Sigurd Lundberg Olsen
Lars Magnus Knutstadmarka Johnsen

Development of a digital tool to assist in designing with reusable building elements

Master's thesis in Engineering and ICT
Supervisor: Sverre Magnus Haakonsen
June 2023

Master's thesis

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

NTNU
Norwegian University of
Science and Technology

Sigurd Lundberg Olsen
Lars Magnus Knutstadmarka Johnsen

Development of a digital tool to assist in designing with reusable building elements

Master's thesis in Engineering and ICT
Supervisor: Sverre Magnus Haakonsen
June 2023

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

NTNU
Norwegian University of
Science and Technology

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

ACCESSIBILITY
OPEN

MASTER THESIS 2023

SUBJECT AREA:	DATE:	NO. OF PAGES:
Conceptual Structural Design	08.06.2023	viii + 47 + 25

TITLE:

Development of a digital tool to assist in designing with reusable building elements

Utvikling av et digitalt verktøy for å forenkle prosjektering med gjenbrukbare bygningselementer

BY:

Sigurd Lundberg Olsen

Lars Magnus Knutstadmarka Johnsen

SUMMARY:

To reach the goal of limiting global warming outlined in the Paris Agreement, CO_2 emissions need to be severely reduced by 2030. Consequently, the building industry of today urgently must transition towards a circular economy. This thesis is a contribution to the ongoing Structural Circle project at the Norwegian University of Science and Technology, which develops a digital design tool intended to simplify the utilization of reusable elements in the conceptual design phase of a building.

The contributions of the thesis include additional optimization algorithms, support for multiple optimization metrics and materials, together with the possibility to include the impact corresponding to the transportation of elements in the optimization algorithms. To improve the interactions between the user and the design tool, a graphical user interface was also developed, as well as an automatically generated PDF report that summarizes and visualizes the results of the design tool. The results demonstrate that an implemented version of the Maximum Bipartite Matching is the best-performing algorithm so far included in the design tool. The conducted case studies illustrate the major impact the user-defined inputs have on the proposed elements matching resulting from the design tool. By utilizing the developed design tool, designers can reduce the additional time required when designing with reusable elements. The design tool can accordingly increase the degree of reuse in upcoming building projects and thereby contribute to the transition towards a circular economy in the building industry of tomorrow.

RESPONSIBLE TEACHER: Sverre Magnus Haakonsen

SUPERVISOR(S): Sverre Magnus Haakonsen

CARRIED OUT AT: Department of Structural Engineering, NTNU

Preface

This thesis represents the completion of the five-year master´s degree program Engineering and ICT at the Norwegian University of Science and Technology. The topic and contents of this thesis are a result of our desire to combine ICT and structural engineering in the final work of the master's degree. The work has given us an increased understanding of both the challenges and possibilities when designing with reusable building elements. We want to use this occasion to give a highly deserved salute and gratitude to our supervisor Sverre Magnus Haakonsen for letting us contribute to the Structural Circle project, as well as for valuable and rewarding feedback during the work. Our interest in the project also motivated us to write a conference paper for the IABSE Symposium Manchester 2024. This conference paper is attached in Appendix D.

Trondheim, June 2023

Sigurd Lundberg Olsen — Lars Magnus K. Johnsen

Sigurd Lundberg Olsen — Lars Magnus Knutstadmarka Johnsen

Abstract

To reach the goal of limiting global warming outlined in the Paris Agreement, CO_2 emissions need to be severely reduced by 2030. Consequently, the building industry of today urgently must transition towards a circular economy. This thesis is a contribution to the ongoing Structural Circle project at the Norwegian University of Science and Technology, which develops a digital design tool intended to simplify the utilization of reusable elements in the conceptual design phase of a building. The contributions of the thesis include additional optimization algorithms, support for multiple optimization metrics and materials, together with the possibility to include the impact corresponding to the transportation of elements in the optimization algorithms. To improve the interactions between the user and the design tool, a graphical user interface was also developed, as well as an automatically generated PDF report that summarizes and visualizes the results of the design tool. The results demonstrate that an implemented version of the Maximum Bipartite Matching is the best-performing algorithm so far included in the design tool. The conducted case studies illustrate the major impact the user-defined inputs have on the proposed elements matching resulting from the design tool. By utilizing the developed design tool, designers can reduce the additional time required when designing with reusable elements. The design tool can accordingly increase the degree of reuse in upcoming building projects and thereby contribute to the transition towards a circular economy in the building industry of tomorrow.

Sammendrag

For å nå målene i Parisavtalen om å begrense den globale oppvarmingen må CO_2-utslippene reduseres kraftig innen 2030. Det haster derfor for dagens byggenæring å omstille seg mot en sirkulær økonomi. Denne avhandlingen er et bidrag til det pågående Structural Circle-prosjektet på Norges teknisk-naturvitenskapelige universitet, som utvikler et digitalt designverktøy for å forenkle utnyttelsen av gjenbrukbare elementer i den konseptuelle designfasen av en bygning. Bidragene fra denne avhandlingen inkluderer ytterligere optimaliseringsalgoritmer, støtte for flere variabler å optimere på, støtte for flere materialer og muligheten til å inkludere bidraget fra transport av elementer i optimaliseringsalgoritmene. For å forbedre samhandling mellom brukeren og designverktøyet, ble det også utviklet et grafisk brukergrensesnitt, samt en automatisk generert PDF-rapport som oppsummerer og visualiserer resultatene fra designverktøyet. Resultatene viser at en implementert versjon av Maxmium Bipartite Matching er den beste algoritmen som hittil er inkludert i designverktøyet. De gjennomførte case-studiene illustrerer hvor stor innvirkning de brukerdefinerte variablene har på elementparrene som foreslås av designverktøyet. Ved å anvende det utviklede designverktøyet kan brukere redusere den ekstra tiden som kreves når de prosjekterer med gjenbrukbare elementer. Designverktøyet kan dermed øke graden av gjenbruk i kommende byggeprosjekter og følgelig bidra i overgangen mot en sirkulær økonomi i morgendagens byggenæring.

Table of Contents

List of Figures

List of Tables

1 Introduction

1.1 Background

The United Nations has in the Paris Agreement declared to keep global warming well below 2°C, and ideally below 1.5°C by the end of this century (United Nations, 2015). To reach this goal, emissions need to be reduced by 45% by 2030 (UNEP, 2022) and reach net zero before 2050 (IPCC, 2022). This affects the building and construction sector, which accounts for 37% of the global carbon dioxide (CO_2) emissions (United Nations Environment Programme, 2022). The sector utilizes approximately 50% of the extracted resources in the world (Miller, 2021) and produces over a third of the waste in the EU (European Commission, n.d.).

According to the United Nations global status report for building and construction conveys, CO_2 emissions from buildings and operations reached an all-time high in 2021; 2% higher than the previous peak in 2019 (United Nations Environment Programme, 2022). The Intergovernmental Panel on Climate Change (IPCC) states that action must be taken within this decade to fully capture the mitigation potential of buildings (IPCC, 2022).

The linear economy of the construction sector, which extracts, manufactures, consumes, and discards building materials and resources, is mostly to blame for the high CO_2 emissions (Oluleye et al., 2022). In order to overcome this damaging problem on a worldwide scale, the building industry of today urgently has to transition to a circular economy of reuse and recycling (Wolf et al., 2018). A circular economy would maximize the value of construction materials by either prolonging their service lives or repurposing them as new resources, rather than discarding them.

The building industry has yet to successfully apply a circular model on a major scale globally (Huang et al., 2021). The barriers to reuse include uncertainties regarding the quality, traceability, and certification of older building materials (NSC, 2017), increased material costs (ENTRA ASA, 2021), and issues related to organizational planning (Gorgolewski, 2008). There are nevertheless several successful examples of reusing building materials (Addis, 2012).

Another important barrier to using reusable materials is the additional time required in the design phase. The KA13-project in Norway estimated that the duration of the design phase was doubled when using reusable materials compared to projects where the materials are obtained exclusively from a manufacturer (ENTRA ASA, 2021). This will affect the cost of using reusable materials and raises the question of whether it is possible to simplify this process by using new technology.

1.2 Research Question

Digital technologies have the potential to increase productivity and efficiency in the construction sector (World Economic Forum, 2016). Supporting literature, presented in Section 2, shows several examples of algorithmic implementations to assist designers in substituting elements in a designed structure with reusable elements. None of these references do however provide the designer the ability to influence the results of the design tool through user inputs, such as choosing the metric the algorithms optimize on, which algorithms to use, the criteria of allowed substitutions, the values of the constants used in the calculations, as well as determining if impacts of transporting the elements should be included. As a result of the discovered research gap this thesis aims to answer the following research question:

How can a digital design tool contribute to reusing building elements and how will the user inputs influence the results of the design tool?

1.3 Problem Definition

Covering the research gap described in Section 1.2 is the ultimate goal of the design tool. The general idea of how the design tool can achieve this goal is to give the designer suggestions of possible substitutions of required elements with reusable elements in an already designed system. In that way, the design and topology of the structure are not affected by the design tool. The design tool contains a set of required building elements, from now on defined as "demand elements". The design tool also includes a set of available reusable elements, defined as "supply elements". The task of finding the best substitutions of demand elements with the supply elements is quite similar to The Assignment Problem - a mathematical optimization problem that involves finding the best assignment of a set of agents to a set of tasks (Hillier & Lieberman, 2010). In this thesis, the assignment of supply elements is defined as "The Matching Problem". Each demand element can only be matched with one supply element, while a supply element can either be matched to one demand element or multiple demand elements if a division of the supply element is possible. The assignments of supply elements must be associated with a given performance measure, further referred to as a metric - such as global warming potential or price. The value of the metric is defined as the score. The objective of the design tool is to minimize the total score. In other words, the output of the design tool will be a set of matched pairs of demand and supply elements and an associated total score of the matching.

1.4 Structure Of The Thesis

This section briefly outlines the structure of the thesis. Section 2 presents the conducted literature review. Section 3 then describes the previous work on the Structural Circle project, followed by the implemented extensions to the design tool. Section 4 covers the developments to improve the interactions and communicability between the user and the design tool. Further, the methods to compare and evaluate the implemented functionality are described in Section 5. The corresponding results are presented in Section 6 and later discussed in Section 7. Section 8 proposes further potential development, before Section 9 concludes the thesis.

2 Literature Review

Before defining the given research question, a literature review of the problem and existing solutions was undertaken. The literature review is split into three parts, where Section 2.1 examines building projects involving reusable elements, Section 2.2 highlights some challenges with reuse in structural projects, and Section 2.3 focuses on existing digital technologies to assist in the repurposing of elements.

2.1 Building Projects With Reused Elements

The most environmental waste measure is to prevent waste from occurring (Leland, 2008). According to Leland (2008), there is a need for an increased focus on the environment through awareness raising and guidance on measures that contribute to a more environmentally friendly construction industry. By utilizing resources multiple times throughout their lifespan, the waste is reduced to a minimum. Effective material element reuse can be done in one of two ways: 1) Design with new elements with the intention of reusing the elements in the future or 2) Design with reusable elements (Pronk et al., 2022).

A way of measuring the environmental impact of building projects is through the global warming potential (GWP) - a measurement of equivalent kilograms of CO_2 (kgCO2eq) emitted into the atmosphere (Lynch et al., 2020). The GWP of a construction material is given by an environmental product declaration (EPD), such that the GWP depends positively on the volume/weight and a GWP factor for the given material (The Norwegian EPD Foundation, 2021). All the materials nevertheless have in common that the reusable elements have the lowest GWP factor (Dunn, 2022). In general, all else being equal, a building will thus lower the GWP by utilizing reusable elements for all materials.

Materials that are most relevant for reuse are materials with high raw material prices and long lifespan (Leland, 2008). Especially materials like steel have energy-intensive production with large CO_2 emissions, and should therefore be designed for disassembly and reuse. Also, concrete has an energy-intensive production, but is not as flexible for direct reuse of elements as steel - except for prefabricated concrete elements. When it comes to timber elements there is a reuse potential given that the quality can be documented and that disassembly is possible. Brütting, Wolf et al. (2019) highlight that the reuse potential is significantly larger for linear steel and timber elements like beams and bars because they are often assembled with reversible connections.

Designing with elements from a manufacturer for the purpose of reuse makes it considerably easier to design with reusable elements in the future. To illustrate this, consider the construction “Marnadal elementhus” in Norway - a construction built with the intention of reuse. The building consists of 88 specially developed components in timber and concrete. 78% of the materials are reusable since all the timber connections are made without nails or screws (Leland, 2008). As a result, the structure can easily be disassembled and reused in new constructions in the future.

This thesis will focus on the latter measure of Pronk et al. (2022): designing new structures with reusable elements - more specifically, reusable *load-bearing* elements. There exist several pieces of literature regarding this topic. Brütting, Wolf et al. (2019) performed a case study on the design of the Lausanne Train Station roof with reused L-sections from disassembled transmission towers. The design with these elements resulted in a GWP reduction of 56% compared to a design with new steel components. Addis (2012) refers to multiple case studies containing reused building elements. One of these is The Beddington Zero Energy Development where 98 tonnes of structural steel was reclaimed and used as columns and beams in the structural system. In the same building, reclaimed timber was used for both internal and external stud work. Interestingly, the purchase price of the reclaimed timber was lower than the timber price from a manufacturer. However, the final costs of the reclaimed timber exceeded the new timber because of additional costs from stress-grading and treatment. Another case study of reuse is the C.K Choi Building at the University of British Columbia. In this building, a considerable part of the load-bearing structure was designed with reclaimed timber beams and columns. According to Addis (2012), the project was important to demonstrate that reclaimed materials do not need to be inferior to virgin materials.

Kristian Augusts gate 13 (KA13) is a unique reuse project from 2021 that involves the rehabilitation of existing real estate and the construction of an attached building. The project aimed to achieve a high degree of reused building components, including load-bearing components. In total, building materials from over 25 demolition buildings were repurposed in KA13 (ENTRA ASA, 2021). Such extensive reuse of building components made this project the first of its kind in Norway.

One of the main load-bearing components that have been repurposed in KA13 is steel elements. According to ENTRA ASA (2021), 70% of the steel used in KA13 was reused from demolition projects. This included excess steel from former projects, temporary constructions, and private waste companies. The reuse of steel resulted in emission savings of 97% compared to the use of new steel elements (Høydahl & Walter, 2020). However, repurposed steel in KA13 was approximately 49% more expensive than new steel (ENTRA ASA, 2021).

Hollow core elements are another type of load-bearing component that has been reused in KA13. In the construction of the attached building, 21 hollow cores, equivalent to 160 square meters, were used in floor dividers (ENTRA ASA, 2021). The reuse of hollow core elements resulted in emissions savings of 89% compared to using new elements. Transportation of the reusable elements accounted for 90% of the emissions due to their massive weight. (Høydahl & Walter, 2020). Høydahl and Walter (2020) further emphasize that hollow cores can be transported up to 890km before their emissions are equivalent to new elements. However, the price of a reusable hollow core element is 5-6 times higher than the price of a new hollow core element.

2.2 Challenges With Reusing Elements

Various papers discuss challenges with reusing building elements. Gorgolewski (2008) states that some great challenges lie in the organizational planning of moving materials from a demolition site to the construction site. NSC (2017) remarks challenges related to certification of material properties, quality, and traceability. Addis (2012) discuss issues related to the storage space of reclaimed elements as well as liquidity, as capital has to be tied up earlier in the process when purchasing reclaimed elements. The KA13 experience report demonstrates that despite the large emission savings potential of repurposing load-bearing components, reusable elements are considerably more expensive than virgin elements (ENTRA ASA, 2021). The report also discusses the challenges regarding the availability of used materials. The project experienced limited access to used building materials because disassembly rarely occurs in a demolition project.

One challenge that occurs in the majority of the mentioned references is the additional time used when designing with reusable elements. According to Leland (2008), a prerequisite for reusing elements must be that sufficient time is allocated to the design phase. The desire for a quick implementation can often come into conflict with thorough planning for good environmental solutions. The extra time used when designing structures with reclaimed elements will naturally increase the cost of the project. Leland (2008) further accentuates that design for reuse will give reduced costs regarding the operation, maintenance, disassembly, and handling of construction waste.

Addis (2012) and Gorgolewski (2008) also acknowledge the additional time required for the design team to incorporate the reclaimed elements into the structure. NSC (2017) highlights another important perspective of the design phase, namely the additional time required within construction programs to allow for using reclaimed steel. Furthermore, ENTRA ASA (2021) emphasizes that the design phase for KA13 was significantly longer than that of an ordinary design project. This phase is estimated to have taken twice as long as similar projects designed with optional profiles. The KA13 experience report also states that lessons learned from this project will hopefully reduce the design phase of future reuse projects.

2.3 Digital Technologies For Reusing Elements

Replacing new elements with reusable elements when designing a construction is, as mentioned in Section 1.3, essentially an assignment problem. To solve this kind of problem, various algorithms already exist (Arora, 2015). There are also several examples of tools that have been developed to aid designers in reusing elements using different algorithms.

The Greedy Algorithm is possibly the most well-known combinatorial optimization algorithm (Vince, 2002). This algorithm attempts to find a global solution by always selecting the locally optimal option at each step. By doing this, it is possible to guarantee a local optimum solution, which in linear cases also approaches a global one. This makes the Greedy Algorithm quite powerful, fast, and well working for a wide range of problems (Cormen et al., 2022). The work of Bukauskas et al. (2017) on a bin-packing definition to assist designers in matching a limited number of diverse demand elements with recycled supply elements illustrates a greedy approach.

The Hungarian Algorithm, developed and introduced by Kuhn (1955), is another classical optimization algorithm. Instead of enumerating all possibilities, the algorithm solves the classical assignment problem in polynomial time (Cormen et al., 2022). Huang et al. (2021) provides an example of parameterized geodesic dome design using recycled wood elements. In their paper, a graph is used to represent the problem and they further utilize the Hungarian Algorithm to determine the best element substitutions. The strength of the Hungarian Algorithm is shown by being 60 times faster than Linear Programming (LP). Smaller problems are computed in real-time, whereas larger problems are computed in a few seconds. Their paper also introduces a Grasshopper tool to implement the algorithm.

Another approach for solving optimization problems is Mixed Integer Programming (MIP), first presented by Dakin (1965). MIP is an algorithm for finding solutions to optimization problems in which some of the variables must take integral values (Arora, 2015). The Matching Problem is well suited for MIP since the variables can have a value of 0 or 1 corresponding to no match and match respectively. Brütting et al. (2018), Brütting, Desruelle et al. (2019), and Brütting et al. (2020) uses MIP to solve the assignment problem. In addition, they ensure structural integrity by introducing both ultimate- and serviceability-limit state conditions, like buckling and stress capacity, as constraints in the problem. After several assumptions, they conclude with optimized truss systems utilizing reused elements embodying above 50% less energy than corresponding systems made of new material.

There are also several more examples of work regarding this subject, among others Parigi (2021) and van Gelderen (2021). To increase the direct reuse of salvaged timber components, Parigi (2021) suggests an algorithm for creating reciprocal frames utilizing cutoff elements. van Gelderen (2021) develops a tool for the design of steel trusses with reusable elements. To generate the designs, he performed a topology optimization, where the volume of the structures is minimized and the average unity check and the reuse percentage maximized.

The aforementioned papers share the goal of automating the assignment and decision-making process when integrating reusable materials in new designs. This task, which takes hours, days, or even weeks to complete manually, can be done much quicker by algorithms. Avoiding manual work may, everything else equal, help the construction sector increase the use of reusable elements because labor costs have a significant impact on how structures are designed.

3 Design Tool Devolopment

In this section, the previous work on the Structural Circle project is first described. Next, the implemented functionality in the design tool is presented. A link to the GitHub repository containing the code for these extensions to the project can be found in Appendix B.

3.1 Previous Work On The Project

The research and development of a GitHub project by Ph.D. candidates Tomczak and Haakonsen (2022) formed the foundation of this thesis. In June 2022, the doctoral candidates launched the "Structural Circle" project. This thesis has been developed in close collaboration with the Ph.D. project throughout the work phase. Since the project had been ongoing for six months leading up to the start of this thesis, the GitHub repository already contained a considerable quantity of functionality. This functionality formed the initial version of the design tool. In order to better demonstrate the contributions made to the project by this thesis, the structure of the artifact developed by Haakonsen and Tomczak prior to January 2023 will be briefly described in this section.

As mentioned in Section 1.3 the general idea of the design tool is to assist users in the process of substituting new elements with reusable elements in a designed system. Despite that the artifact of Tomczak et al. (2023) was programmed in a flexible way and included functionality for designing with different materials, only timber elements were considered at this point. Also, note that the design tool was programmed to always minimize the total GWP of the substitutions. The GWP for each element was calculated as shown in Equation (3.1):

$$GWP = length \cdot area \cdot factor \quad [kgCO2eq] \tag{3.1}$$

where

$length$ = element length [m]
$area$ = element area [m^2]
$factor$ = GWP factor [kgCO2eq/m^3]

To use the design tool, the following 5 inputs are needed from the user:

1. A dataset containing demand elements that represent the designed system.
2. A dataset containing supply elements that represent reusable elements that can substitute the demand elements.
3. Constraint Input to eliminate certain substitutions.
4. GWP factors corresponding to both new and reusable timber elements.
5. The optimization algorithms to employ.

