Optimization and Parametrization of Reinforced Concrete Cantilever Retaining Walls

Parametric optimization of reinforced concrete cantilever retaining walls using genetic algorithms

Structural Engineering and Building Technology (MPSEB)

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CHALMERS UNIVERSITY OF TECHNOLOGY
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Cover: Reinforced Concrete Cantilever Retaining Wall during construction.

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Abstract

Reinforced concrete cantilever retaining walls (RCCRW) are among the most common type of infrastructure projects and require detailed, time-consuming calculations and designs. Time is a key parameter in the construction industry and optimizing the process is therefore advantageous, especially during the bidding phase, where projects are secured. This thesis aims to investigate the potential to streamline the design process using an optimization algorithm. The study consisted of a literature review, development of a calculation model, and implementation of a genetic algorithm (GA) through a Python script to minimize investment cost and environmental impact. A convergence and case study were conducted to evaluate and compare the results.

The RCCRW was designed in accordance with current Eurocodes and the Swedish Transport Agency's national specifications for their implementation, *Transportstyrelsens Författningssamling* (TSFS).

The results show that optimization using GA enables one to quickly develop buildable solutions for RCCRW using optimization algorithms, which can be highly advantageous. The study has also indicated that a certain level of detail in the calculations is required for further optimization, highlighting a trade-off between optimization and generalization.

Keywords: RCCRW, RW, Optimization, Genetic Algorithm, Cost, Enviormental Impact.

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We would like to express our greatest gratitude to our examiner, Carlos Gil Berrocal, our supervisor, Alexandre Mathern, and the entire structural engineering department at NCC for their continuous guidance and feedback during this master thesis. Additionally, we would like to thank NCC as a whole for their hospitality and for giving us the opportunity to write our thesis in collaboration with them.

Björn Aloander, Erik Apelqvist, Gothenburg, May 2026

Contents

List of Acronyms

Below is the list of acronyms that have been used throughout this thesis listed in alphabetical order:

GA	Genetic Algorithm
MOO	Multi Objective Optimization
NSGA	Non-dominated Sorting Genetic Algorithm
RCCRW	Reinforced Concrete Cantilever Retaining Wall
RW	Retaining Wall
TSFS	Transportstyrelsens författningssamling

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Introduction

1.1 Background

In construction projects, many structural components are designed manually using calculation spreadsheets. These spreadsheets generally require repetitive steps and limit the flexibility of the process. Ultimately, spreadsheets make it difficult to handle changes in the planning process effectively. By converting these spreadsheets into digitally automated, parametrically governed tools, one can achieve a more efficient workflow, minimize the occurrence of errors, and optimize construction processes in general. Simultaneously, it is important to ensure that the solutions maintain a high buildability. The need for this type of optimization is especially relevant for ordinary and recurring construction projects and will, in this thesis, be demonstrated with a cast-in-place reinforced concrete cantilever retaining wall (RCCRW) which is a structure of this type.

A retaining wall (RW) is one of the most fundamental geotechnical structures, which retains the masses of earth and soil for roads, railways, and buildings in general Patil and Bagban (2015). The retained soil masses are kept at vertical position, which produces large vertical and horizontal forces on the retaining wall. There are several variations of retaining structures, but the most commonly used is the RCCRW, which consists of a vertical stem, a bottom slab with a heel, and in some cases a toe, see figure 1.1.

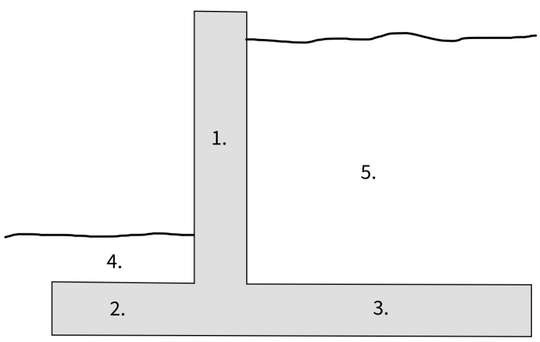


Figure 1.1: Illustration of a RCCRW and its parts: (1) Stem (2) Toe (3) Heel (4) Frontfill (5) Backfill

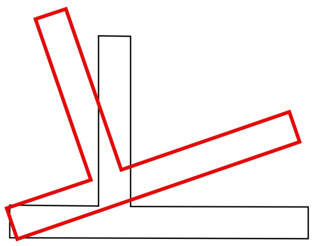
According to Patil and Bagban (2015) and SS-EN 1997-1:2005 there are three different types of failure modes for a retaining structure.

- Overturning due to unbalanced moments
- Sliding failure due to unbalanced horizontal forces
- Structural failure of the wall due to insufficient capacity

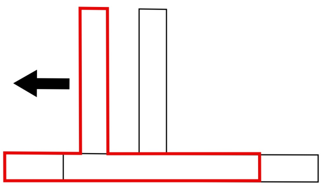
In addition, SS-EN 1997-1:2005 also requires to control the following geotechnical failure modes:

- Crushing of the earth below the retaining wall
- Total failure of the earth

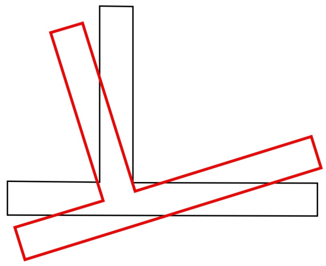
An illustration of these failure modes can be seen in figure 1.2.



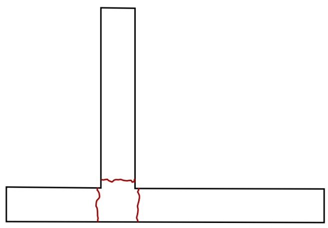
(a) Overturning



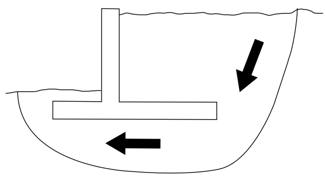
(b) Sliding



(c) Crushing of earth



(d) Structural failure



(e) Total failure of earth

Figure 1.2: Illustration of possible failure modes

A RCCRW is constructed of concrete and steel reinforcement. Both concrete and reinforcing produce large quantities of CO_2 during it's production and thus contribute to global green house gas emissions. According to Mohamad et al. (2022) and Kim et al. (2022) cement and structural steel production is responsible for 5-7 and 7-9 percent of global CO_2 emissions, respectively. As both materials are two of the most common building materials in the world, there is a substantial opportunity to reduce cost and environmental impact by optimizing construction designs. According to Kashani et al. (2022), RCCRW:s are frequently produced to great lengths, leading to large volumes of concrete and reinforcement steel. These factors generate a great opportunity to reduce the environmental impact as well as to reduce the cost of wall designs through optimization.

Optimization can be done in different ways. One way of implementing this to building design is through so called optimization algorithms which are mathematical algorithms designed to find the maximum or minimum solution for an objective function. Depending on how well the objective function is formulated, the more efficient the optimization is able to perform. The objective could, for example, be to find the shortest route on a map, to maximize profit, or to minimize costs. There are different types of optimization algorithms with individual advantages and disadvantages depending on which problem they are applied on Kashani et al. (2022). In construction design, optimization algorithms can be used to find the optimal design to minimize environmental impact or cost, which would be beneficial to both clients, companies, and society as a whole.

1.2 Aim

The aim of the thesis is to develop and evaluate a method for automating and optimizing the design of RCCRW:s within a parametrically governed set-based design process. The study will focus on identifying important parameters, typical configurations, and correct detail levels, while at the same time maintaining flexibility and compatibility to ensure that the method can be used in a variety of projects.

The final objective of the work is to establish a workflow that supports iterative optimization while making alterations possible without compromising safety and simultaneously minimizing time consumption. Furthermore, the method can act as a foundation for broader applications and contribute to the transition towards completely automated, optimization driven design processes. The RCCRW should be optimized for investment cost and environmental impact.

1.3 Research Question

The aim leads to three main research questions that will be investigated in the thesis.

- How can optimization algorithms be used for structural design optimization?
- How can the process of designing an RCCRW be optimized for different projects during the bidding phase?
- How can the optimization be used to evaluate already built RCCRW?
- How can an RCCRW be optimized towards multiple objectives, such as investment cost and environmental impact?

1.4 Scope and Limitations

The design process will use a simplified 2D model with a depth of one meter, assuming that the retaining wall extends sufficiently far in the out-of-plane direction to neglect the effect of the third dimension.

To ensure a quick and reusable solution, some site-specific parameters will be provided as input. This includes parameters that are governed by design codes and geotechnical specification, such as soil properties, surcharge loads, wall height, exposure class, concrete cover, etc. Variables that will go through the optimization process are those related to the wall, such as thickness of the wall, reinforcement amount, length of the toe and heel, etc.

The type of calculations that will be performed during the study is generally time-consuming as a large number of solutions must be evaluated for each case. Due to the time constraints of the project, the process will be made more efficient by using an optimization algorithm. It would be preferable to evaluate every possible design to find the true optimal solution, but the design spaces are simply too large. Depending on how well the algorithm is implemented, a suitable solution can be obtained in a more reasonable time.

Two aspects that are highly situational and vary significantly between projects and are not considered in the analysis are transport costs and labor hours. In both areas, it is difficult to determine values that are applicable in a general context. Including them in the analysis would make the designs either too general and unspecific or introduce inaccurate assumptions, resulting in unusable outcomes.

To ensure a safe design, the calculation will be performed in accordance with Eurocode and TSFS. The following codes will be used during the design process.

- SS-EN 1990:2023:Eurocode – Basis of structural and geotechnical design
- SS-EN 1991-1-1:2025: Eurocode 1 — Actions on structures — Part 1-1: Specific weight of materials, self-weight of construction works, and imposed loads on buildings
- SS-EN 1991-1-3:2025 Eurocode 1 — Actions on structures — Part 1-3: Snow loads
- SS-EN 1991-1-7:2006 Eurocode 1 – Actions on structures – Part 1-7: General actions – Accidental actions
- SS-EN 1992-1-1:2005: Eurocode 2: Design of concrete structures - Part 1-1: General rules and rules for buildings
- SS-EN 1997-1:2005: Eurocode 7: Geotechnical design – Part 1: General rules
- TSFS 2018:57: Transportstyrelsens föreskrifter och allmänna råd om tillämpning av eurokoder

1.5 Method

This section describes how the project process was conducted.

1.5.1 Theory study

The first part of the project consisted of a literature study in which previous research and literature were studied. Notable publications included current European and Swedish national standards, namely Eurocode and Transportstyrelsens författningssamling (TSFS). The study covered the subject of RCCRWs and general optimization. In addition to research, design examples of RCCRWs from IEG (Implementeringskommision för Europastandarder inom Geoteknik) were examined to ensure the literature was understood correctly. The objective of the study was primarily to understand the behavior of the RCCRWs and to identify which calculations constitute the design process, as well as to understand the different optimization methods and concepts. The knowledge acquired through the study was later applied when establishing the calculation model used in the design process. In addition, it also played an essential role in the analysis of the results obtained throughout the project work.

1.5.2 Optimization and Automation Process

The automation was initially developed in Excel where the information and knowledge acquired during the literature study was used. In the calculation spreadsheets, the design process for a specific case was calculated, including checks for different failure modes, deformation limits, and minimum reinforcement. Site-specific data, such as soil profile and exposure classes, were provided as input data by the user. The RCCRW parameters were also selected by the user in Excel, representing an iterative approach that is commonly used in the industry today.

Following the Excel calculations, the process was translated into a Python script that used site-specific data as input data from Excel, making it possible to compare the results obtained from the two approaches. The specific data in question can be seen in Table 3.1. The main difference between the Python script and the Excel calculation was that the script employed an optimization algorithm on the identified parameters from the litterateur study, specifically a genetic algorithm (GA), which iteratively evaluated thousands of designs to identify an optimal solution. As the GA heavily depends on the selected configuration settings that are used, a convergence study was carried out to obtain the optimal configuration settings with respect to population size, number of generations, crossover points, and mutation probability.

1.5.3 Case Study

Furthermore, a case study was conducted, where the designs of two previously constructed RCCRWs were compared to the result produced by the script to assess the quality of the optimization implementation using the selected optimal configurations. Of the two walls, one had been heavily optimized due to strict geometrical constraints and high loads, while the second RCCRW represented a more conventional design without severe geometrical constraints or high loads.

1.6 Societal, Economic and Ethical Aspects

The approach of the study aligns with the ambition of the construction industry to advance through digitization and produce sustainable infrastructure. Both aspects contribute to more efficient decision-making, improved resource utilization, and ultimately a reduced environmental impact of the construction industry. In addition to the ecological benefits, improved time and resource efficiency also contributes to more economically sustainable projects, thus positively influencing societal development.

1.6.1 Usage of AI

During the project, AI was used in several ways. Firstly, it was utilized to improve existing code and generate new code for the project. This was achieved by initially writing a draft version of the code, which was subsequently refined with the assistance of AI. AI also served as a tool to structure data and improve computational efficiency. Lastly, AI was used for LaTeX formatting, which improved the workflow and overall efficiency of the project. All text and code generated with the assistance of AI were carefully analyzed and verified to ensure correctness and proper functionality. This verification process was conducted with great caution, as errors could have significantly affected the final design and potentially led to structural failure.

2

Theory

2.1 Mechanics of an RCCRW

Although there exist several different types of retaining walls, the cantilever type is the most common type produced today. It is classified as yielding because it has no lateral constraints, and thereby being able to rotate (Brooks & Nielsen, 2010). According to Brooks and Nielsen (2010) recurring subcategories of cantilever retaining walls include regular masonry or concrete walls, counter-fort RW, gravity RW, anchored RW, etc. Brooks further explains that the horizontal pressure is often calculated with Rankine theory. Rankine theory is a simplified method of Coloumb theory that gives a conservative value. More precise values of the horizontal pressure can be calculated with Coulomb theory. However, Coloumb theory requires more in depth calculations. To determine the load on a retaining wall, significant factors include the friction angle of the earth, height of the wall and soil unit weight Fenton et al. (2005). In addition, displacements during the construction of a retaining wall are a critical aspect in terms of its functionality.

2.1.1 Loads

According to Patil and Bagban (2015), Gong (2014), and Brooks and Nielsen (2010), several loads are acting on the RCCRW. These include:

- Self-weight of wall
- Earth pressure
- Axial loads
- Adjacent footing loads
- Surcharge loads
- Impact forces

These loads arise from the self-weight of the retaining wall, the attributes of surrounding environment, and the behavior of the soil. According to Brooks and Nielsen (2010), the horizontal pressure can be calculated using Rankine theory, which calculates a coefficient that is multiplied by the vertical earth pressure. This method produces conservative values and is recommended for RW design in general. The vertical and horizontal pressure increase with the depth of the soil, and larger forces act closer to the bottom of the stem rather than the top. If the surrounding soil is homogeneous, the horizontal force increases linearly with depth and can be observed as "7." together with the other loads in Figure 2.1.

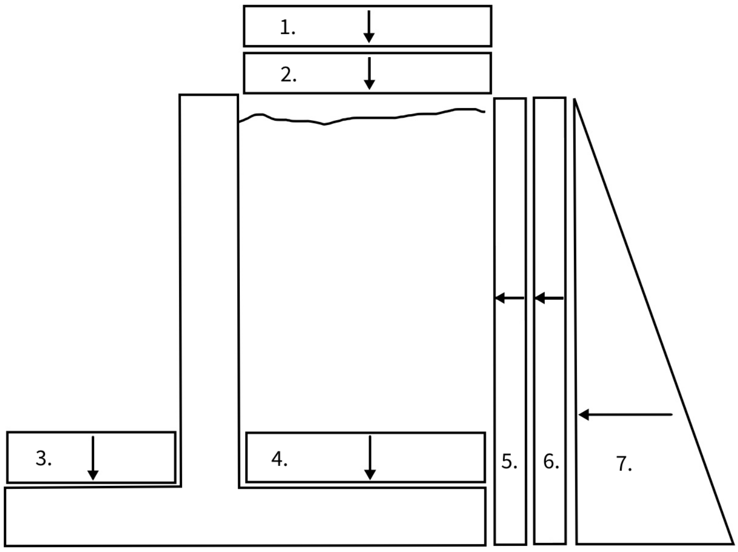


Figure 2.1: Loads acting on the RW: 1. Vertical traffic load, 2. Vertical snow load, 3. Frontfill, 4. Vertical load from backfill, 5. Horizontal traffic load, 6. Horizontal snow load, 7. Horizontal backfill load.

