

Master's Programme in Mathematics and Operations Research

Optimising emission reduction actions in organisations' climate work

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Abstract

The climate work of Finnish companies has still room for improvement and planned climate actions are not enough to reach the greenhouse gas emission reductions required by the Paris Agreement. The studies have found that the costs of climate actions and lack of profit are seen as the most significant challenges within the companies. In the literature, optimisation is used to reduce greenhouse gas emissions for example in operation planning or supply chain management, and many of the models take financial aspect into account. However, models for optimising different kinds of emission reduction actions across an organisation were not found.

In this thesis, we have developed an optimisation model that will help companies to choose the most cost-effective emission reduction actions and timeline for their implementation. The objective of the model is to minimise company's cumulative greenhouse gas emissions in a given time period while staying within the set budget. The optimisation problem is solved using an evolutionary algorithm. The model is then applied to Company A's climate work.

The developed optimisation model is able to show how the company's greenhouse gas emissions would develop if the company implemented the recommended emission reduction actions in the given timeline. The optimisation model gives the company an insight of which emission reduction actions should be implemented so that the cumulative greenhouse gas emissions would be minimised but the set budget is not exceeded. The model can also be used to screen different budgets since it shows how the budget affects the recommended emission reduction actions and the company's cumulative greenhouse gas emissions.

Keywords Climate change, climate roadmap, optimisation



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Tiivistelmä

Suomalaisten yritysten ilmastotyössä on edelleen parantamiseen varaa, eivätkä suunnitellut toimenpiteet riitä vastaamaan Pariisin ilmastosopimuksen asettamiin päästövähennystavoitteisiin. Tutkimuksista selviää, että yritykset näkevät päästövähennystoimenpiteiden kustannukset ja taloudellisen hyödyn puuttumisen yksinä merkittävimmistä haasteista ilmastotyössään. Kirjallisuudessa optimointia on käytetty vähentämään kasvihuonekaasupäästöjä esimerkiksi yritysten toimitusketjuissa ja muissa toiminnoissa, ja monet malleista ottavat huomioon myös taloudellisen näkökulman. Kuitenkaan sellaisia malleja, joissa optimoitaisiin erilaisia päästövähennystoimenpiteitä koko organisaation laajuudella, eikä vain yksittäisen osa-alueen tarkkuudella, ei löytynyt.

Tässä diplomityössä olemme kehittäneet optimointimallin, jonka tavoitteena on auttaa yrityksiä valitsemaan mahdollisimman kustannustehokkaita päästövähennystoimenpiteitä. Malli antaa myös aikataulun, jossa päästövähennystoimenpiteet tulisi toteuttaa. Optimointimalli minimoi yrityksen kokonaiskasvihuonekaasupäästöjä valitulta ajanjaksolta siten, että yrityksen asettama budjetti ei ylity. Muodostettu optimointimalli ratkaistaan evoluutioalgoritmin avulla. Optimointimallia sovelletaan Yritys A:n ilmastotyöhön.

Kehitetty optimointimalli näyttää, miten yrityksen kasvihuonekaasupäästöt kehittyisivät, jos se toteuttaisi suositellut päästövähennystoimenpiteet annetussa aikataulussa. Mallin avulla yritys näkee, mitkä päästövähennystoimenpiteet sen tulisi toteuttaa, jotta kokonaiskasvihuonekaasupäästöt olisivat mahdollisimman pienet, mutta annettu budjetti ei ylittyisi. Mallia voidaan käyttää myös erilaisten budjettien testaamisessa: se näyttää, miten budjetti vaikuttaa suositeltuihin päästövähennystoimenpiteisiin ja yrityksen kasvihuonekaasupäästöihin.

Avainsanat Ilmastonmuutos, ilmastotiekartta, optimointi

Preface

I want to thank my supervisor Kaie Kubjas and my advisor Maija Leino for helping me through this process. I also want to thank my employer UseLess Company for letting me work the thesis during my working hours.

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Contents

Al	ostrac	et		3
Al	ostrac	ct (in Fi	nnish)	4
Pr	eface	•		5
Co	onten	ts		6
Al	obrev	iations		8
1	Intr	oductio	n	9
2	Clin 2.1 2.2 2.3	GHG Finnis	ange: policies and companies' climate workemission accounting standards and climate policiesh companies' current climate work and targetsodology of a climate roadmap	11 11 13 15
3	Opt 3.1 3.2 3.3	Mathe Mathe	on of emission reduction actions ematical programming in reducing GHG emissions ematical programming using Excel Solver ematical model Model notation Optimisation problem Functions for refrigerants Functions for vehicles Functions for energy efficiency and share of renewable energy related to scope 2 Functions for purchased goods and services Functions for waste management Functions for business travel and employee commuting	18 18 19 20 21 22 23 25 26 27 28
	3.4	Exclus	sions	29
4	4.1 4.2	Gener Emiss 4.2.1 4.2.2 4.2.3 4.2.4 4.2.5 4.2.6 4.2.7 4.2.8	a of the emission reduction action optimising tool al assumptions ion reduction actions included in the model Refrigerants Vehicles Electricity Heating Purchased goods and services Waste management Business travel Employee commuting	31 33 33 34 35 35 36 36 37 37
	4.3	Optim	isation problem and algorithm parameters	37

5	Disc	ussion	4
	5.1	Construction of the optimisation model	Z
	5.2	Application of the optimisation model	Z

Abbreviations

$\frac{BEV}{CO_2}$	battery electric vehicle carbon dioxide
CSRD	Corporate Sustainability Reporting Directive
ELY centre	Centre for Economic Development, Transport and the Environment
ERA	emission reduction action
ERDF	European Regional Development Fund
ESRS	European Sustainability Reporting Standards
ETS	emission trading system
EU	European union
GHG	greenhouse gas
GRG	generalised reduced gradient
GWP	global warming potential
IP	integer programming
LP	linear programming
SBTi	Science Based Targets initiative

1 Introduction

Climate change is an acute crisis that needs to be solved if irreversible changes to environment are to be prevented. Climate change has already caused increase in weather extremes, both in magnitude and in frequency (IPCC, 2023). European union, individual countries, and different kinds of organisations have created legislation and guidance to tackle this problem. Still, companies and other entities have a great responsibility on their own to reduce their climate impact.

Some of the Finnish companies' are already ambitious in their climate work but in a bigger picture, the reporting of the greenhouse gas (GHG) emissions and implementation of climate actions are still in progress. In the study of Moilanen et al. (2024), half of the respondents said that their employer has conducted actions to mitigate climate change but only one forth told that their work place has set any climate related targets. The most significant motivations for climate work in industrial sector came from positive brand image and requirements of both clients and regulation (Sitra, 2019). Across the sectors, companies see the lack of time and arising costs along with insufficient funding and political support as challenges for their climate actions (Avidly, 2019; Sitra, 2019).

To mitigate climate change, European union (EU) has set policies that aim to reduce GHG emissions and guide the companies towards more sustainable practices. One of them is Corporate Sustainability Reporting Directive (CSRD) which affects many large companies in EU region (European Commission, n.d.). It requires that the companies report their social and environmental impacts and sustainability actions more precisely than before. EU has also set target for energy sector: 42.5% of the energy has to be from renewable sources by 2030 (Directive 2023/2413). To help companies to reduce their GHG emissions, EU provides funding from its European Regional Development Fund to accelerate green transition (The Ministry of the Environment, n.d.).

Optimisation can be used to find cost-effective ways to reduce GHG emissions. In the literature, the optimisation is mostly used in reducing GHG emissions in more specific applications such as supply chains (see for example Kumar and Kumar (2024)) or operation planning (see for example Sweetapple et al. (2014) and Su et al. (2017)) rather than planning emission reduction actions through a whole organisation. When planning emission reduction actions, the timeline of their implementation is crucial if budget or other resources are limited. Schedule or resource optimisation is also a common field in the literature. It is often applied to construction projects, as for example in Ghoddousi et al. (2013).

The objective of this thesis is to develop a product that can help UseLess Company's customer companies and organisations make better decision regarding their emission reduction actions. The product will help to find the most optimal combination of the emission reduction actions (hereinafter ERAs) to be implemented. In addition, the product will give a recommended timeline for them to be executed.

This thesis sets out to help decision-makers choose ERAs and the order of their implementation so that company's GHG emissions can be reduced as much as it is possible with currently available resources as money and man-hours. The work will answer to following questions: 1) Which resources should be taken into account when

optimising ERAs and their timeline? 2) What are the limitations and possibilities of companies' current climate work, and what should be done differently? 3) What costs or gains arise from implementation of ERAs, and how should they be included to the decision-making model? 4) How the optimisation problem should be formulated and what tools should be used so that it can be applied realistically to the climate work and decision-making of companies?

The outline of the thesis is the following: In Section 2, we will discuss climate change, climate policies, and current climate work of Finnish companies. We will also present the methodology of a climate roadmap which this thesis will use as basis. In Section 3, we will review previous literature on how mathematical programming is used to plan emission reductions. Since the optimisation model is developed using Excel Solver, we will discuss the optimisation algorithms provided by Excel Solver. Finally, we will present the mathematical formulation of the optimisation model of the thesis. In Section 4, the optimisation model is applied in practise. Lastly, we will have discussion and conclusion.

2 Climate change: policies and companies' climate work

Climate change is a global issue that everyone, states, companies, and people, needs to contribute to fighting against. Rockström et al. (2009) presents a framework that identifies nine critical planetary systems that, if crossing certain thresholds, can cause irreversible and unacceptable environmental changes. The thresholds are called *planetary boundaries*. The planetary boundaries define the safe space in which humankind should operate in order to avoid deleterious consequences for planet Earth. Now, six out of the nine boundaries are transgressed (Richardson et al., 2023).

Climate change is one of Earth's systems in which the planetary boundary is transgressed (Richardson et al., 2023). The planetary boundary of climate change had already been crossed in 2009, when Rockström et al. (2009) first published the framework. The global warming has already caused strengthening of weather extremes as heatwaves, droughts, and heavy precipitation (IPCC, 2023). Not only have these extremes become stronger, but their probability has increased (IPCC, 2023). IPCC (2023) points out that effects of climate change hit vulnerable communities that contributed to climate change the least disproportionately hard. Effects of climate change do not divide equally between communities and regions.

IPCC (2023) states in its report that implemented climate policies are not sufficient enough to keep global warming under 2 °C pre-industrial temperatures, even though, the Paris Agreement binds states to limit global warming to 1.5 °C. Therefore, states and other actors need to really accelerate their climate policies and actions in order to keep up with the Paris Agreement.

Next, we will present GHG emission accounting standards and climate policies. Then, we will look into what Finnish companies have done to reduce their GHG emissions and what kind of climate targets they have set. Lastly, we will present the methodology of a climate roadmap which this thesis develops further.

2.1 GHG emission accounting standards and climate policies

Since climate change is a large and global problem, cooperation between countries is important. Climate change mitigation is included to policies in both European Union (EU) and national level. One of the policies being EU's Corporate Sustainability Reporting Directive (hereinafter CSRD), which requires large and listed companies to report their impact to people and the environment (European Commission, n.d.). The CSRD came into effect from January of 2023, and first reports of year 2024 have to be published in 2025. The CSRD demands companies to report their social and environmental impacts according to European Sustainability Reporting Standards (ESRS).