The user-selected datasets containing the supply and demand elements are stored in two individual DataFrames of the Python library "Pandas" (The Pandas Development Team, 2020). The structure of the DataFrames is depicted in Table 3.1. Here, each element has the parameters length, area, and moment of inertia represented as columns. The rows represent the elements, each with a unique ID.

Table 3.1: Structure of the supply and demand DataFrame.

ID	Length [m]	Area [m^2]	Moment of Inertia [m^4]
S0	9.76	1.09e-2	0.10e-4
S1	9.84	3.78e-2	1.19e-4
S2	9.25	2.45e-2	0.50e-4

ID	Length [m]	Area [m^2]	Moment of Inertia [m^4]
D0	4.00	3.06e-2	0.78e-4
D1	8.74	0.56e-2	0.03e-4
D2	2.89	1.95e-2	0.32e-4

The Constraint Input is given as a dictionary of requirements with keys corresponding to which parameter from the supply/demand-DataFrame the requirements apply. The value for each key is a conditional statement. An example of a Constraint Input is depicted in Figure 3.1. In this example, the properties of the area, length, and moment of inertia of a supply element should all be larger or equal to the corresponding properties of a demand element.

```
constraint = {"Area": ">=", "Length": ">=", "Moment of Inertia": ">="}
```

Figure 3.1: Constraint Input.

Before starting the assignment of supply elements to demand elements, some preprocessing is done by the design tool. Firstly, exact copies of the demand elements in the demand DataFrame, hereafter referred to as "new" elements, are added to the supply DataFrame with the ID changed from "D" to "N". This is done to always guarantee a substitution for each demand element. See Table 3.2 for the updated DataFrame structures.

Table 3.2: Structure of the supply and demand DataFrame after preprocessing.

ID	Length [m]	Area [m^2]	Moment of Inertia [m^4]
S0	9.76	1.09e-2	0.10e-4
S1	9.84	3.78e-2	1.19e-4
S2	9.25	2.45e-2	0.50e-4
N0	4.00	3.06e-2	0.78e-4
N1	8.74	0.56e-2	0.03e-4
N2	2.89	1.95e-2	0.32e-4

ID	Length [m]	Area [m^2]	Moment of Inertia [m^4]
D0	4.00	3.06e-2	0.78e-4
D1	8.74	0.56e-2	0.03e-4
D2	2.89	1.95e-2	0.32e-4

Secondly, additional preprocessing is done to reduce the solution space by identifying valid and invalid substitutions. This preprocessing is performed by combining the supply and demand DataFrames with the Constraint Input. This results in an Incidence Matrix **I**, shown in Table 3.3, that contains information about feasible and unfeasible replacements. Value I_{ij} is set to True if the demand element D_i can be replaced by supply element S_j, and False if the replacement is not possible. From this Incidence Matrix, another important matrix is created: the Weight Matrix **W**. The Weight Matrix calculates a score for each True value in the Incidence Matrix based on the user-specified metric, as shown in Table 3.4.

Table 3.3: Incidence Matrix.

	S0	S1	S2	N0	N1	N2
D0	False	True	False	True	False	False
D1	True	True	True	False	True	False
D2	False	True	True	False	False	True

Table 3.4: Weight Matrix.

	S0	S1	S2	N0	N1	N2
D0	-	0.34	-	3.54	-	-
D1	0.21	0.74	0.48	-	1.42	-
D2	-	0.25	0.1	-	-	1.63

After the preprocessing, the tool is ready to start the substitution process. Different algorithms were already implemented by Haakonsen and Tomczak, such as the Greedy Algorithm, the Maximum Bipartite Matching (MBM), and Mixed Integer Linear Programming (MILP). Among these algorithms, it is important to distinguish between the ones that utilize the principles of "single assignment" and the ones with "plural assignment". Single assignment means that one supply element can only replace one demand element, while plural assignment represents that one supply element can be divided into multiple elements and replace more than one demand element - as long as the requirements of the Constraint Input from Figure 3.1 are fulfilled.

Two versions of the Greedy Algorithm were available: one as a single assignment algorithm, from now on referred to as Greedy Algorithm, and one as a plural assignment algorithm, from now on referred to as Greedy Algorithm Plural. MILP is a plural assignment algorithm, while MBM is a single assignment algorithm. The user could specify which of these algorithms to employ in the design tool.

The output from the design tool is a set of matched pairs. The pairs indicate which elements in the designed structure that can be substituted by reusable elements. The total workflow of the functionality per January 2023 is depicted in Figure 3.2

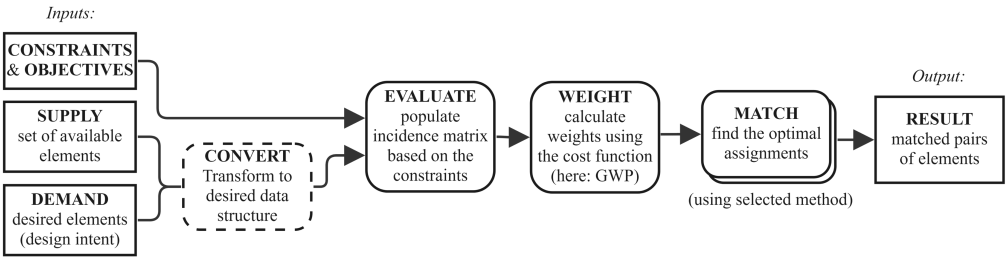


Figure 3.2: Flowchart of the design tool (Tomczak et al., 2023).

3.2 Brute Force Approach

It was desirable to implement a Brute Force Approach in order to verify that the already implemented algorithms performed well compared to the global minimum solution. The Brute Force Approach is a general strategy to systematically search through all possible solutions to an optimization problem (Heule & Kullmann, 2017). In The Matching Problem, described in Section 1.3, the Brute Force Approach involves checking every possible assignment of supply elements to the demand elements that fulfill the Constraint Input. Because the solution space would become extremely large if plural assignment was used, the Brute Force Approach was implemented as a single assignment algorithm. The Brute Force Approach will always find the optimal solution, in other words always return the matching of supply and demand elements that minimizes the optimization metric.

Although the Brute Force Approach guarantees finding the optimal solution, it can also be extremely time-consuming, especially when dealing with large amounts of data. This is due to the search space increasing factorially with the number of supply and demand elements. The manner in which the Brute Force Approach was implemented was therefore crucial for the algorithm to be feasible at all. During the implementation, it became clear how slow the Brute Force Approach might be. Several different upgrades to the initial Brute Force Approach were hence implemented to reduce computation time. The current fastest Brute Force Approach utilizes the Python module "Itertools" (Van Rossum, 2023). It also utilizes the Incidence Matrix, described in Section 3.1, to decrease the solution space. This contributes to the runtime by not wasting time evaluating invalid solutions. The current version of the Brute Force Approach is about 40 000 times faster than the initial Brute Force Approach. This demonstrates how crucial the implementation strategy was. Figure 3.3 illustrates the steps in the latest implementation of the Brute Force Approach.

```
Function Match_Brute()
    Set BestMatch to empty list
    Set LowestScore to a very large number
    Find all possible solutions to the matching problem based on the Incidence Matrix
    For each possible solution
        Check if the solution is a valid solution to the problem
        If the solution is valid
            Set TotalScore to the sum of the matching weights
            If TotalScore is less than LowestScore
                Set LowestScore to TotalScore
                Set BestMatch to Solution
    Create substitution pairs
```

Figure 3.3: Pseudocode for the Brute Force Approach.

3.3 Genetic Algorithm

It was a desire in the Structural Circle project to investigate the applicability of the Genetic Algorithm to The Matching Problem. The Genetic Algorithm, an optimization algorithm proposed by J.H. Holland in 1992 (Katoch et al., 2021), uses the principles of "survival of the fittest" from Darwinian evolutionary theory to determine the globally optimal solution to a given problem. The algorithm starts with an initial population that consists of a set of solutions to the problem - defined as chromosomes, see Figure 3.4. Each chromosome is a collection of genes, often represented with binary encoding (Shorman & Pitchay, 2015). The chromosomes of the initial population are evaluated by a fitness function - the higher value, the better the solution is to the given problem (Gad, 2020). Based on the fitness value, a set of chromosomes is selected to be parents to the next generation. The genes of the parents are combined through a crossover operation. This crossover operation emerges offspring to the next generation. The genes of the chromosomes can be altered to maintain diversity in the population by a process called mutation. After the offspring for the next generation is generated, the whole process is repeated for a given number of generations. The workflow of the algorithm is presented in Figure 3.5.

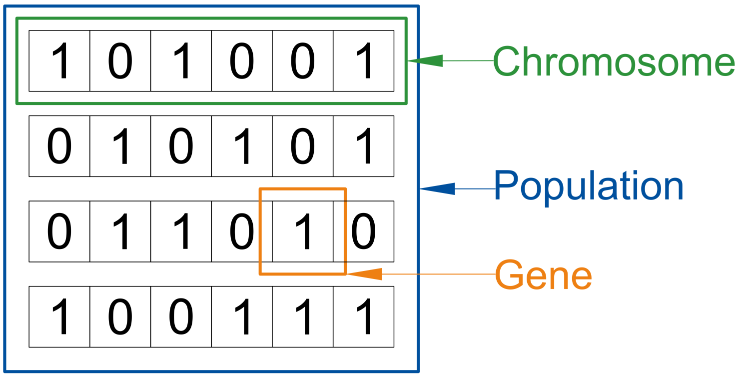


Figure 3.4: Components of the Genetic Algorithm.

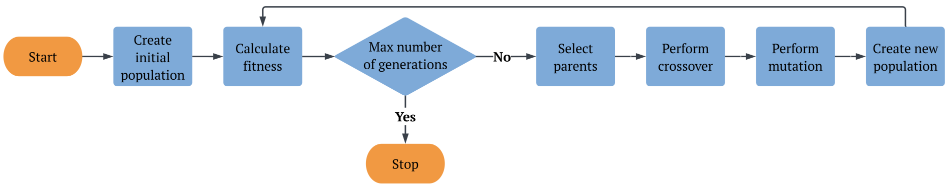


Figure 3.5: Flowchart of the Genetic Algorithm.

The Genetic Algorithm was for simplicity chosen to perform as a single assignment algorithm when investigating how it applied to The Matching Problem. For implementation, the open-source Python library "PyGAD" (Gad, 2023) was used. PyGAD is well-documented through the website https://pygad.readthedocs.io - which made it straightforward to use the functionality in the library. To run the Genetic Algorithm with PyGAD, the chromosome had to be given as a one-dimensional list containing genes of float or integer values (Gad, 2020). Since the objective is to match a demand element with a supply element, a reasonable representation corresponding to no match and match was chosen as 0 and 1 respectively. The transition from a matching table, representing what supply element to match with a given demand element, to a chromosome is shown in Figure 3.6. Here the demand elements are denoted D0 and D1, while the supply elements are denoted S0, S1, and N. If N is matched, the demand element must be obtained directly from the manufacturer. In Figure 3.6, D0 is matched with S0, and D1 is matched with S1. This matching results in the chromosome 100010.

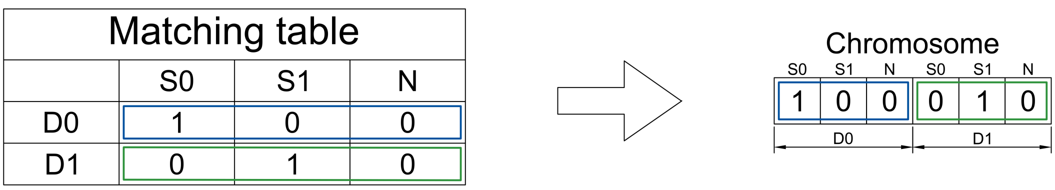


Figure 3.6: Chromosome representation of The Matching Problem.

The class pygad.GA is the component in PyGAD that builds the Genetic Algorithm. This class supports 40 parameters, however, not all are necessary to define. Two of the most important parameters in this class are "initial population" and "number of generations". The parameter defining the initial population contains a set of chromosomes to form the first generation. The subsequent generations will inherit the genes of the best of these chromosomes. Each chromosome in the initial population was generated to have a random value of 0 and 1 for every gene. The number of generations parameter defines how many times the cycle in Figure 3.5 is repeated. Vrajitoru (2000) concluded that the Genetic Algorithm gives better results by starting with a large initial population rather than running the algorithm with a large number of generations with a small initial population. Therefore, having a reasonable size of the initial population was considered critical for the performance of the Genetic Algorithm. Consequently, the initial population was set to be a lot bigger than the number of generations.

The "fitness function" is also an important parameter in the pygad.GA class. This parameter allows for a user-defined evaluation of the fitness of each chromosome - in other words, how good the solution is. The fitness function is treated as a maximization operator by PyGAD and is executed for each chromosome of each generation (Gad, 2020). Since the objective of the design tool is to minimize the total score, the fitness of the solution has to be set to 1 divided by the total score of the matchings. The fitness function is in this problem closely linked to the Weight Matrix described in Section 3.1, as it holds the score of each possible matching. To exclude invalid solutions, the fitness value is receiving a penalty equivalent to the negative value of the highest score of the Weight Matrix for the following cases: 1) Matching elements that cannot be matched 2) A demand element is matched with multiple supply elements 3) A demand element is not matched with any supply elements. For the case where a supply element is matched with multiple demand elements, the fitness value is set to -10^{10} independent of the total score of the matching. This means that when a valid solution is evaluated, the score will be positive and a higher value will indicate a lower total score. When an invalid solution is evaluated, the score will be negative - which means that this solution most likely will not be chosen to reproduce offspring for the next generation.

```
Function fitness_funct(solution, solution index)
    Set fitness to zero
    Set reward to zero
    Set penalty to the negative of the maximum score of the Weight Matrix
    For each demand element in solution
        For each supply element
            If a supply element is matched with a demand element
                If this matching is not possible
                    Add penalty to fitness
                If this matching is possible
                    Add score of matching to reward
        If demand element is matched with multiple supply elements
            Add penalty to fitness
        If demand element is not matched with any supply element
            Add penalty to fitness
    If a supply element is assigned to multiple demand elements
        Set fitness to a large negative number
    If reward is not zero
        Add 100/reward to fitness

    Return fitness
```

Figure 3.7: Pseudocode for the fitness function.

Moreover, Thatpannphyu et al. (2016) found that a better solution is obtained by using a higher number of parents, without considerably increasing the computation time. Therefore, the number of parents chosen for reproduction in each generation was set to half of the population size. This means that half of the population from each generation is removed, while the rest is used to create offspring. Also, note that the PyGAD class includes a parameter called "keep elitism" that allows the class instance to keep a given number of parents in the next generation. Keeping all the parents ensures that the best solutions of the previous generation are saved.

Note that there exists little to no documentation on how to choose the value of the parameters of the pygad.GA-class. As a result, the parameters are mainly tuned by experimentation of different settings. Some literature is found to support the choice of parameters, as seen above. The rest of the parameters used in the algorithm was chosen based on trial and error.

3.4 Maximum Bipartite Matching

Maximum Bipartite Matching (MBM) is a fundamental concept in graph theory and is used to solve a variety of resource allocation problems in various fields, such as assigning tasks to employees based on their skills and preferences. Formally, Cormen et al. (2022) defines a bipartite graph G = (V, E) as a graph where a set of vertices V is partitioned into two subsets - in this case a set "S" for supply elements and a set "D" for demand elements. Set S and D are connected by a set of edges E such that every edge connects the vertices in S and D, see Figure 3.8. The MBM involves finding the largest possible set of edges that can be drawn between the two disjoint sets of vertices S and D in the bipartite graph, without any two edges sharing a common vertex, this is known as a matching.

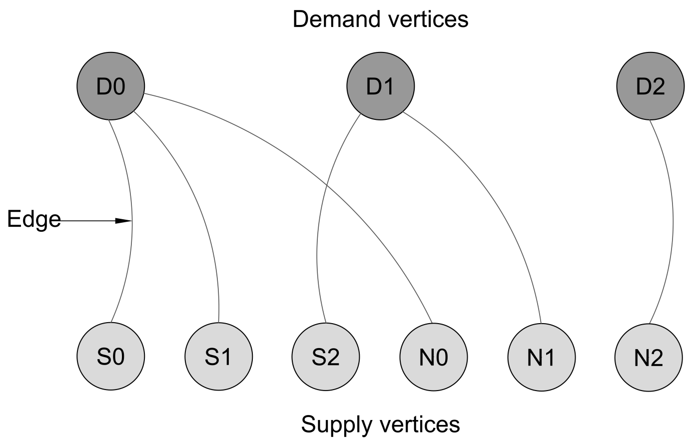


Figure 3.8: Graph representation of The Matching Problem.

Edges in the graph representing The Matching Problem, defined in Section 1.3, are created based on the Incidence Matrix described in Section 3.1. This means that for True values in the Incidence Matrix, an edge is created between the corresponding supply and demand vertex. The edge is then assigned a weight corresponding to the difference between the score of the demand element and the associated score of the match in the Weight Matrix, also described in Section 3.1. This difference is used as the algorithm aims to maximize the total edge weights. The bipartite graph is now by definition called a weighted graph.

To implement MBM in the design tool, the Python library "Igraph" (Csárdi et al., 2023) was used. This library includes functionality for both generating a graph and employing the MBM algorithm. Note that the implementation of this algorithm was done by Tomczak et al. (2023). However, the version developed by the doctoral candidates was implemented as a single assignment algorithm. For that reason, this thesis aimed to improve the algorithm by including functionality allowing for plural assignment.

To allow for plural assignment, two additional algorithms were implemented as an extension to the work of Tomczak et al. (2023) The first new algorithm, called MBM Plural for future references, simply starts with employing the single assignment version of MBM implemented by Tomczak et al. (2023). This returns a set of matches represented by edges. Plural assignment was implemented by iterating through these edges with the following procedure:

1. Cut the supply element to exactly fit the length of the matched demand element.
2. Create a second supply element with the length of the cutoff, but with the same properties as the perfectly fitted supply element.
3. Update the Incidence Matrix and the Weight Matrix to include both perfectly fitted supply elements and cutoff elements.
4. Create a new graph with the perfectly fitted supply elements and the new cutoff elements.
5. Execute the MBM algorithm once more.
6. Extract the new matches represented by edges.

When the MBM algorithm is executed the second time, it includes to the possibility of matching both perfectly fitted supply elements and the cutoff elements with the demand elements.

The second algorithm is quite similar to MBM Plural. What differs is that MBM Plural only cuts the elements once. This second extension algorithm, for future references called MBM Plural Multiple, allows the cutoff elements to be cut into even shorter elements. This is done by repeating steps 1-5 in the procedure above for MBM Plural as long as any element is cut. If no element is cut in an iteration, the MBM is employed one last time to extract the new matches represented by edges.

3.5 Multiple Materials

It was desirable to include the possibility of allowing more materials than only timber in the two dataframes containing supply and demand elements, as this would increase the usefulness of the design tool. Due to the good quality of the project foundation, the only required action for this was to include element material in the two existing dataframes containing supply and demand elements, shown in Table 3.1, and the user-given Constraint Input, shown in Figure 3.1.

Table 3.5 and Table 3.6 display the structure of the supply DataFrame and demand DataFrame with a column representing the element material of each element.

Table 3.5: Structure of supply DataFrame with element material.

ID	Length [m]	Area [m^2]	Moment of Inertia [m^4]	Material
S0	9.76	1.09e-2	0.10e-4	Timber
S1	9.84	3.78e-2	1.19e-4	Steel
S2	9.25	2.45e-2	0.50e-4	Timber

Table 3.6: Structure of demand DataFrame with element material.

ID	Length [m]	Area [m^2]	Moment of Inertia [m^4]	Material
D0	4.00	3.06e-2	0.78e-4	Steel
D1	8.74	0.56e-2	0.03e-4	Timber
D2	2.89	1.95e-2	0.32e-4	Steel

The Constraint Input was consequently expanded to include element material. The property for this requirement is that the material of a supply element should be equal to the material of a demand element. The expanded Constraint Input is shown in Figure 3.9.

```
constraint = {"Area": ">=", "Length": ">=", "Moment of inertia": ">=", "Material": "=="}
```

Figure 3.9: Expanded Constraint Input.

3.6 Impact Of Transportation

The road transport sector accounts for 20% of the greenhouse gas emissions in the European Union and is also a main cause of air pollution in cities (European Commission, 2023). This number is supported by Miljodirektoratet (2022), which establishes that road-transport accounts for 18% of CO_2 emissions in Norway. Considering this, it was desirable to include the GWP corresponding to the transportation of elements in the design tool. The main idea behind this was that the element matching resulting from the design tool could be affected by the required transport distance corresponding to the different elements.

To include the GWP of transporting elements in the design tool, the dataframes containing supply and demand elements, shown in Table 3.1, were expanded. Each element was given a location with corresponding coordinates; more specifically a column with a location name, a column with longitude, and a column with latitude. Table 3.7 illustrates the expanded supply DataFrame, containing location with corresponding coordinates.

Table 3.7: Supply DataFrame with location information.