2.1.2 Failure Mechanisms

According to Patil and Bagban, 2015 there are three types of failure mechanisms of a RW which can be seen in 1.2. Additionally, the wall should be safely designed according to SS-EN 1997-1:2005. SS-EN 1997-1:2005 demands that crushing of the earth below the retaining structure and total geotechnical failure should also be controlled.

Overturning occurs due to a moment imbalance between the destabilizing and stabilizing moments around the front of the wall toe. Gong (2014) states that the overturning moment for a retaining wall that lies directly on soil can be difficult to predict. It is common to consider that an overturning failure occurs when the pressure at the bottom of the heel becomes smaller than or equal to 0 ($P_{bottom.heel} \leq 0$). This is an "indirect" way to calculate the overturning moment Gong (2014).

Sliding is caused by an imbalance of destabilizing and stabilizing horizontal forces according to (Patil & Bagban, 2015). The horizontal earth pressure needs to be smaller than the resisting capacity of the wall due to friction underneath the wall.

Bending failure occurs when the moment capacity of the cross-section is smaller than the internal moment imposed by the external loads. The critical section is located at the bottom of the stem as it acts as a cantilever (Patil & Bagban, 2015). Due to the overturning moment, the heel experiences negative net pressure and tensile stresses at the top. The same overturning moment causes positive net pressure at the toe and tensile stresses at the bottom. Both of these act as cantilevers, and the critical sections have to be designed. Additionally, the same control for shear capacity in critical sections have to be done. The critical sections with regard to shear might not be the same as the critical sections with regard to moment.

Crushing of the earth occurs when the pressure inflicted on the soil beneath the structure exceeds the capacity of the soil (Bergdahl et al., 1993). The type of failure that occurs in the soil depends on the relative density and relative foundation depth. The capacity of the soil is calculated using the general bearing equation shown in Eq. 2.1.

$$q_b = c\, N_c\, \xi_c + q\, N_q\, \xi_q + 0.5\, \gamma'\, b_{\mathrm{ef}}\, N_\gamma\, \xi_\gamma \tag{2.1}$$

Definitions

$$\begin{aligned}
q_b &= \text{ultimate bearing capacity} \\
c &= \text{soil cohesion} \\
q &= \text{overburden pressure at foundation level} \\
\gamma' &= \text{effective unit weight of the soil below foundation level} \\
b_{\mathrm{ef}} &= \text{effective width of the footing} \\
N_c,\ N_q,\ N_\gamma &= \text{bearing capacity factors depending on the soil friction angle} \\
\xi_c,\ \xi_q,\ \xi_\gamma &= \text{correction factors accounting for deviations from ideal conditions}
\end{aligned}$$

Total stability, or slope stability, is the failure of a slope or soil beneath the structure, causing the soil to rotate and slide away. This failure mode is mainly influenced by the properties of the soil CED Engineering (2016). Failure occurs due to a force imbalance that breaks the equilibrium.

2.1.3 Design and Reinforcement Layout

Initial estimates of thicknesses and widths can be made when the height of the RC-CRW is known. Gong (2014) suggests the following initial estimates when designing a RCCRW.

- $0.4H \leq B \leq 0.8H$
- $L_{\mathrm{toe}} \approx \frac{B}{3}$
- $\frac{H}{12} \leq t_{\mathrm{stem}} \leq \frac{H}{8}$
- $t_{\mathrm{slab}} \geq t_{\mathrm{stem}}$

Definitions

$$\begin{aligned}
B &= \text{width of base slab} \\
H &= \text{Height of RW} \\
L_{toe} &= \text{length of toe} \\
t_{stem} &= \text{stem thickness} \\
t_{slab} &= \text{slab thickness}
\end{aligned}$$

One of the main design factors is the stem moment, which occurs at the bottom of the stem. The stem moment needs to be resisted and thereby sets the requirements for stem thickness as well as reinforcement amount. Normally, it is desirable to minimize both of these values with respect to environmental and economic impact. As the internal forces increases with wall height, the top part often requires less resistance. According to Brooks and Nielsen, 2010, this means that the wall dimensions and reinforcement layout should vary throughout the cross-section. Tensile reinforcement is also required in the tensile zones of the heel and toe. The main tensile reinforcement for the critical sections can be seen in Figure 2.2. Additionally, minimum reinforcement is required in all zones to ensure that the widths of the cracks caused by shrinkage are within the limits of the national regulations.

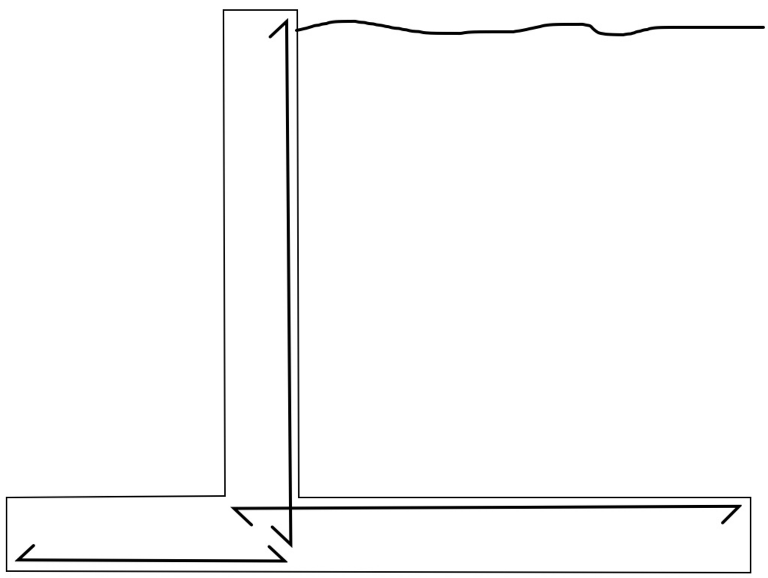


Figure 2.2: Figure of how the main reinforcement in a RCCRW is needed in the critical sections toe, heel and stem.

2.2 Optimization

Optimization can be described as the maximization or minimization of a function subject to constraints on its variables (Wright & Nocedal, 1999). In addition, optimization problems are often described as problems that have multiple possible solutions. These problems often arise from challenges encountered through human activities, which entails that they have been studied extensively throughout history (Ruszczynski, 2006). Finding multiple ways to solve the problem is often easy, while choosing the ideal one poses a greater challenge. The choice of solution is dependent on the *objective* or *objectives* in question. Without an objective, the solver will not know what to optimize. Furthermore, the objective is affected by certain attributes, often known as *variables*, *parameters*, or *unknowns* of the system. Through optimization, the ideal values for the variables within the system are chosen to achieve optimal objective results. Typically, the parameters are subject to some type of *con-*

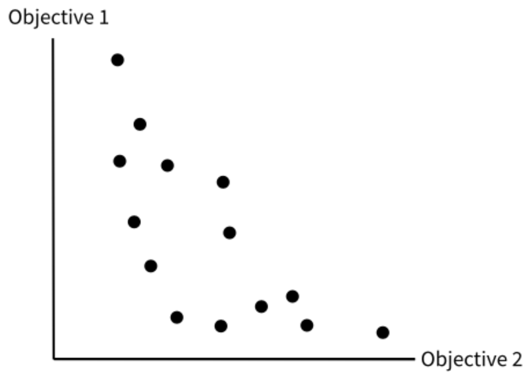
straint. This could, for example, be facts or logical assumptions, such as the electron density in a molecule or interest rates only being able to be positive (Wright & Nocedal, 1999). The act of identifying each of these three elements: objective, variables, and constraints, is called *modeling* and constitutes a crucial part of the optimization process. The quality of the result often depends heavily on the degree to which the modeling is performed. If the model is too simple, the result becomes too weak; if it is too advanced, it may be too demanding to solve (Wright & Nocedal, 1999).

To put this into context, one can observe an optimization problem called "The traveling salesman problem", which has been studied since 1759. The *objective* of the problem is to plan the most effective route for a salesman who starts in his home city and is required to visit every city on a map once before returning. To solve this, one commonly models the choice of using a specific road as a binary *variable*, and a *constraint* is, for example, that every road can only be used once (Larranaga et al., 1999).

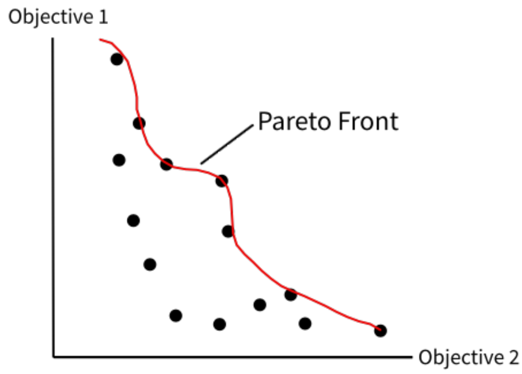
Apart from constrained optimization problems, a problem can also be unconstrained. In unconstrained optimization, no explicit constraints are imposed on the formulation of the problem. A constrained problem can be transformed into an unconstrained one by adding penalty terms to the objective that counteract violations of the original restrictions (Wright & Nocedal, 1999).

2.2.1 Multi-Objective Optimization and Pareto Front

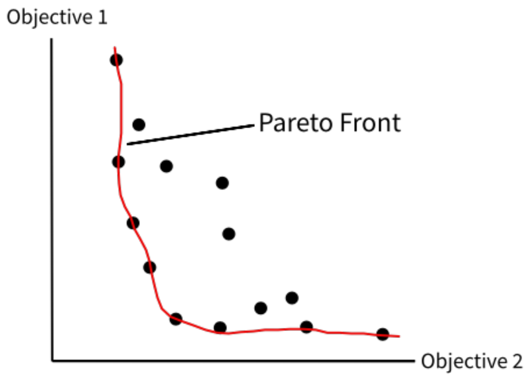
As there are many situations in which multiple objectives concern a problem, one often talks about multi-objective optimization (MOO). A common issue with these optimization problems is that the objectives can conflict with each other. Examples of objectives are time, weight, environmental impact, cost, risk, etc (Wright & Nocedal, 1999). A common practice for presenting results from MOO is to use a *Pareto Front*. A Pareto front consists of the non-dominant solutions of a multi-objective optimization problem. The idea is to present the best trade-off solutions among the different objectives. Every objective is assigned an axis and every solution is assessed for each objective, giving it a position in the graph dependent on its performance, see Figure 2.3 for illustrative examples. Depending on whether the aim is to maximize or minimize the objective, the Pareto front can differ. An advantage of the method is that it is an effective way of highlighting multiple solutions with different degrees of optimization and the relationship between the objectives. A limitation of the method is that the degree of weighting or trade-off between the objectives needs to be set in advance, which can be challenging to determine correctly in certain situations (Veldhuizen et al., 1998).



(a) General result



(b) Pareto front, maximization



(c) Pareto front, minimization

Figure 2.3: Example of a maximum and minimum Pareto front of a sample group.

2.2.2 Continuous or Discrete Optimization

Depending on the problem, the variables of the model may be required to take integer values. These types of problems are known as *integer optimization problems*. Integer programming problems are part of the broader term *discrete optimization*, which implies that a variable x is chosen from a finite set of integer values. In contrast, certain problems allow the variables to be continuous; these are called *continuous optimization problems*. Consequently, these types of problems have an infinite number of solutions. In some situations, the model demands that some variables be discrete, while others can be continuous. These problems are called *mixed-integer problem*. Since mixed-integer problems include continuous variables, they also have an infinite number of solutions (Wright & Nocedal, 1999).

2.2.3 Global and Local Optimization

The solutions reached by the optimization algorithms can be divided into two different types, local and global solutions. A local solution is one that solves the problem but is not guaranteed to be the true optimal solution, while a global is the ideal one. The challenge is often knowing whether the found solution is local or global, especially when the set of variables x is continuous and thereby infinite (Wright & Nocedal, 1999).

2.2.4 Optimization Algorithms

As optimization problems can often be described mathematically, the objective, variables and constraints can be translated to an objective function $f(x)$, variables x, and constraint functions c_i, respectively. Using these notations, an optimization problem can be modeled as follows:

$$\begin{aligned} \min_{x \in \mathbb{R}^n} \quad & f(x) \\ \text{subject to} \quad & c_i(x) = 0, \quad i \in \mathcal{E}, \\ & c_i(x) \geq 0, \quad i \in \mathcal{I}. \end{aligned} \tag{2.1}$$

where $\mathcal{E}$ and $\mathcal{I}$ are the index sets corresponding to the equality and inequality constraints, respectively (Wright & Nocedal, 1999).

Once the model formulation has been achieved, an *optimization algorithm* can be applied, which is commonly done using computers. Today, there exist several optimization algorithms customized for specific problems and it is the user's responsibility to pick the most suitable algorithm for the task at hand. In the case of a poorly chosen algorithm, there is a risk that the problem is solved inefficiently or not at all. If the problem is solved, the model should typically be analyzed and evaluated to determine whether it can be improved further to achieve better results (Wright & Nocedal, 1999).

A common technique for an optimization algorithm is to initially randomize values for the variables and then iterate until it reaches a final estimate. The method used depends on the chosen algorithm, as they all work differently. Regardless of which algorithm is used, a well-functioning method should strive to be robust, efficient, and accurate. These objectives may be in conflict, which is why they need to be weighed against each other to achieve a suitable solution (Wright & Nocedal, 1999).

Furthermore, optimization can be divided into different categories based on type and properties, which are elaborated on in the following sections.

2.2.4.1 Stochastic Meta-Heuristic Algorithms

Stochastic meta-heuristic algorithms are a type of optimization in which the strategy is to find a solution that is "close enough" to the optimal solution by implementing randomization to analyze the system. The concept consists of two main parts: intensification and diversification. The intensification part analyzes, locates, and improves the current best solution, while diversification introduces randomization into the process. By doing this, the algorithm is able to find a wider spectrum of solutions more efficiently, and thereby end up closer to the true optimal solution, avoiding local maxima or minima. Adjusting these types of algorithms implies weighing these two parts against each other. Too much intensification may cause the algorithm to get stuck, while too much diversification can hinder it from converging. Stochastic meta-heuristic algorithms are especially effective when the problem is too complex or when finding the exact solution is too demanding (Gandomi et al., 2013). This is often the case when the optimization problem being studied has multiple objectives to achieve while also being nonlinear and nondeterministic (Mishra & Arora, 2023). Some typical stochastic meta-heuristic algorithms are:

- **Evolutionary Algorithms (EA)**
  A modern heuristic search method based on the evolutionary idea that a population evolves and adapts over generations. An evolutionary algorithm reenacts this by creating a randomized population of solutions that, after a selection process, *reproduces* over iterations, creating new combinations. The new combinations are then evaluated and assigned a fitness score to determine whether they are suitable for future generations. The algorithms also use some form of stochastic element in the form of mutations within the population (Vikhar, 2016)

  - **Genetic Algorithm (GA)**
    The genetic algorithm is one of the most common evolutionary algorithms and simulates genetic evolution by modeling every solution as an individual of a population. Every individual has a set of random chromosomes that represent its properties. Every combination of properties or solution generates a *fitness score*, which corresponds to the objective function. Initially, the population is subjected to a selection process that selects pairs of specimens. These then reproduce to create a new population with merged attributes, this process is called *crossover*. During the process, there is also a possibility of *mutations* occurring, which introduce a randomization factor and increase the variety within the set. After mutating or not, one iteration is thereby completed, and the process repeats with the new population unless the termination criteria are met, at which point the simulation terminates. Usually, the algorithm stops either when a set number of iterations has been performed or when a target fitness score is achieved. Additional factors such as *elitism* can be introduced to protect solutions with high fitness scores if there is a risk of them being eliminated during the selection process (Immanuel & Chakraborty, 2019). Another significant parameter regarding GA is *punishment*. If a constraint is violated, a penalty or punishment can be applied to the algorithm. If the design is not feasible, a more severe punishment can be applied. These are often called "death penalties," where the design receives such a severe penalty that the fitness score becomes one of the lowest and does not make it to the next generation (Barbosa & Lemonge, 2003). The workflow of a genetic algorithm can be seen in Figure 2.4.

