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Optimization of reinforced concrete cantilever retaining walls considering environmental impact and investment cost

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Abstract

Today's civil engineering structures are most often designed through a trial and error approach, which means that the designer tests a design solution and evaluates whether all requirements are met. If any of the requirements are not met, changes are made to the design until a feasible solution is obtained. It is a time-consuming process where the final design is not always optimal concerning material consumption. In this study, a program has been developed in MATLAB® for the design of reinforced concrete retaining walls and by using optimization algorithms, the design process has been made automated and time-efficient. The use of optimization algorithms also allows for finding a solution that is not only feasible but also optimal. The developed program utilizes two objective functions, minimizing environmental impact or investment cost based on material consumption. In addition, the design calculations are developed according to Eurocode and additional national requirements of Swedish standards.

This thesis presents the background to the study, fundamental optimization theory and how the developed program is designed. A case study is also presented where existing retaining walls have been examined to evaluate what savings could have been made using optimization algorithms in the design process. Lastly, guidelines are also presented for designers to facilitate the choice of cross-sectional dimensions and reinforcement bar dimensions when designing retaining walls.

The results obtained in the case study show that using optimization algorithms in the design process can make significant savings (10-20%) on investment cost and environmental impact. Moreover, the results show that an optimized retaining wall concerning environmental impact also leads to a substantial reduction in investment costs and vice versa.

Keywords: Structural optimization, Reinforced concrete cantilever retaining wall, Environmental impact, Investment cost

Sammanfattning

Dagens anläggningskonstruktioner dimensioneras oftast genom ett iterativt förfarande där konstruktören manuellt utvärderar om alla krav är uppfyllda. Om alla krav inte uppfylls utförs ändringar tills en godtagbar konstruktion erhålls. Det är en tidskrävande process där den slutgiltiga konstruktionen inte alltid blir optimal med avseende på materialåtgång och således finns det utrymme för besparingar. I den här studien har ett program utvecklats i MATLAB® för dimensionering av stödmurar i armerad betong och genom att använda optimeringsalgoritmer har dimensioneringsprocessen automatiserats och effektiviserats. Användningen av optimeringsalgoritmer gör det även möjligt att hitta en lösning som inte bara är godtagbar utan också optimal. Det utvecklade programmet har två målfunktioner som baserats på materialåtgång, minimering av miljöpåverkan eller investeringskostnad. Därtill tillgodoser programmet även gällande styrdokument för anläggningskonstruktioner i Sverige.

Denna rapport presenterar bakgrunden till studien, övergripande optimeringsteori samt hur det utvecklade programmet är utformat. Det presenteras även en fallstudie där befintliga stödmurar har undersökts för att utvärdera vilka besparingar som kunde gjorts vid användning av optimeringsalgoritmer i dimensioneringsprocessen. Slutligen presenteras även riktlinjer som har skapats för att underlätta valet av tvärsnitts- och armeringsdimensioner vid dimensionering av stödmurar.

Resultaten erhållna i fallstudien visar att betydande besparingar (10-20 %) kan göras genom att använda optimeringsalgoritmer i dimensioneringsprocessen. Dessutom visar resultaten på att en optimerad stödmur med avseende på miljöpåverkan leder också till en avsevärd minskning i investeringskostnad och vice versa.

Sökord: Strukturell optimering, Stödmur, Miljöpåverkan, Investeringskostnad

Preface

The work presented in this thesis was carried out during the spring of 2021 at the Division of Structural Engineering and Bridges, KTH Royal Institute of Technology, Stockholm, Sweden, and at the Bridge Design department at AFRY, Solna, Sweden.

We want to thank AFRY for giving us the opportunity to write this thesis and for believing in us. We also want to thank the designers at AFRY who have given us their input and help throughout the work. We would also like to thank Prof. Raid Karoumi for showing interest and support in this thesis work. Further, we would like to express our sincere gratitude to our supervisors, Markus Lythell (AFRY) and Elisa Khouri Chalouhi (KTH); their expertise, guidance and feedback have been greatly appreciated.

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Abbreviations

Abbreviation	**Description**
BOS	Buildable optimal solution
BS	Built solution
EI	Environmental impact
GA	Genetic Algorithm
GPS	Generalized Pattern Search
GSS	Generating Set Search
GWP	Global Warming Potential
IC	Investment cost
LCA	Life cycle assessment
MADS	Mesh Adaptive Search
OS	Optimal solution
PS	Pattern Search
RB	Case study structure located by the Roslagsbana in Stockholm
RC	Reinforced concrete
RCCRW	Reinforced concrete cantilever retaining wall
SLS	Serviceability limit state
ULS	Ultimate limit state

VB	Case study structure located at Vårby backe in Stockholm

Contents

Chapter 1

Introduction

1.1 Background

The construction and building sector accounted for 38% of the process-related carbon dioxide emissions in 2019, 10% of which came from building materials manufacturing. It follows that the development and implementation of new technologies are required to reduce the building material consumption (Global Alliance for Buildings and Construction 2020). One approach to reducing the building sector's environmental impact is to optimize the use of materials in the early design stage, directly reducing both the emissions from material production and transportation. Structural optimization is not a new technology per se, but it is still not widely used at design offices. Instead, civil engineering structures are most often designed through a trial and error approach, which means that the designer tests a solution and evaluates whether all requirements are met. If any of the requirements are not met, changes are made until a feasible solution is found. It is a time-consuming process that relies on the designer's experience and the final design is not always optimal concerning material consumption. However, optimization algorithms could make the design process automated, time-efficient and provide design solutions with minimized environmental impact (EI) and other important aspects, such as investment cost (IC).

This study aims to integrate structural optimization into the design process of reinforced concrete cantilever retaining walls (RCCRW). RCCRWs are defined as walls whose weight holds back the lateral earth pressure of soil or rock materials with or without the help of stabilizing masses of soil or fill materials. Retaining wall structures are common at bridge supports, road banks or other places where it is desirable to establish height differences in the ground (CEN 2010).

1.2 Aim and scope

The objectives of this study are to:

– Automate the design process for RCCRWs and use optimization algorithms in MATLAB® to minimize EI and IC.

– Perform a case study to compare existing RCCRWs with their optimized counterpart.

– Evaluate if EI and IC are conflicting or not and determine if a simultaneous analysis is needed.

– Establish design guidelines for engineers to achieve cost-effective and environmentally-friendly structures.

The present study is subject to the following limitations and assumptions:

– Rankine's earth pressure theory has been adopted

– The resisting earth pressure is neglected

– The ground-water table is limited to the assumed level of the resisting soil

– The slab toe is designed as a corbel

– The general ultimate bearing capacity equation has been used when calculating the bearing capacity of the foundation.

– Only the loads presented in Section 3.2.1 has been considered.

– Self-weight of the edge beams and railings are not considered in the design

– Stiffness of the reinforcement is neglected

– Only EI and IC of the two materials concrete and reinforcement has been considered. Furthermore, the life cycle assessment (LCA) method is used to quantify EI. Only the material production phase is included in the calculations and EI corresponds to the global warming potential expressed as kg CO_2-eq (see Section 3.1.2).

1.3 Rules and regulations

The design calculations are developed according to Eurocode and additional national requirements of Swedish standards. The standards treated in this thesis work are presented below:

– SS-EN 1990 Eurocode: Basis of structural design

– SS-EN 1991-1-1 Eurocode 1: Actions on structures - Part 1-1: General actions

– SS-EN 1991-2 Eurocode 1: Actions on structures - Part 2: Traffic loads on bridges

– SS-EN 1992-1-1 Eurocode 2: Design of concrete structures - Part 1-1: General rules and rules for buildings

– SS-EN 1997-1 Eurocode 7: Geotechnical design - Part 1: General rules

– TSFS 2018:57 Transportstyrelsens föreskrifter och allmänna råd om tillämpning av eurokoder

– TDOK 2013:0667 Trafikverkets tekniska krav för geokonstruktioner

– TDOK 2013:0668 Trafikverkets tekniska råd för geokonstruktioner

– TRVINFRA-00226 Bro och broliknande konstruktion, Allmänna krav

– TRVINFRA-00227 Bro och broliknande konstruktion, Byggande

1.4 Outline of the thesis

Chapter 1 aims to introduce the reader to the background, the purpose and the limitations of this thesis work. Additionally, this chapter also presents the rules and regulations used in this work.

In Chapter 2, an overview of concepts, terminology, and optimization theory is presented to introduce the readers to optimization. The chapter is followed by a brief overview of the optimization algorithms treated in this thesis work and their specific properties.

In Chapter 3 an overview of the developed software is presented. It includes the structural analysis of RCCRWs and how optimization has been implemented in the design process.

Chapter 4 presents a case study performed on two RCCRWs treated in the present work. The results obtained from several studies are presented as well as discussions of the results.

Chapter 5 presents a design guide established to facilitate the structural design of RCCRWs. The design guide presents optimized cross-sectional dimensions and reinforcement bar topologies for different total heights of the retaining walls.

In the last chapter, Chapter 6, conclusions drawn in this thesis work are presented as well as suggestions for future research.

Chapter 2

Optimization theory

The following chapter presents an overview of concepts, terminology and the theory of optimization. Furthermore, a brief overview of the optimization algorithms covered in this thesis work is presented together with their specific properties.

2.1 Optimization problem

A non-linear optimization problem can mathematically be formulated according to the equations presented below.

$$
\begin{array}{lll}
\text{Minimize} & f_i(\mathbf{x}), & i = 1, 2, ..., I \\
\text{subject } to & g_j(\mathbf{x}) \leq 0, & j = 1, 2, ..., \ J \\
 & h_k(\mathbf{x}) = 0, & k = 1, 2, ..., \ K \\
 & \mathbf{x} \in X \subset R^n &
\end{array}
$$

Where $f_i(\mathbf{x})$ are called *objective functions*, $g_j(\mathbf{x})$ are called *inequality constraints* and $h_k(\mathbf{x})$ are called *equality constraints*. $\mathbf{x}$ is a vector of n *design variables* and X is the *search space* defined by lower and upper bounds, also known as *side constraints*. A vector $\mathbf{x}$ that satisfies the above equations and eventual upper and lower bounds are called a *feasible solution*. All feasible solutions belong to the *feasible region*. If both the objective and constraint functions are linear, the optimization problem is classified as a linear optimization problem.

2.2 Design variables

Design variables are unknown variables that change during the optimization process. An optimization problem aims to find the design variable values that return the best solution. Design variables can be *continuous*, i.e., they can move continuously in the search space or *discrete*, i.e., they take on integer or binary values. In structural optimization, continuous design variables are, e.g., the thicknesses of the various structural members and discrete design variables are, e.g., the diameter of the reinforcement bars.

2.3 Objective functions

Each objective function is a function that the optimization process aims to minimize. It is a quantitative value dependent on the design variables but also on preassigned parameters. By convention, the objective function is minimized in optimization problems, but it can be maximized by simply inverting the sign.

Optimization problems can be *single-objective* or *multi-objective.* Only one objective function is considered in a single-objective problem, while multi-objective problems consider two or more objective functions that are minimized simultaneously.

2.4 Constraints

An optimization problem can be either constrained or unconstrained. *Unconstrained optimization problems* are generally easier to solve than *constrained optimization problems.* The *direct approach* and the *penalty method* are two procedures that traditionally have been used to handle constrained optimization problems. The direct approach is a straightforward procedure in which the optimization problem's solution is kept if all constraints are satisfied and discarded otherwise. The penalty method is a bit more complicated and is used to approximate a constrained optimization problem into an unconstrained one (Luerberger and Ye 2016). In this method, a penalty is added to the objective function when constraints are violated. Consider the optimization problem subject to both equality and inequality constraints in the previous section; it can be converted into an unconstrained optimization problem by adding a penalty function multiplied by a penalty parameter to the objective function(s):

$$\begin{array}{ll} \text{Minimize} & f(x) + \mu P(x), \\ \text{subject } \textit{to} & x \in R^n \end{array}$$

Where μ is a positive constant and P is a function satisfying (i) P is continuous, (ii) $P(x) \leq 0$ for all $x \in R^n$, and (iii) $P(x) = 0$ if and only if $g_j \leq 0$ and $h_k = 0$. The idea behind a penalty function is that infeasible solutions will be given a penalty while feasible solutions will not. A popular penalty function is presented below:

$$P(x) = \sum_{j=1}^{J} (\max[0, g_j(x)])^2 + \sum_{k=1}^{K} |h_k(x)|^2 \tag{2.1}$$

2.5 Optimization algorithms

Optimization algorithms can be classified in diverse ways. They can, e.g., be classified depending on whether they use the gradient of the objective function or not, i.e., *gradient-based* or *gradient-free*. Gradient-based algorithms can effectively be used when the objective function is continuous. They use information about the gradient to find a solution. On the other hand, gradient-free algorithms only use information about the objective function's value and do not require the objective function to be continuous.

Another classification consists of dividing algorithms into *deterministic* or *stochastic*. Deterministic algorithms work systematically and, given the same initial configuration and input parameters, will undergo the same sequence of events. In contrast to stochastic algorithms, where the exact series of events is not predictable due to randomization elements. The randomization can cause the algorithm to fail to find a minimum in the immediate area. However, at the same time, this may be desirable to increase the probability to find the global minimum (Chalouhi 2019).

Optimization algorithms can also be classified depending on whether they search on a global or local scale. *Local search* algorithms explore the search space close to the current best solution. Consequently, local search algorithms are highly dependent on the initial configuration with the risk to converge prematurely and get stuck in a local minimum. Gradient-based algorithms are usually limited to local search. In contrast, *global search* algorithms explore the search space on a larger scale, not necessarily close to the current best solution. Many global search algorithms use randomization to achieve this and are therefore stochastic. Meta-heuristic algorithms combine global and local search to find the global minimum. Such algorithms need to have a good balance between these two elements to find a solution that converges towards a global minimum and not just a local one (Mourabit 2016).

2.6 Direct search

Hooke and Jeeves (1961) first introduced the direct search method and the specific routine called Pattern Search (PS). Direct search methods are best used to solve optimization problems when there is no information regarding the objective function's gradient. The main idea is to search the vicinity of a current point (or solution) and look for a point where the objective function has a lower value to ultimately find the global optimum.

PS performs two types of actions called moves: *the exploratory move* and *the pattern move*. The exploratory move searches the vicinity of a current point in an N-dimensional space by varying one design variable at a time. The pattern move then uses the information gathered by the exploratory move to move in the direction of the established "pattern" to minimize the objective function. If a move finds a better value of the objective function, it is regarded as a *success*, otherwise a *failure*. The point from which the pattern move originates is called a *base point* and, once the algorithm finds a better value of the objective function, the base point is changed. This process is repeated until one of the stopping criteria is met.

In the Global Optimization Toolbox User's Guide by Inc. (R2021a) three direct search algorithms are included: the generalized pattern search (GPS) algorithm, the generating set search (GSS) algorithm and the mesh adaptive search (MADS) algorithm. The GPS algorithm has been used in this work and is therefore explained in more detail in the following section. For the other two algorithms, the reader is referred to the user guide mentioned above.

2.6.1 Generalized Pattern Search

GPS uses a so-called *pattern* to determine which points to search at each iteration. The pattern is a set of vectors defined by the number of design variables, n. There exist two types of patterns: the *maximal basis* ($2n$) and the *minimal basis* ($n+1$). For simplicity, we say that we have two design variables, x_1 and x_2, then:

$$v_1 = [1\ 0],\ v_2 = [0\ 1],\ v_3 = [-1\ 0],\ v_4 = [0\ -1] \tag{2.2}$$

is the set of unit vectors for the maximal basis and:

$$v_1 = [1\ 0],\ v_2 = [0\ 1],\ v_3 = [-1\ -1] \tag{2.3}$$

is the set of unit vectors for the minimal basis.

The set of points that the GPS algorithm searches each iteration is called a *mesh*. The patterns are multiplied by a *mesh size* (Δ^m) and then added to the current base point. For the maximal basis, the following mesh is obtained:

$$[x_1, x_2] + \Delta^m v_1,\ [x_1, x_2] + \Delta^m v_2,\ [x_1, x_2] + \Delta^m v_3,\ [x_1, x_2] + \Delta^m v_4 \tag{2.4}$$

When the mesh is established, the algorithm evaluates the objective function at the different points; this is called *polling*. If the algorithm finds a value of the objective function lower than the current value, the poll is called *successful* and a new base point is chosen. Otherwise, the poll is called *unsuccessful* and the base point stays the same. The user needs to define whether to stop the polling as soon as a lower value has been found or choose the base point with the lowest value overall, which is called a *complete poll*.

After the polling, the algorithm either *expands* or *contracts* the mesh by multiplying the mesh size with a factor K. For successful polls, K adopts a value larger than 1, i.e., the mesh size increases. For unsuccessful polls, this value is instead between 0 and 1, i.e., the mesh size decreases.

The GPS algorithm stops when one of the stopping conditions is met. The stopping conditions can be divided into two groups: stopping conditions to limit CPU time and stopping conditions that check for convergence towards an optimum solution. The following stopping conditions are used to limit CPU time:

– The time exceeds a user-defined maximum time.

– The number of polls exceed a user-defined maximum number of polls.

– The number of solutions exceeds a user-defined maximum number of solutions.

and the following stopping conditions are used to check for convergence:

– Mesh size is less than a user-defined mesh tolerance.

– After a successful poll, the distance between the base point in the two previous polls and the mesh size are both less than a user-defined step tolerance.

– After a successful poll, the change in the objective function value in the two previous polls is less than a user-defined function tolerance, and the mesh size is less than the previously mentioned step tolerance.

2.7 Genetic Algorithm

Holland (1992) introduced the genetic algorithm (GA) in 1992. The method uses Darwin's theory of evolution to find the best solution. GA can solve both constrained and unconstrained optimization problems and is used for objective functions that are discontinuous, stochastic or highly non-linear. Furthermore, it can handle mixed-integer optimization problems (Inc. R2021a).

GA starts by producing an initial set of *individuals* (points in the search space). These individuals are usually referred to as *genomes* (design vectors) and their content as *genes* (design variables). The complete set of individuals are called the *population*. Suppose the average distance between the individuals in a population is high. In that case, the populations are said to have *high diversity*, which is essential for the algorithm to search on a more global scale. Otherwise, the population has *low diversity*. All individuals in the population are evaluated by calculating their *raw fitness score* (computing the objective function's value). Since the convention is to minimize the objective function, a lower fitness score is favorable. The raw fitness scores are scaled into so-called *expectation values*. Some of the individuals are either chosen as *parents* or *elite children* based on their expectation value. A new generation is produced by combining children from the *crossover* of two parents or making stochastic changes to one single parent by *mutation*. The individuals with the best expectation value are chosen as elite children and survive to the next generation. Finally, the current population is replaced by the new generation and the process is repeated until one of the stopping conditions is met.

Similar to the GPS algorithm, the stopping conditions for GA can be divided into stopping conditions to limit the CPU time and stopping conditions that check for convergence towards an optimum solution. The following stopping conditions are used to limit CPU time:

– The time exceeds a user-defined maximum time.

– The number of generations exceed a user-defined maximum number of generations.

and the following stopping conditions are used to check for convergence:

- The best value of the fitness function for the current generation is less than or equal to a user-defined fitness limit.
- No improvement is made during a user-defined time limit.
- The average relative change in fitness function value between generations is less than a user-defined tolerance.

Chapter 3

Optimization of reinforced concrete cantilever retaining walls

The following chapter presents the three general phases of structural optimization and how they are implemented in the design of reinforced concrete cantilever retaining walls (RCCRW). Section 3.1 follows the same structure as Chapter 2 and describes the *optimization model* used in the present work. In Section 3.2, the *structural model* of RCCRWs is presented. In Section 3.3, the settings used for the *optimization algorithms* are described.

3.1 Optimization model

The optimization model is a parametric model that consists of user-defined parameters. The parameters to be optimized are the design variables, while the rest are specified as preassigned parameters. Furthermore, the objective functions are used to evaluate the investment cost or environmental impact. Lastly, the constraints need to be formulated such that the governing safety requirements and other user-defined requirements are met.

3.1.1 Design variables

The design variables are the cross-sectional dimensions of the structural members (see Figure 3.1). A total number of seven design variables have been used, including:

X_1 = Stem thickness at the top.
X_2 = Stem thickness at the bottom.
X_3 = Slab thickness at the toe.
X_4 = Slab thickness at the clamped section between stem and slab.
X_5 = Slab thickness at the heel.
X_6 = Toe width.
X_7 = Heel width.

The number of design variables greatly influences the computational cost, i.e., the number of iterations the optimization algorithm needs to reach an optimal solution (Mourabit 2016). However, the software is entirely developed in MATLAB and does not involve any external software that could be time-consuming. Consequently, the time it takes to evaluate a single solution is relatively low.