EU has also set climate policies that directly target to decrease GHG emissions in EU. One of them is EU's emission trading system EU ETS whose goal is to decrease GHG emissions in sectors within the ETS and to accelerate EU's green transition (European Union, 2016). The EU ETS follows *cap and trade* system, where a total amount of GHGs emitted in a year are limited by a cap (European Union, 2016). This cap is reduced annually making the GHG emissions decrease overtime. As a central part of the trading system, companies can then sell or buy emission allowances (European Union, 2016). The price is determined by supply and demand. Emission trading is a cost-effective incentive to reduce GHG emissions (Driesen, 2006): Emission reductions are profitable for companies who can do them with relatively low costs since surplus emission allowances can be sold in the carbon market. On the other hand, if reducing GHG emissions is expensive, buying emission allowances can be more feasible option.

EU is also determined to reduce GHG emissions in the energy sector. The current binding target is to increase the share of renewable energy from EU's energy consumption to 42.5% by 2030 (Directive 2023/2413). That is, the share has to increase by 20 percentage points from 2022 levels (European comission - Eurostat, 2023). The energy consumption also covers other branches than just electricity and heating, such as energy consumption in industry and transportation (Directive 2023/2413). The EU directive requires EU's member states to secure that the share of renewable energy reaches the set target of 42.5%. Regarding transportation, EU's Regulation 2023/851 sets carbon dioxide standards for new passenger cars and new light commercial vehicles: by 2035, EU fleets need to emit 100% less carbon dioxide than in 2021, i.e. CO_2 emissions from new vehicles are prohibited. These directives and regulations help EU to achieve climate neutrality by 2050, and furthermore affect the GHG emissions of companies operating in EU. Regulations have to be inserted to national legislation as they are but in the case of directives, member states can choose how they modify their laws in order to reach targets set in directives.

For CSRD and EU ETS, greenhouse gases need to be accounted. As said above, ESRS has to be followed in order to fulfil requirements of CSRD. The main reporting principles of ESRS are made to be in line with The Greenhouse Gas Protocol Corporate Accounting and Reporting Standard (hereinafter GHG Protocol) (Ranganathan et al., 2004) which is a wildly used standard for calculating organisational carbon footprint. The GHG Protocol divides GHG emissions into three scopes. For the visualisation of this division, see Figure 1.1 in Bhatia et al. (2011). Scope 1 includes all the direct GHG emissions arising from company's operations. This can include, for example, combustion of fuels or use of refrigerants. Scope 2 includes GHG emissions from purchased energy, i.e. electricity, steam, heating, and cooling. Lastly, scope 3 includes GHG emissions from company's value chain. The GHG emissions reported in scope 3 do not occur from company's own operations, but are still directly linked to its business. Scope 3 emissions can occur, for example, from purchased goods and services, transportation services, waste management, or use of products the company has sold to customers. Scope 1 and 2 are a compulsory part of the organisational carbon footprint calculations, and scope 3 is optional, but it is highly recommended to include at least categories relevant to the company's business model (Ranganathan et al., 2004). If the company wants to report their GHG emissions in accordance of Ranganathan et al. (2004) and the supplemental Corporate Value Chain (Scope 3) Accounting and Reporting Standard (Bhatia et al., 2011), they shall also include all the scope 3 categories to their carbon footprint.

GHG protocol has no standardised method to screen or address emission reduction actions (Ranganathan et al., 2004). However, it states how GHG emissions should be tracked over time. Companies shall set a base year to which they compare their future GHG emissions. The base year should be recalculated if company's operations undergo significant changes, e.g. structural changes such as mergers or outsourcing, or methodology of the calculations is changed so that they result in significant changes in GHG emissions of the base year. This ensures reliable and transparent comparison in GHG emissions between different reporting years.

On the other hand, ESRS, the standard which large and listed companies bound by CSRD need to follow, states that a company is required to disclose its actions to climate change mitigation and adaptation as well as state the resources allocated for implementing those actions (Regulation 2023/2772, paragraph 26). Also, a company *"shall disclose the climate-related targets it has set"* (Regulation 2023/2772, paragraph 30). The companies shall state whether the targets are in line with limiting global warming to 1.5 °C from pre-industrial temperatures (Regulation 2023/2772, paragraph 34(e)). If the company sets climate targets, ESRS addresses multiple criteria needed to follow in order to fulfil the demands of the CSRD (Regulation 2023/2772):

- 1. The targets set have to be absolute values expressed either in carbon dioxide equivalent tons or as a share of GHG emissions in defined base year.
- 2. The company shall include target at least for the year 2030. Target value for 2050 is recommended but optional.
- 3. From 2030 onwards, the targets have to be set for every 5-year period. The company must describe their actions to achieve set targets.
- 4. The description must include quantitative analysis of the contributions planned.

Climate policies are all not just regulations and prohibitions. For example, companies can apply for monetary aids to their projects or businesses that support green transition. One of the authorities granting funding is the European Regional Development Fund (ERDF), whose purpose is to level differences in development between regions and member states of EU. ERDF funds, among other things, development projects that promote the green transition in wildly utilisable and scalable way (The Ministry of the Environment, n.d.). Themes funded from ERDF in 2021-2027 are energy efficiency, climate change, and circular economy, and the funding is provided by the Centres for Economic Development, Transport and the Environment (hereinafter *ELY centres*) (The Ministry of the Environment, n.d.). ELY centres are also responsible for promoting green transition by smoothing the processing of green transition projects and providing advice in permit processes (Centre for Economic Development, Transport and the Environment, 2024).

2.2 Finnish companies' current climate work and targets

Next, we take a look into companies' current climate work and targets they have set for their GHG emissions. Finnwatch, a non-governmental organisation investigating sustainability and impacts of business enterprises, has conducted a study analysing GHG emission reporting of 24 companies (Finnwatch, 2023). Companies were chosen based on their size, governmental ownership, and climate neutrality claims: the analysis included six largest companies in which state of Finland has a controlling interest, 12 largest private sector companies, and six small and medium enterprises that used carbon neutrality claims in their communications. Finnwatch (2023) concluded that reporting of GHG emissions was quite comprehensive even though some companies had deficiencies on comparing their GHG emissions to set climate targets. Finnwatch (2023) shows that the reporting of smaller companies with carbon neutrality claims was poor and did not show the development of GHG emissions. In general, only a few of the analysed companies reported each greenhouse gas separately even though it is required in the GHG protocol. Also, only a few of the companies reported publicly any evaluation on quality of given data. Still, many companies told Finnwatch (2023) that they are increasing quality of their GHG emission accounting in next reporting period. Thus, it can be assumed that quality of GHG emission reports may increase in the future.

Finnwatch has also reviewed climate and sustainability work in restaurant business (Finnwatch, 2024) and clothing industry (Finnwatch, 2022). In Finnwatch (2024), three large Finnish restaurant businesses were chosen. All three had planned similar ERAs: reducing wastage, increasing energy efficiency in the restaurants, and decreasing consumption of fossil fuels (Finnwatch, 2024). Only one of the three companies had a clear plan on increasing share of vegetarian meals served in their restaurants. However, none of the companies had published numerical targets, either relative or absolute, for their value chain GHG emissions (Finnwatch, 2024).

Globally, the climate impact of clothing industry has been recognised but implemented ERAs have remained superficial, and they have focused on company's direct GHG emissions while the value chain is usually more significant emitter (Finnwatch, 2022). Some of the clothing companies have engaged to Science Based targets initiative's (hereinafter SBTi) targets (see section 2.3) but set targets do not have enough focus on the value chain (Finnwatch, 2022): only half of the companies with SBTi targets that were included in Finnwatch's study had absolute targets for their value chain GHG emissions.

Sitra (2019) studied decision-makers' and experts' views on carbon neutrality as a source of competitiveness in industrial sector. The sample size of the study was 501. Around one third of decision-makers and experts responded that their company has set targets to their carbon dioxide emission (similar results are obtained in Moilanen et al. (2024)). However, only one quarter said that their company has conducted a carbon footprint calculations (Sitra, 2019). The most important drivers to carbon neutrality were positive brand image and reducing wastage followed by decreasing GHG emissions, and requirements from clients and regulation (Sitra, 2019). The most significant challenges to climate neutrality were lack of innovations and monetary profit. Also, some of the decision-makers and experts raised lack of legislation, funding, and political support as a limitation for the carbon neutrality targets. In Avidly (2019) (sample size of 162), biggest challenges for climate actions and decreasing carbon dioxide emissions were lack of time, and costs of the actions.

Moilanen et al. (2024) looked employers' climate actions from employees' point of view. The study of Moilanen et al. (2024) was comprehensive with 1917 respondents from all sectors. The study concluded that there is significant difference between industries in their actions on climate change mitigation. A quarter of employees' said that their employer has set a climate target, and about one third of employees' could not say whether their employer has climate targets or not. The distribution of answers remained same in question about workplaces' climate strategies. Moilanen et al. (2024) discussed that climate actions are not very common, but it is worth of noticing that one third of respondents did not know how to answer to the questions: this suggests that climate actions are not integrated to workplaces' strategy, or strategy is not communicated strongly enough to employees. However, a half of the respondents said that they agree at least on some level with the statement "At my workplace, we have deliberately changed work practices or processes to mitigate climate change" (Moilanen et al., 2024). Thus, companies have done some changes to their ways of working, but climate targets are still fairly rare.

Tapio et al. (2023) studied how the GHG emissions of Finnish companies committed to SBTi have developed. The number of those companies was 99 of which 31 companies did not disclose their carbon footprint and were excluded from the study. Tapio et al. (2023) reports approximately 3% decrease in GHG emissions among those companies between years 2019 and 2021. Since the yearly ambition for near-term targets set by SBTi is 4.2% (Science Based Targets initiative, 2024), the progress of the Finnish companies with SBTi targets seems to be minor. It is worth of noticing that globally the GHG emission reductions of companies (Tapio et al., 2023). Thus, the overall progress of all Finnish companies is likely to be even less than 3% for the same time period.

In conclusion, it seems that there is a lot of room for progress in companies' GHG emission reporting, climate actions, and emission reduction targets. Money is still guiding decision-making: costs of climate actions and lack of profit were seen as a limiting forces for climate neutrality targets. Thus, a model optimising emission reduction actions while taking monetary limits into account could be useful. Also, GHG emission reporting is one of the cornerstones in planning emission reduction actions. If the reporting is not comprehensive enough, planning ERAs effectively is not necessarily obvious. Overall, every actor should take part in climate change mitigation in order to keep temperature rise within sufficient limits, but only half of the Finnish companies have changed their work practices to mitigate climate change and a one fourth has set climate targets.

2.3 Methodology of a climate roadmap

Climate roadmap is a tool to help companies and organisations to quantify the impacts of possible climate actions, and it can help to meet the requirements of the climate policies described in section above. The climate roadmap can visualise estimated effects of company's currently planned emission reduction actions or it can help decision-makers to realise which kind of actions are needed in order to meet set climate targets. UseLess uses following methodology to calculate the climate roadmap:

- 1. Description of the organisation's current state, i.e. its carbon footprint calculated according to GHG protocol
- 2. Qualitative PESTEL analysis to identify changes in organisation's operating environment
- 3. Qualitative description of chosen emission reduction actions
- 4. Quantitative analysis of the effects of chosen emission reduction actions to the company's future GHG emissions.
- 5. Comparing results to emission targets set based on SBTi (science based targets initiative)

Very similar method is used in sector-specific low-carbon roadmaps published by Ministry of Economic Affairs and Employment of Finland (Paloneva & Takamäki, 2020).

