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A Techno-Economic Decision-Support Framework for Semiconductor Fab Decarbonization

YI LUN HUNG

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A Techno-Economic Decision-Support Framework for Semiconductor Fab Decarbonization

Yi Lun Hung

Approved 2026-09-05	Examiner Farzin Golzar	Supervisor Farzin Golzar
TRITA: TRITA-ITM-EX 2026:623	Industrial Supervisor Vincent Schellekens, imec	Contact person Vincent Schellekens, imec

TRITA – TRITA-ITM-EX 2026:623
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www.kth.se

Abstract

Semiconductor manufacturing is resource- and energy-intensive and is currently expanding rapidly due to supply chain diversification and high demand for artificial intelligence (AI) applications. Semiconductor manufacturers face higher costs, greater emission reduction pressure, and different regional conditions. This thesis aims to develop a transparent decision framework to help evaluate semiconductor fabrication facility (fab) decarbonization projects based on cost, emission reduction goals, budget, and regional conditions.

The developed portfolio selection model simulates a 28 nm (N28) fab with 14 candidate projects for Scope 1 process gas and Scope 2 electricity emissions. The projects are evaluated under different grid carbon intensities, carbon prices, and electricity prices. Four main scenarios are compared. Important assumptions are also tested through sensitivity analysis.

The Belgium scenarios achieved 79% of the model annual reduction target and used 97% of the budget. Due to the higher grid carbon intensity used in the Taiwan scenarios, the Taiwan scenarios achieved 110% of the same model annual reduction target and used 96% of the budget. Ten projects were commonly selected across all four main scenarios. Project P07b, a plasma abatement improvement project, had the largest contribution to CO_2e reduction. In the tested cases, increasing the carbon price or electricity price changed the annualized net cost but did not change project selection. In the sensitivity analysis, budget, project cost, and project reduction assumptions changed the selected portfolio.

The model uses proxy input data and a simulated fab. Therefore, the results can support preliminary evaluation but are not intended for direct project selection in a real fab.

Keywords
Semiconductor manufacturing, fab decarbonization, energy efficiency, techno-economic modeling, project portfolio selection, decision support framework, Scope 1 and Scope 2 emissions, regional conditions, budget constraints.

Sammanfattning

Halvledartillverkning är resurs- och energiintensiv och expanderar snabbt på grund av diversifiering av leveranskedjor och hög efterfrågan på AI. Halvledartillverkare står inför högre kostnader, större tryck på utsläppsminskningar och olika regionala förutsättningar. Denna avhandling syftar till att utveckla en transparent beslutsram för att utvärdera avkarboniseringsprojekt i halvledarfabriker baserat på kostnad, utsläppsminskningsmål, budget och regionala förhållanden.

Den utvecklade portföljmodellen simulerar en N28-fabrik med 14 kandidatprojekt för Scope 1-processgaser och Scope 2-elutsläpp. Projekten utvärderas under olika nätkolintensiteter, koldioxidpriser och elpriser. Fyra huvudsakliga scenarier jämförs. Viktiga antaganden testas också genom känslighetsanalys.

Belgien-scenarierna uppnådde 79 % av modellens årliga CO_2e-reduktionsmål och använde 97 % av budgeten. På grund av elnätets högre koldioxidintensitet uppnådde Taiwan-scenarierna 110 % av samma modellmål och använde 96 % av budgeten. Tio projekt valdes i alla fyra huvudsakliga scenarier. P07b hade det största bidraget till CO_2e-minskningen. I de testade fallen förändrade en ökning av koldioxidpriset eller elpriset den årliga nettokostnaden men ändrade inte projektvalet. I känslighetsanalysen ändrade budget, projektkostnad och antaganden om projektets reduktion den valda portföljen.

Nyckelord
Halvledartillverkning, fabriksavkarbonisering, energieffektivitet, tekno-ekonomisk modellering, projektportföljval, beslutsstödsram, Scope 1- och Scope 2-utsläpp, regionala förhållanden, budgetbegränsningar.

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Finally, I would like to thank the imec Sustainable Semiconductor Technologies and Systems team for providing the environment to conduct this thesis on reducing the environmental impact of fab processes.

List of abbreviations

Abbreviation	**Explanation**
AI	Artificial Intelligence
BE	Belgium
CAPEX	Capital Expenditure
CDA	Compressed Dry Air
CDP	Carbon Disclosure Project
CMOS	Complementary Metal-Oxide-Semiconductor
CO_2e	Carbon Dioxide Equivalent
CRF	Capital Recovery Factor
DRE	Destruction and Removal Efficiency
DRAM	Dynamic Random-Access Memory
ETS	Emissions Trading System

EU	European Union
FFU	Fan-Filter Unit
FOM	Hydrofluoric Ozonated Mixture
GHG	Greenhouse Gas
GWP	Global Warming Potential
HTF	Heat Transfer Fluid
HVAC	Heating, Ventilation and Air Conditioning
IC	Integrated Circuit
ICAP	International Carbon Action Partnership
MAC	Marginal Abatement Cost
MACC	Marginal Abatement Cost Curve
MAU	Make-Up Air Unit
MILP	Mixed-Integer Linear Programming
N28	28 nm technology node
OPEX	Operating Expenditure
PCW	Process Cooling Water
TSMC	Taiwan Semiconductor Manufacturing Company
TW	Taiwan
VFD	Variable Frequency Drive
VSD	Variable Speed Drive
WACC	Weighted Average Cost of Capital

WSPM	Wafer Starts per Month

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1 Introduction

1.1 Background

As semiconductor nodes advance, semiconductor manufacturing becomes increasingly challenging. The manufacturing process becomes more complex, more resource-intensive, and more costly. To enable complementary metal-oxide-semiconductor (CMOS) technology further scaling to sub-10 nm nodes, semiconductor manufacturing has adopted new fabrication approaches, including multi-patterning lithography, more complex transistor architectures, and increasingly diverse materials [1]. From 110 to 14 nm technology node evolution, the integrated circuit (IC) manufacturing cumulative energy demand more than doubled [2]. In addition, each time the industry moves to a more advanced technology node, wafer costs usually rise by 20–25%, a commonly accepted benchmark [3]. However, more advanced node transitions have exceeded this range. For example, wafer cost was projected to increase by 32% from 16 nm to 10 nm based on 193 nm immersion multiple-patterning lithography, followed by a further 14% increase at the 7 nm node [2]. As a result, chip manufacturing has become significantly more expensive. Continued scaling is therefore no longer only a technical issue, but also an economic one.

The expansion of semiconductor manufacturing across regions has increased operational pressure because of varying local conditions. AI-related demand has accelerated investment in global 300 mm semiconductor manufacturing capacity, and fab equipment spending is projected to increase to 133 billion USD in 2026 and 151 billion USD in 2027 [4]. Furthermore, led by government policy, localization and self-sufficiency efforts in the semiconductor supply chain have further driven the expansion

of semiconductor manufacturing in different regions. Nevertheless, uneven local conditions, including power supply, water availability, and environmental regulation, strongly influence fab development and operation. For example, Lepawsky noted that around 40 percent of existing facilities, 24–40 percent of facilities under construction, and 40–49 percent of facilities announced since early 2021 are expected to face high or extremely high water stress in 2030 and 2040 [5]. Differences across locations and uneven resource availability can therefore create both environmental and operational risks for global semiconductor supply chain security.

To be more sustainable and remain competitive, semiconductor manufacturers need to balance cost, resource reduction, and technology. Improving equipment and utility infrastructure is a common approach to tackling these challenges. Since not all improvement projects can be implemented, manufacturers need to select projects based on available budgets and regional operating conditions.

1.2 Problem Statement

Semiconductor firms face increasing pressure from investors, regulators, and other stakeholders to demonstrate credible progress toward decarbonization. Fabs implement improvement projects to reduce electricity use, water consumption, and greenhouse gas emissions. For example, Taiwan Semiconductor Manufacturing Company (TSMC) discloses its decarbonization targets and related actions in its annual sustainability report [6]. Many potential improvement projects are available. However, deciding which projects to prioritize is not straightforward. Projects differ in costs and reduction potential. Under limited budgets, manufacturers need to identify which projects can best support greenhouse gas emission targets while still providing long-term economic value. This decision becomes more difficult when local operating conditions are considered, as electricity price, carbon-related cost, and regional environmental requirements differ across locations.

1.3 Research gap

A transparent decision-support framework is needed to compare projects and prioritize investments for a specific fab. Existing studies have investigated the environmental impacts of semiconductor manufacturing and the performance of different reduction measures at fab and subsystem levels. Studies have evaluated facility and utility improvements such as process cooling water (PCW), heating, ventilation and air

conditioning (HVAC), and compressed dry air (CDA), as well as process gas emission reduction measures. These studies mainly focus on the technical performance of individual measures. In addition, economic assessments of individual semiconductor decarbonization projects have been conducted using methods such as marginal abatement cost curves (MACCs), based on project cost, savings, lifetime, emission reduction, and discount rate. Portfolio selection under limited budgets and emission reduction goals has also been studied, but mainly in other industrial sectors.

Within the semiconductor literature reviewed in this thesis, an integrated portfolio framework was not identified that connects fab or subsystem level emission reduction impacts with project economic data, regional electricity and carbon conditions, emission targets, and investment constraints. Such a framework could help compare and prioritize semiconductor fab projects under different locations and user-defined conditions.

1.4 Research questions

Main research question

- Which improvement projects should a semiconductor fab prioritize under local conditions and budget limits to meet its CO_2e reduction target?

Supporting questions

- Which combination of projects can meet the CO_2e reduction target at the lowest annualized net cost?
- How much of the CO_2e reduction target can be achieved under different budget constraints?
- How do local conditions, including electricity price, grid carbon intensity, and carbon price, affect the selected portfolio and model results?

1.5 Purpose and objective

This thesis aims to develop a techno-economic model to evaluate and prioritize improvement projects for semiconductor fab decarbonization. The model compares

candidate projects in terms of reduction potential and economic performance under different user-defined scenario conditions. It incorporates practical decision constraints such as limited budgets and CO_2e reduction targets.

The overall objective is to support semiconductor manufacturers in making project investment decisions by considering technical, economic, and environmental factors together. The thesis presents a decision-support framework and demonstrates its application using a simulated fab and proxy input data. The resulting portfolio illustrates how the framework can be applied.

1.6 Scope and limitations

This thesis simulates an N28 fab under a fixed production capacity. The baseline fab data are based on the imec.netzero N28 dataset. This dataset is used as the reference baseline input for the model. The model evaluates candidate improvement projects that do not affect production throughput, including projects related to process gas, CDA, PCW, exhaust, cooling, and other infrastructure or utility systems. The model mainly includes electricity-saving projects and direct Scope 1 CO_2e reduction projects. The selected projects are evaluated under different scenario settings based on their reduction impact and cost data.

There are several limitations in this thesis. First, the input data are distributed across several departments and are frequently incomplete or unavailable. The reduction impact and subsystem baseline of some projects are estimated. Exact project cost data and operational data, such as capital expenditure (CAPEX), operating expenditure (OPEX), and lead times, are not fully available. In real fab cases, these values can vary depending on tool configuration, process setup, vendor solution, and site conditions. Therefore, some project impacts and cost assumptions are based on literature values, internal information, and proxy estimates. These assumptions are adjusted to fit the simulated N28 fab baseline. The model outputs should only be understood as preliminary results. They are used to show relative trends and demonstrate how the model works, not to provide exact values.

Second, confidentiality prevents the disclosure of raw input data and some absolute output values. CO_2e outputs are normalized relative to a fixed reference baseline to allow project results to be compared and analyzed without exposing sensitive information. Some numerical values shown in the figures and tables are rounded to the nearest thousand or million.

Third, the model only focuses on CO_2e emission reductions from both electricity savings and direct Scope 1 reductions. It does not optimize other resource types, such as water, waste, and chemicals. It also does not include secondary effects from improvement projects, such as induced CO_2e emissions, additional energy demand, installation impacts, or rebound effects.

The model allows the user to define the CO_2e reduction target and regional scenario inputs. This thesis demonstrates the model using different fixed targets and selected regional parameters, including electricity price, grid carbon intensity, and carbon price. The results therefore represent the tested scenarios rather than all possible target and location conditions.

2 Literature Review

2.1 Environmental impacts of semiconductor manufacturing

Semiconductor manufacturing is an energy- and resource-intensive process that requires large amounts of energy, chemicals, water, and gases. The demand and production of semiconductors continue to grow with the development of applications such as artificial intelligence [7]. Ruberti studied major semiconductor foundries and found that, from 2012 to 2021, wafer production increased by 183%, while energy consumption and water use increased by 164% and 163%, respectively [8]. The environmental impact of semiconductor manufacturing is not only related to energy consumption, but also to greenhouse gas (GHG) emissions, water use, and waste generation. These trends show that the environmental impact of semiconductor manufacturing could increase as production continues to grow.

According to the GHG Protocol Corporate Standard, Scope 1 emissions are direct emissions from company-owned or controlled sources, while Scope 2 emissions are indirect emissions from the generation of purchased energy consumed by companies [9]. Scope 1 and Scope 2 are two main sources of GHG emissions from semiconductor companies. Direct process gas emissions under Scope 1, such as fluorinated process gases, can have global-warming effects several times stronger than CO_2, making them a major contributor to GHG emissions from semiconductor manufacturing [10], [11]. Furthermore, Ruberti indicated that from 2012 to 2021, the large increase in Scope 2 emissions was the main reason for the nearly doubled total GHG emissions, while Scope 1 emissions remained relatively stable [8]. In the memory-manufacturing case studied by Kuo et al., approximately 80% of GHG emissions originated from Scope 2 [7]. For

Scope 2 emissions, not only electricity consumption but also the carbon intensity of the electricity supply should be considered. As the shares of fossil and clean electricity vary across regions, Scope 2 emissions can differ between fab locations [12].

As semiconductor node technology advances, the manufacturing process becomes more complex [13]. Process complexity can affect the environmental impact of semiconductor manufacturing [8]. Semiconductor manufacturing involves hundreds of different process steps and complex chemistries, and its environmental performance depends on different manufacturing conditions, such as process recipes, equipment, pumps, abatement systems, and facility infrastructure [14]. Therefore, when assessing the environmental impact of a semiconductor fab, different manufacturing and operating conditions should also be considered.