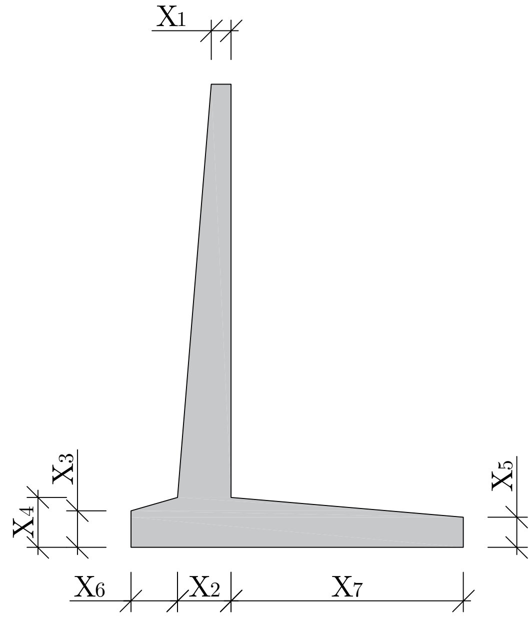


Figure 3.1: Design variables.

3.1.2 Objective functions

The objective functions of the optimization model are the environmental impact and the investment cost of the RCCRW. A single-objective optimization approach was used, which means that the objective functions were treated separately.

The environmental impact is quantified with the LCA method, a standardized method used to determine a product's environmental impact during its whole life cycle in a cradle-to-grave fashion. According to SIS/TK 209 (2019), a structure's life cycle is divided into four stages: Product, construction, use and end of life. The scope of the present work is limited to the product stage only. Furthermore, the environmental impacts are categorized into different impact categories. This work's impact category is global warming potential (GWP) measured in carbon dioxide equivalents (CO_2-eq).

The objective function regarding the investment cost is also based on the product stage, i.e., only the investment costs of the material used for the RCCRW itself are considered.

3.1.3 Constraints

In structural optimization, two types of constraints are generally considered (Chalouhi 2019): structural and operational constraints. The requirements of Eurocode and the Swedish national standards belong to structural constraints. On the other hand, operational constraints are limitations due to common practice, e.g., additional requirements to facilitate the structure's construction. The constraints mentioned above are defined as non-linear inequality constraints on the form:

$$g(x) = C(x) \leq 0 \tag{3.1}$$

Whenever one or more of the constraints are violated ($C > 0$), the objective function will receive a penalty value proportional to the magnitude of the violation. If all constraints are satisfied the penalty value is zero. The penalty function that was introduced in Equation 2.1 have been used. Since no equality constraints are included, the penalized objective function can be described as:

$$\Pi(x, \mu) = f(x) + \mu \sum_{j=1}^{J} (\max[0, g_j(x)])^2 \tag{3.2}$$

The side constraints are implemented by defining lower and upper bound vectors given as input to the optimization algorithm. These vectors limit the search space, meaning that the design variables can only assume values within the specified range.

3.2 Structural model

The structural model consists of the structural design of RCCRWs summarized by Figure 3.2. The structural design is carried out in the ultimate limit state (ULS) and the serviceability limit state (SLS). It consists of structural analysis, verification of the geotechnical stability, verifications of allowable deformations, reinforcement design and calculation of the material quantities to determine the structure's investment cost and environmental impact. A single evaluation of the structural model constitutes a single solution in the optimization process.

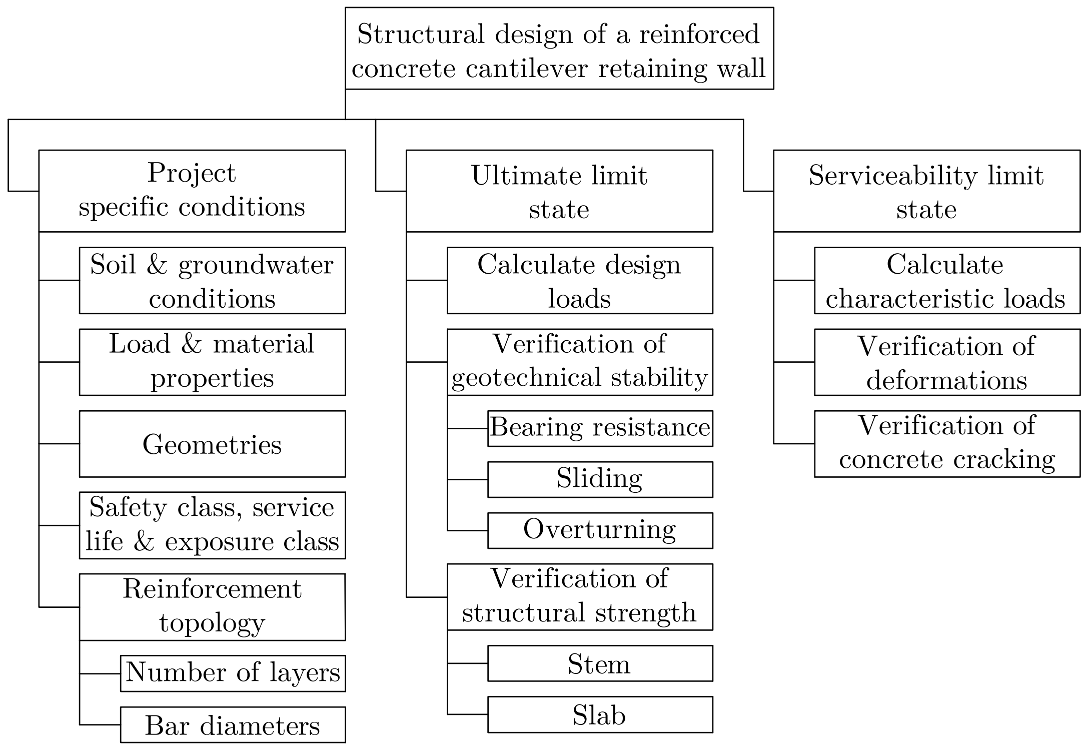


Figure 3.2: The structural design of RCCRWs.

3.2.1 Structural analysis

The first step of the structural design is to perform a structural analysis. The external forces and moments acting on the RCCRW can be determined based on the load and material properties. The loads considered in the design are:

(i) Self-weight of concrete, stem.
(ii) Self-weight of concrete, slab.
(iii) Self-weight of backfill.
(iv) Vertical component of surcharge.
(v) Horizontal component of surcharge.
(vi) Earth pressure (including eventual pore pressure).
(vii) Ground pressure.
(viii) Accidental load (collision with the railing).

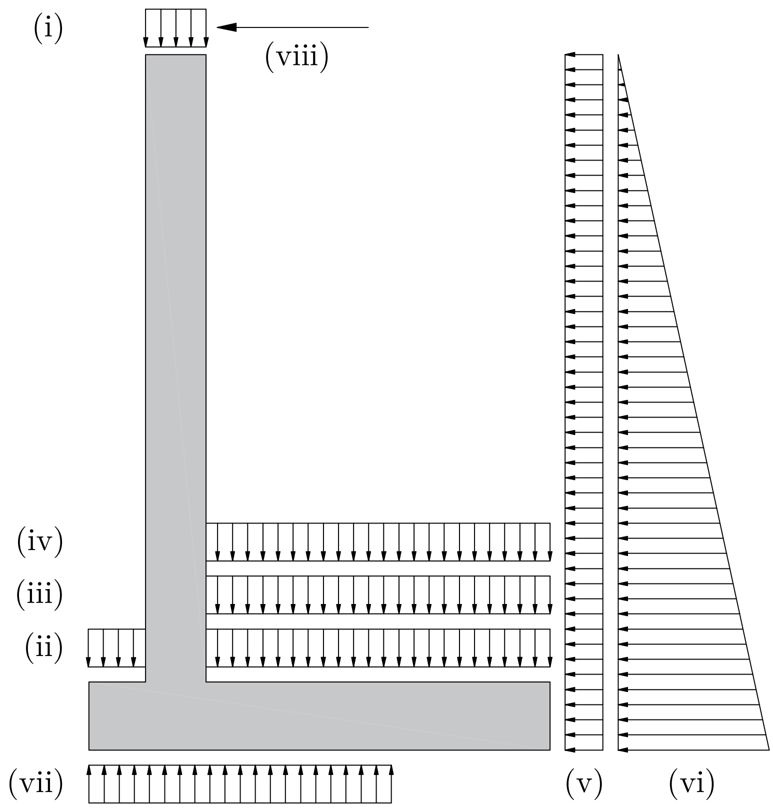


Figure 3.3: Forces acting on the retaining wall.

The vertical and horizontal forces due to the loads described above are calculated and combined according to Eurocode and the Swedish national standards (see Section 1.3). Furthermore, the corresponding ground pressure (vii) for each load case is computed. The resulting forces and moments are used to verify the geotechnical stability described in the subsequent section. In the final step of the structural analysis, the internal forces and moments are extracted for each structural member of the retaining wall to be used in the reinforcement design in Section 3.2.4.

3.2.2 Geotechnical stability

In the verification of the geotechnical stability, typically three failure modes in the ULS are considered: bearing resistance, sliding and overturning. The verification is included in the structural design by implementing the following non-linear inequality constraints:

(i) Sufficient vertical load-bearing capacity, $g(x) = \frac{q_{Ed}(x)}{q_{Rd}(x)} - 1 \leq 0$

(ii) Sufficient resistance against sliding, $g(x) = \frac{H_{Ed}(x)}{R_d(x)} - 1 \leq 0$

(iii) Sufficient load excentricity against overturning, $g(x) = \frac{e_{Ed}(x)}{e_{Rd}(x)} - 1 \leq 0$

3.2.3 Horizontal deformation of the stem

According to Swedish Transport Administration (2020), the stem's horizontal deformation of traffic load should not exceed a threshold of 1/200 times its length. The requirement is implemented as a non-linear inequality constraint:

(i) Allowable horizontal deformation, $g(x) = \frac{\delta(x)}{\delta_{max}(x)} - 1 \leq 0$

3.2.4 Reinforcement design

After the structural analysis, the software performs a reinforcement design for each structural element of the RCCRW. The reinforcement must be designed such that the concrete cross-section can withstand the corresponding bending moments and shear forces. The amount of reinforcement is governed by the requirements in the ULS, SLS and minimum reinforcement stated by Eurocode and TRVINFRA.

In the first step of the reinforcement design, the amount of required bending and shear force reinforcement is calculated in the ULS, such that the following conditions are met:

$$M_{Ed} \leq M_{Rd} \text{ and } V_{Ed} \leq V_{Rd.max} \tag{3.3}$$

In addition to sufficient moment and shear force capacity, the reinforcement must be designed to limit the cracks widths in the SLS. The cross-section has been subjected to the following constraint for the primary reinforcement:

(i) Allowable crack widths, $g(x) = \frac{w_k(x)}{w_{max}} - 1 \leq 0$

Besides the primary reinforcement, secondary reinforcement is installed based on the minimum requirements. Constructability constraints are also considered to ensure that the spacing of the reinforcement follows the requirements in Eurocode (plus an additional requirement of 100 mm to facilitate vibration of the concrete during constructions works) and that the thickness of the structural members is sufficient to fit the reinforcement:

(i) Minimum spacing between reinforcement bars, $g(x) = \frac{s_{min}}{s(x)} - 1 \leq 0$

(ii) Minimum thickness of the structural member, $g(x) = \frac{t_{min}}{t(x)} - 1 \leq 0$

The reinforcement that is inserted in the slab heel is extended to the slab toe. The slab toe is designed as a corbel and treated differently than the stem and slab heel, which are designed as slabs. Verifications of the slab toe are made to ensure that the installed bending reinforcement is sufficient, that shear reinforcement can be avoided and that the geometry is within the bounds of the corbel definition. Furthermore, the nodes of the corbel considered in the strut-and-tie model are also verified such that no stress limit is exceeded and that the inclination of the compression strut is within required limits. The verifications mentioned above are handled with non-linear inequality constraints.

The user can specify the topology of the reinforcement, including bar diameters and the number of layers. The user can also select positions along the structural elements where the reinforcement is to be finished. A detailed reinforcement layout is produced based on the required amount of reinforcement and the user-defined reinforcement topology. The detailed reinforcement design is presented in Figure 3.4 and also includes anchorage lengths.

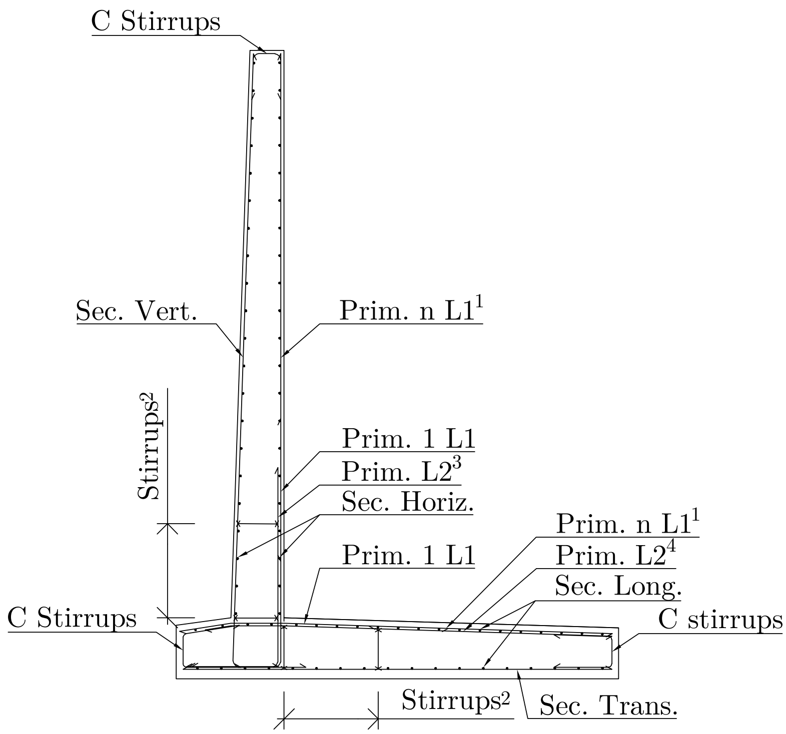


Figure 3.4: Detailed reinforcement design.

[1]Prim. reinf. L1 for each specified section.
[2]Closed stirrups per metre in depth, if required.
[3]Prim. reinf. L2 in stem, ends at the second section if one is specified otherwise continuous.
[4]Prim. reinf. L2 in slab, always continuous if specified.

3.2.5 Investment cost and environmental impact calculation

The material quantities of both concrete and reinforcement are calculated after the reinforcement design is completed. Further, the investment cost and environmental impact can be computed using unit costs and unit emissions defined by the user. The unit values of the present work are presented in Table 3.1. Equation 3.4 shows how the respective objective function is computed.

$$IC = \sum_{m}(C_m \cdot V_m) \qquad EI = \sum_{m}(E_m \cdot V_m) \tag{3.4}$$

Where:
C_m = cost per unit material, m.
E_m = CO2e emissions per unit material, m.
V_m = volume of material, m.

Table 3.1: Unit costs (obtained from Chalouhi (2019)) and unit emissions (obtained from Trafikverket (2020)) of concrete and reinforcement.

Material	**Unit cost [SEK/m^3]**	**Unit emission [kg CO_2-eq/m^3]**
Concrete C32/40	1700	388
Concrete C35/45	1800	388
Reinforcement K500-CT	70650	5495

3.3 Optimization algorithms

Two optimization algorithms have been used in the present work: PS and GA. A description of each algorithm's implementation is presented in the following sections.

3.3.1 Pattern Search

Many settings can be defined for the PS algorithm in MATLAB. Default values have been used for most settings, but some have been tuned to improve performance. The subsequent sections describe some of the settings that have been used and altered. For the complete list of settings used, the reader is referred to Appendix A.

Stopping criteria

As mentioned in Section 2.6.1, the user must specify stopping criteria that cause the PS algorithm to stop. The maximum time, the maximum number of polls and the maximum number of evaluated solutions were all set to infinity to avoid missing out on potentially better solutions. The step, function, and mesh tolerances are all set to 1E-6 (default value), resulting in the algorithm stopping when the mesh size is below this particular value.

3.3.2 Genetic algorithm

GA also has many settings that can be altered. In most cases, the default settings have been used. The following section describe how the stopping criteria have been defined.

Stopping criteria

The default settings have been used as stopping criteria except those that limit CPU time, i.e., the maximum number of generations and maximum time. The same reasoning as for PS has been adopted.

Chapter 4

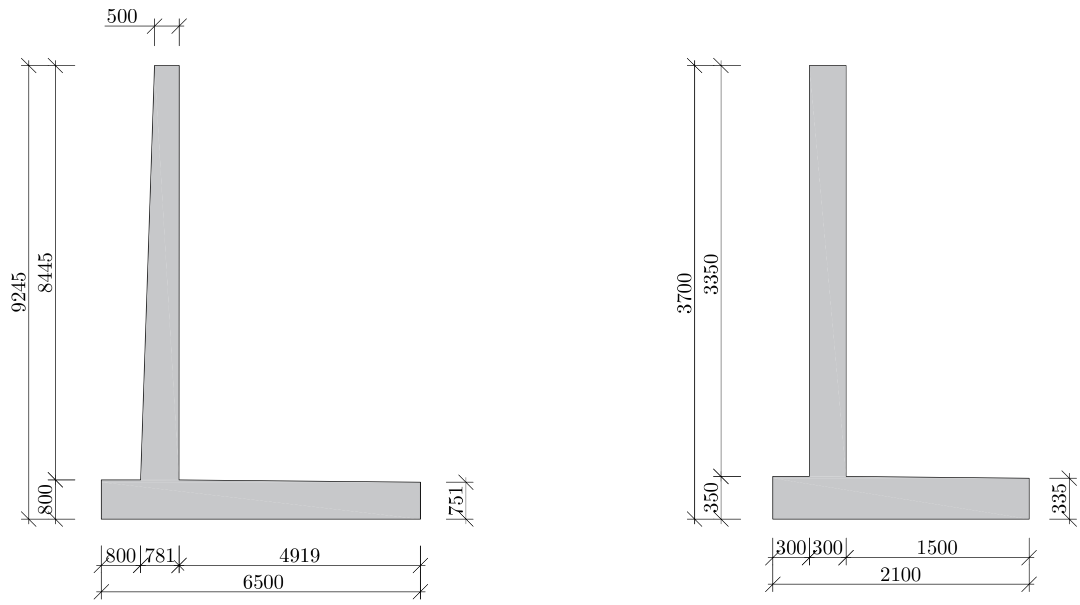
Case Study

The procedure presented in the previous chapter has been applied to redesign two existing RCCRWs using optimization. The primary purpose of the case study is to compare conventional designed RCCRWs with an optimized counterpart to see if savings can be achieved. The case study is further used to check the influence of different assumptions and settings for the studied optimization algorithms. Finally, the performance of different optimization algorithms is tested.

4.1 Built solutions

The case study considers a cast-in-place RCCRW designed by AFRY in 2018 which was supposed to be located in Vårby backe, Stockholm, Sweden. It is an elongated structure with a total length of 220m; the total height and foundation level vary along its length. The concrete is of quality C35/45 and the reinforcement is of quality K500C-T. The RCCRW is divided into ten separate monoliths with a length of 22m each and the case study has been conducted on the monolith with the largest total height. In the following chapter, this monolith will be referred to as VB, short for Vårby backe.

The second structure considered is also a cast-in-place RCCRW located in Vallentuna, Stockholm, Sweden. It was designed in 2012 and it is a part of a series of retaining wall structures standing next to the Roslagsbana light rail line. The studied monolith is 23.55m long and has a total height of 3.7m, it is of concrete quality C32/40 and the reinforcement is of quality B500B. In the following chapter, this monolith will be referred to as RB, short for the Roslagsbana. The cross-sectional dimensions of the two studied monoliths are presented in Figure 4.1.



(a) Vårby backe.

(b) The Roslagsbana.

Figure 4.1: Cross-sectional dimensions of both RCCRWs treated in the present study.