ID	Length [m]	Area [m^2]	Moment of Inertia [m^4]	Material	Location	Latitude	Longitude
S0	9.76	1.09e-2	0.10e-4	Timber	Steinkjer	64.024861	11.489108
S1	9.84	3.78e-2	1.19e-4	Steel	Meråker	63.415312	11.747262
S2	9.25	2.45e-2	0.50e-4	Timber	Namsos	64.467588	11.501161

Regarding the demand DataFrame, illustrated in Table 3.8, the added columns represent where the corresponding new elements are manufactured and transported from if they are not matched to a reusable element from the supply DataFrame. Table 3.8 reveals a notable absence of values for the manufacturer and corresponding coordinates related to demand elements D0 and D2. For demand elements missing these columns, the design tool employs an automated process that fills these columns with the closest material manufacturer and the corresponding coordinates for each element. This is done by providing the design tool with an Excel file containing different material manufacturers with corresponding coordinates. The subsequent identification of the closest manufacturer of each demand element missing manufacturer information is determined through the utilization of the later described OSRM API, which enables the calculation of the driving distance between each manufacturer and the construction site.

Table 3.8: Demand DataFrame with location information.

ID	Length [m]	Area [m^2]	Moment of Inertia [m^4]	Material	Manufacturer	Latitude	Longitude
D0	4.00	3.06e-2	0.78e-4	Steel	Norsk Stål Trondheim	63.438445	10.409940
D1	8.74	0.56e-2	0.03e-4	Timber	-	-	-
D2	2.89	1.95e-2	0.32e-4	Steel	-	-	-

The design tool was developed to let the user define whether the impact of transporting the elements should be included or not. If transportation of the elements is chosen to be included, the coordinates of the construction site must be provided. If the user wants to include transportation, the design tool automatically calculates the driving distance to the construction site for every element - both the driving distance from the manufacturer for new elements and the driving distance from the location of the reusable elements. The driving distance calculation was done by utilizing the Python library "Requests" (Reitz et al., 2023) together with the Open Source Routing Machine (OSRM) application programming interface (API). The OSRM is a routing engine for shortest paths in road networks (OSRM, n.d.), similar to the more commonly known Google Maps. The most important difference between the two is that OSRM is free whereas Google Maps is not (Chathuranga, 2018).

The GWP of transporting the elements was calculated assuming that all transportation was done by road. For the sake of simplicity, the density of reusable and new materials was assumed equal. The values were set to 491 kg/m^3 and 7850 kg/m^3 for timber and steel elements respectively in accordance with (SCA, 2022) and (Larsen, 2020). From this, the weight of the elements in tonnes was found from the product of the element volume and the element density. Knowing the driving distance and the weight, Equation (3.2) could be utilized to find the GWP corresponding to the transportation of elements. From this formula, it can be seen that the GWP increase with the weight of the elements, the driving distance of the elements as well as the factor defining CO_2 emissions per tonne per kilometer transported. This factor is set by the user of the design tool.

$$Transportation\ GWP = distance \cdot weight \cdot factor \tag{3.2}$$

where

$distance$ = driving distance [km]
$weight$ = weight of goods transported [tonne]
$factor$ = gram CO2 equivalents per tonne per kilometer [gCO2eq/tonne/km]

As a result of combining the OSRM API and Equation (3.2), the GWP impact of transporting each element to the construction site was possible to include in the optimization algorithms together with the material GWP of the elements. In other words, the design tool was with this extension able to assign a new element to a demand element if the GWP of transporting a reusable element exceeded the GWP difference between the new and reusable element.

3.7 Additional Optimization Metrics

Based on the findings of Høydahl and Walter (2020) concerning the price difference between new and reusable elements, presented in Section 2.1, it was desirable to implement the possibility of including price in the optimization algorithms. Equation (3.3) and Equation (3.4) are provided for the calculation of the element price for timber and steel elements.

$$Timber\ element\ price = length \cdot area \cdot timber\ price \tag{3.3}$$

where

$length$ = element length [m]
$area$ = element area [m^2]
$timber\ price$ = timber price per cubic meter [NOK/m^3]

$$Steel\ element\ price = length \cdot area \cdot density \cdot steel\ price \tag{3.4}$$

where

$length$ = element length [m]
$area$ = element area [m^2]
$density$ = steel density [kg/m^3]
$steel\ price$ = steel price per kg [NOK/kg]

As described in Section 3.6, the user defines if the impact of transporting the elements should be included in the design tool. The costs of transportation were assumed to depend solely on the driving distance, element weight, and a factor defining the price of transportation per tonne per kilometer. The value for the factor should be determined by the user of the design tool. Equation (3.5) was used to compute the price of transportation.

$$Transportation\ price\ = distance \cdot weight \cdot factor \tag{3.5}$$

where

$distance$ = driving distance [km]
$weight$ = weight of goods transported [tonne]
$factor$ = transportation price per tonne per kilometer [NOK/tonne/km]

The inclusion of price in the design tool led to three possible optimization metrics; *GWP*, *Price*, and *Combined*. When optimizing solely on *Price*, the design tool simply attempts to minimize the total costs of the project. The total costs of the project include the price of the elements and, if wanted, the cost impact corresponding to the transportation of the elements. When optimizing on *Combined*, the design tool finds the best element matching considering both price and GWP. This is possible due to a required user input variable named "Valuation of GWP". This variable reflects the willingness of the user to pay for a reduction in GWP. In other words, the variable aims to answer the following question: "How important is the GWP of the project compared to the total costs?". A high valuation of GWP will make the result approach the result with *GWP* as the optimization metric, whereas a low valuation of GWP will make the result approach the result if *Price* is used as the optimization metric.

4 Visualizing The Design Tool

After the functionality and extensions described in Section 3 were implemented, an intuitive way to interact with the design tool was considered necessary. This section describes the development of a graphical user interface as well as an automatically generated PDF report incorporated into the design tool.

4.1 Graphical User Interface

Due to the increased complexity and number of input variables in the design tool, a graphical user interface (GUI) was considered necessary. A GUI serves as an intermediary between the designer and the code and helps to avoid input errors occurring from entering data manually into the code. As a result, the designer is not required to have any programming knowledge in order to utilize the design tool. Stated differently, the GUI expands the accessibility of the design tool to a wider range of users. Furthermore, inspections of the output results and further analysis benefit greatly from the use of GUI (Zhang, 2010).

The GUI was developed to enable users to intuitively utilize the design tool. This included the possibility to upload Excel or CSV files containing the supply and demand dataset, as well as effortlessly set to coordinates of the construction site in an interactive map. It was desired to have a dropdown menu for different optimization metrics and a checkbox to include transportation. The GUI also needed to include input fields for the relevant input variables together with the opportunity to choose which optimization algorithms to employ. For the sake of simplicity, the Constraint Input was assumed to equal the one shown in Figure 3.9.

After considering several toolkit options for building the GUI, the Python library "Tkinter" (Van Rossum, 2023) was chosen. Moore (2018) lists several advantages of Tkinter, the main ones being that the library likely will run unaltered for decades to come and that it is ideal for applying GUI to existing Python code. Considering this, Tkinter is adequate for the developed design tool. The GUI, with all its functionality, was developed to function on both macOS and Windows operating systems.

The well-known interaction design principles of Don Norman were applied in the development of the GUI. Norman (2002) covers six principles, some more relevant to this GUI than others. Although the principles were presented over 20 years ago, they remain relevant today (Rekhi, 2017). "Visibility" is one of the most important principles. This principle implies that the objects in the GUI are more likely to be used and known by users if they are visible. The main objects in the GUI are therefore visible without the user having to search for them. Furthermore "feedback" is an important principle that involves making the user aware of what action has been performed and the influence of that action. One example of this is that the user receives feedback in the form of a pop-up alert if some input values are missing when trying to employ the design tool. Lastly, the principle of "constraints" limits the user from performing illegal actions. For instance, the GUI allows the user to upload files, but only files with valid file formats. It is also not possible to type invalid characters in the input fields.

4.2 Automatically Generated PDF Report

To present the results of the design tool in an orderly and convenient way, it was concluded beneficial to automatically generate a PDF report after employing the design tool. To achieve this, the Python library "FPDF" (Reingard, 2018) was included in the design tool. This library was chosen because of its modifiability and simplicity. The automatically generated report contains plenty of information, with the most important being:

1. A summary of the results from the design tool corresponding to the optimization metric chosen by the user.
2. An overview of the user-selected constants utilized in the computations.
3. Information about the supply and demand files containing elements used to generate the results. This includes different plots to illustrate the distribution of elements regarding the material type, length, area, and moment of inertia.
4. An overview of the performance of the user-specified optimization algorithms employed in the design tool.

If the user of the design tool chose to include transportation in the calculations, the generated report also contains:

5. A summary of the impact on the results from the transportation of elements. This included two maps to illustrate where the suggested reusable element substitutions and the required manufacturer elements are located.

The suggested substitutions from the design tool, in other words, the specific matching of demand elements with new and reusable elements, are stored in an Excel file. Both the Excel file containing the specific matchings and the generated PDF report was integrated into the GUI described in Section 4.1.

4.3 Demonstration Of The Design Tool

To demonstrate the functionality in the current version of the design tool, as well as the development done to visualize the design tool, a video was created. The video demonstrates how the user operates the GUI to upload files, fill in desired variables values, and choose both optimization metric and which optimization algorithms to employ. Finally, the video demonstrates how the user may open and inspect the proposed element substitutions as well as the automatically generated report and the corresponding maps.

A link to the demonstration video is found in Appendix A. It is a prerequisite to watch this demonstration in order to understand how the current version of the design tool is operated. The demonstration also displays the usefulness and benefits of the GUI and the automatically generated PDF report incorporated within the design tool. A link to the GitHub repository containing the current version design tool, including both the developments presented in Section 3, as well as the code for the GUI and the automatically generated PDF report, can be found in Appendix B.

5 Method

This section describes the methods used to compare and evaluate the implemented algorithms and the extended functionality in the design tool, described in Section 3. The datasets utilized in the analyses are initially discussed, followed by the proposal for input variables in the design tool. Methods for analyzing the performance of the implemented algorithms are thereafter presented. Finally, different case studies used to investigate the influence of various optimization metrics and transportation on the substitutions proposed by the design tool are presented.

5.1 Generating Dataset

Datasets are required in order to demonstrate the result of the substitution process in the design tool. Due to an absence of data from real constructions, separate datasets containing supply and demand elements were generated. Note that the supply dataset and the demand dataset were generated with the same properties except for location. To generate the datasets, a desired dataset size was required. Further, the material of each element was randomly selected as either "Timber" or "Steel". As described in Section 2.1, these materials were chosen because of their great reusability. Regardless of the material, the length of each element was set to a random value between 1 and 10 meters. The area and moment of inertia for steel elements were randomly set to the properties of one of the following steel sections: IPE100, IPE140, IPE160, IPE180, IPE220, IPE270, IPE300. For timber elements, a square cross-section was assumed and chosen randomly between $0.004m^2$ and $0.04m^2$. The moment of inertia was calculated from the assigned area. Additionally, each supply element was given a set of coordinates randomly chosen among the locations depicted in Figure 5.1 as green markers. The locations and coordinates of the demand elements were automatically assigned to the nearest material manufacturer, as described in Section 3.6.

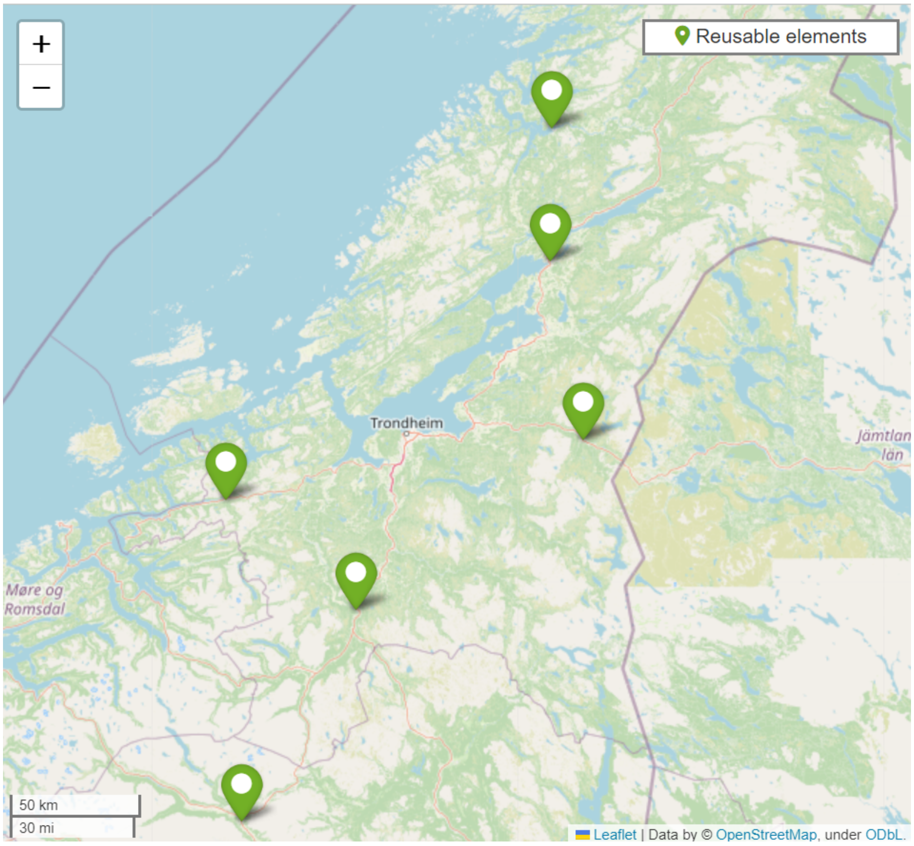


Figure 5.1: Unique locations of reusable elements.

5.2 Proposed Values For Input Variables

This section briefly covers and explains the reasoning behind the chosen values of the required user input variables in the design tool. All the proposed values are presented in Table 5.1. Even though defining these variables is outside the scope of the research question defined in Section 1.2, the values are necessary for carrying out the results from the case studies. Therefore, major assumptions have been made when proposing values for the input variables. As further discussed in the subsections below, the values vary significantly between different building projects. It is consequently intended that the user sets these variables for each project. As shown in the demonstration mentioned in Section 4.3, the proposed variables are pre-filled in the GUI, mainly to provide the user with a suggestion for each variable.

Table 5.1: Proposed values for the input variables in the design tool.

Input variable	Value	Unit
GWP new timber	28.9	$kgCO2eq/m^3$
GWP reusable timber	2.25	$kgCO2eq/m^3$
GWP new steel	9263.0	$kgCO2eq/m^3$
GWP reusable steel	278.0	$kgCO2eq/m^3$
GWP transportation	89.6	g/tonne/km
Price new timber	3400.0	NOK/m^3
Price reusable timber	3400.0	NOK/m^3
Price new steel	67.0	NOK/kg
Price reusable steel	67.0	NOK/kg
Price transportation	4.0	NOK/tonne/km
Valuation of GWP	0.7	NOK/kgCO2eq

5.2.1 GWP Input Variables

New timber elements

The GWP factor for new timber elements is in accordance with ISO 14025 and EN 15804 set equal to 28.9 kgCO2eq per m^3 (SCA, 2022). This value corresponds to the factor in Equation (3.1). The value includes contributions from the start of forestry operations to the end of manufacturing but excludes transportation to the actual site.

Reusable timber elements

Eberhardt et al. (2020) argues that the GWP of reusable timber elements is 92.2% lower compared to new elements, resulting in a factor of 2.25 kgCO2eq in Equation (3.1). This value includes element processing, disassembly, and other GWP contributions.

New steel elements

GWP of steel elements ranges widely depending on steel type, recycled content, and country of origin (Bawden et al., 2016). Norsk Stål AS (2020) reports in their environmental product declaration for beams and form steel a GWP of 1180 kgCO2 per tonne. This declaration is, as for new timber elements, in accordance with ISO 14025 and EN 15804. To enable Equation (3.1), this value is multiplied by the steel density, equal to 7.85 tonnes per m^3 (Larsen, 2020). The GWP factor for new steel elements was hence set to 9263 $kgCO2eq/m^3$.

Reusable steel elements

Høydahl and Walter (2020) argues that the reduction in GWP is 97% compared to new steel elements. 278 $kgCO2eq/m^3$, which is a 97% reduction of the factor corresponding to new steel elements, was hence set as the GWP factor for reusable steel in Equation (3.1).

Transportation

CO_2 emissions per tonne transported one kilometer on the road by trucks was 89.6 gram in 2021 (Engedal et al., 2022). This value is thus used as the factor in Equation (3.2). The factor is heavily affected by the type of truck and the corresponding capacity utilization, and thereby varies between projects.

5.2.2 Price Input Variables

Input variables regarding prices are presented below. It is emphasized that these variables are only intended as suggestions, and on many projects may be far from actual values.

New timber elements

There are large year-to-year variations in the timber price (Treindustrien, 2023). Because of the high degree of volatility, the cost of new timber elements will differ between projects. In the case studies, the material price of new timber elements in Equation (3.3) was set to NOK 3400 per m^3, which was the most recent estimate (Treindustrien, 2023).

Reusable timber elements

Finding a good estimate of the price of reusable timber elements proved to be challenging. As a provisional suggestion, this value was assumed equal to the price of new timber elements, and hence set to NOK 3400 per m^3. The idea behind this significant assumption was that the cost of disassembly, scanning, testing, and processing may sum up to the cost of a new element.

New steel elements

Since the price of steel fluctuates from year to year in a similar manner to the price of timber, the variable reflecting the cost of new steel elements will change depending on the project. ENTRA ASA (2021) estimates a price of NOK 67 per kg of new steel elements. This price provided an indication of the cost of new elements and was used as the factor in Equation (3.4).

Reusable steel elements

According to ENTRA ASA (2021), the cost of reusable steel elements in KA13 was about 50% higher than the cost of new steel elements. This cost includes the search for used components, temporary storage, and transportation to the construction site. All these factors are irrelevant to the price of reusable elements in the design tool. For the sake of simplicity, the cost of reusable steel elements was for the same reason as timber elements assumed equal to new steel elements.

Transportation

A rough estimate for the factor utilized in Equation (3.5) to calculate the cost of transportation in the case studies was set to NOK 4.0 per tonne per kilometer. This value is estimated on the basis of the different costs related to road transport presented by Grønland (2022).

Valuation of GWP

As mentioned in Section 3.7, this value aims to reflect the willingness of the user to pay for a reduction in GWP. This will by definition vary between projects. A reasonable value for this variable was taken from The Organisation for Economic Co-operation and Development (OECD). Their effective carbon rate is the most detailed account of how countries responsible for around 80% of global emission price these emissions. OECD (2021) gives three carbon price benchmarks, whereas the second benchmark is EUR 60 per tonne of CO_2 - described as a low-end 2030 and a mid-range 2020 benchmark. In 2018, 68% of the CO_2 emissions in Norway were priced at EURO 60 per tonne CO_2 (OECD, 2021). This price is also consistent with a slow decarbonization scenario by 2060 (Kaufman et al., 2020). 60 EURO per tonne CO_2 was consequently seen as a reasonable valuation of GWP. After transforming EURO to NOK and tonne to kg, NOK 0.7 per kgCO2eq was set as a suggestion for the variable. This may appear as a relatively low value, and it is important to note that the value may be significantly higher in some projects.

5.3 Performance Of The Implemented Algorithms

To examine the performance of the implemented algorithms, they had to be compared with reasonable algorithms already implemented by the Ph.D. candidates. The ultimate objective of the implemented algorithms is to minimize the total score corresponding to the chosen optimization metric in the shortest amount of time. As mentioned in Section 3.2 and Section 3.3, both the implemented Brute Force Approach and the Genetic Algorithm are single assignment algorithms. They are accordingly compared to the Greedy Algorithm, mentioned in Section 3.1. Regarding the implemented plural assignment versions of Maximum Bipartite Matching, described in Section 3.4, the different versions were first compared to each other. The best-performing version was then compared to the Greedy Algorithm Plural.

The performance of the algorithms was examined for various test sizes, where each test size corresponds to the sum of the number of supply elements and the number of demand elements. To ensure sufficient precision in the reported performance of the algorithms, they were evaluated on 100 independent datasets for each test size. The datasets were generated as described in Section 5.1. Consequently, the presented performances for each test size are the average of the results from 100 independent datasets.

The size of the datasets differs between the algorithms in order to carry out the tests within a reasonable amount of time. The Brute Force Approach was tested with the smallest datasets, the Genetic Algorithm was tested with slightly larger datasets whereas the MBM variants were tested on significantly larger datasets. Each algorithm was tested with GWP as the optimization metric. The GWP impact of transporting the elements was chosen not to be considered. In order to properly compare the runtime of the algorithms, all the tests were executed on the same computer.

5.4 Defining Case Studies

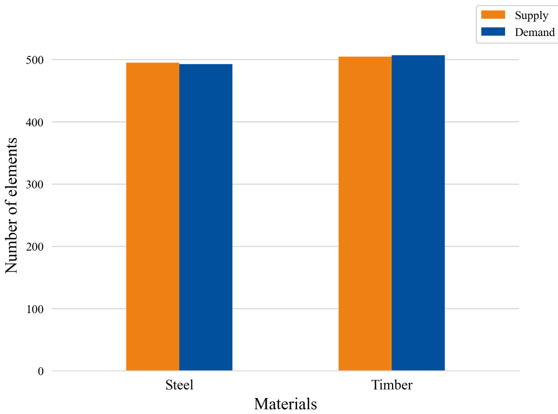
As a way of illustrating the differences resulting from the design tool with respect to the implemented extensions, different case studies were defined:

- **Case Study 1**: *GWP* as the optimization metric without taking the impact of transporting the elements to the construction site into consideration.