Yin and Yang examined several mitigation strategies used in the semiconductor industry and discussed their effectiveness and limitations. They identified process improvements, material substitution, and gas control systems as the main approaches for reducing Scope 1 emissions. Scope 2 mitigation mainly focuses on reducing electricity-related emissions through renewable energy and improved energy efficiency [12].

2.2 Fab decarbonization measures

To reduce GHG emissions from process exhaust in semiconductor manufacturing, one approach is the use of abatement systems. Abatement systems are installed in semiconductor fabs to destroy greenhouse gases, including fluorinated gases used during processes such as etching. For combustion, electric, and plasma treatment systems, Zhou et al. proposed that the destruction and removal efficiency (DRE) should exceed 90%. For N_2O treatment systems, the DRE should exceed 60%. However, although abatement systems can reduce direct emissions, they can also generate CO_2 as a by-product and require energy for operation, such as electricity or fuel [15].

Improving facility and utility systems is also an approach to reduce fab energy consumption, as these systems account for a large share of total energy use. Hu et al. studied a semiconductor manufacturing fab in Hsinchu, Taiwan. Besides process equipment, which accounted for 39% of fab energy consumption, CDA (22.1%), water chillers (20.6%), and PCW (5.8%) were also substantial energy consumers. Several improvement measures were discussed. For CDA, changing the dryer design and using two supply-pressure levels could save 1.81% of whole fab energy, corresponding to an 8.17% reduction in CDA energy use. For the water chiller system, reducing the make-up air unit (MAU) outlet temperature from 19°C to 14°C could save 2.09% of whole-fab

energy, corresponding to a 29.1% reduction. For PCW, reducing the pump head and increasing the temperature difference from 3.2°C to 4°C could save 0.91% of total fab energy, equal to a 15.7% reduction in PCW energy use [16]. Another study investigated several energy efficiency improvements for the MAU in the HVAC system of a Dynamic Random-Access Memory (DRAM) factory in Taiwan. Measures such as changing the MAU fan location, lowering the supply-air temperature, and adding a bypass channel could provide energy savings ranging from 0.04% to 0.67% [17].

These studies show that a wide range of improvement measures can be implemented in semiconductor fabs, with different impacts at the subsystem and whole fab levels.

2.3 Techno-economic assessment and marginal abatement cost

Although various decarbonization measures are available, Yin and Yang pointed out that high costs are a major barrier to adopting more sustainable production processes [12]. Economic viability is an important factor when evaluating semiconductor decarbonization projects. Economic assessment should consider not only the initial investment cost but also other factors that affect project feasibility.

Azevêdo et al. identified several important factors in economic feasibility assessment, including investment cost, operation and maintenance cost, project lifetime, avoided energy cost, and discount rate [18]. The discount rate accounts for the fact that project costs and benefits can occur at different times over the project lifetime. Furthermore, projects can have different reduction potentials, costs, and lifetimes, making direct comparison difficult. A common economic basis is needed to compare their performance. Annualized cost provides one approach for expressing project costs on a common yearly basis [19].

In addition to annualized cost, which provides a common basis for comparing economic costs, decarbonization projects can also have different emission reduction potentials. Therefore, both economic cost and emission reduction potential should be considered when comparing their decarbonization performance.
Marginal abatement cost (MAC) connects the cost of a mitigation measure to the amount of emissions reduced. A marginal abatement cost curve (MACC) presents the abatement cost and emission reduction potential of different measures and ranks them from the lowest to the highest abatement cost. The cost assessment can include investment costs, operation and maintenance costs, and savings such as reduced energy expenses. A negative abatement cost indicates that an emission reduction measure can reduce emissions while also saving money [20]. MACC has also been applied to semiconductor

manufacturing. Using Carbon Disclosure Project (CDP) data on project costs, savings, project lifetime, and emissions, together with an assumed discount rate, Nagapurkar et al. estimated the marginal abatement costs of decarbonization measures implemented by six semiconductor companies. The estimated values ranged from −416 to 12,215 USD/t CO_2e [21].

To address global warming and encourage greener practices, carbon pricing measures are being implemented. This economic pressure affects companies' profitability and encourages them to reduce emissions and innovate [22]. When evaluating a decarbonization project, carbon pricing should be taken into consideration. Kesicki and Strachan explained that mitigation measures with abatement costs below the carbon price can be economically favorable [20]. MACCs give a useful overview of the cost-effectiveness of mitigation measures, but some detailed factors needed for practical decision-making may be overlooked. Secondary effects or other non-cost-related issues may not be fully represented in the cost curve. Beaumont and Tinch considered different combinations of abatement measures in their case study and indicated that the lowest-cost combination might not always be the best practical option. The cheapest combination achieved about 6,574 kg/year of abatement. However, when one measure had a non-cost-related issue, an alternative combination could still achieve about 6,134 kg/year at a slightly higher cost [23].

In conclusion, in the complex semiconductor manufacturing environment, ranking measures only by their individual abatement costs may not be sufficient for decision-making. Evaluating alternative combinations based on both cost performance and other practical factors can provide more useful decision support.

2.4 Decision-support and portfolio optimization

Companies have limited resources and often face operational, time, and cost pressures. Therefore, the number of decarbonization projects that can be implemented is constrained, and not all candidate projects can be selected. A feasible subset must be selected to support corporate emission targets while considering cost constraints [24]. The challenge is how to select the most suitable portfolio of decarbonization projects when multiple objectives and budget limitations need to be considered [25]. It can be difficult to determine which projects provide the greatest long-term benefit and to compare their contributions with their costs. Project selection is also a concern in the energy industry, where candidate projects need to be prioritized for implementation [26]. Therefore, a decision-support method is needed to compare different project combinations and identify the most feasible portfolio under the defined constraints.

Project selection can be represented by a binary decision variable, where each candidate project is either selected or not selected. This type of selection problem can be formulated using integer programming, such as a knapsack problem [27]. An integer programming model can evaluate different combinations of projects and support the selection decision. Constraints such as the available budget define the feasible solutions. An objective function, such as maximizing emission reduction, defines the goal of the model [25].

Foo and Chew developed a mixed-integer linear programming (MILP) model to optimize the selection of decarbonization options while achieving an emission-reduction target under financial expenditure limits. Their work applied the model to a large chemical corporation to determine when decarbonization projects should be implemented across different planning periods [24].

In practice, a company may have more than one objective when making a portfolio decision, such as maximizing emission reduction and maximizing fuel savings. In multiple project combinations, different objectives may need to be considered simultaneously. Weights can be introduced to reflect the importance of those objectives [25].

Uncertainty in the model results comes from incomplete information or uncertain input parameters [28]. Therefore, the completeness of input data is important for the optimization results. Incomplete or uncertain input data can change the results and affect which solution is selected [28], [29].

Decarbonization measures should be evaluated based not only on their emission reduction potential but also on their economic performance, for example using annualized cost and MACC. Projects should also be assessed in combination rather than only individually. The decision can involve different constraints. Therefore, a techno-economic decision-support framework is needed to compare projects, prioritize implementation, and assess progress toward emission reduction targets.

3 Methodology

3.1 Research approach

The model has three main parts: input data, model functions, and outputs, which are explained separately in the following sections. The input data include fab and subsystem baselines, project impact, cost data, and scenario settings. In the model functions, these inputs are used to calculate annual CO_2e reduction and annualized net cost. The model evaluates different project combinations under the defined constraints. The main outputs are the selected projects, target achievement, CAPEX use, and scenario comparison.

To organize the different fab process and utility systems, the model uses a layered structure. This layered structure allows flexibility and expansion. The calculation starts from a reference fab baseline that represents the modeled fab type, production capacity, and operating conditions. Subsystems are based on the imec.netzero categories. Some improvement projects affect the whole fab, while others affect only one subsystem. Subsystems allow the project reduction percentage to be applied to the part of the fab that the improvement projects actually affect. The annual physical saving of each project is calculated based on its impact scope.

After calculating the physical savings, the model combines the results with the project cost data and user-defined scenario inputs. The model aims to select the portfolio with the lowest annualized net cost while meeting the defined target and budget constraints. When the target cannot be met, the model selects the portfolio with the highest total CO_2e emission reduction within the budget constraint.

The outputs are presented in two forms. The scenario comparison gives an overview of all scenarios, including target achievement, budget use, and the project selection

heatmap. The individual scenario analysis provides a more detailed breakdown of how each selected project contributes to the target and how the projects are ranked in the MACC.

3.2 Data collection and input structure

3.2.1 Data sources

The input data are crucial for running the model simulation. They could come from different sources, including the imec.netzero N28 baseline, literature, internal imec project information, and estimation. imec.netzero is imec's virtual fab web application, which uses large datasets and complex models to estimate the environmental impacts of semiconductor manufacturing processes. When values are not available, proxy values are used. Due to confidentiality, exact values are not disclosed. The data structure and categories are shown instead. Table 3.2.1.1 shows how the input data are structured and categorized in the model.

Table 3.2.1.1: Summary of model input data

Input group	**Main data**
Fab baseline	Scope 1 CO_2e, electricity consumption, WSPM
Subsystem baseline	Electricity or Scope 1 CO_2e by subsystem
Project impact data	Project name, subsystem, resource type, reduction percentage, impact scope
Economic data	CAPEX, fixed OPEX, economic lifetime, and lead time
Scenario data	Location, electricity price, grid carbon intensity, carbon price, target, budget, target year, discount rate

3.2.2 Baseline data

The baseline data define the size, consumption, and emissions of the modeled fab and its subsystems. The model only considers electricity consumption and direct Scope 1 CO_2e emissions. These baseline values are provided per wafer. Monthly fab production capacity is expressed as wafer starts per month (WSPM). It is used to calculate the

annual baseline values. WSPM can be adjusted to represent different fab sizes and modeled cases. The fab baseline and subsystem baseline input parameters are summarized in Table 3.2.2.1 and Table 3.2.2.2.

Table 3.2.2.1: Fab baseline data structure

Input parameter	**Description**	**Unit / format**
Fab identifier	Identifier of the modeled fab	Text
Wafer starts per month (WSPM)	Monthly fab production capacity	wafers/month
Electricity consumption	Electricity consumption normalized per wafer	kWh/wafer
Scope 1 CO_2e emissions	Direct Scope 1 CO_2e emissions normalized per wafer	tCO_2e/wafer

Table 3.2.2.2: Subsystem baseline data structure

Input parameter	**Description**	**Unit / format**
Subsystem identifier	Identifier of the subsystem	Text
Subsystem name	Name of the specific subsystem	Text
Resource type	Type of resource or emission represented by the subsystem	Electricity or Scope 1 CO_2e
Subsystem consumption or emissions	Electricity consumption or Scope 1 CO_2e emissions per wafer	kWh/wafer or $kgCO_2e$/wafer

3.2.3 Project impact data

Project impact data describe all projects evaluated in the model. The data include the project name, affected subsystem, resource type, reduction percentage or efficiency improvement, and impact scope. Each project is linked to the subsystem or whole fab that it directly affects. The impact scope depends on how the available project data are classified or reported in the original data source.

Each project impact is defined as a reduction percentage or efficiency improvement. The impact values are based on literature, imec internal project information, or proxy

estimates. In the model, the fixed project reduction percentage is used across different scenarios. Section 4.6.3 further analyzes the uncertainty in the project reduction assumptions through sensitivity analysis.

The evaluated projects mainly focus on facility measures that don't affect fab production throughput. Different vendor options for the same improvement project can also be included. These vendor options may have different technical impacts or economic data, so they are treated as separate candidate projects, as shown by project P07a and P07b in Table 3.2.3.1.

Table 3.2.3.1: Candidate projects included in the model

Project	**Project name**	**Affected subsystem**	**Resource type**	**Impact scope**
P01	hydrofluoric ozonated mixture (FOM) backside wet cleaning retrofit	Backside cleaning	Electricity	Subsystem
P02	Two-pressure CDA with heated dryer	CDA	Electricity	Subsystem
P03	Closed PCW system with reduced pumping head	PCW	Electricity	Subsystem
P04	General exhaust flow optimization	Exhaust	Electricity	Subsystem
P05	MAU coil arrangement optimization	Whole fab	Electricity	Whole fab
P06	Fan-filter unit (FFU) return airflow reduction	Whole fab	Electricity	Whole fab
P07a	Plasma abatement improvement — Vendor A	Dry etch process gas	Scope 1 CO_2e	Subsystem
P07b	Plasma abatement improvement — Vendor B	Dry etch process gas	Scope 1 CO_2e	Subsystem
P08	Low global-warming-potential (GWP) heat transfer fluid (HTF) replacement	Dry etch HTF	Scope 1 CO_2e	Subsystem
P09	Centralized compressor island	Whole fab	Electricity	Whole fab
P10	Pump motor optimization	Whole fab	Electricity	Whole fab
P11	Variable Speed Drive (VSD) installation on cooling tower pumps	Whole fab	Electricity	Whole fab

P12	Compressed-air pressure reduction-3CDA	Whole fab	Electricity	Whole fab
P13	Compressed-air pressure reduction-9CDA	Whole fab	Electricity	Whole fab

3.2.4 Economic data

Economic data include CAPEX, fixed OPEX, economic lifetime, and lead time. These economic inputs can vary depending on the vendor, equipment configuration, project scale, and site conditions. Exact cost and implementation data were not available for the simulated N28 fab. As a result, proxy values were used. Published data from semiconductor manufacturing were limited. References from comparable or relevant industrial equipment, utility systems, and implementation projects were considered. The sources were published in different years and locations and may differ in currency, capacity, equipment configuration, and project scope. They were used only as relative benchmarks and to suggest reasonable ranges and the order of magnitude. The proxy values remain modeling assumptions and do not represent official vendor quotations or exact imec project costs. Table 3.2.4.1 summarizes the economic inputs assigned to each candidate project. Tables 3.2.4.2 and 3.2.4.3 present the basis and references for these inputs. Values without suitable published evidence are identified as modeling assumptions.