In addition to project phases presented above, important part of the climate roadmap project is open and continuous discussion with the client company. Company's ambition on climate work and expectations for climate roadmap should be discussed so that chosen emission reduction actions are in line with company's targets. Also, when the ERAs are chosen together, company can more easily engage to carry them out.

Before the company can make a climate roadmap, it has to be aware of its current GHG emissions. The GHG emissions are usually calculated by following some standard, for example the greenhouse gas protocol (Ranganathan et al., 2004). GHG emission inventory gives important information on which company's processes are significant sources of GHG emissions. Only after this, any realistic emission reduction actions can be planned.

It is also important to recognise changes occurring in company's business environment. This can be done with PESTEL analysis. The earliest version of the framework was published by Aguilar (1967). PESTEL analysis is a qualitative tool that looks into six different factors in company's external operating environment: political, economic, social, technological, environmental, and legal. These factors are in constant change which can affect on company's risks, in both, positive or negative, manner. By addressing those changes, company can discover new business opportunities and recognise more emission reduction potential from its operations.

Using PESTEL analysis and organisational carbon footprint, possible ERAs can be planned. The qualitative description contains 1) sources from which the GHG emissions will be reduced, 2) how the reductions can be done, and 3) what is the planned timeline for implementing the ERAs. All the assumptions used in the climate roadmap calculations are recorded.

Next, the quantitative effects of planned emission reduction actions are calculated based on made assumptions. Based on the calculations, company's future GHG emissions can be modelled, and compared to set targets. It is recommended to have targets that are in line with limiting global warming to 1.5 °C from pre-industrial temperatures. Commonly used targets are set by SBTi and are defined in Net Zero standard of Science Based Targets initiative (2024). The standard guides companies to set targets in which they reach net-zero by year 2050. A cross-sector science-based target is reducing GHG emissions at least 90% by 2050, and rest of the emissions need to be neutralised (Science Based Targets initiative, 2024). Sector-specific target-levels differ but in each sector, remaining GHG emissions need to be neutralised which balances out the differences (Science Based Targets initiative, 2024). There is also other guidelines for setting targets, but a significant share of them refer to SBTi: from the seven guidelines considered in the comparison in Harju et al. (2024), only one (PAS 2060) did not use SBTi's emission reduction pathways as reference since it was published before the Paris Agreement and is not updated to meet its requirements.

Climate roadmap work is an iterative process. A company may not have been aware of the real effects of its climate actions, and may want to modify planned actions to more ambitious direction. In this case, assumptions used in the climate roadmap calculations can be updated and new emission reductions calculated. The process can be repeated multiple times to the point, where company's needs are met.

3 Optimisation of emission reduction actions

3.1 Mathematical programming in reducing GHG emissions

In mathematical programming, the objective is to maximise or minimise a function so that the variables of that function fulfil chosen criteria. The optimal solution is obtained by using algorithms that are based on calculus, algebra, and other mathematical concepts. Mathematical programming is wildly used in different disciplines such as economics, industry, and machine learning.

Optimisation is already used in planning emission reductions and next, a couple of picks from broad selection are presented. Most of the papers use multi-objective optimisation when planning emission reductions even though the papers are from different disciplines. This is understandable since money has a big impact on business decision and with multi-objective optimisation one may maximise emission reductions while simultaneously minimising the costs.

Sweetapple et al. (2014) use Non-Dominated Sorting Genetic Algorithm-II in their study on GHG emission reductions in wastewater treatment plan. The objective functions take into account GHG emissions, operation costs, and effluent quality. The Non-Dominated Sorting Genetic Algorithm-II is chosen due to its fast computing time and its ability to maintain a wider collection of solutions during optimisation than other multi-objective evolutionary algorithms (Sweetapple et al., 2014). Cardenes et al. (2020) have also studied emission reductions in water treatment. They use a combination of linear programming and multi-objective evolutionary algorithm to reduce emissions in water pumping and treatment operations. First, linear programming is used to find the optimal routing for water distribution while obtaining minimum cost. Then, multi-objective evolutionary algorithm is used in finding optimal investment strategies to eliminate bottlenecks in the distribution system (Cardenes et al., 2020). Kumar and Kumar (2024) use multi-objective mixed integer linear programming to design a supply chain attempting to reduce GHG emissions while taking economic and social aspects into account.

Evolutionary algorithms seem to be a popular choice. The use of evolutionary algorithm is mainly justified with acceptable computing time to large-scaled optimisation problems. Both, Sweetapple et al. (2014) and Cardenes et al. (2020), use evolutionary algorithms to solve a set of optimisation problems. In addition, Su et al. (2017) have proposed an optimisation approach that combines reducing carbon emissions with production planning. Su et al. (2017) use both integer programming and an evolutionary algorithm. Integer programming is used to formulate a production planning model, and after that, hybrid discrete particle swarm algorithm is applied to obtain the most optimal solution for this model. The hybrid discrete particle swarm algorithm (see Section 3.2) (Su et al., 2017).

Optimisation approaches have been developed also by governmental bodies. The environmental protection agency of United States has developed an optimisation model (OMEGA) that helps decision-makers reduce GHG emissions from vehicles (United States Environmental Protection Agency, 2024). The tool is implemented to support

regulatory development. The OMEGA uses compliance search and iterative feedback loops in multiple parts of the model, and it takes into account relations between policies, consumer behaviour, and vehicle producers.

It seems that optimisation is commonly used in GHG emission reduction planning within enterprises but the literature is primarily focused on supply chains and operations planning. Very little was found on optimising emission reduction actions across the organisation. This thesis seeks to fill this gap. Even though the papers presented above are not directly related to the objective of this thesis, they give insight to results in optimisation of emission reductions and how they are related to monetary goals and efficiency. The results in Kumar and Kumar (2024) suggest that it is possible to achieve significant GHG emission reductions without any trade-offs with the efficiency or profitability of the supply chain. This is contrary to results in Sweetapple et al. (2014) where the trade-offs between costs, GHG reductions, and effluent quality were significant. However, it is worth noting that the contexts of these papers are different. Additionally, when applying the procedure in Cardenes et al. (2020) to real-life data the financial value set for GHG emissions was found to have a significant influence on results. On the contrary to Sweetapple et al. (2014) and Cardenes et al. (2020), the approach in Su et al. (2017) leaves an economical perspective unaddressed.

Optimising an implementation timeline and related implementation costs of different types of ERAs across the organisation can be seen as resource optimisation or scheduling: one has limited number of resources within which, one needs to reduce as much emissions as possible. Those resources can be renewable or non-renewable. The division is used, for example, by Ghoddousi et al. (2013): Renewable resources are limited per period of time, e.g. per day or year. They can be for example man-hours or yearly budgets. Non-renewable resources, on the other hand, are limited for a longer time-period, as for entire project. Double constrained resources are limited in both ways. An optimisation method for resources or schedule can be chosen from a broad selection of different algorithms. For example, genetic algorithms are used in optimising resources and schedule in construction projects in Kandil and El-Rayes (2006), Hegazy and Kassab (2003), and Ghoddousi et al. (2013).

3.2 Mathematical programming using Excel Solver

The mathematical programming conducted in this thesis is done by using Excel Solver. The choice is based on practical reasons: the optimisation model created as a part of this thesis should be easily modifiable also by people who have little or no experience in programming or mathematical optimisation. The Excel Solver has limited number of possible optimisation methods: LP Simplex method for linear problems, generalised reduced gradient (GRG) nonlinear method for smooth nonlinear problems, and evolutionary method for non-smooth nonlinear problems (Microsoft, n.d.).

The LP Simplex method is commonly used in linear programming (LP), and it is limited to linear problems. In a linear problem, the objective function and all the

constraints are linear. The problem can be written as follows:

$$\max_{x \in \mathbb{R}} \mathbf{c}^{\mathsf{T}} \mathbf{x} \tag{1}$$

s.t.
$$A\mathbf{x} \le \mathbf{b}$$
 (2)

$$\mathbf{x} \ge \mathbf{0}.\tag{3}$$

The equation (1) is the objective function that is to be maximised, and equation (2) contains all the constraints. The last constrain in equation (3) forces variables to be non-negative. In a constrained linear problem, the feasible region is a polygon. The algorithm moves along the edges from vertex to vertex looking for the most optimal solution.

The GRG nonlinear method is suitable for optimisation problems with a nonlinear objective function or nonlinear constraints. The GRG algorithm used in Excel Solver is developed by Lasdon et al. (1974) (Frontline Systems, n.d.-a). The GRG method requires smoothness: the objective function needs to be differentiable at every point, since the method chooses its search direction using the gradient of the objective function. The optimum is found when all the partial derivatives equal zero. Limitations of the GRG method are that it might converge to locally optimal solutions instead of globally optimal. In addition, if the optimisation problem is unconstrained, the method might not find any optimal solution at all.

If the optimisation problem is nonlinear, but not smooth, one can use the third method in Excel Solver, the evolutionary algorithm, which uses genetic algorithm approach to find the optimal solution. Genetic algorithms are based on processes of natural selection such as mutation, selection, and crossover (Whitley, 2001). The algorithms start from randomly sampled generation. For each individual in the generation, the value of objective function is calculated. In other words, fitness of individuals are tested. The most fit individuals will be stochastically selected. Using those individuals, the next generation is formed by modifying selected individuals by crossover and mutation. The procedure is repeated until defined stopping criteria are met. Like other optimisation algorithms, the genetic algorithm has its own limitations as well. In general, evolutionary algorithms cannot verify that the found solution is optimal. Rather, the solution is just better than other solution candidates obtained by the algorithm. In real-life problems, usually this best option available is suitable enough. Since the value of the objective function is calculated for each solution candidate individually, the evolutionary algorithm can be computationally very expensive. When using the evolutionary algorithm, one can choose values for different parameters such as mutation rate and population size. Choosing those values can be difficult since the best suitable values can vary from application to another. If the optimisation problem is complex, testing different values for parameters can also be time consuming.

3.3 Mathematical model

Next, we will define the mathematical formulation of the optimisation model. First, the notation of used sets, functions, and variables is presented.