4.2 Optimal solution - Results and discussion

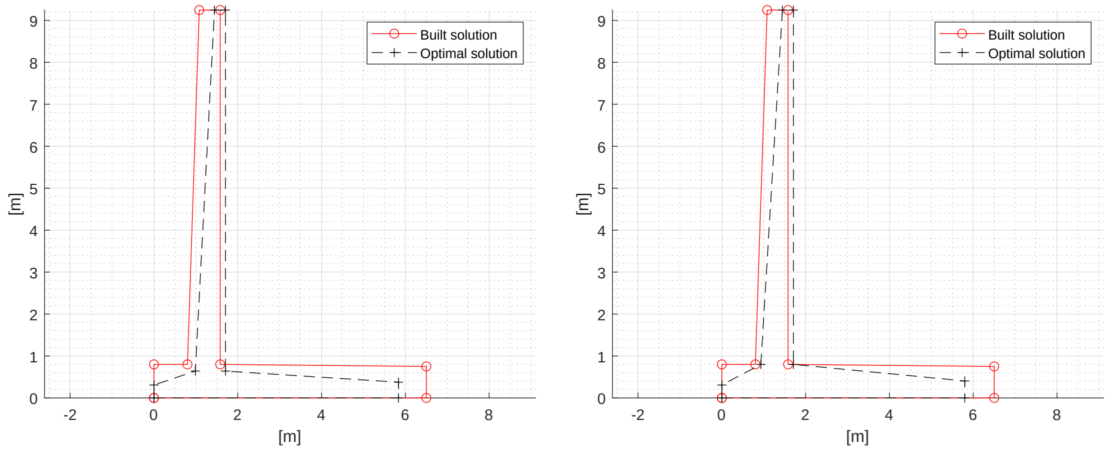
In the following section, the results of the optimal solutions and the influence of different assumptions and optimization algorithm settings are presented for the two RCCRWs. The material quantities of concrete and reinforcement and indirectly the quantities of EI and IC of the optimal solution and the built solution have been calculated using the developed software to make a fair comparison.

4.2.1 Optimal cross-sectional dimensions

The cross-sectional dimensions presented in Figure 3.1 has been optimized twice: minimizing EI and minimizing IC. When minimizing EI, the corresponding value of IC has also been computed, and vice versa. The optimization aims to see if savings can be achieved with respect to the built solution and to see if the objective functions are conflicting.

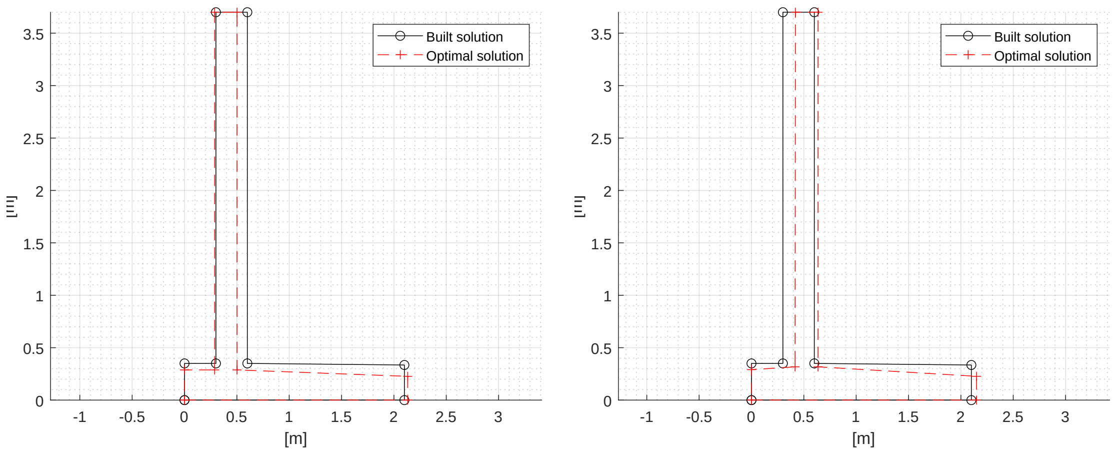
Figure 4.2 and Figure 4.3 compare the built solution's cross-sectional dimensions with the optimal solution for each RCCRW. In each figure, the optimal solution minimizing each objective function is shown. For VB, it can be seen that the thickness of the structural elements diminishes towards their ends. Furthermore, the total width of the base slab is shorter than the built solution. Minimizing EI results in a more slender solution than the solution obtained minimizing IC. Concerning RB, the base slab's thickness also decreases towards its end but is slightly longer than the built solution. The stem remains straight but is thinner. As for VB, the solution where EI is minimized is more slender. Moreover, the stem in the solution minimizing IC has shifted towards the right.

Thicknesses are expected to decrease towards the end since the bending moment decreases as well. An exception is the stem of RB, which has a constant thickness. The reason for this is that the thickness is limited to a certain value to fit the reinforcement. When it comes to the total width of the base slab, it can be seen that for VB it decreased substantially, while for RB it increased slightly. The usage ratios of the maximum allowable ground pressure for the built solutions are quite different in the two cases. It was quite low for VB while it was exceeded for RB, resulting in the total width of the base slab needed to be adjusted in the optimization to satisfy the constraints.



(a) Environmental impact. (b) Investment cost.

Figure 4.2: Cross-sectional dimensions of the built solution (BS) versus the optimal solution (OS). Optimization algorithm: PS. RCCRW: VB



(a) Environmental impact. (b) Investment cost.

Figure 4.3: Cross-sectional dimensions of the built solution (BS) versus the optimal solution (OS). Optimization algorithm: PS. RCCRW: RB

In Table 4.1 and Table 4.2 a comparison has been made between the material quantities and objective function values of the built solution versus the optimal solution for each RCCRW and objective function. The variation of these quantities during the optimization process are presented in Figure 4.4 and Figure 4.5 for each RCCRW when minimizing the objective functions. The quantities are normalized with respect to the corresponding quantities obtained in the first feasible solution.

When minimizing EI and IC, it can be observed that both objective function values are less than the built solution for both RCCRWs. The results leans towards the fact that the objective functions are not conflicting, i.e., minimizing one leads to a significant decrease in the other. One thing to consider, though, is that when minimizing IC, the corresponding savings in EI are not as large as when minimizing EI in the first place, and vice versa. Therefore the designer needs to choose which objective function should be focused on even though significant savings are made in both cases.

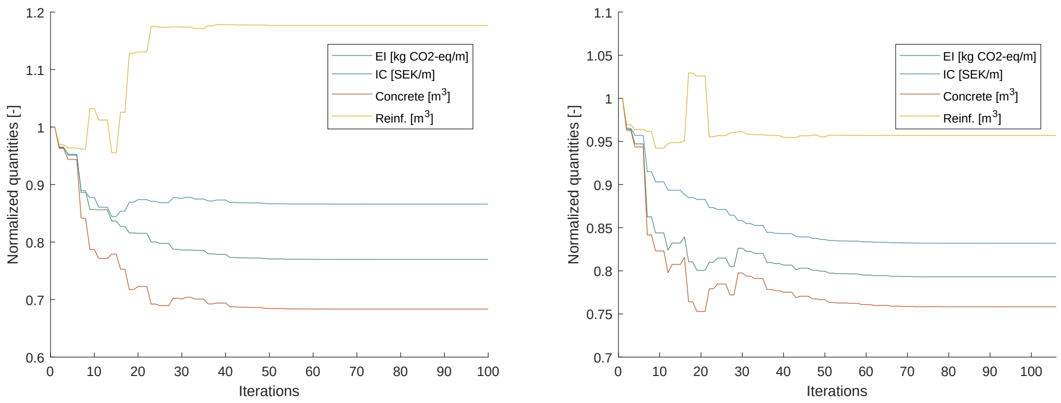
Since both objective function values are calculated based on the material quantities only, the difference between the results is related to the ratio between the unit costs and unit emissions of concrete and reinforcement. Hence, if the ratios are the same for both objective functions, the same solution will be found. The differences in ratio could therefore explain the difference between the objective function values. Using the unit values of Table 3.1, one can compute these ratios. The ratio between the unit costs is higher than the ratio between the unit emissions resulting in that the concrete is more favorable when minimizing IC than minimizing EI. For both RCCRWs, minimizing IC resulted in more concrete being used and less reinforcement, and vice versa when minimizing EI. However, the difference in objective function values due to this is still not that large. Since the unit costs and unit emissions of the two materials can fluctuate depending on several factors and the ratio between them affects the optimal solution, a sensitivity analysis has been performed and is presented in Section 4.2.5 and Section 4.2.6.

Table 4.1: Built solution (BS) versus optimal solution (OS) for Vårby backe (VB) and the Roslagsbana (RB). Objective function: EI. Optimization algorithm: PS.

RCCRW	**Quantity**	**BS**	**OS**	**Difference [%]**
VB	Concrete [m^3]	10.34	7.06	-31.6
	Reinf. [m^3]	0.155	0.182	17.7
	EI [kg CO_2-eq/m]	4860	3743	-23
	IC [SEK/m]	29531	25576	-13.4
RB	Concrete [m^3]	1.71	1.28	-25.6
	Reinf. [m^3]	0.015	0.018	18.1
	EI [kg CO_2-eq/m]	749	597	-20.2
	IC [SEK/m]	4162	3442	-17.3

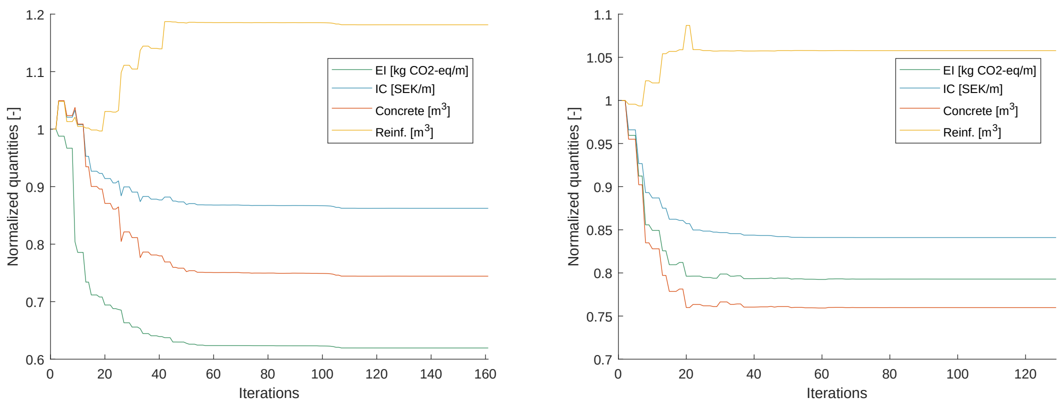
Table 4.2: Built solution (BS) versus optimal solution (OS) for Vårby backe (VB) and the Roslagsbana (RB). Objective function: IC. Optimization algorithm: PS.

RCCRW	Quantity	BS	OS	Difference [%]
VB	Concrete [m^3]	10.34	7.84	-24.2
	Reinf. [m^3]	0.155	0.148	-4.3
	EI [kg CO_2-eq/m]	4860	3854	-20.7
	IC [SEK/m]	29531	24569	-16.8
RB	Concrete [m^3]	1.71	1.33	-22.5
	Reinf. [m^3]	0.015	0.016	6.9
	EI [kg CO_2-eq/m]	749	605	-19.2
	IC [SEK/m]	4162	3416	-17.9



(a) Environmental impact. (b) Investment cost.

Figure 4.4: Variation of the quantities EI, IC, concrete and reinforcement amounts during the optimization. Normalized with respect to the first feasible solution. Optimization algorithm: PS. RCCRW: VB.



(a) Environmental impact. (b) Investment cost.

Figure 4.5: Variation of the quantities EI, IC, concrete and reinforcement amounts during the optimization. Normalized with respect to the first feasible solution. Optimization algorithm: PS. RCCRW: RB.

4.2.2 Effect of the initial guess on the optimal solution (OS)

PS is a deterministic optimization algorithm, thus the same input always yields to the same output. Furthermore, it can be regarded as a local search algorithm. Consequently, the initial guess of the design variables can be essential to find a good solution. There is no guarantee that the global minimum will be found nor easy to prove that the solution is a global minimum (the only thinkable way is to perform an exhaustive search where all possible solutions are evaluated). Therefore, we will most likely have to settle with finding a suboptimal solution (local minima). In the developed software, the designer has to choose the dimensions of the RCCRW, that will constitute the initial guess. It is important that the designer assumes reasonable values from the start. However, since the experience varies between designers, these initial configurations might also vary. The initial guess's influence on the optimization result has been studied by trying different initial guesses. A survey was sent out to the bridge department at AFRY, where the designers could choose a reasonable initial guess based on the total height of the wall and the load specification of the conducted case study. The collected guesses are presented in Table 4.3 together with the dimensions of the built solution (referred to as D1).

Table 4.3: Initial guesses specified by designers at AFRY's bridge department.

RCCRW	**Variable**	**D1**	**D2**	**D3**	**D4**	**D5**	**D6**
VB	X_1 [mm]	500	500	300	500	300	400
	X_2 [mm]	781	800	600	650	400	900
	X_3 [mm]	800	800	650	600	400	900
	X_4 [mm]	800	800	700	600	410	950
	X_5 [mm]	751	600	600	550	400	900
	X_6 [mm]	800	800	500	600	300	900
	X_7 [mm]	4919	4500	5500	4500	2000	4640
RB	X_1 [mm]	300	500	200	400	200	300
	X_2 [mm]	300	600	400	500	200	370
	X_3 [mm]	350	600	400	500	300	350
	X_4 [mm]	350	600	450	500	300	420
	X_5 [mm]	335	500	350	450	300	350
	X_6 [mm]	300	600	300	500	300	350
	X_7 [mm]	1500	1600	2000	2500	1500	2630

The results presented in this section show that all initial guesses gave different suboptimal solutions and one guess led to no solution at all (see Table 4.4 and Table 4.5). However, the differences in the obtained results are relatively similar for the two RCCRWs studied, especially if we look at the obtained final values of the objective functions. Further, none of the initial guesses gave the best solution for both objective functions, making it difficult to see a pattern of which starting value would be the best.

The initial guess that does not result in a solution, D5, performed approximately as many iterations as the other guesses but still found no reasonable solution. This is due to the cross-sectional dimensions specified being too small, causing multiple constraints to be violated. Thus, a very high penalty cost was applied to the objective function from the very first iteration. Consequently, the algorithm did not succeed in finding a set of design variables without being penalized and instead converged on a solution that was not feasible.

Table 4.4: Optimal solutions of the initial guesses specified by AFRY's designers. Objective function: EI. Optimization algorithm: PS.

RCCRW	**Quantity**	**D1**	**D2**	**D3**	**D4**	**D5**	**D6**
VB	Concrete [m^3]	7.06	6.95	7.18	7.21	–	7.31
	Reinf. [m^3]	0.182	0.194	0.186	0.170	–	0.175
	EI [kg CO_2-eq/m]	3743	3763	3821	3737	–	3800
	IC [SEK/m]	25576	26193	26047	25027	–	25529
RB	Concrete [m^3]	1.28	1.36	1.33	1.36	–	1.36
	Reinf. [m^3]	0.0180	0.0158	0.0163	0.0158	–	0.0158
	EI [kg CO_2-eq/m]	597	618	606	619	–	618
	IC [SEK/m]	3442	3429	3408	3429	–	3430

Table 4.5: Optimal solutions of the initial guesses specified by AFRY's designers. Objective function: IC. Optimization algorithm: PS.

RCCRW	**Quantity**	**D1**	**D2**	**D3**	**D4**	**D5**	**D6**
VB	Concrete [m^3]	7.84	7.91	8.31	7.64	–	7.81
	Reinf. [m^3]	0.148	0.152	0.135	0.153	–	0.148
	EI [kg CO_2-eq/m]	3854	3903	3965	3802	–	3844
	IC [SEK/m]	24569	24982	24506	24535	–	24523
RB	Concrete [m^3]	1.47	1.42	1.33	1.37	–	1.37
	Reinf. [m^3]	0.0152	0.0152	0.0163	0.0158	–	0.0158
	EI [kg CO_2-eq/m]	652	636	605	619	–	617
	IC [SEK/m]	3569	3499	3415	3455	–	3446

To summarize this section with a few remarks on the results. First, it was observed that neither of the initial guesses outperforms the others, meaning that none of them gave the same best solutions for both objective functions. Second, the results indicate that it is essential that the guess specified should not violate too many constraints, e.g., by making the RCCRW too slender. With this in mind, it is concluded that the starting points significantly impact the outcome of the optimization process and thus, it is suitable to try several starting to verify the results obtained.

4.2.3 Comparison between Pattern Search (PS) and Genetic Algorithm (GA)

This section presents a comparative study of the two algorithms treated in this thesis work. It was conducted to verify the solutions obtained and to compare the performance of the two algorithms. The results obtained are then presented as optimal solutions compared to the built solution for each algorithm. Optimization was performed for both objective functions but in this section only the optimal solutions when minimizing EI are presented. The interested reader is referred to Appendix B and Appendix C for results of optimization considering IC for each case study, respectively. Furthermore, the results presented for the PS algorithm are the optimal solutions that gave the best final values from the initial guesses specified by AFRY's designers. In comparison, the results obtained with GA used all the initial guesses for its randomized initial population matrix.

The results obtained from the two algorithms are very similar in terms of the final values of the objective function. The savings presented, as compared to the built solution, differ by approximately 1 % between the two algorithms for both RCCRWs (see Table 4.6 and Table 4.7). Although, the cross-sectional dimensions and the volumes of concrete and reinforcement vary somewhat more between the algorithms (see Figure 4.6).

Another aspect considered in the comparative study is the CPU time (see Table 4.8). The results show that the time required to obtain the final values differs significantly between the algorithms. Considering the number of evaluations computed to reach the final values, PS requires approximately one-tenth or fewer evaluations than GA, given that default optimization configurations have been used for the two algorithms with no stopping criteria regarding the CPU time.

Table 4.6: Built solution (BS) versus optimal solution (OS). Objective function: EI. Optimization algorithm: PS.

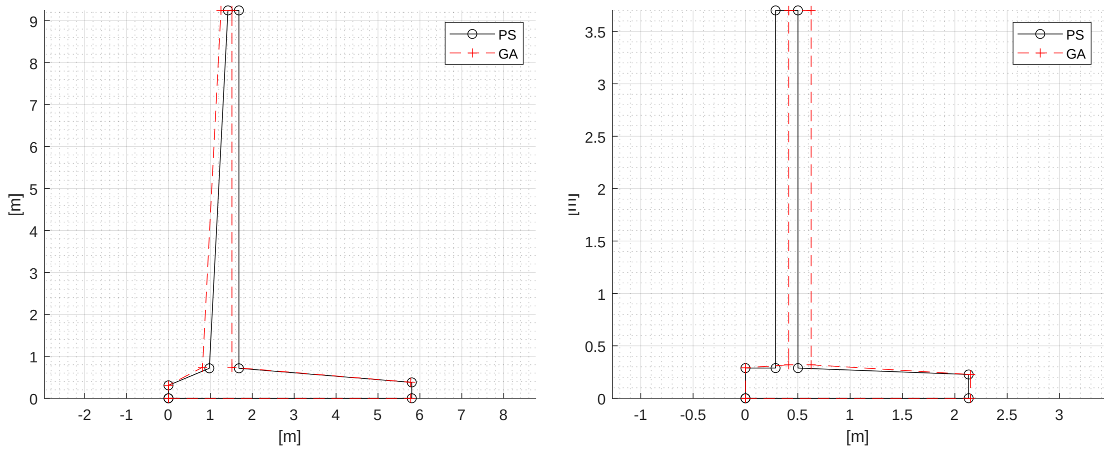
RCCRW	Quantity	BS	OS	Difference [%]
VB	Concrete [m^3]	10.34	7.21	-30.2
	Reinf. [m^3]	0.155	0.170	+10.2
	EI [kg CO_2-eq/m]	4860	3737	-23.1
	IC [SEK/m]	29531	25027	-15.3
RB	Concrete [m^3]	1.71	1.28	-25.6
	Reinf. [m^3]	0.0153	0.0180	+18.1
	EI [kg CO_2-eq/m]	749	597	-20.2
	IC [SEK/m]	3991	3442	-13.8

Table 4.7: Built solution (BS) versus optimal solution (OS). Objective function: EI. Optimization algorithm: GA.

RCCRW	Quantity	BS	OS	Difference [%]
VB	Concrete [m^3]	10.34	7.26	-29.7
	Reinf. [m^3]	0.155	0.171	+10.7
	EI [kg CO_2-eq/m]	4860	3759	-22.7
	IC [SEK/m]	29531	25162	-14.8
RB	Concrete [m^3]	1.71	1.32	-23.2
	Reinf. [m^3]	0.0153	0.0169	+10.5
	EI [kg CO_2-eq/m]	749	606	-19.1
	IC [SEK/m]	3991	3428	-14.1

Table 4.8: Iterations and evaluations computed to obtain optimal solutions. Objective function: EI.

RCCRW	Algorithm	Iterations	Evaluations
VB	PS	108	1382
	GA	112	21490
RB	PS	161	2198
	GA	132	25290



(a) Vårby backe. (b) The Roslagsbana.