Table 3.2.4.1: Proxy economic input values for candidate projects

Project	**CAPEX [€]**	**Fixed OPEX [% of CAPEX/year]**	**Economic lifetime [years]**	**Implementation lead time [years]**
P01	150,000	2	7	0.50
P02	400,000	2	10	0.75
P03	1,000,000	2	15	1.00
P04	0	0	5	0.08
P05	250,000	2	10	0.75
P06	50,000	0.5	5	0.25
P07a	50,000	0.5	7	0.25

P07b	10,000	5	7	0.25
P08	10,000	0	5	0.08
P09	3,000,000	3	15	2.00
P10	50,000	2	10	0.25
P11	50,000	1	10	0.50
P12	0	0	3	0.08
P13	0	0	3	0.08

Table 3.2.4.2: Supporting basis and references for CAPEX and fixed OPEX

Project	**CAPEX basis and reference**	**Fixed OPEX basis and reference**
P01	A semiconductor cost model example used approximately USD 180,000 for chemical generation, distribution, monitoring, and handling equipment [30]. In addition, a USD 58,750 contract for an acid wet bench was used in a NanoFab facility [31]. A €150,000 CAPEX value was used as the proxy.	Annual equipment maintenance and repair costs are reported as 2–20% of equipment cost [32]. 2% was used as a lower-bound fixed OPEX proxy.
P02	Hu et al. estimated approximately USD 430,000 for eight heated adsorption dryers in a semiconductor fab [16]. A €400,000 CAPEX value was used as the proxy.	Annual equipment maintenance and repair costs are reported as 2–20% of equipment cost [32]. 2% was used as a lower-bound fixed OPEX proxy.
P03	Hu et al. proposed changing an open PCW system to a closed system, but the piping modification cost was not included [16]. Comparable cooling-water projects cost USD 1.6 million and USD 1.93 million [33], [34]. A €1,000,000 CAPEX value was used as the proxy.	Annual equipment maintenance and repair costs are reported as 2–20% of equipment cost [32]. 2% was used as a lower-bound fixed OPEX proxy.
P04	Hu et al. state that no additional equipment is required for the exhaust-flow adjustment [16]. Therefore, no CAPEX was assigned.	Since no additional equipment is required, no additional fixed OPEX was assigned [16].

P05	Cooling-coil replacement projects with budgets of USD 242,000 and USD 525,000 have been reported [35], [36]. A €250,000 CAPEX value was used as the proxy.	Annual equipment maintenance and repair costs are reported as 2–20% of equipment cost [32]. 2% was used as a lower-bound fixed OPEX proxy.
P06	Advanced fan-control packages incorporating VFD functionality had controller costs of approximately USD 2,200–4,142 per unit, with an average installed cost of USD 4,172 [37]. VFD installations are also reported at USD 200–500 per installed horsepower [38]. A €50,000 CAPEX value was used as the proxy.	The comparable project retrofitted advanced controllers onto existing HVAC units rather than replacing the complete units [37]. 0.5% was used as a modeling assumption.
P07a	Based on approximate imec project data.	Based on approximate imec project data.
P07b	Based on approximate imec project data.	Based on approximate imec project data.
P08	Based on approximate imec project data.	Based on approximate imec project data.
P09	A large industrial compressed-air improvement project cost USD 800,000 [39], while a central compressed-air plant and distribution-system upgrade was budgeted at USD 29 million [40]. These projects were used to support the €3 million proxy.	Annual equipment maintenance and repair costs are reported as 2–20% of equipment cost [32]. 3% was used as a lower-range proxy.
P10	A pump system optimization involving pump downsizing and motor replacement cost USD 15,693 for one 200-hp pump [41].	Annual equipment maintenance and repair costs are reported as 2–20% of equipment cost [32]. 2% was used as a lower-bound proxy.
P11	An assessment estimated USD 264,000 for installing 12 variable speed drives (VSDs) on cooling-tower pumps [42]. Another industrial project reported £25,116 for VSD-based controls on two cooling water pumps [43]. A €50,000 CAPEX value was used as the proxy.	Annual equipment maintenance and repair costs are reported as 2–20% of equipment cost [32]. Since P11 only adds VSDs and controls to existing pumps, 1% was used as a lower proxy.

P12	No CAPEX was required because the project only changes the compressed air pressure setting and does not require new equipment.	Since no new equipment is installed, no additional fixed OPEX was assigned.
P13	No CAPEX was required because the project only changes the compressed air pressure setting and does not require new equipment.	Since no new equipment is installed, no additional fixed OPEX was assigned.

Table 3.2.4.3: Supporting basis and references for economic lifetime and lead time

Project	**Economic lifetime basis and reference**	**Lead time basis and reference**
P01	Diodes reports a useful life range of 3–10 years for machinery and equipment [44]. Seven years was selected within this range.	Semiconductor process changes require engineering tests, production-wafer qualification, review, and approval [45]. A six-month qualification period was assumed.
P02	A UNIDO working paper presents the lifecycle cost of a compressed air system based on a 10-year lifetime [46]. A 10-year lifetime was assumed for the dryers and related CDA modifications.	An industrial compressed-air-system replacement involving multiple compressors, regenerative dryers, air receivers, piping, and centralized controls included separate design, procurement, installation, commissioning, and verification stages [47]. P02 has a smaller scope but involves eight dryers. Nine months was used as an assumption.
P03	A typical medium-size industrial pumping system has a reported lifespan of 15–20 years [48]. 15 years was selected as a lower-bound lifetime proxy.	A closed loop cooling water installation contract specified a duration of 365 calendar days [34]. One year was used as a comparative lead time proxy.
P04	A five year measure life is reported for business retrocommissioning and HVAC control measures [49]. Five years was used.	Exhaust balancing and airflow measurement work is required to be completed within 30 days [50]. The lead time was set to 0.08 years.
P05	A 10 year life is reported for continuous HVAC retrocommissioning [51]. Ten years was used for the MAU optimization.	The U.S. Department of Energy reports a lead time of six to nine months for energy-efficiency projects [52]. 0.75 years was used.
P06	A five year measure life is reported for retrocommissioning and HVAC	An HVAC replacement project that included building automation system controls specified a

	control measures [49]. Therefore, five years was used.	90-day project duration [53]. Therefore, three months, or 0.25 years, was used as a conservative comparative lead-time proxy.
P07a	Diodes reports a life range of 3–10 years for machinery and equipment; the model uses seven years [44].	Based on approximate imec project data.
P07b	Diodes reports a useful life range of 3–10 years for machinery and equipment; the model uses seven years [44].	Based on approximate imec project data.
P08	Inventec reports a minimum five-year shelf life for THERMASOLV CF5 [54]. Five years was used as an assumed economic lifetime in the model.	Based on approximate imec project data.
P09	Industrial air compressors have a reported lifespan of 10–15 years; the model uses 15 years [55].	The industrial compressed air project was implemented over two years [39]. Therefore, two years was used as a comparative proxy.
P10	Diodes reports a useful life range of 3–10 years for machinery and equipment; the model uses ten years [44].	A comparable water pump installation project indicated 90 calendar days [56]. Three months was used as a lead time proxy.
P11	Diodes reports a useful-life range of 3–10 years for machinery and equipment [44]. The ten-year model value is within this range.	An EPA permit provided six months for installing and commencing operation of VFDs on condenser-water pumps [57]. Six months was used as a proxy.
P12	Operational and maintenance measures have a typical measure life of 1–3 years [58].	For most compressed air applications that are not affected by weather, a measurement period of one month or less is acceptable [59]. One month (0.08 years) was used as a proxy.
P13	Operational and maintenance measures have a typical measure life of 1–3 years [58].	For most compressed air applications that are not affected by weather, a measurement period of one month or less is acceptable [59]. One month (0.08 years) was used as a proxy.

3.2.5 Scenario data

Scenario settings are user-defined and are used to simulate project selection under different conditions. The inputs are divided into two groups:

- Planning inputs: CO_2e reduction target, budget, discount rate, reference year, and target year.
- Regional inputs: location, electricity price, grid carbon intensity, and carbon price.

The CO_2e reduction target defines the annual CO_2e reduction amount required by the model. The budget limits the total CAPEX available for project selection. The discount rate is used to annualize CAPEX over the project's economic lifetime. Changes in these inputs can affect the economic performance and selection of the projects.

Four main scenarios are used in the model: Belgium base, Taiwan base, Belgium high carbon price, and Taiwan high electricity price. Since imec is located in Belgium and the modeled N28 fab is based on imec.netzero data, the Belgium base scenario is used as the reference case. The Taiwan base scenario is added to compare how the same candidate projects perform under different regional conditions. The Belgium high carbon price and Taiwan high electricity price scenarios are added to test how changes in these market parameters affect project selection. These four scenarios form the main scenario comparison. Additional sensitivity analyses based on the Belgium base scenario are described after Table 3.2.5.1.

The CO_2e reduction calculated by the model includes reductions from direct Scope 1 emissions and electricity savings. The model uses 5.6% as a reference annual reduction rate for the four main scenarios. Based on imec's target of reducing Scope 1 CO_2e emissions by 50% by 2030 compared with the 2018 baseline [60], this thesis calculates an equivalent compound annual reduction rate of approximately 5.6% over the 12-year period. Although imec's target applies only to Scope 1 emissions, this thesis applies the 5.6% reference rate to the combined Scope 1 and Scope 2 CO_2e baseline for model demonstration. The rate is applied once to the fixed 2024 reference baseline for the annual portfolio evaluation. The model does not calculate a year-by-year emission pathway from 2024 to 2030. The target year 2030 is only used to determine whether projects can be completed based on their lead times.

Since the actual project budget is not available for the simulated case, the base scenario budget is set at 20% of the total CAPEX of all candidate projects. This budget level limits project selection but still allows different project portfolios to be selected. The discount rate is assumed to be 8%, which is close to the reported 8.3% weighted average cost of capital (WACC) for semiconductor manufacturers operating in the EU [11].

For the Belgium scenario inputs, Eurostat reports Belgium's industrial electricity price at 0.1522 EUR/kWh for 2025-S2, equal to 152.2 EUR/MWh [61]. The carbon price for Belgium is based on the 2025 average EU ETS auction price of €73.43/tCO_2e reported on the ICAP EU ETS webpage [62]. The high carbon price scenario uses 150 EUR/tCO_2e to test how a higher carbon price affects project selection. The grid carbon intensity of 0.22 tCO_2e/MWh used for the Belgium scenario was taken from the European industry average in imec.netzero.

For the Taiwan scenario, the electricity price assumption is based on the tariff structure for large extra high voltage users published by Taiwan Power Company, with prices ranging roughly from 70 to 170 EUR/MWh. An electricity price of 125 EUR/MWh is used for the Taiwan base scenario [63]. In the Taiwan high electricity price scenario, the base electricity price is multiplied by 1.3, resulting in 162.5 EUR/MWh. The carbon price is based on the standard carbon fee of NT$300/$tCO_2e$, corresponding to 8.85 EUR/tCO_2e in the model [64]. The grid carbon intensity of 0.57 tCO_2e/MWh used for the Taiwan scenario was taken from the Asian industry average in imec.netzero. Table 3.2.5.1 shows the scenario input settings, where BE and TW refer to Belgium and Taiwan, respectively.

Table 3.2.5.1: Scenario input settings

Scenario	**Electricity price [€/MWh]**	**Carbon price [€/tCO_2e]**	**Grid carbon intensity [tCO_2e/MWh]**	**Annual CO_2e reduction target [%]**	**CAPEX budget [€]**
BE – Base	152.2	73.43	0.22	5.6	€1.004M
TW – Base	125.0	8.85	0.57	5.6	€1.004M
BE – High carbon price	152.2	150.0	0.22	5.6	€1.004M
TW – High electricity price	162.5	8.85	0.57	5.6	€1.004M

Because several model inputs are based on proxy values or modeling assumptions, a sensitivity analysis is performed to examine how changes in these inputs affect the model results and project selection. Each parameter is tested separately, while all other inputs remain the same as in the Belgium base scenario. The sensitivity settings are summarized in Table 3.2.5.2.

Table 3.2.5.2: Sensitivity analysis settings

Parameter	**Factor 1**	**Factor 2**	**Factor 3**
Project reduction	0.5×	1.0× (reference)	1.5×
CAPEX and fixed OPEX	0.5×	1.0× (reference)	1.5×
Discount rate	0.5×	1.0× (reference)	1.5×
Budget	0.4×	0.75×	1.0× (reference)
Annual CO_2e reduction target	0.5×	1.0× (reference)	1.5×

The factors are applied relative to the Belgium base values. For the discount rate, the factors 0.5, 1.0, and 1.5 correspond to 4%, 8%, and 12%, respectively. For the annual CO_2e reduction target, they correspond to 2.8%, 5.6%, and 8.4%, respectively.

3.3 Model development and calculations

The purpose of the model is to identify the project portfolio with the lowest annualized net cost while meeting the CO_2e reduction target and budget constraints. The model first calculates the annual physical savings and CO_2e reduction of each project. These impacts are then combined with the economic data to calculate the annualized net cost. Finally, the model evaluates feasible project combinations based on the objective function and constraints.

3.3.1 Project impact calculation

CO_2e savings of each improvement project come from two sources: direct Scope 1 reduction and electricity savings. For electricity-saving projects, the annual electricity saving is converted into CO_2e reduction using the grid carbon intensity of the location.

Depending on the scope, improvement projects can affect either the whole fab or a specific subsystem. For projects that affect the whole fab, the project reduction percentage is applied to the whole fab baseline:

$$Annual\ Saving_i = Fab\ Baseline \times WSPM \times 12 \times Reduction\ Rate_i$$

For projects that affect the subsystem, the reduction percentage is applied to the subsystem baseline:

$$Annual\ Saving_i = Sub\ system\ Baseline_i \times WSPM \times 12 \times Reduction\ Rate_i$$

where $WSPM$ is the number of wafer starts per month, and $Reduction\ Rate_i$ is the reduction percentage of project i.

The baseline data from imec.netzero are provided per wafer. Therefore, WSPM and 12 months of operation are used to calculate the annual values. In the model, the fab has a fixed WSPM, and the evaluated projects mainly focus on facility measures that don't affect fab production throughput.

The total annual CO_2e saving of each project is calculated as:

$$CO2\ Save_{i,s} = Scope1\ Save_i + Elec\ Save_i \times Grid\ Carbon\ Intensity_s$$

where $Scope1\ Save_i$ is the annual direct Scope 1 CO_2e reduction of project i, $Elec\ Save_i$ is the annual electricity saving, and $Grid\ Carbon\ Intensity_s$ is the grid carbon intensity used in scenario s. Therefore, the same electricity-saving project can result in different calculated CO_2e reductions under different regional scenarios.

3.3.2 Economic calculation

The projects have different costs and lifetimes, and each project can generate economic benefits from electricity cost savings and CO_2e reduction. To fairly compare the economic performance of different projects, the model calculates the annualized net cost of each project on the same yearly basis.