3.3.1 Model notation

Sets:

- Ι set of all the ERAs
- I_k set of all the ERAs corresponding to a category k; $I_k \subseteq I$
- *K* set of emission categories
- *M* set of modes of travel
- set of years; the set T specifies a timeline within which the ERAs can be Т implemented

Functions:

B(t)	budget for extra costs as a function of time
$c_k(t)$	extra costs related to category k
$c_i(t)$	extra costs related to ERA <i>i</i>
$D_k^{(m)}(t)$	distance travelled with the mode of travel m related to category k
	as a function of time
$E_k(t)$	emissions from category k as a function of time
$E_i(t)$	emissions related to ERA <i>i</i> as a function of time
$EC_k(t)$	energy consumption related to category k as a function of time
$S_i(t)$	share of some quantity related to category or ERA <i>i</i> as a function
	of time
$S_i^{(n \to m)}(t)$	share of baseline kilometres of a mode of travel n that is changed to other mode of travel m in year t due to ERA i

Decision variables:

(1)	(1)	
$t_{i}^{(1)}$	starting year of ERA <i>i</i> 's transition period; $t_i^{(1)}$	$\in T$

- $t_i^{(2)}$
- starting year of ERA *i*'s transition period; $t_i^{(1)} \in T$ ending year of ERA *i*'s transition period; $t_i^{(2)} \in T$ binary variable whether ERA *i* is implemented or not; 1 if implemented, a_i 0 otherwise

Fixed parameters:

$c_{i}^{(0)}$	recurring costs before implementing the ERA <i>i</i>
$c_{i}^{(1)}$	initial costs from implementing the ERA <i>i</i>
$c_{i}^{(0)}$ $c_{i}^{(1)}$ $c_{i}^{(2)}$ $c_{i}^{(m)}(0)$	recurring costs after implementing the ERA <i>i</i>
$D_k^{(m)(0)}$	distance travelled with the mode of travel m related to category k
	in the base year
$\begin{array}{c} E_{k}^{(0)} \\ E_{k}^{(2)} \\ E_{i}^{(0)} \\ EC_{k}^{(0)} \\ EC_{k}^{(2)} \\ EC_{k}^{(2)} \end{array}$	emissions of the category k in the base year $t^{(0)}$
$E_{k}^{(2)}$	target emissions of the category k
$E_{i}^{(0)}$	emissions related to ERA <i>i</i> in the base year
$EC_k^{(0)}$	energy consumption related to category k in the base year
$EC_{k}^{(2)}$	target energy consumption related to category k
e_m	emission factor of the corresponding mode of travel $m \in M$

 $S_i^{(0)}$ share of some quantity related to category of ERA *i* in base year $t^{(0)}$

- \sim_i since of some quantity related to category of ERA *i* in bas $S_i^{(2)}$ target share of some quantity related to category of ERA *i*
- $t^{(0)}$ base year; the base year is the year to which future years' emissions are compared

3.3.2 Optimisation problem

The optimisation problem for optimising emission reduction actions and their timeline is defined as follows:

$$\min_{a,t^{(1)},t^{(2)}} \quad \sum_{k \in K} \sum_{t \in T} E_k(t) \tag{4}$$

s.t.
$$\sum_{k \in K} c_k(t) \le B(t) \quad \forall t \in T$$
 (5)

$$t_i^{(1)} \le t_i^{(2)} \quad \forall i \in I \tag{6}$$

$$t_i^{(1)}, t_i^{(2)} > t^{(0)} \quad \forall i \in I$$
(7)

$$a_i \in \{0, 1\} \quad \forall i \in I \tag{8}$$

$$t_i^{(1)}, t_i^{(2)} \in T \quad \forall i \in I.$$

$$\tag{9}$$

Functions E_k and c_k for categories $k \in K$ are defined in the following sections. The objective is to minimise cumulative emissions of the organisation by choosing which emission reduction actions are implemented (decision variable a), and in which timeline the implementation is done (decision variables $t^{(1)}$ and $t^{(2)}$). The total extra costs in year t shall not exceed annual budget B(t) set for that year. The starting year has to be before the ending year for each ERA. Also, the timeline for implementation cannot be before a base year. The decision variable a_i is a binary variable that indicates whether the ERA i is implemented or not.

At the moment, monetary limitations are the main constraint in the optimisation model since costs of the ERAs and lack of monetary profit are seen as significant challenges within companies (Avidly, 2019; Sitra, 2019). The model minimises cumulative GHG emissions of the company instead of annual GHG emissions at the end of the reference period. If annual GHG emissions at the end of the reference period were minimised, the timeline of implementing the ERAs would not affect the value of the objective function. However, it is important to reduce overall GHG emissions to mitigate climate change.

In Section 4, we will apply the optimisation model to Company A's situation which is presented in the beginning of that section. The categories and emission reduction actions, for which the functions are formulated, are chosen based on Company A's carbon footprint.

3.3.3 Functions for refrigerants

GHG emissions from use of refrigerants are reported in category 1.1 *Company facilities*. Thus, k = 1.1. In this model, all the emission reduction actions related to

refrigerants are assumed to be exclusive, i.e. at most one of them can be implemented. The options are either buying a new device that uses low-emitting refrigerants or using low-emitting alternatives that are compatible with the existing device. Since all of the refrigerant within a device needs to be changed to alternative one at the same time, we get a constraint

$$t_i^{(1)} = t_i^{(2)} \quad \forall i \in I_{1.1}.$$
(10)

It is also possible that the company has multiple devices that uses refrigerants. In that case, the constraint above can be dismissed, since the change to alternative refrigerant can be done device by device. However, this model focuses only on the case where the compay owns only one device.

The total emissions in year t from category 1.1. are

$$E_{1.1}(t) = \sum_{i \in I_{1.1}} \begin{cases} E_{1.1}^{(0)} & \text{if } t < t_i^{(1)}, \\ a_i E_{1.1}^{(2)} + (1 - a_i) E_{1.1}^{(0)} & \text{if } t \ge t_i^{(1)}. \end{cases}$$
(11)

The extra costs related to ERA $i \in I_{1,1}$ in year t are

$$c_{1.1}(t) = \sum_{i \in I_{1.1}} \begin{cases} 0 & \text{if } t < t_i^{(1)}, \\ a_i(c_i^{(1)} + c_i^{(2)} - c_i^{(0)}) & \text{if } t = t_i^{(1)}, \\ a_i(c_i^{(2)} - c_i^{(0)}) & \text{if } t > t_i^{(1)}. \end{cases}$$
(12)

The ERA related to decreased use of refrigerants is excluded from this version of the model. The scenario where the use of refrigerants decreases is possible, but it was not seen as a relevant scenario to be included to the model at this stage of the product development.

3.3.4 Functions for vehicles

Direct GHG emissions from company's own vehicles are accounted in category 1.2 *Company vehicles*, i.e. k = 1.2. The ERA $bio \in I_{1,2}$ is to start using biodiesel in a existing vehicle instead of fossil diesel. ERA $e \in I_{1,2}$ indicates buying a new electric vehicle. These ERAs are exclusive. It is assumed that the annual driven kilometres remain the same through the years.

First, let us define functions for ERA $bio \in I_{1,2}$. The share of biodiesel used in the vehicle is

$$S_{bio}(t) = \begin{cases} S_{bio}^{(0)} & \text{if } t < t_{bio}^{(1)}, \\ S_{bio}^{(0)} + a_{bio} \frac{S_{bio}^{(2)} - S_{bio}^{(0)}}{t_{bio}^{(2)} - t_{bio}^{(1)} + 1} (t - t_{bio}^{(1)} + 1) & \text{if } t_{bio}^{(1)} \le t < t_{bio}^{(2)}, \\ a_{bio} S_{bio}^{(2)} + (1 - a_{bio}) S_{bio}^{(0)} & \text{if } t \ge t_{bio}^{(2)}, \end{cases}$$
(13)

where $S_{bio}^{(0)}$ is the share of biodiesel in a base year and $S_{bio}^{(2)}$ is a target level for the share of biodiesel. Since consumption of biodiesel has no direct fossil GHG emissions, emissions from category 1.2, if implementing ERA *bio*, are

$$E_{bio}(t) = E_{bio}^{(0)} \frac{(1 - S_{bio}(t))(1 - S_{DO}(t))}{(1 - S_{bio}^{(0)})(1 - S_{DO}^{(0)})},$$
(14)

where function $S_{DO}(t)$ and $S_{DO}^{(0)}$ refer to share of biodiesel within a fossil diesel due to distribution obligation of the year t ad the base year, respectively. Indirect GHG emissions of biodiesel, i.e. GHG emissions from biodiesel production, are assumed to be the same as in fossil diesel. Therefore, this ERA does not affect the GHG emissions in category 3.3 Other fuel related activities that arise from diesel consumption.

Extra costs from use of biodiesel are

$$c_{bio}(t) = \begin{cases} 0 & \text{if } t < t_{bio}^{(1)}, \\ a_{bio}(c_{bio}^{(1)} + (1 - S_{bio}(t))c_{bio}^{(0)} + S_{bio}(t)c_{bio}^{(2)} - (1 - S_{bio}^{(0)})c_{bio}^{(0)}) & \text{if } t = t_{bio}^{(1)}, \\ a_{bio}((1 - S_{bio}(t))c_{bio}^{(0)} + S_{bio}(t)c_{bio}^{(2)} - c_{bio}^{(0)}) & \text{if } t > t_{bio}^{(1)}, \end{cases}$$
(15)

where $c_{bio}^{(0)}$ refers to total costs before any biodiesel is consumed, $c_{bio}^{(2)}$ refers to total costs after all consumed fuel is biodiesel, and $c_{bio}^{(1)}$ are initial costs from implementing the ERA bio.

Other ERA $e \in I_{1,2}$ is the purchase of a new battery electric vehicle (BEV). This results in a change of motive power. Share of BEVs from company's vehicles is

$$S_{e}(t) = \begin{cases} S_{e}^{(0)} & \text{if } t < t_{e}^{(1)}, \\ a_{e} \frac{S_{e}^{(2)} - S_{e}^{(0)}}{t_{e}^{(2)} - t_{e}^{(1)} + 1} (t - t_{e}^{(1)} + 1) + S_{e}^{(0)} & \text{if } t_{e}^{(1)} \le t < t_{e}^{(2)}, \\ a_{e} S_{e}^{(2)} + (1 - a_{e}) S_{e}^{(0)} & \text{if } t \ge t_{e}^{(2)}. \end{cases}$$
(16)

Since driving an electric vehicle has no direct GHG emission, if the ERA e is implemented, the emissions of category k = 1.2 are

$$E_e(t) = (1 - S_e(t))E_{1,2}^{(0)},$$
(17)

where $E_{1,2}^{(0)}$ is the emissions related to category 1.2 in the base year. Unlike ERA *bio* \in $I_{1,2}$, changing to BEV affects the GHG emissions $E_{3,3}$ in category k = 3.3 since GHG emissions from production of electricity and diesel differ more significantly. Thus, those GHG emissions that are affected by ERA $e \in I_{1,2}$ are

$$E_{3.3(e)}(t) = \frac{1 - S_e(t)}{1 - S_e^{(0)}} E_{3.3(e)}^{(0)} + \frac{S_e(t)}{S_e^{(0)}} D_{1.2} r_{BEV} e_{elec},$$
(18)

where $D_{1,2}$ is the driven distance with company vehicles (that is assumed to remain constant), e_{elec} is the emission factor of electricity production with unit of kgCO₂e/kWh, and r_{BEV} is the energy consumption of BEV per one kilometre.

Extra costs from ERA $e \in I_{1,2}$ are

$$c_{e}(t) = \begin{cases} 0 & \text{if } t < t_{e}^{(1)}, \\ a_{e}(c_{e}^{(1)} + (1 - S_{e}(t))c_{e}^{(0)} + S_{e}(t)c_{e}^{(2)} - c_{e}^{(0)}) & \text{if } t = t_{e}^{(1)}, \\ a_{e}((1 - S_{e}(t))c_{e}^{(0)} + S_{e}(t)c_{e}^{(2)} - c_{e}^{(0)}) & \text{if } t > t_{e}^{(1)}, \end{cases}$$
(19)

where $c_e^{(0)}$ refers to total costs before purchasing BEV, and $c_e^{(2)}$ refers to total costs after all vehicles are BEVs.

Total extra costs related to category k = 1.2 are

$$c_{1.2}(t) = c_{bio}(t) + c_e(t).$$
⁽²⁰⁾

3.3.5 Functions for energy efficiency and share of renewable energy related to scope 2

All of the functions and emission reduction actions presented below are the same for categories 2.1 *purchased electricity*, 2.2 *purchased steam*, 2.3 *purchased heating*, and 2.4 *purchased cooling*. Emission reduction actions related to these categories are $ee \in I_k$, i.e. increasing energy efficiency, and $re \in I_k$, i.e. increasing share of renewable energy.