Figure 4.6: Optimal dimensions of both RCCRWs treated in the present study. Objective function: EI. PS versus GA.

Regarding the results presented above, both algorithms result in somewhat different suboptimal solutions, but neither outperforms the other in terms of final values. There are, however, significant differences in CPU time required to obtain the results. With this in mind, GA was not considered suitable for further studies but instead helpful for verifying results.

4.2.4 Effect of initial mesh size on the optimal solution (OS)

When using PS as optimization algorithm, the initial mesh size might also affect the results. A study has been carried out to evaluate the influence of the initial mesh size on the optimal solution. A total of five initial mesh sizes (0.001 0.01 1.0 10 100) have been tested for each RCCRW and objective function.

In Figure 4.7 and Figure 4.8, the quantities IC, EI, concrete and reinforcement amounts are shown for the optimal solutions using the initial mesh sizes mentioned above when minimizing IC for VB and RB, respectively. The quantities are normalized with respect to the corresponding quantity of the optimal solution using the default initial mesh size (1.0). The results show a difference of about 2% in IC between the optimal solutions for VB and a difference of about 4% for RB. The results for EI are presented in Appendix B and Appendix C.

The initial mesh size do have an effect on the optimal solution but no trend has been observed and no conclusion on the best value has been drawn. In most cases, the differences between the objective function values are small enough to be negligible but it can happen that the difference is more significant, as in the case for RB.

To conclude, using different initial mesh sizes might lead to slight differences in the optimal solution and sometimes the difference is more significant. Since no pattern has been observed, it is recommended to test different initial mesh sizes to ensure that the best solution is found.

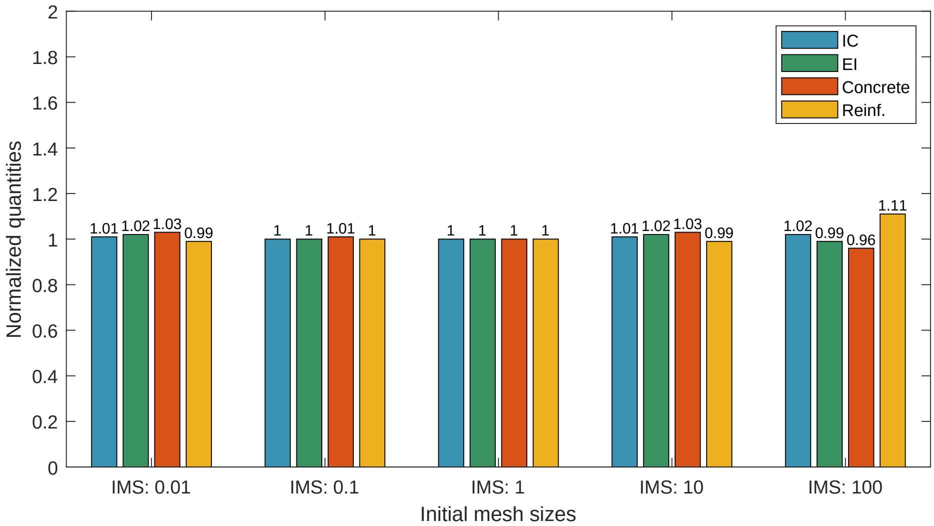


Figure 4.7: Comparison between optimal solutions using different initial mesh sizes. Normalized with respect to the optimal solution with the default initial mesh size (1). Objective function: IC. Optimization algorithm: PS. RCCRW: VB.

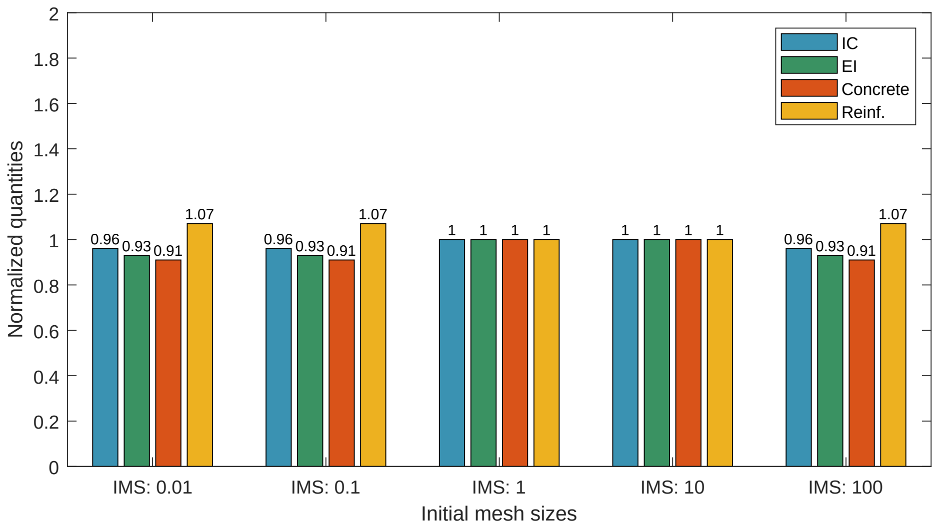


Figure 4.8: Comparison between optimal solutions using different initial mesh sizes. Normalized with respect to the optimal solution with the default initial mesh size (1). Objective function: IC. Optimization algorithm: PS. RCCRW: RB.

4.2.5 Effect of unit emissions on the optimal solution (OS)

The unit emissions of concrete and reinforcement are not fixed values and they can fluctuate depending on several factors. For example, reinforcement can either be scrap-based or ore-based. The latter is more energy-consuming than the former due to large CO_2 emissions being emitted when iron ore is reduced to iron using coal (Energimyndigheten 2019). The unit emission of reinforcement is therefore dependent on the amount of recycled steel. When it comes to the unit emission of concrete, it is mainly based on the amount of cement clinker and what kind of fuels are used in the heating of the cement clinker (Betong 2017). These are only a few factors, but other factors also affect both materials' unit emissions.

Since the unit emission can differ depending on the factors mentioned above, a sensitivity analysis has been performed to see how different unit emissions of reinforcement affect the optimal solution. Figure 4.9 presents the quantities EI, IC, concrete and reinforcement amounts for the different optimal solutions obtained by decreasing and increasing the unit emission of reinforcement for VB. The quantities are normalized with respect to the optimal solution obtained using the default values. Only the unit emission of reinforcement is varied because it is the ratio between the two materials' unit emissions that affect the optimal solution (discussed in Section 4.2.1). It can be observed that when increasing its unit emission, the reinforcement quantity decreases while the concrete quantity increases. When increasing the unit emission beyond 80 % the same, or very similar, optimal solutions are found. However, when decreasing the unit emission similar optimal solutions are found as the default optimal solution. When it comes to the objective function values, it can be seen that EI is proportional to the unit emission. Instead, the corresponding values of IC differs of maximum 4%. The results of the other RCCRW is presented in Appendix C and show similar patterns.

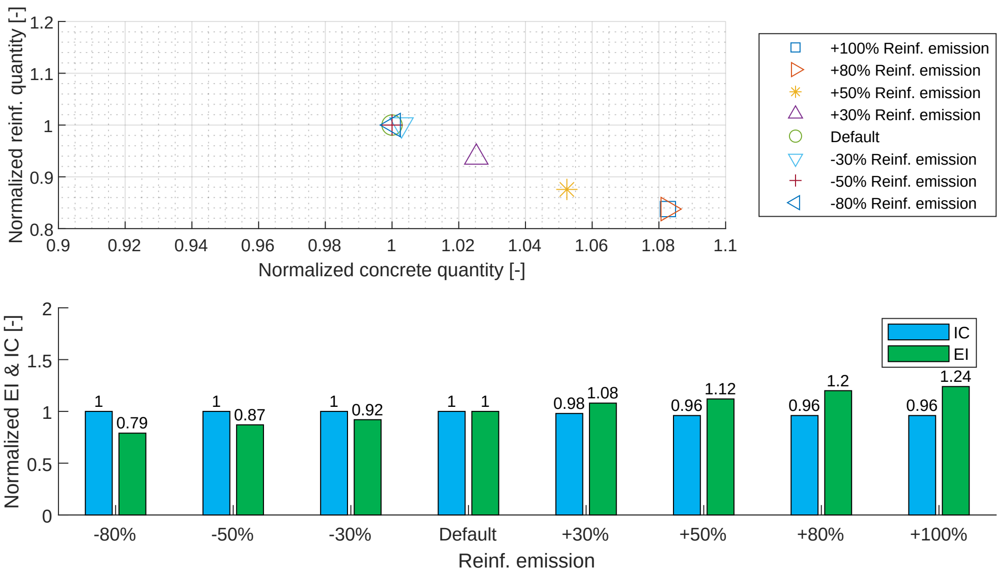


Figure 4.9: Effect of the change in reinforcement unit emission on the optimal solution (OS). Normalized with respect to the corresponding quantities of the optimal solution with the default unit emission. Objective function: EI. Optimization algorithm: PS. RCCRW: VB.

When increasing the unit emission of the reinforcement the concrete becomes more favorable in the optimization and thus its amount is increased to reduce the reinforcement amount. Decreasing the emission, however, resulted in no particular change compared to the default optimal solution. It has partly to do with the default optimal solution not being allowed to contain more reinforcement since the distance between the bars of the primary reinforcement is constrained by a minimum distance. Other constraints could also limit what values the material quantities can assume as it is seen when increasing the unit emission beyond 80%.

As previosuly mentioned, an increase in the unit emission leads to an increase in the total EI and vice versa. However, it is mainly due to the change in unit emission and not due to variations in the concrete and reinforcement volumes. The small variations in IC confirms this observation indicating that the optimal solution is not very sensitive to changes in unit emissions.

To conclude, the optimal solution is affected by the change in unit emission in terms of material quantities, EI and IC. However, the optimal solution is not very sensitive to such changes, which partly has to do with the observed limitations of what values the material quantities can assume.

4.2.6 Effect of unit costs on the optimal solution (OS)

The unit costs of both reinforcement and concrete can also fluctuate, depending on the market. In the same manner as for the unit emissions a sensitivity analysis has been performed to see how changes in the unit cost of reinforcement affect the optimal solution. The unit cost of reinforcement has been both decreased and increased and the results are presented in Figure 4.10 where the quantities EI, IC, concrete and reinforcement amounts are shown for different unit costs for VB. All values are normalized with respect to the corresponding quantities of the default optimal solution.

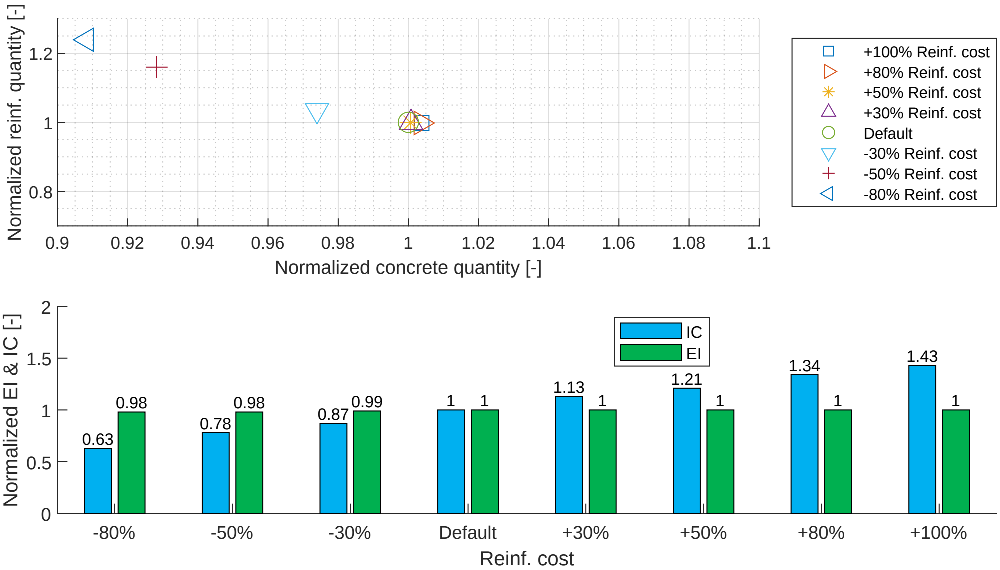


Figure 4.10: Effect of the change in the reinforcement unit cost on the optimal solution (OS). Normalized with respect to the optimal solution with the default unit cost. Objective function: IC. Optimization algorithm: PS. RCCRW: VB.

The results show that by decreasing the unit cost of reinforcement, the concrete quantity is decreased while the reinforcement quantity is increased. However, when the unit cost is increased similar optimal solutions are found as the default optimal solution. When it comes to the objective function values, it can be seen that by increasing the unit emission, the total IC is increased and vice versa. Furthermore, the corresponding value of EI adopts values that differs maximum of 2%. The results of the other RCCRW is presented in Appendix B and show similar patterns.

The same observations as in Section 4.2.5 can be made here. The increase in the total IC is mainly due to the change in unit cost, which is also confirmed by the small variation in EI. It can also be observed that the material quantities seems to be limited of what values they can assume.

The same conclusion can be drawn as in Section 4.2.5. The optimal solution is affected by the change in unit costs in terms of material quantities, EI and IC. However, the optimal solution is not very sensitive to such changes.

4.2.7 Built solution (BS) versus Buildable optimal solution (BOS)

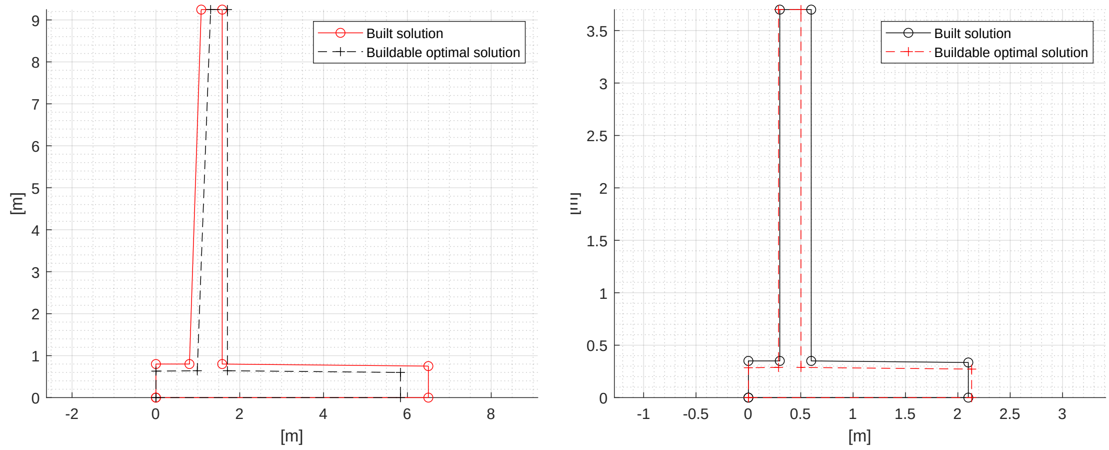
All cross-sectional dimensions except the total height and slope of the RCCRW have been optimized to minimize IC and EI. It has been observed that the structural members are tapered to reduce the concrete volume. It is expected as the moment decreases towards the ends of the structural members. However, excessive slopes can make the structure less buildable; it is more difficult to cast the concrete and specially manufactured building forms must be constructed. For the base slab, the slope is usually limited to 1% to enable water drainage. The stem is usually cast with decreasing thickness if the material savings exceed the extra cost of inclined building forms. It must also be pointed out that casting the stem with a varying thickness is more manageable than casting the base slab with a varying thickness due to gravity.

A solution to this problem is to reduce the number of design variables so that some of the dimensions become constant parameters or that constraints are defined that limit excessive slopes. Alternatively, the software can optimize all design variables and then the optimal solution can be manually adjusted afterward to improve buildability. The latter has been shown to give better results when optimizing RC beam bridges according to Chalouhi (2019) and the proposed method has therefore been used. The study that has been performed aims to see if it is still possible to make savings, even if certain changes that lead to higher buildability also mean extra materials must be used. The optimized solution has been adjusted so that the base slab (both heel and toe) only has a slope of 1 %. The thickness at the top of the stem has been increased to 400 mm for VB to facilitate concrete pouring. For RCCRWs with large heights such as VB, the concrete pouring becomes more difficult and might risk decreasing the quality of the concrete. The value has been deemed adequate to use after consultation with an experienced coworker at AFRY.

The results in Table 4.9 show that it is still possible to make savings when minimizing EI and adjusting the solution afterward for both RCCRWs. The savings that are made are less compared to the results obtained in Section 4.2.1. In Figure 4.11 it can be observed that the buildable optimal solution has similar cross-sectional dimensions as the built solution for both RCCRWs.

It is evident that if the varying thickness is either reduced or eliminated, the savings will decrease. For VB, significant savings could still be made because the width of the base slab was reduced quite a lot compared to the built solution. However, the same did not apply to RB, which had a slightly longer base slab. Savings could instead be made because the optimal solution and the buildable optimal solution were very similar.

To conclude, for the studied RCCRWs savings could still be made even after adjusting the solution afterward.



(a) Vårby backe. (b) The Roslagsbana.

Figure 4.11: Built solution (BS) versus buildable optimal solution (BOS) for both RCCRWs. Objective function: EI. Optimization algorithm: PS.

Table 4.9: Built solution (BS) versus buildable optimal solution (OS) for Vårby backe (VB) and the Roslagsbana (RB). Objective function: EI. Optimization algorithm: PS.

RCCRW	Quantity	BS	OS	Difference [%]
VB	Concrete [m^3]	10.34	8.29	-19.8
	Reinf. [m^3]	0.155	0.177	14.2
	EI [kg CO_2-eq/m]	4860	4186	-13.9
	IC [SEK/m]	29531	27396	-7.2
RB	Concrete [m^3]	1.71	1.31	-23.4
	Reinf. [m^3]	0.0153	0.0181	18.4
	EI [kg CO_2-eq/m]	749	609	-18.7
	IC [SEK/m]	3991	3507	-12.1

Chapter 5

Design guide

Further measures to reduce EI and IC are to optimize the installed reinforcement. One way to achieve this is to implement mixed-integer optimization using GA. Mixed-integer optimization handles both continuous and discrete design variables. The discrete design variables could then consist of the reinforcement topology. In the present study, this has not been included due to limited time. Moreover, the implementation of a mixed-integer optimization might increase the CPU time, which might concern the designer. Instead, as a guide to the designer, a parametric study has been conducted where various reinforcement topologies have been tested for different total heights. The parametric study aims to develop guidelines to facilitate the choice of reinforcement topology to achieve solutions where both EI and IC are significantly decreased.

5.1 Conditions

This study was conducted on fictitious RCCRWs with varying total heights and reinforcement bar topology. The input data used in this study were gathered from the case study referred to as VB in Chapter 4 of this thesis. Optimization was performed using PS according to the configuration presented in Chapter 3, with EI as the objective function. The starting points varied with respect to the total height, and the configuration used is presented in Table 5.1.

Table 5.1: Configuration of starting points for design variables.

X_1	X_2	X_3	X_4	X_5	X_6	X_7
0.1^*H_{tot}	0.11^*H_{tot}	0.1^*H_{tot}	0.11^*H_{tot}	0.1^*H_{tot}	0.1^*H_{tot}	0.6^*H_{tot}

Nine total heights were studied, ranging from 2-10m at even intervals. The secondary reinforcement of the stem varied between two rebar sizes, 12 or 16mm in diameter. In contrast, the secondary reinforcement of the slab only utilised rebars of size 16mm. Likewise, only rebars of size 16mm were used for the stirrups in the structures. A total of 14 primary reinforcement layouts were evaluated and they are presented in Table 5.2. It should be noted that the primary reinforcement of the slab and stem were at all times of the same layout.

Table 5.2: Evaluated primary reinforcement bar layouts (with layers as L1+L2).

One layer [mm]	**L1 Ø12** [mm]	**L1 Ø16** [mm]	**L1 Ø20** [mm]	**L1 Ø25** [mm]
12	12+12	16+12	20+12	25+12
16		16+16	20+16	25+16
20			20+20	25+20
25				25+25

Two sections were considered when calculating the required reinforcement amount; at the clamped section between the stem and the slab and one-quarter of the total height up from this section. The reinforcement, dimensions and design variables considered in this study are presented in Figure 5.1.