The model first annualizes CAPEX using the capital recovery factor (CRF). The CRF is calculated based on the discount rate and the economic lifetime of each project:

$$CRF_i = \frac{r(1+r)^{n_i}}{(1+r)^{n_i} - 1}$$

where r is the discount rate and n_i is the economic lifetime of project i.

The annualized CAPEX is then calculated as:

$$Annualized\ CAPEX_i = CAPEX_i \times CRF_i$$

Fixed OPEX is calculated as a percentage of the project CAPEX:

$$FOM_i = CAPEX_i \times Fixed\ OPEX\ Rate_i$$

For electricity-saving projects, the annual electricity saving reduces the annual electricity cost. The CO_2e reduction also provides an economic benefit by avoiding the carbon cost based on the carbon price. As a result, the annualized net cost of each project is calculated as:

$$\begin{aligned} &Net\ Annualized\ Cost_{i,s} \\ &\quad = CAPEX_i \times CRF_i + FOM_i - Electricity\ Price_s \times Elec\ Save_i \\ &\quad - Carbon\ Price_s \times CO2\ Save_{i,s} \end{aligned}$$

A positive value means that the project has a net annual cost. A negative value means that the annual electricity savings and carbon value are larger than the annualized project cost.

A marginal abatement cost curve (MACC) compares the annualized net cost with the annual CO_2e saving of each project. The MACC is calculated as:

$$MACC_{i,s} = \frac{Annualized\ Net\ Cost_{i,s}}{CO_2e\ Saving_{i,s}}$$

where i represents the project and s represents the scenario. A negative MACC indicates that the project produces a net annual cost saving, while a positive MACC indicates that the project has a net annual cost. A lower MACC indicates better cost-effectiveness.

3.3.3 Portfolio selection model

After calculating the CO_2e saving and annualized net cost of each project, the model evaluates different project combinations to find the lowest annualized net cost while meeting the CO_2e reduction target and CAPEX budget constraints.

Each project has a binary decision variable:

$$x_i = \begin{cases} 1, & \text{if project } i \text{ is selected} \\ 0, & \text{if project } i \text{ is not selected} \end{cases}$$

The main objective function is:

$$\min Z = \sum_i Net\ Annualized\ Cos\ t_{i,s} x_i$$

The annualized net cost includes annualized CAPEX, fixed OPEX, avoided electricity cost, and avoided carbon value, as explained in Section 3.3.2.

The selected portfolio must meet the CO_2e reduction target:

$$\sum_i CO_2e\ Sav\ e_{i,s} x_i \geq Target\ CO_2e_s$$

The total CAPEX of the selected projects must also stay within the available budget:

$$\sum_i CAPE\ X_i x_i \leq Budget_s$$

The lead time of each selected project should also allow the project to be implemented by the target year, which is used as the project completion deadline. For the same improvement project with different vendor options, each vendor option is treated as a separate candidate project, but only one of them can be selected:

$$x_a + x_b \leq 1$$

If no feasible portfolio can meet the CO_2e reduction target under the available budget and other constraints, the model uses an alternative objective to maximize the total achievable CO_2e reduction:

$$\max \sum_i CO2\ Sav\ e_{i,s} x_i$$

The model then selects the portfolio with the highest possible CO_2e reduction under the available constraints. If several portfolios achieve the same maximum CO_2e reduction, the portfolio with the lowest annualized net cost is prioritized. If both the CO_2e reduction and annualized net cost are the same, the portfolio with the lower CAPEX is selected.

3.3.4 Model implementation

This section briefly describes how the model code is organized and run. The model is implemented in Python. The Python code was developed and revised with assistance from ChatGPT and Copilot. The input data are stored in five Excel files: fab baseline, subsystem baseline, project impact, cost, and scenario settings.

The model first combines the five input files into one summary workbook. It checks for input problems such as missing data or incorrect links between input files. It also calculates the physical savings of each project and combines the results with the economic input data for the portfolio analysis.

Currently, 14 candidate projects are included in the model. Since each project has a binary decision, either selected or not selected, there are $2^{14} = 16{,}384$ possible project combinations. Complete enumeration is able to evaluate all 16,384 possible combinations for the optimization. The actual number evaluated depends on how many projects remain after the initial filtering. The enumeration method is used for the current model. For larger datasets covering a whole fab in industrial applications, a Mixed-Integer Linear Programming (MILP) solver would be more suitable for the optimization. For each scenario, the model first calculates the CO_2e savings and economic results. Based on their lead times, projects that cannot be completed by the target year are filtered out. Afterwards, the code checks all possible combinations of the remaining projects and calculates the total CO_2e reduction, CAPEX, and annualized net cost.

The model selects the portfolio with the lowest annualized net cost while meeting the model's annual CO_2e reduction target and staying within the budget. If this target cannot be met within the budget and other project constraints, the model selects the portfolio with the highest possible annual CO_2e reduction while keeping those budget and project constraints.

The model has two types of analysis. First, the single-scenario analysis provides detailed results for one scenario selected by the user. It shows target achievement, CAPEX use, project contributions, MACC ranking, and subsystem contribution. The other, the scenario-comparison analysis compares the results across different scenarios. It shows the differences between scenarios in target achievement, budget use, annualized net cost, and project selection. Target achievement is calculated as the annual CO_2e reduction of the selected portfolio divided by the annual model target.

Because the input data used in the model are confidential, the CO_2e results presented in the thesis are normalized relative to a fixed reference baseline. A value of 0 means no CO_2e reduction, while 1.0 represents a reduction equal to the fixed reference CO_2e baseline. The reference baseline is calculated as:

$$B_{\text{ref}} = Scope1_{\text{ref}} + Electricity_{\text{ref}} \times CI_{\text{ref}}$$

where B_{ref} is the total CO_2e emissions of the fixed 2024 reference case before applying any projects, $Scope1_{\text{ref}}$ is the annual direct Scope 1 emissions, $Electricity_{\text{ref}}$ is the annual electricity consumption, and CI_{ref} is the reference grid carbon intensity. The subscript ref refers to the fixed 2024 reference case.

Each CO_2e result is normalized by dividing the original value by the fixed reference baseline:

$$Q_{\text{norm}} = \frac{Q}{B_{\text{ref}}}$$

where Q_{norm} is the normalized CO_2e result and Q is the original CO_2e result. The same reference baseline is used for all scenarios. The model still uses the original absolute values for all calculations and portfolio selection.

4 Results

4.1 Overview of the results

The results are presented in five parts: the Belgium reference case, the main scenario comparison, the budget sensitivity analysis, the cost sensitivity analysis, and the additional sensitivity analyses. The analyses use indicators such as target achievement, budget utilization, annualized net cost, project selection, and CO_2e contribution.

4.2 Reference case: Belgium base

Based on the imec.netzero simulation data for an N28 semiconductor fab, Belgium was used as the reference scenario for the model analysis. Table 4.2.1 summarizes the main results of this scenario.

Table 4.2.1: Main results for the Belgium base scenario

Indicator	Belgium base result
Normalized CO_2e reduction target	0.0560
Normalized portfolio reduction	0.0441
Target achievement	79%
Scope 1 reduction	0.0331
Electricity-derived Scope 2 reduction	0.0110

Selected projects	11
CAPEX used	€970K
Budget utilization	97%
Annualized net cost	–€3.18M/year

The portfolio for the Belgium base scenario selected by the model did not reach the model annual reduction target, with a 79% achievement rate. The normalized total was 0.0441, below the normalized target of 0.0560. Figure 4.2.1 shows that the contribution from Scope 1 emission reduction projects was greater than that from Scope 2 reduction projects. Negative values in the CO_2e reduction target achievement figures represent CO2e reductions from the reference baseline.

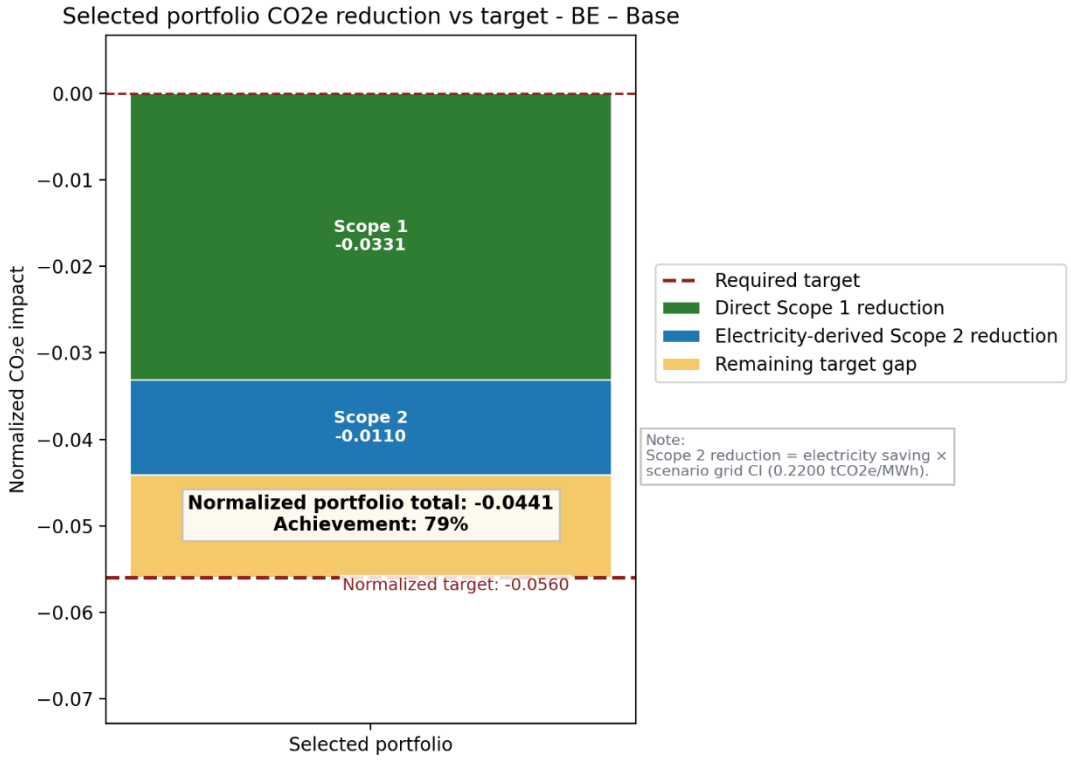

Figure 4.2.1: CO_2e reduction target achievement for the Belgium base scenario

The model used nearly all of the available budget. Approximately 97% of the budget was used. As illustrated in Figure 4.2.2, the projects are ranked from the lowest MACC to the highest one. The projects selected by the model are marked in green. 11 out of 14 projects were selected. Projects P03 and P09 were not selected even though they had negative

MACC values. Since the model could select only one of the two P07 alternatives, P07b was selected because it provided a higher CO_2e reduction with less CAPEX than P07a.

However, P08 was still selected even though it had a positive MACC value. When the model cannot reach the target, it maximizes the total CO_2e reduction within the budget rather than minimizing the annualized net cost. Therefore, a project can still be selected even if it has a positive MACC value.

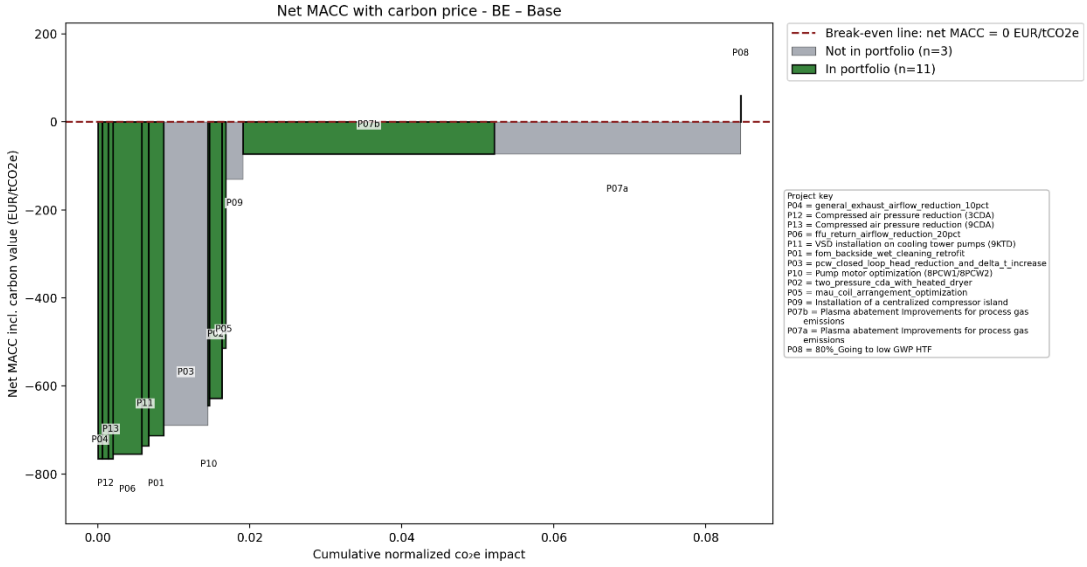

Figure 4.2.2: Net MACC and project selection for the Belgium base scenario

Figure 4.2.3 shows that the dry etch process gas subsystem made the largest contribution to the reduction, accounting for approximately 75% of the overall impact. The project on HTF had a very small impact on the savings.

Overall, the selected portfolio had an annualized net cost of –€3.18M/year because the electricity cost savings and carbon value were higher than the annualized CAPEX and OPEX, as shown in Figure 4.2.4.