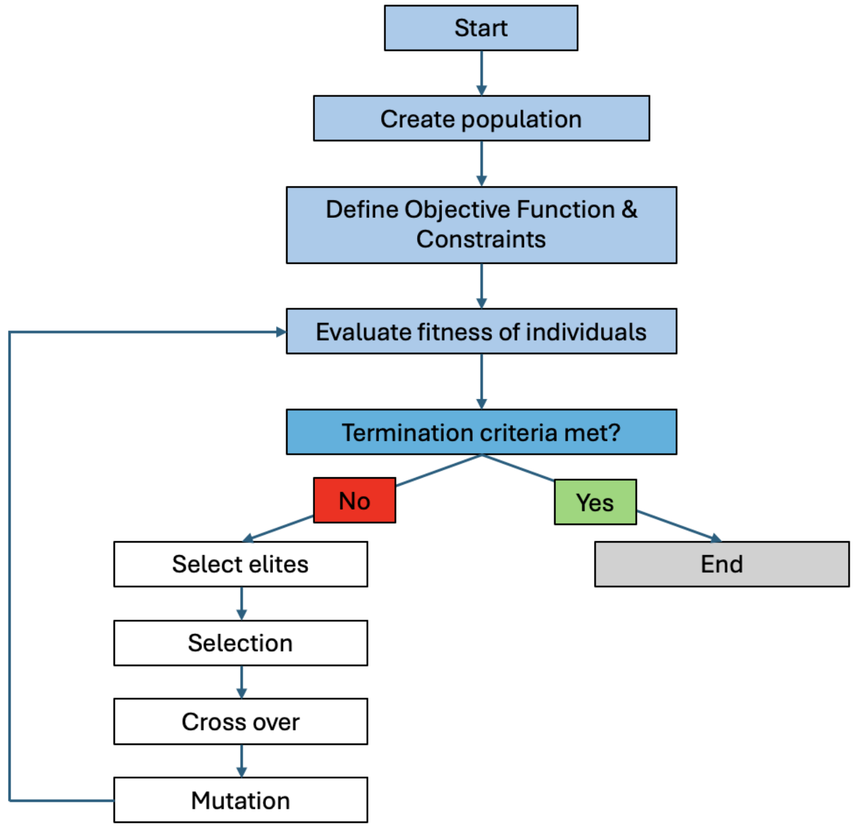


Figure 2.4: Flow chart of GA.

- **Swarm Intelligent Algorithms (SIA)**
  These types of algorithms consist of a population of random solutions that together achieve *swarm intelligence*. The population is known as the *swarm*, and each solution is known as a *particle*. Every particle evolves through experience, called cognitive learning, and through interactions with surrounding particles, called social learning. After each iteration, every particle stores the optimal global solution as well as its personal best solution in its memory. This procedure makes the swarm evolve toward an improved and more precise solution over time. Common SIAs include Particle Swarm Optimization and Ant Colony Optimization (Bansal et al., 2019).

2.2.4.2 Multi-Objective Optimization Algorithms

Optimization algorithms specific for multiple objectives are presented in this section.

- **Non-Dominated Sorting Genetic Algorithm (NSGA)**
  The non-dominated sorting genetic algorithm (NSGA) is a technique that combines GA with the non-dominated sorting method (Ma et al., 2023). A population of N solutions is first generated randomly and evaluated using the objective functions. The solutions are stored in a temporary population T, where the non-dominated solutions are identified. These solutions form the first front and are assigned the best rank. The non-dominated solutions are

then removed from T, and the process is repeated for the reduced population to identify the second front. This procedure continues until all solutions have been assigned to a front according to their non-domination level. The obtained ranks are then used during selection, recombination, and mutation to generate the next population.

A solution is said to dominate another solution if it performs at least as well in all objectives together with it performing strictly better in at least one objective. A solution is non-dominated if no other solution in the population dominates it (Ma et al., 2023).

- **NSGA-II**
  NSGA-II is an improved version of NSGA (Ma et al., 2023). NSGA-II computes the rank of a solution by considering both the solutions that dominate it and the solutions that it dominates. In addition, a crowding distance is calculated for each solution to preserve diversity among solutions within the same front. The crowding distance is determined using the neighboring solutions along each objective function.

  The crowding distance is used as a secondary sorting criterion when solutions belong to the same front. Solutions with larger crowding distances are preferred since they are located in less crowded regions of the objective space.

2.2.5 Seeds

When running an optimization algorithm, it is possible and likely that the result differs between each run. This phenomenon is due to each run having different so-called seeds. A seed is a set of random variables used in an algorithm that results in a solution within the *design space* of the algorithm, which consists of all possible solutions (Schulz et al., 2013). Every seed generates a particular result and can be used in multiple ways for analysis. For example, using multiple seeds, one can find the standard deviation of the algorithm, or by using the same seed multiple times with multiple configurations, the performance of specific configurations can be assessed. When using the same seed twice, the algorithm yields the same result both times if performed correctly and can thereby enable a fair comparison (Colas et al., 2018).

2.3 Choice of Algorithm

According to Kashani et al. (2022), multi-objective evolutionary algorithms have gained much popularity due to their effectiveness and easy implementation in multi-objective optimization. Mishra and Arora (2023) state that meta-heuristic algorithms are required to solve nonlinear, complex, multi-objective, and nondeterministic problems, much like an RCCRW optimization problem. Mishra and Arora (2023) also state that meta-heuristic algorithms are known as approximation algorithms and yield solutions that are functional and as effective as possible.

3
Methodology

To choose the best optimization algorithm, an evaluation of the objective, variables, and constraints was conducted. The objective of the optimization was to minimize the investment cost, environmental impact, or both. Since variables such as the thickness of concrete and the number of reinforcement bars are not continuous functions but rather a discrete set of values, this limited the options of algorithms to discrete optimization. National regulations and Eurocode standards were modeled as constraints to ensure a safe structure.

This resulted in the genetic algorithm being the most suitable choice. The design constraints can be controlled directly when all the parameters are known. This is similar to how the design process is performed in the industry today, through trial and error. However, with the genetic algorithm, many more combinations can be tested to find the most suitable one in a short amount of time.

The method of obtaining the optimal result was an iterative process. Firstly, a simple design with few parameters was optimized toward a single objective. The aim was to keep the design changeable for further improvements and development in the future. The model was kept simple, and a MOO to minimize both cost and environmental impact was performed.

To achieve easy implementation of the optimization without prior knowledge of programming, the input of site-specific data was provided through Excel, a common tool used in the industry and one that most engineers have prior knowledge of. The optimization algorithm used in Python took values from specific cells in Excel and imported them into the script, where the optimization was performed using the GA.

3.1 Calculations in Excel

After studying the standards, calculations for an arbitrary retaining wall were performed in Excel in accordance with the requirements of the standards. The purpose of the calculations was to define the resistances, loads, and standard requirements such as concrete cover and maximum crack width. Starting from a clean sheet, the process clarified and ensured that adequate requirements and design limits were used throughout the project. In addition to regulations, the Excel analysis also clarified which parameters would be adjustable and which needed to be set in advance as inputs. See Table 3.1 and 3.2 for the identified input data and variables that were used in the design of the wall. Reinforcement diameter, spacing, and number of reinforcement layers are all variables in the heel, toe, and stem.

Input Data	**Unit/possible value**
Height difference	m
Frontfill difference	m
Groundwater level	m
Drainage	yes/no
Safety class	1-5
Exposure class	e.g XS1
Service life	years
Concrete type	e.g C30/37
Relative humidity	%

Table 3.1: Input data specific for each site.

Parameter	**Variable**	**Unit**
Thickness stem	t_s	m
Width toe	w_t	m
Width heel	w_h	m
Thickness base slab	t_b	m
Reinforcement diameter	ϕ_s	m
Reinforcement spacing	s	m
Number of reinforcement layers	n_{layers}	-

Table 3.2: Identified variables for the GA.

A visual illustration of the variables can be seen in Figure 3.1.

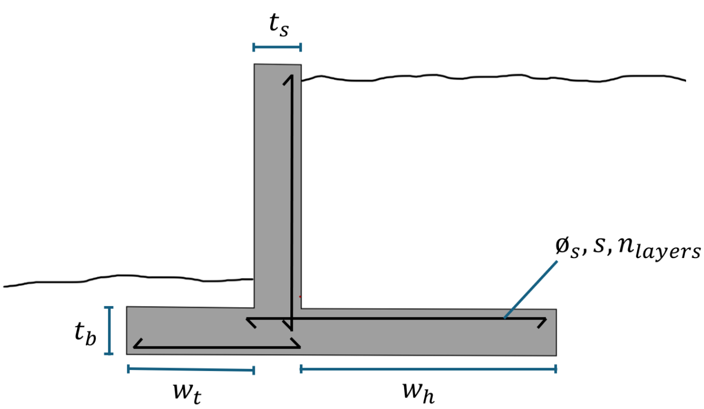


Figure 3.1: Visual illustration of identified variables of a RCCRW.

To achieve the "optimal" design in Excel, the parameters were changed manually by the user of the spreadsheet and could be iterated toward an optimal design. As the parameters affect all utilization rates, this can be a difficult process, much like the one commonly used in the dimensioning process today.

3.2 Environmental and Cost Analysis

The environmental impact is tracked as kg CO_2-eq/m^3 of concrete and kg CO_2-eq/kg of reinforcement in the retaining wall. The investment cost is evaluated using SEK/m^3 of concrete and SEK/kg of reinforcement steel. The majority of the CO_2 emissions of concrete originate from cement production Mohamad et al. (2022). In addition, the location where the cement is produced also plays a significant role in determining the environmental impact due to transportation.

The environmental impact is modeled as a linear function of the characteristic strength of concrete. The values used for the calculation are for climate-improved concrete from Boverket (2026) that include the environmental impact during production of the material, excluding transportation and construction waste. The function can be seen in Figure 3.2. There is a possibility that the values are conservative according to Boverket (2026).

$$\frac{\text{kg CO}_2 eq}{m^3_{\text{concrete}}} = 5.1977\, f_{ck} + 100.38$$

where f_{ck} is the characteristic strength of concrete, given in MPa.

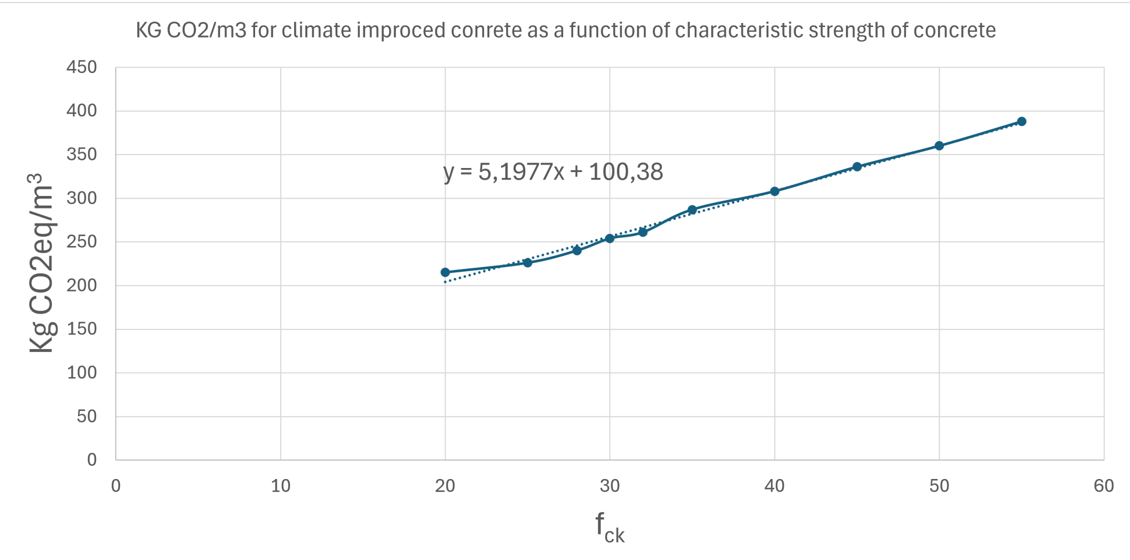


Figure 3.2: $kgCO_2eq/m^3_{\text{concrete}}$ as a function of characteristic strength of concrete.

The environmental impact of reinforcement steel is also given as:

$$\frac{0.745 \text{ kg CO}_2}{\text{kg}_{\text{steel}}}$$

The cost of concrete also varies with the quality of concrete. Mathern et al. (2022) uses the function $1.08\, f_{ck} + 151$ €/m^3 to describe the correlation between cost and concrete class. The cost of steel is 1371 €/ton. The conversion rate used in this thesis is 1 € = 10.8 SEK, (22/3/2026) which corresponds to:

$$\frac{11.7f_{ck} + 1084.1 \text{ kr}}{m^3_{\text{concrete}}}$$

and

$$\frac{14.8 \text{ kr}}{\text{kg}_{\text{steel}}}$$

3.3 Implementation in Python

Using the analysis performed in Excel, the same calculations were implemented in Python functions. In the script, an optimization was performed to minimize cost and environmental impact using the optimization algorithm. A GA was chosen for the optimization due to its ease of implementation and ability to find a large and diverse set of solutions. Another advantage of the algorithm is that it is effective in avoiding local extreme points, due to mutation. A further advantage of the GA is the possibility of including elitism, which ensures that the optimal solutions are not discarded. The calculations and results generated in Python were also compared with the values in Excel to verify the script and the calculation model.

The package used in Python for the optimization was Pymoo. Variables were assigned as an array within an interval of possible values, which can be seen in Table 3.3. An integer was later randomly chosen between 0 and the size of the array, where the integer was associated with the value of the position of the array. The minimum and maximum values of the stem, slab, toe, and heel were then rounded up or down in intervals of 10 millimeters. Possible values for the geometrical variables were given as a function dependent on the height of the stem instead of a fixed values to eliminate less desirable designs, such as a one meter high retaining wall with a 500 millimeters thick wall and slab. The spacing of the reinforcement is varied in intervals of 10 millimeters. The algorithm also had the option of including two layers of reinforcement in the wall and slab, where different diameters, spacings, and number of layers were possible. In addition, minimum reinforcement was applied to all required zones.

Design Variable	Range / Possible Values
W_{toe}	$0 \leq W_{\text{toe}} \leq \frac{h_{\text{stem}}}{3}$
W_{heel}	$0.5\,\text{m} \leq W_{\text{heel}} \leq h_{\text{stem}}$
t_{slab}	$\frac{h_{\text{stem}}}{12} \leq t_{\text{slab}} \leq \frac{h_{\text{stem}}}{8}$
t_{stem}	$\frac{h_{\text{stem}}}{12} \leq t_{\text{stem}} \leq \frac{h_{\text{stem}}}{8}$
$S_{\text{reinforcement}}$	$100\,\text{mm} \leq S_{\text{reinforcement}} \leq 400\,\text{mm}$
ϕ_s	$[8, 10, 12, 16, 20, 25]\,\text{mm}$
n_{layers}	$[1, 2]$

Table 3.3: Possible values for the design variables used in the GA.