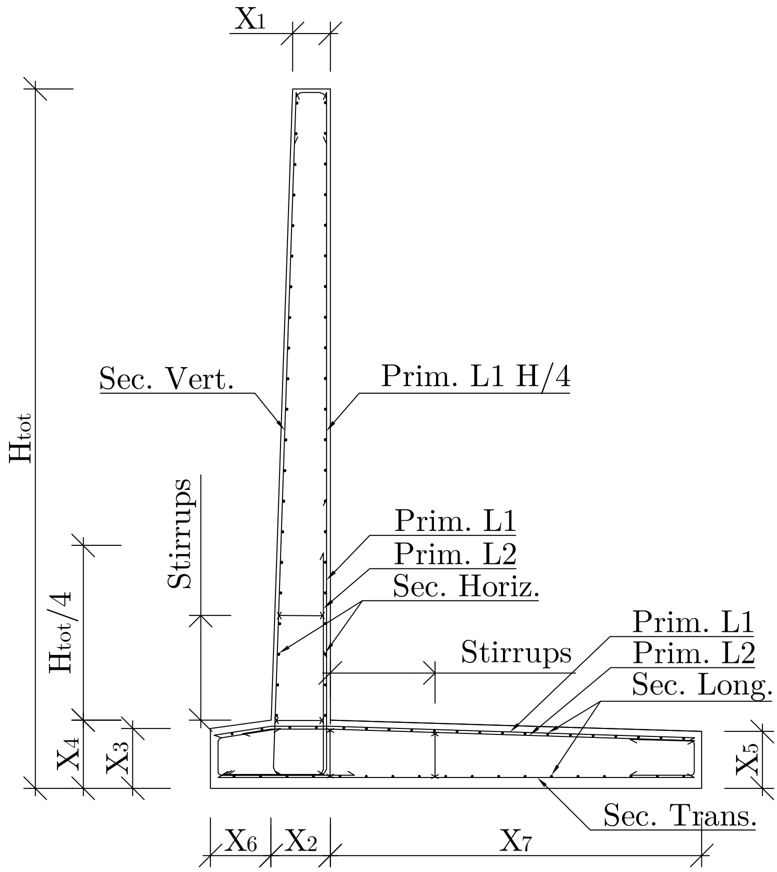


Figure 5.1: Reinforcement, dimensions and design variables considered.

The authors refer to Appendix B for a detailed presentation of the input data used in this study.

5.2 Guidelines

The results presented in this section are the optimized concrete thicknesses and reinforcement bar topologies which gave the lowest environmental impact for a given total height. It should be noted that the software program created does not handle mixed-integer optimization, thus the study was conducted by optimizing every combination individually.

The results show that using two layers of smaller reinforcement bar diameter could be preferable compared to using a larger reinforcement bar diameter with only one layer. Indeed, it yields thicker concrete dimensions, but in return, lower environmental impact is achieved. Further, it is observed that stirrups are preferable at total heights from about 5m and up. Although stirrups may be a feature that can affect the buildability, it may be worth the extra effort at construction if it is of interest to reduce the environmental impact.

The results from the previous chapters indicate that both algorithms yield to similar results in terms of final values. However, the CPU time required to obtain equivalent results is significantly longer for GA than for PS. Thereby, it was found suitable to perform this study with PS.

The objective functions treated in this work show no signs of being conflicting; when minimizing the environmental impact, the investment cost also decreases significantly. Additionally, the results from the two case studies performed show that optimization considering minimizing EI yields significant savings on IC too. With that in mind, it was decided to perform this study considering EI as the objective function.

The number of reinforcement bar layouts examined could have been increased to potentially obtain better solutions. One example of this is the secondary reinforcement which could have been investigated in more reinforcement bar diameters. Similarly, a variation of project-specific parameters could have been considered - for example, several backfill materials and different surcharge loads. Additionally, several starting points and initial mesh sizes could have been included for each total height.

Ultimately, the design process of RCCRWs is highly dependent on project-specific conditions and the usefulness of the guidelines may vary moderately from project to project. There are, of course, countless parameters that can be included to find even better solutions. However, a study with more investigated parameters immediately becomes more extensive. Thus, the number of parameters included had to be limited to what was considered sufficient to obtain useful guidelines.

Table 5.3: Cross-sectional dimensions for each evaluated total height.

Total height [m]	$\mathbf{X_1}$ [mm]	$\mathbf{X_2}$ [mm]	$\mathbf{X_3}$ [mm]	$\mathbf{X_4}$ [mm]	$\mathbf{X_5}$ [mm]	$\mathbf{X_6}$ [mm]	$\mathbf{X_7}$ [mm]
2	238	238	295	326	232	433	1418
3	238	281	295	313	232	404	1681
4	238	311	295	366	281	502	1943
5	245	318	303	373	293	463	2412
6	246	387	303	446	297	567	2721
7	246	474	303	474	297	667	3035
8	246	600	303	589	311	768	3350
9	262	680	308	615	308	991	3908
10	262	748	308	703	307	992	4461

Table 5.4: Reinforcement topology of the stem for each evaluated total height.

Total height [m]	**Sec. Horiz.** [mm]	**Sec. Vert.** [mm]	**Prim. L1** [mm]	**Prim. L1 H/4** [mm]	**Prim. L2** [mm]	**Stirrups** [mm]
2	Ø12s265	Ø12s265	Ø12s215	Ø12s265	–	–
3	Ø12s265	Ø12s265	Ø12s115	Ø12s170	–	–
4	Ø12s265	Ø12s265	Ø12s115	Ø12s210	Ø12s115	–
5	Ø12s155	Ø12s265	Ø20s145	Ø20s285	Ø16s145	–
6	Ø12s130	Ø12s265	Ø20s145	Ø20s280	Ø20s145	–
7	Ø12s115	Ø12s265	Ø20s130	Ø20s230	Ø20s130	–
8	Ø12s115	Ø12s235	Ø20s130	Ø20s215	Ø20s130	–
9	Ø16s170	Ø16s300	Ø25s170	Ø25s280	Ø25s170	2Ø16s300
10	Ø16s145	Ø16s300	Ø25s145	Ø25s235	Ø25s145	4Ø16s255

Table 5.5: Reinforcement topology of the slab for each evaluated total height.

Total height [m]	**Sec. Trans.** [mm]	**Sec. Long.** [mm]	**Prim. L1** [mm]	**Prim. L2** [mm]	**Stirrups** [mm]
2	Ø16s300	Ø16s300	Ø12s250	–	–
3	Ø16s300	Ø16s300	Ø12s115	–	–
4	Ø16s300	Ø16s300	Ø12s145	Ø12s145	–
5	Ø16s300	Ø16s300	Ø20s170	Ø16s170	7Ø16s175
6	Ø16s270	Ø16s270	Ø20s170	Ø20s170	8Ø16s225
7	Ø16s190	Ø16s190	Ø20s125	Ø20s125	11Ø16s180
8	Ø16s190	Ø16s190	Ø20s125	Ø20s125	14Ø16s160
9	Ø16s145	Ø16s145	Ø25s145	Ø25s145	22Ø16s140
10	Ø16s125	Ø16s125	Ø25s125	Ø25s125	30Ø16s120

Chapter 6

Concluding remarks

The following chapter present the conclusions drawn in this thesis work as well as suggestions for future research.

6.1 Conclusions

In this thesis work, a software program was developed that automates the design process for RCCRWs and finds optimal solutions. Through various optimization studies conducted on two case studies, the following conclusions have been drawn:

- It has been shown that significant savings (10-20 %) could have been made on EI and IC through the use of optimization algorithms in the design process.
- EI and IC are not conflicting, i.e., minimizing one of them reduces the other significantly. However, best results for the two objective functions are given when each one is actively minimized. Thus, the designer needs to choose which objective function to focus on.
- The initial guess has a significant influence on the optimal solution when optimizing with PS. Thus, it is preferable to optimize with several initial guesses to obtain a better solution.
- Comparing PS and GA showed that very similar results were obtained and neither of the two algorithms outperformed the other in terms of EI and IC. Additionally, even though six different initial guesses were used with PS to compare results with GA, PS still proved to be a time-efficient optimization algorithm compared to GA.
- The ratio of the unit costs and the unit emissions between concrete and reinforcement has an effect on the optimal solution. A sensitivity analysis has been performed where the unit cost and unit emission of reinforcement have been decreased and increased separately. When decreasing the unit cost or unit emission of reinforcement, it results in more reinforcement and less concrete used in the optimal solution. The opposite applies when increasing the unit cost or unit emission. Furthermore, even though there is a variation

of the material quantities of the optimal solution, the final value of the objective function is not very sensitive to changes in the unit values.

- The initial mesh size can have a significant effect on the optimal solution. However, no pattern has shown which initial mesh size would perform better than others. Therefore, it is recommended to test different initial mesh sizes to ensure that the best solution is found.
- For both RCCRWs analyzed in Section 4.2.7, savings can still be made for both EI and IC even though adjustments to improve buildability results in more material amounts being used.

6.2 Future research

The developed software application has proven to be a helpful tool in the design of RCCRWs as significant savings can be made on the objective functions. However, there are opportunities for development in several areas. The following suggestions may further improve the usability and reliability of the software:

- Include more design variables in the software application. One example of this could be implementing discrete design variables such as reinforcement bar diameters and concrete classes. This can improve the software by possibly providing even better optimized solutions.
- Implement life cycle cost (LCC) and life cycle assessment (LCA) as objective functions. This is a further development that would enable the whole life cycle of an RCCRW to be analyzed.
- Implement a database that stores structures optimized. Thus, making it possible to build a library of optimized RCCRWs.
- Include pile foundations. Thus, different cases can be compared to investigate whether it is, for example, more environmentally friendly with or without piles.

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Appendix A

Optimization options

A.1 PS options

```
'AccelerateMesh':           false
'ConstraintTolerance':      1E-06
'FunctionTolerance':        1E-06
'InitialMeshSize':          1.0
'MaxFunctionEvaluations':   Inf
'MaxIterations':            Inf
'MaxTime':                  Inf
'MeshContractionFactor':    0.50
'MeshExpansionFactor':      2.0
'MeshTolerance':            1e-6
'MeshRotate':               'Off'
'PollMethod':               'GPSPositiveBasis2N'
'PollOrderAlgorithm':       'Consecutive'
'ScaleMesh':                false
'SearchFcn':                []
'StepTolerance':            1E-06
'Cache':                    'On'
'CacheTol':                 eps
'CacheSize':                1e4
'UseCompletePoll':          true
'UseCompleteSearch':        false
'UseParallel':              false
'UseVectorized':            false
```

A.2 GA options

'ConstraintTolerance':	1E-6
'FitnessLimit':	-Inf
'FitnessScalingFcn':	'fitscalingrank'
'FunctionTolerance':	1E-6
'InitialPopulationMatrix':	xn
'InitialPopulationRange':	[lb ub]'
'InitialScoresMatrix':	[]
'MaxGenerations':	Inf
'MaxStallGenerations':	20
'MaxStallTime':	Inf
'MaxTime':	Inf
'PopulationSize':	200
'EliteCount':	ceil(0.05*popsize)
'PopulationType':	'doubleVector'

Appendix B

RCCRW at Vårby backe

B.1 Input data

Table B.1: Geometrical input data. RCCRW: VB

Parameter	**Value**	**Unit**
Total height	9245	mm
Total length	22000	mm
Stem thickness at the top (X1)	500	mm
Stem thickness at the bottom (X2)	781	mm
Slab thickness at the toe (X3)	800	mm
Slab thickness below stem (X4)	800	mm
Slab thickness at the heel (X5)	751	mm
Toe width (X6)	800	mm
Heel width (X7)	4919	mm

Table B.2: Geotechnical input data. Characteristic values. RCCRW: VB

Parameter	**Value**	**Unit**
Lateral earth pressure	At-rest	-
Swedish design praxis	DA3	-
Unit weight of water	10	kN/m^3
Unit weight of backfill and foundation soil	18	kN/m^3
Effective unit weight of backfill and foundation soil	11	kN/m^3
Friction angle of backfill and foundation soil	45	$^\circ$
Backfill slope	0	$^\circ$
Unit weight of soil below foundation	18	kN/m^3
Effective unit weight of soil below foundation	11	kN/m^3
Friction angle of soil below foundation	45	$^\circ$
Lateral compaction pressure	16	kPa
Distributed surcharge load	20	kPa
Ground-water level, measured from the top of the stem	8245	mm

Table B.3: Structural input data. Characteristic values. RCCRW: VB

Parameter	**Value**	**Unit**
Safety class	3	-
Service life	L100	-
Traffic, VGC or JVG	VGC	-
Cast-in-place structure	Yes	-
Casted directly on the foundation soil	Yes	-
Concrete class	C35/45	-
Unit weight of concrete	25	kN/m^3
Exposure class, stem, facing air	XD3	-
Exposure class, stem, facing backfill	XC2	-
Exposure class, slab, top	XC2	-
Exposure class, slab, bottom	XC2	-
Reinforcement class	K500C-T	-
Unit weight of steel	78.5	kN/m^3
Modulus of elasticity	200	GPa
Studied sections, measured from the junction, stem	0, 2550	mm
Size of primary reinforcement, stem, first layer	25	mm
Size of primary reinforcement, stem, second layer	16	mm
Size of horizontal secondary reinforcement, stem	16	mm
Size of vertical secondary reinforcement, stem	16	mm
Size of stirrups, stem	16	mm
Studied sections, measured from the junction, slab	0	mm
Size of primary reinforcement, slab, first layer	25	mm
Size of primary reinforcement, slab, second layer	25	mm
Size of longitudinal secondary reinforcement, slab	16	mm
Size of transversal secondary reinforcement, slab	16	mm
Size of stirrups, slab	12	mm
Undistributed horizontal collision load to railing	200	kN
Center distance of railing posts	1800	mm
Distance between collision load and the top of the stem	1000	mm

B.2 Optimal cross-sectional dimensions

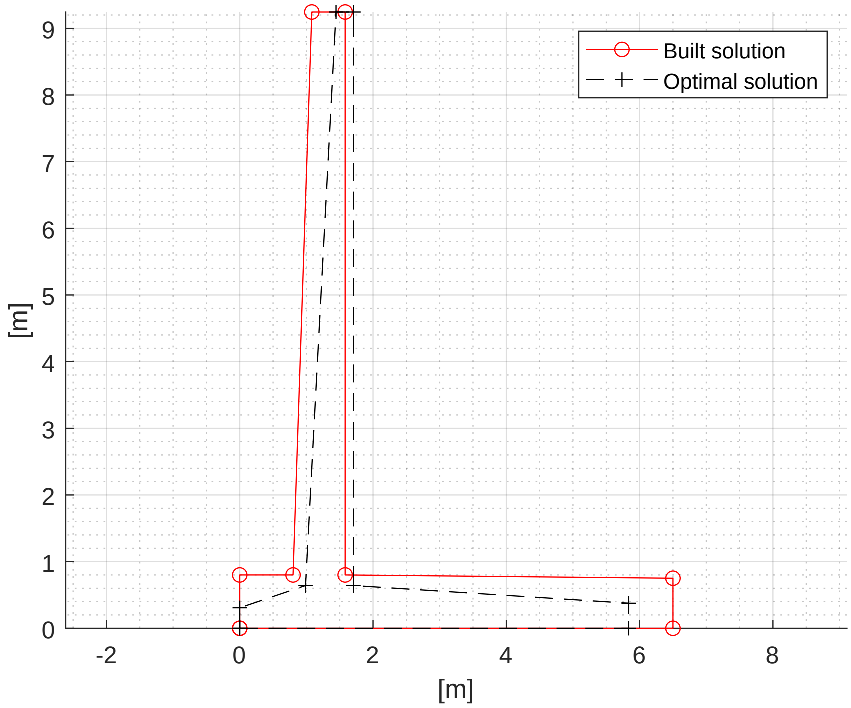

Figure B.1: Cross-sectional dimensions of the built solution (BS) versus the optimal solution (OS). Objective function: EI. Optimization algorithm: PS. RCCRW: VB.

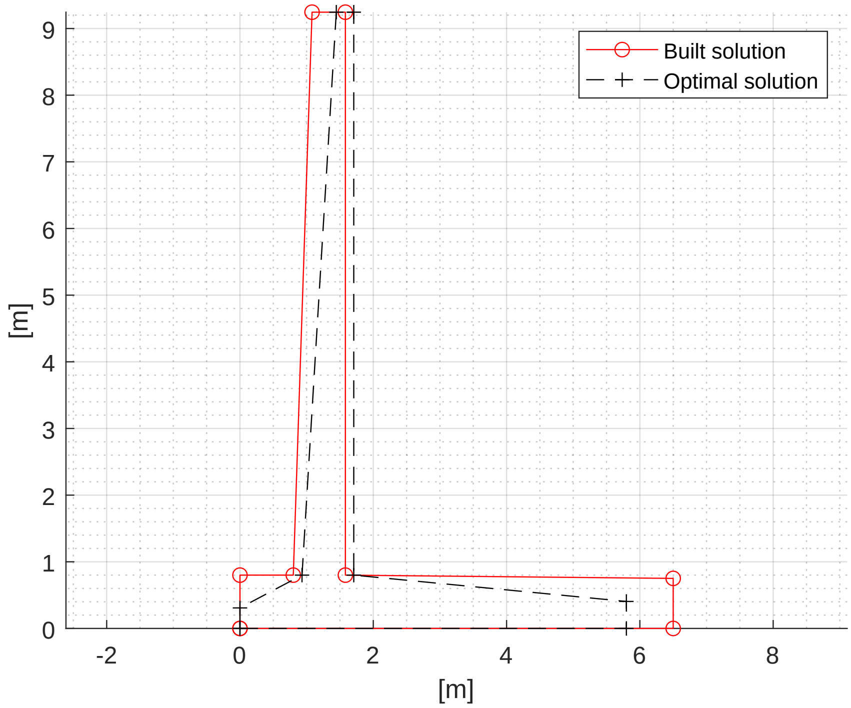

Figure B.2: Cross-sectional dimensions of the built solution (BS) versus the optimal solution (OS). Objective function: IC. Optimization algorithm: PS. RCCRW: VB.

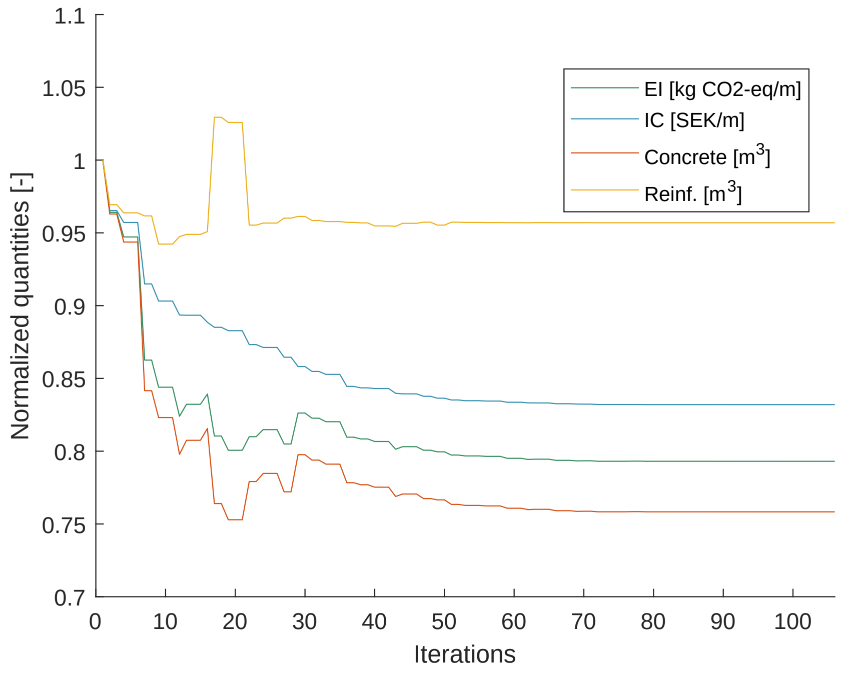

Figure B.3: Variation of the quantities EI, IC, concrete and reinforcement amounts during the optimization. Normalized with respect to the first feasible solution. Objective function: IC. Optimization algorithm: PS. RCCRW: VB.

