN/m ³	0,95 kN/m ³
γ_d layer 3	17 kN/m ³	18,52 kN/m ³	0,85 kN/m ³
E_{oed} layer 3	15000 kN/m ²	23076 kN/m ²	3750 kN/m ²
Sand, slightly silty clayey			
φ layer 4	27 ⁰	32,30 ⁰	2,7 ⁰
γ_{sat} layer 4	19 kN/m ³	20,69 kN/m ³	0,95 kN/m ³
γ_d layer 4	18 kN/m ³	19,61 kN/m ³	0,9 kN/m ³
E_{oed} layer 4	35000 kN/m ²	53846 kN/m ²	8750 kN/m ²
Sand, clean, loose			
φ layer 5	30 ⁰	35,89 ⁰	3 ⁰
γ_{sat} layer 5	19 kN/m ³	20,69 kN/m ³	0,95 kN/m ³
γ_d layer 5	17 kN/m ³	18,52 kN/m ³	0,85 kN/m ³
E_{oed} layer 5	15000 kN/m ²	23076 kN/m ²	3750 kN/m ²
Clay, slightly sandy, weak			
φ layer 6	22,5 ⁰	26,91 ⁰	2,25 ⁰
γ_{sat} layer 6	15 kN/m ³	16,34 kN/m ³	0,75 kN/m ³
γ_d layer 6	15 kN/m ³	16,34 kN/m ³	0,75 kN/m ³
E_{oed} layer 6	1500 kN/m ²	2307 kN/m ²	375 kN/m ²
Sand, clean, solid			
φ layer 7	32,5 ⁰	38,88 ⁰	3,25 ⁰
γ_{sat} layer 7	20 kN/m ³	21,79 kN/m ³	1 kN/m ³
γ_d layer 7	18 kN/m ³	19,61 kN/m ³	0,9 kN/m ³
E_{oed} layer 7	75000 kN/m ²	115384 kN/m ²	18750 kN/m ²

¹ In PLAXIS the following stiffness relations are used. $E_{50} = E_{oed}$ and $3 * E_{50} = E_{ur}$

A remark regarding the standard deviations in Table 5, these are derived from the coefficients of variations as defined by NEN9997. It is assumed that these coefficients of variation are spatially averaged values. This assumption is further explained below.

Soil properties are not uniform in space. They can be different in every direction. A commonly applied method to include this spatial variability, is averaging the variations along a soil layer. This method is called Spatial Averaging and is described in (Joint Committee on Structural Safety JCSS, 2001).

The concept of this method is that the obtained point variance, found by for example site investigations, is averaged over a soil layer. The idea behind this method is that a single weak spot doesn't lead to failure along the slip plane. The weak spots can be averaged along a soil layer. Thus, using the theory of Spatial Averaging one can obtain a reduction in the coefficients of variation. In this thesis it is assumed that the coefficients of variation as defined by NEN9997 are spatially averaged values.

To finalize this section regarding the geotechnical parameters, correlation between the soil parameters needs to be addressed. The correlation coefficients are based upon previous studies. Both (Wolters, 2012) and (Bach, 2014) have determined correlation coefficients based on the database of (Gemeentewerken Rotterdam, 2003). This database consists of a large number of triaxial tests done in the area of Rotterdam. The parameters in each layer are assumed to be correlated according to the correlation matrix, Table 6. The different layers are assumed to be uncorrelated.

Table 6 Correlation Matrix

	φ	γ_{sat}	γ_d	E_{oed}^2
φ	1	0,5	0,5	0,25
γ_{sat}	0,5	1	1	0,5
γ_d	0,5	1	1	0,5
E_{oed}	0,25	0,5	0,5	1

² The E_{50} , E_{oed} and E_{ur} are assumed to be fully correlated, a correlation coefficient equal to one.

4.4.3 Geometrical parameters

The next set of parameters to discuss is the geometrical parameters. These describe the ground and water levels both behind and in front of the quay. They are assumed to be deterministic, as both the water levels and the ground levels can be relatively easily and accurately determined. To further support the decision for fixed water levels, a drainage system is present in the quay. Therefore if this system is well maintained, no significant water level difference can occur over the quay. The levels are determined based on Appendix C and are shown here:

- Ground level NAP + 5,10 m
- Design depth NAP - 8,95 m
- Groundwater level NAP - 0,34 m
- Harbor water level NAP - 0,84 m

The groundwater level and the harbour water level are fluctuating over time. In the calculations they are assumed to be fixed. They are chosen consistent with the design documents (Timmermans, 2015). The choice of the levels influences the obtained results and to obtain the most accurate result, one should use the levels consistent with the levels present when the measurements are taken. If one is to perform test loading, these water levels should be determined in order to obtain the most realistic model results. As in this thesis fictitious measurement cases are introduced, the water levels are assumed to be in line with the design values.

In the design of the quay a design depth (DD) is determined. This design depth is a conservative choice for the height of the passive zone. It is based on the following depths and clearances (Timmermans, 2015):

$$DD = NGD - h_{maintenance} - d_{bottomprotection} - 2 * \sqrt{\delta_{dredging}^2 + \delta_{bottomprotection}^2} - h_{disturbance}$$

In which:

- NGD Nautical Guaranteed Depth (for shipping purposes) NAP -6,10 m
- $h_{maintenance}$ Maintenance clearance defined by port of Rotterdam 1,00 m
- $d_{bottomprotection}$ Thickness bottom protection 0,55 m
- $\delta_{bottomprotection}$ Tolerance on execution of bottom protection 0,25 m
- $\delta_{dredging}$ Dredging tolerance 0,30 m
- $h_{disturbance}$ Thickness of the by dredging disturbed layer 0,50 m
- DD Design Depth NAP - 8,95 m

The above determine design depth is a safe choice, including execution tolerances. As in the probabilistic calculations mean values are used. Also, for the depth a mean value is used. In the calculation an average depth equal to NAP - 8,15 m is used. This is equal to the above calculation, but without the tolerances on the dredging and placing of the bottom protection. The average depth, as used in the following chapters, is thus calculated as:

$$AD = NGD - h_{maintenance} - d_{bottomprotection} - h_{disturbance} = -6,10 - 1 - 0,55 - 0,5 = NAP - 8,15 m$$

On the passive side, the harbour bottom, a bottom protection is placed. The function of this protection is to prevent a scour hole in front of the quay. The weight of this protection can be added to the stress on the passive side of the quay. The bottom protection applied is loose rock with a grading of 40-200 kg penetrated with 160 l/m^2 underwater concrete. The thickness of this layer is 0,55 m. This weight is calculated as: (Timmermans, 2015)

- $\rho_s = 2650 \text{ kg/m}^3$ Weight of the stones in bottom protection
- $d = 0,55 \text{ m}$ Thickness of bottom protection
- $v = 0,55$ Void ratio of bottom protection
- $\rho_c = 1900 \text{ kg/m}^3$ Weight of concrete used to penetrate the protection
- $W = \frac{2650 \cdot 0,55 \cdot (1 - 0,55) + 0,160 \cdot 1900}{1000} = 9,60 \text{ kN/m}^2$

The thickness of the bottom protection has a certain spread. Dredging and placing the protection is subject to tolerances. Therefore, the load is varying over the harbour bottom. The influence is assumed to be little and, in the calculations, it is a deterministic value.

4.4.4 Acting loads on quay

Continuing with the same reasoning as applied for the water levels, a surcharge is assumed to be present on the quay. For the following chapters, it is assumed that measurements are obtained from an actual test load on the quay. In the test, the quay has been loaded up to 100 kN/m^2 . This 100 kN/m^2 is consistent with the design requirements (Timmermans, 2015) of the quay. The additional load cases investigated during the design are neglected. As it is assumed that the measurements are obtained from a test load, these additional load cases will not be present. It is furthermore assumed that the magnitude of the load is controlled, i.e. with limited variation. The surcharge is thus chosen as deterministic parameter.

4.4.5 Monitoring data

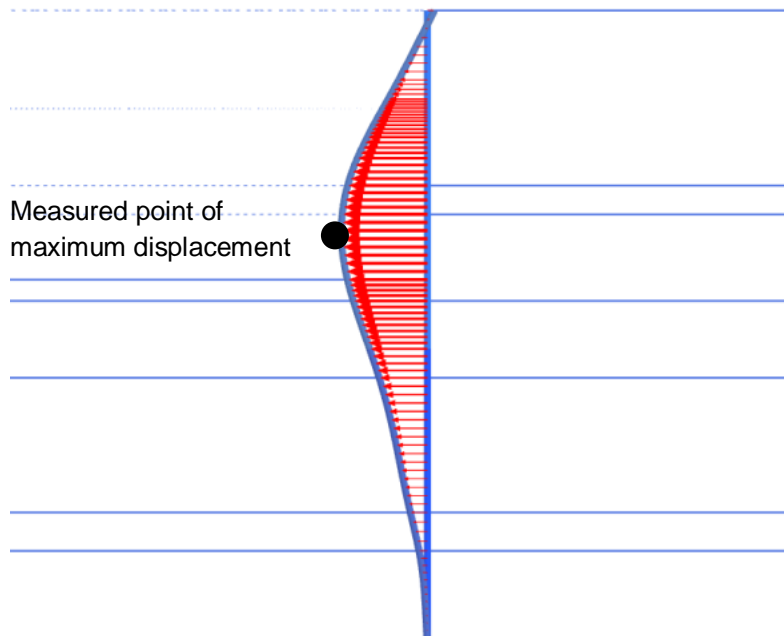
The starting points and information listed up to now make it possible to predict the prior failure probability of the quay. The next step is to update the probabilistic model. This update requires evidence. Evidence can be all sorts of measured data for example: structure or soil deformations, strains or rotations. Another possibility is knowledge about the survived load on the quay. If it is known that a certain extreme load is placed on the quay, then also this information can be used to update the probabilistic model. In this thesis the evidence are fictitious measurements.

Two types of measurements are used. It is assumed that the displacement of the quay is measured and that the anchor tube is equipped with strain gauges. To show the possible outcomes of Bayesian updating, three different cases are defined per type of measurement. This results in a total of six cases and thus six Bayesian updates. The cases are:

- High less displacement or strain is measured than is predicted.
- Average equal displacement or strain is measured than is predicted.
- Low more displacement or strain is measured than is predicted.

For the measured displacements additional assumptions are required. It is assumed that the full displaced profile of the quay is measured. The input for the update is then the point of maximum

horizontal displacement. This is illustrated in Figure 23. The figure shows the displaced profile as predicted by PLAXIS. The black dot indicates the point of maximum horizontal displacement. This point is used in the Bayesian update.



Total displacements u_x (scaled up 50,0 times)

Maximum value = $7,261 \cdot 10^{-3}$ m (Element 1 at Node 10052)

Minimum value = -0,08961 m (Element 10 at Node 12484)

Figure 23 PLAXIS predicted displacement of quay

5 Bayesian update with Blum Model

In this chapter the Bayesian update is applied to a Blum model of the case. The principle of the model as defined by Blum is treated in section 2.1. This chapter is structured in the following order: first the model specific starting points are listed, second the prior results are provided and the final step is to determine the posterior distributions using fictitious measurement cases. Two types of measurements are used: displacements measurements and anchor strain measurements. The calculation is performed with a Python script which is based on the code found in (Verruijt, 2012). The input data required for the calculation is described in chapter 4.

5.1 Starting points Blum

In addition to the starting points listed in section 4.4 the model specific starting points for applying the model of Blum are listed here.

The quay is a combi-wall anchored by two anchors, as shown in the cross-section in Figure 38. A calculation with two anchors is not possible with the model of Blum. Therefore, the two anchors located at NAP +1,5 m and NAP +0,5 m, are schematized to a single anchor at NAP +1,0 m. This single anchor has the capacity equal to both anchors.

The concrete capping beam and slab, which is located from NAP +5,1 m to NAP -2 m, is not taken into account. In the model the top level of the retaining structure is located at NAP +5,1 m and the tip of the retaining structure is at NAP -27,5 m.

The applied retaining structure is a combi-wall. The wall consists of both tubular piles and sheet piles. The tubular piles reach to a depth of NAP -27,5 m, while the sheet piles are placed to a depth of NAP -12,5 m. So, the stiffness of the wall is not constant over the height of the wall. In the Blum calculations this is not included. It is assumed that both the tubular piles and sheet piles are placed to a depth of NAP -27,5 m.

The script found in (Verruijt, 2012) calculates the embedded depth of a sheet pile. The calculations done in this thesis are probabilistic and in principle each combination of samples has a different embedded depth. As the script iteratively determines the embedded depth, the calculation time will quickly increase for a large number of samples. In the calculation a fixed embedded depth is chosen. The influence of this assumption is estimated to be limited and will not significantly impact the results found in this chapter.

5.2 Prior prediction

To show the effect Bayesian updating has on the failure probability and to compare the changed variables with their influence coefficients, two Limit States are defined. One limit state considers the quay to be failed if a maximum displacement is exceeded and the other limit state is related to a maximum anchor force.

The first limit state is defined by the design requirement, which states that the displacement of the quay may not be larger than 1,0 % of the retaining height. For this case, that is a maximum displacement of 140 mm.

The second limit state is the structural failure of the anchor. It is assumed that the steel tube of the anchor is the critical part, in practice this is almost never the case. Failure of the anchor tube is a brittle failure mechanism. Brittle failure of structures needs to be avoided and therefore usually the

geotechnical failure of the anchor is governing. In case of grout anchors, it is usually ensured that the anchor tube is stronger than the grip force of the grout body. As the interest is limited to showing the difference between prior and posterior, this assumption is justified.

It is assumed that the anchor fails when the tube starts to yield, plastic behaviour is neglected. The maximum anchor force can then be calculated by:

- F_{amax} $A * f_{y;d}$
- Area $A = 5.510 \text{ mm}^2$
- Yield strength $f_{y;d} = 500 \text{ N/mm}^2$
- F_{amax} $A * f_{y;d} = 5510 * 500 = 2755 \text{ kN}$

The above calculated value is over the system size (the tubular pile and the three sheet piles) the anchor force per running meter is given by:

- $F_{amax} = \frac{2755}{2.941} = 918,33 \text{ kN/m}$

The above calculated anchor force is determined for one anchor. If the maximum anchor force for two anchors is used, this results in very high reliability indices. In the design of the quay effects such as settling soil and corrosion of steel tube have been included, these effects are in the definition of this limit state neglected. This simplification leads to a much lower failure probability. The limit state for anchor failure is thus defined as the maximum force for one anchor.

To summarize, the two limit states to be evaluated are:

- Limit state 1 Displacements $d < 140 \text{ mm}$
- Limit state 2 Anchor force $F_{amax} < 918,33 \text{ kN/m}$

These definitions of failure and the distributions of variables as defined in Table 3 and section 4.3 results in the following prior results. The reliability is calculated with a FORM calculation and is shown below:

Limit state 1 Displacements

- $\beta = 2,22$

Limit state 2 Anchor Force

- $\beta = 5,72$

In addition to the reliability the prior distributions of the maximum moment, displacement and anchor force are shown in Table 7:

Table 7 Prior Blum moment-, displacement-, and anchor force distribution

Prior results	Mean μ	Standard deviation σ
Maximum moment	883,6 kNm	294,0 kNm
Displacement	47,56 mm	35,04 mm
Anchor force	464,31 kN/m	69,15 kN/m
Anchor strain	0,59 mm/m	0,09 mm/m

Figure 24 and Figure 25 show the influence coefficients for both limit states. The influence coefficients represent the influence of a stochastic variable on the reliability. In the figures the five most important variables are shown.

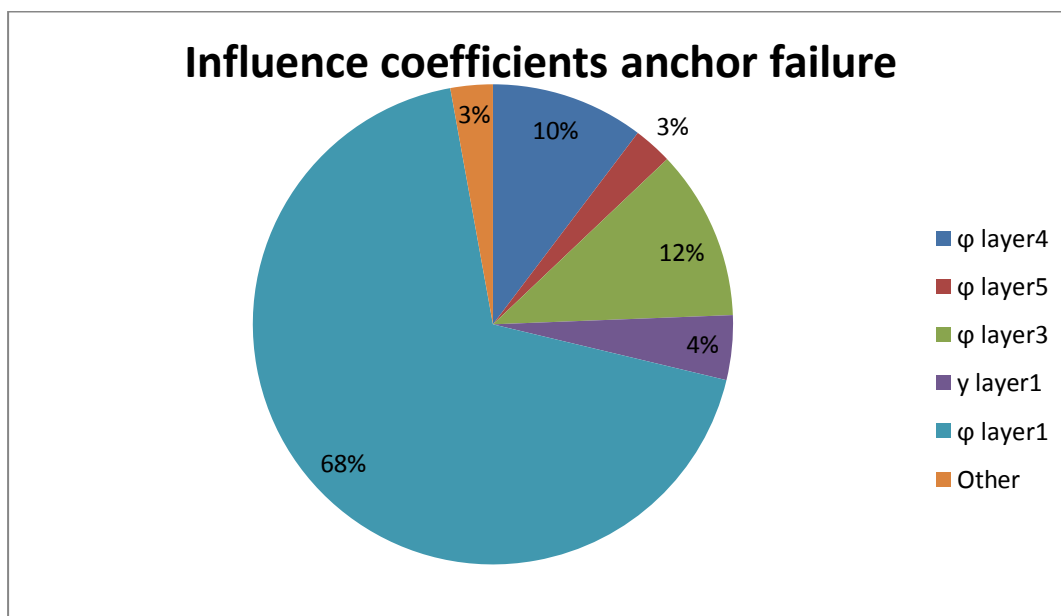


Figure 24 Blum Influence coefficients anchor failure

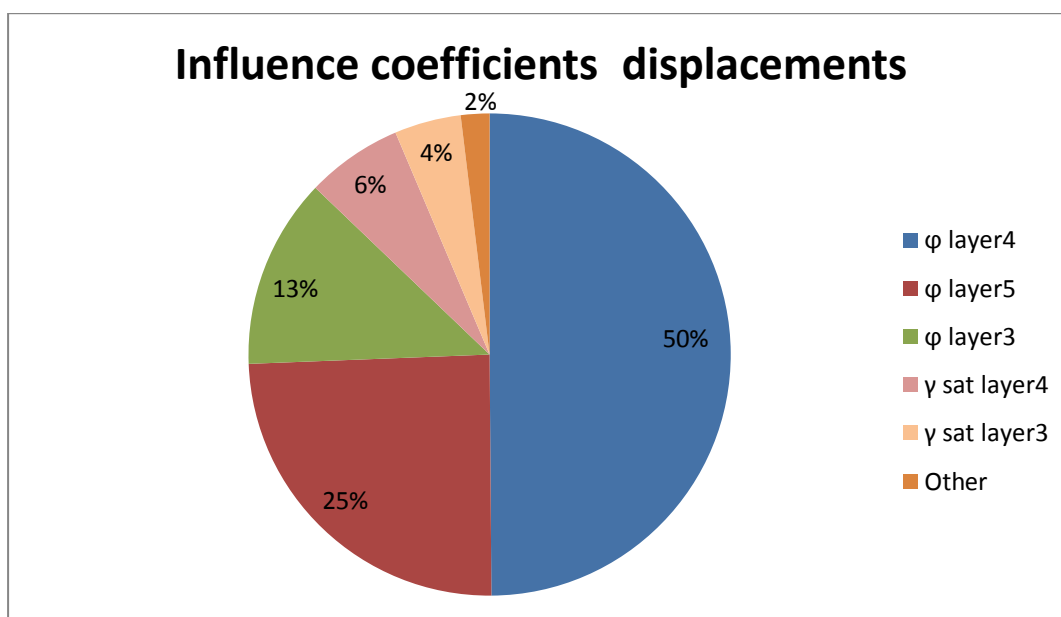


Figure 25 Blum Influence coefficients displacements

5.3 Posterior prediction

The posterior prediction is obtained after using the measurements to update the prior prediction. As is described in section 4.4.5, fictitious measurements are used. The choice for fictitious measurements allows showing the results for different scenario's. In the calculations with Blum the six cases presented in Table 8 are used.

Table 8 Measurement cases Blum

Case	Measurement μ	Measurement error σ
Anchor strain		
High	0,90 mm/m	0,01 mm/m
Average	0,60 mm/m	0,01 mm/m
Low	0,30 mm/m	0,01 mm/m
Displacement		
High	80,0 mm	5,00 mm
Average	45,0 mm	5,00 mm
Low	10,0 mm	5,00 mm

The model of Blum calculates an anchor force. The calculated anchor force by Blum is a horizontal force. In reality the anchor is inclined and thus to obtain the axial force the anchor needs to be adjusted. This correction for an inclined angle is not included in the results presented in this chapter.

In the Bayesian update strain measurements are used. The anchor force is related through the strain in the anchor by:

$$\varepsilon = \frac{F_a}{EA}$$

In which:

- F_a is the anchor force per running meter quay wall
- E is the young's modulus of the anchor. A steel tube is applied so:
 - $E = 2,10 * 10^8 \text{ kN/m}^2/\text{m}$
- A is the area of the anchor per running meter quay wall. Two anchors of type Jetmix ϕ 101.6 mm x 22,2 mm are applied.
 - The area per anchor is $A = 5,50 * 10^{-3} \text{ m}^2$
 - Distance between anchor is 2,941 m
 - Two anchors per 2,941 m
 - $A = \frac{5,50 * 10^{-3} * 2}{2,941} = 3,75 * 10^{-3} \text{ m}^2/\text{m}$

In the above calculation of strains in the anchor tube, it is assumed that the anchor forces are equally divided over both anchor tubes. This is not entirely correct as is also shown in the PLAXIS calculation in Appendix F.

The Bayesian update is applied using the Matlab script described in Appendix B. The following input is required:

- Number of samples in each Subset

It is chosen to generate 1000 samples in each Subset.

- Conditional acceptance probability, p_0

(Au & Beck, 2001) suggest a value of $0,1 \leq p_0 \leq 0,3$, $p_0 = 0,1$ is chosen

- Likelihood function

It is assumed that the measurements can be described by a normal distribution with mean and standard deviation as specified in Table 8. The likelihood function can thus be described by the probability density function of a normal distribution. This results in the following likelihood function:

$$L(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$$

x is the calculated displacement or strain using the model of Blum.

- Prior distributions

The prior distributions of the variables are specified in Table 3 and section 4.3.

In Table 9 and Table 10 the updated reliability is provided. The reliability is calculated using FORM. Furthermore in Figure 26, Figure 27 and Figure 28 the effect of the six measurements are shown for the maximum moment, displacement and anchor force. In addition to anchor forces and displacements, which are directly related to the limit states, also the maximum moment in the combi-wall is shown. Moments inside the wall are of interest for design calculations and usually determine the properties of the wall. It is interesting to see how the maximum predicted moments in the wall are influenced by the measurements.