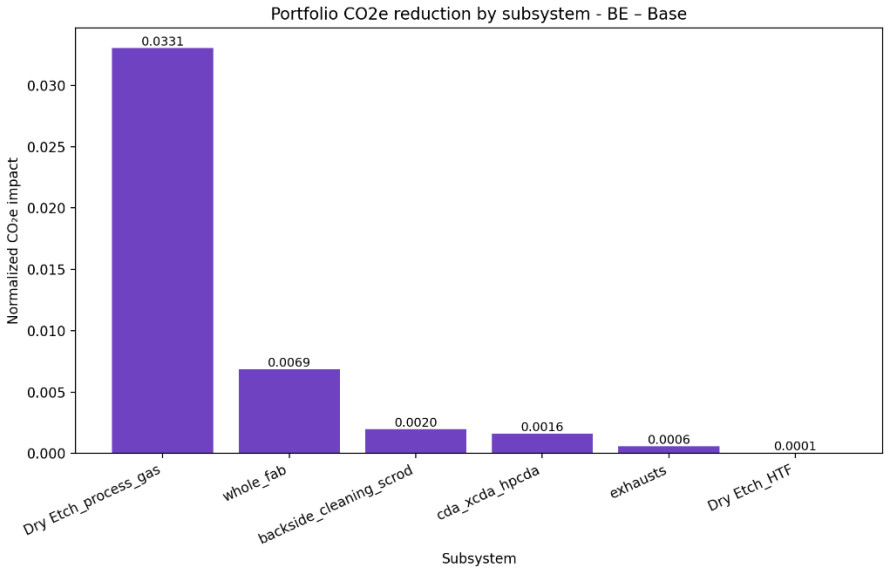

Figure 4.2.3: Normalized portfolio CO2e reduction by subsystem for the Belgium base scenario

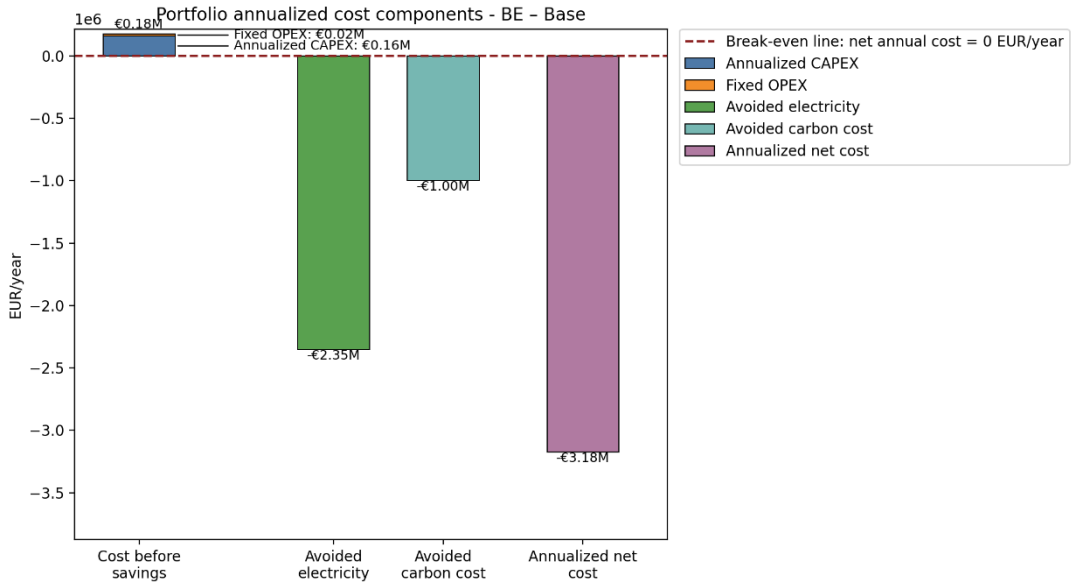

Figure 4.2.4: Annualized cost components for the Belgium base scenario

4.3 Main scenario comparison

To examine how scenario parameters affect the model results, four main scenarios were compared: Belgium base, Taiwan base, Belgium high carbon price, and Taiwan high electricity price. The scenario parameters and main scenario results are shown below in Table 4.3.1 and Table 4.3.2.

Table 4.3.1: Main scenario parameters

Scenario	**Electricity price (€/MWh)**	**Carbon price (€/tCO2e)**	**Grid intensity (tCO2e/MWh)**
Belgium base	152.2	73.43	0.22
Taiwan base	125.0	8.85	0.57
Belgium high carbon price	152.2	150.00	0.22
Taiwan high electricity price	162.5	8.85	0.57

Table 4.3.2: Main scenario results

Result	**Belgium base**	**Taiwan base**	**Belgium high carbon price**	**Taiwan high electricity price**
Target achievement	79%	110%	79%	110%
Normalized reduction	0.0441	0.0616	0.0441	0.0616
CAPEX used	€970K (97%)	€960K (96%)	€970K (97%)	€960K (96%)
Annualized net cost	−€3.18M/year	−€1.93M/year	−€4.22M/year	−€2.51M/year
Selected projects	11	10	11	10

As shown in Figure 4.3.1, with an achievement rate of 79% of the target, both Belgium scenarios did not reach the target. However, both Taiwan scenarios surpassed the target, with an achievement rate of up to 110%. The higher grid intensity in Taiwan made the Taiwan scenarios more likely to reach the target. However, the higher carbon price or electricity price did not change the target achievement rate within each country scenario.

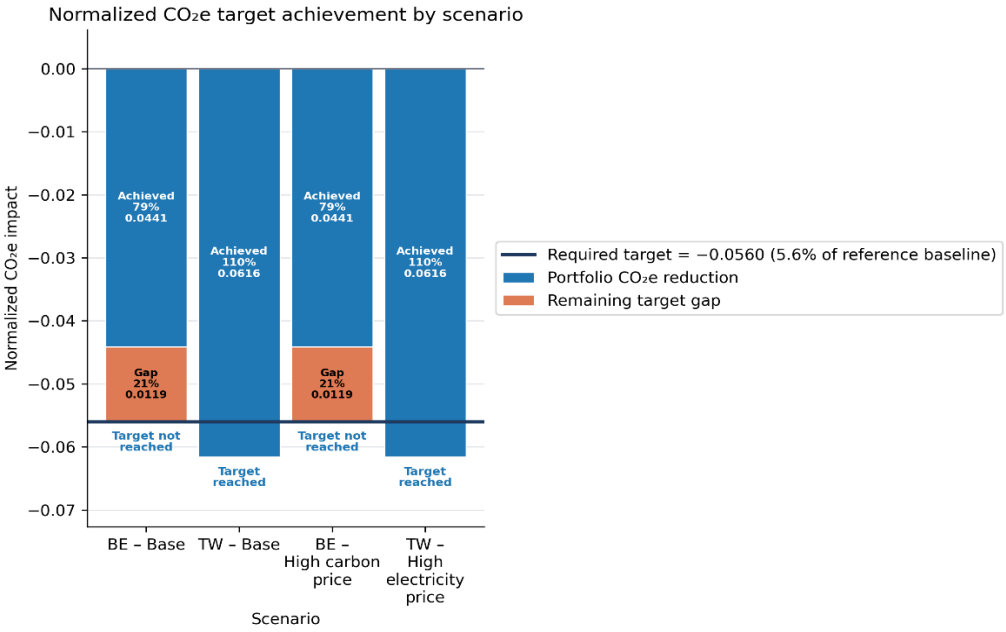

Figure 4.3.1: CO2e target achievement across the four main scenarios

The impact of Taiwan's higher grid intensity can also be seen in the normalized portfolio reduction by subsystem in Figure 4.3.2. The subsystem with the highest reduction impact across all four scenarios was dry etch process gas, a Scope 1 emission reduction project. This project had the same normalized impact of 0.0331 across all scenarios. However, its percentage contribution was lower because the Taiwan scenarios had greater total CO_2e reduction amounts. The electricity-saving projects for the whole fab had an impact of 0.0178 in Taiwan, whereas they had an impact of 0.0069 in Belgium.

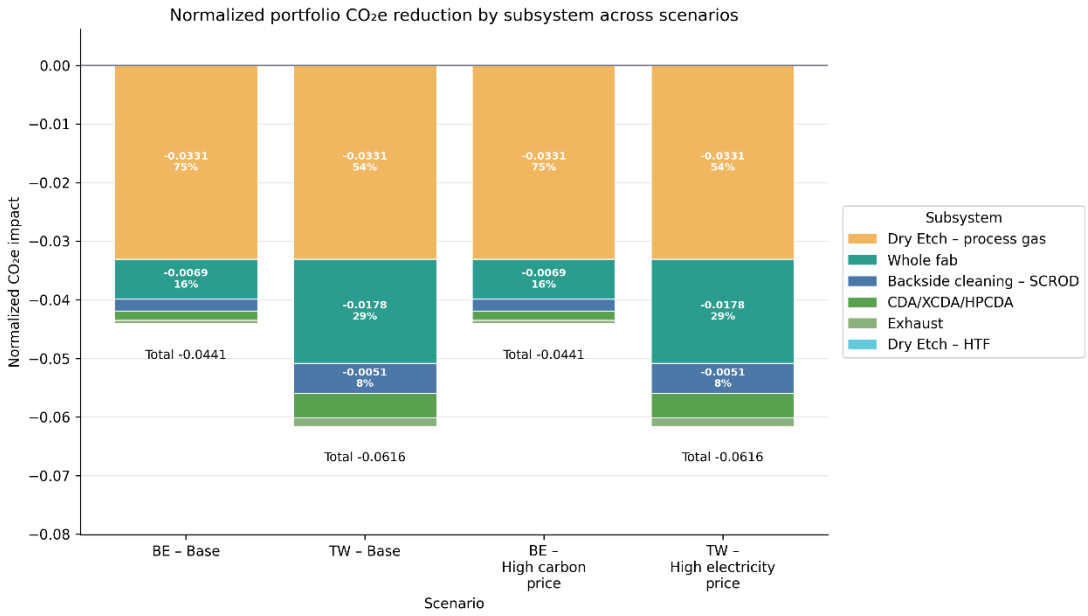

Figure 4.3.2: Normalized portfolio CO2e reduction by subsystem across the four main scenarios

All four scenarios had high utilization rates of the budget, reaching approximately 97% for the Belgium scenarios and 96% for the Taiwan scenarios. It should be noted that because the Belgium scenarios did not reach the target, the model aimed to maximize the CO_2e reduction.

As shown in Figure 4.3.3, both Belgium scenarios selected the additional project P08 to maximize the CO2e reduction, but neither of the Taiwan scenarios selected it. Table 4.3.3 summarizes the result for P08 and the reason for its selection.

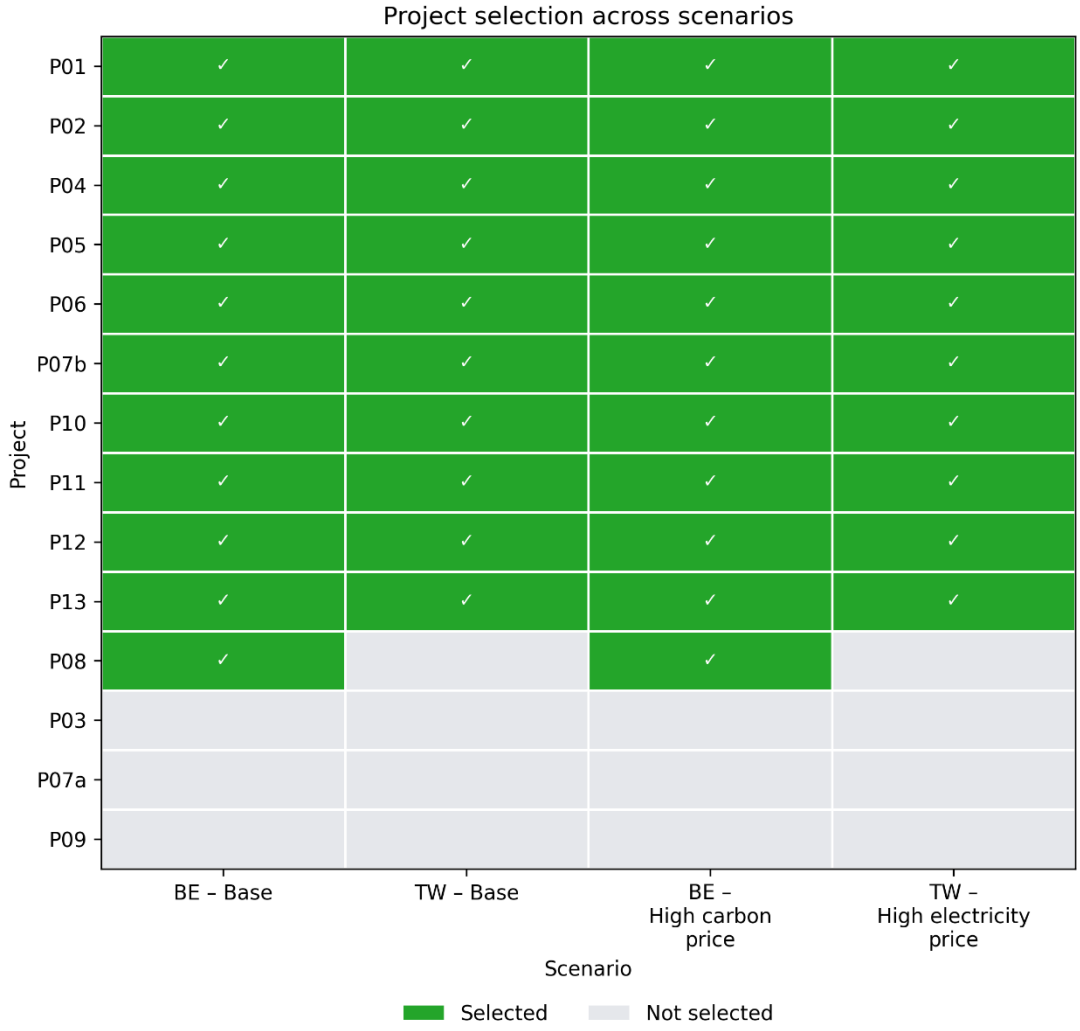

Figure 4.3.3: Project selection across the four main scenarios

Table 4.3.3: Summary of P08 results

Scenario	P08 result	Selected?	Reason
BE – Base	+€1k/year	Yes	The target could not be reached, so the model selected P08 to maximize the CO_2e reduction even though it had a positive annualized net cost.
TW – Base	+€2k/year	No	The target was reached. The model did not need to select the additional project P08, which would increase the annualized net cost.

BE – High carbon price	−€0.3k/year	Yes	The target could not be reached, so the model selected P08 to maximize the CO_2e reduction. Due to the higher carbon price, P08 became cost-saving.
TW – High electricity price	+€2k/year	No	The target was reached. The model did not need to select the additional project P08.

Based on Figure 4.3.4, Belgium high carbon price had the largest annualized net savings, at approximately €4.22M/year. Taiwan base had the smallest annualized net savings, at approximately €1.93M/year. Most of the total savings were generated by a few large projects. P07b had an obvious impact on the difference in annualized net savings. It generated approximately €1.53M/year in annualized net savings in the Belgium high carbon price scenario but generated much smaller savings in Taiwan due to Taiwan's low carbon price.