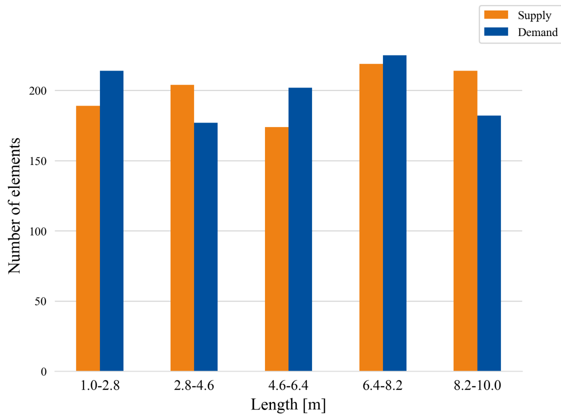
- **Case Study 2**: *GWP* as the optimization metric, taking transportation into consideration.
- **Case Study 3**: *Combined* as the optimization metric, considering transportation.
- **Case Study 4**: Same properties as Case Study 3, except lower prices on reusable elements, and a higher valuation of GWP.

Case Study 4 was created to illustrate a possible future scenario, where the usage of reusable construction elements has increased. It was consequently considered reasonable to assume lower future prices for reusable elements. The valuation of GWP was also assumed to increase in the future. To enhance these effects, the price of reusable elements was halved and the valuation of GWP was tenfold in Case Study 4 compared to Case Study 3. Hence, the price input variables for reusable elements mentioned in Section 5.2.2 were set to 1700 NOK/m^3 for timber and 33.5 NOK/kg for steel. The valuation of GWP was set to NOK 7 per kgCO2eq.

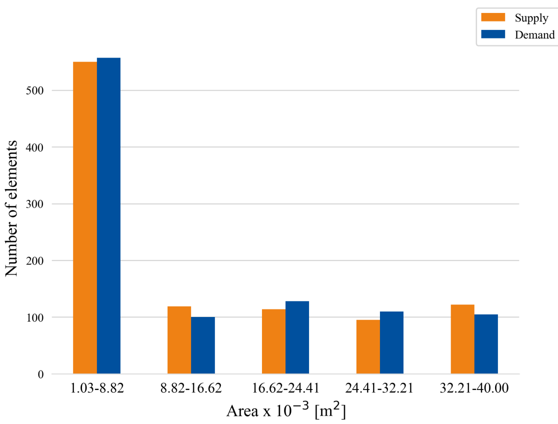
All the case studies utilize the same supply and demand dataset, each set to contain 1000 elements, generated as described in Section 5.1. Figure 5.2 describes the properties of the elements in the randomly generated datasets. Figure 5.2a shows the material distribution of the supply and the demand elements. Figure 5.2b reveals the length distribution, whereas Figure 5.2c and Figure 5.2d display the distribution of the area and the moment of inertial respectively.



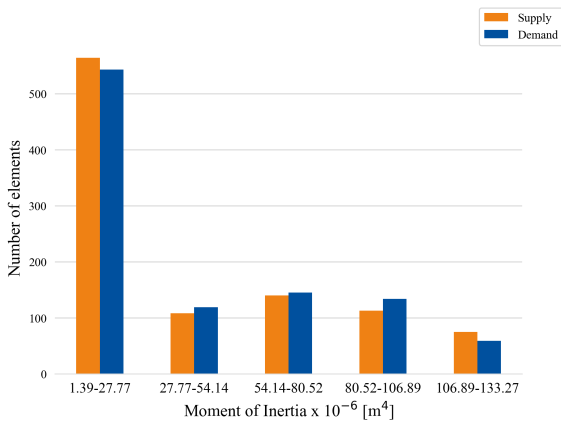
(a) Material distribution.



(b) Length distribution.



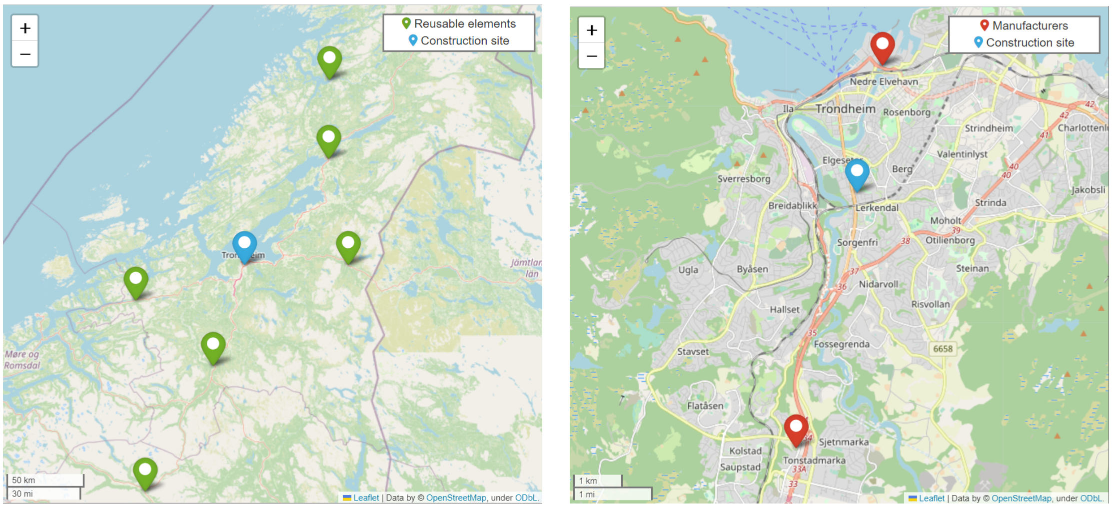
(c) Area distribution.



(d) Moment of inertia distribution.

Figure 5.2: Property distributions of the randomly generated elements used in the case studies.

Since Case Study 2-4 are taking the impact of transporting the elements into consideration, a location with corresponding coordinates of the construction site was required. To demonstrate the impact of transportation on the results, the NTNU campus development project (NTNU, n.d.) was seen as a relevant example and hence chosen as the location of the construction site in these case studies. Figure 5.3a displays the construction site together with the locations of reusable elements. Figure 5.3b additionally shows the construction site together with the closest manufacturers of the two materials in the dataset. The northernmost marker shows the steel manufacturer, and the southernmost marker shows the timber manufacturer.



(a) Locations of reusable elements.

(b) Locations of manufacturers.

Figure 5.3: Maps showing locations of elements and the location of the construction site.

To evaluate the total score of the case studies, the following algorithms were employed: Greedy Algorithm, Greedy Algorithm Plural, and MBM Plural. For each case study, the results corresponding to the best-performing algorithm are displayed in Section 6.2.

6 Results

This section first carries out the results from the implemented optimization algorithms before presenting the findings from the defined case studies.

6.1 Implemented Algorithms

The performance of an algorithm is determined by the total matching score considered in the context of the corresponding runtime. It is here emphasized that concerning both matching score and runtime, low values are better than high values. As explained in Section 5.3, the number of elements in the test sizes was defined as the combined number of elements in the supply and demand dataset.

6.1.1 Brute Force Approach

Figure 6.1 shows the total score of the Brute Force Approach compared to the Greedy Algorithm. The algorithms were tested on datasets of up to 20 elements combined. As expected, the total score of the matchings derived from the Brute Force Approach was equal to or marginally lower than the one derived from the Greedy Algorithm.

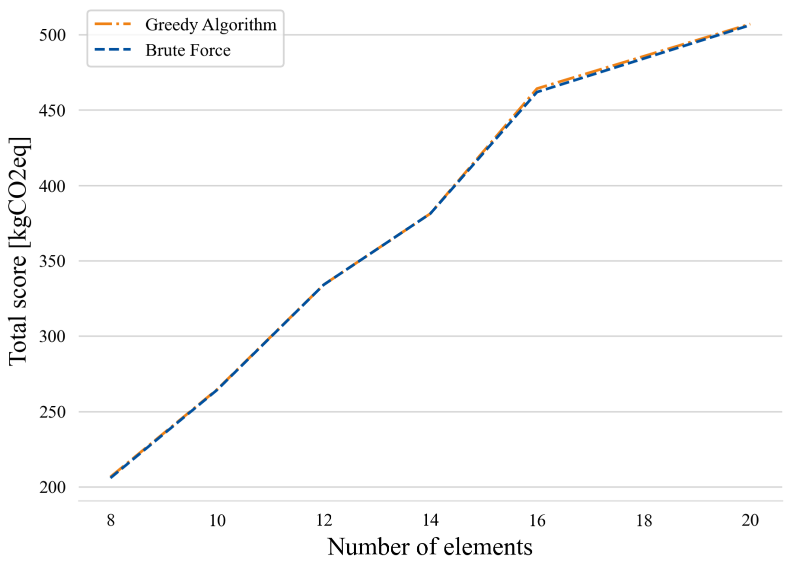
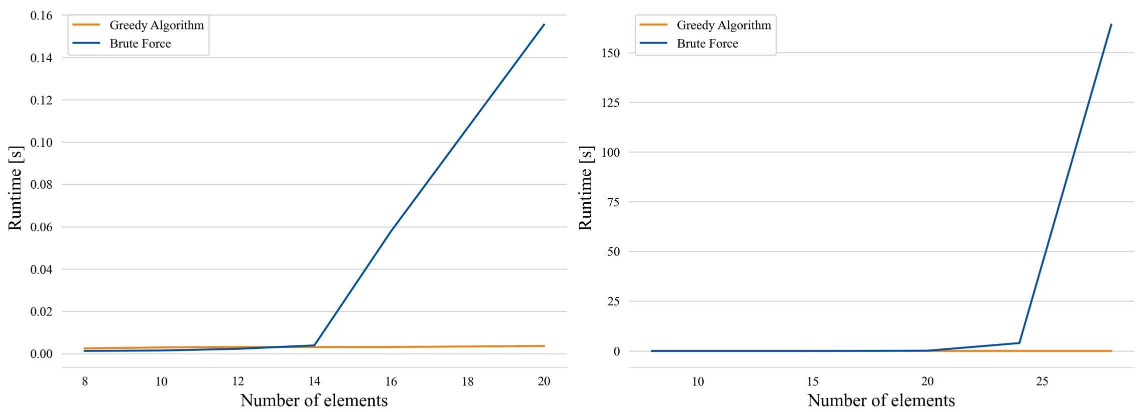


Figure 6.1: Performance Brute Force - Total score [kgCO2eq].

Additionally, Figure 6.2 reveals the runtime of the Brute Force Approach compared to the Greedy Algorithm. Figure 6.2a shows the runtime of up to 20 elements while Figure 6.2b shows the runtime of up to 28 elements.



(a) Up to 20 elements.

(b) Up to 28 elements.

Figure 6.2: Performance Brute Force - Runtime [s].

As clearly seen from the figures, the Brute Force Approach is becoming significantly slower than the Greedy Algorithm when the number of elements increases. Already at a total of 28 elements, the Brute Force Approach is averaging at around two and a half minutes while the Greedy Algorithm completes almost instantly.

6.1.2 Genetic Algorithm

Figure 6.3 displays that the substitutions proposed by the Genetic Algorithm yield a higher score in regard to kgCO2eq compared to the Greedy Algorithm. The difference in total score between the two algorithms is also increasing with the total number of elements.

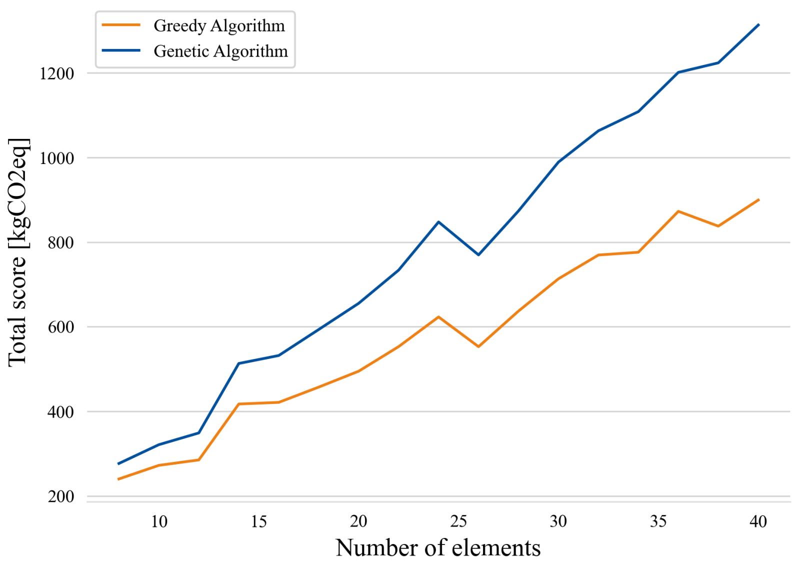


Figure 6.3: Performance Genetic Algorithm - Total score [kgCO2eq].

Regarding the computational cost, Figure 6.4 depicts that the two algorithms have approximately the same runtime for less than a total of 16 elements. For more than 16 elements, the runtime of the Genetic Algorithm increases significantly while the runtime for the Greedy Algorithm remains stable at lower than 1 second.

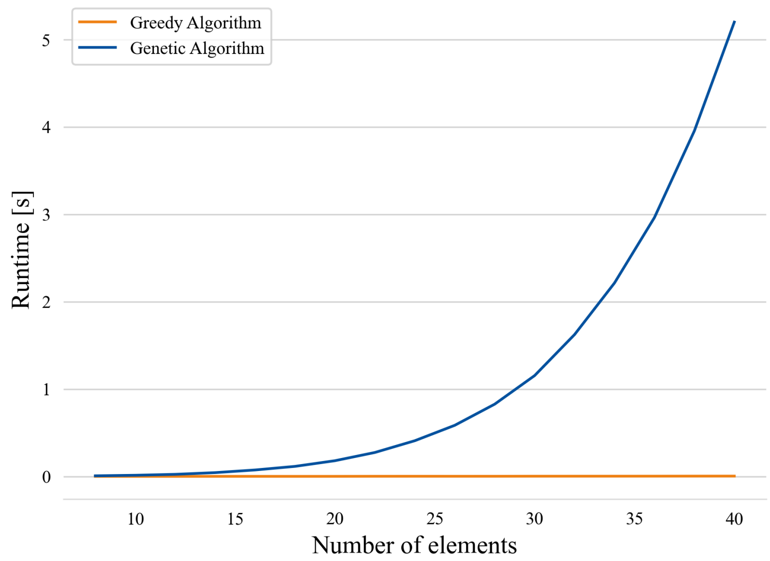


Figure 6.4: Performance Genetic Algorithm - Runtime [s].

6.1.3 Maximum Bipartite Mathing

Figure 6.5 illustrates the implemented MBM Plural and MBM Plural Multiple together with the standards version of MBM. As seen, the total score of the three algorithms is almost equal. It is nevertheless possible to observe that both the plural and the plural multiple version have a consistently lower, and hence a better, score than the MBM version implemented by the Ph.D. candidates.

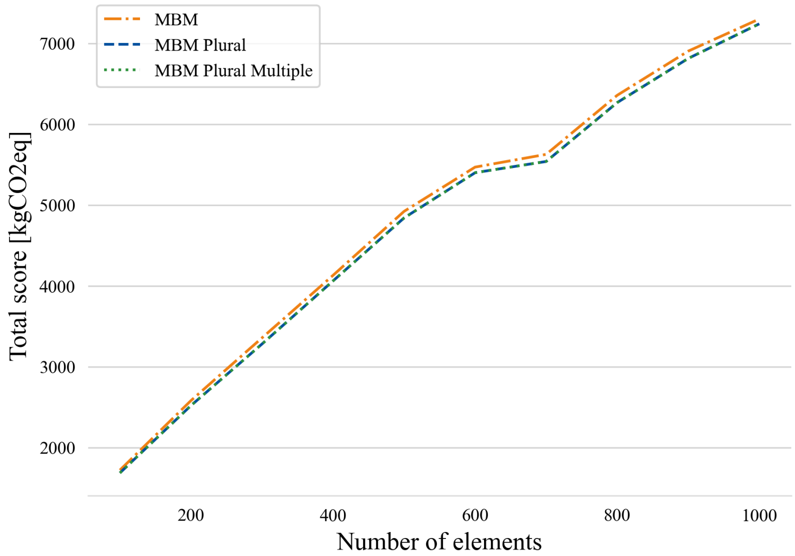


Figure 6.5: Performance MBM variants - Total score [kgCO2eq].

Figure 6.6 shows the performance of the three MBM versions in regard to computational cost. The MBM has the lowest runtime, averaging below one second at 1000 elements. MBM Plural has approximately twice as high runtime, whereas the MBM Plural Multiple averages above five seconds at 1000 elements.

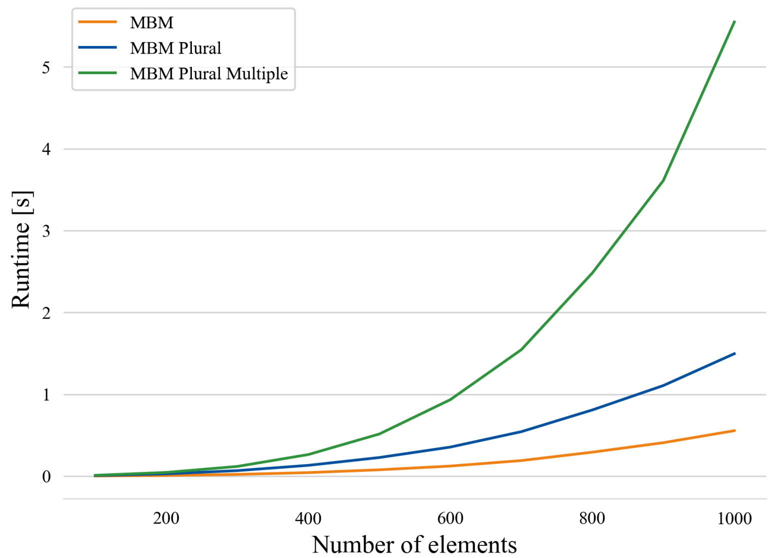


Figure 6.6: Performance MBM variants - Runtime [s].

As described in Section 5.3, the best-performing MBM version in regard to both total score and runtime was compared to the plural version of the Greedy Algorithm. Due to the low total score and the non-deterrent runtime, the MBM Plural was compared to the Greedy Algorithm

Plural. Figure 6.7 depicts this comparison and reveals that the MBM Plural has a consistent and significantly better average score than the Greedy Algorithm Plural.

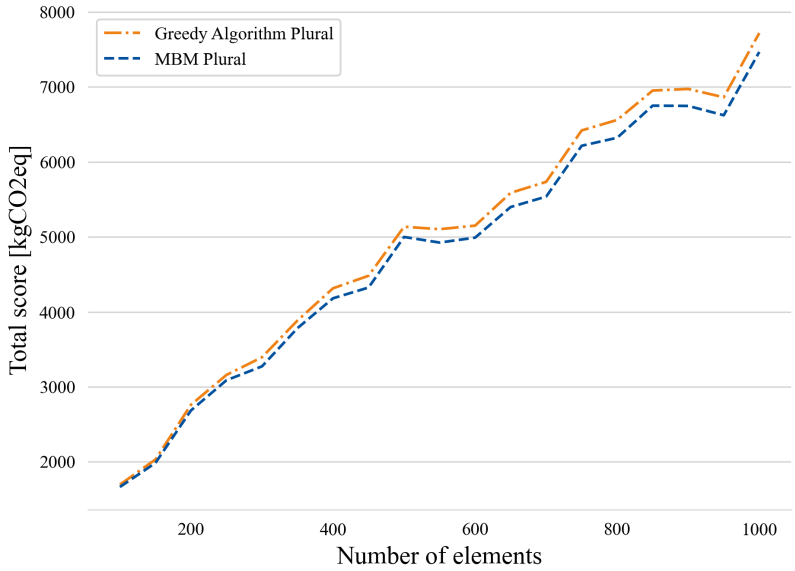


Figure 6.7: Performance MBM Plural - Total score [kgCO2eq].

Figure 6.8 further illustrates the performance of the MBM Plural compared to the Greedy Algorithm Plural in regard to runtime. The figure reveals that the MBM Plural has a lower average runtime for all the different numbers of elements included in the tests compared to the Greedy Algorithm Plural.