Table 9 Reliability results Blum of update limit state displacements

Case	β [-]
Prior	2,22
Displacement high	1,59
Displacement average	2,77
Displacement low	3,46

Table 10 Reliability results Blum of update limit state anchor failure

Case	β [-]
Prior	5,72
Anchor strain high	3,53
Anchor strain average	6,69
Anchor strain low	8,72

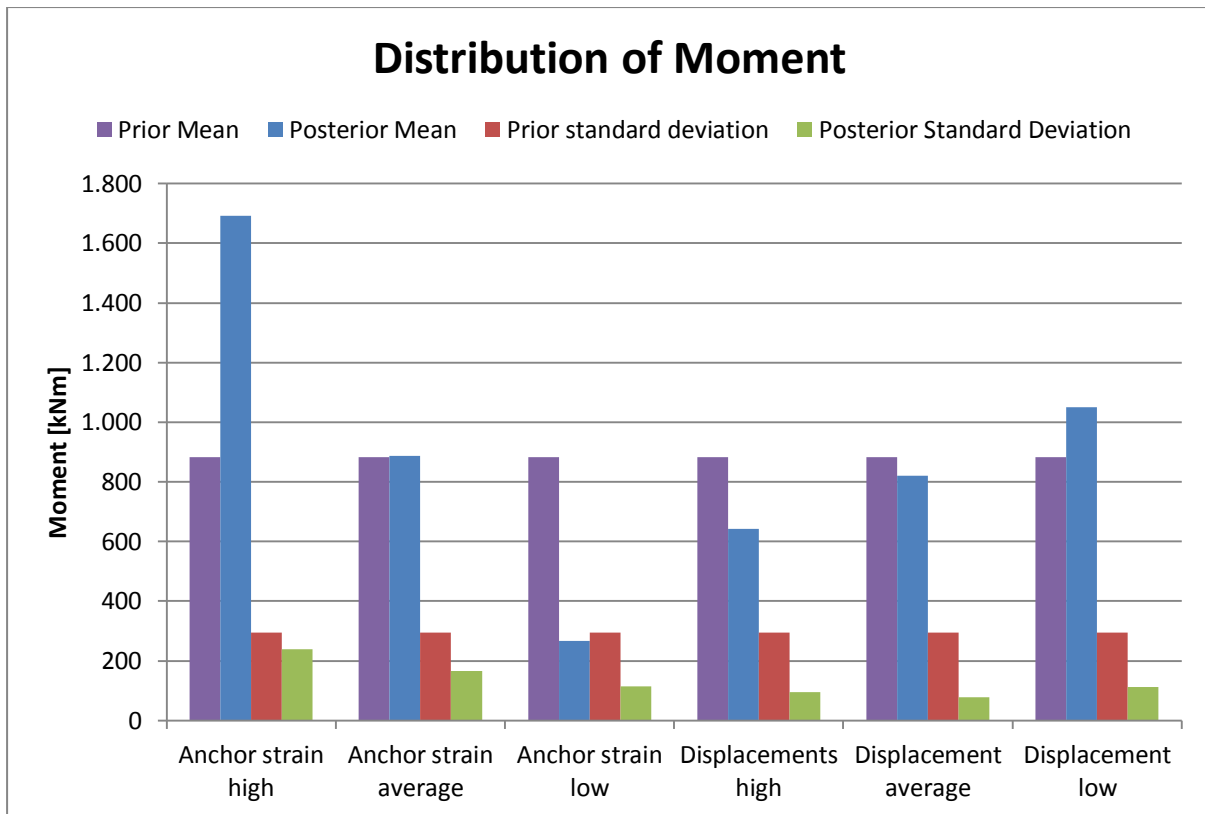


Figure 26 Results Blum update maximum moment

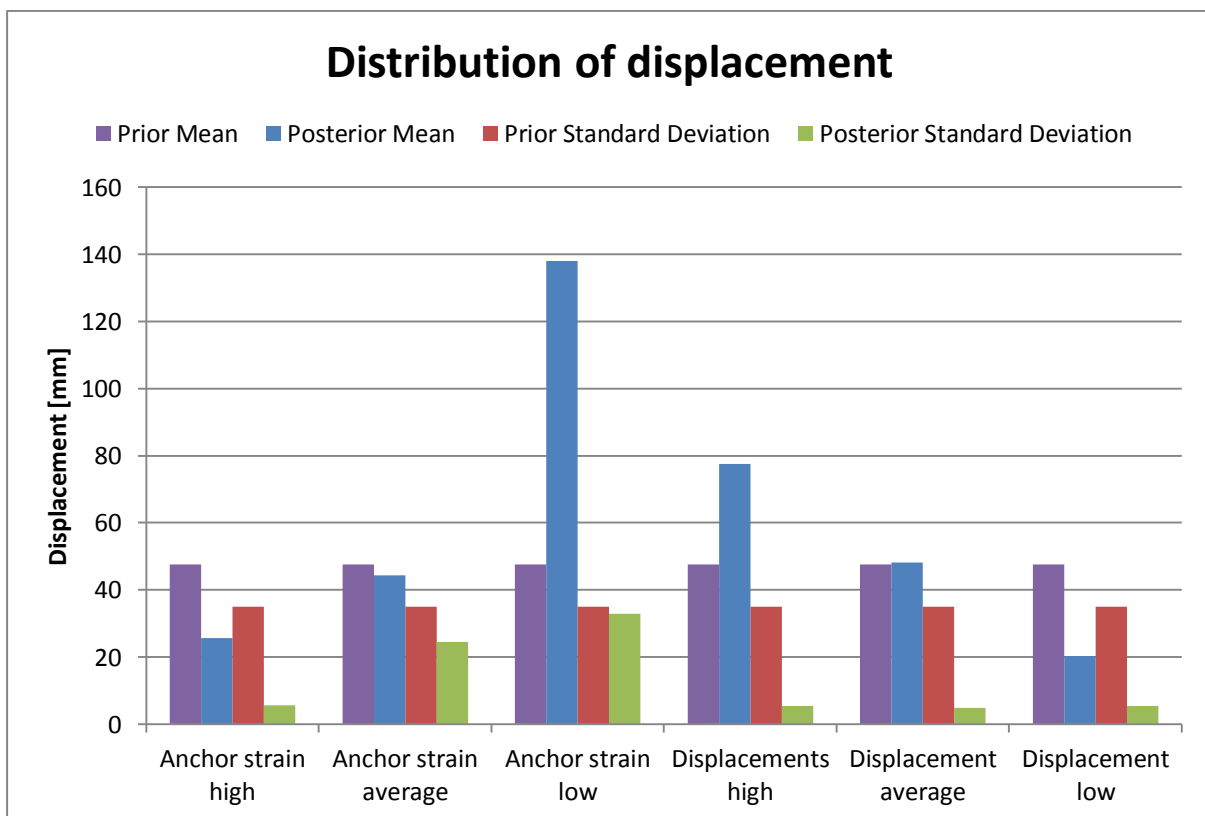


Figure 27 Results Blum update displacement

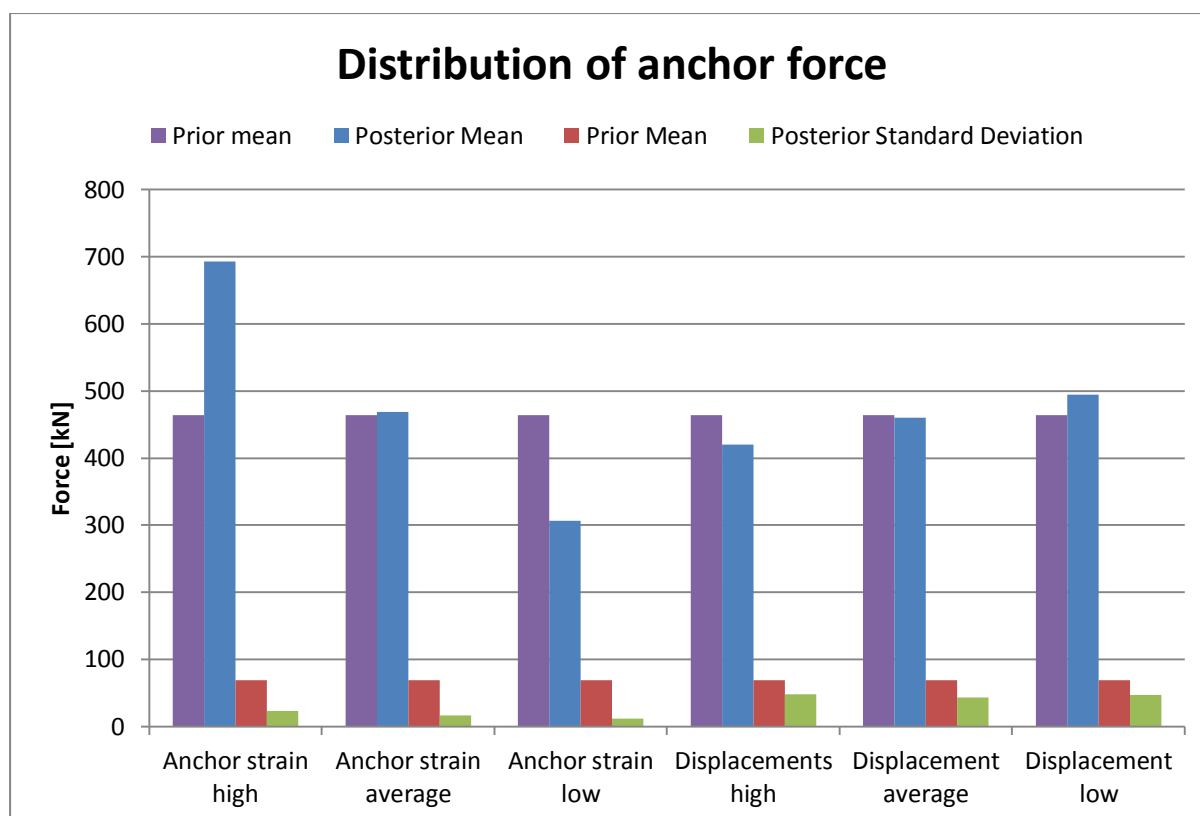


Figure 28 Results Blum update anchor force

5.4 Review of results

Using Bayesian updating one determines the statistic most likely combination of parameters. It is important to determine if this most likely combination is also likely by the physical explanation. This section will therefore be dedicated to reviewing the obtained results.

By looking at the provided figures and tables, Figure 26, Figure 27, Figure 28, Table 9 and Table 10, the following observations can be made:

- The case high strain leads to an increase in anchor force and moments, while the displacements are reduced. The case low strain provides the exact opposite.
- The case high displacements leads to a decrease in anchor force and moments, while the displacements increase. The case displacements low shows the opposite effect.
- The average cases show for all provided distributions a posterior mean equal to the prior mean.
- In all update cases the standard deviation is significantly reduced.
- The update cases high show a reduced reliability for both limit states.
- The average update and the low update show an increase of reliability for both limit states.

Looking at Figure 28, which shows the effect of the measurements on the anchor force, the most straightforward observation is the change in posterior anchor forces. As the stiffness and area of the anchor are chosen deterministic, one directly updates the anchor force. So it makes sense that, a lower measured strain leads to a low anchor force. The opposite is also true, a higher measured strain leads to a higher anchor force.

The displacements are also affected by the anchor strain measurements. Measuring a low strain and thus a low anchor forces leads to an increase in displacements. This can be explained by the reasoning that if the anchor is taking less force, the structure behaves less stiff relative to the soil. A less stiff structure results in more displacements and also a lower moment in the wall, visible in Figure 26. This effect is also visible with the cases related to a measured displacement. If a low displacement is measured the result is an increase in moment and anchor force and a high displacement gives a reduced moment and anchor force.

By the same reasoning, the results of a high strain can also be explained. The high strain case leads to a higher anchor force. This higher anchor causes the structure to be relatively stiffer with respect to the soil and thus less displacements and a larger moment in the combi-wall.

In the starting points in section 4.4.1, it is assumed that the structural parameters are deterministic values. This choice is based on the reasoning that the structural parameters have less uncertainty than the soil parameters and thus the update would be less interesting for the structural parameters. The influence of this assumptions is assessed here.

If stiffness and the steel area are stochastic values the above described effect, the effect that a change in strain directly results in a change in anchor force, will be less visible. A lower strain can also be explained by a larger area and a stiffer anchor. So, if stiffness and area are treated stochastic the effect will be a smaller change in anchor forces. To what extent the results are affected by the stochastic definition of area and stiffness is dependent on the chosen distributions.

A larger uncertainty or standard deviation will cause a stronger reduction, as these parameters will then become more dominant. In the same way, if the standard deviation is relatively small the results will be close to the presented results.

In addition to the posterior distributions of moments, displacements and anchor forces in section 5.2 graphs of the posterior variables and the influence coefficients are shown. Looking at the influence coefficients for both limit states, Figure 24 and Figure 25, the main difference between the graphs is that the most influential parameters for anchor failure are found in the active zone of the soil body, while for displacements the influential parameters are located in the passive zone.

The anchor force is largely dependent on the load on the quay. The loads on the quay are dependent on the active part of the soil body. So, it makes sense that for anchor failure the most influential parameters are found in the active part.

The displacements are dependent on how fixed the wall is in the soil. This fixedness is determined by the strength of the passive soil part. Therefore, the influential parameters for the limit state displacements are found in the passive zone.

The figures in Appendix E show the change variables due to the updates. In general, the change in variables is mainly in the friction angles. For the case anchor strain high, Figure 39, one sees that the posterior means of φ in the active zone are reduced. This causes more load on the wall and thus explains the result of a larger anchor force.

The same holds for the displacements measurement cases. For the case displacements high, the φ decreases, resulting in a larger load in the active part and a smaller resistance in the passive part. This explains the larger displacement of the combi-wall.

5.5 Conclusions

Based on the results obtained from updating the Blum model some remarks can be made. In this thesis fictitious measurements are used. The obtained posterior means are directly related to these assumed measurements and thus these posterior means might not be realistic. The conclusions are therefore not focused on the exact values, but on the general trend which is visible in the posterior results.

In general, it can be seen that for each quantity of interest (moment, displacement and anchor force) the standard deviation significantly decreases after including the measurements. The posterior standard deviation decreases to a value which is in the same order of magnitude of the assumed measurement error. The samples are filtered based on the assumed measurement distribution. So, it is logical that the posterior standard deviation follows this distribution.

This reduced posterior standard deviation allows for a more accurate and less conservative determination of the failure probabilities of the system. The effect of the reduced deviation can be seen in the results of the 'average' update. The measurements support the prior prediction, the posterior and prior or mean are almost equal while only the standard deviations decrease. The result is that the posterior failure probability is significantly lower than the prior one.

In section 5.2 graphs of the posterior variables and the influence coefficients are shown. The posterior means change with 5-10% relative to the prior mean. A larger change is found in the standard deviations.

If one compares the graphs of the changed variables with the influence coefficients for the two different limit states, the most influential parameters also have the largest change in the posterior distribution. This effect can aid in reducing the computational time of more complex models. In the updating process one could eliminate the variables with a low influence coefficient based on a prior calculation of the failure probability.

6 Bayesian update with finite element model

In the previous chapter the Bayesian update is applied using the model of Blum. As it is known that Blum's model is relatively simple, a comparable calculation is performed with finite element software. The finite element model is used to confirm the results found with Blum and to show that these calculations can already be performed with more accurate and more commonly applied models.

The finite element software used in this thesis is PLAXIS 2017 2D. The followed procedure is similar to the update with the model of Blum. First, a prior prediction is made. Thereafter measurement cases are defined and the posterior distributions are determined. Finally, a review of the results is given.

6.1 PLAXIS model and starting points

In chapter 4 all technical details, starting points and assumptions required are listed. Based on this a PLAXIS model has been setup. The specific model choices and details of this model are elaborated in Appendix F. The general process of setting up the model is treated here.

In the first step a base model is defined. This base model is assumed to be the best, currently possible, representation of the real quay behaviour. The base model is then compared to the results of Blum found in chapter 5 and D-Sheet piling calculation, which has been used for the design of the quay.

Some minor differences between the results are found. These differences can for the largest part be attributed to the facts that D-Sheet piling neglects arching and the different soil behaviour models (D-Sheet piling uses elastoplastic springs and PLAXIS the hardening soil model). Another minor contribution is due to a different water level schematization.

So, the base model and the D-Sheet piling model provide comparable results. From this it is assumed that the PLAXIS model has been setup correctly. The next step is then to optimize the PLAXIS model in calculation time. The base model takes about 300 seconds to run, which is too long for the probabilistic calculations. Therefore, stepwise optimizations have been tested and evaluated. Resulting in a model which is still reasonably accurate with an as short as possible calculation time.

The optimization has led to the use of 6-Noded elements instead of the commonly applied 15-Noded elements. The difference between the 6-Noded – and 15-Noded elements is explained in (Plaxis bv, 2017). The key issue with 6-Noded elements is the fact that in failure analysis the 6-Noded elements provide a too favourable result. For two reasons this simplification is justifiable.

First, as the focus of the research is on the effect of the measurements, the calculated failure probabilities are used for illustrative purposes. The resulting inaccuracy in the calculated failure probabilities due to the use of 6-Noded elements is thus negligible.

Second, the use of 'average' values instead of the characteristic values results in a model which is not close to the failure boundary. In the prior predictions and the calculations to determine the posterior predictions the model provides accurate results.

In the PLAXIS calculation a fixed relation between the dry – and wet volumetric weight is assumed. This has been done to avoid obtaining draws which have a larger dry weight than wet weight. The distributions assumed in Table 5 show that it is likely that such a draw is obtained. The calculations done with Blum and the research of (Wolters, 2012) indicate that the influence of the dry weight on the failure probability is limited. Therefore, the following fixed relation, based on (Rippi, 2015), is used:

$$y_d = y_{sat} - U(0,2)$$

In which: U (0, 2) represents a uniform distribution within the range of 0 to 2.

The final assumption is that the concrete capping beam and slab which is located from NAP +5,1 m to NAP -2 m is not taken into account. In the model the top level of the retaining structure is located at NAP +5,1 m and the tip of the retaining structure is at NAP -27,5 m.

6.2 Prior predictions

Similar to the case with Blum, two limit states are defined for calculating the reliability. The limit states are used to show the effect Bayesian updating has on the reliability and to compare the changed variables with their influence coefficients. The first limit state considers the quay to be failed if a maximum displacement is exceeded and the other limit state is related to a maximum anchor force.

The procedure used for calculating the reliability in PLAXIS is the following. The Deltares Probabilistic Toolkit is used. This toolkit is connected through PLAXIS by a Python script. The Toolkit takes care of the probabilistic part, i.e. it tells PLAXIS which samples need to be calculated. PLAXIS then provides the resulting displacement or anchor force.

At first FORM is used to determine the reliability. This has proven to be ineffective as the toolkit was unable to find convergence, more details about the convergence is given in section 9.1. Instead of FORM, Importance Sampling is used to determine the reliability. The method of Importance Sampling is explained in section 2.2.4.

To increase the efficiency of Importance Sampling the probability of obtaining a failure must be increased. For the method of Importance Sampling, it is required to have a sufficient number of failures to accurately determine the failure probability. To increase the probability of obtaining a failure, two solutions are used.

First, on experience gained from the Blum calculations and model runs in PLAXIS, the mean of the samples has been shifted towards failure boundary.

Second solution is to change the limit states to have an increased number of failures, a lower maximum displacement and lower maximum anchor forces. The new limit states are:

- Limit state 1 Displacements $d < 90 \text{ mm}$
- Limit state 2 Anchor force $F_{amax} < 600 \text{ kN/m}$

As in PLAXIS both anchors can be modelled. Limit state 2 relates to the force in the top anchor. Based on the model runs, the highest force occurs in this anchor.

These definitions of failure and the distributions of variables as defined in Table 3 and section 4.3 results in the following prior results. The reliability is calculated with Importance Sampling. A limited number of samples is used, so the calculated values are approximations. The values are shown below:

Limit state 1 Displacements

- $\beta = 1,49$

Limit state 2 Anchor Force

- $\beta = 4,01$

In addition to the prior reliability the prior distributions of the maximum moment, displacement and anchor force are shown in Table 11.

Table 11 Prior PLAXIS moment-, displacement-, and anchor force distribution

Prior results	Mean μ	Standard deviation σ
Maximum moment	945,05 kNm	74,25 kNm
Displacement	59,61 mm	11,57 mm
Anchor force (top anchor)	474,77 kN/m	18,71 kN/m
Anchor strain (top anchor)	0,6092 mm/m	0,023 mm/m

Figure 29 and Figure 30 show the influence coefficients for both limit states. The influence coefficients represent the influence of a stochastic variable on the reliability. In the figures the five most important variables are shown.

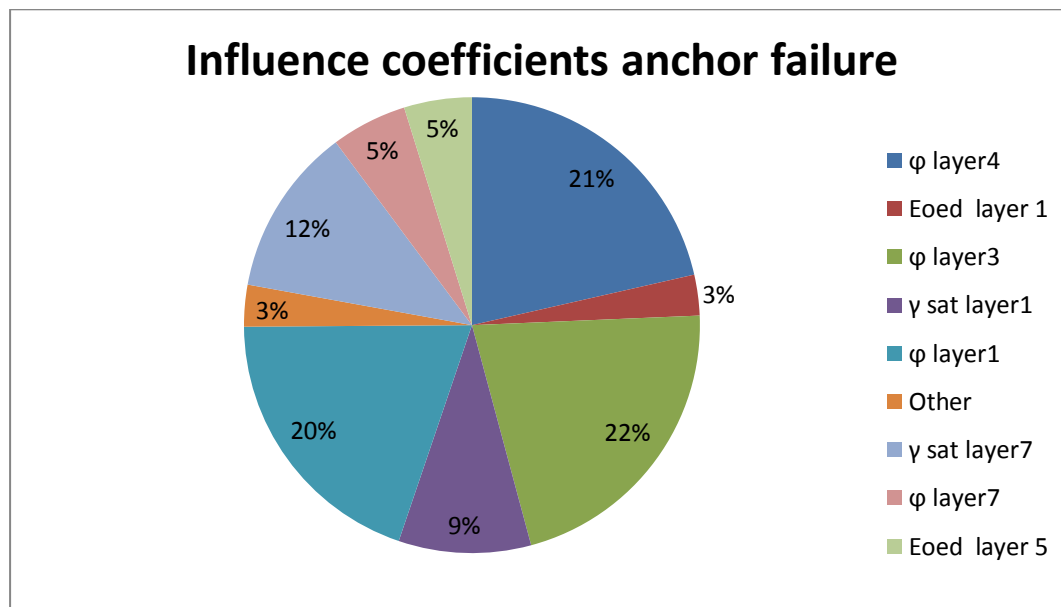


Figure 29 PLAXIS Influence coefficients anchor failure

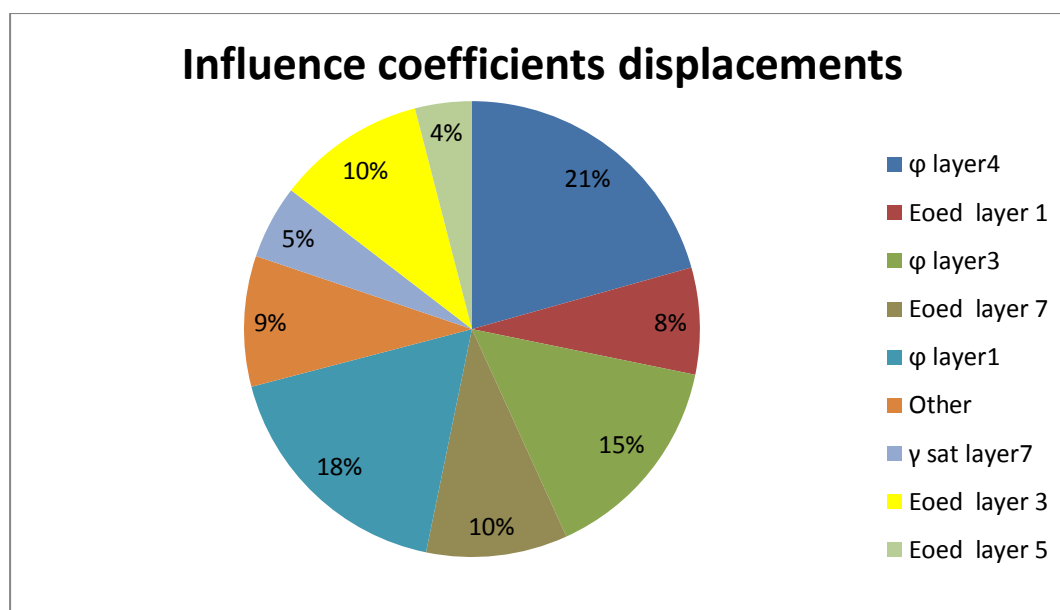


Figure 30 PLAXIS influence coefficients displacements

6.3 Posterior predictions

As advised in chapter 3, the use of BUS in combination with Subset Simulation is preferred over the use of MCS. Obtaining the posterior distributions with Subset Simulation is much more efficient. This higher efficiency is especially beneficial when using finite element software. However due to software related issues the author was unable to combine the use of the MATLAB script in Appendix B and PLAXIS.