Because the algorithm works with discrete values, there was a possibility that duplicates were created. To reduce unnecessary calculations and enhance diversity in the population, duplicates were removed and a new individual was created randomly.

To improve the efficiency of the algorithm, a penalty was given to designs that were not feasible. An example of this is a design that has too large of an eccentricity to calculate the contact pressure on the slab. High sectional design forces $M_{Ed} = 10^{12}$ kNm and $V_{Ed} = 10^{12}$ kN will be assigned to the individual, and the fitness of the individual will be drastically reduced, and will not be selected for the selection process.

To find the best configuration of the algorithm, different configurations and evolutionary operators were tested in a configuration study. For the algorithm, different configurations of population size and number of generations were tested. The total number of evaluated designs for each configuration was 10 000. The evolutionary operators that were tested were population size, number of generations, crossover points and mutation probability, resulting in 27 different algorithm configurations. A total of 10 seeds were run for each configuration to ensure reproducibility and reduce the likelihood of producing favorable results due to the random properties of the GA. The configuration study was performed for both cost and environmental impact. The number of elites was set to one, as only the best-performing design is kept.

3.4 Assumptions

The RCCRW was designed with several assumptions that gave structure to the calculations but also imposed limitations on the design. The RCCRW was assumed to be cast in soil that had sufficient capacity, with no need for a piled foundation. Control of total stability/slope stability was not analyzed, due to the failure mode being mainly influenced by soil properties. This failure mode could be controlled separately, and appropriate measures could be taken if there was a risk of failure.

3.4.1 Loads

The loads assumed to act on the structure were self-weight, earth pressure, surcharge, and snow load. Wind load was neglected, as the contribution to the wall is neglectable compared to the other loads acting on the wall. An exception to this would be if, for instance, a noise barrier were mounted on the top of the wall, where wind loads would cause large horizontal forces that would need to be taken into account. The horizontal loads were calculated using Rankine theory. For the variable surcharge loads, they were assumed to act on the entire surface of the elevated part of the retaining wall. This resulted in both a horizontal and a vertical contribution from the variable load(s).

In the calculations of the geotechnical failure modes, the assumption of fully developed active pressure was made. To achieve geotechnical failure, a large moment in the soil is needed, which then develops the full active earth pressure. For structural failure, at-rest earth pressure was used, as large soil movements cannot be assumed to take place before the failure of the structure.

3.4.2 Load Combinations

Different load combinations were applied according to Eurocode Eq. 6.10 and TSFS. TSFS proposed that Design Approach 3 should be used for retaining structures. Design approaches include recommended partial factors for loads (A), soil properties (M), and resistances (R) used in design. DA3 includes A1 and A2 for loads in combination with M2 for soil properties and R3 for resistance. The load combinations were performed as follows: the loss of static equilibrium (EQU) was evaluated using Eq. 6.10 Set A. Structural and geotechnical failure (STR/GEO) were evaluated using Eq. 6.10 Set B.

3.4.3 Contact Pressure

The contact pressure on the slab was calculated with the assumption of a stress distribution according to Navier's formula Bergdahl et al. (1993). The vertical load V is assumed to act centrally on the slab and be distributed evenly on the ground. If a moment is acting on the slab, an eccentricity e_x is introduced and the contact pressure varies linearly. If e_x is within the limit of $e_x \leq B/6$, the contact pressure is calculated using Eq. 3.1. If the eccentricity is within $B/6 < e_x \leq B/3$, the contact pressure is distributed according to Eq. 3.2 over the distance $3c$ where $c = B/2 - e$

$$\sigma_{x1,2} = \frac{V}{b} \pm \frac{6M}{B^2} \tag{3.1}$$

$$\sigma_{x1} = \frac{4V}{3} \cdot \frac{1}{(B - 2e_x)} \tag{3.2}$$

Definitions

$$\begin{aligned}
\sigma_{x1,2} &= \text{Contact pressure at the edge of the slab} \\
V &= \text{Total vertical force} \\
M &= \text{Net moment} \\
e_x &= \text{Eccentricity caused by non centric forces (M/V)} \\
B &= \text{Width of base slab}
\end{aligned}$$

3.4.4 Vertical Pressure in the Ground

The vertical pressure in the ground under the RW was assumed to be distributed over an effective area Bergdahl et al. (1993). The moment introduces an eccentricity, and an effective area was calculated with Eq 3.3.

$$A_{ef} = B - 2e_x \tag{3.3}$$

3.4.5 Reinforcement Layout

To ensure that the retaining wall was buildable, both the bottom and top reinforcement in the slab were extended throughout the entire length of the slab so that the reinforcement could easily be tied together before casting. This can be seen in Figure 3.3. Doing this also simplified the tying of the horizontal reinforcement needed for crack control. The increase in reinforcement length naturally led to an increased total amount of reinforcement steel and hence higher cost and environmental impact, but ensured constructability. As the process of installing shear reinforcement throughout the entire retaining wall can be time-consuming, it should be avoided for ease of installation. Shear reinforcement could, however, be materially effective in the case of high shear forces, but it is often up to the engineer to decide whether it is beneficial. To ensure that shear reinforcement is inserted only when it is worthwhile, it is placed outside the algorithm limits.

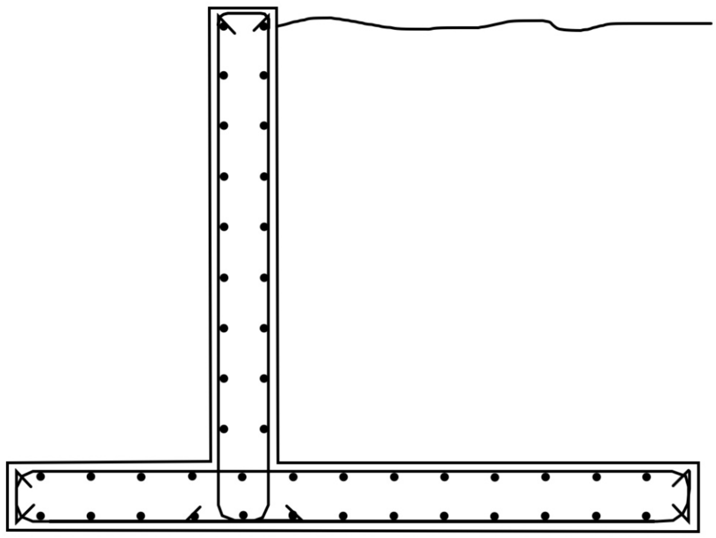


Figure 3.3: Illustration of the assumed reinforcement design.

3.5 Configuration Study

To find the best algorithm configuration and evolutionary operators for the GA, seeded runs with varying values of these operators and configurations were investigated through a so-called grid search. Sweeping parameters over a manually specified input subset (Mathern et al., 2021). The different operators and configurations tested were population size, number of generations, number of crossover points, and the mutation rate. The fixed operators and configurations were the number of elites and the number of designs evaluated. The fixed and variable operators and configurations are presented in Table 3.4. The study presented the feasible design with the lowest cost or environmental impact evaluated in each generation, and the configuration with the lowest average value after 10,000 evaluated designs was used in subsequent optimization.

Category	Configuration
Fixed settings	Number of elites = 1 Total evaluated designs = 10 000
Population size vs generations	Population size = 50 → Generations = 200 Population size = 100 → Generations = 100 Population size = 200 → Generations = 50
Crossover points	2, 4, 6
Mutation probability	0.05, 0.1, 0.2

Table 3.4: Genetic algorithm configurations used in the parametic study.

3.6 Case Study

Subsequent to obtaining a final design produced by the Python script, the result could be compared to the already built RCCRWs. The comparison mainly focused on reinforcement, concrete volumes, and dimensions. Notable is that the GA produces designs aimed for the bidding phase, where as the built walls are dimensioning after acquiring the project, enabling for higher detail in the calculations. All the compared parameters can be seen in Table 3.5. By making the comparison, the quality of the design of the optimization algorithm could be evaluated and thus also the script's ability to optimize. The study consisted of two built walls located in different cities, Trollhättan and Malmö, with varied site-specific characteristics. Notably, the built wall designs were calculated more in depth after the project had been acquired. This level of detail thereby differed from the level of design produced by the script. Major differences consisted of shortening of reinforcement, more exact load calculations etc.

Parameter	Variable	Unit
Wall thickness	t_w	$[m]$
Toe length	L_{toe}	$[m]$
Heel length	L_{heel}	$[m]$
Slab thickness	t_{slab}	$[m]$
Concrete volume	V_c	$[m^3/m]$
Reinforcement volume	V_s	$[m^3/m]$
Reinforcement diameter	ϕ_s	$[mm]$
Reinforcement spacing	s	$[mm]$
Cost per meter	-	$[kr/m]$
Environmental Impact per meter	-	$[kg\ CO_2eq/m]$

Table 3.5: Compared parameters in the case study.

3.6.1 RCCRW in Trollhättan

The RCCRW in Trollhättan is a relatively standard RW with a total height of 5.57 meters, stem thickness of 0.4 meters, heel and toe width of 2.4 and 0.4 meters, respectively. The wall is exposed to a uniformly distributed 20 kPa surcharge load caused by traffic. The wall contains shear reinforcement, which is neglected in the script.

The RCCRW in Trollhättan has no geometric restrictions and is free to vary in geometry. The height of the stem is set to 5 meters. The surrounding soil is frictional soil with a characteristic friction angle of 40°. The stem has a concrete quality of C32/40 and the base slab has a concrete quality of C30/37. Reinforcement used was K500C-T. The RCCRW was designed with safety class 2 and a design life of 100 years.

3.6.2 RCCRW in Malmö

In Malmö, the RW is unique in the sense that it had strict limitations and requirements due to the proximity of the nearby railway and the corresponding platform. Additionally, the closest area on the lower level of the wall was to be built on, and therefore the RW design had to be relatively narrow. The passing trains result in significant traffic loads, which in this specific case were set to 69 kPa and were a decisive factor in the design. In addition, the safety class, service life, and exposure class were directly affected by the railway. Primarily, this makes the production stage complicated due to active traffic; however, as the study neglects the production stage, it was ignored. Another distinctive feature of the RW is that it was intended to allow the installation of a sound barrier on top of the wall. If implemented, it would cause significant wind loads that would need to be taken into account. As the script did not take wind loads into account, this was also ignored.

The RW located in Malmö has surrounding frictional soil with a characteristic friction angle of 35°, and has the site-specific aim of keeping the heel short with a maximum heel length of 2.9 meters. The height of the stem is 5.6 meters, but the soil level is only up to a height of 4.8 meters above the top of the base slab. The stem is 0.4 meters thick. The concrete quality used for the entire wall is C35/45. Reinforcement used was K500C-T. The RW is designed with safety class 3 and a design life of 100 years.

In the design of the built wall, the load effects were calculated by geotechnicians. With detailed calculations for the specific project, the load effects were reduced. In projects with large surcharge loads, this can have a crucial effect on the design of the wall.

4
Results

In this chapter, the results for both cost and environmental impact are presented. As described in section 3.5 10,000 designs are evaluated for each algorithm configuration. The computational time to evaluate 10,000 designs is roughly 30 seconds. However, this varies slightly depending on the algorithm configuration used.

4.1 Cost Optimization

In this section results from an optimization towards cost using the GA will be presented. Results when the GA had the possibility of using two layers of reinforcement and when it was restricted to only one layer of reinforcement.

4.1.1 Cost Optimization with Two Layers of Reinforcement

The parametric study was conducted with the possibility of using two layers of reinforcement in the stem, heel, and toe. In the study, a total of 10,000 design solutions with 27 different GA configurations were evaluated. The configurations consisted of different population sizes, number of generations, crossover points, and mutation probabilities as seen in Table 3.4. As mentioned previously, the number of generations and the population size were interlinked to produce the desired number of 10,000 designs valuated.
In addition to the different algorithm configurations, 10 different seeds were used for each configuration to compare the results obtained from different variations. The seeds ensured that the results of the study could be reproduced. If the variables for one configuration of the algorithm was randomly initialized close to the true minimum of the function, this could lead to misleading results. Using different seeds, the same configuration is less likely to be favorable due to the randomness of the GA, making the comparison more reliable.

4.1.1.1 Mean Convergence for Cost with Two Layers of Reinforcement

Subsequent to running all 10 seeds, they were compiled into a collective graph, see Figure 4.1, showing the average minimum cost for the 10 seeds, indicating the performance of the configuration. The graph presents the 27 configurations with the best performing average algorithm configuration highlighted in gray, which consisted of a population of 200 individuals, 50 generations, six crossover points, and a mutation probability of 0.2. The configuration in question was ultimately terminated at a minimum cost of 13 186 SEK/m. Comparing the averages of the configurations, one sees that the different configurations do not achieve a large difference of results, spanning between the lowest 13,186, and the highest 13,800 SEK/m, resulting in a variation of 614 SEK/m. Furthermore, one can see that the GA converges after approximately 7 000 to 8 000 design evaluations, from which the cost development is relatively stable.

When studying the starting points of the curves more closely, it can be seen that the starting points of the configurations vary depending on when the first feasible solution is reached. It can also be observed that the curves start at different evaluations and that, for some configurations, the average minimum cost increases at the beginning of Figure 4.1. This indicates that different seeds found their first feasible solutions after different numbers of evaluations.

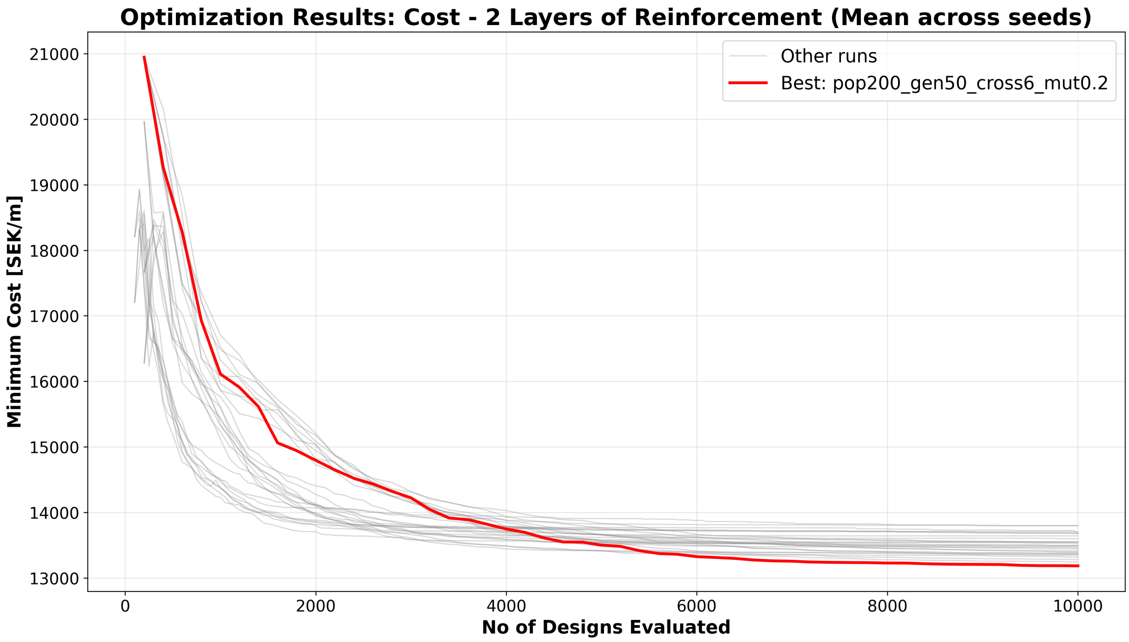


Figure 4.1: Graph showing the mean minimum cost for all 10 seeds for each configuration vs number of evaluated designs. Two possible layers of reinforcement.