First, let us define a function for energy consumption of energy categorised to category k in year t related to energy efficiency ERA $ee \in I_k$:

$$EC_{k}(t) = \begin{cases} EC_{k}^{(0)} & \text{if } t < t_{ee}^{(1)}, \\ EC_{k}^{(0)} + a_{ee} \frac{EC_{k}^{(2)} - EC_{k}^{(0)}}{t_{ee}^{(2)} - t_{ee}^{(1)} + 1} (t - t_{ee}^{(1)} + 1) & \text{if } t_{ee}^{(1)} \le t < t_{ee}^{(2)}, \\ a_{ee} EC_{k}^{(2)} + (1 - a_{ee}) EC_{k}^{(0)} & \text{if } t \ge t_{ee}^{(2)}, \end{cases}$$
(21)

where $EC_k^{(0)}$ is the energy consumption in a base year and $EC_k^{(2)}$ is the target energy consumption.

Another ERA $re \in I_k$ is changing to renewable energy. The share of renewable energy related to category k is calculated with a function defined below:

$$S_{k}(t) = \begin{cases} S_{k}^{(0)} & \text{if } t < t_{re}^{(1)}, \\ a_{re} \frac{S_{k}^{(2)} - S_{k}^{(0)}}{t_{re}^{(2)} - t_{re}^{(1)} + 1} (t - t_{re}^{(1)} + 1) + S_{k}^{(0)} & \text{if } t_{re}^{(1)} \le t < t_{re}^{(2)}, \\ a_{re} S_{k}^{(2)} + (1 - a_{re}) S_{k}^{(0)} & \text{if } t \ge t_{re}^{(2)}, \end{cases}$$
(22)

where $S_k^{(0)}$ is share of renewable energy in a base year and $S_k^{(2)}$ is a target level for share of renewable energy. The extra costs from implementing ERA $re \in I_k$ and ERA $ee \in I_k$, that are to change to renewable energy and to increase energy efficiency, respectively, are defined with following functions:

$$c_{re}(t) = \begin{cases} 0 & \text{if } t < t_{re}^{(1)}, \\ a_{re}(c_{re}^{(1)} + \frac{EC_k(t)}{EC_k^{(0)}}((1 - S_k(t))c_{re}^{(0)} + S_k(t)c_{re}^{(2)}) - (1 - S_k^{(0)})c_{re}^{(0)}) & \text{if } t = t_{re}^{(1)}, \\ a_{re}(\frac{EC_k(t)}{EC_k^{(0)}}((1 - S_k(t))c_{re}^{(0)} + S_k(t)c_{re}^{(2)}) - (1 - S_k^{(0)})c_{re}^{(0)}) & \text{if } t > t_{re}^{(1)}, \end{cases}$$
(23)

and

$$c_{ee}(t) = \begin{cases} a_{ee}c_{ee}^{(1)} & \text{if } t = t_{ee}^{(1)}, \\ 0 & \text{otherwise,} \end{cases}$$
(24)

where $c_{re}^{(0)}$ are the annual costs related to purchasing regular energy with base year energy consumption, $c_{re}^{(2)}$ are the costs from consumption of renewable energy with

base year energy consumption if all of the consumed energy was renewable, $c_{re}^{(1)}$ and $c_{ee}^{(1)}$ are initial costs from the implementation of the ERAs (either energy efficiency or renewable energy), and $EC_k^{(0)}$ is energy consumption during the base year. Decreased costs due to decreased energy consumption are included in the costs c_{re} . The cost c_{ee} includes only the initial costs from conducting an energy renovation that increases energy efficiency. Now, the total costs related to category k are

$$c_k(t) = c_{ee}(t) + c_{re}(t).$$
 (25)

It is assumed that the electricity that is not purchased as renewable, follows national targets and pathways for renewable energy. Production of renewable energy has no direct GHG emissions, and the distribution of the energy from fossil sources is assumed to remain the same through the years. GHG emissions in scope 2 from energy source k are defined by following function:

$$E_k(t) = E_k^{(0)} \frac{EC_k(t)(1 - S_k(t))(1 - S_{NA}(t))}{EC_k^{(0)}(1 - S_k^{(0)})(1 - S_{NA}^{(0)})},$$
(26)

where $S_{NA}(t)$ is share of renewable energy in 'regular' energy based on national targets.

It is assumed that indirect GHG emissions from energy productions, e.g. GHG emissions from manufacturing an energy plant, are the same with 'regular' and renewable energy. Thus, GHG emissions in category 3.3 are affected only by the ERA to increase energy efficiency, and the GHG emissions and energy consumption are assumed to be directly proportional. In reality, indirect GHG emissions from renewable energy production are usually a bit higher (see for example Schlömer et al. (2014)).

3.3.6 Functions for purchased goods and services

GHG emissions from purchased goods and services are reported in category 3.1 *Purchased goods and services*. One ERA related to this category is purchasing more low-emitting services. Let us denote the ERA with *s*. Share of those services follows function

$$S_{s}(t) = \begin{cases} 0 & \text{if } t < t_{s}^{(1)}, \\ a_{s} \frac{S_{s}^{(2)} - S_{s}^{(0)}}{t_{s}^{(2)} - t_{s}^{(1)} + 1} (t - t_{s}^{(1)} + 1) & \text{if } t_{s}^{(1)} \le t < t_{s}^{(2)}, \\ a_{s} S_{s}^{(2)} & \text{if } t \ge t_{s}^{(2)}. \end{cases}$$
(27)

Let us assume that low-emitting services emit x% less GHG emissions than regular services. Now, total GHG emissions from purchased services in year *t* are

$$E_s(t) = E_s^{(0)} - E_s^{(0)} S_s(t)(x\%),$$
(28)

where $E_s^{(0)}$ are the GHG emissions from services in the base year.

Costs from low-emitting services are assumed to be higher than the ones from regular services. Amount of services purchased in each year are assumed to remain a constant. The extra costs related to ERA *s* are

$$c_s(t) = S_s(t)c_s^{(2)} + (1 - S_s(t))c_s^{(0)} - c_s^{(0)},$$
(29)

where $c_s^{(0)}$ is the total costs before implementation of the ERA *s* and $c_s^{(2)}$ total costs after the implementation.

Also purchased goods are reported in category 3.1. Hence, another ERA related to this category is purchasing low-emitting goods, e.g. monitors or office furniture. Let us denote this ERA with g. GHG emissions from purchased goods if ERA g is implemented are calculated similarly to GHG emissions arising from purchased services, i.e. share of less emitting goods is

$$S_{g}(t) = \begin{cases} S_{g}^{(0)} & \text{if } t < t_{g}^{(1)}, \\ a_{g} \frac{S_{g}^{(2)} - S_{g}^{(0)}}{t_{g}^{(2)} - t_{g}^{(1)} + 1} (t - t_{g}^{(1)} + 1) + S_{g}^{(0)} & \text{if } t_{g}^{(1)} \le t < t_{g}^{(2)}, \\ a_{g} S_{g}^{(2)} + (1 - a_{g}) S_{g}^{(0)} & \text{if } t \ge t_{g}^{(2)}. \end{cases}$$
(30)

Let us assume that low-emitting goods emit y% less GHG emissions than regular goods. Now, total GHG emissions from purchased goods in year *t* are

$$E_g(t) = E_g^{(0)} - E_g^{(0)} S_g(t)(y\%),$$
(31)

where $E_g^{(0)}$ are the GHG emissions from purchased goods in the base year. Similarly, the extra costs related to ERA g are

$$c_g(t) = S_g(t)c_g^{(2)} + (1 - S_g(t))c_g^{(0)} - c_g^{(0)}.$$
(32)

The total GHG emissions from category 3.1 in year t can be calculated by adding GHG emission from purchased services and goods together. The total GHG emissions are

$$E_{3.1}(t) = E_g(t) + E_s(t).$$
(33)

In addition, the total extra costs in year t from ERAs related to category 3.1 are calculated as follows:

$$c_{3,1}(t) = c_g(t) + c_s(t).$$
(34)

3.3.7 Functions for waste management

GHG emissions from waste management are reported in category 3.5 *Waste generated in operations*, and thus, k = 3.5. It is assumed that the amount of waste generated is directly proportional to costs and GHG emissions related to waste management. The ERA to reduce the GHG emissions from waste management is denoted with letter w. The reduction of GHG emissions from waste management can happen gradually, and therefore GHG emissions from category 3.5 in year t are modelled with the following function:

$$E_{3.5}(t) = \begin{cases} E_{3.5}^{(0)} & \text{if } t < t_w^{(1)}, \\ a_w \frac{E_{3.5}^{(2)} - E_{3.5}^{(0)}}{t_w^{(2)} - t_w^{(1)} + 1} (t - t_w^{(1)} + 1) + E_{3.5}^{(0)} & \text{if } t_w^{(1)} \le t < t_w^{(2)}, \\ a_w E_{3.5}^{(2)} + (1 - a_w) E_{3.5}^{(0)} & \text{if } t \ge t_w^{(2)}. \end{cases}$$
(35)

Extra costs related to category 3.5 are

$$c_{3.5}(t) = \begin{cases} 0 & \text{if } t < t_w^{(1)}, \\ a_w(c_w^{(1)} + c_w^{(2)} - c_w^{(0)}) & \text{if } t = t_w^{(1)}, \\ a_w(c_w^{(2)} - c_w^{(0)}) & \text{if } t > t_w^{(1)}. \end{cases}$$
(36)

3.3.8 Functions for business travel and employee commuting

GHG emissions from business travel are reported in category 3.6 *Business travel*, and GHG emissions from employee commuting in category 3.7 *Employee commuting*. Business travel and commuting can be done by different modes of travel $m \in M$. Activity data from business travel and employee commuting are in kilometres, e.g. 100 km travelled by train. The ERAs can take two different forms: travelling with a mode of travel can be reduced or the same route can be travelled with alternative modes. Thus, one of the elements of M refers to not travelling at all.

Travelled distance with the mode of travel m related to category k in year t follows the function

$$D_{k}^{(m)}(t) = D_{k}^{(m)(0)} + \sum_{i \in I_{k}} \sum_{n \in M} (S_{i}^{(n \to m)}(t) D_{k}^{(n)(0)} - S_{i}^{m \to n}(t) D_{k}^{(m)(0)}), \quad (37)$$

where function $S_i^{(n\to m)}(t)$ indicates share of base year's kilometres of the mode of travel *n* travelled with the alternative mode of travel *m* and $D_k^{(m)(0)}$ is the distance travelled with a mode of travel *m* in base year. Index *i* refers to ERAs related to category 3.6. The function $S_i^{(n\to m)}$ is defined as

$$S_{i}^{(n \to m)}(t) = \begin{cases} 0 & \text{if } t < t_{i}^{(1)}, \\ a_{i} \frac{S_{i}^{(n \to m)(2)}}{t_{i}^{(2)} - t_{i}^{(1)} + 1} (t - t_{i}^{(1)} + 1) & \text{if } t_{i}^{(1)} \le t < t_{i}^{(2)}, \\ a_{i} S_{i}^{(n \to m)(2)} & \text{if } t \ge t_{i}^{(2)}. \end{cases}$$
(38)

GHG emissions related to category k are calculated with function

$$E_k(t) = \sum_{m \in M} D_k^{(m)}(t) \cdot e_m, \tag{39}$$

where e_m refers to emission factor of the corresponding mode of travel. The unit of e_m is kgCO₂e/km for all $m \in M$.