Therefore, it is chosen to use the solution based on Monte Carlo simulation, as explained in section 3.1. The main disadvantage on the use of MCS is that only after generating a large number of samples, it can be determined which of these samples are in the posterior distribution.

The chance that a sample falls in the posterior distribution is dependent on the difference between the prior distributions and the measurement. If the distributions have a large difference, the chance of obtaining posterior samples is low and thus a large amount of calculations is required. By assuming the fictitious measurements close to the prior distributions, the effect of Bayesian updating can still be shown with acceptable efficiency.

Similar to Blum, six measurements cases are defined. A low, average and high measurement is defined for both measured displacements and anchor strains. Each is assumed to have a normal distribution with mean and standard deviation as specified in Table 12.

Table 12 Measurement cases PLAXIS

Case	Measurement μ	Measurement error σ
Anchor strain		
High	0,63 mm/m	0,01 mm/m
Average	0,60 mm/m	0,01 mm/m
Low	0,57 mm/m	0,01 mm/m

Case	Measurement μ	Measurement error σ
Displacement		
High	75 mm	5,00 mm
Average	60 mm	5,00 mm
Low	45 mm	5,00 mm

For applying the script in Appendix A, the scaling constant 'c' needs to be defined. As explained in chapter 3, this scaling constant ensures that $cL(X) \leq 1$. If the scaling constant ensures results close to one, the acceptance rate is optimal. A constant which gives results larger than one will cause falsely accepted posterior samples.

The update is applied based on a single measurement with a known distribution. Therefore, the maximum of the likelihood function is known on beforehand. The measurements are normally distributed, so the likelihood function is also normally distributed and the maximum of this function can be calculated as:

- $c = \max(L(x))^{-1}$
- $c = \sqrt{2\pi\sigma^2}$
- For anchor strain measurements:
 - $c = \sqrt{2\pi\sigma^2} = 0,025$
- For displacement measurements
 - $c = \sqrt{2\pi\sigma^2} = 12,53$

After performing 3000 calculations using PLAXIS the results are filtered to obtain the samples which are in the posterior distribution. As the number of samples in the posterior can only be determined afterwards, a different number of samples are obtained for each measurement case. The number of samples which are in the posterior distribution of each measurement case is shown in Table 13

Table 13 Number of samples in posterior distribution

Case	Measurement μ	Measurement error σ	Samples in posterior
Anchor strain			
High	0,63 mm/m	0,01 mm/m	372
Average	0,60 mm/m	0,01 mm/m	780
Low	0,57 mm/m	0,01 mm/m	403
Displacement			
High	75 mm	5,00 mm	427
Average	60 mm	5,00 mm	808
Low	45 mm	5,00 mm	447

After filtering the results to obtain the posterior distributions, the following results have been obtained. In Table 14 and Table 15 the updated reliabilities are shown.

Table 14 Reliability results of PLAXIS update limit state displacements

Case	β [-]
Prior	1,49
Displacement high	1,06
Displacement average	1,92
Displacement low	3,02

Table 15 Reliability results of PLAXIS update limit state anchor failure

Case	β [-]
Prior	4,01
Anchor strain high	3,42
Anchor strain average	4,42
Anchor strain low	4,81

In Figure 31, Figure 32 and Figure 33 the effect of the six measurements are shown for the maximum moment, displacement and anchor force.

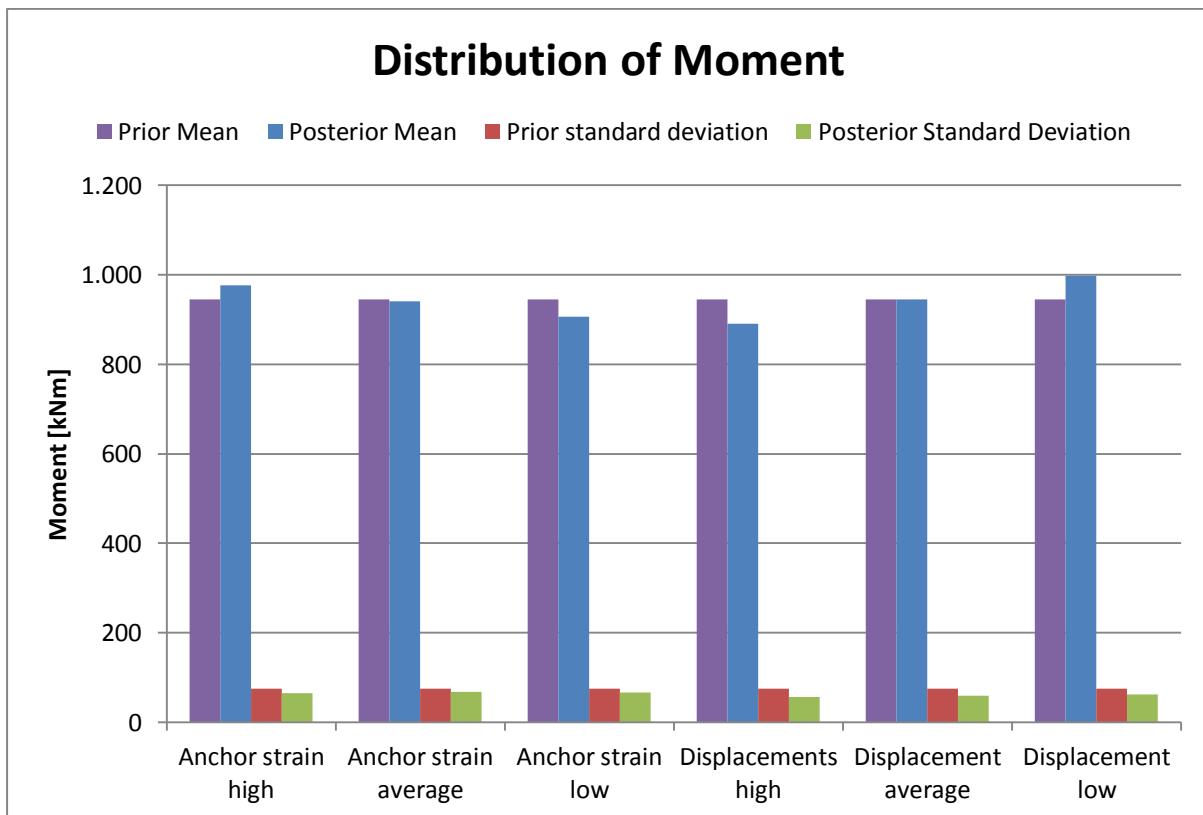


Figure 31 Results PLAXIS update maximum moment

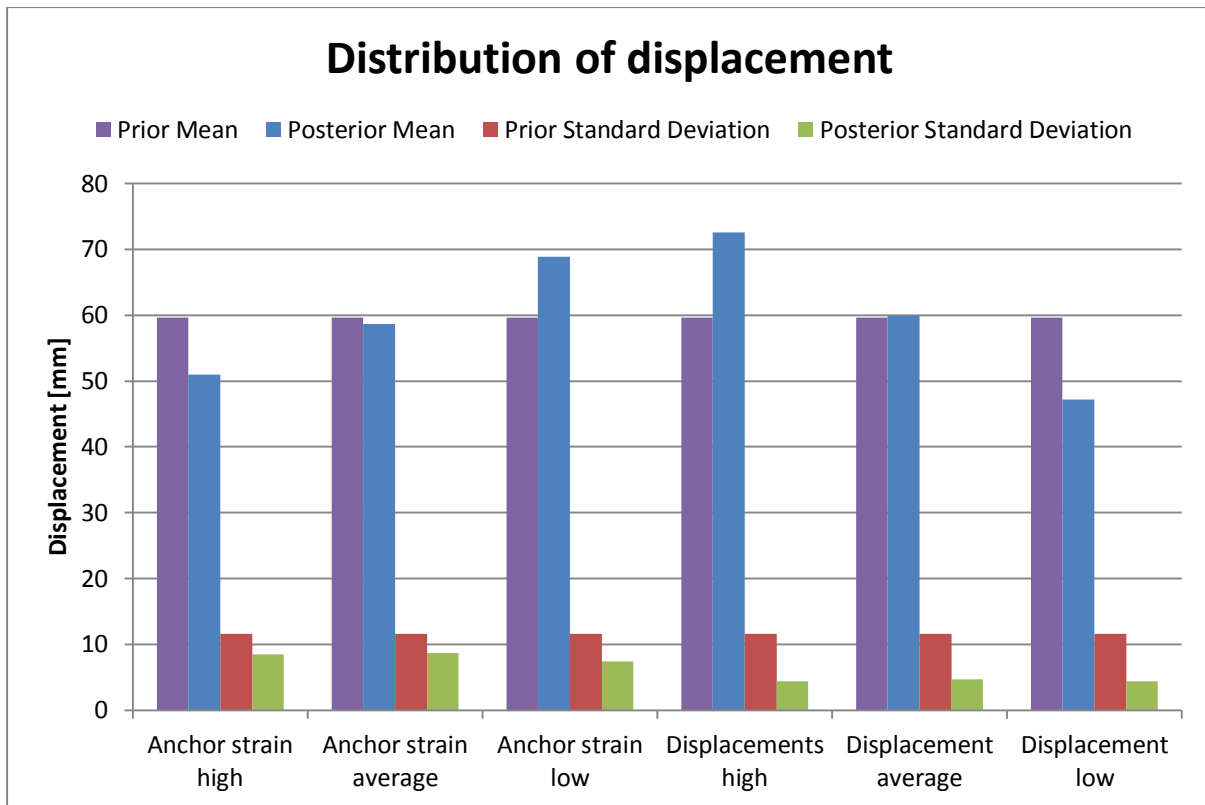


Figure 32 Results PLAXIS update maximum displacement

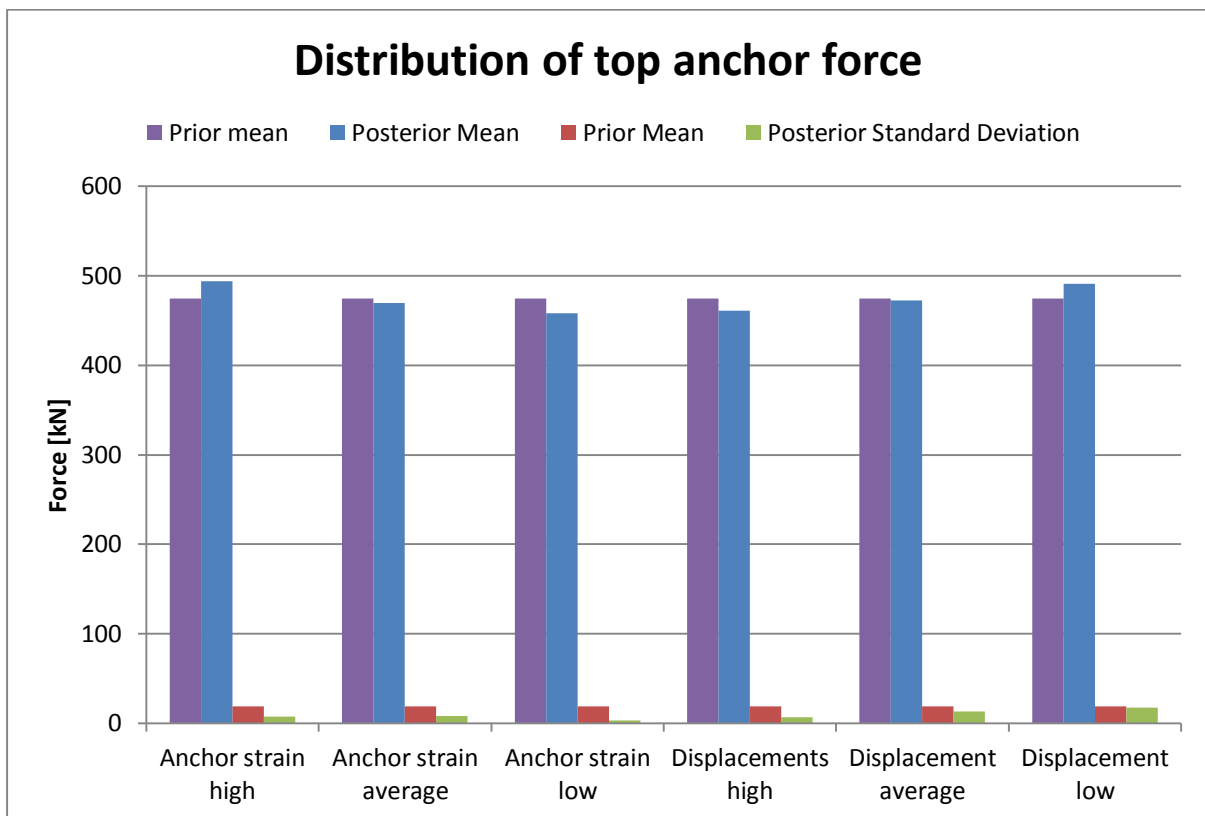


Figure 33 Results PLAXIS update top anchor force

6.4 Review of results

The results found with PLAXIS are similar to the results with Blum. The measurements have a similar impact on the prior prediction. One of the main results found with Blum is the reduced standard deviation in all posterior predictions. This reduction can also be seen in the results from PLAXIS.

Furthermore, the effect of the measurement cases is the same. The low strain case leads to lower anchor forces, lower moments and more displacement. While the high strain case does the exact opposite. For the displacement measurements the same is visible. A higher measured displacement leads to a reduction in anchor forces and moments, while less measured displacements lead to an increase of anchor forces and moments.

The average update cases result in posterior means equal to the prior ones. The standard deviations decrease significantly.

The change in calculated failure probabilities with PLAXIS show the same trend as initially found with Blum. The high strain and high displacement cases result in a reduced reliability while the other measurement cases increase the reliability.

The effect of Bayesian updating seems less on the PLAXIS model, compared to the results with Blum. The posterior means with PLAXIS are much closer to their prior ones as compared to the posterior and prior means with Blum. The reasons for this smaller change are the following two. First, in PLAXIS the measurements are assumed to be closer to the prior mean. Therefore, the resulting posterior change is also less. This assumption is made to increase the efficiency of the PLAXIS simulation.

The second reason is the fact that the prior standard deviations in PLAXIS are much lower compared to the Blum values. The difference between measurement error and prior standard deviation is less with PLAXIS and thus the following reduction in standard deviation is also less.

In Appendix G the posterior distributions of the variables and in section 6.2 the influence coefficients are shown. The main changing variables are the friction angles and the soil stiffness moduli. These variables are also the most influential variables, as can be seen in the graphs for the influence coefficients. This trend, in which the most influential parameters show the largest change, is also visible in the results of Blum.

With respect to the means, the standard deviations show a larger change between prior and posterior. These reduced standard deviations explain the results which are observed in the graphs in section 6.3. In all posterior distributions the standard deviations reduce, so this effect must also be visible in the included variables.

The influence coefficients found with the calculations of Blum, shown in Figure 22 and Figure 23, differ from the influence coefficients found with PLAXIS, shown in Figure 27 and Figure 28. In the failure probabilities calculated by Blum there is one parameter very influential with respect to the remaining parameters. The influence of the parameters with PLAXIS is divided across multiple parameters. It can be seen that multiple parameters have an influence of approximately 20%.

In general the same parameters appear to be influential. The friction angles are both in PLAXIS and Blum highly influential. Furthermore, in PLAXIS the stiffness's of the soil layers are important. Soil stiffness is not included in Blum and thus the influence is mainly in friction angles. While for PLAXIS the influence is both in soil stiffness's as in soil friction angles.

6.5 Conclusions

By a first comparison of the results with PLAXIS and Blum, it seems that the effect of the update is more favourable with Blum. As explained, this is due to a difference in chosen measurements in PLAXIS and the fact that PLAXIS shows a lower prior standard deviation.

So, the change shown in this chapter is less but still is significant. Even if the PLAXIS prediction is almost equal to a real measurement (a result similar to average update cases), it is still worthwhile to perform. As the increased reliability by the average update is a significant increase.

The results of PLAXIS show that the posterior prediction has a much smaller standard deviation. The updated model will therefore show a more accurate prediction of reliability. This holds for all update cases. So, even if the measurement shows an unfavourable behaviour, the effect of reinforcements can also be evaluated with more certainty.

By performing the calculations with PLAXIS and showing that it is possible with a reasonable efficiency, the method can also be applied to larger and more complicated quay structures. In principle the application of the Bayesian update is the same, however the PLAXIS model is more complicated which will result in longer calculation time. As PLAXIS is used even applications besides quay's can be thought of.

7 Potential load capacity gained by Bayesian update

In the previous chapters Bayesian updating has been applied to a probabilistic Blum- and PLAXIS model. In several update cases an increase of reliability is determined. To evaluate the significance of the increased reliability, it is determined if it is possible to increase the load on top of the quay. If this top load can be increased, the user of the quay can decide to for example increase storage on the quay.

The used procedure to determine this increase in load capacity; is to assume that the measurement case 'displacement low' is measured at the quay. In the calculation models the surcharge on the quay is stepwise increased until the calculated reliability index is equal to the prior predicted reliability.

Furthermore, in this approach it is assumed that failure due to excessive displacements is the governing failure mechanism. In practice displacements usually do not govern the design of a quay and thus the results are not fully representative for a real quay. The choice for this assumption is made to have a comparison with the previous chapters.

The measurement case 'displacement low' assumes less displacement then initially predicted. This indicates that the behaviour, with respect to displacements, is more favourable than predicted. The results in chapter 5 and 6 have shown that the moments and anchor forces have increased and thus for other failure mechanisms, the used measurement case can be less favourable.

7.1 Blum

In chapter 5 a Bayesian update is done in combination with the model of Blum. Six measurement cases are investigated and thus six changed sets of input parameters are determined. The updated parameters from the measurement case 'displacement low' are used.

The case 'displacement low' is related to a lower displacement then predicted, so a stiffer soil behaviour then initially expected. The changed parameters along with their initial value are shown in Table 16. The values used in the calculation are found in the columns with the posterior values. In general, the difference between the prior- and posterior values is found in the friction angle, most of the soil layers show an increase of friction angle.

Table 16 Input Blum

Variable	Prior values		Posterior values	
	Mean	Standard deviation	Mean	Standard deviation
Sand, clean, loose				
φ layer 1 [°]	35,89	3,00	36,27	2,88
γ_{sat} layer 1 [kN/m ³]	20,69	0,95	20,60	0,97
γ_{d} layer 1 [kN/m ³]	18,52	0,85	18,45	0,62
Clay, slightly sandy, weak				
φ layer 2 [°]	26,91	2,25	26,72	2,34
γ_{sat} layer 2 [kN/m ³]	16,34	0,75	16,28	0,75
γ_{d} layer 2 [kN/m ³]	16,34	0,75	16,28	0,75
Sand, clean, loose				
φ layer 3 [°]	35,89	3,00	37,08	2,79
γ_{sat} layer 3 [kN/m ³]	20,69	0,95	21,03	0,81
γ_{d} layer 3 [kN/m ³]	18,52	0,85	18,71	0,47

Variable	Prior values		Posterior values	
	Mean	Standard deviation	Mean	Standard deviation
Sand, slightly silty clayey				
φ layer 4 [°]	32,30	2,70	33,51	1,96
γ_{sat} layer 4 [kN/m ³]	20,69	0,95	21,07	0,80
γ_d layer 4 [kN/m ³]	19,61	0,90	18,89	0,76
Sand, clean, loose				
φ layer 5 [°]	35,89	3,00	37,11	2,98
γ_{sat} layer 5 [kN/m ³]	20,69	0,95	20,95	0,95
γ_d layer 5 [kN/m ³]	18,52	0,85	18,68	0,57
Clay, slightly sandy, weak				
φ layer 6 [°]	26,91	2,25	27,15	2,02
γ_{sat} layer 6 [kN/m ³]	16,34	0,75	16,39	0,68
γ_d layer 6 [kN/m ³]	16,34	0,75	16,40	0,69
Sand, clean, solid				
φ layer 7 [°]	38,88	3,25	38,57	3,27
γ_{sat} layer 7 [kN/m ³]	21,79	1,00	21,65	1,00
γ_d layer 7 [kN/m ³]	19,61	0,90	19,48	0,92

The reliability of the quay is calculated according to the following limit state function:

- Limit state Displacements $d < 140 \text{ mm}$

FORM is used to determine the reliability. The prior reliability is:

- Prior reliability $\beta = 2,22$

Using the determined posterior variables, the reliability index is increased to the following:

- Posterior reliability $\beta = 3,46$

If it is assumed that the prior reliability is sufficiently safe and based on the Bayesian update the reliability is increased, then an increase of allowable surcharge load is possible. The result of several reliability calculations with a stepwise increased surcharge load is shown in Figure 34.

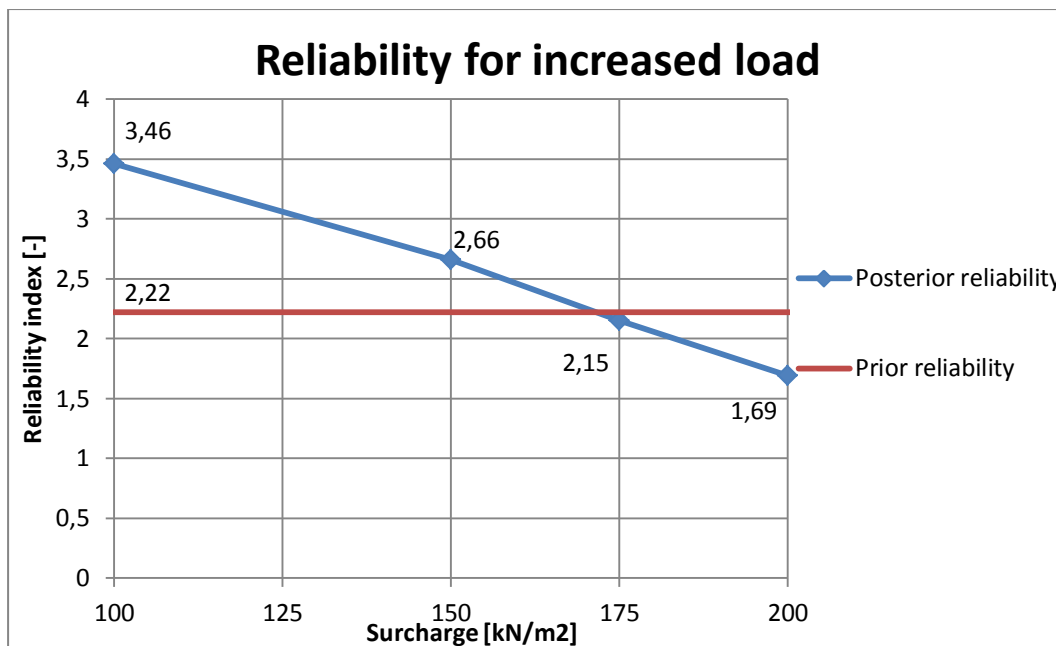


Figure 34 Blum reliability for increased surcharge load

Figure 34 shows that due to the updated parameters the surcharge load can be increased to almost 175 kN/m². Compared to the design requirement of 100 kN/m², this is a significant increase.