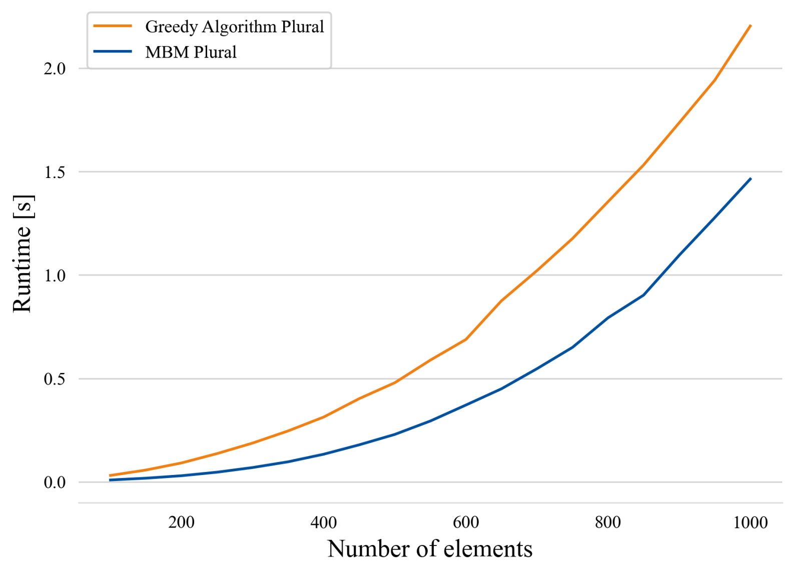


Figure 6.8: Performance MBM Plural - Runtime [s].

6.2 Case Studies

This section presents the findings from the defined case studies in Section 5.4. The automatically generated PDF reports from each case study can be found in Appendix C.

6.2.1 Case Study 1

Table 6.1: Results from Case Study 1.

Total score	Score without reuse	Savings	Substitutions
8 333 kgCO2eq	73 037 kgCO2eq	88.59%	90.10%

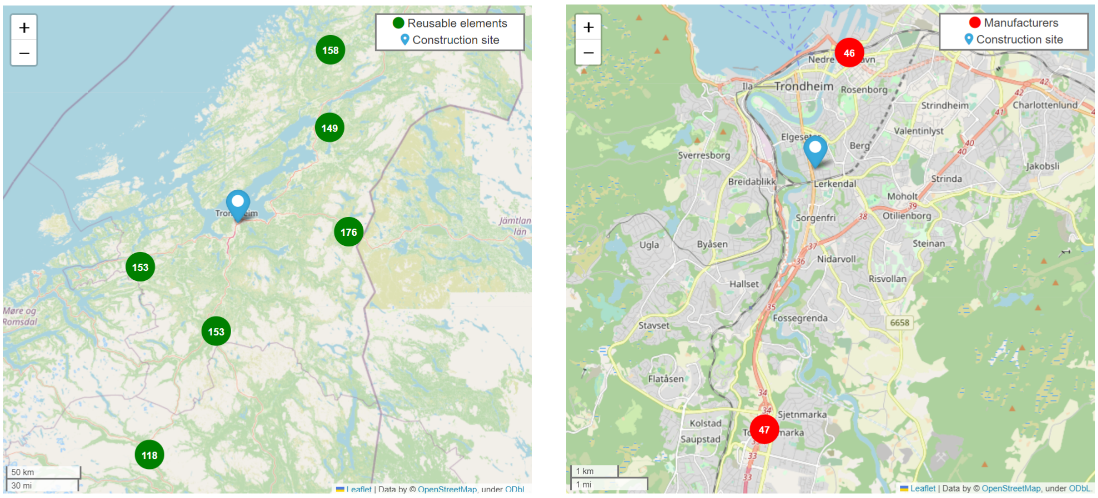
For Case Study 1, the design tool successfully substituted 90.10% of the demand elements with reusable elements, as seen in Table 6.1. By optimizing on *GWP* and not considering the transportation of elements, a total score of 8 333 kgCO2eq was achieved. Without any substitutions, the total score would have been 73 037 kgCO2eq. This implies that the use of reusable elements leads to an 88.59% reduction in kgCO2eq.

6.2.2 Case Study 2

Table 6.2: Results from Case Study 2.

Total score	Score without reuse	Savings	Substitutions	Impact of transportation
9 083 kgCO2eq	73 074 kgCO2eq	87.57%	90.70%	948 kgCO2eq

According to Table 6.2, the inclusion of the GWP impact corresponding to the transportation of elements in Case Study 2 results in savings of 87.57% when utilizing the reusable elements. The impact of transportation was 948 kgCO2eq, which corresponds to 10.44% of the total score in this case study. If none of the 90.70% substitutions were made, the total score would have been 73 037 kgCO2eq. The locations of the design tool suggestions for reusable elements and manufacturer elements are shown in Figure 6.9a and Figure 6.9b respectively. A relatively evenly distributed spread of elements is present in both figures.



(a) Reusable elements.

(b) Elements from manufacturers.

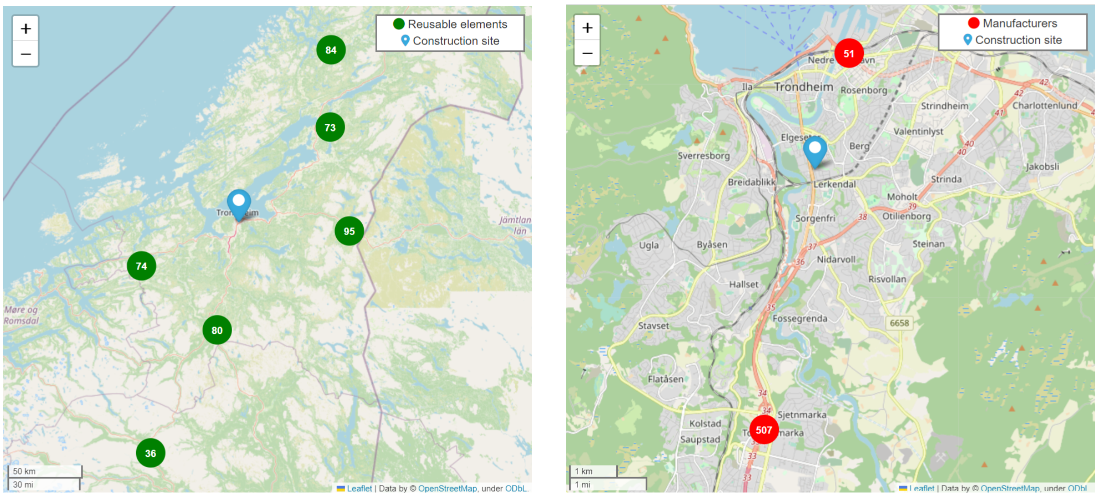
Figure 6.9: Maps showing the location distribution of the suggested element substitutions from the design tool for Case Study 2. The numbers on the maps indicate the number of elements transported from each location.

6.2.3 Case Study 3

Table 6.3: Results from Case Study 3.

Total score	Score without reuse	Savings	Substitutions	Impact of transportation
NOK 4 292 427	NOK 4 309 674	0.40%	44.20%	NOK 27 749

In Case Study 3, where *Combined* was used as the optimization metric, the design tool substituted 44.20% of the demand elements with reusable elements. This can be seen in Table 6.3. The substitutions resulted in savings of 0.40%, further resulting in a total score of NOK 4 292 427. Transportation accounted for NOK 27 749, corresponding to 0.65% of the total cost. The locations of matched elements are shown in Figure 6.10. Figure 6.10b demonstrates that all timber elements are proposed to be obtained directly from the manufacturer, while Figure 6.10a illustrates the locations of the matched reusable steel elements.



(a) Reusable elements.

(b) Elements from manufacturers.

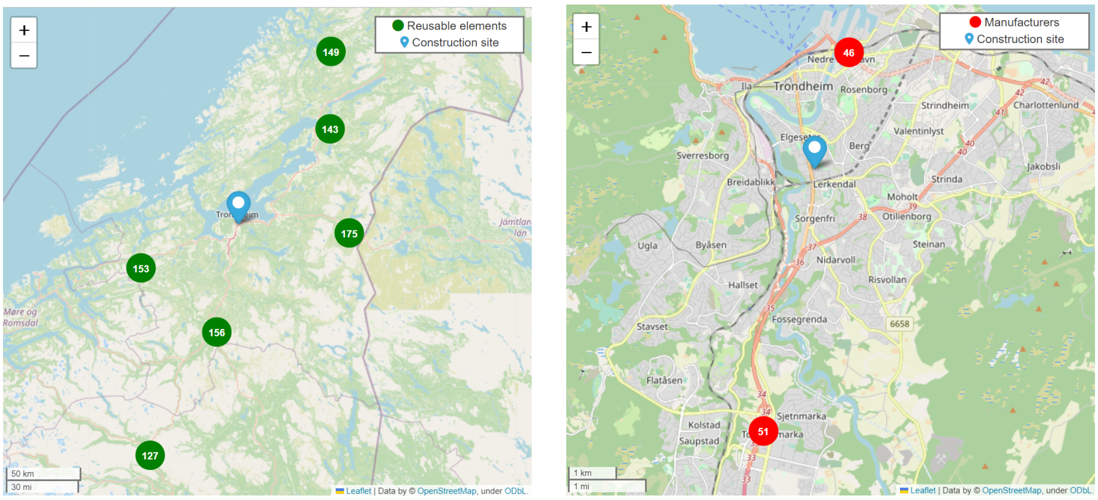
Figure 6.10: Maps showing the location distribution of the suggested element substitutions from the design tool for Case Study 3. The numbers on the maps indicate the number of elements transported from each location.

6.2.4 Case Study 4

Table 6.4: Results from Case Study 4.

Total score	Score without reuse	Savings	Substitutions	Impact of transportation
NOK 2 442 463	NOK 4 770 039	48.80%	90.3%	NOK 48 605

The results from Case Study 4 are outlined in Table 6.4. In contrast to a score of NOK 4 770 039 if no reusable elements were employed, a score of NOK 2 442 463 was achieved with reusable elements. NOK 48 605 of the total score originated from the impact of transportation, which is equivalent to 1.99%. The proportion of the demand elements replaced was 90.30%, resulting in a 48.80% cost reduction. According to Figure 6.11a and Figure 6.11b, the minority of the steel and timber elements are transported from the manufacturer, whereas the reusable elements are transported from all six possible locations.



(a) Reusable elements.

(b) Elements from manufacturers.

Figure 6.11: Maps showing the location distribution of the suggested element substitutions from the design tool for Case Study 4. The numbers on the maps indicate the number of elements transported from each location.

6.2.5 Comparison Of The Proposed Substitutions

To illustrate the differences in the proposed substitutions from the design tool for the four case studies, a similarity matrix was made. A similar substitution is present for two case studies if, for instance, element D0 is substituted with S0 in both case studies. Figure 6.12 shows that only Case Study 2 and Case Study 4 share over 50% of the same proposed substitutions. The lowest similarity is between Case Study 1 and Case Study 3, with a fraction of 0.23. The rest of the fractions are around 0.4, in other words, around 40% similar substitutions.

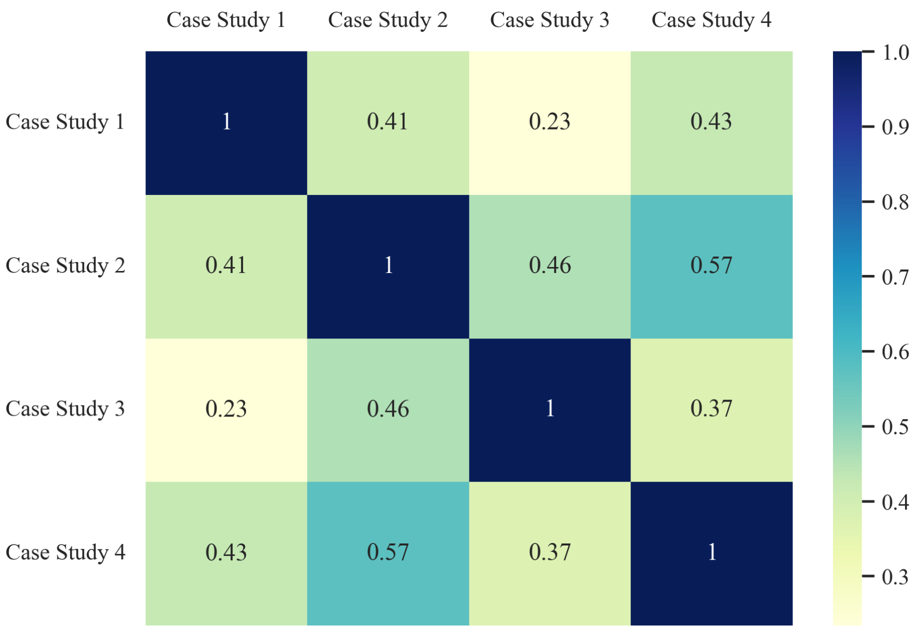


Figure 6.12: Fraction of similar substitutions between the case studies.

7 Discussion

This section first discusses the implemented optimization algorithms in regard to the performances presented in Section 6.1. Further, the findings from the case studies are discussed.

7.1 Implemented Algorithms

As described in Section 5.3, the presented results of the implemented algorithms are the average of multiple test sizes with 100 different datasets, meaning 100 different Incidence Matrices for each test size. The tests were designed like this due to the Incidence Matrix significantly affecting the performance of the algorithms, particularly the required runtime. Also, keep in mind that the specific computer on which the algorithms are executed significantly affects the runtime.

A limitation of the tests is that they all employed symmetrically sized supply and demand datasets. An asymmetrical size of the supply and demand datasets would change the dimensions of the Incidence Matrix and make it contain fewer possible matches. This would affect both the total score and the runtime. Despite this, the symmetrical datasets gave an adequate indication of the performance of the algorithms.

The results related to the implemented Brute Force Approach, presented in Section 6.1.1, revealed the expected outcome. The Brute Force Approach always finds a better or equal solution compared to other algorithms. This can be seen in Figure 6.1, where the Greedy Algorithm gives the same total score as the Brute Force Approach for up to 16 total elements, while the Brute Force Approach finds solutions that are slightly better compared to the Greedy Algorithm for larger datasets. The Brute Force Approach always finds the optimal solution because the algorithm evaluates every possible solution to the optimization problem.

The Brute Force Approach has the benefit of ensuring the best possible solution, but the corresponding required runtime is far from ideal. The runtime is rapidly increasing with the number of elements, as shown in Figure 6.2. The difference in runtime for 24 and 26 elements in Figure 6.2b clearly demonstrates this. The Brute Force Approach is therefore only appropriate for small problems where the user is prepared to wait for the ideal element substitutions. However, an authentic project will almost certainly include a lot more elements than the number of elements included in the tests, making the Brute Force Approach impractical. The Brute Force Approach might be a viable choice if the user of the design tool is operating on an extremely powerful computer (supercomputer), but the solution space of the optimization problem will quickly become too big even for these computers.

When it comes to the results of the Genetic Algorithm, presented in Section 6.1.2, the performance was not as good as desired. The performance of the Genetic Algorithm was inferior compared to the Greedy Algorithm for every test size, as shown in Figure 6.3. The Greedy Algorithm discovered some reusable element substitutions that the Genetic Algorithm was unable to find, which accounts for the difference in the total score reported in Figure 6.3. If the number of generations and/or the size of the initial population had been increased, it is possible that the Genetic Algorithm could have produced a better total score. Because the initial population consists of randomly generated chromosomes, as explained in Section 3.3, the chances of including the optimal solution at the start of the algorithm would increase by giving the Genetic algorithm a larger initial population. Also, increasing the number of generations would give the algorithm more chances to produce offspring containing the optimal solution. However, doing these changes would also significantly increase the runtime of the Genetic Algorithm. This is because the runtime is determined by the evaluation of each chromosome in the population using the fitness function for every generation. As shown in Figure 6.4, the Genetic Algorithm was significantly slower than the Greedy Algorithm already at a total of 20 elements. The Genetic Algorithm can further be considered impractically slow for more than a total of 40 elements.

Regarding the two plural versions of MBM, a lower average score was consistently obtained compared to the single assignment version of MBM, as seen in Figure 6.5. This indicates that a certain number of the supply elements were successfully assigned to numerous demand elements by the two algorithms. Figure 6.6 shows a natural consequence of the plural assignment, namely an increase in the required runtime. As explained in Section 3.4, the MBM Plural Multiple repeats the steps of MBM Plural multiple times. Therefore, MBM Plural Multiple exhibits a noticeably higher increase in the runtime compared to the MBM Plural, shown in Figure 6.6.

Due to the method in which the two plural versions of MBM were implemented, the total score of MBM Plural Multiple will always be lower than or equal to that of MBM Plural. Figure 6.5 displays that all of the total scores were similar for the two algorithms. This suggests that the same substitutions have been assigned for both variations even though MBM Plural Multiple most likely has divided the supply elements into more pieces than MBM Plural. The reason for the equal total score is probably due to the fact that the tests were performed with supply and demand elements with identical upper and lower bounds for the length attribute. The results would likely be different if the lengths of the supply elements were increased, as MBM Plural multiple really shows its strength when the lengths of the supply elements are significantly longer than the lengths of the demand elements. In that case, the supply elements would be cut multiple times, giving an increased number of matching possibilities.

The runtime of the MBM Plural Multiple was, as shown in Figure 6.6, around 5 times the runtime of MBM Plural for a total of 1000 elements. If the user accepts a longer wait time, the MBM Plural Multiple can be considered the better option since it will always give a lower or equal score compared to MBM Plural. Receiving the results within a reasonable amount of time was however deemed an important factor for the performance of the algorithms, especially considering that the runtime grows somewhat exponentially with the number of elements. On bigger data sets the time difference thus becomes more severe. The MBM Plural was consequently regarded as the best-performing MBM version and further compared to the Greedy Algorithm Plural as described in Section 5.3.

The Greedy Algorithm Plural was slightly outperformed by the MBM Plural in terms of the average total score, as seen in Figure 6.7. With regards to the runtime of the algorithms, shown in Figure 6.8, the MBM plural was also somewhat quicker than Greedy Algorithm Plural. However, as stated in Section 5.3, the scores and runtimes were determined from the average of 100 individual tests for the same number of elements. As a result, MBM Plural will not necessarily always produce better results than Greedy Algorithm Plural. Also, keep in mind that there is little to no difference between waiting 1.5 seconds and 2 seconds to receive the results from the design tool, which corresponds to the runtimes of MBM Plural and Greedy Algorithm Plural for a total of 1000 elements.

7.2 Case Studies

This section discusses the results presented in Section 6.2 associated with the different case studies defined in Section 5.4. When optimizing on *GWP* and not taking the transportation of elements into consideration in Case Study 1, the difference in kgCO2eq between utilizing reusable elements and only using new elements was severe, almost 89%. When the impact of transportation was included in Case Study 2, the savings were still above 87%. This was despite the fact that reusable elements were located far away from the construction site compared to the new elements, as shown in Figure 6.9. This contradicts a possible argument that the GWP corresponding to the transportation of reusable elements exceeds the reduction in GWP of substituting them with newly manufactured elements. According to Table 6.2, the impact of transporting the matched elements in Case Study 2 was 948 kgCO2eq, accounting for 10.44% of the total score. As seen in Table 6.1 and Table 6.2, the difference in the score without reuse between the two case studies implies the impact of transporting exclusively manufactured elements to the construction site to be 37 kgCO2eq. This further implies that the impact of transporting the proposed element substitutions was 125.6 times larger than only transporting manufactured elements. Nevertheless, only a minor change in the savings between Case Study 1 and Case Study 2 was reported. This minor difference can be explained by two observations. Firstly, the impact of transportation is relatively small compared to the corresponding total score, and secondly, the total score in both Table 6.1 and Table 6.2 is relatively small compared to the corresponding scores without reuse.

The findings from Case Study 3, presented in Section 6.2.3, illustrate the results when optimizing on *Combined*, i.e. both GWP and price. The presented savings from using reusable elements was only 0.4%, even though 44.2% of the demand elements were substituted with reusable elements. This emphasizes that the price of elements was the most significant contributor to the total score. The prices for new and reusable elements were in this case study assumed equal. Due to this assumption, the only differences between utilizing reusable elements and only using new elements are the costs of transportation, as well as the valuation of the total GWP reduction. Remark that the increased total transportation distance due to the use of reusable elements increases the total GWP, as illustrated in Case Study 2. The transportation impact can hence be split up into two parts when optimizing on *Combined*, namely the cost of transportation and the valuation of the increased GWP originating from the increased total transportation distance.

A useful comparison between the total cost of transportation and the valuation of the GWP reduction from using reusable elements can be seen from Figure 6.10. As shown, all the demand elements of timber in the case study were proposed to be obtained from the manufacturer, whereas the greater part of the demand elements of steel was proposed substituted with reusable elements transported from all six possible locations. This interesting event can be explained by the fact that the GWP difference between new and reusable steel elements is significantly larger than for timber elements. Consequently, the combined cost of transporting reusable timber elements exceeds the valuation of the GWP savings originating from substituting the demand elements of timber with reusable timber elements. Regarding the demand elements of steel, the valuation of the reduction in GWP originating from substituting them with reusable steel elements was greater than the combined cost of transporting the reusable steel elements to the construction site. This observation illustrates the importance of the user input values as well as the driving distance between elements locations and the construction site in the case studies.

Case Study 4, described in Section 5.4 with corresponding results presented in Section 6.2.4, underlines the impact of the user input values on the proposed element matchings. The proportion of proposed reusable elements was increased from 44% to 90% and the total score with reuse was more than halved compared to Case Study 3. Also, Figure 6.10 shows that reusable timber elements were proposed utilized, in contrast to Case Study 3. Further, the impact of transportation was more than tripled in Case Study 4 compared to Case Study 3. This is due to the increased total driving distance as well as the increased valuation of the GWP originating from transportation.