It is assumed that the total costs before and after the implementation of the ERA are known. Those extra costs can rise for example from more expensive tickets or costs from employees' bike benefits. Thus, for category k, the extra costs are

$$c_{k}(t) = \sum_{i \in I_{k}} \begin{cases} 0 & \text{if } t < t_{i}^{(1)}, \\ a_{i}(\frac{c_{i}^{(2)} - c_{i}^{(0)}}{t_{i}^{(2)} - t_{i}^{(1)} + 1}(t - t_{i}^{(1)} + 1) + c_{i}^{(1)}) & \text{if } t = t_{i}^{(1)}, \\ a_{i}\frac{c_{i}^{(2)} - c_{i}^{(0)}}{t_{i}^{(2)} - t_{i}^{(1)} + 1}(t - t_{i}^{(1)} + 1) & \text{if } t_{i}^{(1)} < t < t_{i}^{(2)}, \\ a_{i}(c_{i}^{(2)} - c_{i}^{(0)}) & \text{if } t \ge t_{i}^{(2)}. \end{cases}$$
(40)

3.4 Exclusions

There are some exclusions that had to be made in order to keep the mathematical model simple enough and computation time reasonable. The exclusions are listed below.

It is always possible that even though the implementation of a ERA is started it might not be carried out as a whole. Since it cannot be predicted in advance, possible failures in implementing ERAs are excluded. Thus, it is assumed that once the implementation of an ERA is started it is also finished. In addition, the model does not have possibility to determine if one ERA needs to be implemented before another, i.e. ERAs cannot have initially specified order. Some ERAs might still be dependent on each other, e.g. heating efficiency and renewable heating both affect the same emissions category simultaneously.

Biogenic carbon dioxide emissions are also excluded from the model. Biogenic carbon dioxide emissions arise from combustion or biodegradation of biomass. For example, combustion of biofuels emits biogenic carbon dioxide. If biogenic carbon would have been included to the mathematical model, the model's complexity would have increased considerably. However, the formulas for biogenic carbon dioxide emissions are similar to ones defined above. Thus, they can be added to the model in the future.

Monetary costs from needed human resources are assumed to be included in human resources budget separate from the so called climate action budget. In real life, the man-hours available for planning the implementations are limited and might affect the outcomes of the optimisation problem. It is assumed that planning the ERAs does not require more time than the company would be able to use, and thus, the limitations due to man-hours are excluded from the model.

It can be assumed that value of money will change in the future. However, the changes are hard to predict without significant uncertainties. In this optimisation model, it is assumed that inflation and deflation will affect the company's revenue and the costs of the emission reduction actions the same way. Thus, the changes in the value of money are excluded.

One way to reduce company's climate impact would be completely changing the business model, for example, closing down a restaurant to start carbon capturing business. As this is so significant structural change and not so much of an ERA, possibility for this kind of changes are excluded from the current model.

4 Application of the emission reduction action optimising tool

Now, the optimisation model described in section above is applied in practice. Let us use Company A as a example. Company A's carbon footprint of 2023 is presented in Table 1 and is used as a base year for emission reduction action optimisation.

Catagony	GHG emissions	Share of total	
Category	(kgCO2e)	GHG emissions (%)	
1.1 Company facilities	34	0.51%	
1.2 Company vehicles	409	6.1%	
2.1 Purchased electricity (market based)	267	4.0%	
2.2 Purchased steam	0	0%	
2.3 Purchased heating energy (market based)	1031	15%	
2.4 Purchased cooling energy	0	0%	
3.1 Purchased goods and services	2420	36%	
3.2 Capital goods	0	0%	
3.3 Fuel and energy related activities	249	3.7%	
3.4 Upstream transportation and distribution	0	0%	
3.5 Waste generated in operations	124	1.8%	
3.6 Business travel	1687	25%	
3.7 Employee commuting	333	4.9%	
3.8 Upstream leased assets	189	2.8%	
3.9 Downstream transportation	0	0%	
3.10 Processing of sold products	0	0%	
3.11 Use of sold products	0	0%	
3.12 End-of-life treatment of sold products	0	0%	
3.13 Downstream leased assets	0	0%	
3.14 Franchises	0	0%	
3.15 Investments	0	0%	
Total	6744	100%	

Table 1: Carbon footprint of Company A in 2023 used as the base year.

Company A is a small enterprise focusing mainly on consulting. Thus, GHG emissions from its own operations (scope 1) are relatively small (6.6% from the total carbon footprint). The company owns one diesel car and a mini-fridge which emit its scope 1 emissions. Purchased energy makes up around one fifth of the total carbon footprint of 2023.

Almost two thirds of the emissions arise from Company A's value chain (scope 3) (see Figure 1). The most significant emission sources are purchased goods and services and business travel which make up of 36% and 25% of the total emissions, respectively. Almost 80% of the emissions in category 3.1 *Purchased goods and services* arise from services. Company A's business travelling consists solely of business flights. Company A has not purchased large amounts of goods or transported products and thus, purchased services are highlighted in the scope 3 emissions.

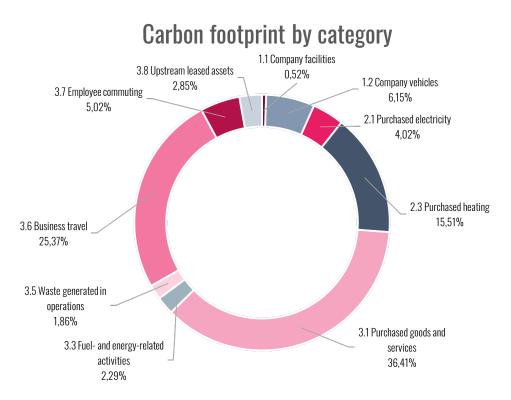


Figure 1: Carbon footprint of Company A in 2023 by category.

Company A has set emission reduction targets for the future. The targets are based on Science Based Targets initiative (2024): The near-term absolute reduction targets are defined for scope 1 and 2 by formula

$$Target_{1,2} = \begin{cases} 4.2\% \cdot (Target year - Base year), & \text{if Base year} \le 2020 \\ 4.2\% \cdot (Target year - 2020), & \text{if Base year} > 2020, \end{cases}$$
(41)

and for scope 3 by formula

$$Target_{3} = \begin{cases} 2.5\% \cdot (Target year - Base year), & \text{if Base year} \le 2020\\ 2.5\% \cdot (Target year - 2020), & \text{if Base year} > 2020. \end{cases}$$
(42)

As Company A's base year is 2023, the near-term target for year 2030 are 42% for scope 1 and 2, and 25% for scope 3. The long-term absolute reduction target for 2050 is set to 95%.

To meet these targets, Company A needs to reduce its GHG emissions but it has a limited budget. Company A has planned some emission reduction actions but may not be able to implement all of them due to monetary limits. Thus, the mathematical model described in 3.3 is used to find the most cost-effective ERAs to be implemented and the optimal timeline for the implementation. Next, the used assumptions and the planned ERAs are presented.

4.1 General assumptions

Company A has annual target to grow 5% with respect to revenue. The Company A is a consulting enterprise so the revenue growth is assumed to be directly linked to number of employees. Increasing number of employees requires more travelling, a larger office, and more purchased services (e.g. more visits to occupational healthcare). Since all the GHG emission sources and emission reduction actions described below are either directly or indirectly linked to the number of employees, it is assumed that the GHG emissions of Company A would increase with the same rate as the revenue if no ERAs were implemented. The ERAs cause costs to Company A. As the ERAs are also linked to the number of employees, the costs from ERAs are also assumed to grow with the same rate as the revenue. It is realised that this is not the direction Company A should be headed at. Sustainable enterprises should have growth of revenue separated from the GHG emissions. But since there is still not enough data on how the GHG emissions start to change with respect to revenue, this is the best assumption available.

Company A has set an annual budget in which the costs from ERAs should stay. In 2024, the budget is $2500 \in$. The budget is set as a specific share from Company A's revenue and thus, it also grows 5% a year. As the GHG emissions, extra costs from ERAs, and the budget all grow 5% a year, the growth rate does not affect the optimisation model and its results. Thus, regardless of the growth rate, the optimal timeline and the ERAs that should be implemented remain the same. Still, the revenue growth should be taken into account in the results, e.g. in cumulative GHG emissions and costs through the years.

The optimisation of emission reduction actions are examined for the next ten years, i.e. for year 2024-2033 since 2023 is the base year. This is, the ERAs can be implemented between 2024-2033 and cumulative GHG emissions for the time period are minimised.

4.2 Emission reduction actions included in the model

4.2.1 Refrigerants

Company A has a cooling device that uses R134a as its refrigerant. Now, the refrigerants used have a major global warming potential (GWP), and thus changing them to low-emission alternatives will decrease Company A's GHG emissions. The refrigerant R134a can be replaced with R450a which has GWP of 547 (Makhnatch et al., 2017) which is 62% smaller GWP than R134a. Changing to R450a does not require new device purchases. Thus, only costs from the ERA would be increased costs from refrigerant purchases. In this application, it is assumed that R134a costs 48 C/kg and R450A costs 69 C/kg. Makhnatch et al. (2017) found that replacing R134a with R450a may slightly decrease in energy performance of the refrigeration system, but this is excluded from the calculations.

In the future, it may be possible to update the whole device so that it can use carbon dioxide (CO_2) as a refrigerant. This will decrease scope 1 emissions drastically but, on the other hand, scope 3 emissions will increase since new device has to be

purchased. This also increases additional costs. At a moment, CO₂ refrigerants (R774) are not commonly used in household refrigerators (Danfoss, 2022) and they require high pressure to operate which will increase the energy consumption of the device. Still, they are seen as a promising low-emitting solution. Thus, one ERA is to update Company A's cooling device to new device which is compatible with R774. Following assumptions are made: R774 costs two times more than R134a, i.e. 98 C/kg. A new refrigerator will cost 200 C.

Only one of the ERAs presented above can be implemented. This is included as a constraint to the optimisation model. For both ERAs, it is assumed that the whole implementation has to be done at once. This is because Company A owns only one cooling device and the implementation cannot happen bit by bit.

4.2.2 Vehicles

Company A owns one diesel car. The car is used occasionally for travelling to customer sites. Two ERAs are included to the model: 1) fossil diesel is switched to biodiesel, and 2) leasing contract is changed from diesel car to battery electric vehicle (BEV). First option is more affordable since it does not require leasing a more expensive vehicle but the GHG emission reductions remain in lower level.

In both cases, a distribution obligation is taken into account. The distribution obligation determines how big share of sold fuels must be of biological origin. This means that emission reductions will decrease in the future without Company A's contribution since also the "normal" diesel will have larger biodiesel content. The distribution obligation results in an uncertainty because it can be changed by the government. For example, Orpo's government has planned reductions to the percentages for the future years. Thus, distribution obligation used in this optimisation model may not reflect the real situation later on.

It is assumed that manufacturing and distribution of biodiesel emits as much GHG emissions as manufacturing and distribution of fossil diesel. Also, if changed to BEV, the vehicle will not be charged at the office. Thus, indirect emissions from use of BEV are reported in category 3.3 *Other fuel related activities*. Charged electricity is assumed to have same GHG emissions per kilowatt-hour than electricity in Finland had in 2022.