This increase is calculated with the assumption that failure due to excessive displacements is the governing mechanism. To determine the actual allowable increase, the updated model should be used to verify that the other failure mechanisms are not more governing.

7.2 PLAXIS

The previous section has determined the possible increase of surcharge load based on the model of Blum. This section will use the same procedure to determine the increase of surcharge which based on the PLAXIS model can be allowed on the quay. The posterior variables determined from the measurement case 'displacement low' are used. These posterior values along with their prior values are shown in Table 17.

Table 17 Input PLAXIS

Variable	Prior values		Posterior values	
	Mean	Standard deviation	Mean	Standard deviation
Sand, clean, loose				
φ layer 1 [°]	35,89	3,00	37,72	2,73
γ_{sat} layer 1 [kN/m ³]	20,69	0,95	20,37	0,91
E_{oed} layer 1 [kN/m ²]	23076	3750	23110	3734
Clay, slightly sandy, weak				
φ layer 2 [°]	26,91	2,25	27,00	2,21
γ_{sat} layer 2 [kN/m ³]	16,34	0,75	16,35	0,76
E_{oed} layer 2 [kN/m ²]	2307	375	2319	380
Sand, clean, loose				
φ layer 3 [°]	35,89	3,00	37,44	2,88
γ_{sat} layer 3 [kN/m ³]	20,69	0,95	20,92	0,98
E_{oed} layer 3 [kN/m ²]	23076	3750	23350	3567
Sand, slightly silty clayey				
φ layer 4 [°]	32,30	2,70	33,92	2,46
γ_{sat} layer 4 [kN/m ³]	20,69	0,95	20,84	0,92
E_{oed} layer 4 [kN/m ²]	53846	8750	54216	8906
Sand, clean, loose				
φ layer 5 [°]	35,89	3,00	36,51	2,79
γ_{sat} layer 5 [kN/m ³]	20,69	0,95	20,74	0,93
E_{oed} layer 5 [kN/m ²]	23076	3750	23000	3782
Clay, slightly sandy, weak				
φ layer 6 [°]	26,91	2,25	26,80	2,22
γ_{sat} layer 6 [kN/m ³]	16,34	0,75	16,36	0,77
E_{oed} layer 6 [kN/m ²]	2307	375	2315	345
Sand, clean, solid				
φ layer 7 [°]	38,88	3,25	39,72	3,15
γ_{sat} layer 7 [kN/m ³]	21,79	1,00	21,79	0,97
E_{oed} layer 7 [kN/m ²]	115384	18750	113754	17759

The reliability of the quay is calculated according to the following limit state function:

- Limit state Displacements $d < 90 \text{ mm}$

As reliability method importance sampling is used. The prior reliability is:

- Prior reliability $\beta = 1,49$

Using the determined posterior variables, the reliability index is increased to the following:

- Posterior reliability $\beta = 3,12$

By performing a Bayesian update the reliability is increased. This increase of reliability indicates that it is possible to increase the surcharge load. Several reliability calculations are performed to determine the possible increase until the posterior reliability is equal to the prior reliability level. The result is shown in Figure 35.

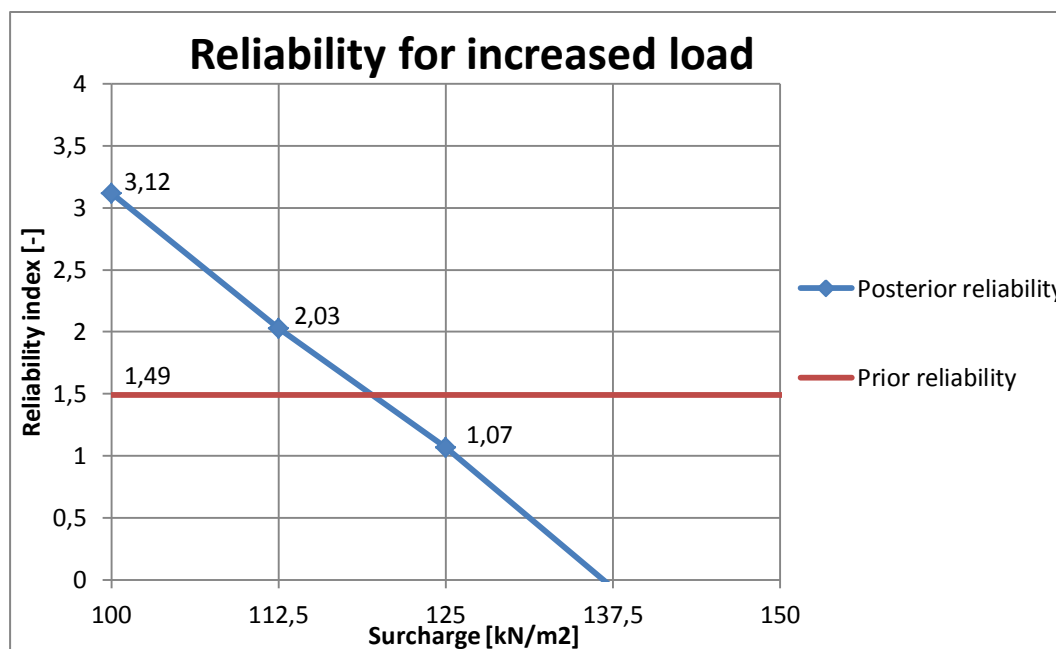


Figure 35 PLAXIS reliability for increased surcharge load

Figure 35 shows that compared to the prior reliability, the surcharge can increase to almost 120 kN/m². This indicates an increase of 20 kN/m² with respect to the design requirements. This increase is determined with the assumption that failure due to excessive displacements is governing. For an actual increase in surcharge, the failure probability of all failure mechanisms needs to be calculated and verified that these are not more governing.

7.3 Application in practice

This chapter has determined if based on fictitious measurements and the evaluation of only one limit state the surcharge can be increased. In this section an overall strategy is provided for determining this increase in practice. The strategy resembles an ideal situation without considering the costs aspects.

In the ideal situation of performing a Bayesian update, a test loading is applied to an existing quay under controlled conditions. The statement of controlled conditions means that boundary conditions such as water and groundwater level, retaining height and surcharge are known and can thus be included as deterministic parameters or with a small uncertainty. Measures to achieve this are (Inventec b.v., 2018):

- Piezometers to monitor groundwater level
- Water level meter for the water level in front of the quay
- Determining harbour bottom depth by measuring the level and if present inspecting the bottom protection to determine thickness and weight of bottom protection
- Loading the quay in fixed steps using elements of an equal and known weight. As an example, using sand-filled containers which have a known predetermined weight.

The first step is to determine the prior soil and structural parameters. The calculations performed in this thesis use soil parameters based on local CPT data. To determine the soil profile the data obtained from a CPT is reliable. However, for determining volumetric weight, friction angles, cohesion and soil stiffness's it is more accurate to determine these based on laboratory testing.

Structural parameters need to be identified based on design documents and for older quays possibly in situ investigation, such as wall thickness measurements, is required to determine the state of the structural elements.

The most important aspects to the procedure of test loading, is how to apply the load and for how long the load needs to be applied. To answer the first question, it must be possible to load and more important to unload the quay quickly. To avoid damaging the quay, in case of unexpected behaviour the load must be removed quickly. Therefore as suggested before, elements which are easy to handle with a uniform size and weight need to be used. Sand-filled containers are seen as a feasible solution. In a more detailed study other fill materials or different elements can be evaluated.

The second question focusses on is the duration of the applied load. This depends on the soil profile. The interest of test loading is in the long-term behaviour of the quay. The procedure should therefore resemble drained conditions and ideally excess pore pressures need to be dissipated before the next load step can be placed. If a quay is located in permeable soils, the duration of the load and the time between load steps can be relatively short. In case of less permeable soils the test loading will be longer. The prior prediction needs to be used to determine the duration of the dissipation of the pore pressures and in situ this can be verified by using piezometers.

Another aspect to take care of in the chosen loading strategy, is to avoid an influence caused by 3D effects. The load needs to be applied over a long enough section of the quay to allow the test load to be analysed by a 2D calculation. As a rough estimate, if a 10 m long section of a quay is equipped with monitoring devices. The load needs to be applied for a length of 15 m on both sides of the measured section. This results in a total of 40 m quay wall to be loaded.

During the test load, the following should be monitored: the displacement of the front wall and if an anchored quay or a quay with relief platform is to be loaded, strains in anchors and piles. To have a redundant setup also the soil displacement and soil pressures behind the quay need to be measured. This combination of measurement data can then be used to determine the posterior distributions of the variables. The following equipment can be used to measure the above-mentioned items (Inventec b.v., 2018):

- ShapeAccelArray/Field (SAAF) to measure displaced profile of the front wall
- Fibre optic cable to measure distributed strain over the full length of pile or anchor. Another option is to use local strain sensors.
- SAAF to measure soil displacement behind the quay
- Total pressure cells can be used to measure soil pressures and to determine the actual surcharge load.

As calculation model PLAXIS is advised. PLAXIS results in general in the most realistic prediction. This thesis has shown that even though the calculation times are significant, it is feasible to perform Bayesian updating with PLAXIS.

A risk to be avoided is that during the test load the load capacity of the quay is exceeded. This could lead to damage or in the worst-case destruction of the quay. Therefore, the prior prediction should be used to determine the maximum test load. This maximum test load should be determined such that the quay will not fail by a brittle failure mechanism. The failure mechanisms which slowly develop can be prevented by continuous monitoring of the quay behaviour.

The prior prediction should furthermore be used to determine stop criteria. A stop criterion can be a maximum allowable deformation of the quay. The test should be stopped once the deformation exceeds this limit.

The benefit of performing a Bayesian update is that it is not required to load the quay up to maximum capacity. The reference case used in this thesis can be based on design requirements be loaded up to 100 kN/m^2 . If for example a test load is performed up to 60 kN/m^2 , the model prediction can then be updated to these measurements. The updated posterior model can then be used to evaluate the behaviour of the quay under different surcharges.

To summarize this section, the procedure to determine the load capacity can be roughly described by the flowchart in Figure 36.

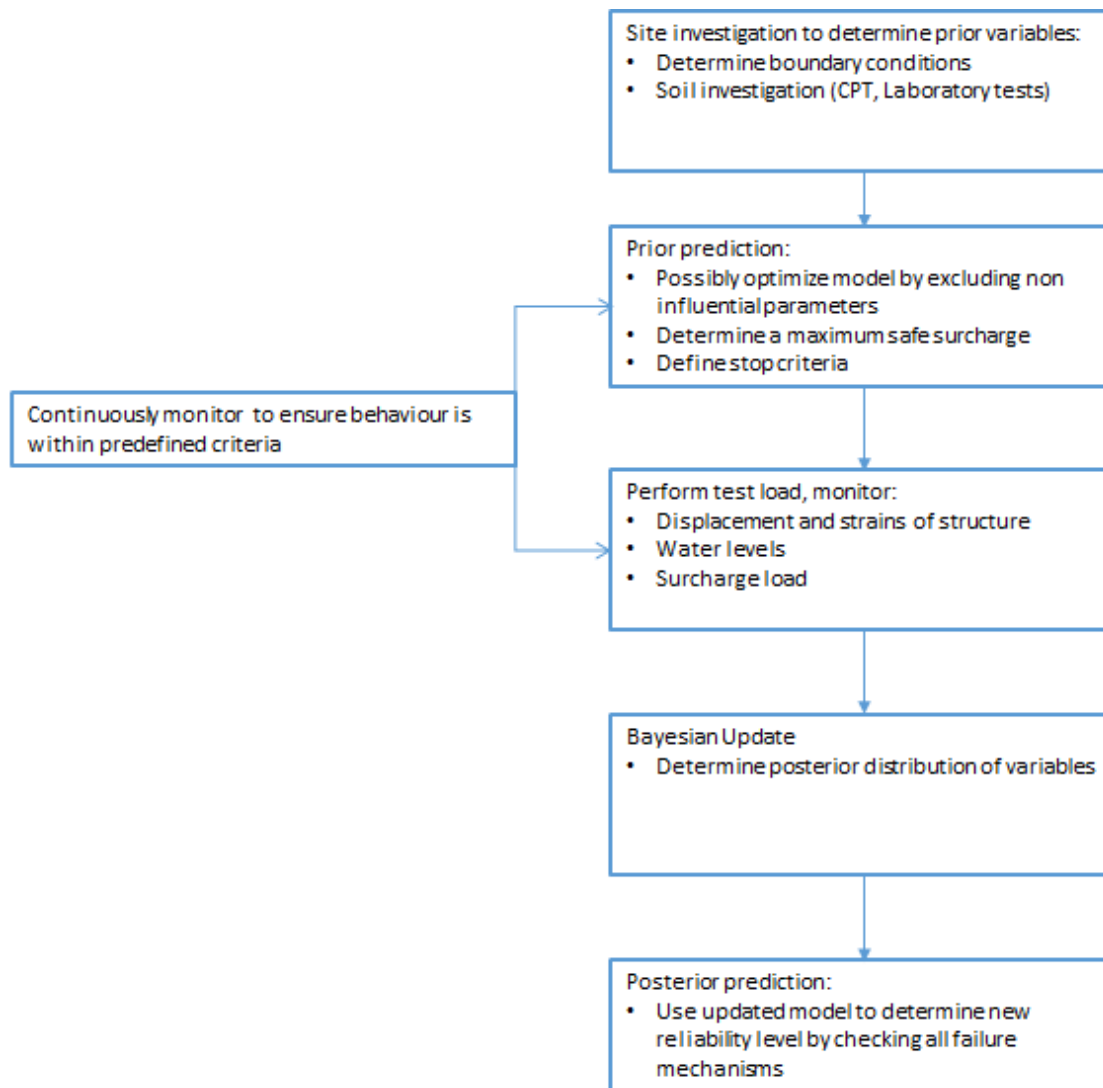


Figure 36 Flowchart to determine posterior reliability

The presented strategy is mainly focused on application with existing quays. Another option is to monitor a quay during the construction stages. If during the construction phase monitoring equipment is placed on the quay, the data can directly be used.

An example of a construction stage which can be monitored is construction in dry conditions. Often quays are constructed in dry conditions. In that case a temporary retaining structure and temporary sand fill are placed in front of the to be constructed quay. After finishing the construction works, the retaining structure and sand fill are removed. During the removal of the sand fill the quay starts to deform and the data obtained during this phase can be used for Bayesian updating. This procedure will be much more cost effective than actually loading an existing quay.

Furthermore, the obtained data can be used to determine the actual load capacity of the quay and also the data can in more general sense be used to verify the design process.

7.4 Conclusions

For both models, PLAXIS and Blum, holds that based on the measurement case 'displacement low' the allowable load on the quay can be increased to remain at a reliability equal to the prior prediction.

The update performed with Blum showed a much larger possible increase of the top load. The reason for this larger difference can be found in the assumed measurement cases. The measurement case assumed with PLAXIS is closer to the prior mean and thus the posterior means change less. This results in a lower increase in reliability.

The determined increase in reliability is largely dependent on the measurements. As they are assumed values, it cannot be assessed how realistic the calculated increase is. The used procedure in this chapter illustrates how measurements can be used to increase the functionality of the quay.

The reason for the possible increase is the fact that the included variables are known with more certainty and thus the posterior prediction has a smaller standard deviation.

The same holds for the case in which the quay is behaving worse than initially predicted. If that measurement case is reviewed, the maximum load will most likely decrease. The benefit for this case is that the maximum allowable load can be determined with more accuracy and also reinforcement measures can more effectively be reviewed. So, if the measurement shows a worse behaviour this still is a valuable result as in that case it can be proven that reinforcing or replacing is actually necessary.

A final point to be noted is the increased reliability is only calculated for the limit state displacements. It is assumed that failure due to excessive displacements is the governing failure mechanism. As this procedure is done for one limit state, the calculated increase in load might not be representative for actual failure of the quay. To determine the actual allowable increase of surcharge load, the updated parameters should be used to check all failure mechanisms.

8 Conclusions and recommendations

In this thesis Bayesian updating is applied to a probabilistic model of a quay wall. Based on fictitious measurement cases, the effect of using measurements to enhance model predictions is determined. Bayesian updating is applied according to the method of BUS which is developed by (Straub & Papaioannou, 2014). First BUS is applied to a well-known example of a cantilever beam after which BUS is used in combination with BLUM and finally the effect is demonstrated on a PLAXIS model.

Several aspects of Bayesian updating are shown: posterior distributions of moments, displacements and anchor forces and the posterior distributions of the included variables. The conclusions and recommendations are given in this chapter. The conclusions are based on the results found in this thesis and the recommendations are more focussed on how to apply the method in practice.

Before stating the conclusions and recommendations, first the problem statement is recalled. The introductory chapter of this thesis lists possible cases for which the safety of an existing quay wall needs to be reassessed. Proving the safety of existing quay walls in situations out of their initially designed scope, higher loads or deepening the harbour, is no easy task. The main difficulty in this is the large amount of uncertainty. Large factors of uncertainty are for example soil parameters, soil behaviour or current state of the structural parts. To cope with this uncertainty, the structural- and soil parameters are estimated. As estimates are used, it is uncertain how 'well' the model predicts the real behaviour.

A solution for this uncertainty is to perform test loading on quay walls. During the test loading the real behavior of the quay can be monitored. Using the obtained monitoring data, the uncertainty in the prediction can be reduced. The starting point of the research has been to evaluate the use of test loading. This is done by proving that the obtained monitoring data aids in reducing the uncertainty.

8.1 Conclusions

The conclusions are listed with respect to the sub questions and main research question.

Sub question:

What improvements to the probabilistic model can be obtained through performing a Bayesian update?

The main improvement which is gained by performing Bayesian updating is the reduced uncertainty. The graphs in chapter 5 and 6 show that the posterior standard deviations of moments, anchor forces and displacements are reduced. The reduced uncertainty can be explained by the fact that the model is probabilistically calibrated to the measurement. There is a difference between manually fitting the model according to measurements and using a probabilistic technique.

By manually adjusting parameters one obtains a possible combination of parameters. It will then still be unknown if this is the combination that will occur and also how many more combinations are possible. Another point is that with a large number of variables this can be a time-consuming process.

Bayesian updating results in the most likely combination of parameters. This most likely combination is determined based on the specified prior distributions and the measurement. The benefit of Bayesian updating is that this probabilistic update provides insight into how the stochastic definition of the variables change.

The result of performing this technique is thus updated parameters with changed means and changed standard deviations. Conservative or optimistic choices are changed accordingly and in general the provided standard deviations tend to reduce. The updated parameters result in a more accurate determination of the failure probability.

Sub question:

How are the results of the Bayesian update influenced by the type of evidence?

Two different measurements are used for updating the probabilistic model; measuring strain in the anchor tube and the displacement of the combi-wall. Comparing the results, the first conclusion is that the largest influence is found on the posterior distributions of the quantity which is measured. Measuring displacements results in the largest changes in the posterior distribution of displacements and for strains the largest effects is in the anchor force.

In the results (chapter 5 and 6) it is visible that measuring displacements also impacts the prediction of anchor forces and vice versa. Furthermore, it can be seen that both measuring displacements and strains have an effect on the posterior distribution. The displacement update cases tend to have a larger effect on the posterior moment distribution than the strain measurement.

In general, it can be concluded that both types of evidence result in a significant reduction of the uncertainty.

Research question:

How to use Bayesian updating to improve the prediction of the failure probability of a quay wall?

The effect Bayesian Updating has on the predicted failure probability is shown using both PLAXIS and Blum. For each measurement case a significant change in failure probability is found. In general, three possible outcomes from a measurement can occur: the behaviour is better than predicted, equal to prediction or worse than predicted. Two different limit states are used and all of the three possible outcomes are simulated.

If the behaviour of the quay is better than or equal to prediction, the reliability increases. If the behaviour is worse, then accordingly the reliability decreases. In all cases a useful result can be found. Either the reliability is increased and thus reinforcing might not be necessary and in the best case more loads could be applied or the reliability is decreased and it is certain that measures are required. As the model will be more accurate, also the effect of possible reinforcement measures can be evaluated better.

So, the use of Bayesian updating in reassessment of quays either proves the quay to be safe or it is known with more certainty that measures are required.

The main cause for starting the research and also the main reasoning behind the assumptions which have been made throughout the thesis is to evaluate test loading on quay walls. Test loading is seen as a possible option to obtain monitoring data to use in Bayesian updating. To determine the effectiveness of test loading more aspects of this procedure should be investigated. Aspects to investigate are for example the procedure of test loading, the possible costs and the benefits. This thesis has shown an effective method of using measurements in reliability calculations. The next step is then to determine the most efficient way of obtaining the required data.

The focus of the thesis has been on the use of Bayesian updating for quay walls. However, the method is not limited to application on quays. The method can be used on any kind of structure. The thesis has shown that it can be combined with the use of finite element software and thus towards application on complex retaining structures.

8.2 Recommendations

The first and one of the main recommendations is the use of Subset simulation. For practical application of Bayesian updating, a more efficient method than Monte Carlo simulation is required. Subset simulation is able to determine the posterior distributions with a much higher efficiency and this should therefore be used if applied on a case with real measurements. In this study problems with the coupling between PLAXIS and the matlab SuS script occurred. Two major problems need to be solved for Subset simulation to work in combination with PLAXIS.

First, the SuS script should be in python. PLAXIS provides support for the programming language Python and if the script is in the same language, the coupling is expected to be easier. The script used in this thesis is written in Matlab. Nearing the end of the thesis also a Python version of this script has come available, which will make the coupling with PLAXIS easier.

The second problem is related to the input for the Hardening Soil model. PLAXIS requires stiffness parameters to be within a validity range. In Subset simulation random draws are taken from the distributions, it is therefore unavoidable that during the calculation a draw is obtained which is outside this validity range. If such a draw is obtained, the process is aborted and the calculation needs to be restarted. To perform a Bayesian update with Subset simulation, the script should ensure that only 'valid' combinations are sent to PLAXIS.

Based on the experience with the performance of Subset simulation, it should be possible to obtain an accurate result with approximately 3000 calculations. As explained, subset simulation solves for low probabilities by a stepwise procedure. Each subset represents a step towards this lower failure probability. In this thesis it took approximately six subsets to solve for the posterior distributions. The number of samples in each subset can be specified as input, this also gives control over the total number of calculations required.

The accuracy in the determination of the posterior distributions is dependent on the number of samples. Literature (Au & Beck, 2001) has suggested the use of 500 samples per subset. Resulting in a total of 3000 calculations, which seems achievable in combination with finite element software.

If one is to use Bayesian updating in practice, the main difficulty will be to obtain the measurements. For quays it is more and more common to equip quays with measuring equipment during the construction stage. To use measured data for Bayesian updating, the data should be 'clean'. It should be known which load has caused the quay to move and preferably more boundary conditions such as the water level difference over the quay should also be known.

Theoretically it is possible to include both effects with a certain spread. However, for the results to be most useful, i.e. to obtain the most accurate posterior model, any uncertainty which can be ruled out from the start, should be ruled out. Therefore, the situation in which the data is obtained should be well known and secondly the used model needs to be able to describe this situation. If these criteria are not met, the use of the updated parameters remains uncertain.