4.1.1.2 Seed Convergence for Cost with Two Layers of Reinforcement

When examining specific seeds, it can be seen that some configurations clearly outperformed others in certain cases. For seed two, there was a relatively large variation in the final design cost. In this case, the algorithm using a population size of 200, 50 generations, two crossover points, and a mutation probability of 0.1 produced a final design with a cost of more than 10% lower than that of the second-best configuration; see Figure 4.2. Similar behavior can be observed for seeds seven, nine, and ten. In contrast, some seeds showed relatively small differences, such as seed three, shown in Figure 4.3, where the final costs differed by only 737 SEK/m.

Regarding the starting points of the variations, there is no clear sign that indicates if a configuration will excel in the subsequent evaluations. For example, looking at the convergence rate of seed two in Figure 4.2, the optimal configuration has one of the highest design costs in the initial stages and later successively decreases to the lowest.

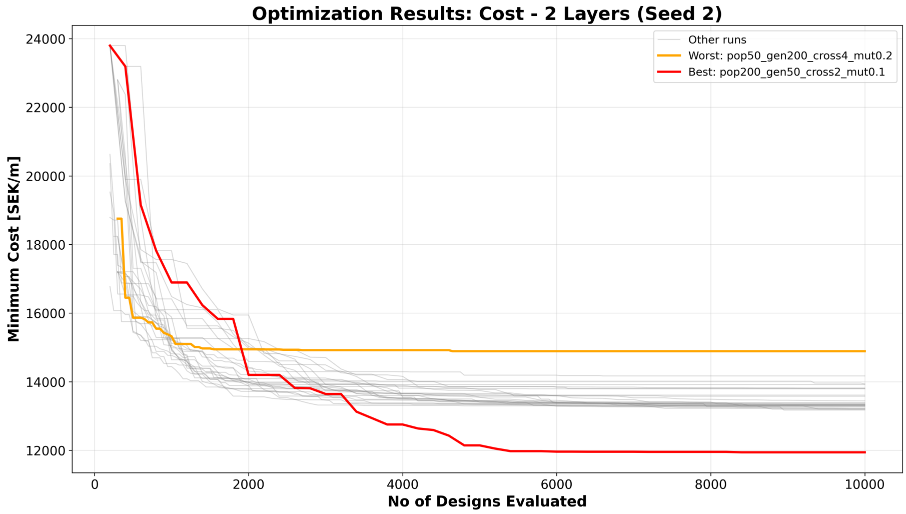


Figure 4.2: Convergence study for seed two. Displaying the minimum cost vs number of evaluated designs. Two layers of reinforcement.

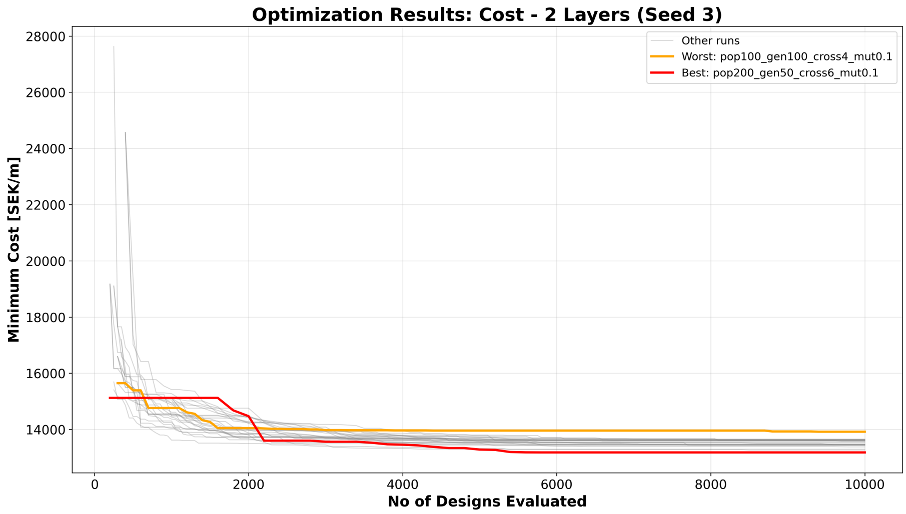


Figure 4.3: Convergence study for seed three. Displaying the minimum cost vs number of evaluated designs. Two layers of reinforcement.

The minimum cost found in all seeds and configurations for two reinforcement layers was obtained using seed two, a population size of 200, 50 generations, two crossover points, and a mutation probability of 0.1, as presented in Figure 4.2. The final cost was 11,941 SEK/m.

When the GA has the ability to design the RCCRW with two layers of reinforcement, nine additional variables are used compared to when the GA has the ability to use one layer of reinforcement. These variables include the number of reinforcement layers, the diameter of the reinforcement, and the reinforcement spacing for the second layer in the stem, toe, and heel, thus increasing the size of the design space accordingly. However, using two layers of reinforcement also enables additional design possibilities that are not achievable with a single layer.

4.1.2 Cost Optimization with One Layer of Reinforcement

The same convergence study was carried out for the algorithm configurations with the version in which only one reinforcement layer was allowed.

4.1.2.1 Mean Convergence for Cost with One Layers of Reinforcement

The study analyzed 10,000 design solutions using the same 27 configurations and 10 seeds as in the previous study. It concluded that the best designs on average were produced using a population size of 50, 200 generations, four crossover points, and a mutation probability of 0.2, resulting in a final cost of 13,237 SEK/m. Observing Figure 4.4, it can be seen that the best average-performing configuration converged earlier, at approximately 2,500 evaluations, while the remaining configurations converged at approximately the same number of evaluations as the two-layer reinforcement version, namely around 7,000 to 8,000 evaluations. The graph also shows that the best configuration was consistently one of the top-performing, if not the best-performing, configurations throughout the optimization process. This was not observed in the two-layer version, which exhibited a more varied performance over time. In terms of cost, both versions converged at approximately 13,300 SEK/m.

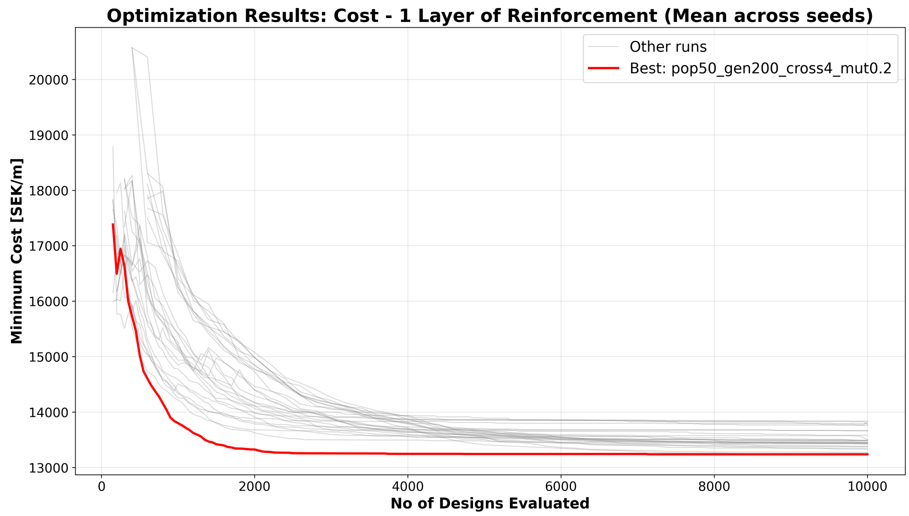


Figure 4.4: Graph showing the mean minimum cost for all 10 seeds for each configuration vs number of evaluated designs. One possible layer of reinforcement.

4.1.2.2 Seed Convergence for Cost with One Layer of Reinforcement

As in the previous study, some seeds stood out from the others in terms of performance. By examining Figure 4.5, it can clearly be seen that the configuration with a population size of 50, 200 generations, two crossover points, and a mutation probability of 0.2 outperformed the others by a large margin. The graph for seed nine also illustrates the range of the final solution costs, which spans 2,129 SEK/m. Similar behavior could be observed for seeds one, four, and eight. Much like in Figure 4.4, the optimal configuration converged during the early stages of the evaluations.

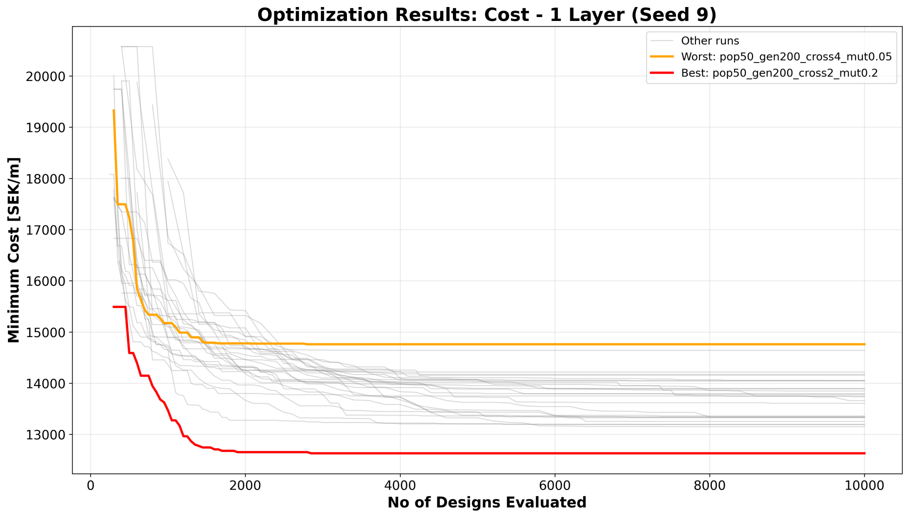


Figure 4.5: Convergence study for seed nine. Displaying the minimum cost vs number of evaluated designs. One layer of reinforcement.

Another similarity between the model with one-layer of reinforcement and two-layers of reinforcement was that it also contained seeds with a relatively small spread in the final design costs. This can be observed, for example, for seed 10, as shown in Figure 4.6, where the spread of the final costs was 783 SEK/m. The graph also shows that the changes in cost after approximately 3,000 evaluations were relatively small.

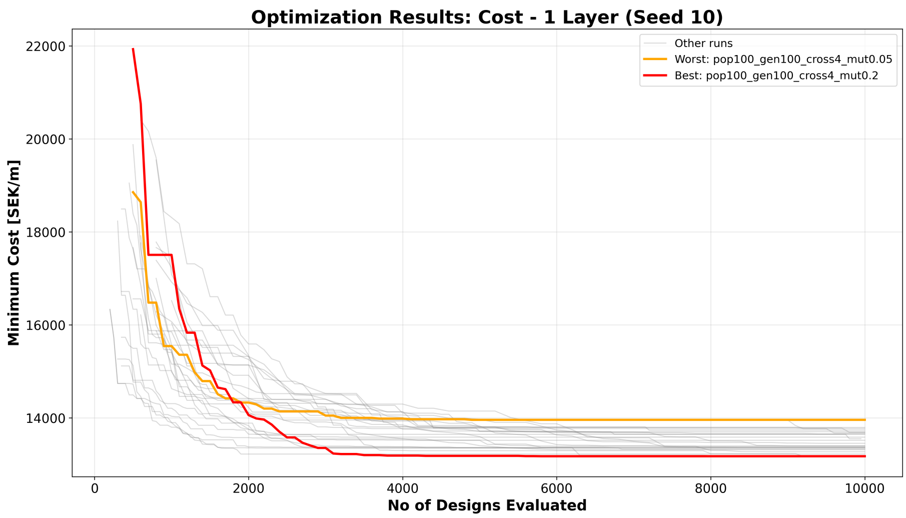


Figure 4.6: Convergence study for seed ten. Displaying the minimum cost vs number of evaluated designs. One layer of reinforcement.

One observation regarding the one-layer version was that the final design costs exhibited a larger spread compared to the two-layer version. Overall, the version using one layer of reinforcement produced the lowest design cost, namely 11,876 SEK/m. Another finding was that, in the cases where specific configurations excelled, the majority of the remaining configurations clustered in close proximity.
The best solution across all seeds for the one-layer reinforcement version was obtained using seed four and is presented in Figure 4.7, with a final cost of 11,876 SEK/m of constructed wall. This cost was marginally lower than the cheapest solution found for the design using two layers of reinforcement.

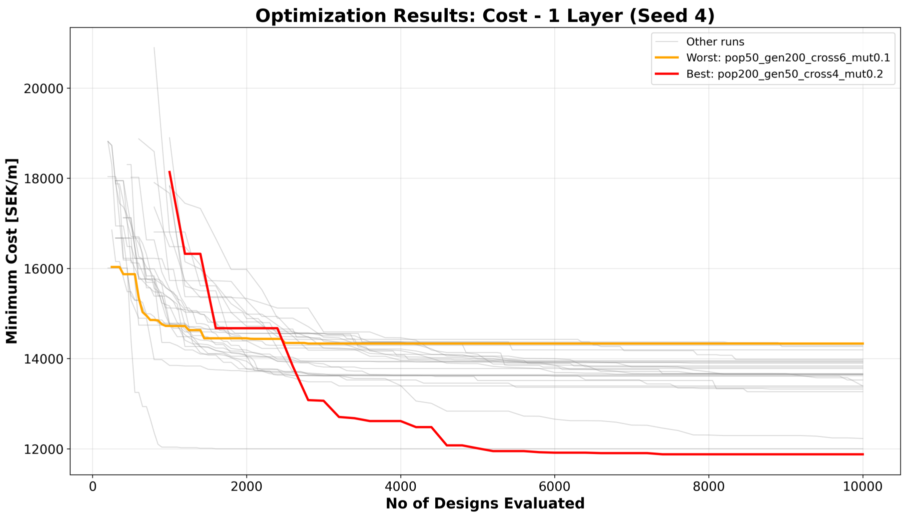


Figure 4.7: Convergence study for seed four. Displaying the minimum cost vs number of evaluated designs. One layer of reinforcement.

4.2 Environmental Impact Optimization

During the configuration study for the algorithm optimized for minimizing environmental impact, the same 27 different configurations as in the chapter 3.5 were used, evaluating 10,000 designs.

4.2.1 EI Optimization with Two Layers of Reinforcement

Similarly to the cost optimization, the same GA used for cost optimization with two possible layers of reinforcement were first tested through the 10 seeds.

4.2.1.1 Mean Convergence for Environmental Impact with Two Layers of Reinforcement

Observing Figure 4.8, it can be seen that the different configurations produced fairly similar results after 10,000 analyzed designs, ranging from 1,732 to 1,860 kg CO_2eq/m, which resembles the behavior observed in the cost analysis presented in Figure 4.1. This corresponds to a variation of 7% between the results obtained.

Additionally, the script tended to converge after approximately 7,000 to 8,000 design evaluations, which closely mirrors the convergence behavior observed in the cost analysis using two layers of reinforcement.

As in previous cases, there was no early indication whether a configuration would excel in the later stages of the evaluation process or not. In general, the best-performing configuration on average used a population size of 200, 50 generations, six crossover points, and a mutation probability of 20%.

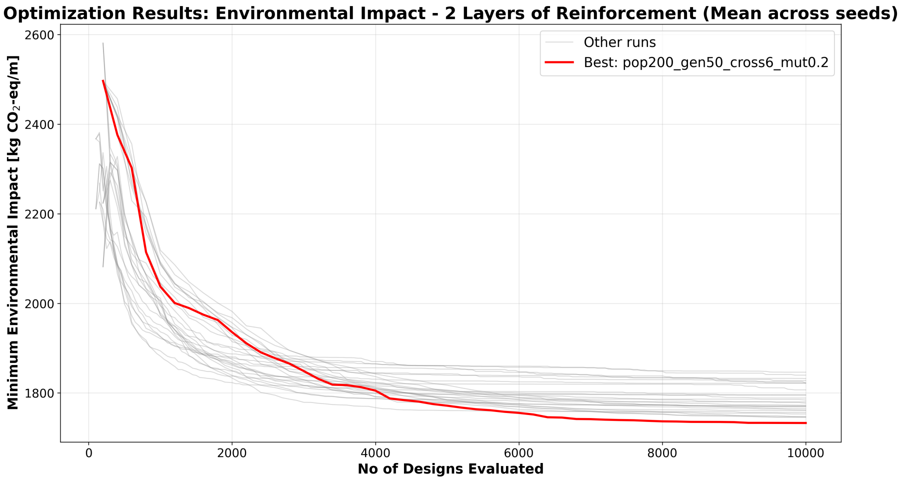


Figure 4.8: Graph showing the mean minimum environmental impact for all 10 seeds for each configuration vs number of evaluated designs. Two possible layers of reinforcement.