Overall, all four portfolios had a negative annualized net cost. The higher carbon price and electricity price resulted in a more negative annualized net cost.

Figure 4.3.4: Annualized net cost across the four main scenarios

4.4 Effect of the budget constraint

Three Belgium budget cases were compared to show how the budget affected the model results. In addition to the base case, the two constrained cases used budgets of 40% and

75% of the base budget. All other model inputs remained unchanged. Table 4.4.1 summarizes the results.

Table 4.4.1: Results of the three Belgium budget cases

Result	BE – Base	Budget 40%	Budget 75%
Available budget	€1.004M	€401.6K	€753K
Normalized reduction	0.0441	0.0420	0.0436
Target achievement	79%	75%	78%
Target gap	21%	25%	22%
Selected projects	11	9	10
CAPEX used	€970K	€320K	€720K
Budget utilization	97%	80%	96%
Annualized net cost	–€3.18M/year	–€2.78M/year	–€3.09M/year

As shown in Figures 4.4.1 and 4.4.2, none of the three cases reached the target. The target achievement decreased from 79% in the base case to 78% in the 75% budget case. The base and 75% budget cases used 97% and 96% of their budgets, respectively. However, the 40% budget case used only 80% of its budget and achieved 75% of the target. This means that more of the budget remained unused in the 40% budget case.

Figure 4.4.3 shows the differences in project selection. Nine projects were selected in all three cases. P02 was selected in the 75% budget and base cases but not in the 40% budget case. P05 was selected only in the base case. P02 was added when the budget increased from 40% to 75%. With a further increase in the budget, P05 was added.

Based on the annualized net cost graph in Figure 4.4.4, the annualized net cost was –€2.78M/year in the 40% budget case, –€3.09M/year in the 75% budget case, and –€3.18M/year in the base case. Figure 4.4.5 shows that dry etch process gas remained the largest contributor to CO_2e reduction in all three budget cases.

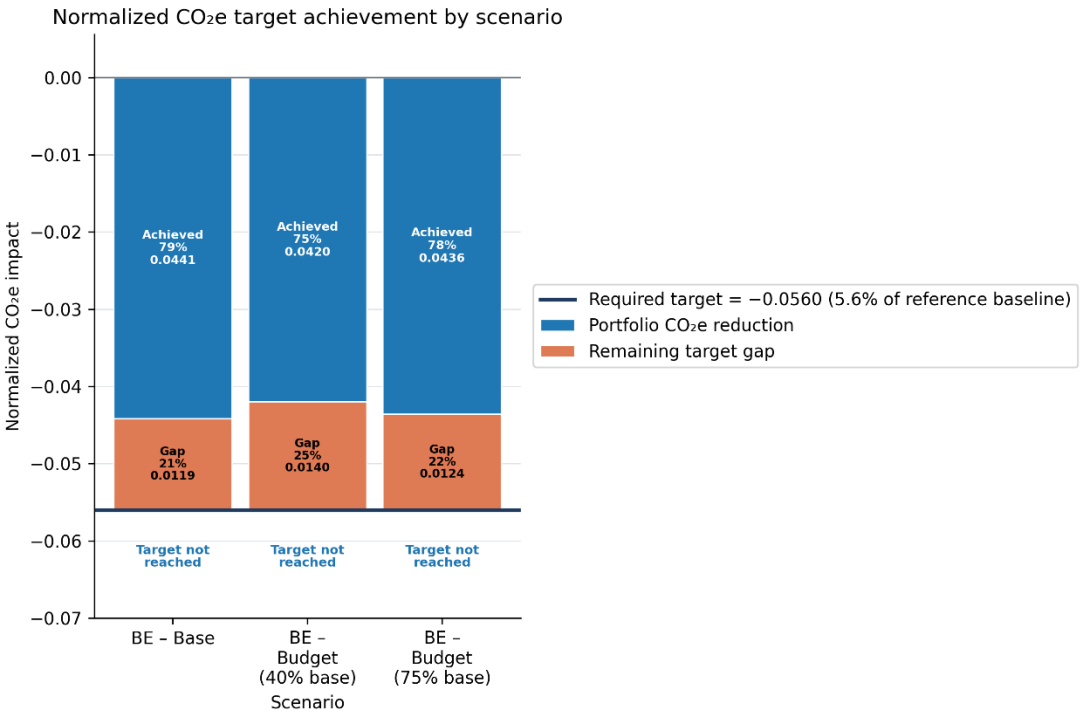

Figure 4.4.1: CO2e target achievement under the base and budget-constrained scenarios

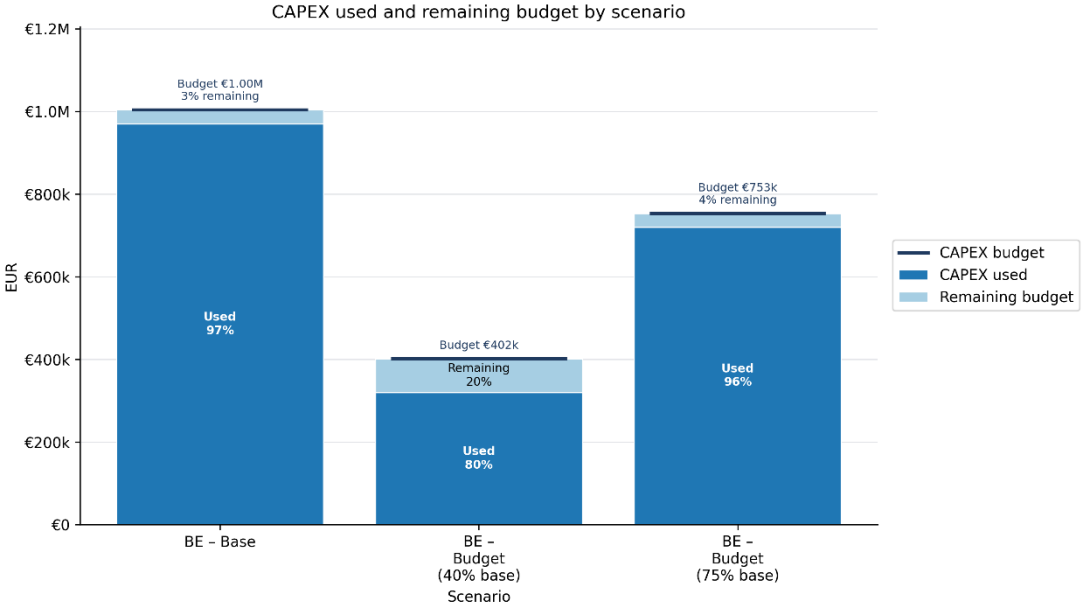

Figure 4.4.2: CAPEX used and remaining budget under the base and budget-constrained scenarios

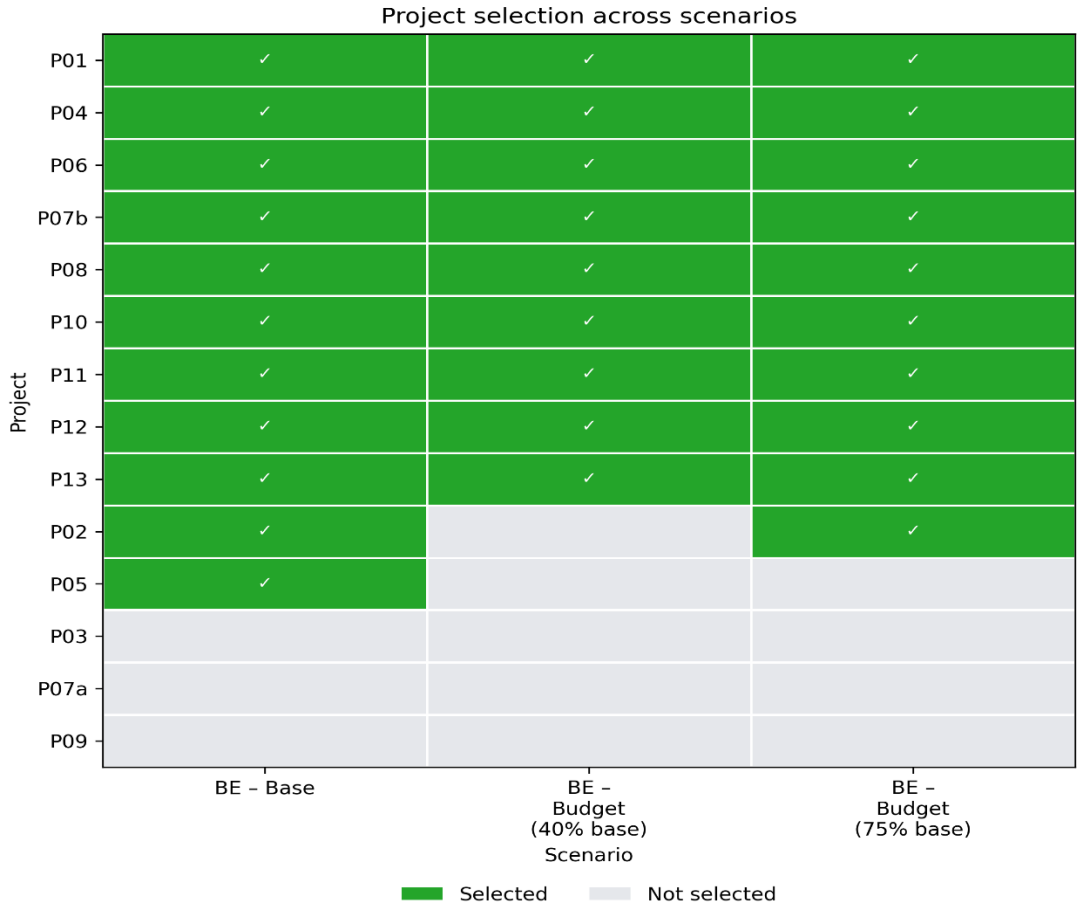

Figure 4.4.3: Project selection under the base and budget-constrained scenarios

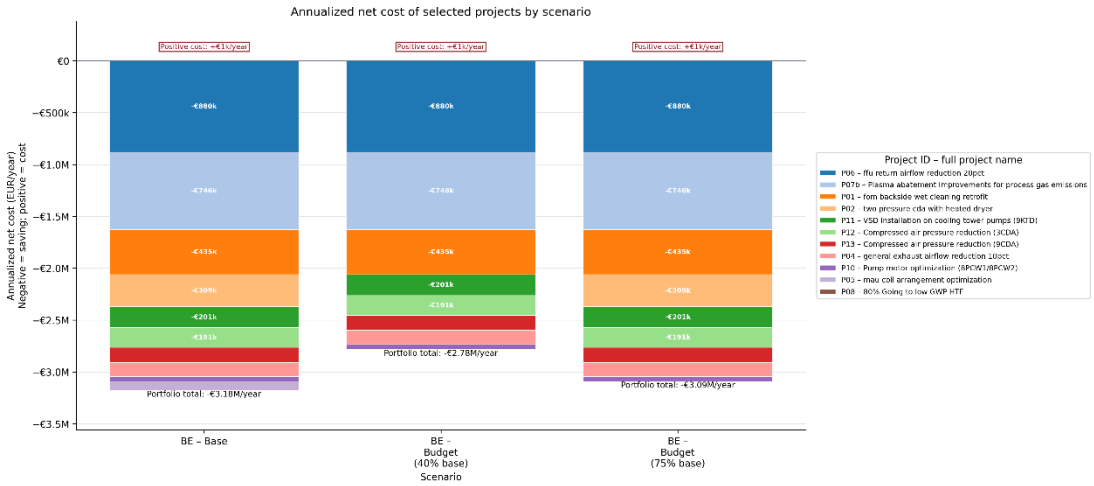

Figure 4.4.4: Annualized net cost under the base and budget-constrained scenarios

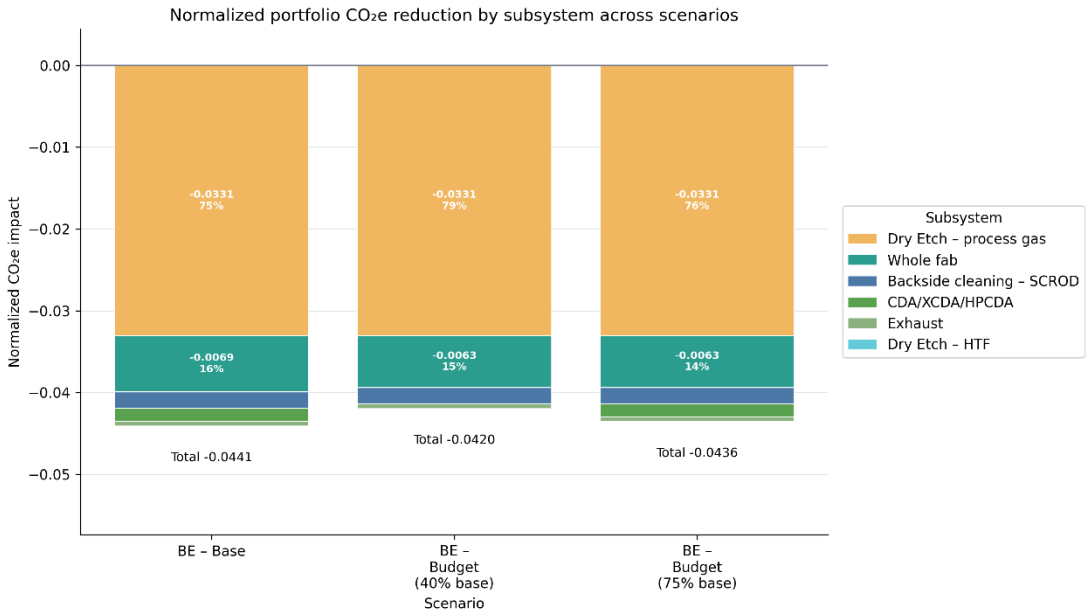

Figure 4.4.5: Normalized portfolio CO2e reduction by subsystem under the base and budget-constrained scenarios

4.5 Cost sensitivity analysis

The CAPEX and OPEX data are highly dependent on the specific site location and operating conditions. The actual data are confidential for imec projects, and the data available in the literature for other projects are not fully applicable. Therefore, a cost sensitivity analysis was conducted to test how different proxy cost data used in the model affect the model results.