In the current application of BUS, a single measurement has been used to update the parameters. If test load or any monitoring program is executed it will be more extensive than just one displacement or strain measurement. So in practice multiple measurements are available and it is advised to use a combination of measurements to obtain the posterior variables. The effect of using multiple measurements is not determined in this thesis so only an expectation of the results is given.

By updating the model according to multiple measured points, the combined space, in which the posterior distributions can be found, will be smaller. As one provides more evidence to define the displacement of the quay, the result will be a further reduction in uncertainty.

A drawback is that the calculation time will also increase. The probability of obtaining a posterior sample will be lower, so for MCS a lower acceptance rate and for SuS more subsets to evaluate. For both methods holds that more model evaluations are required to obtain an equal number of posterior samples. As in Subset simulation the total evaluations required are related to the

number of subsets and the evaluations per subset can be limited, the total increase of calculations will be far less than for Monte Carlo simulation. Due to the higher efficiency of Subset simulation, the use of Subset simulation is advised to obtain the samples with a reasonable calculation time. So if one is to monitor the behaviour of the structure, it is advised to use the data from multiple measurements to determine the posterior distributions. The increased accuracy will be beneficial over the longer calculations.

To summarize, the main recommendations are the use of Subset simulation over the use of Monte Carlo simulation and to use a combination of evidence to obtain posterior samples.

9 Discussion

This chapter will review the obtained results and provides subjects for further research.

9.1 Review of results

The obtained results in the chapters 5, 6 and 7 are reviewed. It is assessed how the starting points influence the final result.

The main starting point in the research is the limitation of the parameters which are included in the updating procedure. A choice is made for using only the geotechnical parameters as stochastic variables. The main argument used for this, is that the largest part of the uncertainty is present in those parameters.

The parameters with possible high influence coefficients that are not included are the stiffness's of the structural parts; the stiffness of the anchor tube, tubular piles and sheet piles. If it is known that even though steel properties can be described accurately, the stiffness is subject to some uncertainty.

In addition to stiffness parameters, retaining height and yield strength of the structural elements can also be influential.

As the updated parameters have shown the largest change in parameters with high influence coefficients, a theoretical more correct approach would be to first include all parameters as stochastic variables and then to eliminate the parameters with low influence coefficients.

The effect of including stiffness as a stochastic variable is dependent on the influence the stochastic definition has on the failure probability. In general, the stiffness will reduce the effect of the strain- and displacement updates. As, less strain or less displacements can also be caused by a higher stiffness.

To further elaborate this, two extremes of including the stiffness as stochastic variable are reviewed. In the results found with Blum, the change in anchor force caused by the different measurement cases is quite large. If the stiffness is included with a large standard deviation, most likely it will become very influential and the result is that no change in anchor force will be observed. The stiffness parameter will then show a significant change. The same reasoning also applies if stiffness is included with only a small standard deviation. In that case the change found in the results will, for the largest part, still be visible. The effect of the stiffness is thus dependent on its distribution but should in general reduce the changes found in the moments and anchor forces.

A second important starting point is to use fictitious measurements. As the found results are directly related to these fictitious measurements, one could argue that this makes the results less interesting for practical use. The purpose of fictitious measurements is to show in a more general sense the effect of applying a Bayesian update. Different measurement cases are assumed to show this effect. For this purpose, fictitious measurements are useful as they show the trend in the results and allow for a more theoretical comparison between results.

Therefore, fictitious measurements are chosen and thus the results are suitable for qualitative comparison. The exact determined quantities should be reviewed with the assumption of fictitious measurements in mind.

The quay is equipped with monitoring equipment. During the construction phase and for a small part of its lifetime monitoring data is available. For this research, the data was available in a too late stadium. The use of this data, especially the data obtained during the excavation of the quay, would make the results more case specific. This holds in particular for the results in chapter 7.

Accompanied with the fictitious measurements, an assumed measurement error is used. The results show that the posterior distributions have a remaining standard deviation in the order of this measurement error. In the original publication of (Straub & Papaioannou, 2014) the used error is a sum of the model uncertainty and the measurement uncertainty. In this case the assumed model uncertainty is equal to zero. So, to be theoretically correct also a certain model error should be included into the definition of the Likelihood functions. As the posterior distribution tends to follow the assumed error, including the model uncertainty will lead to larger posterior standard deviations and thus a slightly less favourable result.

In this thesis parameters have been determined based on CPT data and for the advanced PLAXIS parameters expert judgement is used. For the purpose of this thesis, which is to show changes in the parameter estimates based on measurements, the used procedure is sufficient. However, the goal of performing the update in practice is to determine the reliability of a quay. If the objective is to determine the reliability, the parameters should be determined more accurately. For example, the soil parameters can be determined with a more extensive soil investigation including laboratory testing instead of only CPT data.

To show the effect of the different measurement cases, reliability indices have been calculated. FORM has been used with Blum to calculate these indices. At first, the same approach was used with PLAXIS. However, the PLAXIS FORM calculation was unable to converge. So instead of FORM, the reliability indices with PLAXIS are calculated with Importance Sampling. They are calculated with a limited number of samples. The indices are thus approximations of the actual reliability.

The reason for the inability of FORM to converge in combination with PLAXIS is unknown. To aid the algorithm in converging several steps have been performed:

- Reducing the step size in between FORM iterations
- Reducing the total number of variables, the least influential parameters were excluded. Instead of 20 variables the number was reduced to 8
- Using the experience from the PLAXIS model runs and Blum to shift the variables towards the failure boundary
- Using a limit state which has a higher probability of being exceeded
- Increasing the convergence limit from 1% to 10%

All of the above listed options have proven unsuccessful. Further study is required to determine why the algorithm couldn't converge. This is not included in this research, as the time required to perform 30-40 FORM iterations with PLAXIS is significant and also the research is not focussed on determining the exact failure probability. The reliability indices are used to show the differences between the measurement cases and for this purpose the estimation with Importance Sampling is sufficiently accurate.

9.2 Further research subjects

To assume fictitious measurements, the real problem of Bayesian updating is directly solved. To perform a Bayesian update, accurate measurements are required. The thesis has shown how effective an update can be to enhance the probabilistic model. The effectiveness of the method is however dependent on the measurements and how well the model can describe the situation.

A specific item which is mentioned several times during the chapters is test loading on quays. It is a possible option to obtain the measurements which have now been assumed. A possible option to perform test loading is stacking sand-filled containers behind the quay. This idea of test loading is however very conceptual and more study should be done before this could actually take place. So, how to perform a test loading on a quay is a subject which needs further study.

As test loading is just a possible option for obtaining the measurements, a more general research subject can be defined as how to obtain measurements which can be used for Bayesian updating.

A possible option to investigate is using monitoring data obtained during the construction of a quay. The case used in this thesis is equipped with monitoring equipment. During the construction stage and for a short period of its lifetime this data has been collected

The quay is roughly constructed in the following steps. Dry conditions were created during the construction of the quay. A temporary water retaining structure and a sand fill is placed in front of the quay. After finishing the quay, this retaining structure is removed and the sand fill is dredged.

An interesting option to perform BUS would be to use the data obtained from the dredging. Both PLAXIS and D-Sheet Piling have the possibility to include construction phases and thus it should be possible to perform a Bayesian update with these measurements.

The use of data obtained during construction is another possible option to obtain input for a Bayesian update. An additional benefit of this method is that this data could directly be used to determine the additional safety which is included in the design and possibly if the allowable surcharge can already be increased at the start of the quay's lifetime.

Another subject to investigate is to further determine how the quay should be monitored. In this thesis only structural parts are measured, displacements of the wall and strains in the anchor, another option is measuring displacements of the soil body behind the quay. The option of monitoring the soil body is could be useful for quays that are not easily accessible and not equipped with monitoring devices. Costs and installation aspects need to be considered to determine the most optimal solution for monitoring a quay.

Near the final stage of this thesis, the monitoring data of the quay has come available. It would be an interesting further research subject to use the method of Bayesian updating in combination with the obtained data. Especially the results obtained in chapter 7 will be more relevant if real measurements are used. It would then also be interesting to perform a check on the remaining failure mechanisms and thus to exactly determine if the surcharge can be increased.

One should keep in mind that if measurements from the construction phases are used, ideally boundary conditions such as water levels and ground level should also be known during this phase.

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Appendix A Python script BUS with Monte Carlo simulation

The python script written in this appendix executes BUS based on a Monte Carlo simulation. This method is explained in section 3.2. The script is shown in Figure 37. The script is based on (Straub & Papaioannou, 2014)

As input to the script is required:

- Distribution of variables
- Likelihood function
- Required number of samples in posterior distribution

```

## update function
K=1
R=1
N=100000

wu=np.zeros(N)
Eu=np.zeros(N)
Iu=np.zeros(N)
Fu=np.zeros(N)
Lu=np.zeros(N)

while K < N:
    R+=1
    E=np.random.normal(30000,1500)
    I=np.random.normal(6.75e8,6.75e6)
    L=np.random.normal(5000,100)
    F=np.random.normal(10000,500)
    w=(F*L**3)/(3*E*I)
    y=norm.pdf(w,18,1)
    c=0.5*np.sqrt(2*np.pi)
    u=uniform.rvs()
    if u-c*y<0:
        wu[K]=w
        Eu[K]=E
        Iu[K]=I
        Fu[K]=F
        Lu[K]=L
        K+=1
    #Ensure N number of samples in posterior distribution
    #Counts total number of calculations
    #Create random draws
    #
    #
    #
    #Probability density function of measurements
    #Scaling constant to ensure c*L<1, best value is max(L)^-1
    #Random draw from uniformdistribution [0,1]
    #Criteria for value to be in posterior
    #Store the samples which are in posterior

    #Counter of samples in posterior

```

Figure 37 Python script for BUS with MCS

The script returns samples which are in the posterior distribution. These samples can be used for further analyses.

Appendix B Matlab script BUS with Subset simulation

For application of BUS with Subset simulation, as explained in section 3.3, a MATLAB script is used. The script is made available by the Engineering Risk Analysis Group of the Technical University of Munich (Technical University of Munich, 2018). To apply Subset Simulation in fact three scripts are required. The functionality of each script is shortly explained here.

Script: ERADist.m

As input for the BUS approach stochastic variables need to be defined. Using the ERADist script variables with a certain distribution can be generated. The distribution can be defined on its parameters, moments or data obtained from experiments. The script supports generating variables from 20 different probability distributions. With ERADist the following functions are possible:

- Determine mean value
- Determine standard deviation
- Calculate probability from PDF
- Calculate values from CDF
- Calculate values from inverse CDF
- Draw random numbers from given distribution

Script: ERANataf.m

The second step for applying BUS with Subset Simulation is to transform the variables to standard normal independent variables. This transformation is done with the ERANataf script. It transforms the marginal distributions defined with ERADist to a joint distribution. The marginal distributions are transformed with the Nataf transformation. As input is required a set of variables defined with ERADist function and a correlation matrix. Once defined the following functionalities can be called:

- Transformation from physical space to normal space
- Transformation from normal space to physical space
- Draw random numbers from joint distribution
- Calculate probability from joint PDF
- Calculate values from joint CDF

Script: aBUS_SuS.m

Once the variables and their distributions are defined and transformed to the standard normal space, the Bayesian update can be applied. The script aBUS_SuS applies this update, according to the procedure explained in section 3.3. The required input is:

- Standard normal prior distribution, obtained from ERANataf
- Intermediate conditional probability p_0
- Logarithm of the likelihood function
- Number of samples in each subset level

The script has as output results:

- Samples in posterior distribution, both in normal space and in physical space
- The marginal likelihood
- The intermediate subset levels

Appendix C Cross section quay wall

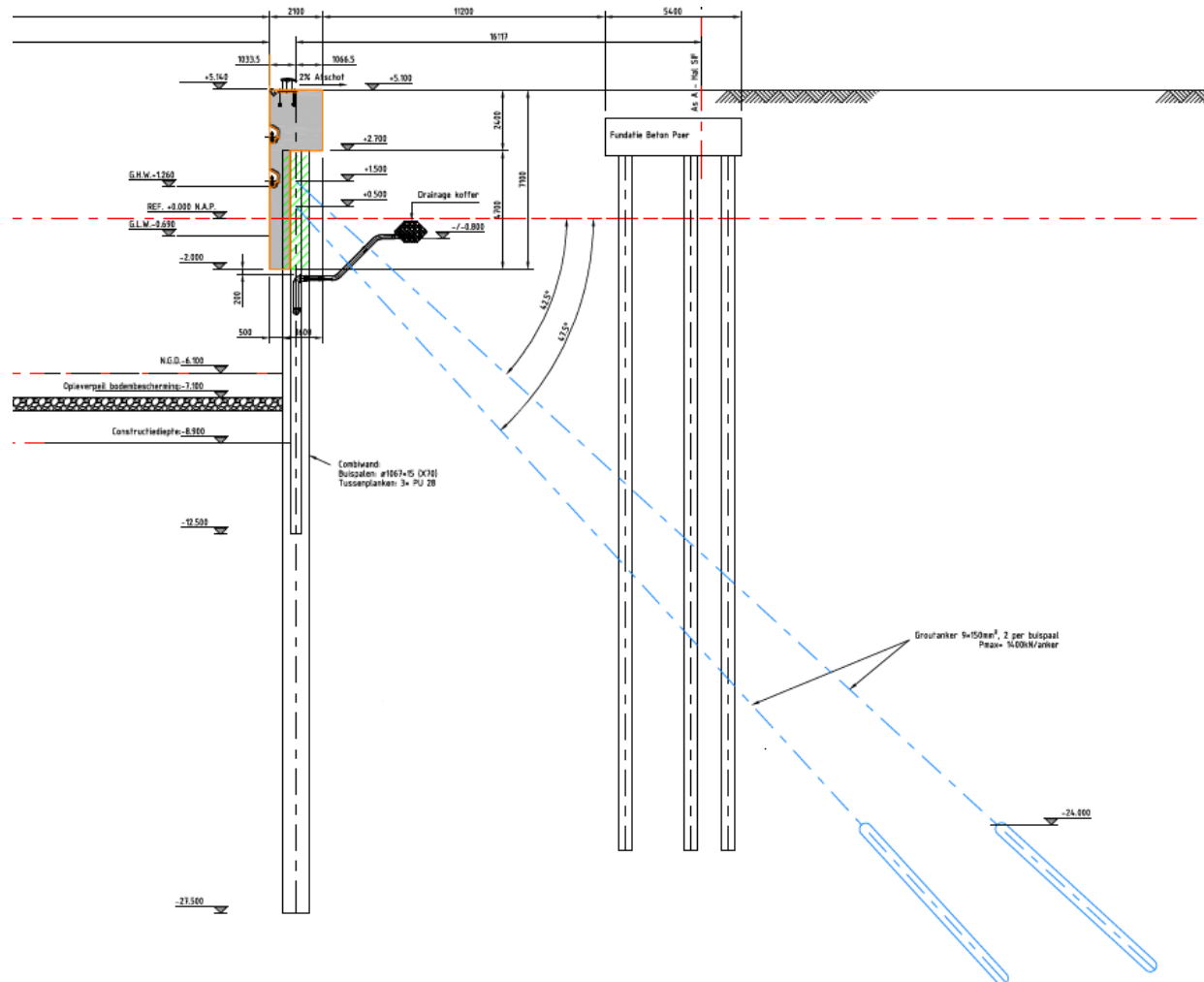


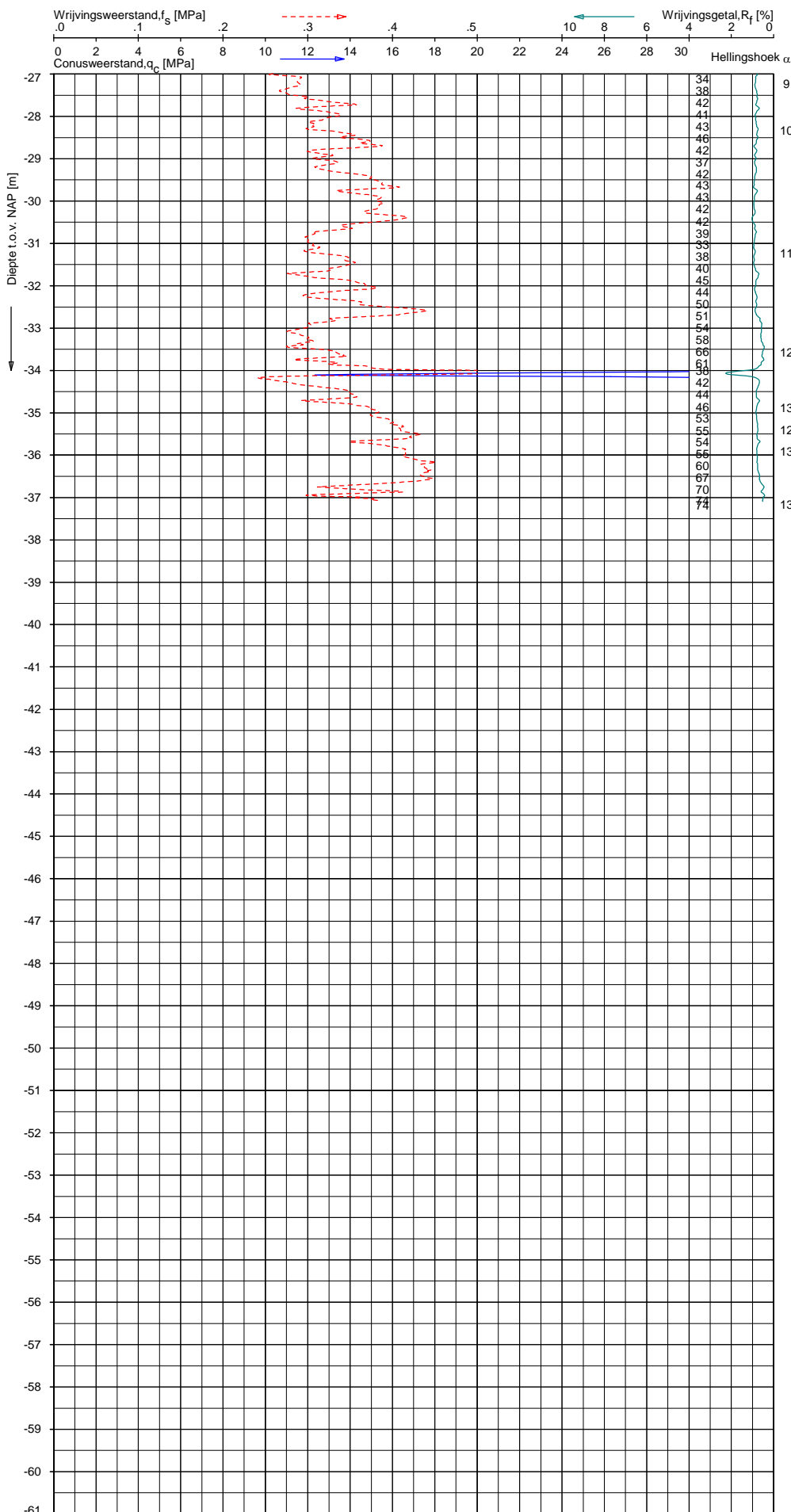
Figure 38 Cross section quay

Appendix D CPT at quay

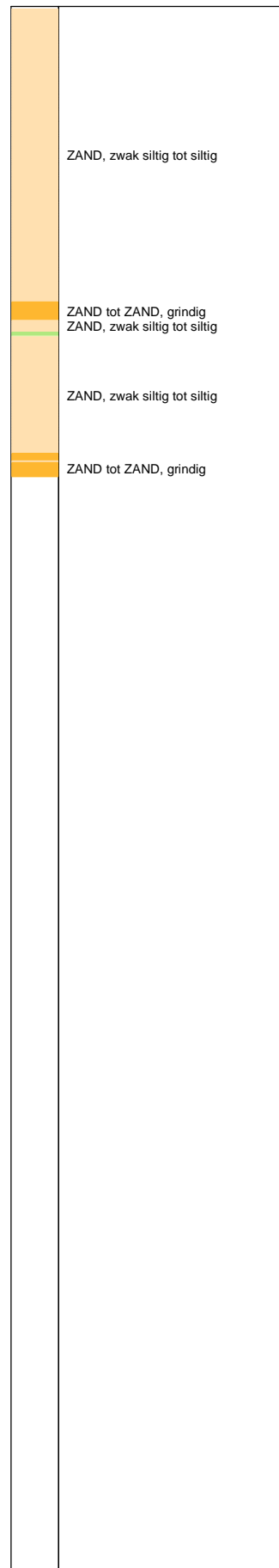
DNIPLOT 05.27.11/GS-Class-R3cmd/2015-06-03 09:35:47

1315-0141-000

DKMP124 - 2



Indicatieve bodembeschrijving
 Automatisch gegenereerd uit data van de sondering, geldig onder grondwaterpeil (Robertson 1990, NL corr.)



Opg.: CV/ d.d. 01-jun-2015 Coord.: X= 59997.3m Y= 442654.5m Systeem: RD Sondering volgens norm NEN-EN-ISO 22476-1
 Get.: BOSCHG d.d. 02-jun-2015 MV = NAP +5.15m Conus: CP15-CF75PB7SN2 1701-2685 Toepassingsklasse 2, Test type TE2
 Conustype: $A_c = 1510 \text{ mm}^2$; $A_s = 19895 \text{ mm}^2$



SONDERING MET PLAATSELIJKE KLEEFMETING

TERREIN E KADEMUUR MAASVLAKTE

Opdr. 1315-0141-000
 Sond. DKMP124

Appendix E Results update Blum model

The results of updating the Blum model of the quay wall are presented here. In section 5.3 the results of the update for the maximum moment, displacement, anchor force and anchor strain are provided. In this appendix the results of the update for each included variable and each of the six cases defined in section 5.3 are shown here in Figure 39 till Figure 44. It is chosen to plot the relative change of the posterior distributions. The relative change is defined as:

$$Change = \frac{Posterior}{Prior}$$

A relative change larger than value one indicates that the posterior value is larger than the prior value. If the change is smaller than one, this means a lower posterior value. The red bars represent the relative change in posterior mean and the blue bars represent the relative change in posterior standard deviation.