It is noted that reducing driven kilometres and evaluating if leasing a vehicle is even necessary are also possibilities. However, since they are not seen as a feasible options from Company A's perspective, they are excluded from the model.

 cents per kWh (Statistics Finland, 2024b) compared to diesel which costs 1.75 € per litre. The electricity consumption of the BEV is assumed to be 0.40 kWh/km (VTT, 2018).

4.2.3 Electricity

Company A has consumed approximately 1 750 kWh of electricity in a base year 2023. Company A did not have separate renewable electricity contract.

One ERA is to increase energy efficiency. The target is to decrease electricity consumption by one fifth by changing to led lighting. Energy renovations will have initial costs. Changing to led lighting is assumed to cost 411 €. This ERA will not have reoccurring costs.

Another ERA related to electricity is to start purchasing renewable electricity. In the base year, the share of purchased renewable electricity contracts was 0%. The target is set to 100%. The electricity provider, from which Company A purchases its electricity, had already 77% renewable electricity in their consumption mix. As Finland's target for renewable energy is 51% for year 2030 (Motiva, 2024), the share of renewable energy is assumed to stay at the base year level till 2030. Tahir et al. (2019) has presented a pathway for 80% renewable energy in 2050. This is seen as a feasible target and will be used as the target level for 2050. The assumptions are targets and estimates for the future and thus, they contain uncertainties. The consumption mix of Company A's electricity provider may have annual fluctuation which cannot be predicted. Thus, the annual emission may differ.

It is assumed that starting to purchase renewable energy will have no initial costs but renewable electricity will cost 0.04 C/kWh more than regular electricity following national targets. Changing to renewable electricity will decrease Company A's scope 2 emissions. It also may have effect on scope 3.3 emissions, but in this model it is assumed that production and distribution of renewable energy will emit the same amount of GHG emissions as the electricity from fossil sources.

4.2.4 Heating

Company A has consumed approximately 6 350 kWh heat in the base year 2023. Company A did not have separate renewable heating contract.

One ERA is to increase energy efficiency. The target is to decrease heat consumption by 12.5% by weatherproofing windows and doors. It is assumed that weatherproofing windows and doors at the office building will cost 400 \mathbb{C} . After that there will be no reoccurring costs.

Another ERA related to heating is to start purchasing renewable heating. In the base year, the share of purchased renewable heating was 0%. The target is set to 100%. The consumption mix of Company A's district heating provider had 20% renewable energy in the base year. As targets in Motiva (2024) and Tahir et al. (2019) are for energy as whole, they are also used as national pathways for 'regular' heating. This means, the share of renewable district heating will be 51% in 2030 and 80% in 2050.

It is assumed that starting to purchase renewable energy will have no initial costs but renewable heating will cost 0.10 C/kWh more than regular heating following national targets. Changing to renewable heating will decrease Company A's scope 2 emissions. It also may have effect on scope 3.3 emissions, but in this model it is assumed that production and distribution of renewable heating will emit the same amount of GHG emissions as the heating from fossil sources.

4.2.5 Purchased goods and services

Company A has purchased products and services during the base year, and has planned ERAs to decrease their emission. The emission intensity of the services would be screened during competitive tendering. This is assumed to result in a 25% decrease in emissions from purchased services. However, including the emission intensity to competitive tendering will have an opportunity cost of 450 \mathbb{C}/a .

An ERA related to purchased goods is to buy second-hand IT products (e.g. monitors) and office furniture. This would be done by creating guidelines for company purchases. No GHG emissions are allocated to the purchase of second-hand products. Buying second-hand products will most likely be more inexpensive. However, finding suitable products from second-hand markets will require more time than buying them from retailers. These assumptions are assumed to cancel each other out. Thus, the ERA will not have any initial or reoccurring costs.

It is probable that the carbon footprint of services decreases in future since companies providing those services start to decrease their own GHG emissions. This would also decrease Company A's GHG emissions. However, it is still Company A's responsibility to ensure that they use services providers that are engaged in reducing their climate impact. Therefore, it is assumed that if Company A does not implement the ERA to purchase low-emitting services, the GHG emissions of those service remain at the base year level.

4.2.6 Waste management

It was estimated that Company A generated 200 kg of waste per each full-time equivalent (FTE). One ERA is to reduce waste by 50%. Planning a waste reduction campaign will have an opportunity cost of $600 \in$. This is seen as a implementing cost. There are no reoccurring costs related to this ERA.

Some companies might save money by reducing waste due to reduced waste management costs. In the case of Company A, the costs are fixed and are included in the rental of Company A's office. Thus, no monetary gains are achieved with waste reductions. Waste generation can be reduced gradually: the change in the amount of emissions from waste management is assumed to be linear between the starting year and the ending year of the ERA.

4.2.7 Business travel

In the base year, all Company A's employees took a trip to science conference in Stuttgart, Germany. This has been an annual tradition. As an ERA, the travelling would be done by train. Distance from Helsinki to Stuttgart is assumed to be the same by aeroplane and by train. This will decrease emissions but increase costs.

A one-way flight from Helsinki to Stuttgart, Germany is assumed to cost $120 \in$ per passenger (estimated from *momondo.fi*) and travelling the same route by train is assumed to cost $191 \in$ (Interrail, 2024). Extra costs related to change of the mode of travel, e.g. increased amount of daily allowances needed to pay to employees due to longer travel times, are excluded.

4.2.8 Employee commuting

A company can reduce its emissions by offering commuting benefits to its employees. Two options are considered: One is offering a bike benefit which is assumed to reduce commuting by tram and bus by 40%. Other is to offer public transportation benefit. With this benefit, employees are assumed to make 40% of their previous car commuting by train.

Offering these benefits will have reccurring costs. Bike benefit is assumed to cost 12 C/month per employee, i.e. 144 C/a per employee. Public transport benefit is assumed to cost 79 C/10 trips. Thus, the costs from ERAs related to employee commuting depend on the number of employees the benefits are addressed. The ERAs have no initial costs from implementation.

4.3 Optimisation problem and algorithm parameters

The objective of the application is to minimise Company A's cumulative emissions of the next ten years, i.e. 2024-2033. Thus, T = [2024, 2025, ..., 2033]. The base year is 2023, i.e. $t^{(0)} = 2023$. Company A has set an annual budget of 2500 \mathbb{C} for extra costs from emission reduction actions and thus, B(t) = 2500 for all t. The extra costs $c_k(t)$ and emissions $E_k(t)$ for each year and category are calculated based on assumptions described in Section 4.2.

The formulation of the optimisation problem in Excel has been modified slightly from one presented in Section 3.3. The number of decision variables are reduced by omitting the variables a_i for all $i \in I$ to corresponding starting and ending years. In the Excel model, if the ERA *i* is not implemented, the starting and ending years are forced to be zero ($0 \notin T$). The Excel model is implemented using functions configured to Excel.

In this thesis, an evolutionary algorithm is used to solve the optimisation problem defined in Section 3.3. The Excel solver allows one to choose values for different parameters, which are constraint precision, integer optimality, convergence, population size, mutation rate, and terminal time. Values for these parameters, excluding population size and mutation rate, are presented in Table 2. The values of population

size and mutation rate will be chosen later in this section. Automatic scaling is used and the decision variables are forced to be constrained.

Parameter	Value	Unit
Terminal time without better solution	1 800	S
Overall terminal time	1 800	S
Convergence	0.01	
Constraint precision	1	%
Integer precision	1	%

Table 2: Fixed parameter values used in Excel Solver.

The constraint precision determines how precisely the constraints have to be satisfied. The integer optimality discloses which values of decision variables are seen as integers. For example, if the integer optimality is 1%, value 1.009 is seen as an integer equal to 1. A population (or generation) in the evolutionary algorithms means a sample of candidate solutions to the optimisation problem that are compared to each other and used to generate a new population. Thus, the population size determines how large sample is used. Larger population sizes result in a longer computing time but may lead to more a better solution. The evolutionary algorithm has also a probabilistic component, the mutation. The mutation rate gives the probability in which the individual in a generation is mutated. The stopping criteria are the terminal time and convergence. The terminal time has two parts: one is the total computing time and the other is the computing time without improvement to the solution. Convergence determines how close the objective values of individuals in one population have to be to each other so that the algorithm can be said to have converged to an optimum.

To choose the best parameter values, we have tested different values of mutation rate and population size. Large values of mutation rate increase the randomness of the search process of the evolutionary algorithm. Having a large mutation rate will prevent algorithm from converging to a local optimum instead of a global but on the other hand, might increase the computation time. With a smaller mutation rate the algorithm might find only a local optimum, but the convergence will be faster (Frontline Systems, n.d.-b).

The default value for mutation rate in Excel solver is 0.0075. For population size, it is ten times the number of decision variables but at most 200 (Frontline Systems, n.d.-b). With the ERAs described in Section 4.2, the problem has 28 decision variables, since variables a_i for all $i \in I$ are omitted for starting and ending years of the ERAs.

Tested values for population size and corresponding results are presented in Table 3. Fixed mutation rate of 0.005 is used. Same population sizes are tested with different random seeds to see how the results differ between runs. We see that with smaller population sizes, the algorithm converges faster. A population size of 280 is tested since the default size used in Excel solver was ten times the number of decision variables. The smallest cumulative emissions were found with population sizes and shorter computing times. The two other solutions with population size of 10 000 were not as

Population size	Computing time (s)	Value of the objective function (tCO2e)	Cumulative costs (t€)
100	603	29.54	25.18
100	379	34.41	24.27
100	386	59.54	6.04
280	916	28.97	25.48
280	817	34.28	24.33
280	878	28.94	25.61
1 000	654	28.94	25.61
1 000	1 308	28.94	25.61
1 000	1 848	29.35	24.50
10 000	1 840	28.96	25.47
10 000	1 848	28.81	25.55
10 000	1 889	28.94	25.42

Table 3: Analysis of different population sizes with mutation rate of 0.005.

good. Thus, a large population does not guarantee the best solution. The model did not perform well with the population size of only 100. When using the optimisation model in customer projects, the computing time is important: it must be possible to run the algorithm several times in limited time periods. Thus, we will use the population size of 280 in the subsequent analysis.

Next, we will test different mutation rates to see how they affect the computing time and the value of the objective function (Table 4). The population size is fixed to 280. Larger values in mutation rate increase the computing time significantly but the found results improved only a little. Since the mutation rate of 0.0075 was the default value in Excel Solver, we will use rate of 0.01 to obtain the results.

For the results, a population size of 280 and a mutation rate of 0.01 was chosen. The optimisation algorithm is run five times with different random seeds. The results of the iterations are presented in Table 5. Value of the objective function is the smallest in the fourth iteration. Results of this iteration are presented in Section 4.4.

Mutation rate	Computing time (s)	Value of the objective function (tCO2e)	Cumulative costs (t€)
0.005	1 104	28.97	25.19
0.01	1 069	28.97	25.50
0.05	1 107	28.94	25.61
0.1	2 000	28.82	25.58
0.2	1 804	28.94	25.61
0.4	1 805	28.94	25.61

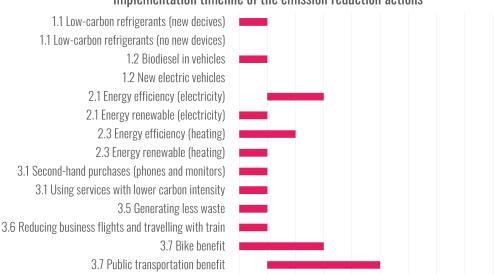
Table 4: Analysis of different mutation rates with population size of 280.