Low-, base-, and high-cost cases were compared using cost factors of 0.5, 1.0, and 1.5. All other parameters remained unchanged. The main results of the three cost cases are summarized in Table 4.5.1.

Table 4.5.1: Summary of the three cost cases

Indicator	**Low-cost case**	**Base-cost case**	**High-cost case**
CAPEX and fixed OPEX cost factor	0.5	1.0	1.5
Normalized portfolio reduction	0.0500	0.0441	0.0433
Target achievement	89%	79%	77%
Target met	No	No	No

Selected projects	12	11	8
CAPEX used	€985K	€970K	€990K
Budget utilization	98%	97%	99%
Annualized net cost	–€4.57M/year	–€3.18M/year	–€2.98M/year

As shown in Figure 4.5.1, none of the three cases reached the target. The low-cost case had the highest target achievement rate, at 89%, while the high-cost case had the lowest rate, at 77%. In general, the lower the project costs, the higher the target achievement rate. In contrast, when the project costs increased by 50%, the target achievement rate decreased by only 2 percentage points from the base case. When the project costs decreased by 50%, the target achievement rate increased by 10 percentage points.

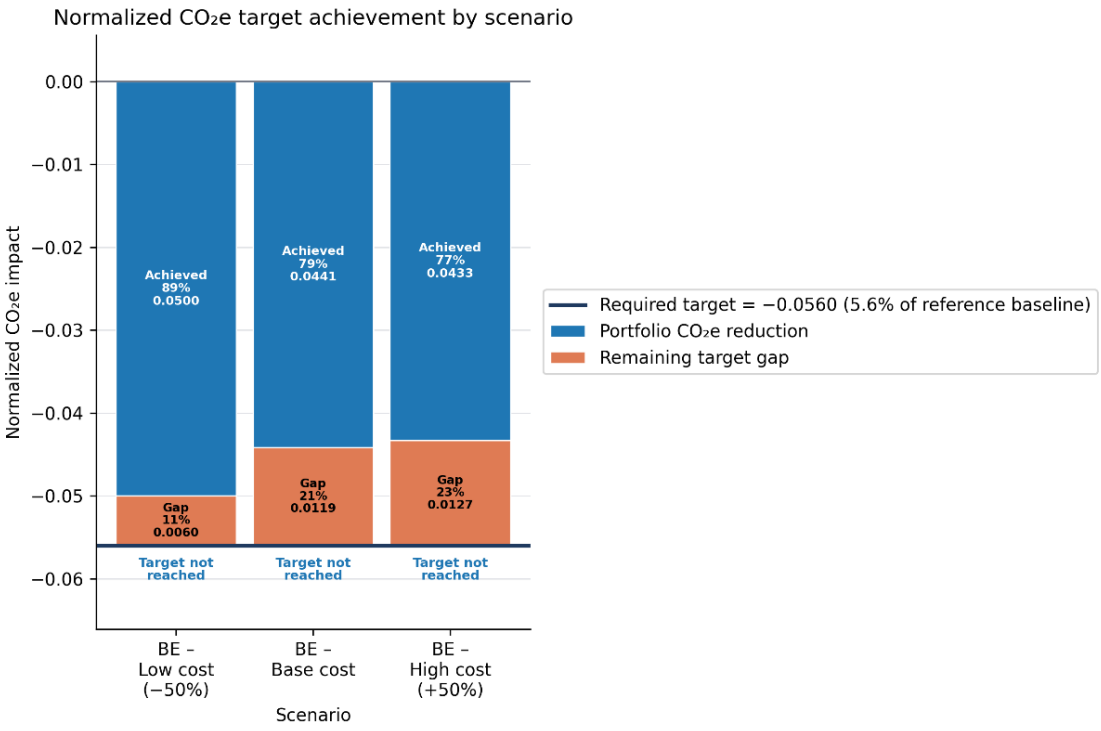

Figure 4.5.1: CO2e target achievement under the low-, base-, and high-cost cases

Since none of the three cases met the target, the model tried to maximize CO_2e reduction within the budget. All three cases had high budget utilization rates. Figure 4.5.2 shows that the base-cost case used approximately 97% of the budget, while the high-cost and low-cost cases used 99% and 98%, respectively. The budget utilization rate did not

change consistently with the project costs because it depended on which combination of projects could fit within the fixed budget.

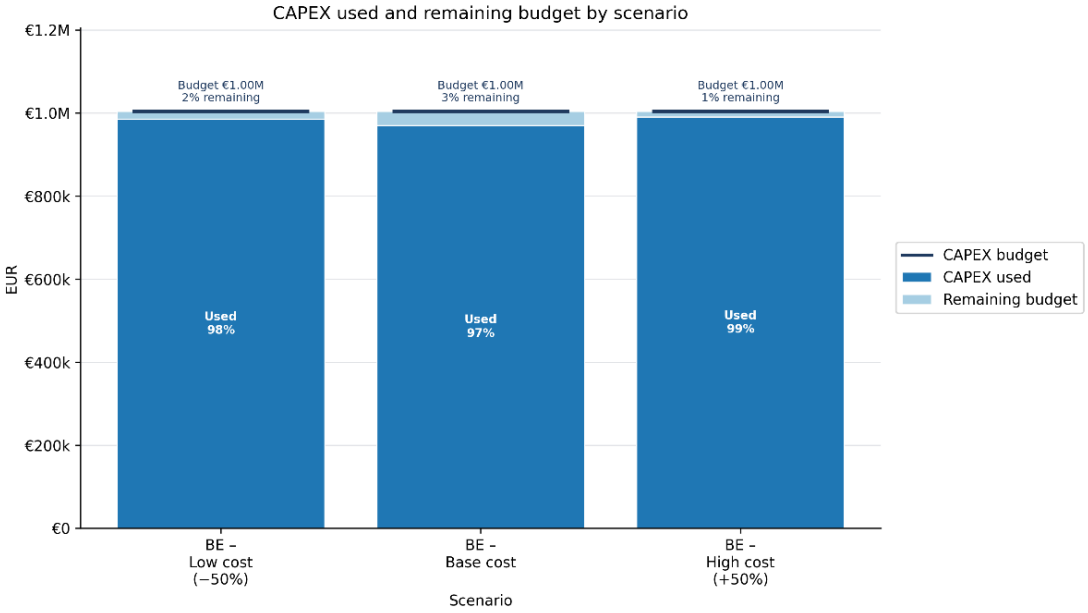

Figure 4.5.2: CAPEX used and remaining budget under the low-, base-, and high-cost cases

As shown in Figure 4.5.3, the number of selected projects increased as the project costs decreased. Therefore, the low-cost case had the most selected projects, with 12 projects, while the high-cost case had only 8 selected projects. Figure 4.5.4 presents the annualized net cost results. With lower project costs and a greater number of selected projects, the low-cost case had annualized net savings of €4.57M/year. The low-cost case not only selected more projects but also included P03, a high-impact, high-cost project that made a large contribution. The high-cost case had annualized net savings of €2.98M/year, while the base-cost case had annualized net savings of €3.18M/year. These two values were relatively close, although the base-cost case selected 3 additional projects that made relatively small contributions to the annualized net savings.

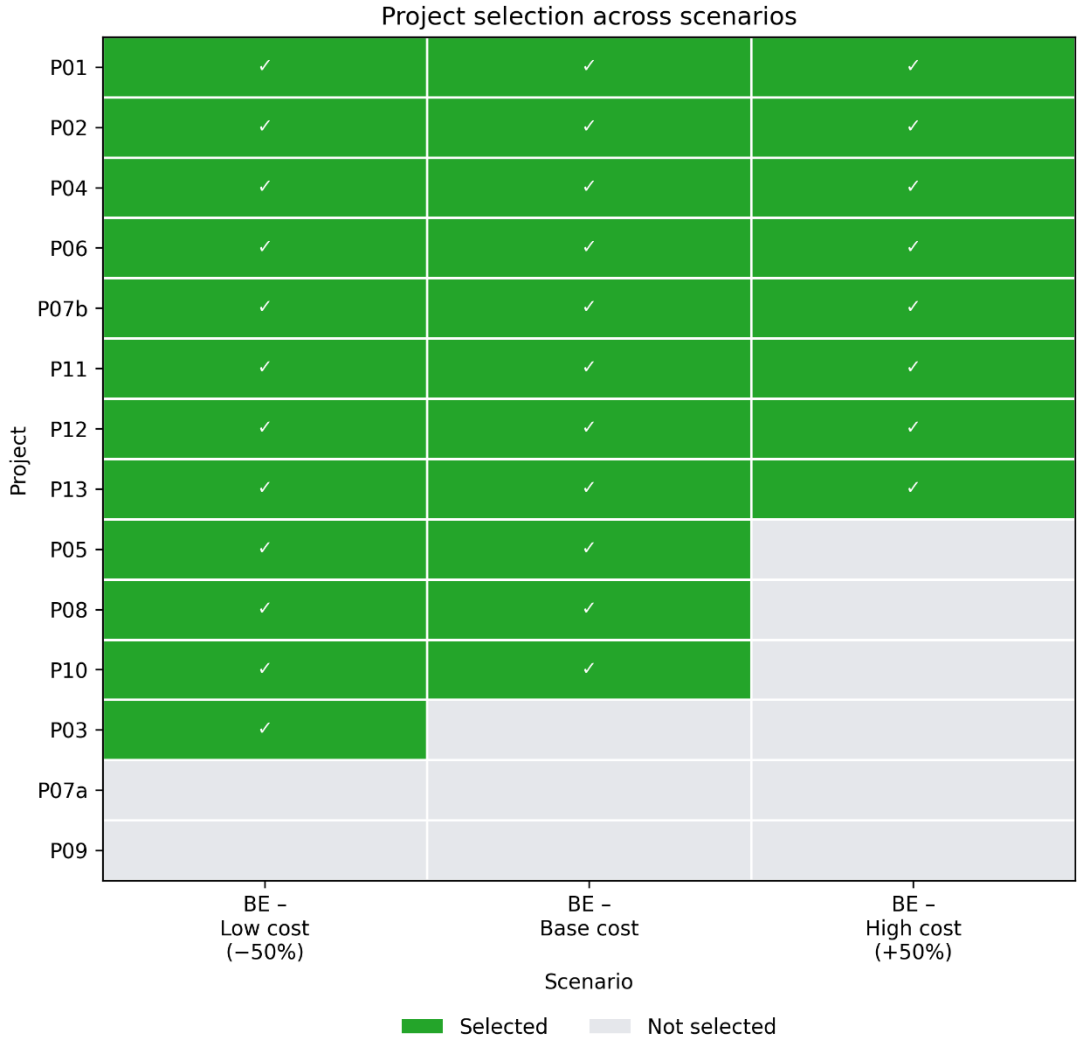

Figure 4.5.3: Project selection under the low-, base-, and high-cost cases

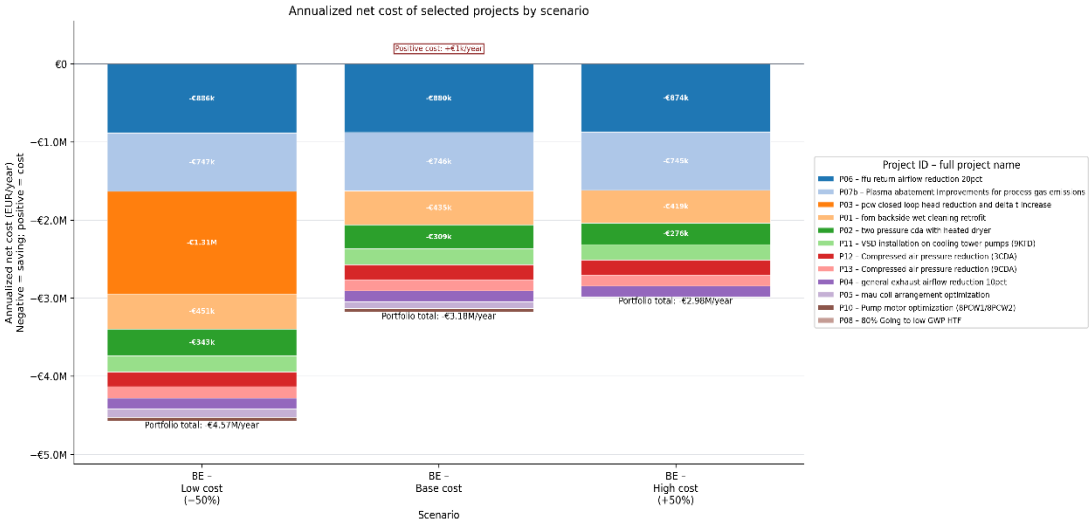

Figure 4.5.4: Annualized net cost under the low-, base-, and high-cost cases

4.6 Additional sensitivity analyses

Different discount rates, annual CO2e reduction targets, and project reduction assumptions were examined in the additional sensitivity analyses. Each parameter was tested separately. The other inputs remained unchanged as in the Belgium base scenario.

4.6.1 Discount rate sensitivity

Based on Table 4.6.1.1 which summarizes the discount rate sensitivity results, the discount rate did not change the normalized CO2e reduction, target achievement, CAPEX use, or project selection. The same 11 projects were selected in all three cases. Only the annualized net cost changed, from −€3.20M/year in the low discount rate case to −€3.15M/year in the high discount rate case. Figure 4.6.1.1 shows the change in annualized net cost under the different discount rates. Project selection is identical across all three discount rate cases, as shown in Figure 4.6.1.2.