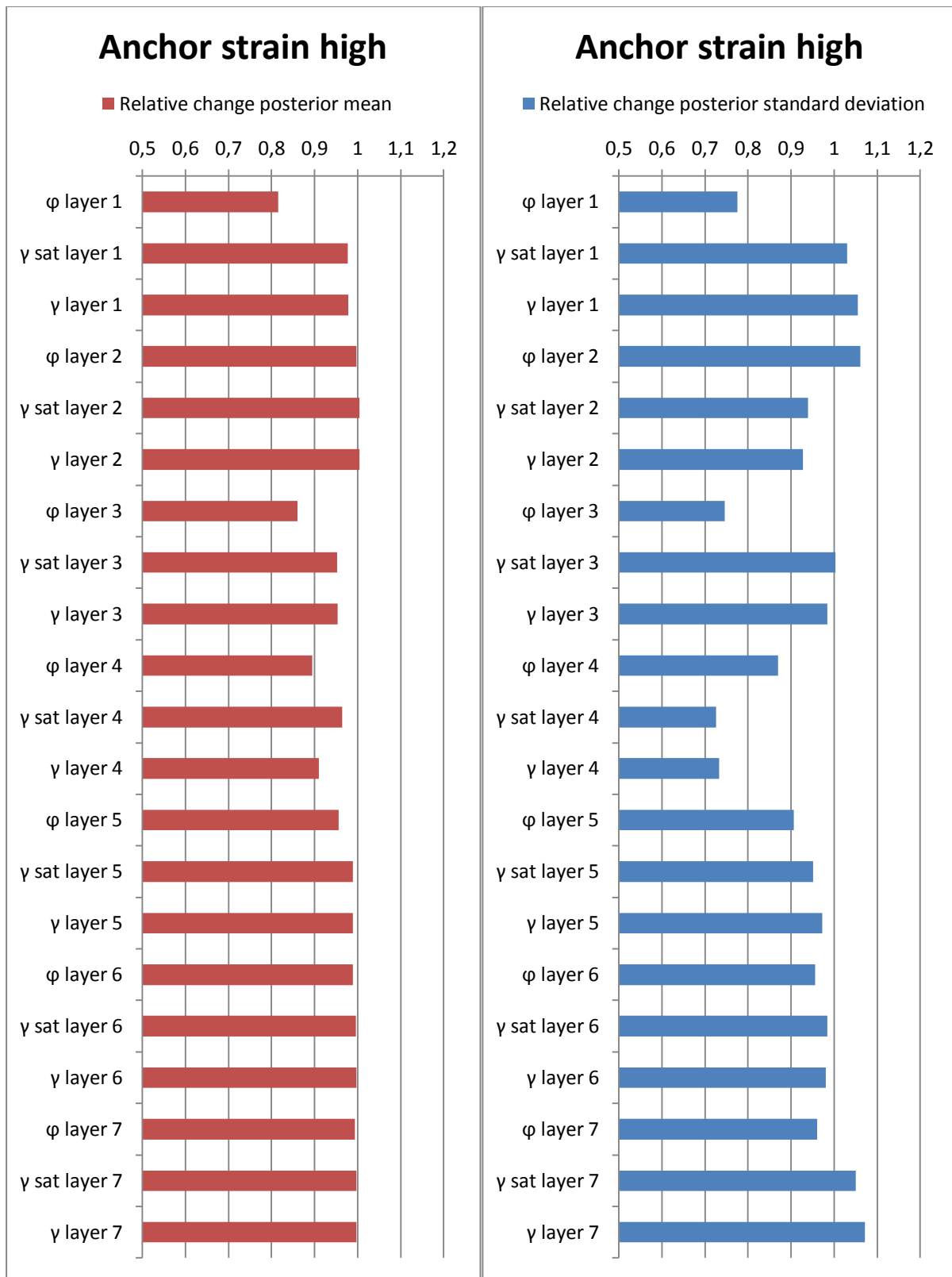


Figure 39 Blum updated variables case anchor strain high

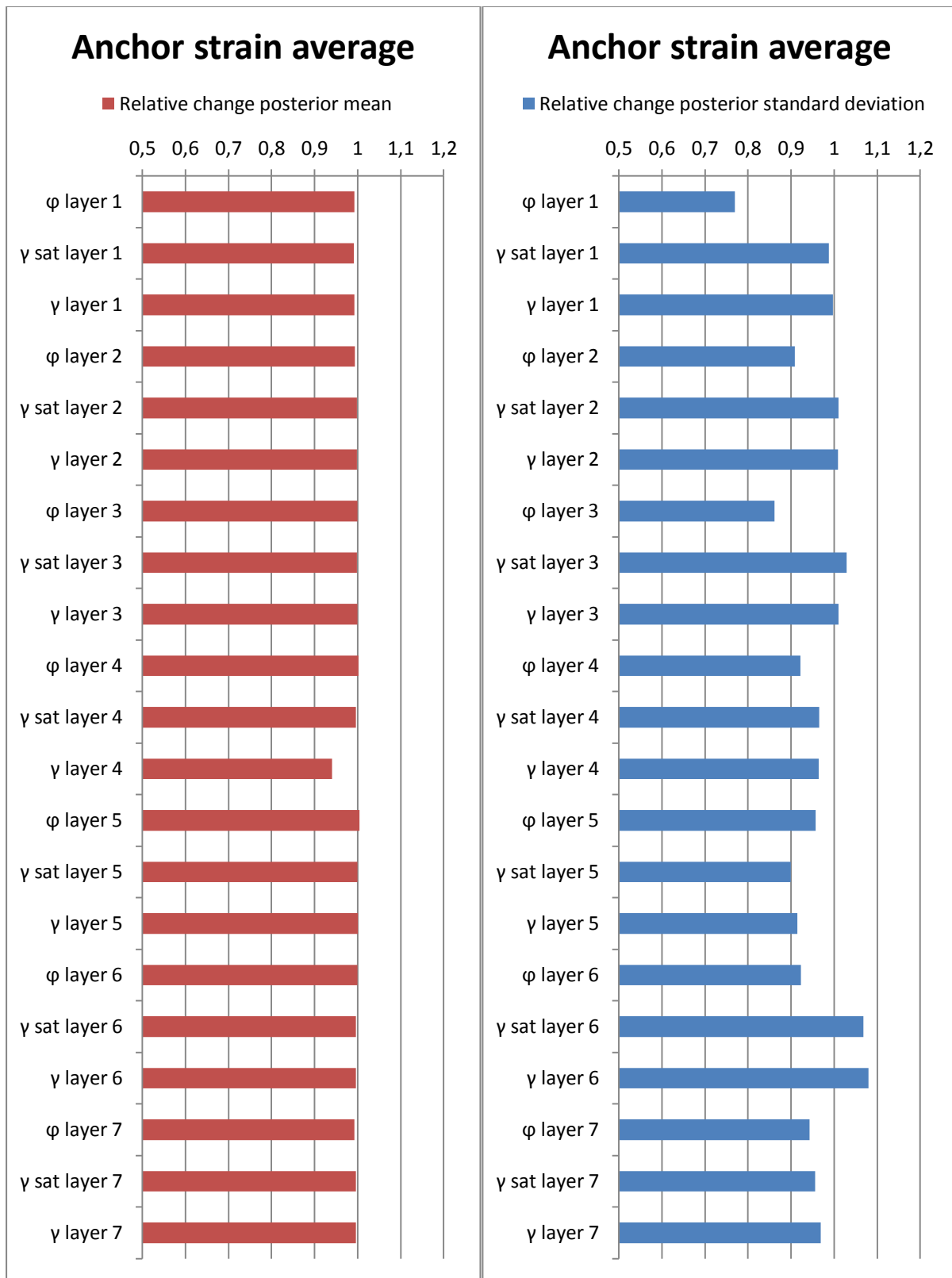


Figure 40 Blum updated variables case anchor strain average

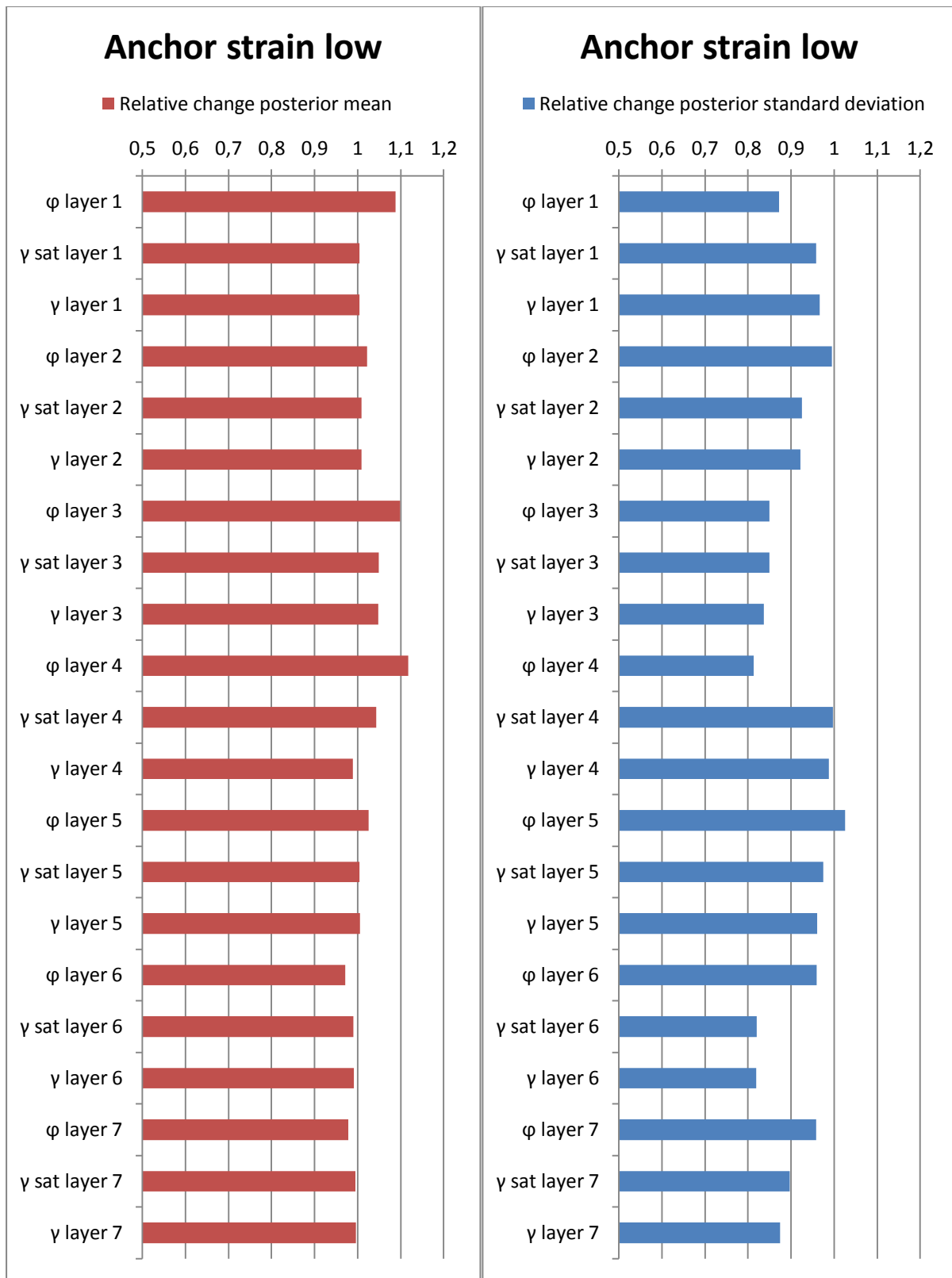


Figure 41 Blum updated variables case anchor strain low

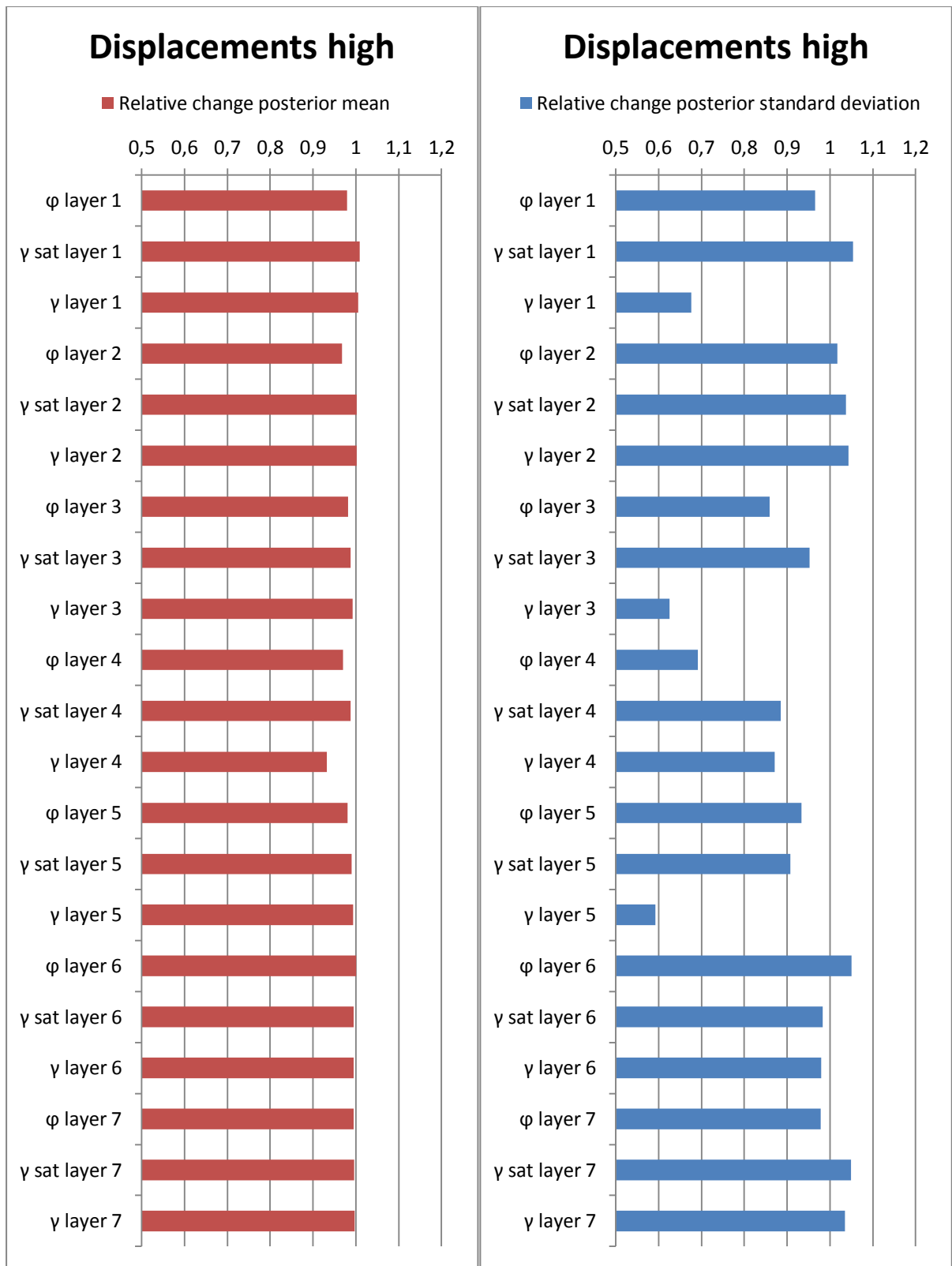


Figure 42 Blum updated variables case displacement high

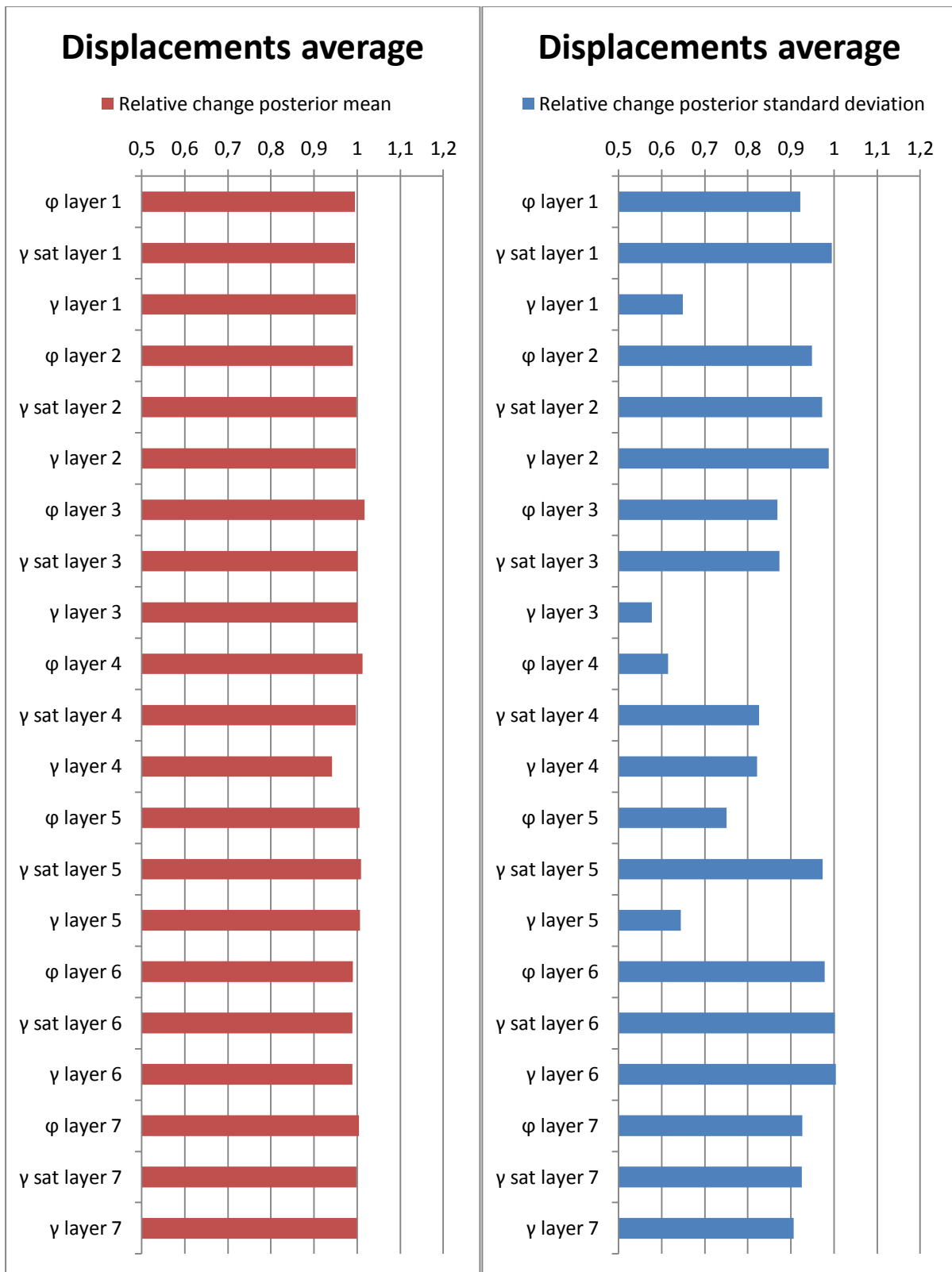


Figure 43 Blum updated variables case displacement average

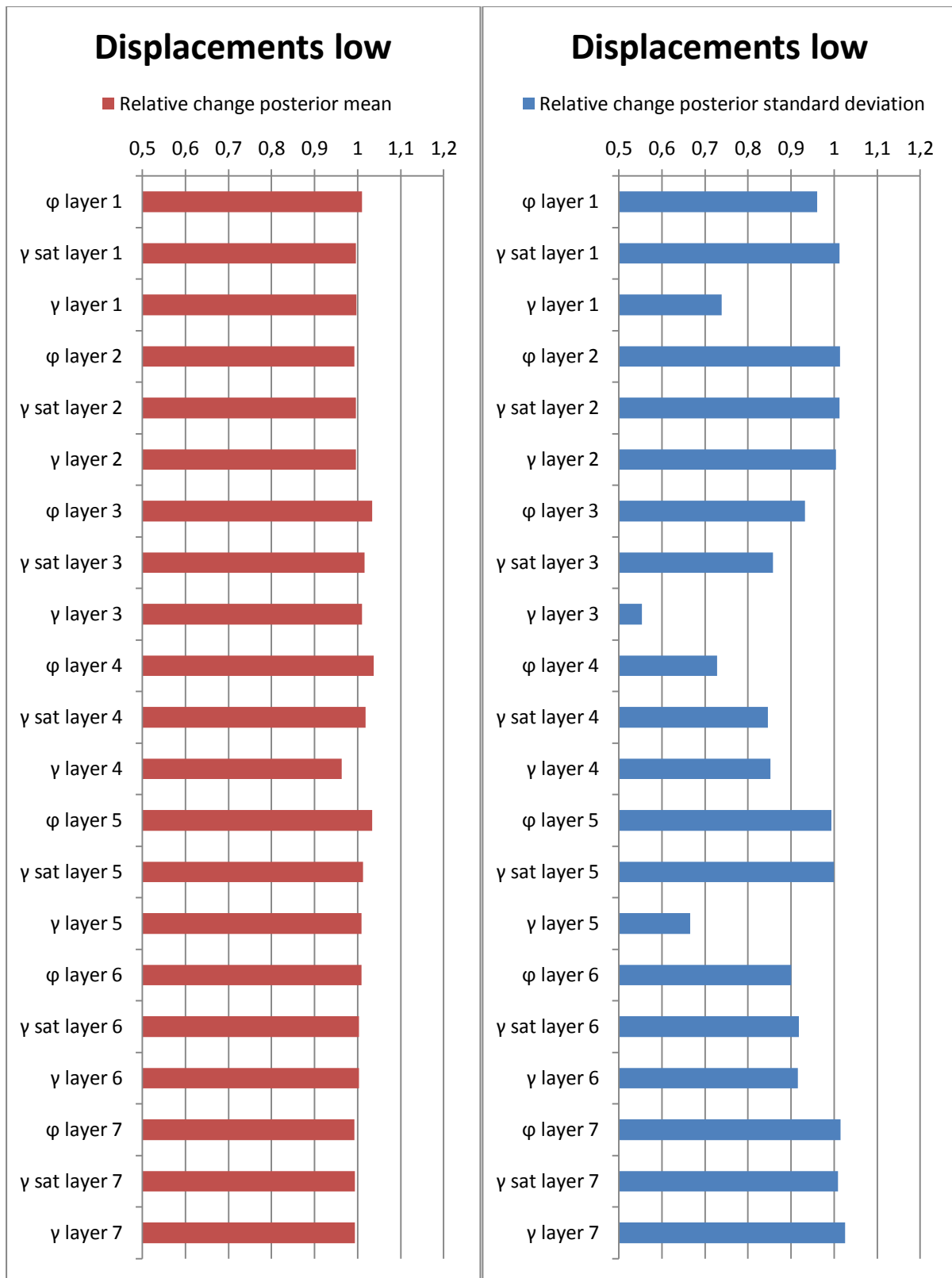


Figure 44 Blum updated variables case displacement low

Appendix F Elaboration PLAXIS model

This appendix contains the explanation of the PLAXIS model which is used in chapter 5, all model specific settings are elaborated here. First a base model is built. This base model is the best currently possible representation of the actual soil behavior. After which this base model is optimized in terms of calculation time. In order to limit the calculation time, for the probabilistic calculation a model is required which provides accurate results but has an as short as possible calculation time.

Base model

The first step into setting up the model is determining some general project properties. These are:

- Model type: Plane Strain
In this thesis a 2D model of a quay wall is used. Therefore, Plane Strain is the appropriate choice.
- Elements: 15-Noded
A choice can be made for 15-Noded elements or 6-Noded elements. By default, 15-Noded elements are used. Using 15-Noded elements the solution is more accurate at the cost of being more computationally intensive. Especially in failure analyses it is advised to use 15-Noded elements, as failure loads and safety factors are over predicted in 6-Noded elements.
- Contour
The contour should be chosen such that the model is large enough that the results are not influenced by the boundary conditions. For this case the following boundaries are used:

$$\begin{aligned}y_{min} &= -40,0 \text{ m}, & y_{max} &= +5,1 \text{ m} \\x_{min} &= -50,0 \text{ m}, & x_{max} &= +50,0 \text{ m}\end{aligned}$$

After defining the general properties, setting up a PLAXIS model consists of five main steps. For each of these steps it is explained which choices are made. The steps are:

- Soil
- Structures
- Mesh
- Flow Conditions
- Staged construction

Soil

The next step is defining the soil profile and the model used to describe the soil behavior. The soil profile is determined in chapter 4 and also shown in Table 18. The parameters are based on the CPT found in Appendix D and table 2b in NEN9997-1.