Put together, the four presented case studies accentuate the significance of both the user-defined variables and the chosen optimization metric on the proposed elements substitutions resulting from the design tool. This effect is substantiated by Figure 6.12, where the amount of similarly suggested substitutions between the case studies varies considerably. The comparison between Case Study 1 and Case Study 2 is a good illustration of how the specific element substitutions may change extensively without affecting the total score to an equal extent. The two case studies have a difference in the score of less than 10% but only 41% similar proposed substitutions.

When examining the similar substitutions between Case Study 1 and the other case studies depicted in Figure 6.12, a significant decrease in similarities can be observed from Case Study 2 to Case Study 3. This decrease in similarities can be explained by the fact that none of the reusable timber elements were utilized in Case Study 3, as already mentioned. Additionally, Figure 6.12 reveals that the highest fraction of similar substitutions occurred between Case Study 2 and Case Study 4. This can be attributed to the fact that these two case studies are resembling, as they both favor the transportation of as many reusable elements as possible to the construction site, rather than obtaining the elements directly from the manufacturer.

Varying the optimization metric and the input variables was seen as the most efficient way to emphasize the intended purpose of the design tool, namely being flexible and suitable for different projects. Although the case studies did not demonstrate different datasets and different locations of the construction site, the design tool was developed to manage that as well.

8 Further Devolopment

This section proposes potential further development and extensions to the design tool. The proposals mostly aim to make the design tool more accurate with fewer assumptions, consequently increasing its usefulness.

One significant assumption implemented in the current version of the design tool is the Constraint Input shown in Figure 3.9. Here, it was stated that the length, area, and moment of inertia of the supply elements had to be larger than or equal to the values of the demand elements. In reality, there may not always be enough space to accommodate a larger cross-section than necessary. As an example, installing an IPE300 where an IPE100 is demanded may be impossible due to space restrictions. Further development should address this issue by implementing functionality for the user of the design tool to edit the Constraint Input on the basis of requirements for the exact elements size in the project. This could be done by allowing the constraints to be set within a requested interval. For example, the user could define that the area of the proposed substituted supply elements should be between 10% and 20% larger than the demanded elements. The GUI might also include the possibility for the users to edit the Constraint Input in an intuitive manner.

Many of the assumptions implemented in the design tool are related to the different input variables, defined in Section 5.2. According to Grønland (2022), the transportation cost depends on driving distance, truck type, and driving duration. To get a more accurate measure of the GWP and the cost of transportation, the user could input the specific truck used to transport elements - corresponding to how Norsk Stål AS (2020) do in their environmental product declarations. To further improve the accuracy of the transportation cost, the driving duration between the element locations and the construction site could be collected from the OSRM API and used in the cost calculations.

The price of elements should also be more accurate than simply being calculated on the basis of the price per kg and price per m^3 for steel and timber elements respectively. A possible way of doing this is to include the price of each distinct element in the data sets containing all elements. In addition, if the exact price of an element is missing in the dataset, the design tool could simply calculate the price with the method used in the current version.

Another important assumption in the current version of the design tool corresponds to the transportation of reusable elements. These elements are assumed to be transported directly to the construction site. This assumption contradicts the experience from the KA13 project where the utilization of reusable elements required temporary storage of these elements (ENTRA ASA, 2021). It may be beneficial to include functionality that allows the user to set the location of temporary storage. This will increase the degree of accuracy in the cost estimates corresponding to the transportation of reusable elements.

Additional materials could also be implemented in the design tool. Keep in mind that the design tool requires the supply elements to be reusable. This implies that the building material must be demountable. As described in Section 2.1, concrete has an energy-intensive production. Therefore, prefabricated concrete elements, which easily could be disassembled and relocated, would be relevant to include in the design tool. More specifically, hollow core elements, as such elements have shown promising emission savings in the KA13 project (ENTRA ASA, 2021).

Finally, the design tool should be incorporated into traditional modeling software. Structures are typically designed using modeling software such as Grasshopper, Tekla, or Revit. As of today, the design tool can be accessed through a Python script or by using the developed GUI. Therefore, a possible extension is to incorporate the design tool into modeling software. For example, a Grasshopper Component that loads the Python functionality of the design tool could be developed. The inputs of the Grasshopper Component would correspond to the required inputs in the design tool, making Grasshopper function like a GUI.

9 Conclusion

To answer the research question "How can a digital design tool contribute to reusing building elements and how will the user inputs influence the results of the design tool?" existing solutions from the academic literature were first analyzed. The conducted literature review revealed that designing with reclaimed elements entails a greater complexity compared to designing with virgin materials. The literature review further uncovered that the manual assignment of reusable elements in a design phase is time-consuming. The goal of the developed digital tool was consequently to simplify the process of designing with reusable elements, and in that way lower the costs associated with the design process.

The implemented Brute Force Approach enabled the possibility of ensuring the optimal solution. However, the required runtime makes it incapable of solving real problems. Unfortunately, the performance of the implemented Genetic Algorithm was not satisfying, and the algorithm was hence concluded unsuitable for The Matching Problem. Conversely, the performance corresponding to the two implemented plural assignment versions of the MBM was superior compared to already implemented algorithms in the Structural Circle project. Both versions, with manageable runtimes, outperformed the Greedy Algorithm Plural in terms of the average total score.

To simplify the interactions between the design tool and the user, the design tool was visualized through the implementation of a GUI. In addition, the automatically generated PDF report was implemented to improve the communicability of the results from the design tool. The video demonstration of the current version of the design tool, including the GUI and the automatically generated PDF report, illustrated how easily the design tool is operated and how quickly it proposes suggestions of demand elements with suitable reusable elements. This implies a reduction in the additional time required when designing with reusable elements.

Four case studies were defined to investigate the influence on the design tool from the user inputs, which included different values for the constants used for calculations, different optimization metrics, and a selection of whether the impact of transporting the elements to the construction site should be included in the optimization algorithms or not. The conducted case studies revealed a significant impact of the user inputs on the design tool in terms of proposed element matchings. Further, this also emphasizes the usefulness of the design tool. Several of the user input variables may change during the design phase of a project, for instance, the price of the elements. The ability to update these values and almost instantly get new proposed element substitutions, adjusted for the changes in input variables, is a major benefit of the design tool. While the current version of the design tool is fully functioning, the proposed extensions and potential further development will make it even more accurate with fewer assumptions.

The developed design tool can help users make up-to-date and reasonable decisions when designing a building. It has consequently the potential to increase the degree of reuse in future building projects and contribute to the shift towards a circular economy in the industry.

Bibliography

Addis, B. (2012). *Building with reclaimed components and materials: A design handbook for reuse and recycling*. https://doi.org/10.4324/9781849770637

Arora, R. K. (2015). *Optimization: algorithms and applications*. https://www.routledge.com/Optimization-Algorithms-and-Applications/Arora/p/book/9781498721127

Bawden, K. R., Williams, E. D., & Babbitt, C. W. (2016). Mapping product knowledge to life cycle inventory bounds: a case study of steel manufacturing. *Journal of Cleaner Production*, *113*, 557–564. https://doi.org/10.1016/J.JCLEPRO.2015.10.014

Brütting, J., Desruelle, J., Senatore, G., & Fivet, C. (2019). Design of Truss Structures Through Reuse. *Structures*, *18*, 128–137. https://doi.org/10.1016/J.ISTRUC.2018.11.006

Brütting, J., Senatore, G., & Fivet, C. (2018). Optimization formulations for the design of low embodied energy structures made from reused elements. *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, *10863 LNCS*, 139–163. https://link.springer.com/chapter/10.1007/978-3-319-91635-4_8

Brütting, J., Vandervaeren, C., Senatore, G., De Temmerman, N., & Fivet, C. (2020). Environmental impact minimization of reticular structures made of reused and new elements through Life Cycle Assessment and Mixed-Integer Linear Programming. *Energy and Buildings*, *215*. https://doi.org/10.1016/J.ENBUILD.2020.109827

Brütting, J., Wolf, C. D., & Fivet, C. (2019). The reuse of load-bearing components. *IOP Conference Series: Earth and Environmental Science*, *225*(1). https://doi.org/10.1088/1755-1315/225/1/012025

Bukauskas, A., Shepherd, P., Walker, P., Sharma, B., & Bregulla, J. (2017). Form-Fitting strategies for diversity-tolerant design. *Proceedings of IASS annual symposia*. https://www.researchgate.net/publication/320011783_Form-Fitting_Strategies_for_Diversity-Tolerant_Design

Chathuranga, J. (2018). Leaving Google Maps? Use OSRM for Routing | by Janaka Chathuranga | Medium. https://janakachathuranga.medium.com/leaving-google-maps-use-osrm-for-routing-aa1afc912df3

Cormen, T. H., Leiserson, C. E., Rivest, R. L., & Stein, C. (2022). *Introduction To Algorithms*.

Csárdi, G., Nepusz, T., Horvát, S., Traag, V., Zanini, F., & Noom, D. (2023). *Igraph* (Version latest). Zenodo. https://doi.org/10.5281/zenodo.7573267

Dakin, R. J. (1965). A tree-search algorithm for mixed integer programming problems. *The Computer Journal*, *8*(3), 250–255. https://doi.org/10.1093/COMJNL/8.3.250

Dunn, C. (2022). How Reuse Of Materials Helps With Sustainable Construction. https://asti.com/blog/how-reuse-of-materials-helps-with-sustainable-construction/

Eberhardt, L. C. M., van Stijn, A., Rasmussen, F. N., Birkved, M., & Birgisdottir, H. (2020). Development of a Life Cycle Assessment Allocation Approach for Circular Economy in the Built Environment. *Sustainability 2020, Vol. 12, Page 9579*, *12*(22), 9579. https://doi.org/10.3390/SU12229579

Engedal, M. I., Lyle, C., & Pilskog, G. (2022). Mindre utslipp per transportarbeid. https://www.ssb.no/natur-og-miljo/forurensning-og-klima/artikler/mindre-utslipp-per-transportarbeid

ENTRA ASA. (2021). Erfaringsrapport ombruk - Kristian Augusts gate 13. https://entra.no/storage/uploads/article-documents/1_ka13-erfaringsrapport-ombruk-20012021.pdf

European Commission. (n.d.). Construction and demolition waste. https://environment.ec.europa.eu/topics/waste-and-recycling/construction-and-demolition-waste_en

European Commission. (2023). CO2 emission standards for Heavy-Duty Vehicles. https://ec.europa.eu/commission/presscorner/detail/en/qanda_23_763

Gad, A. F. (2020). PyGAD - Python Genetic Algorithm. https://pygad.readthedocs.io/en/latest/

Gad, A. F. (2023). *Geneticalgorithmpython* (Version latest). https://github.com/ahmedfgad/GeneticAlgorithmPython

Gorgolewski, M. (2008). Designing with reused building components: Some challenges. *Building Research and Information*, *36*(2), 175–188. https://doi.org/10.1080/09613210701559499

Grønland, S. E. (2022). Kostnadsmodeller for transport og logistikk. Basisår 2021. https://www.toi.no/getfile.php?mmfileid=73913

Heule, M. J. H., & Kullmann, O. (2017). The Science of Brute Force. *COMMUNICATIONS OF THE ACM*, *60*(8). https://doi.org/10.1145/3107239

Hillier, F., & Lieberman, G. (2010). Introduction to Operations Reasearch.

Høydahl, V., & Walter, H. (2020). Ombruk av byggematerialer og-produkter i et bærekraftperspektiv. https://ntnuopen.ntnu.no/ntnu-xmlui/bitstream/handle/11250/2738114/Walter%20og%20H%C3%B8ydahl.pdf?sequence=1

Huang, Y., Alkhayat, L., De Wolf, C., & Mueller, C. (2021). Algorithmic circular design with reused structural elements: Method and tool. https://web.mit.edu/yijiangh/www/papers/circular_dome_2021.pdf

IPCC. (2022). Climate Change 2022: Mitigation of Climate Change. https://www.ipcc.ch/report/ar6/wg3/downloads/report/IPCC_AR6_WGIII_FullReport.pdf

Katoch, S., Chauhan, S. S., & Kumar, V. (2021). A review on genetic algorithm: past, present, and future. *Multimedia Tools and Applications*, *80*(5), 8091–8126. https://link.springer.com/article/10.1007/s11042-020-10139-6

Kaufman, N., Barron, A. R., Krawczyk, W., Marsters, P., & McJeon, H. (2020). A near-term to net zero alternative to the social cost of carbon for setting carbon prices. *Nature Climate Change 2020 10:11*, *10*(11), 1010–1014. https://doi.org/10.1038/s41558-020-0880-3

Kuhn, H. W. (1955). The Hungarian method for the assignment problem. *Naval Research Logistics Quarterly*, *2*(1-2), 83–97. https://doi.org/10.1002/NAV.3800020109

Larsen, P. K. (2020). *Dimensjonering av stålkonstruksjoner*.

Leland, B. N. (2008). Prosjektering for ombruk og gjenvinning. https://www.byggemiljo.no/wp-content/uploads/2014/10/26_Prosjektering-for-Ombruk-og-Gjenvinning.pdf

Lynch, J., Cain, M., Pierrehumbert, R., & Allen, M. (2020). Demonstrating GWP*: a means of reporting warming-equivalent emissions that captures the contrasting impacts of short- and long-lived climate pollutants. *Environmental Research Letters*, *15*(4), 044023. https://doi.org/10.1088/1748-9326/AB6D7E

Miljodirektoratet. (2022). Klimagassutslipp fra transport. https://miljostatus.miljodirektoratet.no/tema/klima/norske-utslipp-av-klimagasser/klimagassutslipp-fra-transport/

Miller, N. (2021). The industry creating a third of the world's waste. https://www.bbc.com/future/article/20211215-the-buildings-made-from-rubbish

Moore, A. D. (2018). *Python GUI Programming with Tkinter: Develop responsive and powerful GUI*. Packt Publishing. https://books.google.com/books/about/Python_GUI_Programming_with_Tkinter.html?id=2kBbDwAAQBAJ

Norman, D. A. (2002). *The design of everyday things*. http://kowym.com/wp-content/uploads/2018/08/The-Design-of-Everyday-Things-Don-Norman.pdf

Norsk Stål AS. (2020). Bjelker og Formstål. https://www.norskstaal.no/Files/Files/Norsk/Sertifikater/EPD/NEPD-2526-1260_Bjelker-og-Formstal.pdf

NSC. (2017). Structural steel reuse. https://www.newsteelconstruction.com/wp/structural-steel-reuse/

NTNU. (n.d.). Campus development - NTNU. https://www.ntnu.edu/campusdevelopment

OECD. (2021). Effective Carbon Rates 2021 report. *Effective Carbon Rates 2021*. https://www.oecd-ilibrary.org/docserver/0e8e24f5-en.pdf?expires=1685264355&id=id&accname=ocid42012887&checksum=4E6CCAB506A643AED8CF186D5E6915E3

Oluleye, B. I., Chan, D. W. M., Saka, A. B., & Olawumi, T. O. (2022). Circular economy research on building construction and demolition waste: A review of current trends and future research directions. *Journal of Cleaner Production*, *357*, 131927. https://doi.org/10.1016/j.jclepro.2022.131927

OSRM. (n.d.). Project OSRM. http://project-osrm.org/docs/v5.24.0/api/#

Parigi, D. (2021). Minimal-waste design of timber layouts from non-standard reclaimed elements: A combinatorial approach based on structural reciprocity. https://doi.org/10.1177/09560599211064091

Pronk, A., Brancart, S., & Sanders, F. (2022). Reusing Timber Formwork in Building Construction: Testing, Redesign, and Socio-Economic Reflection. *Urban Planning*, *7*(2), 81–96. https://doi.org/10.17645/UP.V7I2.5117

Reingard, M. (2018). *Pyfpdf* (Version latest). https://github.com/reingart/pyfpdf

Reitz, K., Benfield, C., Cordasco, I. S., & Prewitt, N. (2023). *Requests: Http for humans* (Version latest). https://requests.readthedocs.io/en/latest/

Rekhi, S. (2017). Don Norman's Principles of Interaction Design | by Sachin Rekhi | Medium. https://medium.com/@sachinrekhi/don-normans-principles-of-interaction-design-51025a2c0f33

SCA. (2022). Environmental Product Declaration Sawn dried timber of Spruce and Pine SCA Wood AB The Norwegian EPD Foundation. https://www.epd-norge.no/getfile.php/1324058-1653305090/EPDer/Byggevarer/Heltreprodukter/NEPD-3442-2053_Sawn-dried-timber-of-Spruce-and-Pine-with-an--average-moisture-content-of-16-.pdf

Shorman, S., & Pitchay, S. (2015). Significance of parameters in genetic algorithm, the strengths, its limitations and challenges in image recovery. https://www.researchgate.net/publication/273064539_Significance_of_parameters_in_genetic_algorithm_the_strengths_its_limitations_and_challenges_in_image_recovery

Thatpannphyu, S., That, S. P., Phyu, P., & Srijuntongsiri, G. (2016). *Effect of the number of parents on the performance of multi-parent genetic algorithm* (tech. rep.). https://www.researchgate.net/publication/311536142

The Norwegian EPD Foundation. (2021). NPCR PART A: Construction products and services. https://www.epd-norge.no/getfile.php/1318361-1619429934/PCRer/NPCR%

20Part % 20A % 20for % 20Construction % 20products % 20and % 20services % 20ver2 % 20260421.pdf

The Pandas Development Team. (2020). *Pandas-dev/pandas: Pandas* (Version latest). Zenodo. https://doi.org/10.5281/zenodo.3509134

Tomczak, A., Haakonsen, S. M., & Luczkowski, M. (2023). Matching Algorithms To Assist In Design With Building Elements [Manuscript submitted for publication].

Tomczak, A., & Haakonsen, S. M. (2022). *structuralCircle* (Version Alpha). https://doi.org/10.5281/zenodo.7396796

Treindustrien. (2023). Trelastprisen har falt 42 % på et år. https://www.treindustrien.no/pressemeldinger/pressemeldinger-2023/trelastprisen-har-falt-42-pa-et-ar

UNEP. (2022). Emissions Gap Report 2022. https://www.unep.org/resources/emissions-gap-report-2022

United Nations. (2015). The Paris Agreement. https://unfccc.int/sites/default/files/english_paris_agreement.pdf

United Nations Environment Programme. (2022). 2022 Global Status Report for Buildings and Construction | UNEP - UN Environment Programme. https://www.unep.org/resources/publication/2022-global-status-report-buildings-and-construction

Van Rossum, G. (2023). *The python library reference* (Version latest). https://docs.python.org/3/library/

van Gelderen, T. (2021). Truss topology optimization with reused steel elements: An optimization tool for designing steel trusses with a set of reclaimed elements. https://repository.tudelft.nl/islandora/object/uuid%3A8be6c365-80a9-48d1-8b39-8cabe0ea0078

Vince, A. (2002). A framework for the greedy algorithm. *Discrete Applied Mathematics*, *121*(1-3), 247–260. https://doi.org/10.1016/S0166-218X(01)00362-6

Vrajitoru, D. (2000). Large Population or Many Generations for Genetic Algorithms? Implications in Information Retrieval. https://www.cs.iusb.edu/~danav/papers/LargePop.pdf

Wolf, C. D., Fivet, C., & Brütting, J. (2018). Embodied Carbon Benefits of Reusing Structural Components in the Built Environment. https://www.researchgate.net/publication/333824490

World Economic Forum. (2016). Shaping the Future of Construction. https://www3.weforum.org/docs/WEF_Shaping_the_Future_of_Construction_full_report__.pdf

Zhang, P. (2010). Human–machine interfaces. *Advanced Industrial Control Technology*, 527–555. https://doi.org/10.1016/B978-1-4377-7807-6.10013-0

Appendix

A Demonstration Of The Design Tool

The demonstration of the design tool can be accessed through the following link:

https://www.youtube.com/watch?v=4rOyXB1unGM&ab_channel=CSDGNTNU

B GitHub Repository

The GitHub repository containing the Python code developed in this thesis can be found here:

https://github.com/marcinluczkowski/structuralCircle/tree/student_dev/standard

C Automatically Generated PDF Reports

The automatically generated PDF reports for each case study can be found below.

C.1 Generated PDF Report for Case Study 1

NTNU

June 07, 2023

Results from the Design Tool

Project name: Case Study 1

Construction site located at: 63.4154, 10.3995

Summary of results

Total score	Score without reuse	Savings	Substitutions
8 333 kgCO2eq	73 037 kgCO2eq	88.59%	90.1%

The best results was obtained by the following algorithm: Greedy Algorithm Plural. This algorithm sucessfully substituted 901/1000 (90.1%) of the demand elements with reusable elements. Using 'GWP' as the optimization metric, a total score of 8 333 kgCO2eq was achieved. For comparison, a score of 73 037 kgCO2eq would have been obtained by employing exclusively new materials. This resulted in a total saving of 88.59%, which corresponds to 64 704 kgCO2eq. The savings is equivalent to 628 flights for one person between Oslo and Trondheim. Note that impacts of transporting the materials to the construction site was not accounted for. Open the Excel file "Case_Study_1_substitutions.xlsx" to examine the substitutions.