4.2.1.2 Seed Convergence for Environmental Impact with Two Layers of Reinforcement

In general, the results for the environmental impact exhibited greater variation during the final stages of the evaluation process. By examining the results obtained with seed two, depicted in Figure 4.9, it can be observed that the different configurations ranged from 1,723 to 2,051 kg CO_2-eq/m, resulting in a variation of 16%. The design with the lowest environmental impact produced by the program resulted in 1,706 kg CO_2-eq/m and was obtained using seed nine.

Similarly to the cost analysis, some seeds exhibited a lower overall variation in the results, such as seed 10, which showed a variation of 12%, as presented in Figure 4.10. However, by examining the graph, it can be seen that some configurations most likely did not fully converge after 10,000 iterations. Upon examination of the initial stages of the process, it can be observed that there was a wide spread in the results between the configurations, which was then significantly reduced during the later stages of the evaluation process.

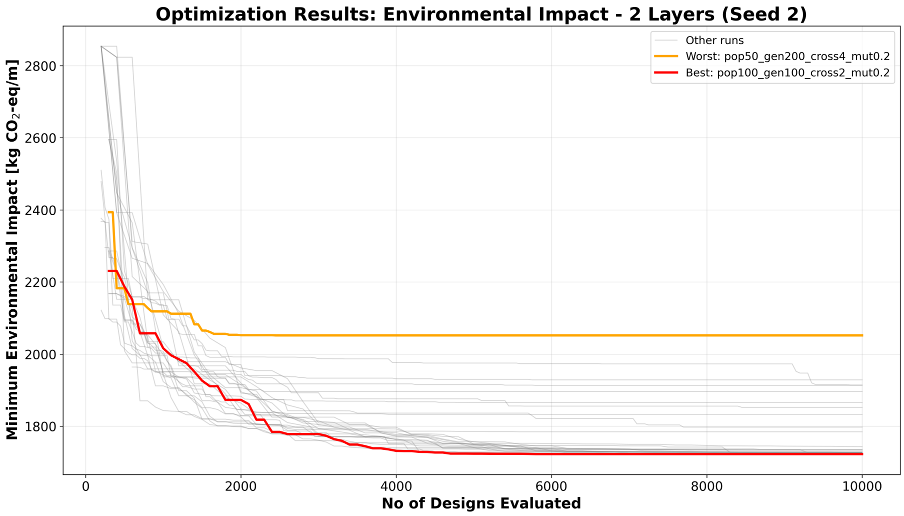


Figure 4.9: Convergence study for seed two. Displaying the minimum environmental impact vs number of evaluated designs. Two layers of reinforcement.

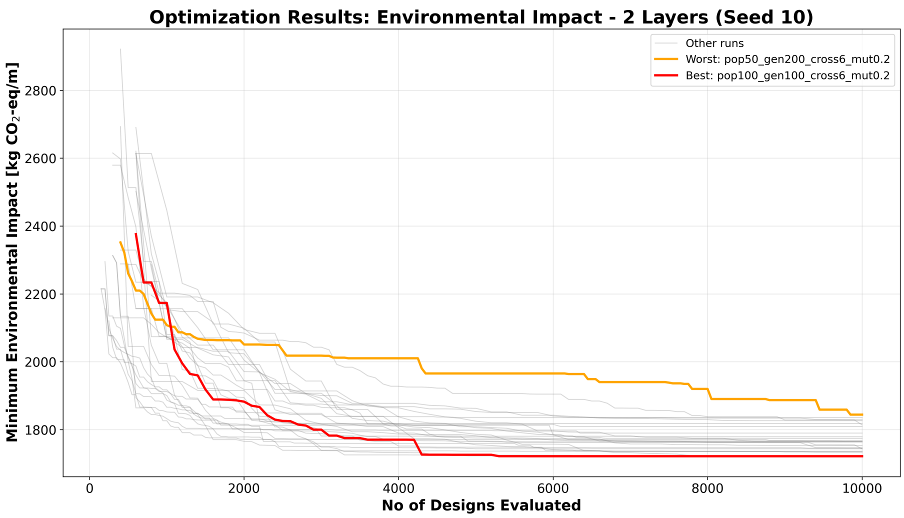


Figure 4.10: Convergence study for seed ten. Displaying the minimum environmental impact vs number of evaluated designs. Two layers of reinforcement.

4.2.2 Environmental Impact Optimization with One Layer of Reinforcement

The same convergence study optimized towards environmental impact was done with the GA but limited to only one layer of reinforcement. The achieved result is presented in this section.

4.2.2.1 Mean Convergence for Environmental Impact with One Layer of Reinforcement

The mean lowest environmental impact for each seed and configuration can be seen in Figure 4.11. The configuration that produced the design with the lowest mean environmental impact had a population size of 200, 50 generations, four crossover points, and a mutation probability of 0.10. Looking at the best-performing configuration, it produced an average environmental impact of 1,725.8 kg CO_2-eq/m of constructed wall, while the configuration with the highest average environmental impact used a population size of 50, 200 generations, two crossover points, and a mutation probability of 0.05, resulting in 1,847 kg CO_2-eq/m of constructed wall. This corresponds to a difference of 7%.

Another observation of the study is that the convergence analysis for the environmental impact indicates that the algorithm had not completely stagnated and still appeared to be converging toward a lower environmental impact.
No clear similarities could be observed between the optimal configurations, apart from the number of crossover points, when comparing the environmental impact optimization with the cost optimization for the one-layer reinforcement version presented in Section 4.1.2.1 and Figure 4.4.

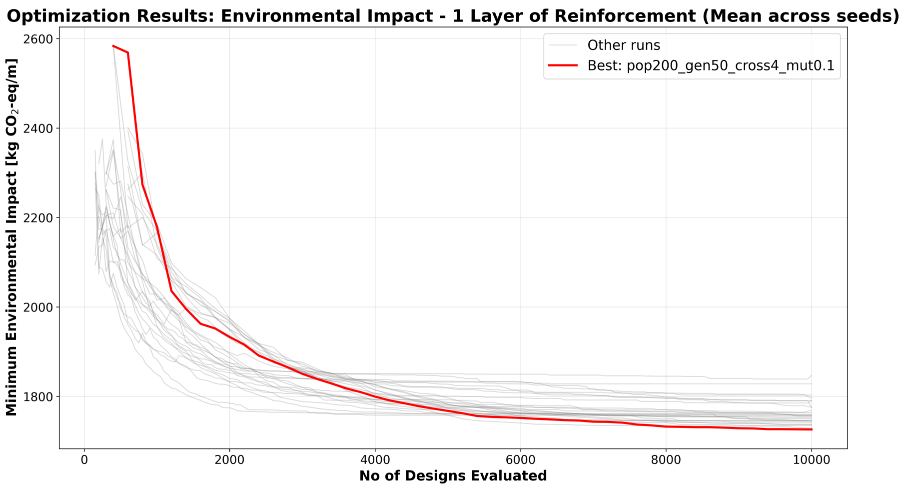


Figure 4.11: Graph showing the mean minimum environmental impact for all 10 seeds for each configuration vs number of evaluated designs. One possible layer of reinforcement.

4.2.2.2 Seed Convergence for Environmental Impact with One Layer of Reinforcement

The lowest environmental impact for seed one can be seen in Figure 4.12. An important observation is that the majority of the curves had not yet converged, indicating that additional generations would be required for the convergence study. Similar results can be observed for seeds four, seven, nine, and ten. The minimum environmental impact also varied significantly for this seed, ranging from approximately 2,000 to 1,700 kg CO_2-eq/m.

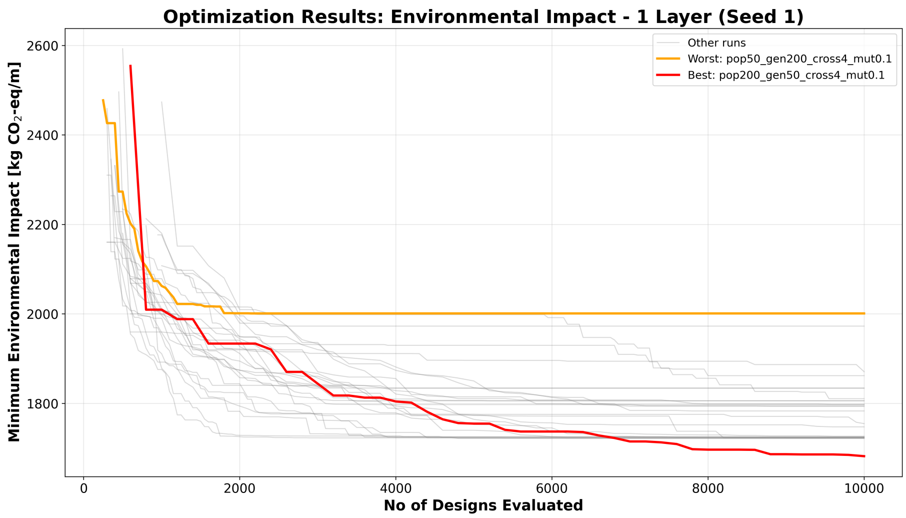


Figure 4.12: Convergence study for seed one. Displaying the minimum Environmental Impact vs number of evaluated designs. One layer of reinforcement.

4.3 Convergence over Number of Generations

An observation from the results of the convergence studies presented in Sections 4.1 and 4.2 is that some configurations converged earlier than others when comparing the number of designs evaluated. Because of this, an additional convergence study with the aim to minimize cost for the version with one-layer reinforcement was carried out using the number of generations instead of the number of evaluated designs on the x-axis. The results can be seen in Figure 4.13.

It can be observed that almost all configurations converged after approximately 50 generations. This indicates that increasing the number of generations beyond 50 does not significantly reduce the average cost produced by the algorithm.

By examining the individual seeds, it can be observed that for some, the cost continued to decrease after 50 generations. This indicates that even though the algorithm converged on average after 50 generations, further improvements could still be achieved, as shown in Figure 4.14. This further indicates that some configurations may require 100 or more generations to fully converge.

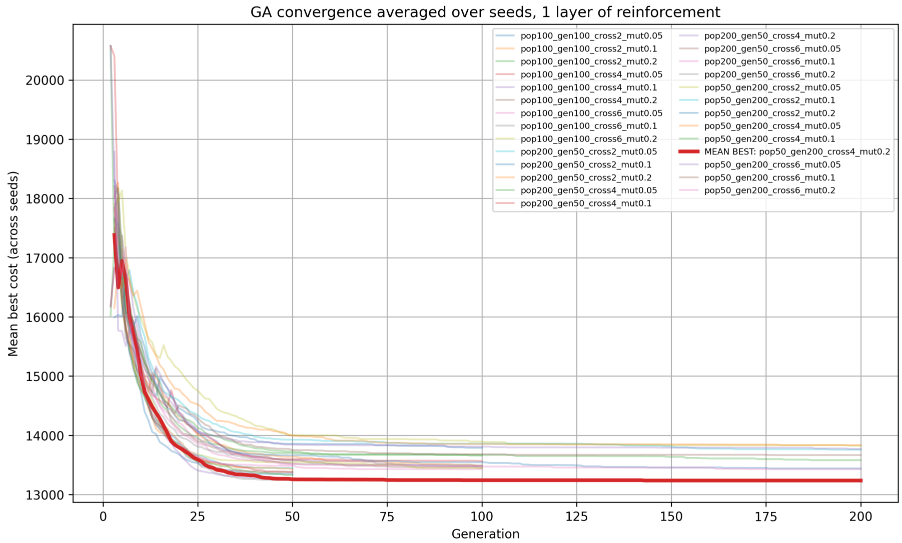


Figure 4.13: Graph showing the mean minimum cost for all 10 seeds for each configuration vs number of generation. One possible layer of reinforcement.

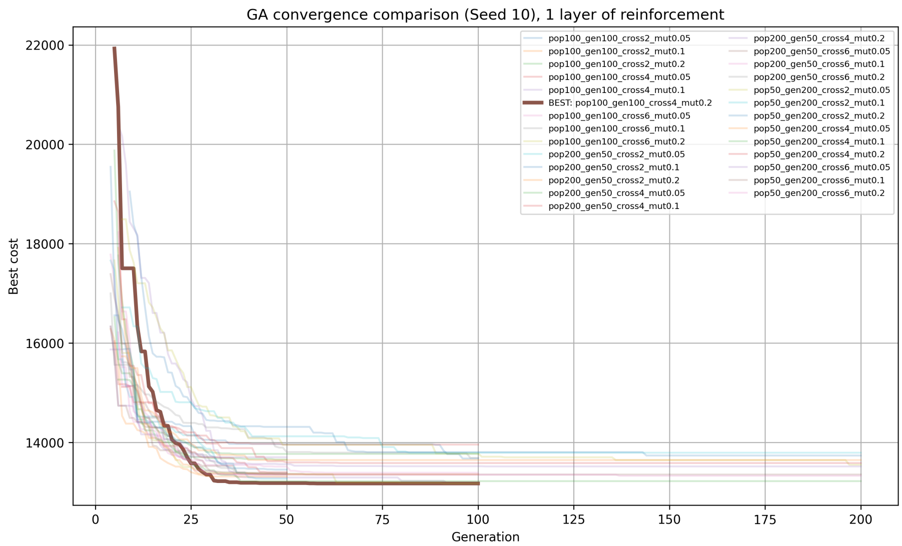


Figure 4.14: Convergence study for seed ten. Displaying the minimum cost vs number of generations. One layer of reinforcement.

4.4 Choice of Algorithm Configuration

In the configuration studies presented in Sections 4.1 and 4.2, three of the four best-performing configurations on average used a population size of 200 and 50 generations, while the fourth used a population size of 50 and 200 generations. A larger population entails a more diverse design pool, which has proven advantageous as the GA explores a wider range of designs. By examining the convergence behavior with respect to the number of generations in Chapter 4.3, it can be observed that the algorithm rarely improved significantly after 50 generations. Hence, the configuration using a population size of 200 and 50 generations was selected for the algorithm.

Regarding the probability of mutation, three of the four best-performing configurations used a mutation probability of 0.2, while one used 0.1. This indicates that a mutation probability of 0.2 would be most suitable for the algorithm.

With respect to the number of crossover points, the best-performing configurations on average used either four or six crossover points, with two configurations for each alternative and none using two crossover points. However, six crossover points were more favorable for the two-layer reinforcement version, while four crossover points were more favorable for the one-layer reinforcement version. The final mean cost of the design using one layer of reinforcement was marginally higher than the corresponding cost for the design using two layers of reinforcement.

Since two layers of reinforcement are avoided when possible to facilitate the installation of reinforcement, and no significant differences in cost or environmental impact were found between one or two possible layers of reinforcement, the final configuration selected for the GA used the variables presented in Table 4.1, with only one layer of reinforcement allowed.

Parameter	**Value**
Population size	200
Number of generations	50
Crossover points	4
Mutation probability	0.2

Table 4.1: Chosen configuration for the GA.

4.5 Case Study

This section presents the results of the case study conducted on the two RCCRWs built in Malmö and Trollhättan using the GA with the chosen algorithm configuration presented in the chapter 4.4.

4.5.1 RCCRW in Malmö

Results obtained for the case study preformed on the RCCRW in Malmö are presented in this section.