In chapter 2 several soil models available in PLAXIS are described. Based on this, either the Hardening Soil or the Hardening Soil Small Strain would be most suitable for the modelling of quay walls.

The most accurate would be to use the Hardening Soil Small Strain. This soil model is used in the base model.

A drained analysis is performed, as mostly sand is present, with only small clay layers in between, allowing pore pressure to dissipate quickly. Furthermore, no backfill will be placed behind the quay, so no excess pore pressures are expected.

Table 18 Characteristic Soil Parameters PLAXIS

Top level layer [m NAP]	Soil type	γ [kN/m ³]	γ_{sat} [kN/m ³]	φ [°]	c [kN/m ²]	E_{oed}^{ref} [kN/m ²]	m
+5,1	Sand, clean, loose	17	19	30	0	15000	0,5
-4,0	Clay, slightly sandy, weak	15	15	22,5	0	1500	1
-5,5	Sand, clean, loose	17	19	30	0	15000	0,5
-10,0	Sand, slightly silty clayey	18	19	27	0	35000	0,5
-14,0	Sand, clean, loose	17	19	30	0	15000	0,5
-21,0	Clay, slightly sandy, weak	15	15	22,5	0	1500	1
-23,0	Sand, clean, solid	18	20	32,5	0	75000	0,5

For the following parameters a ratio is defined:

- $E_{oed}^{ref} = E_{50}^{ref}$ and $3 * E_{50}^{ref} = E_{ur}^{ref}$

The stiffness ratio used above is the default ratio. The used ratio between $E_{oed}^{ref} = E_{50}^{ref}$ holds mainly for sandy soils. For clay it is normally the case that $E_{oed}^{ref} < E_{50}^{ref}$. The influence of this assumed ratio should be small as only small clay layers are present.

- $\psi = \max(0, \varphi - 30)$

For frictional materials, sands, the angle of dilatancy is determined by the above formula. In case of clay or peat the angle is equal to zero. (Plaxis bv, 2017)

- $R_{int} = 0,8$

The ratio of the interface shear strength is determined with the Handbook Quay Walls (Broeken & de Gijt, 2013), this gives a ratio of R_{int} of 0,8 to 0,9.

For the Hardening Soil Small Strain two additional parameters are required. These are:

- $\gamma_{0,7} = 10^{-4}$

This parameter describes the shear strain for which the shear modulus is reduced to 70% of its small strain value. A value based on experience is used. (van der Giessen & Wolters, 2015). The assumed value for $\gamma_{0,7}$ is mostly reasonable for sandy soils. The stiffness of the clay layers is lower and thus the value of $\gamma_{0,7}$ should be higher for the clay layers. It is assumed that the influence of this is limited, as the clay layers are small relative to the sand layers.

- $G_0 = 1,2 * E_{ur}^{ref}$
 G_0 represents the shear strain at very small strain. A value based on experience is used. (van der Giessen & Wolters, 2015)

The parameters $\gamma_{0,7}$ and G_0 are assumptions based on experience. It is however, always preferred to use parameters which can be based on in-situ tests. As these tests are not available the values are assumed.

As advised by the PLAXIS Materials Model, for any parameter not mentioned, the default value is used.

Structures

In the structures step, the geometry of the quay is defined, the structural parts and the loads are defined.

The geometry is defined as:

- Ground level NAP + 5,10 m
- Design depth NAP - 8,90 m

The next step is to include the structure in the model. The structure is an anchored combi-wall with the characteristics and dimensions as shown in chapter 4. The combi-wall consists of two parts with different characteristics. The top part consists of both sheet piles and tubular piles, while the bottom part has only the tubular piles. In PLAXIS these parts are modeled as two different plate elements.

The input for the two plate elements is:

- Sheet piles and Tubular Piles
 - Level: NAP +5,1m – NAP -12,5 m
 - $EA_1 =$ $6,32 * 10^6 \text{ kN/m}$
 - $EI =$ $5,65 * 10^5 \text{ kNm}^2/\text{m}$
 - $w =$ $2,4 \text{ kN/m}$
 - $\nu =$ 0,2
- Tubular Piles:
 - Level: NAP -12,5 m – NAP -27,5 m
 - $EA_1 =$ $3,54 * 10^6 \text{ kN/m}$
 - $EI =$ $4,89 * 10^5 \text{ kNm}^2/\text{m}$
 - $w =$ $1,30 \text{ kN/m}$
 - $\nu =$ 0,2

Also, the anchors need to be specified, the characteristics of the anchors need to be determined per running meter. The anchors behave linear elastically. This results in the following input:

- Specifics of anchor 1
 - Top level NAP + 1,5 m
 - Model Type: Fixed-end anchor
 - $EA =$ $3,92 * 10^5 \text{ kN/m}$
 - Angle $42,5^\circ$
 - Equivalent length $L_{eq} = 43,5 \text{ m}$
 - Prestress 425 kN

- Specifics of anchor 2
 - Top level NAP + 0,5 m
 - Model Type: Fixed-end anchor
 - $EA =$ $3,92 * 10^5 \text{ kN/m}$
 - Angle $47,5^\circ$
 - Equivalent length $L_{eq} = 39 \text{ m}$
 - Prestress 325 kN

In the structures step, also the loads must be defined. The loading conditions are assumed to be equal to the loads with the Blum model. So, a surcharge of 100 kN/m^2 is applied on the ground level.

On the passive side of the quay the weight of the bottom protection is included in the calculation. The bottom protection applied is loose rock with a grading of 40-200 kg penetrated with 160 l/m^2 underwater concrete. The thickness of this layer is 0,55 m. This weight is calculated as: (Timmermans, 2015)

- $\rho_s = 2650 \text{ kg/m}^3$ Weight of the stones in bottom protection
 - $d = 0,55 \text{ m}$ Thickness of bottom protection
 - $v = 0,55$ Void ratio of bottom protection
 - $\rho_c = 1900 \text{ kg/m}^3$ Weight of concrete used to penetrate the protection
- $$W = \frac{2650 * 0,55 * (1 - 0,55) + 0,160 * 1900}{1000} = 9,60 \text{ kN/m}^2$$

Summarizing both the soil input and the structural input, the model is shown in Figure 45.

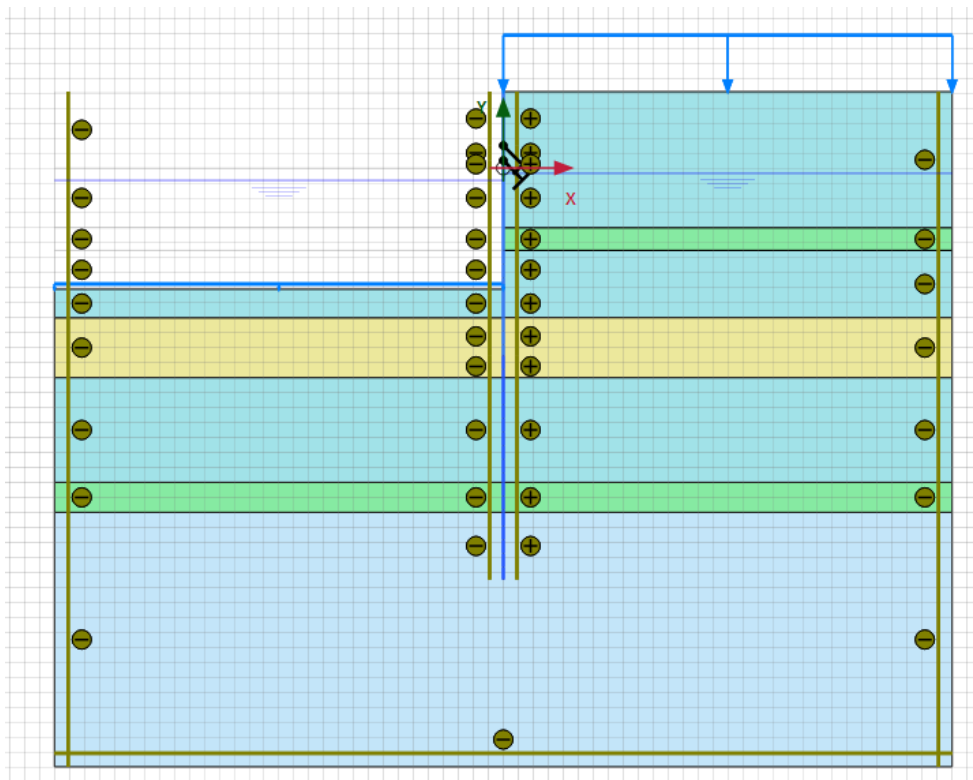


Figure 45 PLAXIS input

Mesh

PLAXIS divides the model into a finite number of finite elements. The composition of elements is called the mesh. PLAXIS can automatically generate the mesh, but the user has the possibility to define the fineness of the mesh. The finer the mesh, the more accurate the result but also the computation becomes more intensive. In combination with the 15-Noded elements, a mesh fineness of medium is selected.

Flow Conditions

In the step Flow Conditions, the water levels can be defined. It is assumed that the water levels are at NAP +0,0 m during the construction phases and during loading conditions the water levels are at:

- Groundwater level NAP - 0,34 m
- Harbor water level NAP - 0,84 m

Due to this water level difference, there will be a head difference below the tip of the sheet piles. This physically cannot be true, therefore in the staged construction options the pore pressures are calculated according to Steady state groundwater flow. PLAXIS then takes into account this head difference and ensures an equal water pressure on both sides below the tip of the sheet pile.

Staged Construction

The final step is to define the phases. The phases can be used to simulate the construction of the quay and to evaluate different loading conditions. The phases shown in Table 19 are used. These phases represent both the construction and the loading conditions of the quay. The settings which are not mentioned in Table 19 are set to their default values.

Table 19 Used calculation phases in PLAXIS

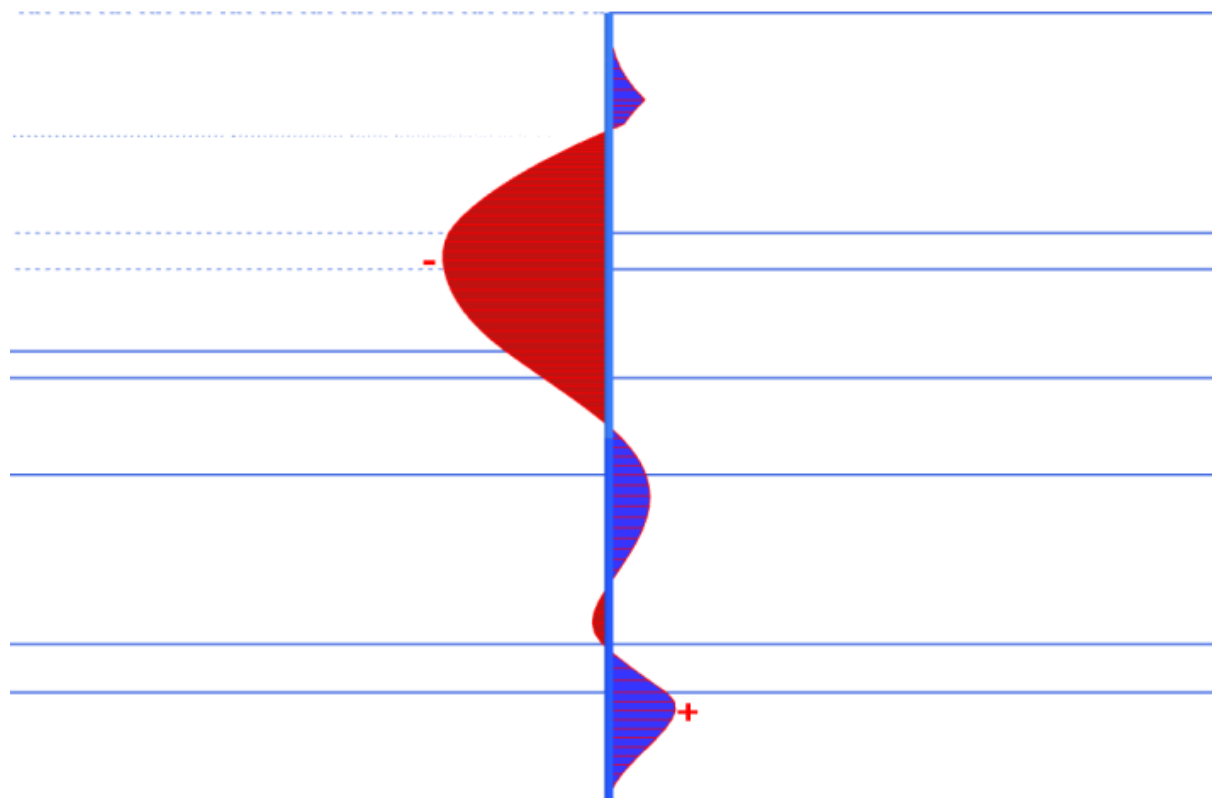
Phase	Description
Initial Phase	In the Initial Phase PLAXIS calculates the initial stresses in the soil using the K0-procedure. This represents the situation prior to the construction process.
Phase 1	Placing the combi-wall and reset displacements (strains) to zero, stresses remain equal to Initial Phase
Phase 2	Excavate to NAP + 0,5 m.
Phase 3	Placing anchors at NAP + 1,5 m and NAP + 0,5 m and prestressing top anchor to 425 kN and bottom anchor to 325 kN.
Phase 4	Excavate to final depth, NAP – 8,90 m.
Phase 5	Apply the water level difference : Groundwater level NAP - 0,34 m Harbor water level NAP - 0,84 m In this phase and the next phase, the pore pressure calculation is set to Steady state groundwater flow to ensure that the water pressure below the tip, NAP -12,5, of the sheet piles is equal on both sides.
Phase 6	Apply surcharge of 100 kN/m ² at ground level

Results

Using the input defined above, the following results are obtained in phase 6. The x-axis is positive defined towards the landside, so a positive deflection is towards the soil and a negative deflection is towards the harbor.

- Moments in wall: $M_{max} = 550,7 \text{ kNm}$ $M_{min} = -1337 \text{ kNm}$
- Deflection wall: $D_{max} = -0,089 \text{ m}$
- Anchor force 1 $T_1 = 568,53 \text{ kN/m}$
- Anchor force 2 $T_2 = 539,21 \text{ kN/m}$
- Calculation time $t = 312 \text{ s}$

In Figure 46 the moment diagram as output from PLAXIS is shown.



Bending moments M (scaled up $5,00 \cdot 10^{-3}$ times)

Maximum value = 550,7 kN m/m (Element 21 at Node 13912)

Minimum value = -1373 kN m/m (Element 9 at Node 12451)

Figure 46 PLAXIS moment diagram

The above presented results are compared to a D-Sheet Piling model that was used for the design of the quay. The results of PLAXIS and D-Sheet piling should be in the same order of magnitude. The PLAXIS model and D-Sheet Piling model are compared in the SLS conditions. In both of the models the characteristic values are used without applying partial factors. The D-Sheet Piling results are:

- Moments in wall: $M_{max} = 500,7 \text{ kNm}$ $M_{min} = -1453,6 \text{ kNm}$
- Deflection wall: $D_{max} = -0,0589 \text{ m}$
- Anchor force 1 $T_1 = 502,5 \text{ kN/m}$
- Anchor force 2 $T_2 = 441,9 \text{ kN/m}$

In general, the results of PLAXIS and D-Sheet Piling are quite similar. The largest difference in the results is in the moments, the field moment predicted in D-Sheet Piling is larger than PLAXIS predicts. Several reasons can be given for this difference. The major contribution to this difference is caused by neglecting arching in D-Sheet Piling. The calculation model of D-Sheet Piling is based on elasto-plastic springs, these springs are uncoupled and the software is therefore unable to model arching in the soil. Arching leads to a reduced field bending moment and an increased support bending moment and anchor force. In this case the M_{min} represents the field moment and the M_{max} the support bending moment. So, the difference in the predicted moments is expected.

Furthermore, some minor differences are found in the results, these can be contributed due to the fact that PLAXIS uses a different soil behavior model. Another minor contribution is expected by a difference in pore pressures. In the D-Sheet Piling model the water level difference is not corrected at the tip of the sheet pile, i.e. the pore pressures at the tip are not equal at the left and right side of the pile. In the PLAXIS model this effect is taken into account as explained in Table 19.

In chapter 5 Blum calculations have been performed for the quay. In chapter 5 mean values are used. The results presented here are based on the characteristic values. Furthermore, the anchor force shown here is corrected for its inclination. The anchors are placed with an average angle of 45° . The anchor force as calculated by Blum is only the horizontal component while both PLAXIS and D-Sheet Piling show the axial anchor force. For comparison the Blum anchor force is transferred to the axial force.

Furthermore, only one anchor is included in the Blum calculation. The force shown here is thus the total anchor force which in reality is divided over two anchors.

The Blum results are:

- Moments in wall: $M_{min} = -1086,82 \text{ kNm}$
- Deflection wall: $D_{max} = -0,087 \text{ m}$
- Anchor force $T = 781,81 \text{ kN/m}$

Relatively larger differences are found with Blum compared to PLAXIS and D-Sheet Piling. This can be explained by the approximation used in Blum. This approximation is reasonable if the structure is close to failure. As noted before, the quay is not close to failure and thus the results of Blum show a larger difference.

It is concluded that the differences between the calculation models are explainable and thus that the PLAXIS model can be used for the calculations.

Optimized model

The results found in the base model are obtained after 312 seconds. If one would execute the same calculation as done for the model of Blum, BUS with Subset Simulation, on average 3000 calculations are required. These 3000 calculations are under the assumption that 500 samples are used in each Subset. The total time to evaluate this model would then be 7,2 days. Furthermore, six model runs are required to determine the result for the different measurement cases.

This is too long for the purpose of this thesis. Therefore, optimizations are sought for. These are sought in the following settings:

- 15-Noded vs 6-Noded
- Hardening Soil Small Strain vs Hardening Soil
- Reducing the number of phases
- Reducing the number of layers
- Fineness of mesh
- Model Boundaries

The results of the optimization process are found in Table 20. Iteratively the base model is changed and the results are presented. In green is indicated which optimized model is selected for the probabilistic calculations. The optimizations V6, V7, V9 and V10 in which the number of phases and the number of soil layers is reduced are explained here:

Step V6	The Initial Phase and Phase 1 are combined. Phase 5 and Phase 6 are also combined.
Step V7	In addition to the steps in V6, also Phase 2 and Phase 3 are combined.
Step V9	The Clay, slightly sandy, weak layer at NAP – 4 till NAP -5,5 m is removed. Resulting in a Sand Loose layer running from NAP 5,1 m till NAP -10 m
StepV10	In addition to step V9, also the Clay, slightly sandy, weak layer from NAP -21 m till NAP -23 m is removed.
Step V11	In PLAXIS it is possible to locally increase the density of the mesh. This allows a higher number of elements in high stress areas. In this optimization step in an area between $-2 < x < 2$ the mesh size is increased by a factor 2.

Selection of optimized model

Looking at the results in Table 20 some remarks can be made:

- Base → V1
The use of the Hardening Soil instead of Hardening Soil Small Strain changes the result significantly. The resulting moments and anchor forces change in the order of 5-10% and the relative change in displacements is even larger. However, the calculation time is more than halved. Due to the much faster calculation time, the Hardening Soil mode will be used.

- V1 → V2/3
The reduced model size influences the calculated displacements, with only a minor reduction of the calculation time. The predicted moments and forces are more or less equal to predicted with the larger boundaries. In the probabilistic model the larger model size is used.
- V1 → V7
In the process from model V1 to model V7, the results have changed in the order of 1%. This change does have the result that the calculation time significantly reduces. Therefore, the optimizations in 6-Noded elements, mesh size and phasing are used in the final model.
- V7 → V8
Combining Phase 2 and Phase 3, so the first small excavation and the placing of the anchors, results in a significant impact on the predicted displacements, while the moments and anchor forces remain in the same order of magnitude. As the calculation time does not significantly reduce, therefore in the final model five phases will be used.
- V7 → V9/V10
Using the same reasoning, reducing the number of soil layers has a significant impact on the results and only a minor influence on the calculation time. Therefore, seven layers will be used. In this deterministic calculation the influence of the reduced layers on the calculation time cannot be determined. In probabilistic calculations this influence might be more pronounced due to the fact that fewer variables need to be included.
- V7 → V11
The locally increased mesh density has a significant impact on the calculation time. The calculation takes almost four times longer, while the results are more or less equal. The global coarse mesh seems to be an optimal solution for results and calculation time.

Using the results presented in Table 20 an optimized model is determined. This optimized model uses the following settings:

- Number of Phases 5 phases
Combining Initial Phase and Phase 1 and combining Phase 5 and Phase 6.
- Soil model Hardening Soil
- Boundaries $x_{min} = -50,0 m, x_{min} = +50,0 m$
If smaller boundaries are applied the results change significantly without any change in the soil parameters, so these boundaries are chosen.
- Mesh size Coarse
- Number of Nodes per element 6-Noded elements
- Number of layers 7 layers

These settings represent the use of the optimized model number V7, as indicated in green.

Table 20 Optimization steps

Model	Results per running meter quay							Settings:					
	M_{min} [kNm]	M_{max} [kNm]	T_1 [kN]	T_2 [kN]	D_{top} [m]	D_{max} [m]	Time [s]	# phases	Soil model	Boundaries [$x_{min} - x_{max}$]	Mesh Size	Nodes per elements	# layers
Base	-1373,0	550,70	568,53	539,21	0,006	-0,089	312	7 phases	HS-SS ³	-50 till +50	Medium	15-noded	7 layers
V1	-1454,0	381,80	572,81	519,753	0,013	-0,100	123	7 phases	HS ⁴	-50 till +50	Medium	15-noded	7 layers
V2	-1454,0	354,60	569,140	517,253	0,013	-0,098	113	7 phases	HS	-40 till +40	Medium	15-noded	7 layers
V3	-1459,0	374,30	560,170	510,907	0,014	-0,096	113	7 phases	HS	-30 till +30	Medium	15-noded	7 layers
V4	-1449,0	389,60	571,329	519,627	0,014	-0,098	66	7 phases	HS	-50 till +50	Fine	6-noded	7 layers
V5	-1445,0	400,70	571,38	518,196	0,014	-0,098	27	7 phases	HS	-50 till +50	Medium	6-noded	7 layers
V6	-1448,0	391,40	571,53	516,81	0,014	-0,099	23	7 phases	HS	-50 till +50	Coarse	6-noded	7 layers
V7	-1447,0	390,20	572,67	517,42	0,013	-0,099	20	5 phases	HS	-50 till +50	Coarse	6-noded	7 layers
V8	-1534,0	393,30	584,54	520,40	0,038	-0,095	16	4 phases	HS	-50 till +50	Coarse	6-noded	7 layers
V9	-1293,0	392,90	561,78	496,81	0,011	-0,093	17	5 phases	HS	-50 till +50	Coarse	6-noded	5 layers
V10	-1272,0	310,00	570,97	506,79	0,003	-0,087	19	5 phases	HS	-50 till +50	Coarse	6-noded	4 layers
V11	-1449,0	386,60	574,531	519,704	0,011	-0,101	60	5 phases	HS	-50 till +50	Coarse+	6-noded	7 layers

³ HS-SS = Hardening Soil Small Strain

⁴ HS = Hardening Soil

Appendix G Results update PLAXIS model

The results of updating the PLAXIS model are presented here. In section 6.3 the results of the update for the maximum moment, displacement and anchor force are provided. In this appendix the results of the update for each included variable and each of the six cases defined in section 6.3 are shown here in Figure 47 till Figure 52. It is chosen to plot the relative change of the posterior distributions. The relative change is defined as:

$$Change = \frac{Posterior}{Prior}$$

A relative change larger than value one indicates that the posterior value is larger than the prior value. If the change is smaller than one, this means a lower posterior value. The red bars represent the relative change in posterior mean and the blue bars represent the relative change in posterior standard deviation.