Constants used in the calculations

Constant	Value	Unit
Density timber	491.0	kg/m^3
Density steel	7850.0	kg/m^3
GWP new timber	28.9	kgCO2eq/m^3
GWP reusable timber	2.25	kgCO2eq/m^3
GWP new steel	9263.0	kgCO2eq/m^3
GWP reusable steel	278.0	kgCO2eq/m^3

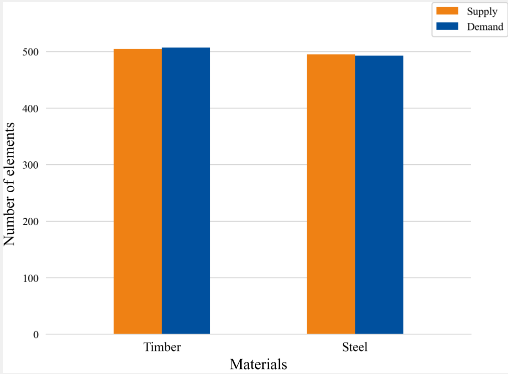
NTNU

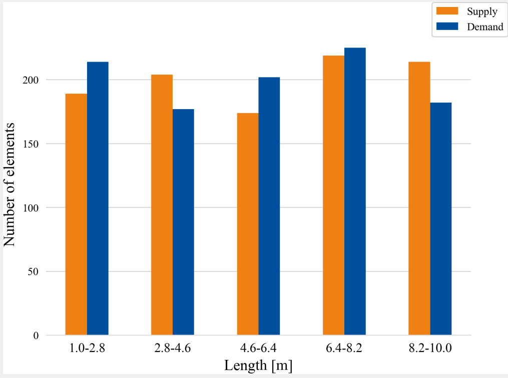
June 07, 2023

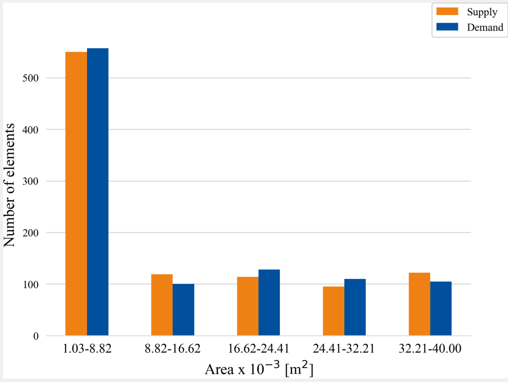
Information about the datasets

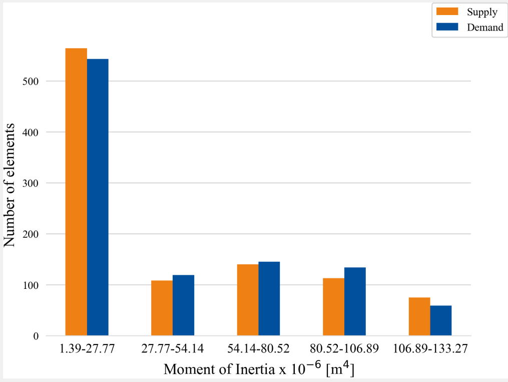
Elements	Filename	Number of elements
Supply	master_thesis_supply.xlsx	1000
Demand	master_thesis_demand.xlsx	1000

The datasets contains 1000 supply elements and 1000 demand elements. The graphs below depicts the distribution of some of the properties of the elements, including the material, length, area, and moment of inertia.









NTNU June 07, 2023

Performance of the optimization algorithms

Algorithm name	Total score	Substitutions	Time
Greedy Algorithm Plural	8 333 kgCO2eq	90.1%	11.24s
MBM Plural	8 465 kgCO2eq	90.6%	12.29s
Greedy Algorithm	9 320 kgCO2eq	89.0%	7.08s

The design tool was executed with 3 algorithms, namely: Greedy Algorithm Plural, MBM Plural, and Greedy Algorithm. The Greedy Algorithm Plural yielded the lowest score, as shown in the table. The substitutions by this algorithm was completed in 11.245 seconds.

C.2 Generated PDF Report for Case Study 2

NTNU

June 07, 2023

Results from the Design Tool

Project name: Case Study 2

Construction site located at: 63.4154, 10.3995

Summary of results

Total score	Score without reuse	Savings	Substitutions
9 083 kgCO2eq	73 074 kgCO2eq	87.57%	90.7%

The best results was obtained by the following algorithm: Greedy Algorithm Plural. This algorithm sucessfully substituted 907/1000 (90.7%) of the demand elements with reusable elements. Using 'GWP' as the optimization metric, a total score of 9 083 kgCO2eq was achieved. For comparison, a score of 73 074 kgCO2eq would have been obtained by employing exclusively new materials. This resulted in a total saving of 87.57%, which corresponds to 63 991 kgCO2eq. The savings is equivalent to 620 flights for one person between Oslo and Trondheim. Note that impacts of transporting the materials to the construction site was accounted for and contributed to 10.44% of the total score. Open the Excel file "Case_Study_2_substitutions.xlsx" to examine the substitutions.

Constants used in the calculations

Constant	Value	Unit
Density timber	491.0	kg/m^3
Density steel	7850.0	kg/m^3
GWP new timber	28.9	kgCO2eq/m^3
GWP reusable timber	2.25	kgCO2eq/m^3
GWP new steel	9263.0	kgCO2eq/m^3
GWP reusable steel	278.0	kgCO2eq/m^3
GWP transportation	89.6	gCO2eq/tonne/km

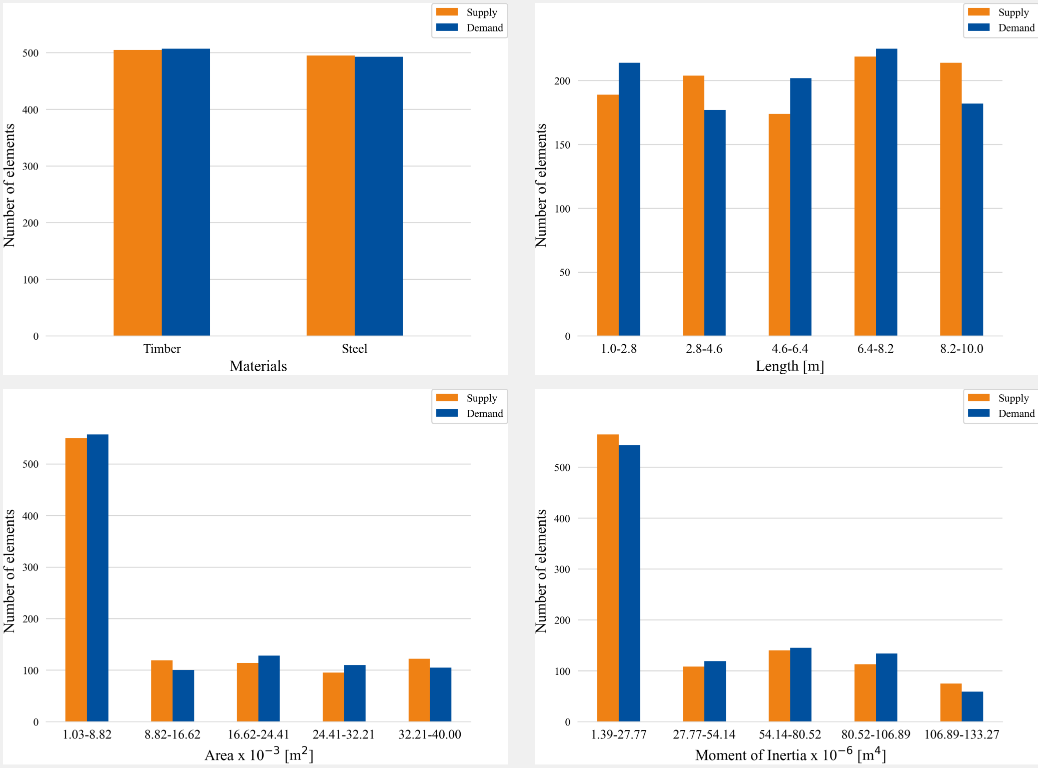
NTNU

June 07, 2023

Information about the datasets

Elements	Filename	Number of elements
Supply	master_thesis_supply.xlsx	1000
Demand	master_thesis_demand.xlsx	1000

The datasets contains 1000 supply elements and 1000 demand elements. The graphs below depicts the distribution of some of the properties of the elements, including the material, length, area, and moment of inertia.



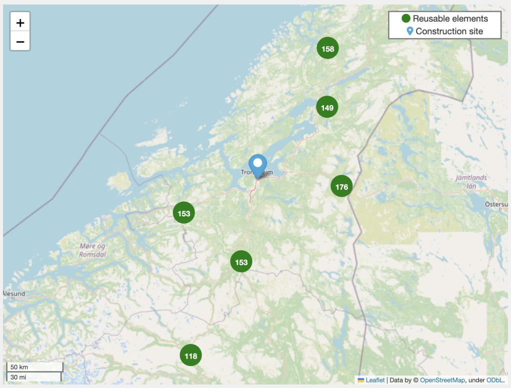
NTNU

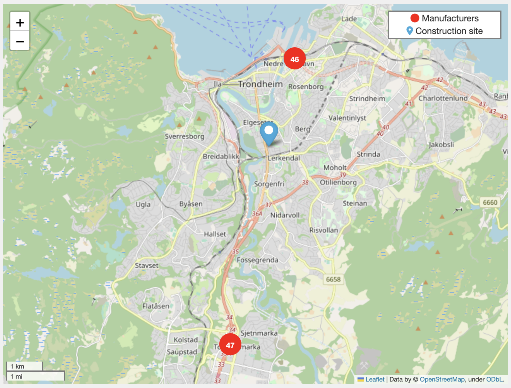
June 07, 2023

Impact of transportation

Utilizing reusable elements	Percentage of total score	Only manufactured elements
948 kgCO2eq	10.44%	37 kgCO2eq

All calculations in this report accouned for the effects of material transportation to the construction site. Transportation itself was responsible for 948 kgCO2eq. This accounts for 10.44% of the total score of 9 083 kgCO2eq. For comparison, the transportation impact for exclusively using new materials would have been 37 kgCO2eq. Two maps are included to show the locations of the suggested element substitutions from the design tool. The numbers on the maps indicate the number of elements transported from each location.





NTNU

June 07, 2023

Performance of the optimization algorithms

Algorithm name	Total score	Substitutions	Time
Greedy Algorithm Plural	9 083 kgCO2eq	90.7%	11.09s
MBM Plural	9 225 kgCO2eq	90.7%	20.9s
Greedy Algorithm	10 284 kgCO2eq	89.0%	6.94s

The design tool was executed with 3 algorithms, namely: Greedy Algorithm Plural, MBM Plural, and Greedy Algorithm. The Greedy Algorithm Plural yielded the lowest score, as shown in the table. The substitutions by this algorithm was completed in 11.086 seconds.

C.3 Generated PDF Report for Case Study 3

NTNU

June 07, 2023

Results from the Design Tool

Project name: Case Study 3

Construction site located at: 63.4154, 10.3995

Summary of results

Total score	Score without reuse	Savings	Substitutions
NOK 4 292 427	NOK 4 309 674	0.4%	44.2%

The best results was obtained by the following algorithm: Greedy Algorithm Plural. This algorithm sucessfully substituted 442/1000 (44.2%) of the demand elements with reusable elements. Using 'Combined' as the optimization metric, a total score of NOK 4 292 427 was achieved. For comparison, a score of NOK 4 309 674 would have been obtained by employing exclusively new materials. This resulted in a total saving of 0.4%, which corresponds to NOK 17 246. Note that impacts of transporting the materials to the construction site was accounted for and contributed to 0.65% of the total score. Open the Excel file "Case_Study_3_substitutions.xlsx" to examine the substitutions.

NTNU

June 07, 2023

Constants used in the calculations

Constant	Value	Unit
Density timber	491.0	kg/m^3
Density steel	7850.0	kg/m^3
GWP new timber	28.9	kgCO2eq/m^3
GWP reusable timber	2.25	kgCO2eq/m^3
GWP new steel	9263.0	kgCO2eq/m^3
GWP reusable steel	278.0	kgCO2eq/m^3
Valuation of GWP	0.7	NOK/kgCO2eq
Price new timber	3400.0	NOK/m^3
Price reusable timber	3400.0	NOK/m^3
Price new steel	67.0	NOK/kg
Price reusable steel	67.0	NOK/kg
GWP transportation	89.6	gCO2eq/tonne/km
Price of transportation	4.0	NOK/tonne/km

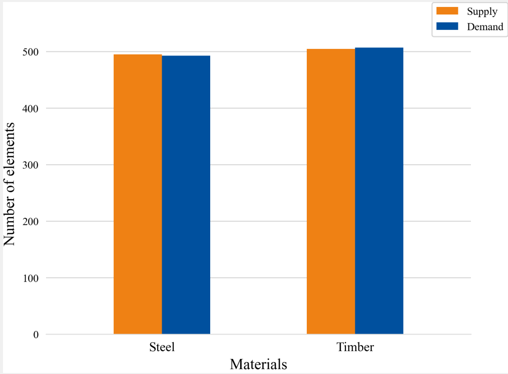
NTNU

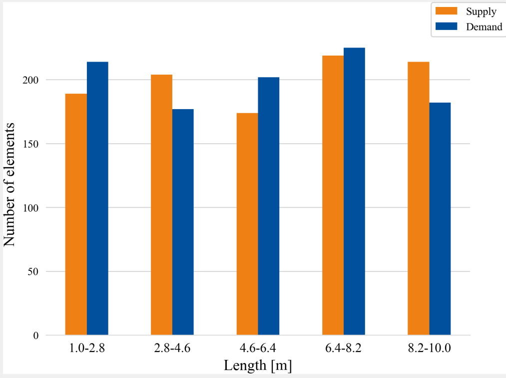
June 07, 2023

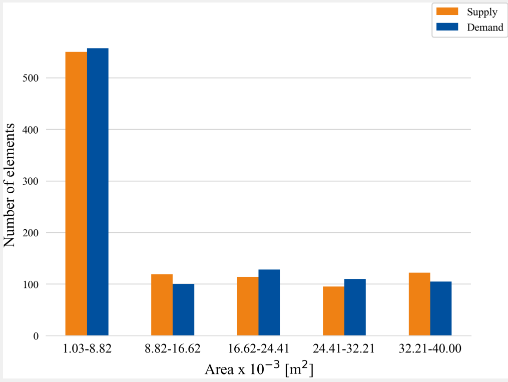
Information about the datasets

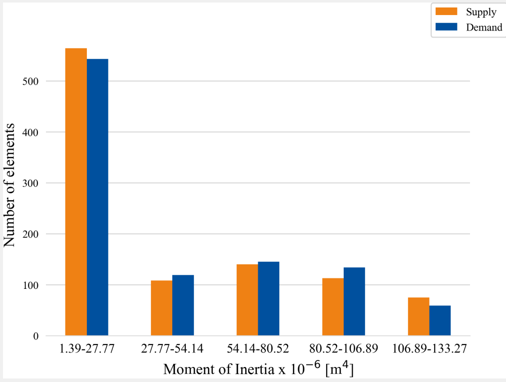
Elements	Filename	Number of elements
Supply	master_thesis_supply.xlsx	1000
Demand	master_thesis_demand.xlsx	1000

The datasets contains 1000 supply elements and 1000 demand elements. The graphs below depicts the distribution of some of the properties of the elements, including the material, length, area, and moment of inertia.









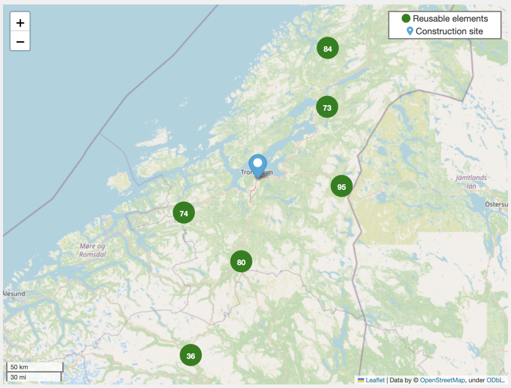
NTNU

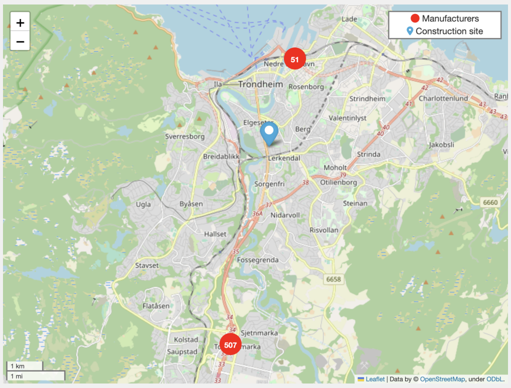
June 07, 2023

Impact of transportation

Utilizing reusable elements	Percentage of total score	Only manufactured elements
NOK 27 749	0.65%	NOK 1 693

All calculations in this report accouned for the effects of material transportation to the construction site. Transportation itself was responsible for NOK 27 749. This accounts for 0.65% of the total score of NOK 4 292 427. For comparison, the transportation impact for exclusively using new materials would have been NOK 1 693. Two maps are included to show the locations of the suggested element substitutions from the design tool. The numbers on the maps indicate the number of elements transported from each location.





NTNU

June 07, 2023

Performance of the optimization algorithms

Algorithm name	Total score	Substitutions	Time
Greedy Algorithm Plural	NOK 4 292 427	44.2%	11.82s
MBM Plural	NOK 4 292 439	44.0%	5.58s
Greedy Algorithm	NOK 4 292 519	42.8%	6.9s

The design tool was executed with 3 algorithms, namely: Greedy Algorithm Plural, MBM Plural, and Greedy Algorithm. The Greedy Algorithm Plural yielded the lowest score, as shown in the table. The substitutions by this algorithm was completed in 11.817 seconds.

C.4 Generated PDF Report for Case Study 4

NTNU

June 07, 2023

Results from the Design Tool

Project name: Case Study 4

Construction site located at: 63.4154, 10.3995

Summary of results

Total score	Score without reuse	Savings	Substitutions
NOK 2 442 463	NOK 4 770 040	48.8%	90.3%

The best results was obtained by the following algorithm: MBM Plural. This algorithm sucessfully substituted 903/1000 (90.3%) of the demand elements with reusable elements. Using 'Combined' as the optimization metric, a total score of NOK 2 442 463 was achieved. For comparison, a score of NOK 4 770 040 would have been obtained by employing exclusively new materials. This resulted in a total saving of 48.8%, which corresponds to NOK 2 327 576. Note that impacts of transporting the materials to the construction site was accounted for and contributed to 1.99% of the total score. Open the Excel file "Case_Study_4_substitutions.xlsx" to examine the substitutions.

NTNU

June 07, 2023

Constants used in the calculations

Constant	Value	Unit
Density timber	491.0	kg/m^3
Density steel	7850.0	kg/m^3
GWP new timber	28.9	kgCO2eq/m^3
GWP reusable timber	2.25	kgCO2eq/m^3
GWP new steel	9263.0	kgCO2eq/m^3
GWP reusable steel	278.0	kgCO2eq/m^3
Valuation of GWP	7.0	NOK/kgCO2eq
Price new timber	3400.0	NOK/m^3
Price reusable timber	1700.0	NOK/m^3
Price new steel	67.0	NOK/kg
Price reusable steel	33.5	NOK/kg
GWP transportation	89.6	gCO2eq/tonne/km
Price of transportation	4.0	NOK/tonne/km

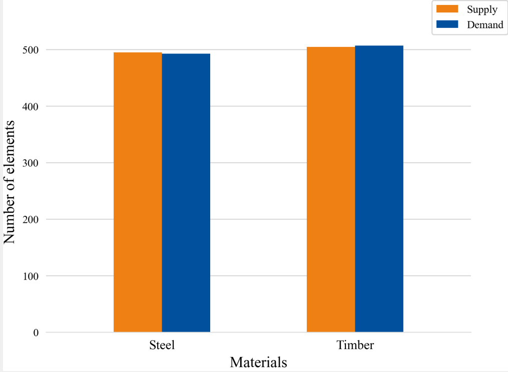
NTNU

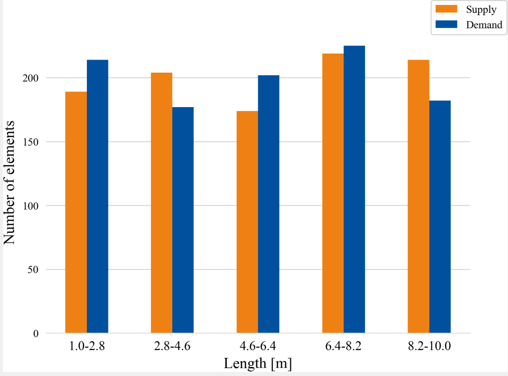
June 07, 2023

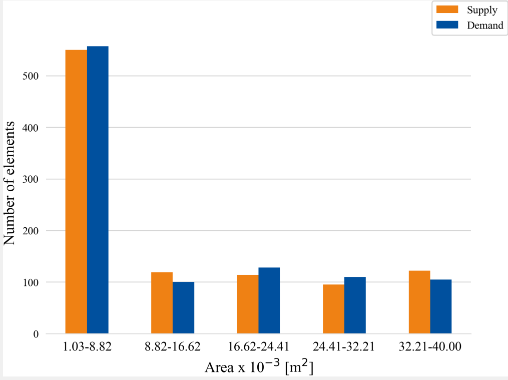
Information about the datasets

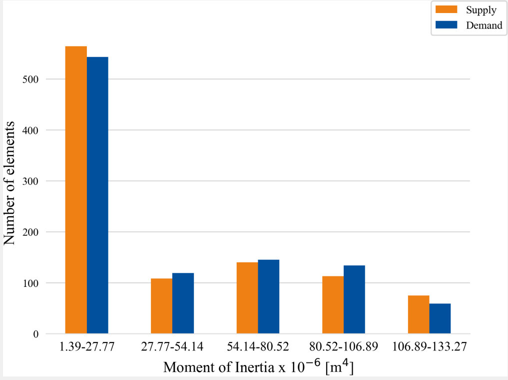
Elements	Filename	Number of elements
Supply	master_thesis_supply.xlsx	1000
Demand	master_thesis_demand.xlsx	1000

The datasets contains 1000 supply elements and 1000 demand elements. The graphs below depicts the distribution of some of the properties of the elements, including the material, length, area, and moment of inertia.