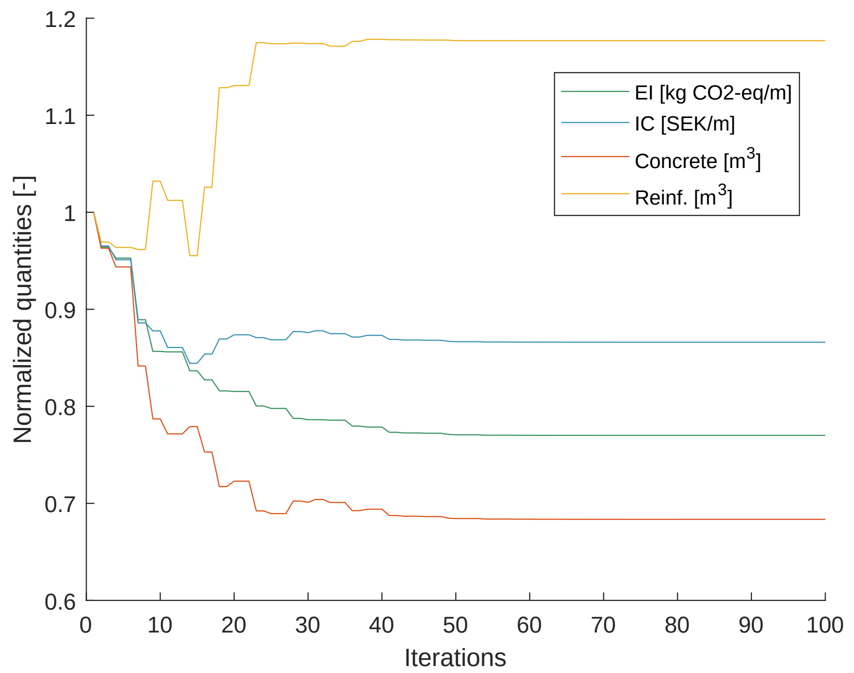

Figure B.4: Variation of the quantities EI, IC, concrete and reinforcement amounts during the optimization. Normalized with respect to the first feasible solution. Objective function: EI. Optimization algorithm: PS. RCCRW: VB.

Table B.4: Built solution (BS) versus optimal solution (OS). Objective function: IC. Optimization algorithm: PS. RCCRW: VB.

Quantity	**BS**	**OS**	**Difference** [%]
Concrete [m^3]	10.34	7.84	-24.2
Reinf. [m^3]	0.155	0.148	-4.3
EI [kg CO_2-eq/m]	4860	3854	-20.7
IC [SEK/m]	29531	24569	-16.8

Table B.5: Built solution (BS) versus optimal solution (OS). Objective function: EI. Optimization algorithm: PS. RCCRW: VB.

Quantity	**BS**	**OS**	**Difference** [%]
Concrete [m^3]	10.34	7.06	-31.6
Reinf. [m^3]	0.155	0.182	17.7
EI [kg CO_2-eq/m]	4860	3743	-23.0
IC [SEK/m]	29531	25576	-13.4

B.3 Effect of the initial guess on the optimal solution (OS)

Table B.6: Initial guesses specified by designers at AFRY's bridge department. RCCRW: VB.

Variable	**D1**	**D2**	**D3**	**D4**	**D5**	**D6**
X_1 [mm]	500	500	300	500	300	400
X_2 [mm]	781	800	600	650	400	900
X_3 [mm]	800	800	650	600	400	900
X_4 [mm]	800	800	700	600	410	950
X_5 [mm]	751	600	600	550	400	900
X_6 [mm]	800	800	500	600	300	900
X_7 [mm]	4919	4500	5500	4500	2000	4640

Table B.7: Optimal solutions of the initial guesses specified by AFRY's designers. Objective function: EI. RCCRW: VB.

Quantity	**D1**	**D2**	**D3**	**D4**	**D5**	**D6**
Concrete [m^3]	7.06	6.95	7.18	7.21	–	7.31
Reinf. [m^3]	0.182	0.194	0.186	0.170	–	0.175
EI [kg CO_2-eq/m]	3743	3763	3821	3737	–	3800
IC [SEK/m]	25576	26193	26047	25027	–	25529

Table B.8: Optimal cross-sectional dimensions of the initial guesses specified by designers at AFRY's bridge department. Objective function: EI. RCCRW: VB.

Variable	**D1**	**D2**	**D3**	**D4**	**D5**	**D6**
X_1 [mm]	262	262	262	262	263	268
X_2 [mm]	719	728	722	707	400	775
X_3 [mm]	308	308	308	308	239	308
X_4 [mm]	641	594	652	714	549	634
X_5 [mm]	376	380	350	379	549	378
X_6 [mm]	988	882	1000	975	1000	955
X_7 [mm]	4130	4188	4375	4126	1000	4079

Table B.9: Optimal solutions of the initial guesses specified by AFRY's designers. Objective function: IC. RCCRW: VB.

Quantity	**D1**	**D2**	**D3**	**D4**	**D5**	**D6**
Concrete [m^3]	7.84	7.91	8.31	7.64	–	7.81
Reinf. [m^3]	0.148	0.152	0.135	0.153	–	0.148
EI [kg CO_2-eq/m]	3854	3903	3965	3802	–	3844
IC [SEK/m]	24569	24982	24506	24535	–	24523

Table B.10: Optimal cross-sectional dimensions of the initial guesses specified by designers at AFRY's bridge department. Objective function: IC. RCCRW: VB.

Variable	**D1**	**D2**	**D3**	**D4**	**D5**	**D6**
X_1 [mm]	262	262	262	262	263	262
X_2 [mm]	777	729	747	716	400	773
X_3 [mm]	308	308	308	308	239	308
X_4 [mm]	800	800	950	845	549	816
X_5 [mm]	406	544	493	379	549	381
X_6 [mm]	931	824	981	975	1000	888
X_7 [mm]	4091	4223	4067	4117	1000	4131

B.4 Comparison between Pattern Search (PS) and Genetic Algorithm (GA)

Table B.11: Built solution (BS) versus optimal solution (OS). Objective function: EI. Optimization algorithm: PS. RCCRW: VB.

Quantity	**BS**	**OS**	**Difference [%]**
Concrete [m^3]	10.34	7.21	-30.2
Reinf. [m^3]	0.155	0.170	+10.2
EI [kg CO_2-eq/m]	4860	3737	-23.1
IC [SEK/m]	29531	25027	-15.3

Table B.12: Built solution (BS) versus optimal solution (OS). Objective function: EI. Optimization algorithm: GA. RCCRW: VB.

Quantity	**BS**	**OS**	**Difference [%]**
Concrete [m^3]	10.34	7.26	-29.7
Reinf. [m^3]	0.155	0.171	+10.7
EI [kg CO_2-eq/m]	4860	3759	-22.7
IC [SEK/m]	29531	25162	-14.8

Table B.13: Iterations and evaluations computed to obtain the optimal solutions. Objective function: EI. RCCRW: VB.

Algorithm	**Iterations**	**Evaluations**
PS	108	1382
GA	112	21490

Table B.14: Built solution (BS) versus optimal solution (OS). Objective function: IC. Optimization algorithm: PS. RCCRW: VB.

Quantity	**BS**	**OS**	**Difference [%]**
Concrete [m^3]	10.34	8.31	-19.6
Reinf. [m^3]	0.155	0.135	-12.7
EI [kg CO_2-eq/m]	4860	3965	-18.2
IC [SEK/m]	29531	24506	-17.0

Table B.15: Built solution (BS) versus optimal solution (OS). Objective function: IC. Optimization algorithm: GA. RCCRW: VB.

Quantity	BS	OS	Difference [%]
Concrete [m^3]	10.34	7.78	-24.8
Reinf. [m^3]	0.155	0.148	-4.1
EI [kg CO_2-eq/m]	4860	3832	-21.2
IC [SEK/m]	29531	24481	-17.1

Table B.16: Iterations and evaluations computed to obtain the optimal solutions. Objective function: IC. RCCRW: VB.

Algorithm	Iterations	Evaluations
PS	176	2158
GA	112	21490

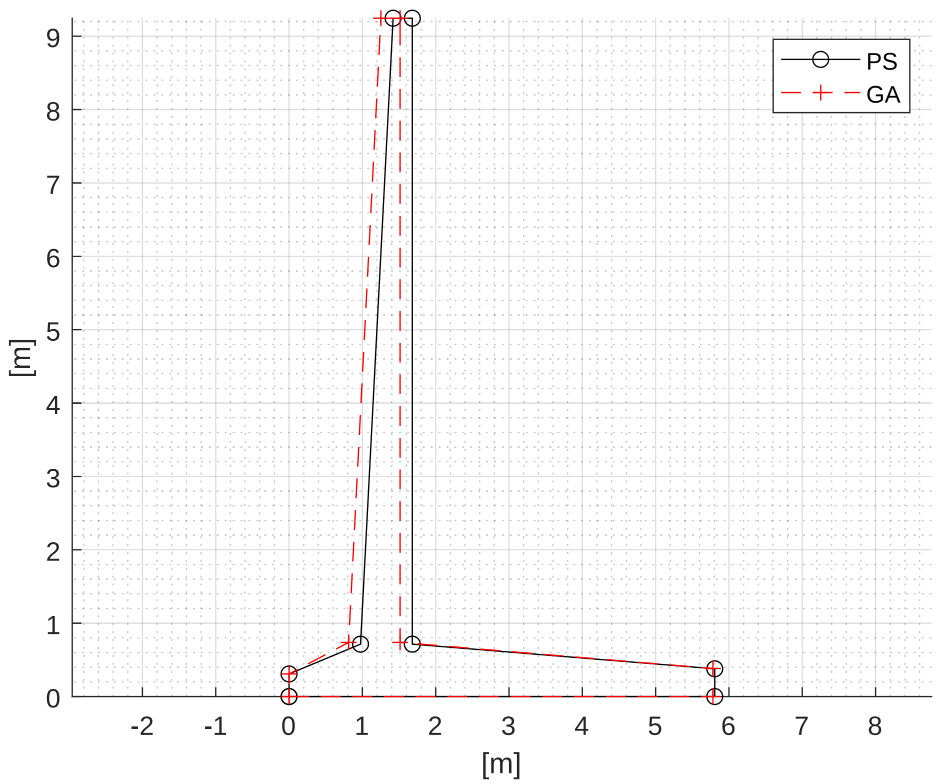

Figure B.5: Optimal cross-sectional dimensions of PS versus GA. Objective function: EI. RCCRW: VB.

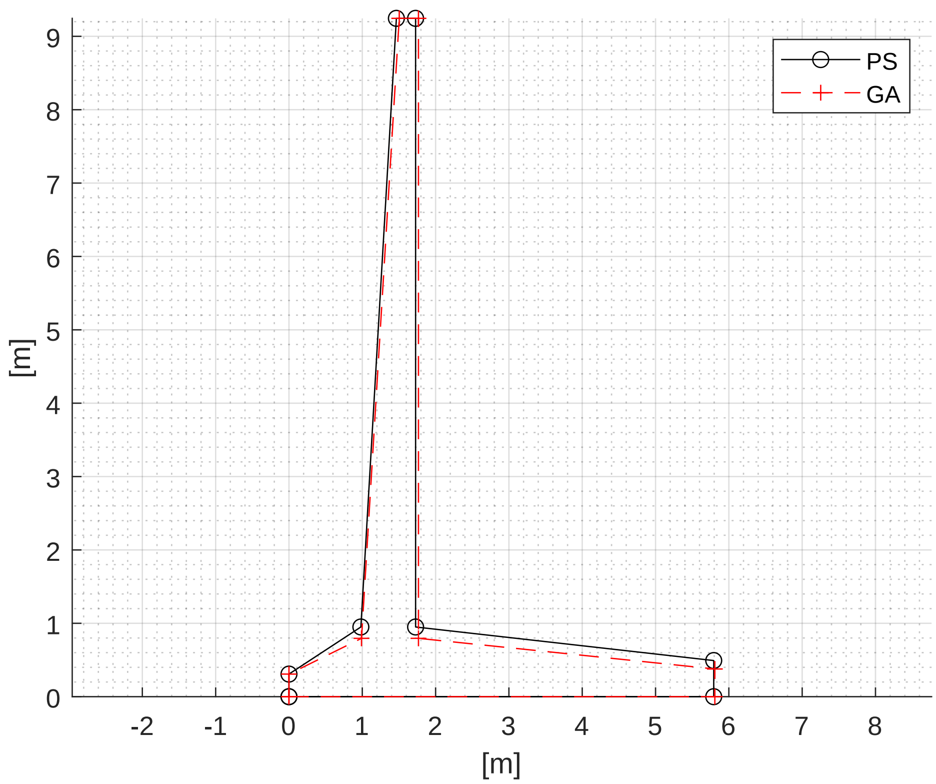

Figure B.6: Optimal cross-sectional dimensions of PS versus GA. Objective function: IC. RCCRW: VB.

B.5 Effect of initial mesh size on the optimal solution (OS)

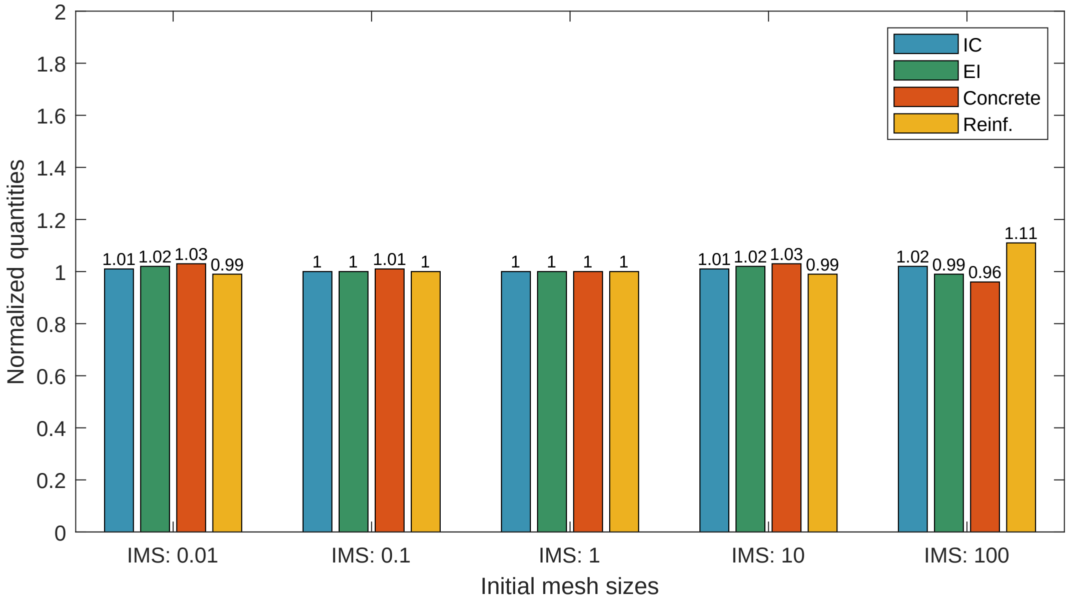

Figure B.7: Comparison between optimal solutions using different initial mesh sizes. Normalized with respect to the optimal solution with the default initial mesh size (1). Objective function: IC. Optimization algorithm: PS. RCCRW: VB.

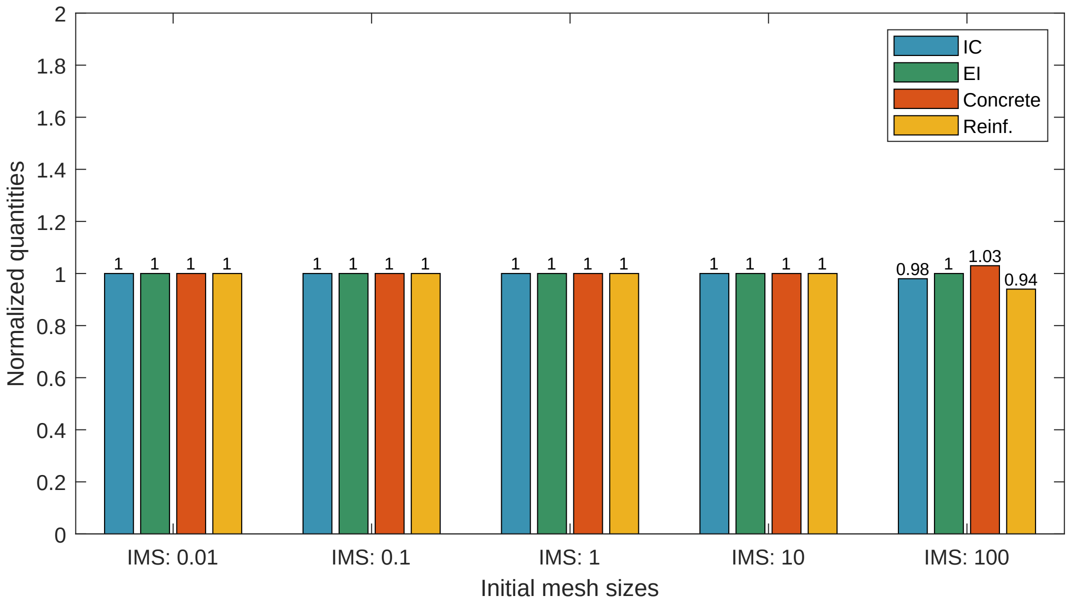

Figure B.8: Comparison between optimal solutions using different initial mesh sizes. Normalized with respect to the optimal solution with the default initial mesh size (1). Objective function: EI. Optimization algorithm: PS. RCCRW: VB.

B.6 Effect of unit emission on the optimal solution (OS)

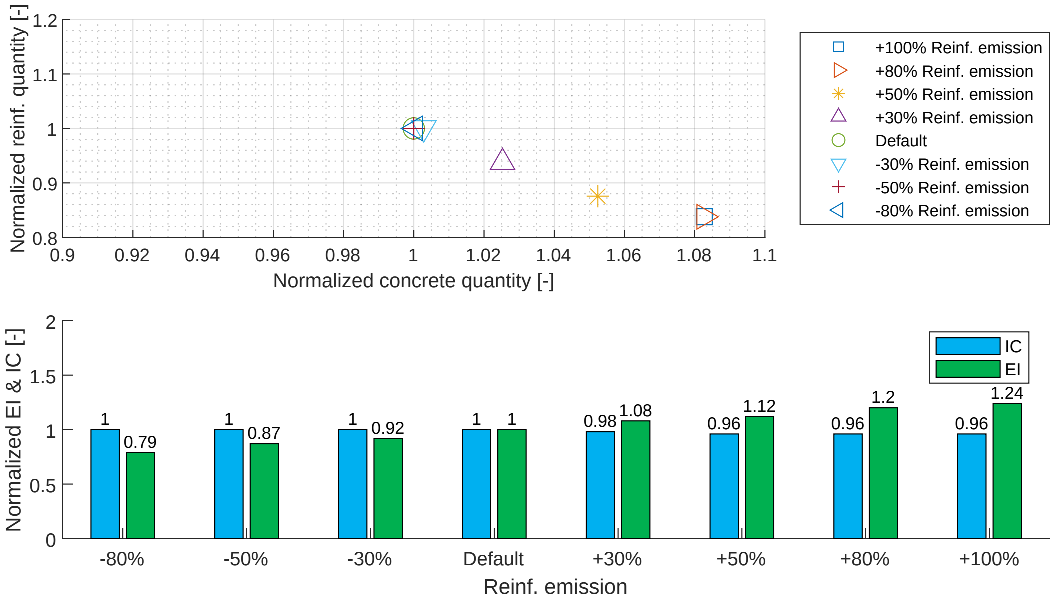

Figure B.9: Effect of the change in reinforcement unit emission on the optimal solution (OS). Normalized with respect to the optimal solution with the default unit emission. Objective function: EI. Optimization algorithm: PS. RCCRW: VB.

B.7 Effect of unit cost on the optimal solution (OS)

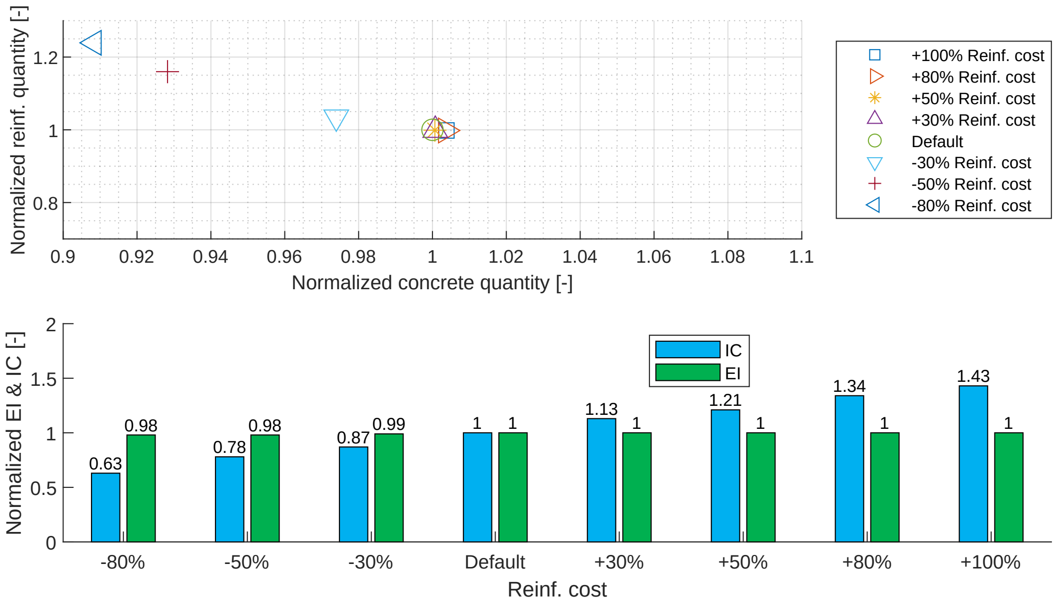

Figure B.10: Effect of the change in the reinforcement unit cost on the optimal solution (OS). Normalized with respect to the optimal solution with the default unit cost. Objective function: IC. Optimization algorithm: PS. RCCRW: VB.