4.5.1.1 Cost and Environmental Impact of the Existing RCCRW

The geometry of the constructed wall is presented in Table 4.2, while Table 4.3 presents the material usage, cost, and environmental impact of the retaining wall constructed in Malmö.

Table 4.2: Geometry of the built RW in Malmö.

Geometrical parameter	Dimension
Toe width	1 200 mm
Stem width	400 mm
Heel width	2 900 mm
Total width	4 500 mm
Slab thickness	700 mm

Table 4.3: Material usage, cost, and environmental impact for the built RW in Malmö.

Parameter	Value
Concrete volume	5.46 m^3/m
Vertical reinforcement	297 kg/m
Horizontal reinforcement	126 kg/m
Total reinforcement	423 kg/m
Cost	14 415 SEK/m
Environmental impact	1 856 kg CO_2eq/m

4.5.1.2 Cost Optimization GA

When analyzing the retaining wall in Malmö, no feasible solutions were found within the current geometric limitations imposed on the retaining wall in the GA. This is likely due to the large surcharge loads acting on the wall, which generate high forces.

By examining Table 4.4, it can be observed that only the constraints related to the shear force in each part of the wall and the crack width in the heel were not fulfilled. The vertical reinforcement in the toe was not close to the maximum allowable amount of reinforcement, while the stem and heel were at the maximum allowable amount of reinforcement.
When allowing a greater thickness for both the stem and the bottom slab within the range of $\frac{h_{\text{stem}}}{12} \leq t_{\text{stem}} \leq \frac{h_{\text{stem}}}{6}$ and $\frac{h_{\text{stem}}}{12} \leq t_{\text{slab}} \leq \frac{h_{\text{stem}}}{6}$, no feasible solution was found; however, only one constraint was violated, namely the shear capacity in the heel seen in Table 4.6. Since the maximum tensile reinforcement in the heel had

Table 4.4: Constraint violations for the best non-feasible solution found with limited geometry for the RCCRW in Malmö, where an utilization rate (UR) above one leads to failure.

Constraint	**UR**	**Status**
Sliding	0.620382	PASS
Overturning	0.569585	PASS
Crushing	0.462305	PASS
Stem Shear	1.120081	FAIL
Stem Moment	0.998468	PASS
Stem Crack Width	0.972163	PASS
Stem Horizontal Displacement	0.622161	PASS
Toe Shear	1.144710	FAIL
Toe Moment	0.700263	PASS
Toe Crack Width	0.000000	PASS
Heel Shear	2.013204	FAIL
Heel Moment	0.875081	PASS
Heel Crack Width	1.250025	FAIL

Table 4.5: Geometry and reinforcement for the best non-feasible solution found for the RW with limited geometry in Malmö.

Parameter	**Value**
Stem thickness	0.580 m
Slab thickness	0.590 m
Toe length	0.650 m
Heel length	2.900 m
Stem vertical reinforcement	ϕ25 s120 mm
Stem horizontal reinforcement	ϕ10 s270 mm
Toe vertical reinforcement	ϕ10 s100 mm
Toe horizontal reinforcement	ϕ10 s130 mm
Heel vertical reinforcement	ϕ25 s100 mm
Heel horizontal reinforcement	ϕ10 s130 mm
Number of violated constraints	4/12

already been utilized and shear reinforcement was not allowed, the thickness of the slab needed to be increased.

Table 4.6: Constraint violations for the best non-feasible solution with increased thickness limits for the RW in Malmö, where an utilization rate (UR) above one leads to failure.

Constraint	UR	Status
Sliding	0.606608	PASS
Overturning	0.422142	PASS
Crushing	0.190197	PASS
Stem Shear	0.988013	PASS
Stem Moment	0.961709	PASS
Stem Crack Width	0.971178	PASS
Stem Horizontal Displacement	0.53307	PASS
Toe Shear	0.983908	PASS
Toe Moment	0.963888	PASS
Toe Crack Width	0.511667	PASS
Heel Shear	1.441199	FAIL
Heel Moment	0.646002	PASS
Heel Crack Width	0.969514	PASS

When the geometric limitations were changed to $\frac{h_{\text{stem}}}{12} \leq t_{\text{stem}} \leq \frac{h_{\text{stem}}}{6}$ and $\frac{h_{\text{stem}}}{12} \leq t_{\text{slab}} \leq \frac{h_{\text{stem}}}{4}$, a feasible solution was found. The final design can be seen in Table 4.7.

The final cost and environmental impact of the RW optimized with respect to cost can be seen in Table 4.8. The amount of concrete used was 8.09 m^3/m, while the amount of vertical reinforcement was 309 kg/m and the amount of horizontal reinforcement was 91.3 kg/m, resulting in a total reinforcement amount of 400 kg/m. The minimum cost for the retaining wall was 18,009 SEK/m, and the environmental impact was 2,582 kg CO_2-eq/m.

4.5.1.3 Environmental Impact Optimization GA

The final cost and environmental impact of the optimized RW with respect to environmental impact can be seen in Table 4.10.

The amount of concrete used was 7.72 m^3/m, while the amount of vertical reinforcement was 332 kg/m and the amount of horizontal reinforcement was 90.4 kg/m, resulting in a total reinforcement amount of 422 kg/m. The minimum cost for the retaining wall was 17,792 SEK/m, and the environmental impact was 2,495 kg CO_2-eq/m. This resulted in a design with less concrete and more steel reinforcement. When the objective function was set to minimize the environmental impact, both the cost and the environmental impact were reduced compared to when the objective was to minimize the cost.

Table 4.7: Optimal geometry and reinforcement layout for the cost-optimized RW in Malmö.

Parameter	**Value**
Stem thickness	0.640 m
Slab thickness	1.120 m
Toe length	0.940 m
Heel length	2.900 m
Stem vertical reinforcement	ϕ25 s130 mm
Stem horizontal reinforcement	ϕ10 s240 mm
Toe vertical reinforcement	ϕ10 s140 mm
Toe horizontal reinforcement	ϕ12 s100 mm
Heel vertical reinforcement	ϕ16 s100 mm
Heel horizontal reinforcement	ϕ12 s100 mm

Table 4.8: Cost and EI for the cost-optimized RW in Malmö.

Parameter	**Value**
Concrete volume (stem)	3.07 m^3/m
Concrete volume (slab)	5.02 m^3/m
Total concrete volume	8.09 m^3/m
Concrete cost (stem)	4,588.34 kr/m
Concrete cost (slab)	7,494.29 kr/m
Total concrete cost	12,082.63 kr/m
Vertical steel mass	309.15 kg/m
Horizontal steel mass	91.29 kg/m
Reinforcement cost	5,926.60 kr/m
Total cost	18,009.23 kr/m
Environmental impact (stem)	867.22 kg CO_2-ekv/m
Environmental impact (slab)	1,416.47 kg CO_2-ekv/m
Environmental impact (reinforcement)	298.33 kg CO_2-ekv/m
Total environmental impact	2,582.02 kg CO_2-ekv/m

Table 4.9: Optimal geometry and reinforcement layout for the environmental impact optimized RW in Malmö.

Parameter	**Value**
Stem thickness	0.640 m
Slab thickness	1.050 m
Toe length	0.890 m
Heel length	2.900 m
Stem vertical reinforcement	ϕ25 s130 mm
Stem horizontal reinforcement	ϕ10 s240 mm
Toe vertical reinforcement	ϕ10 s150 mm
Toe horizontal reinforcement	ϕ12 s100 mm
Heel vertical reinforcement	ϕ20 s120 mm
Heel horizontal reinforcement	ϕ12 s100 mm

Table 4.10: Cost and environmental impact for the RW optimized towards environmental impact in Malmö.

Parameter	**Value**
Concrete volume (stem)	3.07 m^3/m
Concrete volume (slab)	4.65 m^3/m
Total concrete volume	7.72 m^3/m
Concrete cost (stem)	4,588.34 kr/m
Concrete cost (slab)	6,947.48 kr/m
Total concrete cost	11,535.82 kr/m
Vertical steel mass	332.31 kg/m
Horizontal steel mass	90.41 kg/m
Reinforcement cost	6,256.29 kr/m
Total cost	17,792.11 kr/m
Environmental impact (stem)	867.22 kg CO_2-ekv/m
Environmental impact (slab)	1,313.12 kg CO_2-ekv/m
Environmental impact (reinforcement)	314.93 kg CO_2-ekv/m
Total environmental impact	2,495.27 kg CO_2-ekv/m

4.5.2 RCCRW in Trollhättan

Results obtained for the case study preformed on the RCCRW in Trollhättan is presented in this chapter.

4.5.2.1 Cost and Environmental Impact of the Built RCCRW

The geometry of the RW in Trollhättan can be seen in Table 4.11, while Table 4.12 presents the use of material, cost, and environmental impact of the RW constructed in Trollhättan.

Table 4.11: Geometry of the Built RW in Trollhättan.

Geometrical parameter	Dimension
Toe width	400 mm
Stem width	400 mm
Heel width	2 400 mm
Total width	3 200 mm
Slab thickness	600 mm

Table 4.12: Material usage, cost, and environmental impact for the built RW in Trollhättan.

Parameter	Value
Concrete volume	3.92 m^3/m
Vertical reinforcement	180.9 kg/m
Horizontal reinforcement	70.8 kg/m
Total reinforcement	251.6 kg/m
Cost	9 396 SEK/m
Environmental impact	1 213 kg CO_2eq/m

4.5.2.2 Cost Optimization GA

The final design of the GA is shown in Table 4.13. The GA favored a long heel when possible.
The final cost and environmental impact for the RW in Trollhättan optimized with respect to cost can be seen in Table 4.14. The amount of concrete used in the stem was 2.50 m^3/m, while the slab used 2.84 m^3/m, resulting in a total concrete volume of 5.34 m^3/m. The amount of vertical reinforcement was 266.5 kg/m, while the amount of horizontal reinforcement was 54.7 kg/m, resulting in a total reinforcement amount of 321.2 kg/m. The minimum cost for the RW was 12,482 SEK/m, and the environmental impact was 1,635 kg CO_2-eq/m.

4.5.2.3 Environmental Impact Optimization GA

The final design produced by the GA is shown in Table 4.15. The length of the toe is 0.290 meters, while the length of the heel is 4.270 meters. The stem thickness

Table 4.13: Optimal geometry and reinforcement layout for the cost-optimized RW in Trollhättan.

Parameter	**Value**
Stem thickness	0.500 m
Slab thickness	0.560 m
Toe length	0.310 m
Heel length	4.270 m
Stem vertical reinforcement	ϕ20 s130 mm
Stem horizontal reinforcement	ϕ10 s300 mm
Toe vertical reinforcement	ϕ10 s390 mm
Toe horizontal reinforcement	ϕ10 s140 mm
Heel vertical reinforcement	ϕ20 s100 mm
Heel horizontal reinforcement	ϕ10 s140 mm

Table 4.14: Cost and EI for the cost-optimized RCCRW in Trollhättan.

Parameter	**Value**
Concrete volume (stem)	2.50 m^3/m
Concrete volume (slab)	2.84 m^3/m
Total concrete volume	5.34 m^3/m
Concrete cost (stem)	3,646.25 kr/m
Concrete cost (slab)	4,082.57 kr/m
Total concrete cost	7,728.82 kr/m
Vertical steel mass	266.47 kg/m
Horizontal steel mass	54.67 kg/m
Reinforcement cost	4,752.84 kr/m
Total cost	12,481.67 kr/m
Environmental impact (stem)	666.77 kg CO_2-ekv/m
Environmental impact (slab)	729.15 kg CO_2-ekv/m
Environmental impact (reinforcement)	239.25 kg CO_2-ekv/m
Total environmental impact	1,635.17 kg CO_2-ekv/m

is 0.470 meters, and the thickness of the slab is 0.510 meters. When optimizing with respect to environmental impact, the GA still favored a long heel; however, the thicknesses of the slab and stem were reduced, while the amount of reinforcement in the heel and stem increased.

Table 4.15: Optimal geometry and reinforcement layout for the environmental impact optimized RCCRW in Trollhättan.

Parameter	**Value**
Stem thickness	0.470 m
Slab thickness	0.510 m
Toe length	0.290 m
Heel length	4.270 m
Stem vertical reinforcement	ϕ20 s120 mm
Stem horizontal reinforcement	ϕ10 s300 mm
Toe vertical reinforcement	ϕ8 s400 mm
Toe horizontal reinforcement	ϕ10 s150 mm
Heel vertical reinforcement	ϕ25 s120 mm
Heel horizontal reinforcement	ϕ10 s150 mm

The final cost and environmental impact of the retaining wall in Trollhättan optimized towards minimizing EI can be seen in Table 4.16. The amount of concrete used in the stem was 2.35 m^3/m, while the slab used 2.57 m^3/m, resulting in a total concrete volume of 4.92 m^3/m. The amount of vertical reinforcement was 311.5 kg/m, while the amount of horizontal reinforcement was 51.3 kg/m, resulting in a total reinforcement amount of 362.8 kg/m. The minimum cost for the RW was 12,478 SEK/m, and the environmental impact was 1,554.5 kg CO_2-eq/m.

4.5.3 Comparison of the Case Studies

A comparison of the results for the RCCRW in Malmö can be seen in Table 4.17. The script could not improve the design with respect to either cost or environmental impact; instead, it produced designs with higher costs and greater environmental impact.

When comparing the two designs from the GA one can observe that the optimization with respect to cost produced designs that used less reinforcement and more concrete compared to the environmental impact optimization. In contrast, the GA optimized with respect to environmental impact used less concrete and more reinforcement.
A comparison of the results for the RCCRW in Trollhättan can be seen in Table 4.18. The GA could not improve the design of the retaining wall with respect to either cost or environmental impact. The same observation was made as for the Malmö case: when the GA optimized with respect to cost, it used less reinforcement and more concrete, whereas optimization with respect to environmental impact resulted in more reinforcement and less concrete.

Table 4.16: Cost and environmental impact for the RW in Trollhättan optimized towards environmental impact.

Parameter	**Value**
Concrete volume (stem)	2.35 m^3/m
Concrete volume (slab)	2.57 m^3/m
Total concrete volume	4.92 m^3/m
Concrete cost (stem)	3,427.48 kr/m
Concrete cost (slab)	3,681.46 kr/m
Total concrete cost	7,108.94 kr/m
Vertical steel mass	311.48 kg/m
Horizontal steel mass	51.30 kg/m
Reinforcement cost	5,369.12 kr/m
Total cost	12,478.06 kr/m
Environmental impact (stem)	626.76 kg CO_2-ekv/m
Environmental impact (slab)	657.51 kg CO_2-ekv/m
Environmental impact (reinforcement)	270.27 kg CO_2-ekv/m
Total environmental impact	1,554.54 kg CO_2-ekv/m

Table 4.17: Comparison of the RW designs in Malmö.

Parameter	**Built wall**	**GA: Cost optimization**	**GA: EI optimization**
Concrete volume [m^3/m]	5.46	8.09	7.72
Vertical reinforcement [kg/m]	297	309	332
Horizontal reinforcement [kg/m]	126	91.3	90.4
Total reinforcement [kg/m]	423	400	422
Cost [SEK/m]	14 415	18 009	17 792
Environmental impact [kg CO_2eq/m]	1 856	2 582	2 495

Table 4.18: Comparison of RW designs in Trollhättan.