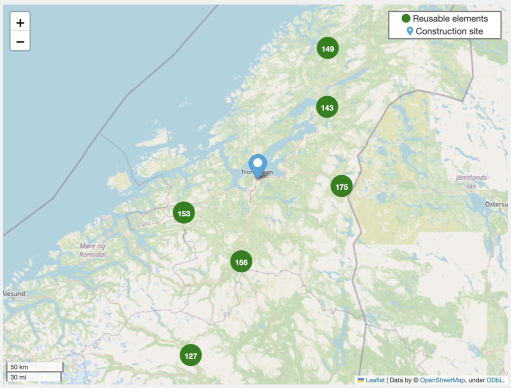
NTNU

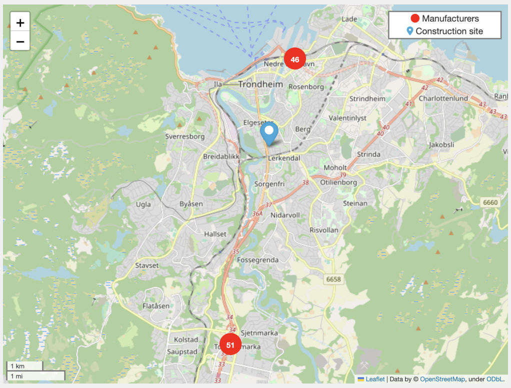
June 07, 2023

Impact of transportation

Utilizing reusable elements	Percentage of total score	Only manufactured elements
NOK 48 606	1.99%	NOK 1 928

All calculations in this report accouned for the effects of material transportation to the construction site. Transportation itself was responsible for NOK 48 606. This accounts for 1.99% of the total score of NOK 2 442 463. For comparison, the transportation impact for exclusively using new materials would have been NOK 1 928. Two maps are included to show the locations of the suggested element substitutions from the design tool. The numbers on the maps indicate the number of elements transported from each location.





NTNU

June 07, 2023

Performance of the optimization algorithms

Algorithm name	Total score	Substitutions	Time
MBM Plural	NOK 2 442 463	90.3%	15.88s
Greedy Algorithm Plural	NOK 2 445 273	90.5%	11.3s
Greedy Algorithm	NOK 2 488 957	88.6%	7.31s

The design tool was executed with 3 algorithms, namely: MBM Plural, Greedy Algorithm Plural, and Greedy Algorithm. The MBM Plural yielded the lowest score, as shown in the table. The substitutions by this algorithm was completed in 15.883 seconds.

D Conference Paper

The conference paper written for the IABSE Symposium Manchester 2024, with the general topic of *Construction's Role for a World in Emergency*, can be found below. More specifically, the topics for the conference include *designing and building for net zero*, *regneration, rehabilitation and adaptation of existing structures*, and *reducing waste*.

Investigating the Influence of CO_2 Emission Pricing on the Degree of Reuse in Building Projects

Lars Magnus Johnsen
lmjohnse@ntnu.no
Norwegian University of Science and Technology
Trondheim, Norway

Sigurd Lundberg Olsen
sigurd.olsen@ntnu.no
Norwegian University of Science and Technology
Trondheim, Norway

Sverre Magnus Haakonsen
sverre.m.haakonsen@ntnu.no
Norwegian University of Science and Technology
Trondheim, Norway

……..

ABSTRACT

By 2030, CO_2 emissions must be drastically decreased to meet the goal of the Paris Agreement of reducing global warming. As a result, the modern construction sector urgently needs to transition to a circular economy. Different benchmarks for pricing CO_2 emissions are one way of expediting this transition.

This paper investigates the impact of pricing CO_2 emissions at different levels on the viability of reuse in building projects. A recently developed design tool is used in two case studies to find appropriate reclaimed steel elements for a truss structure at Old Trafford, Manchester. Utilizing optimization algorithms, the design tool automatically proposes substitutions of elements in a designed building with reusable elements.

The conducted case studies demonstrate that an increased CO_2 emission price encourages a higher utilization of reusable elements, even when considering the substantial driving distance involved in acquiring them. The results indicate that increasing the CO_2 emission price in the future will increase the degree of reuse for the building projects of tomorrow.

Keywords: Reuse Digital design tool Circular economy CO_2 emission pricing

1 INTRODUCTION

In the Paris Agreement, the United Nations made a commitment to limiting global warming to well below 2°C and ideally below 1.5°C by the end of this century (United Nations, 2015). To accomplish this goal, emissions must decrease by 45% by 2030 (UNEP, 2022) and reach net zero before 2050 (IPCC, 2022). This has an impact on the building and construction sector, which uses about 50% of extracted resources worldwide (Miller, 2021). The sector is responsible for 37% of global CO_2 emissions (United Nations Environment Programme, 2022) and accounts for over 33% of the waste in the EU (European Commission, n.d.).

The primary cause of the high CO_2 emissions in the construction sector is the linear economy, which discards resources and building materials after use (Oluleye et al., 2022). According to Wolf et al. (2018), the construction industry must quickly make the switch to the circular economy to reduce CO_2 emissions.

One method to price the CO_2 emissions in the construction sector is to use the carbon price benchmarks from The Organisation for Economic Co-operation and Development (OECD). The first benchmark defined by the OECD of EUR 30 per tonne CO_2 (OECD, 2021) is a historic low-end and minimum price level to start triggering meaningful efforts. The second benchmark, which is described as a low-end 2030 and a mid-range 2020 benchmark, is EUR 60 per tonne of CO_2. This price is also in line with a 2060 scenario of gradual decarbonization (Kaufman et al., 2020). The third benchmark, which is set at EUR 120 per tonne of CO_2, is a central estimate of the carbon costs in 2030. To investigate how the price of CO_2 emissions affects the use of reusable building elements, this paper aims to answer the following research question:

How is the price of CO_2 emissions affecting the reuse of building elements?

First, the digital design tool utilized to answer the research question is described. Then, two case studies are defined. Lastly, the results of the case studies are presented and briefly discussed.

2 METHOD

2.1 Design tool

Olsen & Johnsen (2023) implemented extensions and new functionality to a digital design tool first presented by Tomczak et al. (2023). The design tool intends to simplify the utilization of reusable elements in the conceptual design phase of a building by utilizing optimization algorithms. This design tool required two datasets, one demand dataset containing the demand elements of a designed system, and a supply dataset, representing available reusable elements. The goal of the design tool is to identify the best substitutions of demand elements with accessible reusable elements.

The design tool also provides the designer the ability to influence the results through a set of user inputs - such as choosing the optimization metric, which optimization algorithms to employ, the values of the constants used in the calculations, and determining if the impacts of transporting the elements should be included in the optimization. The value of the optimization metric is defined as a score, and the objective of the design tool is to minimize the total score of the problem.

The design tool measures the environmental impact of building projects through the global warming potential (GWP). GWP is a measurement of equivalent CO_2 emissions (kgCO2eq) emitted into the atmosphere (Lynch et al., 2020). The design tool calculates the GWP of each element as shown in Equation (1):

$$\mathrm{GWP} = \mathrm{L} \cdot A \cdot f \quad [kgCO2eq] \tag{1}$$

where

L = element length [m]
A = element area [m^2]
f = GWP factor [kgCO2eq/m^3]

To calculate the GWP and price of transporting the elements, the design tool utilizes the OSRM API (OSRM, n.d.)to obtain the driving distance between the element locations and the construction site. The GWP and price can then be calculated by utilizing the driving distance together with element weight and a factor. For GWP the factor is given as gram CO_2 equivalents per tonne per km, and for the price, the factor is given as EUR per tonne per km.

For this paper, the most interesting user input variable in the design tool is the variable named "Valuation of GWP". This variable captures the willingness of the user to pay for a reduction in GWP and hence answers the question: "How much is a reduction in the GWP of the project worth in Euro?". This paper utilizes the developed design tool and especially the Valuation of GWP variable to answer the research question defined in Section 1.

2.2 Case studies

To investigate how the price of CO_2 emissions impacts the reuse of building elements, two case studies were defined. Both case studies use the optimization metric *Combined,* which enables the algorithms to optimize on both GWP and price (Olsen & Johnsen, 2023). To carry out the results from the design tool, the Greedy Algorithm Plural implemented by Tomczak et al., (2023) and the Maximum Bipartite Matching algorithm implemented by Olsen & Johnsen (2023) were used. The impact of transporting both the manufactured and reusable elements to the construction site was included in both case studies. The values of the constants used for calculations in the design tool were set to the proposed values by Olsen & Johnsen (2023), shown in Table 1, except for the Valuation of GWP variable:

- **Case Study 1**: Valuation of GWP was set to the first benchmark of OECD at EUR 30 per tonne CO_2.
- **Case Study 2**: Valuation of GWP was set to the third benchmark of OECD at EUR 120 per tonne CO_2.

Table 1: Constants used in the design tool.

Input variable	Value	Unit
GWP new steel	9263.0	kgCO2eq/m^3
GWP reusable steel	278.0	kgCO2eq/m^3
GWP transportation	89.0	gCO2eq/tonne/km
Price new steel	5.7	EUR/kg
Price reusable steel	5.7	EUR/kg
Price transportation	0.34	EUR/tonne/km

Because no available datasets of real constructions were found, the datasets were generated. To create reasonably realistic datasets, the design of a new football stadium roof in steel was considered. The roof of the Millennium Stadium in Cardiff was used for inspiration. The roof reached a total weight of 9 000 tonnes and consisted of circular hollow sections with lengths ranging from 2.5 meters to 12.1 meters (Emerald Publishing, 2000). Therefore, the elements in the datasets were generated with lengths between 2.5 and 12.1 meters, and the weight of the elements in each dataset was ensured to sum up to about 9 000 tonnes. The cross-section of each steel element in the datasets, with the corresponding area and moment of inertia, was chosen randomly among the circular hollow sections listed in Table 2.

The location of Old Trafford, Manchester, was chosen as the location for the construction site for the new football stadium roof, and the coordinates of the supply elements were chosen randomly among 5 locations of large football stadiums in Liverpool, Sheffield, Birmingham, London, and Newcastle. The location of the manufacturer elements was automatically set by the design tool to a steel manufacturer in Manchester close to Old Trafford. The generation of the datasets resulted in a total of 2 300 demand elements and 2 343 supply elements. The GWP for the 9 000 tonnes of demand steel elements, including the transportation from the steel manufacturer in Manchester to the construction site at Old Trafford, summed up to 10 459 tonne CO_2 equivalents.

Table 2 Properties of the cross-sections in the datasets (EurocodeApplied, 2023).

Ext. diameter [mm]	Thickness [mm]	Area [mm^2]	Moment of Inertia [$x10^6$ mm^4]
457	40	52 402	1 149
508	30	45 050	1 292
610	30	54 664	2 305
813	30	73 796	5 664
1067	25	81 838	11 110
1219	25	93 777	16 720

RESULTS & DISCUSSION

The results of Case Study 1 are presented in Table 1. In this case study, the valuation of GWP was set to the first benchmark of OECD, namely EUR 30 per tonne CO_2. As shown, only 40.65% of the demand elements were substituted with reusable elements by the design tool, resulting in CO_2 emission savings of 37.7% compared to only utilizing elements from the manufacturer.

Table 3 Results from Case Study 1.

Total Score	Substitutions	CO_2 emission savings	Impact of transportation
EUR 50 723 073	40.65%	37.7%	EUR 86 054

The locations of the substitutions are visualized in Figure 1 and Figure 2. As the figures show, reusable elements are transported from Sheffield and Liverpool, while around 60% of the demand elements are transported from the manufacturer in Manchester. This means that with the Valuation of GWP variable set to EUR 30 per tonne CO_2, the optimization algorithms in the design tool favor substituting demand elements with manufactured elements rather than transporting reusable elements from further away than Sheffield and Liverpool to the construction site.

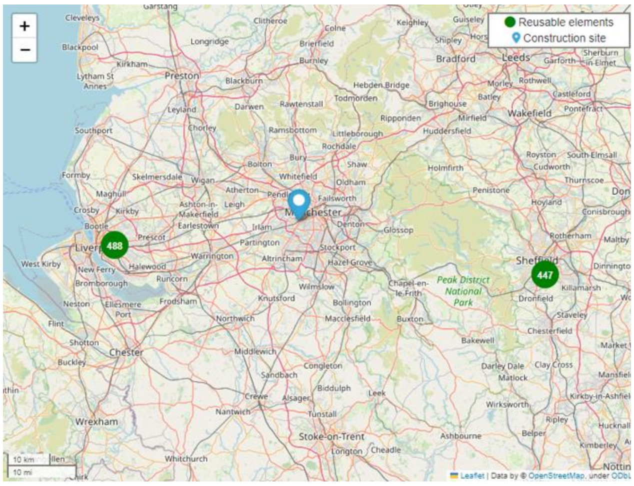


Figure 1: Reusable elements locations.

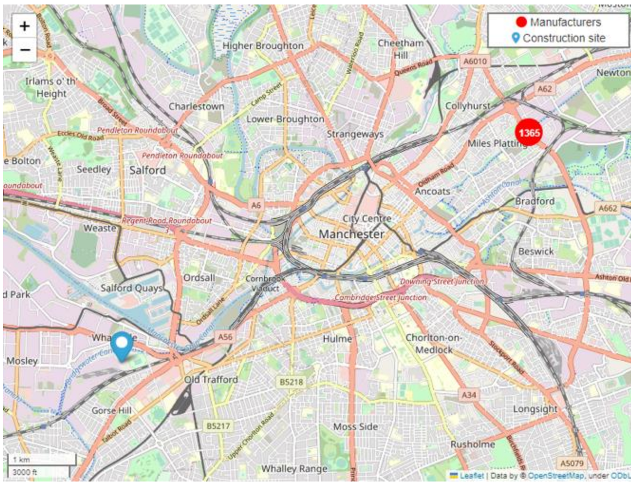


Figure 2: Manufacturer elements locations.

Table 4 presents the results of Case Study 2, where the Valuation of GWP variable was set to the third benchmark of OECD, more specifically EUR 120 per tonne CO_2. In this case study, 94.78% of the demand elements were successfully substituted with reusable elements. Consequently, the CO_2 emission savings was 89.3% compared to exclusively utilizing elements from the manufacturer.

Table 4 Results from Case Study 2.

Total Score	Substitutions	CO_2 emission savings	Impact of transportation
EUR 51 014 467	94.78%	89.3%	EUR 450 906

The locations of the substitutions in Case Study 2 are visualized in Figure 3 and Figure 4. As displayed in the figures, the design tool proposes to substitute demand elements with reusable elements from all five possible supply locations. Only 120 elements are proposed transported from the manufacturer in Manchester. Due to this, the impact of transportation is over five times higher in Case Study 2 compared to Case Study 1.

Figure 3: Reusable elements locations.

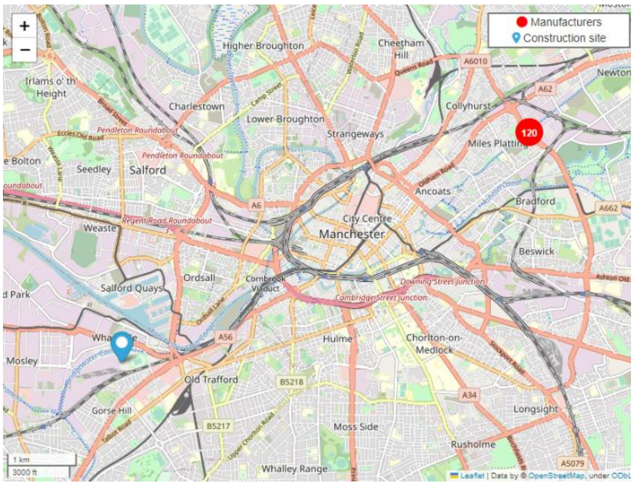


Figure 4: Manufacturer elements locations.

When using a higher value for the Valuation of GWP variable, as done in Case Study 2, it was favorable in the design tool to transport reusable elements a considerable distance instead of obtaining the demand elements from the close manufacturer. This further resulted in a significant increase in the CO_2 emissions savings in Case Study 2 compared to Case Study 1. The main reason why the total score in the two case studies is almost equal is that the price of reusable and new steel elements is identical. The cost of elements is the biggest contributor to the total score in both case studies.

4 CONCLUSION

To answer the research question: "How is the price of CO_2 emissions affecting the reuse of building elements?", two case studies were defined and conducted.

The case studies demonstrated how the percentage of proposed utilized reusable elements changes with different values for the Valuation of GWP variable. In Case Study 1, when the first benchmark of OECD was set as the price of CO_2 emissions, only 40.65% of the demand elements were proposed substituted with reusable elements. Elements from London, Birmingham, and Newcastle were considered not beneficial to utilize. In Case Study 2, on the other hand, reusable elements from all five possible locations were proposed substituted with demand elements, resulting in 94.78% substitutions. This emphasizes that a higher valuation of GWP justifies an increased transport distance for reusable steel elements.

The third benchmark of OECD is, as mentioned in Section 1, a central estimate of the carbon costs in 2030. The implications of the results are consequently that the degree of reuse in construction projects will increase in the future, as the optimal substitutions of demand elements will contain more reusable building elements when the price of CO_2 emissions rises.

REFERENCES

Emerald Publishing. (2000). SHSs for stadium roof. *Anti-Corrosion Methods and Materials*, *47*(1), 11–14. https://doi.org/10.1108/ACMM.2000.12847AAB.019/FULL/XML

EurocodeApplied. (2023). *Table of properties for steel tubes / circular hollow sections CHS*. https://eurocodeapplied.com/design/en1993/chs-design-properties

European Commission. (n.d.). *Construction and demolition waste*. Retrieved June 4, 2023, from https://environment.ec.europa.eu/topics/waste-and-recycling/construction-and-demolition-waste_en

IPCC. (2022). *Climate Change 2022: Mitigation of Climate Change*. https://www.ipcc.ch/report/ar6/wg3/downloads/report/IPCC_AR6_WGIII_FullReport.pdf

Kaufman, N., Barron, A. R., Krawczyk, W., Marsters, P., & McJeon, H. (2020). A near-term to net zero alternative to the social cost of carbon for setting carbon prices. *Nature Climate Change 2020 10:11*, *10*(11), 1010–1014. https://doi.org/10.1038/s41558-020-0880-3

Lynch, J., Cain, M., Pierrehumbert, R., & Allen, M. (2020). Demonstrating GWP*: a means of reporting warming-equivalent emissions that captures the contrasting impacts of short- and long-lived climate pollutants. *Environmental Research Letters*, *15*(4), 044023. https://doi.org/10.1088/1748-9326/AB6D7E

Miller, N. (2021). *The industry creating a third of the world's waste*. https://www.bbc.com/future/article/20211215-the-buildings-made-from-rubbish

OECD. (2021). Effective Carbon Rates 2021 report. *Effective Carbon Rates 2021*. https://www.oecd-ilibrary.org/docserver/0e8e24f5-en.pdf?expires=1685264355&id=id&accname=ocid42012887&checksum=4E6CCAB506A643AED8CF186D5E6915E3

Olsen, S. L., & Johnsen, L. M. K. (2023). *Development of a digital tool to assist in designing with reusable building elements*.

Oluleye, B. I., Chan, D. W. M., Saka, A. B., & Olawumi, T. O. (2022). Circular economy research on building construction and demolition waste: A review of current trends and future research directions. *Journal of Cleaner Production*, *357*, 131927. https://doi.org/10.1016/j.jclepro.2022.131927

OSRM. (n.d.). *Project OSRM*. Retrieved April 19, 2023, from http://project-osrm.org/docs/v5.24.0/api/#

Tomczak, A., Haakonsen, S. M., & Luczkowski, M. (2023). *Matching Algorithms To Assist In Design With Building Elements [Manuscript submitted for publication]*.

UNEP. (2022). *Emissions Gap Report 2022*. https://www.unep.org/resources/emissions-gap-report-2022

United Nations. (2015). *The Paris Agreement*. https://unfccc.int/sites/default/files/english_paris_agreement.pdf

United Nations Environment Programme. (2022). *2022 Global Status Report for Buildings and Construction | UNEP - UN Environment Programme*. https://www.unep.org/resources/publication/2022-global-status-report-buildings-and-construction

Wolf, C. De, Fivet, C., & Brütting, J. (2018). *Embodied Carbon Benefits of Reusing Structural Components in the Built Environment*. https://www.researchgate.net/publication/333824490

NTNU

Norwegian University of
Science and Technology