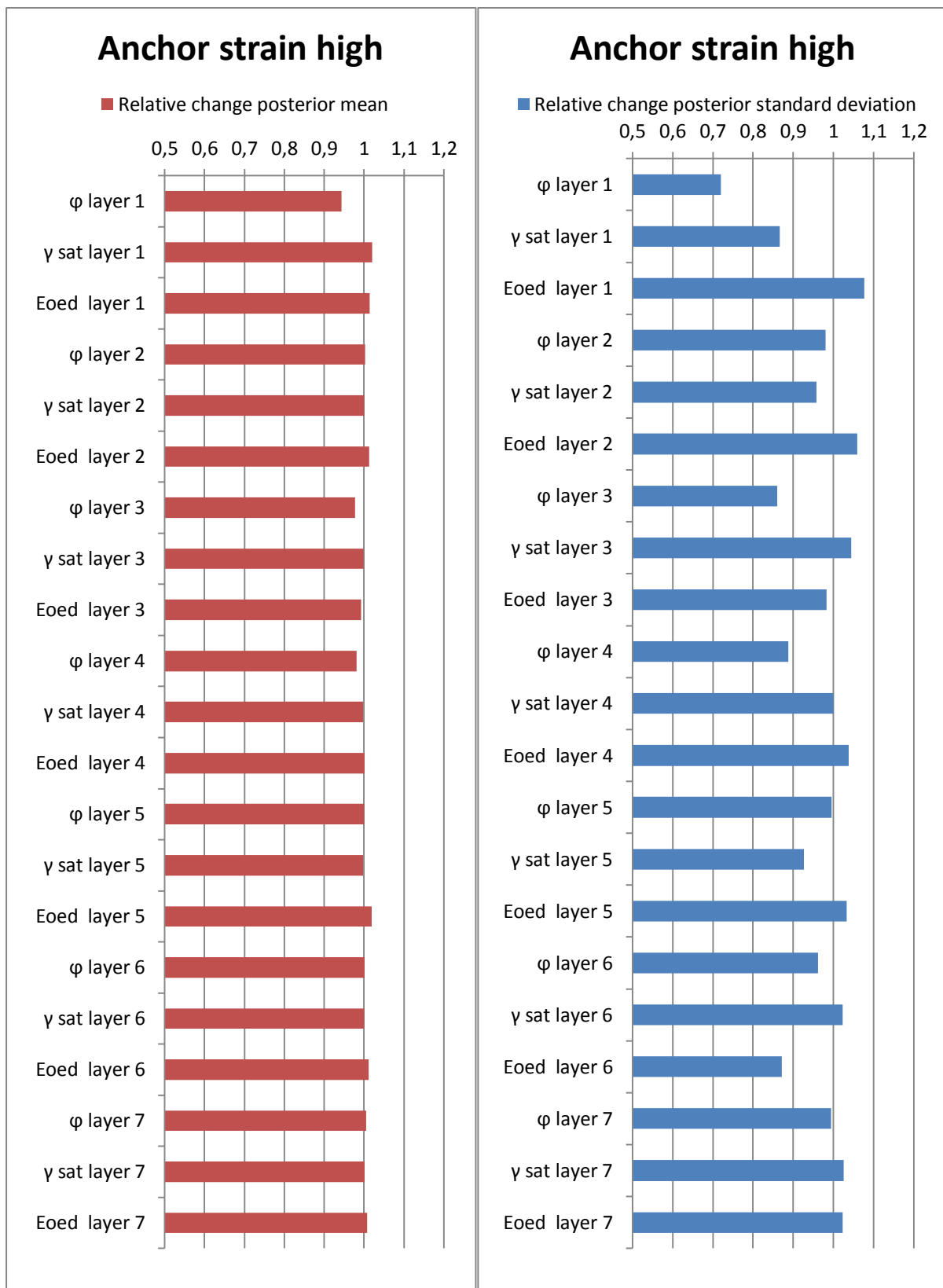


Figure 47 PLAXIS updated variables case anchor strain high

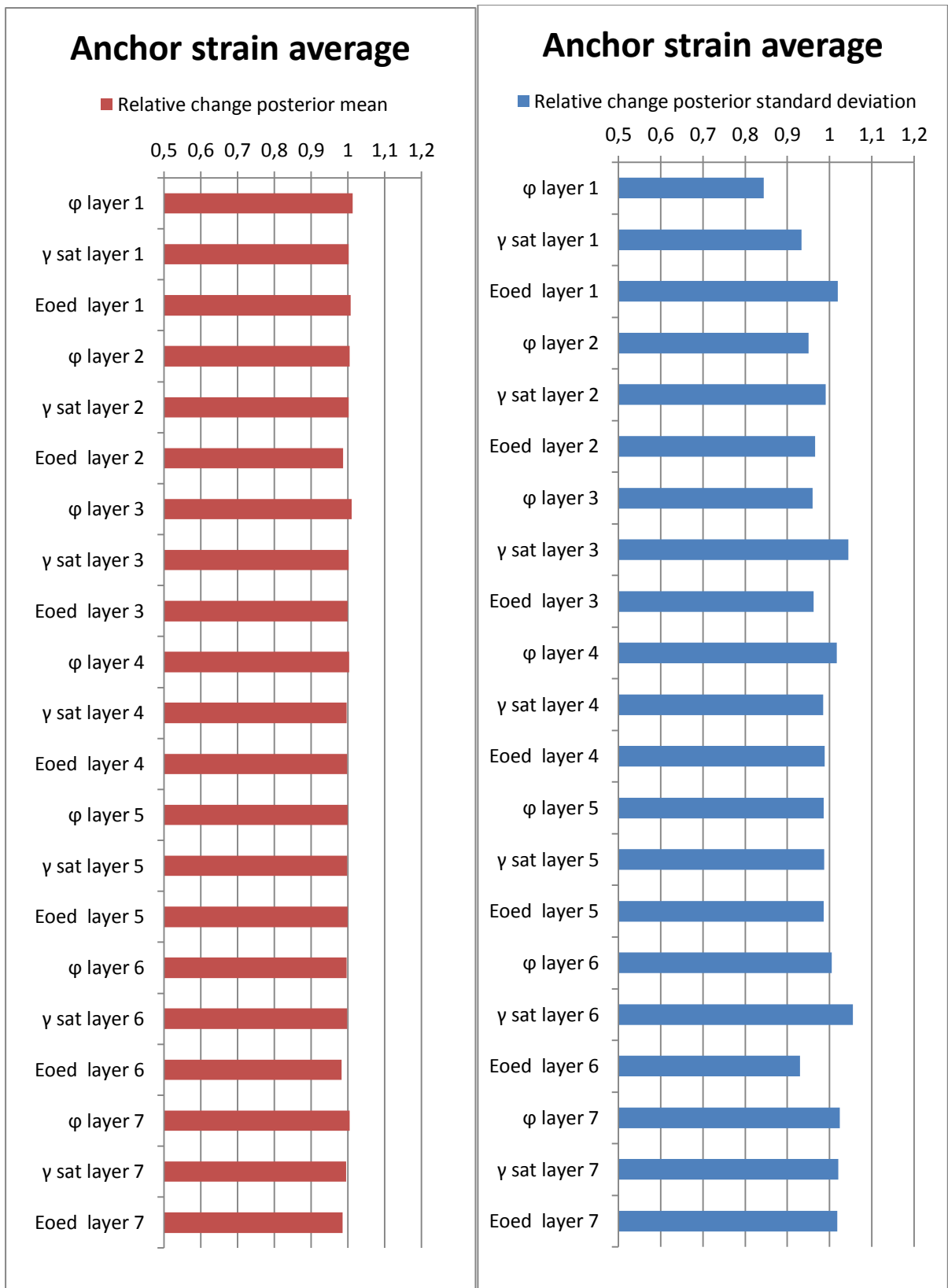


Figure 48 PLAXIS updated variables case anchor strain average

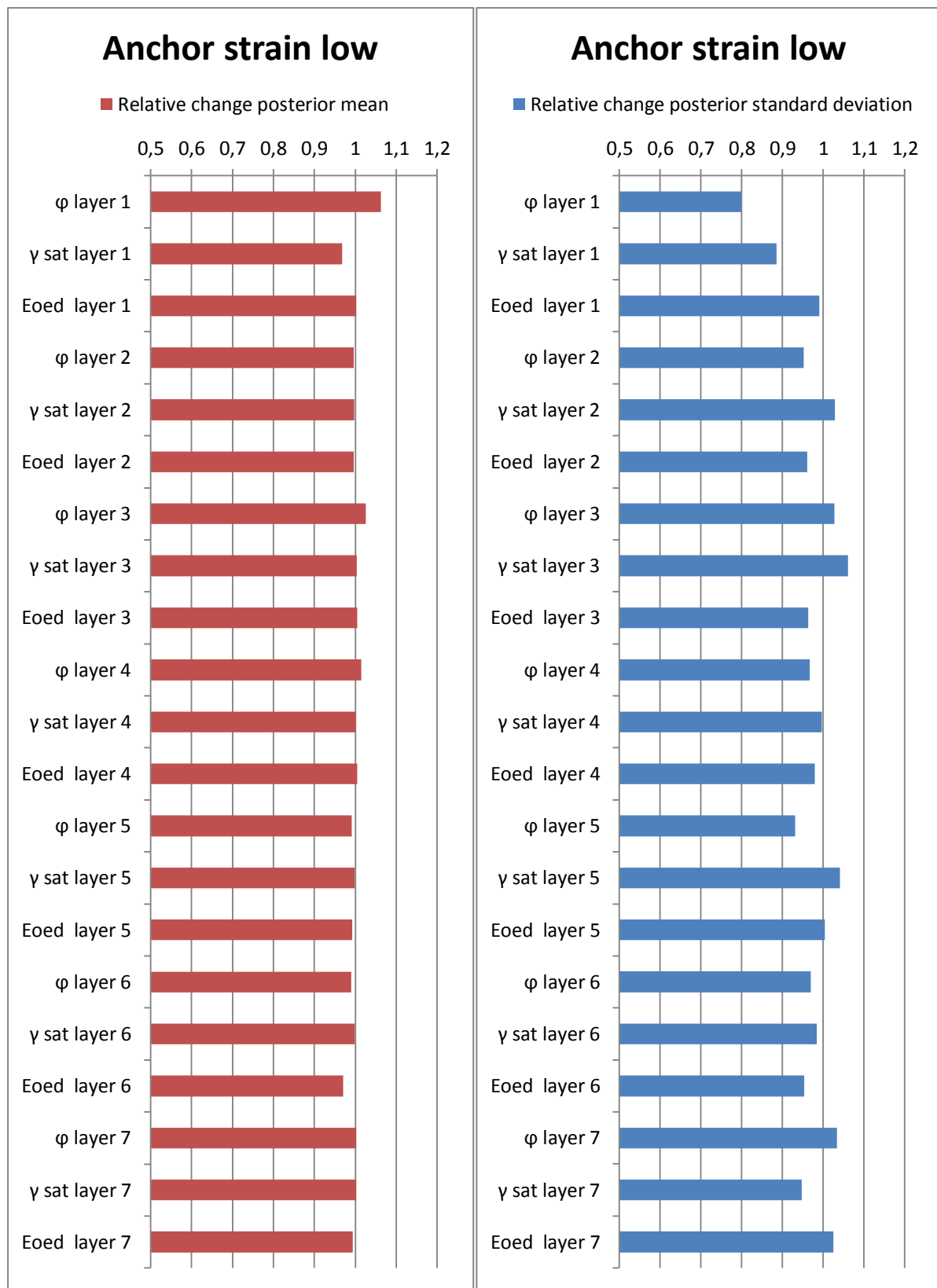


Figure 49 PLAXIS updated variables case anchor strain low

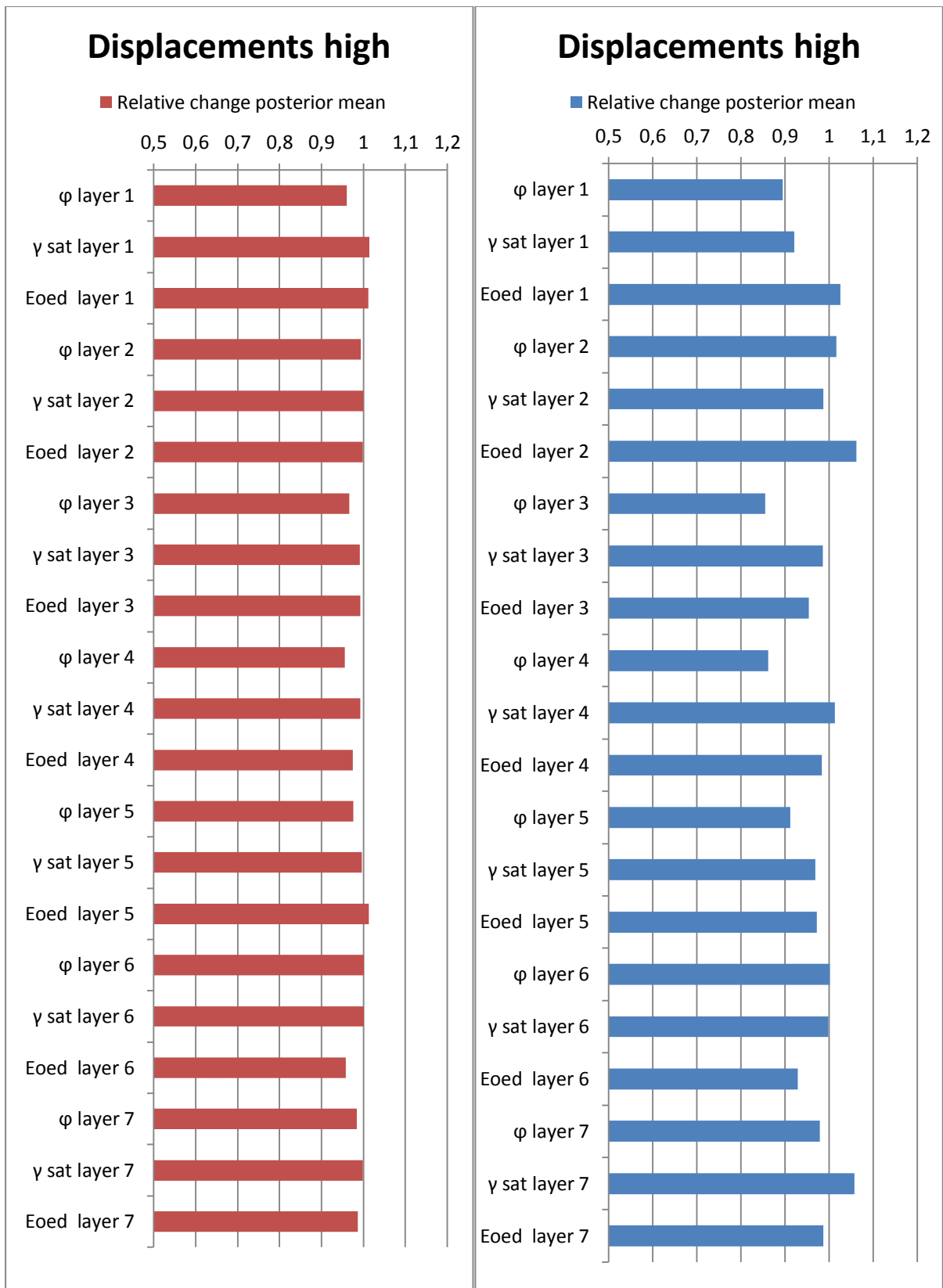


Figure 50 PLAXIS updated variables case displacements high

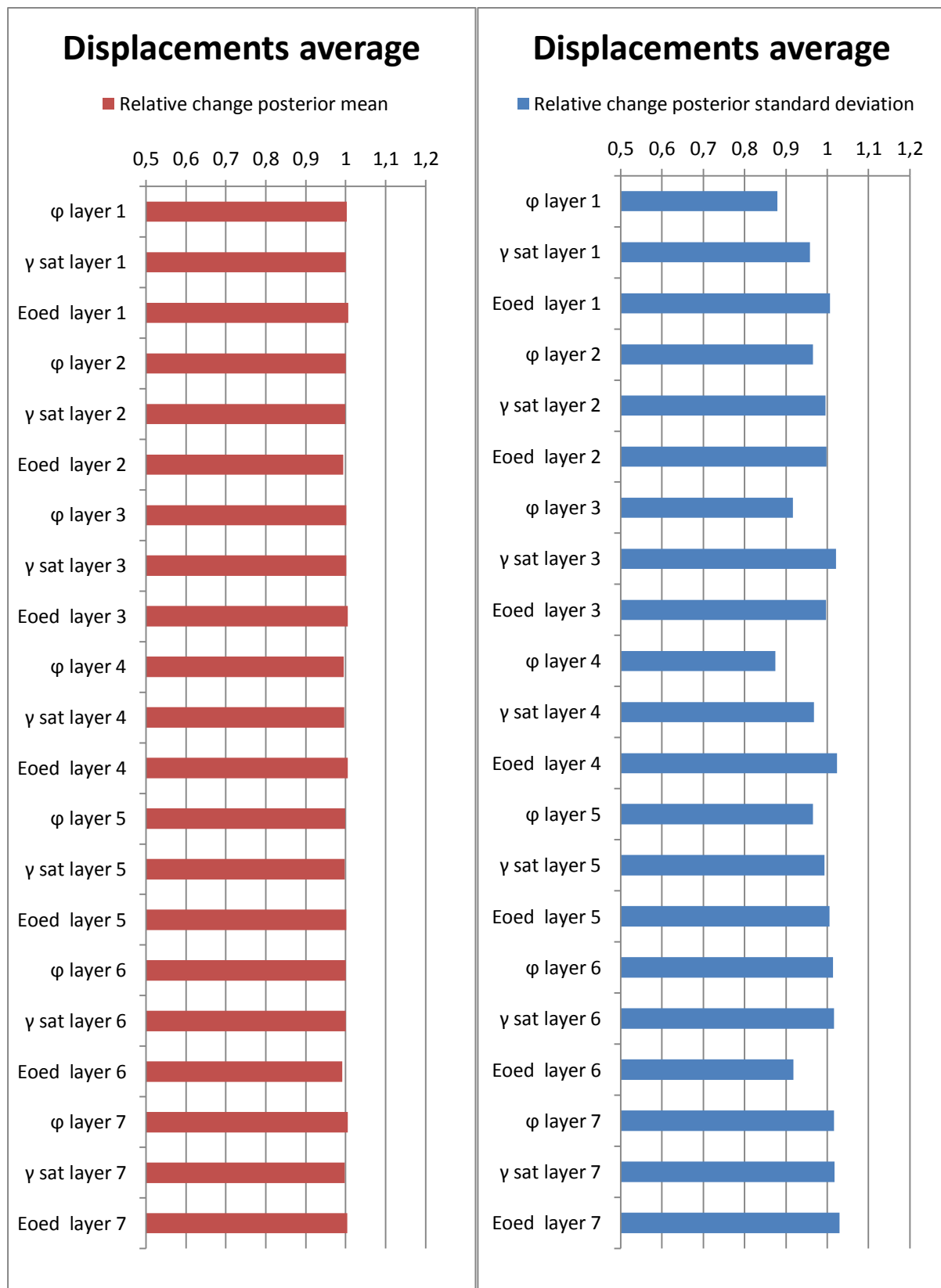


Figure 51 PLAXIS updated variables case displacements average

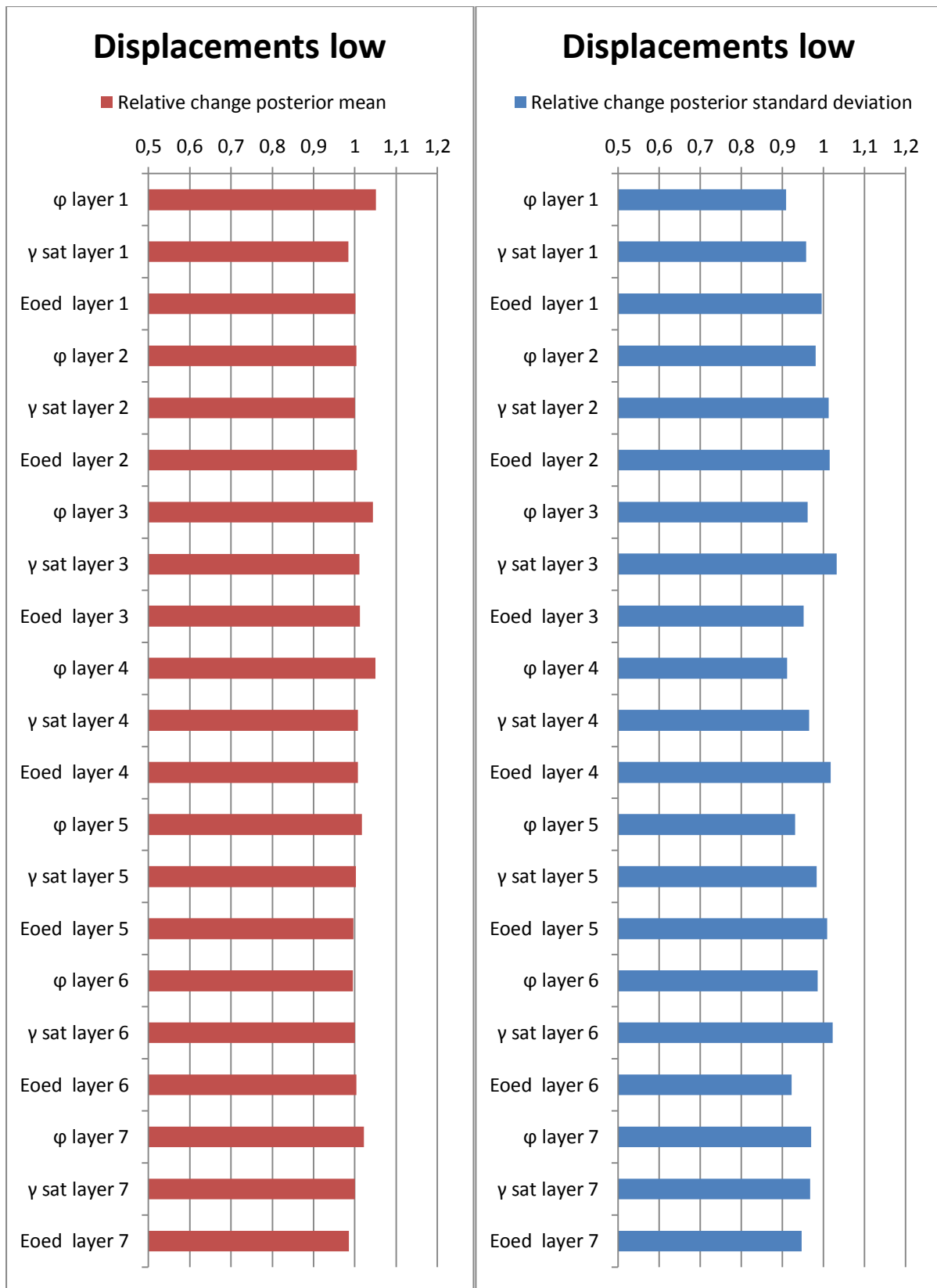


Figure 52 PLAXIS updated variables case displacements low