B.8 Built solution (BS) versus Buildable optimal solution (BOS)

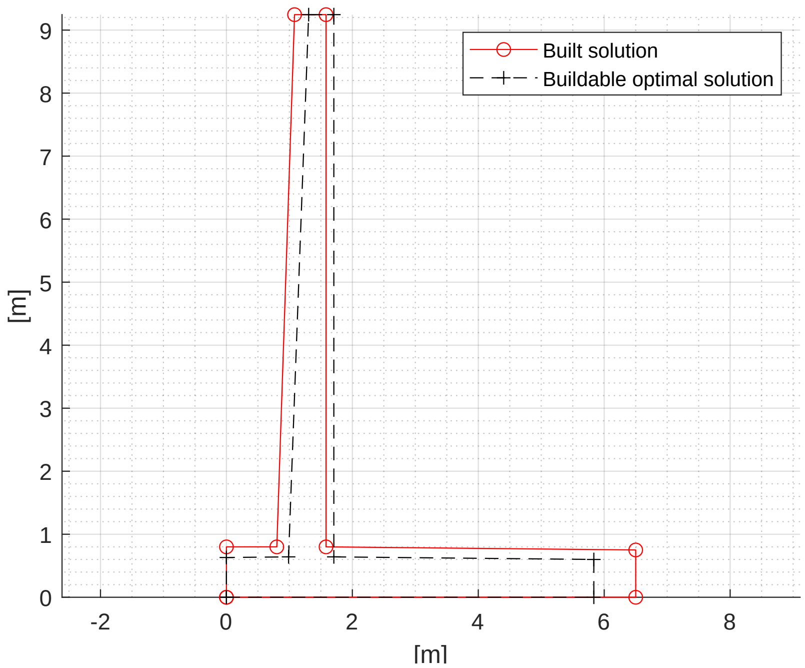

Figure B.11: Built solution (BS) versus buildable optimal solution (BOS). Objective function: EI. Optimization algorithm: PS. RCCRW: VB.

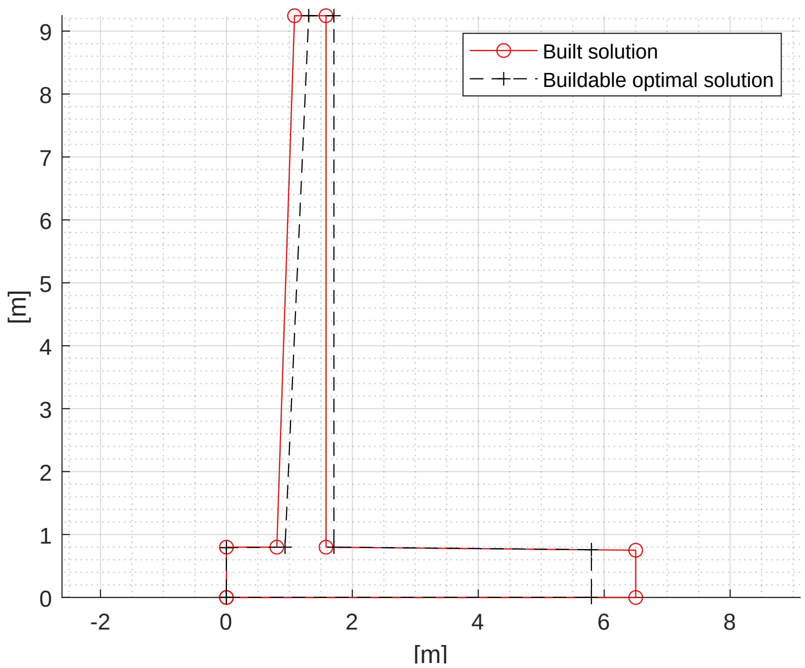

Figure B.12: Built solution (BS) versus buildable optimal solution (BOS). Objective function: IC. Optimization algorithm: PS. RCCRW: VB.

Table B.17: Built solution (BS) versus buildable optimal solution (BOS). Objective function: EI. Optimization algorithm: PS. RCCRW: VB.

Quantity	**BS**	**BOS**	**Difference (%)**
Concrete [m^3]	10.34	8.29	-19.8%
Reinf. [m^3]	0.155	0.177	14.2 %
EI [kg CO_2-eq/m]	4860	4186	-13.9%
IC [SEK/m]	29531	27396	-7.2%

Table B.18: Built solution (BS) versus buildable optimal solution (BOS). Objective function: IC. Optimization algorithm: PS. RCCRW: VB.

Quantity	**BS**	**BOS**	**Difference (%)**
Concrete [m^3]	10.34	9.37	-9.4%
Reinf. [m^3]	0.155	0.146	-5.3 %
EI [kg CO_2-eq/m]	4860	4440	-8.7%
IC [SEK/m]	29531	27207	-7.9%

Appendix C

RCCRW by the Roslagsbana

C.1 Input data

Table C.1: Geometrical input data. RCCRW: RB.

Parameter	**Value**	**Unit**
Total height	3700	mm
Total length	23550	mm
Stem thickness at the top (X1)	300	mm
Stem thickness at the bottom (X2)	300	mm
Slab thickness at the toe (X3)	350	mm
Slab thickness below stem (X4)	350	mm
Slab thickness at the heel (X5)	335	mm
Toe width (X6)	300	mm
Heel width (X7)	1500	mm

Table C.2: Geotechnical input data. Characteristic values. RCCRW: RB.

Parameter	**Value**	**Unit**
Lateral earth pressure	Active	-
Unit weight of water	10	kN/m^3
Unit weight of backfill and foundation soil	18	kN/m^3
Effective unit weight of backfill and foundation soil	11	kN/m^3
Friction angle of backfill and foundation soil	45	$^\circ$
Backfill slope	26.6	$^\circ$
Unit weight of soil below foundation	20	kN/m^3
Effective unit weight of soil below foundation	11	kN/m^3
Friction angle of soil below foundation	40	$^\circ$
Distributed surcharge load	4	kPa
Ground-water level, measured from the top of the stem	3700	mm

Table C.3: Structural input data. Characteristic values. RCCRW: RB.

Parameter	**Value**	**Unit**
Safety class	2	-
Service life	L100	-
Traffic, VGC or JVG	VGC	-
Cast-in-place structure	Yes	-
Casted directly on the foundation soil	Yes	-
Concrete class	C32/40	-
Unit weight of concrete	25	kN/m^3
Exposure class, stem, facing air	XC4	-
Exposure class, stem, facing backfill	XC2	-
Exposure class, slab, top	XC2	-
Exposure class, slab, bottom	XC2	-
Reinforcement class	B500B	-
Unit weight of steel	78.5	kN/m^3
Modulus of elasticity	200	GPa
Studied sections, measured from the junction, stem	0	mm
Size of primary reinforcement, stem	12	mm
Size of horizontal secondary reinforcement, stem	12	mm
Size of vertical secondary reinforcement, stem	12	mm
Studied sections, measured from the junction, slab	0	mm
Size of primary reinforcement, slab	12	mm
Size of longitudinal secondary reinforcement, slab, bottom	16	mm
Size of longitudinal secondary reinforcement, slab, top	12	mm
Size of transversal secondary reinforcement, slab	16	mm

C.2 Optimal cross-sectional dimensions

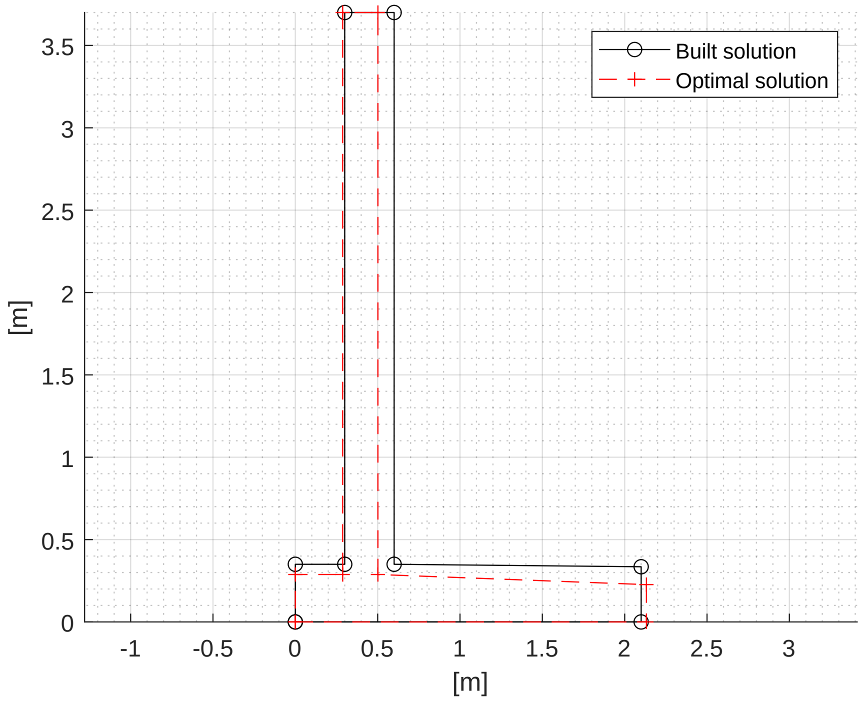

Figure C.1: Cross-sectional dimensions of the built solution (BS) versus the optimal solution (OS). Objective function: EI. Optimization algorithm: PS. RCCRW: RB.

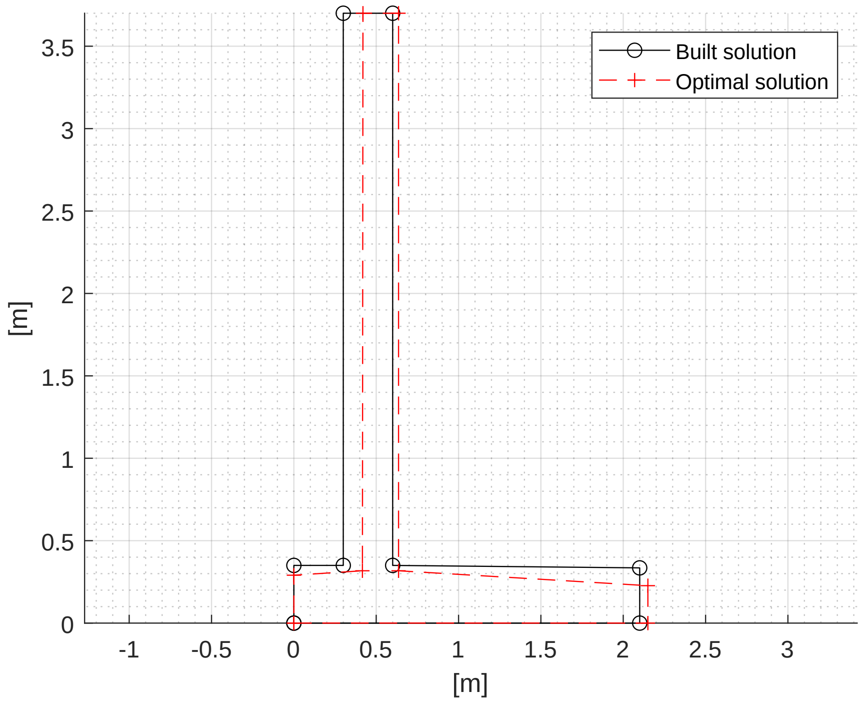

Figure C.2: Cross-sectional dimensions of the built solution (BS) versus the optimal solution (OS). Objective function: IC. Optimization algorithm: PS. RCCRW: RB.

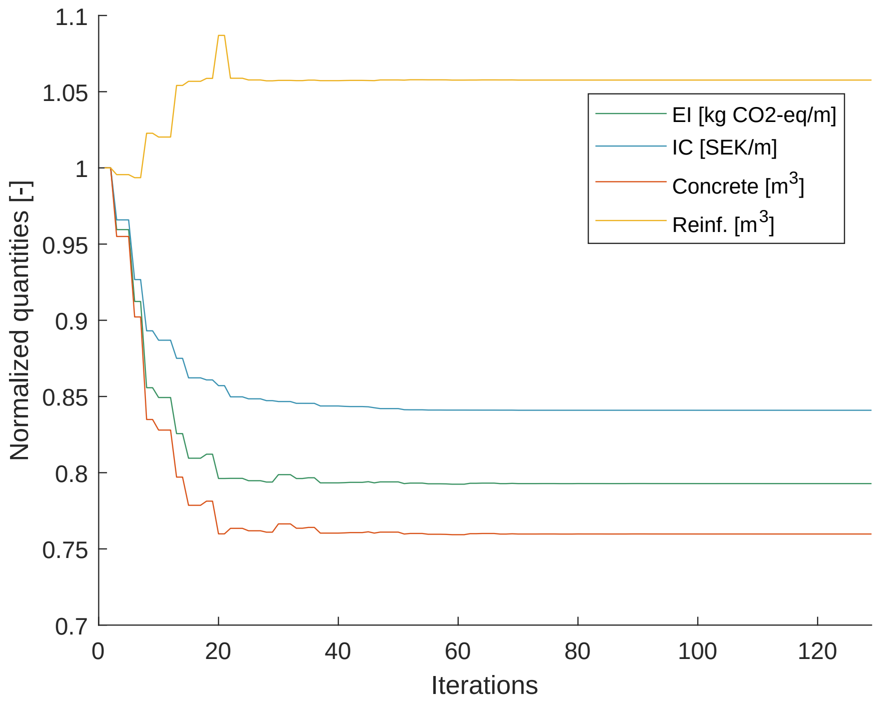

Figure C.3: Variation of the quantities EI, IC, concrete and reinforcement amounts during the optimization. Normalized with respect to the first feasible solution. Objective function: IC. Optimization algorithm: PS. RCCRW: RB.

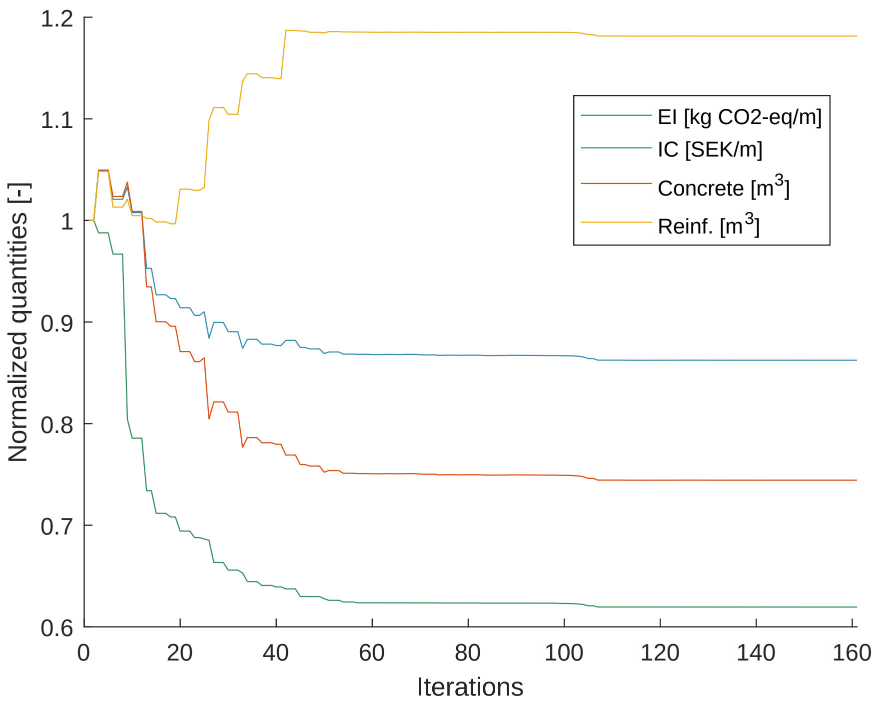

Figure C.4: Variation of the quantities EI, IC, concrete and reinforcement amounts during the optimization. Normalized with respect to the first feasible solution. Objective function: EI. Optimization algorithm: PS. RCCRW: RB.

Table C.4: Built solution (BS) versus optimal solution (OS). Objective function: EI. Optimization algorithm: PS. RCCRW: RB.

Quantity	**BS**	**OS**	**Difference** [%]
Concrete [m^3]	1.71	1.28	-25.6
Reinf. [m^3]	0.015	0.018	18.1
EI [kg CO_2-eq/m]	749	597	-20.2
IC [SEK/m]	4162	3442	-17.3

Table C.5: Built solution (BS) versus optimal solution (OS). Objective function: IC. Optimization algorithm: PS. RCCRW: RB.

Quantity	**BS**	**OS**	**Difference** [%]
Concrete [m^3]	1.71	1.33	-22.5
Reinf. [m^3]	0.015	0.016	6.9
EI [kg CO_2-eq/m]	749	605	-19.2
IC [SEK/m]	4162	3416	-17.9

C.3 Effect of the initial guess on the optimal solution (OS)

Table C.6: Initial guesses specified by designers at AFRY's bridge department. RCCRW: RB.

Variable	**D1**	**D2**	**D3**	**D4**	**D5**	**D6**
X_1 [mm]	300	500	200	400	200	300
X_2 [mm]	300	600	400	500	200	370
X_3 [mm]	350	600	400	500	300	350
X_4 [mm]	350	600	450	500	300	420
X_5 [mm]	335	500	350	450	300	350
X_6 [mm]	300	600	300	500	300	350
X_7 [mm]	1500	1600	2000	2500	1500	2630

Table C.7: Optimal solutions of the initial guesses specified by AFRY's designers. Objective function: EI. RCCRW: RB.

Quantity	**D1**	**D2**	**D3**	**D4**	**D5**	**D6**
Concrete [m^3]	1.28	1.36	1.33	1.36	–	1.36
Reinf. [m^3]	0.0180	0.0158	0.0163	0.0158	–	0.0158
EI [kg CO_2-eq/m]	597	618	606	619	–	618
IC [SEK/m]	3442	3429	3408	3429	–	3430

Table C.8: Optimal cross-sectional dimensions of the initial guesses specified by designers at AFRY's bridge department. Objective function: EI. RCCRW: RB.

Variable	**D1**	**D2**	**D3**	**D4**	**D5**	**D6**
X_1 [mm]	214	214	216	213	200	214
X_2 [mm]	214	214	219	213	200	214
X_3 [mm]	288	291	291	291	289	291
X_4 [mm]	288	365	318	366	289	365
X_5 [mm]	227	227	227	227	227	227
X_6 [mm]	288	504	416	498	289	503
X_7 [mm]	1631	1431	1516	1437	1643	1432

Table C.9: Optimal solutions of the initial guesses specified by AFRY's designers. Objective function: IC. RCCRW: RB.

Quantity	**D1**	**D2**	**D3**	**D4**	**D5**	**D6**
Concrete [m^3]	1.47	1.42	1.33	1.37	–	1.37
Reinf. [m^3]	0.0152	0.0152	0.0163	0.0158	–	0.0158
EI [kg CO_2-eq/m]	652	636	605	619	–	617
IC [SEK/m]	3569	3499	3415	3455	–	3446

Table C.10: Optimal cross-sectional dimensions of the initial guesses specified by designers at AFRY's bridge department. Objective function: IC. RCCRW: RB.

Variable	**D1**	**D2**	**D3**	**D4**	**D5**	**D6**
X_1 [mm]	218	217	217	216	200	215
X_2 [mm]	300	239	219	216	200	215
X_3 [mm]	291	291	291	291	291	291
X_4 [mm]	306	377	319	366	305	364
X_5 [mm]	234	228	227	232	227	228
X_6 [mm]	392	531	417	492	305	507
X_7 [mm]	1461	1381	1516	1441	1628	1427

C.4 Comparison between Pattern Search (PS) and Genetic Algorithm (GA)

Table C.11: Built solution (BS) versus optimal solution (OS). Objective function: EI. Optimization algorithm: PS. RCCRW: RB.

Quantity	BS	OS	Difference [%]
Concrete [m^3]	1.71	1.28	-25.6
Reinf. [m^3]	0.0153	0.0180	+18.1
EI [kg CO_2-eq/m]	749	597	-20.2
IC [SEK/m]	3991	3442	-13.8

Table C.12: Built solution (BS) versus optimal solution (OS). Objective function: EI. Optimization algorithm: GA. RCCRW: RB.