Iteration	Computing time (s)	Value of the objective function (tCO2e)	Cumulative costs (t€)
1	565	33.37	24.38
2	1218	29.21	25.59
3	963	50.11	18.15
4	693	28.85	24.74
5	878	29.57	25.06

Table 5: Analysis of the results with a mutation rate of 0.01 and a population size of 280.

4.4 Results

The objective of the application is to minimise cumulative emission of Company A. With a budget of 2 500 euros and implementation timeline of ten years, i.e. 2024-2033, the optimal timeline to implement ERAs described in Section 4.2 is presented in Figure 2. In this Figure, the pink bars refer to the time period in which the ERA is implemented, i.e. the bar goes from the starting year to the ending year of the implementation. If the ERA has no bar, it is not implemented.



Implementation timeline of the emission reduction actions

Figure 2: Optimal timeline for implementation of the planned ERAs.

There were exclusive ERAs within categories 1.1 *Company facilities* and 1.2 *Company vehicles* meaning that only one ERA within the category could be implemented. From Figure 2 we see that in category 1.1 ERA to purchase a new device with low-emitting refrigerants was implemented, and in category 1.2 ERA to change to biodiesel was implemented. All other ERAs were implemented. Thus, no ERAs

^{2024 2025 2026 2027 2028 2029 2030 2031 2032 2033 2034}

Measure	Value	Unit
Target year emissions (2033)	3 546	kgCO2e/a
Cumulative emissions (2024-2033)	28 846	kgCO2e
Total costs (2024-2033)	24 737	€

Table 6: GHG emissions and extra costs from implementing recommended emission reduction actions.

were excluded due to monetary limitations. Almost all the ERAs are implemented in 2024 which is the first possible year for the implementation.

Emission reduction actions were planned for the next ten years, i.e. 2024-2033, and the annual GHG emissions for that time period are in Figure 3. The cumulative GHG emissions of those years are estimated to be 28 846 kgCO₂e. The costs from the ERAs would be 24 737 \in for the same time period. The results are also presented in Table 6. If Company A did not implement any ERAs, its cumulative GHG emissions between years 2024-2033 would be 89 069 kgCO₂e which is 209% more than with recommended ERAs. A comparison on the development of GHG emissions with and without implementing the ERAs is in Figure 4.

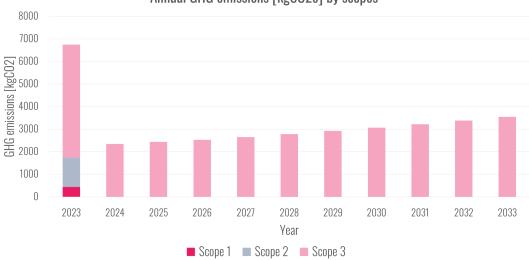




Figure 3: Estimated GHG emissions of Company A for ten year time period.

Estimated GHG emissions of Company A for years 2023-2033 are presented in Figure 3. Since majority of the ERAs are implemented in the first possible year, we see a significant drop in GHG emissions between year 2023 and 2024. As it is assumed that Company A's revenue grows annually 5% and the GHG emissions grows at a same rate, we see that right after 2024 the emissions start to increase. There are no scope 2

GHG emissions, i.e. the GHG emissions from purchased energy, after the base year 2023, since all the energy contracts are changed to renewable ones in 2024. Thus, GHG emissions rise from scope 1 and 3 activities. However, the GHG emissions in scope 1 are so low after the base year, they cannot be seen in Figure 3.

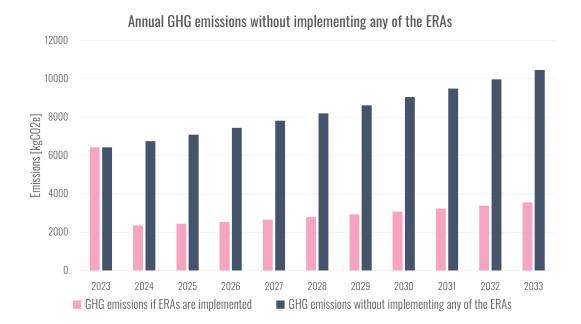
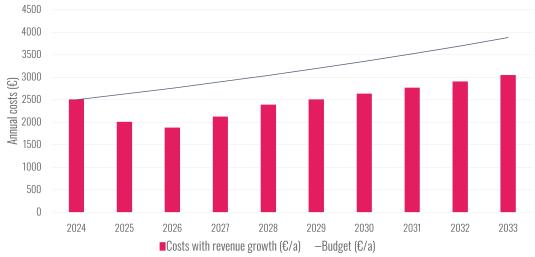


Figure 4: Comparison of GHG emissions in a scenarios where the ERAs are implemented in the given timeline and where none of the ERAs are implemented.

The budget was set to be $2500 \\ \\mbox{ constraints}$, and it is assumed to grow 5% a year, i.e. with the same rate as the revenue. Annual extra costs and the budget are presented in Figure 5. As we see from the figure, the extra costs from the ERAs remain below the budget, and after 2024, there is a gap of 500-1 000 \\mbox{ costs} between the extra costs and the budget in every year. This means that the budget is actually not a binding constraint. If the growth of Company A was excluded, the extra costs would remain constant from 2028 onwards.

In Figure 6, the line indicates Company A's emission reduction targets. The target for year 2030 is to reduce scope 1 and 2 GHG emissions 42% from the base year and scope 3 GHG emissions 25% from the base year. These targets are combined in Figure 6. In 2050, the total GHG emissions should be reduced 95% from the base year. As we can see, Company A will meet the targets set to 2030 if the implementation of recommended ERAs is done in given timeline. However, without additional ERAs, Company A will not meet the SBTi based target of year 2050 (Figure 6).



Extra costs from implementing ERAs

Figure 5: Extra costs for Company A from implementing the optimal emission reduction actions in recommended timeline.

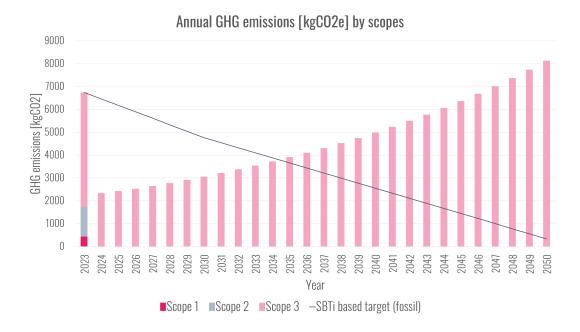


Figure 6: Estimated GHG emissions of the Company A for 2023-2050 compared with SBTi-target.

5 Discussion

5.1 Construction of the optimisation model

In this thesis, we have created an optimisation model that will help enterprises choose the most feasible emission reduction actions and timeline for their implementation. The model minimises the cumulative GHG emissions of the company over some time period. Constraints arise from monetary limitations which are included to the model by setting an annual budget that cannot be exceeded. The optimisation model is able to show which emission reduction actions are the most cost-effective. Cost-effectiveness is often one of the decision-making criteria, and thus, the annual costs are important information for the companies.

The optimisation model has room for improvements. Now, as the optimisation was completed in Excel, available algorithms were limited. Therefore, the model could be improved by implementing it in different software or writing it in some programming language that provides optimisation tools. This could lead to a broader selection of optimisation algorithms.

In general, it is possible to have an optimisation problem with two objective functions. One could minimise cumulative GHG emissions while simultaneously minimising costs. Multi-objective optimisation is used for this purpose for example in Kumar and Kumar (2024), Cardenes et al. (2020), and Sweetapple et al. (2014). Now, the costs are managed only by budgets and thus, it might be possible to obtain the same emission reductions but with lower costs. As lack of time was also seen as a challenge for climate actions within enterprises (Avidly, 2019), needed human resources could be integrated to the optimisation model as an additional constraint. Currently, time needed to plan the ERAs are just seen as a cost and the needed time might exceed available resources of the company. This would lead to situation where the recommended emission reduction actions cannot be implemented.

It was also assumed that the GHG emissions increase with the same rate with the revenue if no emission reduction actions are implemented. This is always not the case. Thus a feature, where one could set a separate growth rates for GHG emissions and revenue, should be added. This will make it more dynamic for different applications.

5.2 Application of the optimisation model

The optimisation model created in this thesis was then applied to Company A's situation. With the set budget and planned emission reduction actions, the Company A is able to meet the SBTi based targets for 2030 but not for 2050. Company A's annual GHG emissions dropped 45% from 2023 to 2033. This means annual decrease of 4.5% from the base year. Tapio et al. (2023) found that Finnish companies with SBTi targets reduced their GHG emissions 3% in a three year interval, i.e. the companies have had 1% annual decrease from the base year. Thus, with the recommended emission reduction actions and the implementation timeline, Company A would stand out from this trend. However, it is important to notice that the current recommendations will not reach the SBTi based target of 2050, if Company A wants to grow 5% a year. In

fact, the annual GHG emissions in 2050 would be even larger than in the base year. Comparing own GHG emissions to ones of other companies may be sensible, but the GHG emissions should also be screened against science based targets.

The optimisation revealed that with the set budget, Company A has money to implement additional emission reduction actions not presented in Section 4.2 to decrease its GHG emissions. In general, if the budget was a binding constraint in all years 2024-2033, a company could use the optimisation model to screen effects of larger budgets. For example, how much the budget should be increased that the company could implement all the planned ERAs within chosen time period. This would be meaningful especially in the case where the company is not sure how large budget they are willing to give for emission reduction actions.

Since the optimisation model is developed to be used in optimising real-world companies' emission reduction actions, it should be viewed from the business point of view. Now, the model implies that many of the ERAs should be implemented right at the first year. If the implementation is done in one year, the model assumes that the GHG emissions drop to zero at the beginning of that year. This would mean that majority of the ERAs should be implemented at the same day, which is, in reality, not feasible due to limited human resources. Also, in business world, a ten year time-horizon is relatively long. In this application, all the ERAs are recommended to be implemented during the first three years. Therefore, there is no need for investment planning far to the future. In the other applications however, the implementation timeline may be a lot longer which may force the companies to make long-term decisions. The possible time-frame for implementation of the ERAs can be changed in the model and therefore, it can be fitted to be aligned with company's decision-making horizon.

6 Conclusions

This thesis consists of two parts. In the first part, we have implemented a mathematical model that can be used to minimise companies' climate impact by choosing which emission reduction actions should be implemented and in which timeline. As costs of the climate actions were seen one of the significant challenges within the companies, one of the inputs of the optimisation model was budget that limits extra costs arising emission reduction actions. In the second part, the optimisation model was applied to Company A's GHG emissions and emission reduction actions they have planned. This is to see how the model works in practice.

The model was created to help companies plan their emission reduction actions. The climate work of Finnish companies has a lot room for improvements: even the GHG emissions of the companies that have committed to SBTi targets have not decreased enough. Thus, there would be need for tools that will help companies to make informed cost-efficient decisions. To make the model feasible to users with no prior programming experience, the model is implemented in Excel. The optimisation is conducted using Excel solver and an evolutionary algorithm.

Even though the optimisation model has possibilities for improvement, it is able to give a picture of the effects and costs of the emission reduction actions. As the model is made to be customisable to customers needs, relevant features, as new emission reduction actions or additional constraints, can be inserted afterwards.

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