Parameter	**Built wall**	**GA: Cost optimization**	**GA: environmental impact optimization**
Concrete volume [m^3/m]	3.92	5.34	4.92
Vertical reinforcement [kg/m]	180.9	266.5	311.5
Horizontal reinforcement [kg/m]	70.8	54.7	51.3
Total reinforcement [kg/m]	251.6	321.2	362.8
Cost [SEK/m]	9 396	12 482	12 478
Environmental impact [kg CO_2eq/m]	1 213	1 635	1 554.5

4.5.4 Multi-Objective Results

A MOO was also carried out using NSGA-II for the retaining wall in Trollhättan. The results are shown in Figure 4.15, which indicates a close correlation between cost and environmental impact in this optimization model, with a single Pareto optimum. However, it can be observed from the results of the single-objective optimization that the retaining walls in the case studies presented in Chapter 4.5.3 that, when optimizing with respect to cost, the GA used more concrete and less reinforcement steel, whereas optimization with respect to environmental impact resulted in more reinforcement steel and less concrete.

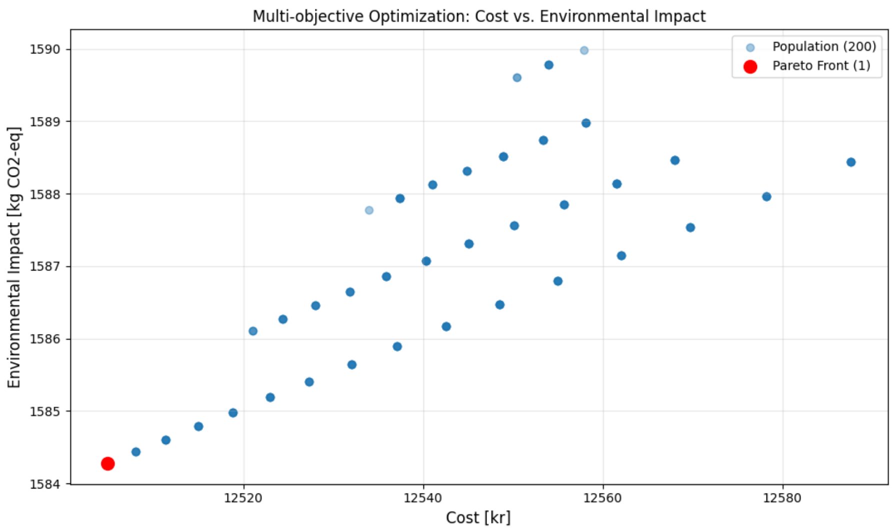


Figure 4.15: Solutions found for the MOO for the RW in Trollhättan.

5
Discussion

This chapter presents and discusses the findings of the study.

5.1 Optimization

The challenges in creating an optimization framework that can be reusable and applied to any case are that generalization and optimization often contradict each other. To allow the evaluation of different designs, without going into project-specific challenges, requires simplifications and assumptions that are most often on the conservative side. These can, for example, be assumptions regarding different earth pressure theories that change the magnitude of the loads. Rankine theory, in general, is a simpler version of Coulomb theory and ignores factors like wall friction. This facilitates the calculations for the optimization, as it more efficiently achieves results for all cases. According to Brooks and Nielsen (2010) Coulomb theory can only be used for cantilevered retaining walls with a short heel. However, this is not known until the RCCRW design process is complete. As time is limited in projects, these assumptions are sometimes already made without the time to optimize the design in the bidding phase, in which case this algorithm can help improve efficiency.

The configuration study showed that there was no configuration that excelled in all cases. However, the study indicated that a larger population size is advantageous. The mean minimum cost and environmental impact for the convergence study for one and two possible reinforcement layers gave the same results. However, certain designs stood out with significantly lower costs than the rest of the designs when looking at different seeds. The average minimum cost being 13 500 SEK/m of built wall, while some designs were below 12 000 SEK/m of built wall. The reason for this is most probably that the algorithm gets stuck in a local minimum, which is significantly more costly than the global minimum. The size of the design space $N_{designs}$ is determined by the Cartesian product of all possible values for the design variables and can be expressed as

$$N_{\text{designs}} = \prod_{i=1}^{n} x_i$$

where x_i represents the number of discrete values available for design variable i. In the case when only one layer of reinforcement is possible, there are still 10 variables. If there were 10 possible values for each variable, the number of possible designs would be $N_{\text{designs}} = 10^{10}$. With only 10 000 designs evaluated, only a fraction of the design space is evaluated. However, since the purpose of the algorithm was to find a feasible and cost-optimized solution in a limited time, it might not be necessary to find the true minimum. As the difference in results is quite large, measures to minimize this variation such as, decreasing the design space and increasing the population size and are discussed below.

As the design space is dependent on the height of the RCCRW, the calculated design space for a 5-meter RCCRW model is approximately $N_{\text{designs}} = 6 \cdot 10^{14}$. Since the calculation is purely analytical, the computational time is relatively short. However, if each evaluated design takes one millisecond, evaluating the entire design space would take $6 \cdot 10^{14}$ milliseconds, which corresponds to approximately 19,000 years. If measures to reduce the whole design space to a computationally reasonable size are taken, one might consider using high speed computers to evaluate every possible design.

To achieve the best degree of optimization, the implementation of the chosen algorithm played a major role. Due to the time constraint of the project, the algorithm had to be efficient and easy to implement, As mentioned previously, due to the design space being extensive, there was a probable risk that the optimization algorithm would terminate at a final design originating from a local minimum of the objective function. To counteract this phenomenon, a possible solution would be to increase the number of designs evaluated when running the script. When carrying out the convergence study, we evaluated 10 000 designs for each configuration. As the specific configuration is chosen, the number of designs can be increased to explore more outcomes. The most straightforward solution would be to increase the population size or to increase the number of generations of the optimization process. One could argue that an increased population size would be preferred due to it leading to a wider range of designs being investigated. The number of generations could also be increased up towards 100 generations to ensure that the algorithm has converged but at the cost of computational time. This is further emphasized by the results seen in the convergence study, where the majority of configurations with larger populations led to better results. If we instead increased the number of generations, it would be expected that the script would find fewer general solutions and then make small adjustments to refine the design.

To further improve the efficiency of the algorithm, an additional termination criterion could be implemented. If no improvement is observed after, for example, five or ten additional generations, the algorithm could be terminated. This would avoid unnecessary computational time in cases of early convergence. As mutation plays an important role in escaping local optima, this possibility is reduced if the genetic algorithm stops immediately after no improvement is observed. Therefore, the trade-off between computational time and the possibility of escaping local optima must be carefully considered.

Another possibility to improve the optimization algorithm might be to increase the mutation rate in the algorithm configuration. As the mutation rate chosen was the highest of the possible values in the configuration study, there is a chance that an even higher mutation rate might be beneficial to achieve a better result. To ensure this, another configuration study with higher mutation rates could be conducted. Possible values for the mutation rate could be [0.1, 0.2, and 0.3]. A possible consequence of increasing the mutation would be that the algorithm would be less likely of finding a local minimum as it counteracts this.

Another option for achieving a more reliable configuration would have been to perform a Monte Carlo simulation. This would have provided further validation that the selected configuration was the best-performing one. However, due to the limited time frame of the project, it was not possible to conduct both methods.

A further measure that could possibly lead to improvements would be to change the type of algorithm used, as it has a great impact on the calculation process and ultimately the result. The decision was made to use a GA because it being effective in handling complex problems with multiple variables and effectively processing multiple parallel solutions. Additionally, a GA is relatively better at avoiding local extremes compared to other algorithms. The biggest disadvantage of the GA is that the user cannot be certain that the final solution is the global and not a local extreme. Additionally, the algorithm has the risk to be more time consuming compared to others. Similar algorithms that would also be possible to choose would be Particle Swarm Optimization or Ant Colony Optimization which are also nature inspired optimization algorithms. The choice of optimization algorithm was based on the literature study, where GA was deemed the most suitable one.

5.2 RCCRW Model

As the optimization process depends heavily on how the RW is modeled, it constituted a key role for the final result. The constraints were formed through Eurocode and TSFS with nationally recommended values. If the model were built on different codes, recommended safety coefficients, and assumptions, the design could possibly be even more optimized. Ultimately, the project client decides which specific codes and values that are used, which thereby dictates how optimized the structure can be made.

The wall is now assumed to be built without shear reinforcement to ease the construction. This has proven in the case studies to provide thicker structures than the possible optimal solution with regards to material cost and environmental impact in order to have sufficient shear capacity. An improvement of the optimization model would be to give the user the option to use shear reinforcement in the calculations. If the results from the algorithm give excessive thickness without reinforcement, the option to run it again with shear reinforcement can be used by the user.

When having the possibility, the optimization algorithm would often choose 2 layers of reinforcement for some part of the retaining wall, sometimes with a suboptimal reinforcement layout. One possible explanation for this is that the algorithm gets stuck at a local minimum and, with a large design space due to 19 design variables, new solutions are not properly explored. Restricting the design to only one reinforcement layer reduces the number of design variables to 10 instead of 19, greatly reducing the design space.

The range of possible values for the variables used in the model is relatively large. When using small discrete step sizes of 10 mm, the objective function appears more continuous and smooth. Since the end values are fixed, increasing the step size to 50 or 100 mm significantly reduces the number of possible variable values and therefore decreases the size of the design space. As a result, the objective function becomes less smooth and more discrete. This can also lead to fewer unique solutions being identified by the optimization algorithm compared to using smaller step sizes. In those cases, the optimization algorithm is less likely to get stuck in a local minimum.

5.3 Cost vs Environmental Impact

As only one Pareto optimal solution is found during the multi-objective optimization, it can be concluded that cost and environmental impact are closely linked in this optimization model, as only the materials are used to calculate environmental impact and cost. If other factors such as transportation, labor cost, formwork, and more were included in the optimization, the correlation might not be as strong and more solutions would appear on the Pareto front. Right now, both objectives are weighted equally. If the project has certain demands to lower the environmental impact, it can be weighted higher to prioritize environmental impact over cost.

As the concrete used in this model is climate-improved concrete with lower EI but a higher cost, the observations seen in the single-objective optimization that cost optimization tends to use less steel and more concrete might be more clear if non-climate-improved concrete were used.

5.4 Case Study

When looking at the result from the case study in Malmö, the optimization algorithm did not successfully reduce the cost or environmental impact. This is likely due to the difference in details of the calculations such as for the soil and surcharge load effects. With more detailed calculations of the load effects, the structure has a lower climate impact and a lower cost. In cases of extreme surcharges or other load effects, this suggests that more precise load calculations may improve optimization performance. When performing the same structural checks as in the GA using the designs of the built walls, neither of the RCCRWs passes the checks, further emphasizing that the GA produces more conservative designs.

When looking at the constraints violated in Table 4.4 in Chapter 4.5, there is not enough shear capacity in the heel, toe, and stem. In addition to that, only the constraint of crack width in the heel is violated in the limited geometry case. This corresponds to a slab thickness of 0.59 meters seen in Table 4.5. In the final design the slab, seen in Table 4.7, is 1 .05 meters when all the constraints are fulfilled. Having the possibility of including shear reinforcement may be beneficial when optimizing towards material cost and environmental impact, as the thickness increases significantly only to satisfy the shear capacity constraint. However, this is outside of the current capabilities of the optimization algorithm and must be done manually by the engineer.

The case study in Trollhättan resulted in a design without altering the possible range of values for the design variables. However, it did not improve either the cost or environmental impact of the RCCRW. For both case studies, the load effects on the wall have been greater when calculated with the script than the capacity of the built walls, indicating that the conservative assumptions made in the calculations play a significant role in the optimization process. As the final design that is built is likely not the design that was calculated in the bidding phase, the comparison might not be completely fair. Using the optimization script with the load effects calculated in the final design process might give better results for the GA.

When analyzing the design of the constructed walls against the structural checks performed by the GA, it was observed that the constructed walls did not have sufficient capacity. This indicates that the final designs produced underwent a more detailed design process with respect to load effects. Together with a more detailed reinforcement design, including the shortening of reinforcement in the stem, even more optimized structures could be achieved.

5.5 User-Friendliness and Flexibility

As the Python script now takes input from Excel to use in the GA, it is relatively user friendly for users without Python knowledge. However, the possibility of editing and modifying the GA is limited. If, for example, a parameter needs to be added to the optimization or an increase in evaluated designs is desired, the script needs to be modified. This makes the process more complicated, and if the user does not have prior experience with Python, it limits the flexibility of the optimization. This requires that the user has Python experience, which is not general knowledge in the industry today.

5.6 Future Improvements

Further improvements of the optimization model would be to divide the stem into smaller sections. This would enable the calculation of the moment and shear resistance required in the upper parts of the wall. As the stem acts as a cantilever and the earth pressure increases with the depth of the soil, the internal forces decrease quickly in the upper parts of the wall, hence requiring less capacity. This could then be utilized to make the final designs more optimized with, for example, shorter reinforcement lengths, different sizes of reinforcement bars, varying cross-sections, etc. This would further optimize the RCCRW, reducing the amount of material used and thereby cutting down on both environmental impact and cost.

Looking at the variability in results from different seeds used for the same algorithm configuration, one could argue that the optimization algorithm could be adjusted and improved further to increase the chance of finding or converging closer to the global optimal design. A measure to achieve a more thoroughly explored design space would be to increase the population size, thereby increasing the total number of evaluated designs. This change would be possible to implement in the script instantaneously, but would increase computational time.

Furthermore, the design process could also use FE analysis tools as a basis to calculate the loads and capacities of the RCCRW instead of the analytical calculations currently performed. This could also simplify the process of adding loads and performing load combinations. This would likely increase computational time but decrease load effects caused by conservative load assumptions.

Multiple optimization algorithms have not been tested in this study. It might not be the case that a GA is the optimal optimization algorithm for this optimization problem. In practice, to find the optimal optimization algorithm, they all should be tested for the specific problem at hand but as time was limited it was not possible for this project.

5.7 Neglected Factors

Other aspects neglected during the study that could possibly have changed the results are transport and production. Both of these impact the environmental impact and cost respectively and can vary heavily depending on geographical location and design. Both pose individual challenges for the optimization process, as it can be difficult to define correct values that should suit general calculations. The implementation of buildability would be possible in the script but would most likely require a significant amount of work to gather correct data. An option would be to calculate the amount of work hours that go into the retaining wall. However, this is highly dependent on the type of project in question and would further complicate the generalization of the script.

6
Conclusion

This study on RCCRW optimization using GA has shown that it is possible to quickly develop buildable solutions for RCCRW using optimization algorithms, which can be highly advantageous during the bidding phase of a project. The study has also demonstrated that more precise load calculations and reinforcement detailing are required for further optimization. This is due to optimization and generalization conflict with each other. Several areas for improvement have been identified and listed below, which can be a subject for future research and development of the program.

MOO resulted in a single Pareto optimal solution. This is due to the optimization objectives being closely linked together. Reducing the amount of concrete or steel would reduce cost and environmental impact. However, when performing a single-objective optimization towards cost, the GA tends to use less reinforcement steel and more concrete, and when optimizing towards environmental impact, the GA uses less concrete and more reinforcement steel.

Among the different possible configurations, the algorithm favored a large population with a high mutation rate. Besides, when optimizing towards cost as a single objective, the configuration that performed best on average had a small population, but converged quickly. The most suitable number of crossover points appeared to be related to the number of variables used. When using a higher number of variables, the algorithm achieved better results when using more crossover points. Consequently, the optimization with two possible reinforcement layers, using 19 variables, favored six crossover points, while the algorithm using one reinforcement layer consisted of 10 variables and favored four crossover points.

6.1 Future improvements

This section lists the identified improvements that could be made:

- Increase the population size to explore a wider range of solutions.
- Refined reinforcement detailing and cross-section calculations in the stem to reduce material usage.
- Include more parameters in the objective function, such as labor hours and transportation.

- Include a finite element analysis to achieve more precise load effects.
- Reduce the design space by increasing the step size for reinforcement spacing, toe, and heel width to steps of 50 millimeters instead of 10 millimeters.
- Improve computational efficiency by implementing an additional termination criterion that ends the optimization process if no improvement is observed after a predefined number of generations.
- Strengthen the robustness of the algorithm by performing a Monte Carlo simulation to ensure that the optimal algorithm configuration is used.

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