Quantity	BS	OS	Difference [%]
Concrete [m^3]	1.71	1.32	-23.2
Reinf. [m^3]	0.0153	0.0169	+10.5
EI [kg CO_2-eq/m]	749	606	-19.1
IC [SEK/m]	3991	3428	-14.1

Table C.13: Iterations and evaluations computed to obtain the optimal solutions. Objective function: EI. RCCRW: RB.

Algorithm	Iterations	Evaluations
PS	161	2198
GA	132	25290

Table C.14: Built solution (BS) versus optimal solution (OS). Objective function: IC. Optimization algorithm: PS. RCCRW: RB.

Quantity	BS	OS	Difference [%]
Concrete [m^3]	1.71	1.33	-22.5
Reinf. [m^3]	0.0153	0.0163	+6.93
EI [kg CO_2-eq/m]	749	605	-19.2
IC [SEK/m]	3991	3415	-14.4

Table C.15: Built solution (BS) versus optimal solution (OS). Objective function: IC. Optimization algorithm: GA. RCCRW: RB.

Quantity	**BS**	**OS**	**Difference [%]**
Concrete [m^3]	1.71	1.33	-22.5
Reinf. [m^3]	0.0153	0.0163	+6.93
EI [kg CO_2-eq/m]	749	605	-19.2
IC [SEK/m]	3991	3416	-14.4

Table C.16: Iterations and evaluations computed to obtain the optimal solutions. Objective function: IC. RCCRW: RB.

Algorithm	**Iterations**	**Evaluations**
PS	169	2279
GA	141	27000

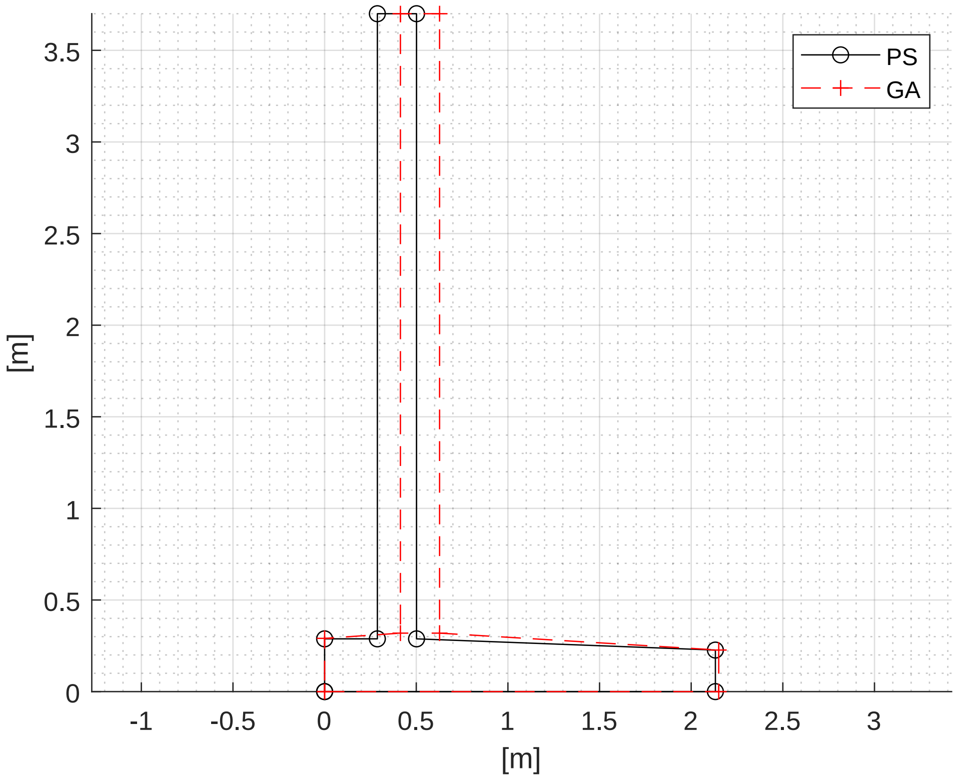

Figure C.5: Optimal cross-sectional dimensions of PS versus GA. Objective function: EI. RCCRW: RB.

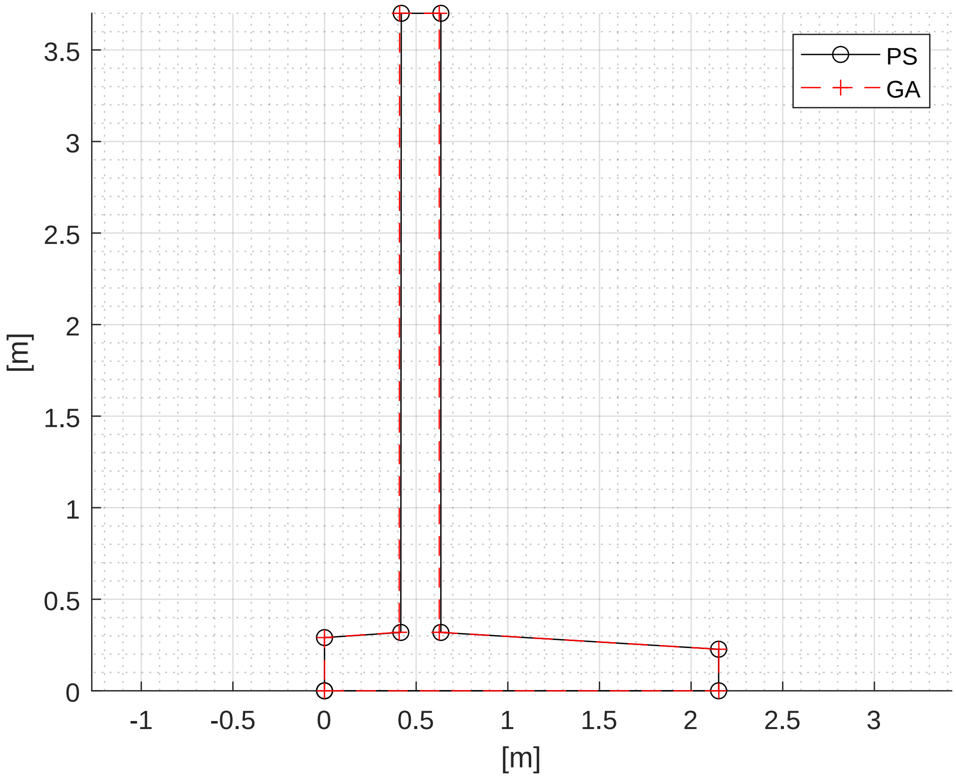

Figure C.6: Optimal cross-sectional dimensions of PS versus GA. Objective function: IC. RCCRW: RB.

C.5 Effect of initial mesh size on the optimal solution (OS)

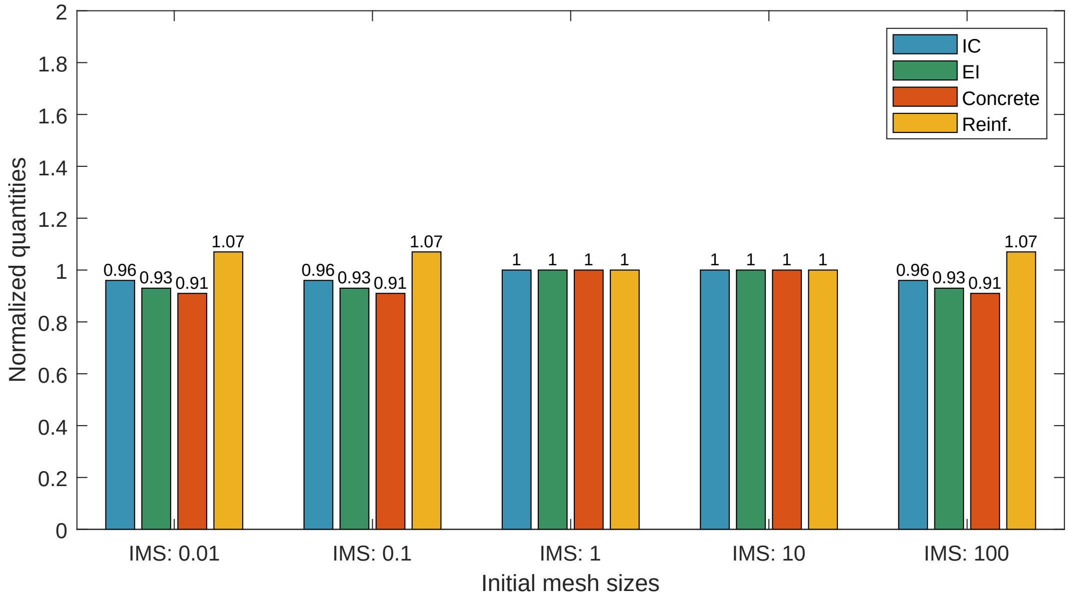

Figure C.7: Comparison between optimal solutions using different initial mesh sizes. Normalized with respect to the optimal solution with the default initial mesh size (1). Objective function: IC. Optimization algorithm: PS. RCCRW: RB.

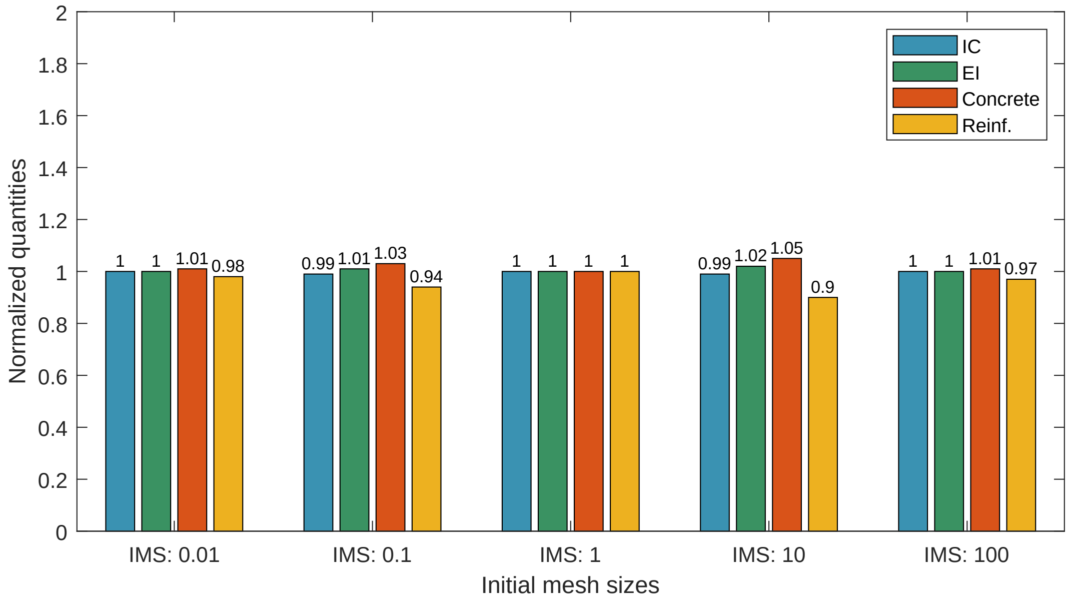

Figure C.8: Comparison between optimal solutions using different initial mesh sizes. Normalized with respect to the optimal solution with the default initial mesh size (1). Objective function: EI. Optimization algorithm: PS. RCCRW: RB.

C.6 Effect of unit emission on the optimal solution (OS)

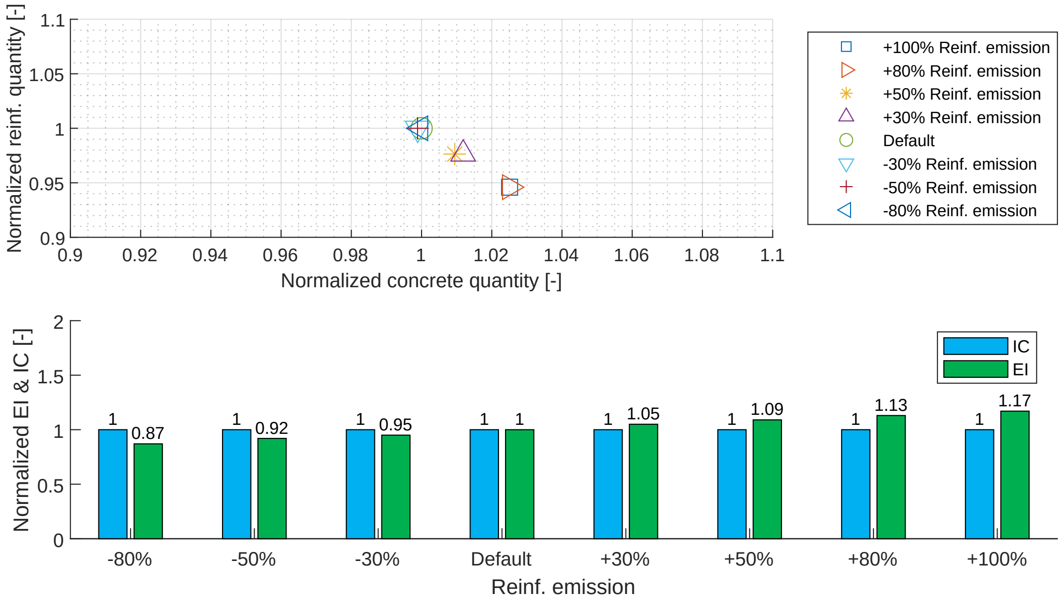

Figure C.9: Effect of the change in reinforcement unit emission on the optimal solution (OS). Normalized with respect to the optimal solution with the default unit emission. Objective function: EI. Optimization algorithm: PS. RCCRW: RB.

C.7 Effect of unit cost on the optimal solution (OS)

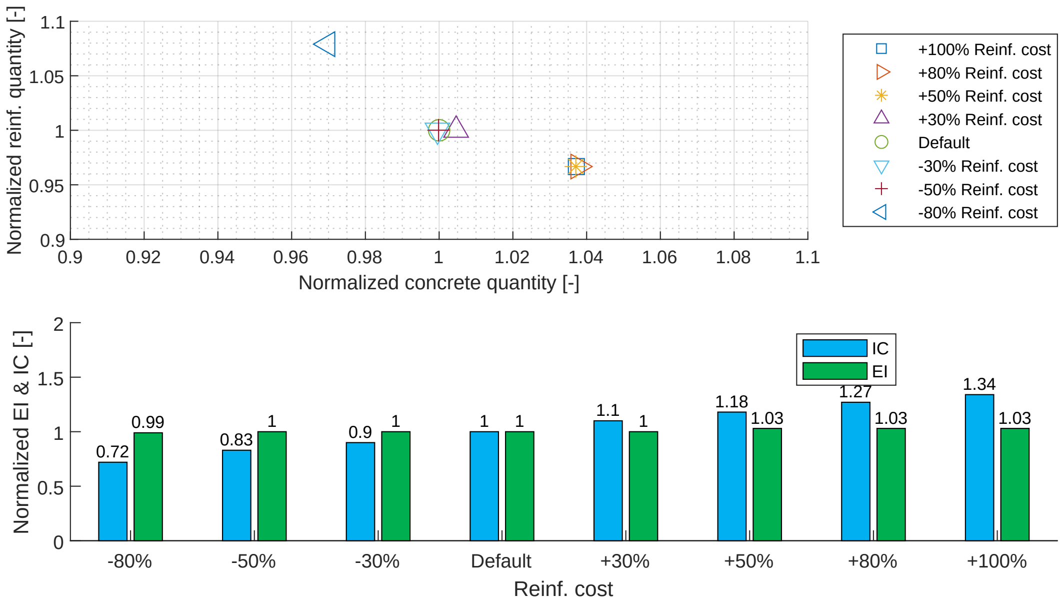

Figure C.10: Effect of the change in the reinforcement unit cost on the optimal solution (OS). Normalized with respect to the optimal solution with the default unit cost. Objective function: IC. Optimization algorithm: PS. RCCRW: RB.

C.8 Built solution (BS) versus Buildable optimal solution (BOS)

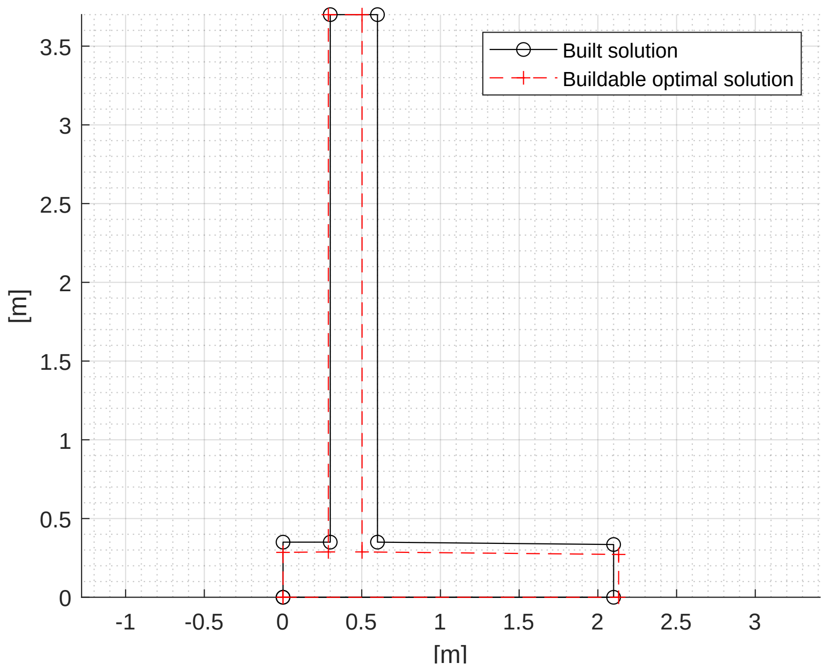

Figure C.11: Built solution (BS) versus buildable optimal solution (BOS). Objective function: EI. Optimization algorithm: PS. RCCRW: RB.

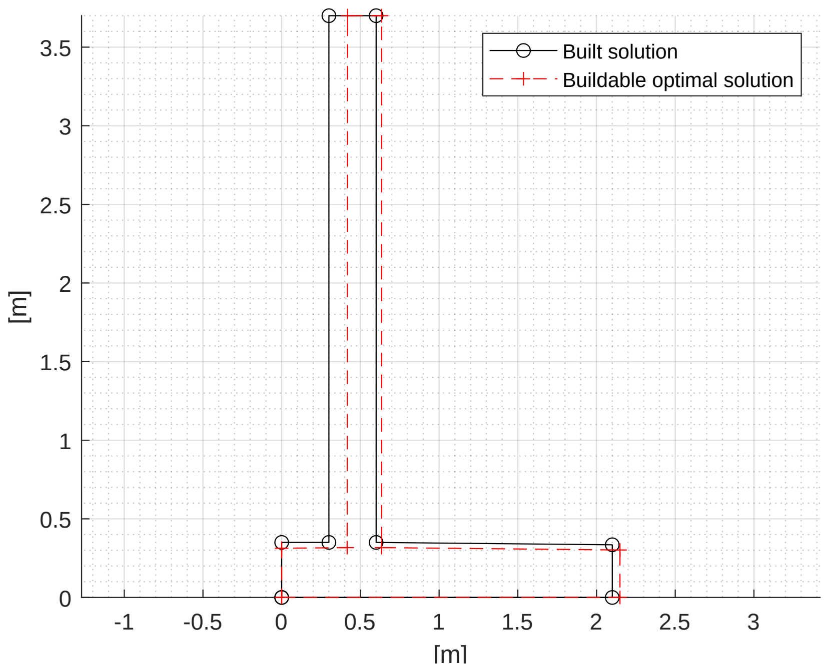

Figure C.12: Built solution (BS) versus buildable optimal solution (BOS). Objective function: IC. Optimization algorithm: PS. RCCRW: RB.

Table C.17: Built solution (BS) versus buildable optimal solution (BOS). Objective function: IC. Optimization algorithm: PS. RCCRW: RB.

Quantity	**BS**	**BOS**	**Difference (%)**
Concrete [m^3]	1.71	1.39	-19.0%
Reinf. [m^3]	0.0153	0.0164	7.3 %
EI [kg CO_2-eq/m]	749	629	-16%
IC [SEK/m]	3991	3517	-11.9%

Table C.18: Built solution (BS) versus buildable optimal solution (BOS). Objective function: EI. Optimization algorithm: PS. RCCRW: RB.

Quantity	**BS**	**BOS**	**Difference (%)**
Concrete [m^3]	1.71	1.31	-23.4%
Reinf. [m^3]	0.0153	0.0181	18.4 %
EI [kg CO_2-eq/m]	749	609	-18.7%
IC [SEK/m]	3991	3507	-12.1%