Table 4.6.1.1: Discount rate sensitivity results

Indicator	Low discount rate (4%)	Base discount rate (8%)	High discount rate (12%)
Normalized portfolio reduction	0.0441	0.0441	0.0441
Target achievement	79%	79%	79%
Target met	No	No	No

Selected projects	11	11	11
CAPEX used	€970K	€970K	€970K
Budget utilization	97%	97%	97%
Annualized net cost	–€3.20M/year	–€3.18M/year	–€3.15M/year

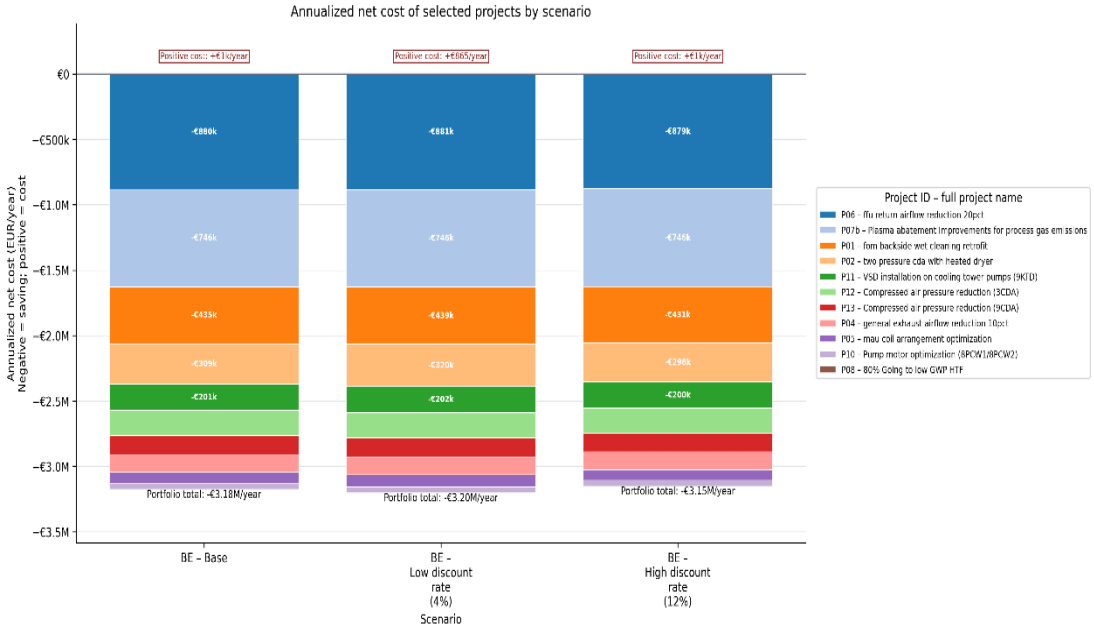

Figure 4.6.1.1: Annualized net cost under different discount rates

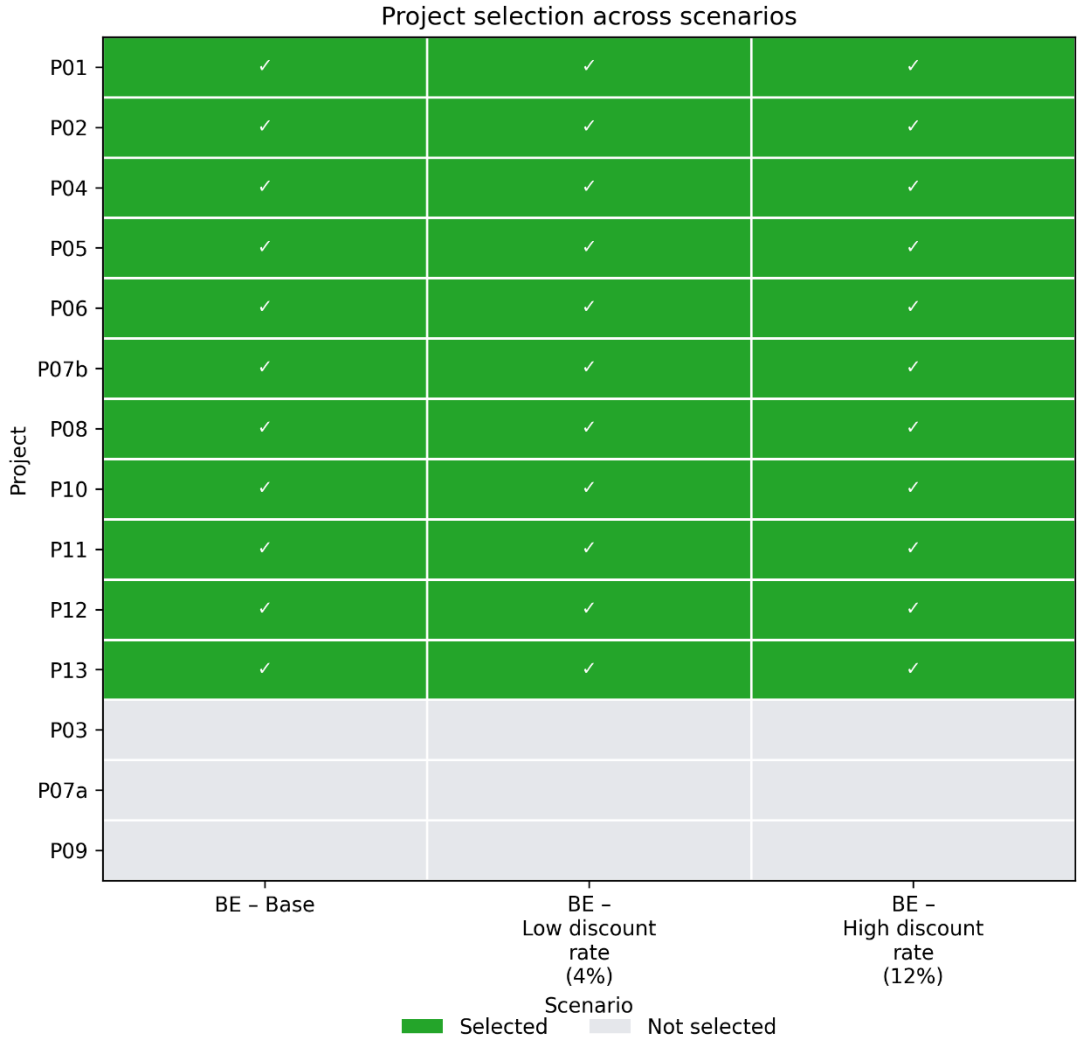

Figure 4.6.1.2: Project selection under different discount rates

4.6.2 Reduction target sensitivity

Table 4.6.2.1 and Figure 4.6.2.1 show that under different reduction targets, even though the target achievement rates were different, the normalized portfolio CO_2e reduction remained approximately 0.0441 in all three cases. In addition, each case showed similar economic results, with similar budget utilization and annualized net cost. Budget utilization remained between 96% and 97%, while the annualized net cost remained approximately –€3.18M/year. The difference in annualized net cost between the low target and base cases was only about €1,100/year and was visible only before rounding.

As shown in Figure 4.6.2.2, the low target case achieved 157% of its target but selected 10 projects, with P08 removed. The base and high target cases selected the same 11 projects, so their budget utilization was slightly higher than in the low target case, even though neither case met its target.

Table 4.6.2.1: Reduction target sensitivity results

Indicator	Low target (2.8%)	Base target (5.6%)	High target (8.4%)
Normalized portfolio reduction	0.0441	0.0441	0.0441
Target achievement	157%	79%	53%
Target met	Yes	No	No
Selected projects	10	11	11
CAPEX used	€960K	€970K	€970K
Budget utilization	96%	97%	97%
Annualized net cost	–€3.18M/year	–€3.18M/year	–€3.18M/year

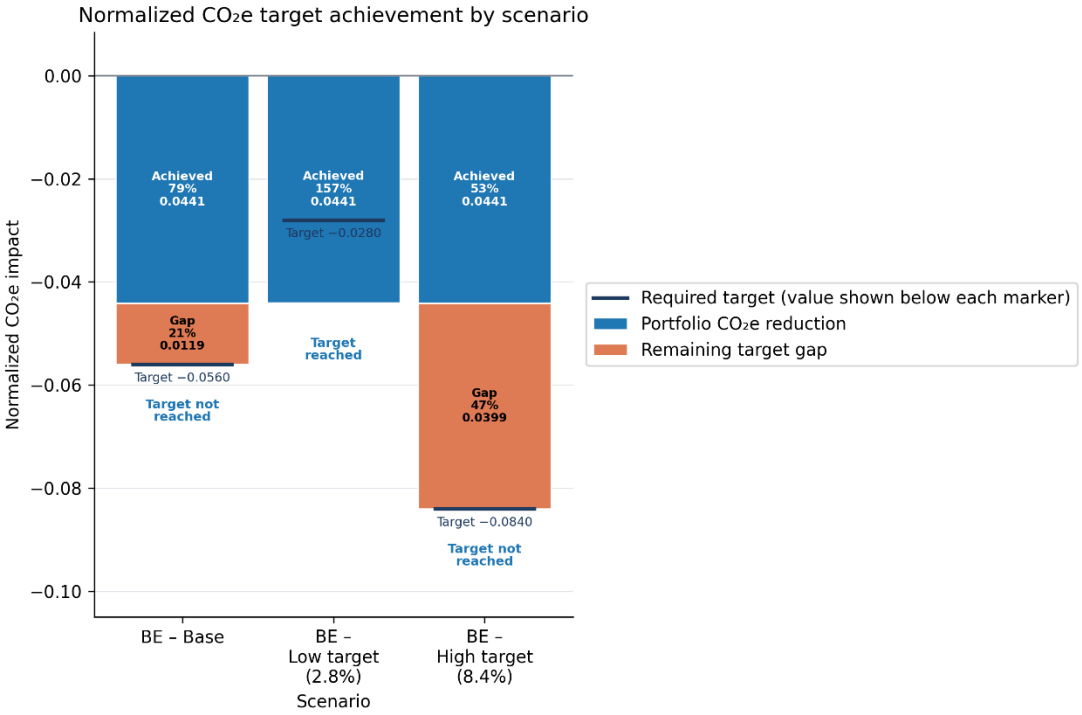

Figure 4.6.2.1: CO2e target achievement under different reduction targets

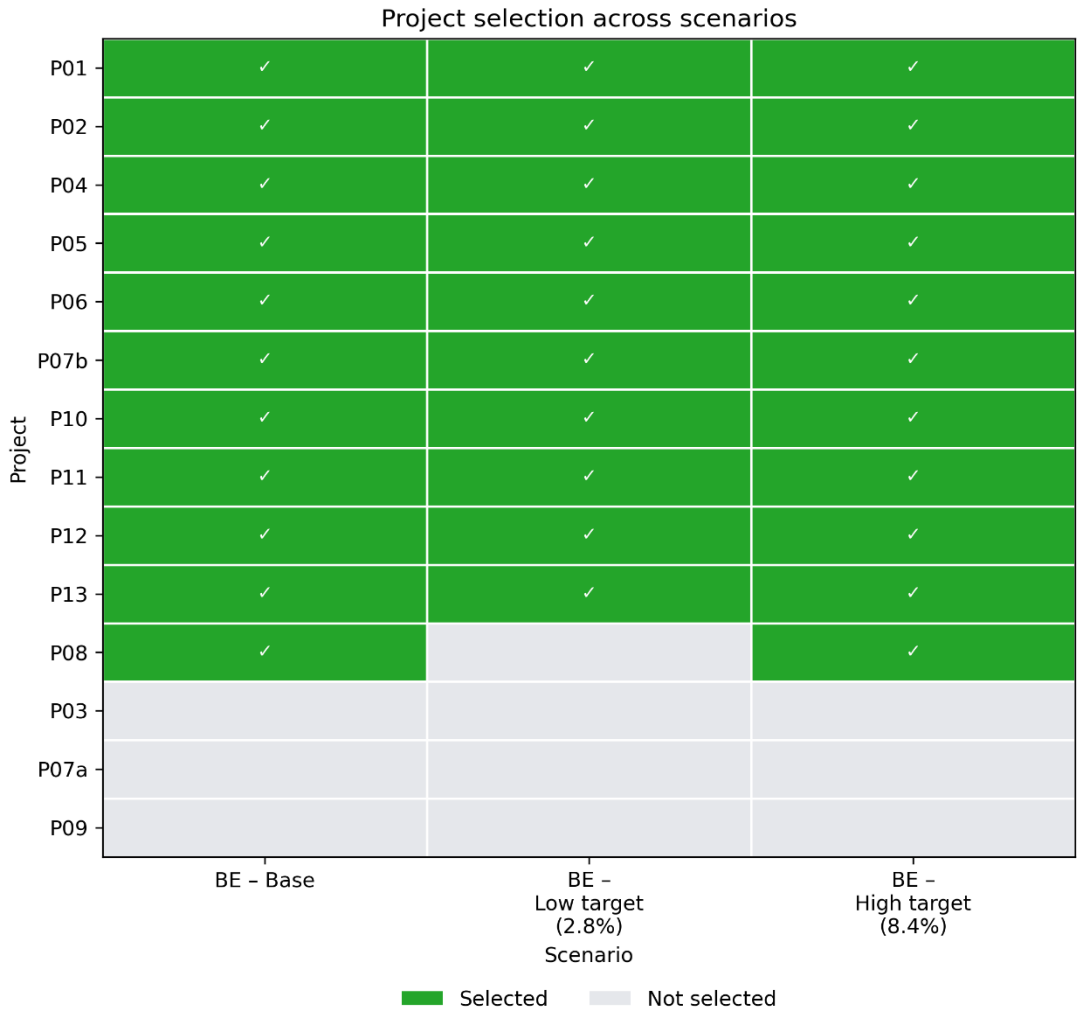

Figure 4.6.2.2: Project selection under different reduction targets

4.6.3 Project reduction sensitivity

The normalized CO_2e reduction changed significantly across the project reduction cases as shown in Table 4.6.3.1 and Figure 4.6.3.1. It decreased to 0.0221 in the low project reduction case and increased to 0.0661 in the high project reduction case. Only the high project reduction case reached the target, with a target achievement of 118%. In the low project reduction case, the target achievement decreased from 79% in the base case to 39%.

In the high project reduction case, CAPEX use and budget utilization were slightly lower because only 10 projects were selected, with P08 removed, as shown in Figure 4.6.3.2. However, the annualized net cost became more negative, reaching –€4.85M/year. In the

low project reduction case, CAPEX use and budget utilization remained the same as in the base case, with 11 projects selected. However, the annualized net cost decreased in magnitude to –€1.50M/year. Figure 4.6.3.3 shows that Dry Etch process gas remained the largest contributor to the portfolio CO_2e reduction in all three cases.

Table 4.6.3.1: Project reduction sensitivity results

Indicator	Base case	Low project reduction (–50%)	High project reduction (+50%)
Normalized CO_2e reduction	0.0441	0.0221	0.0661
Target achievement	79%	39%	118%
Target reached	No	No	Yes
Projects selected	11	11	10
CAPEX used	€970K	€970K	€960K
Budget utilization	96.6%	96.6%	95.6%
Annualized net cost	–€3.18M/year	–€1.50M/year	–€4.85M/year

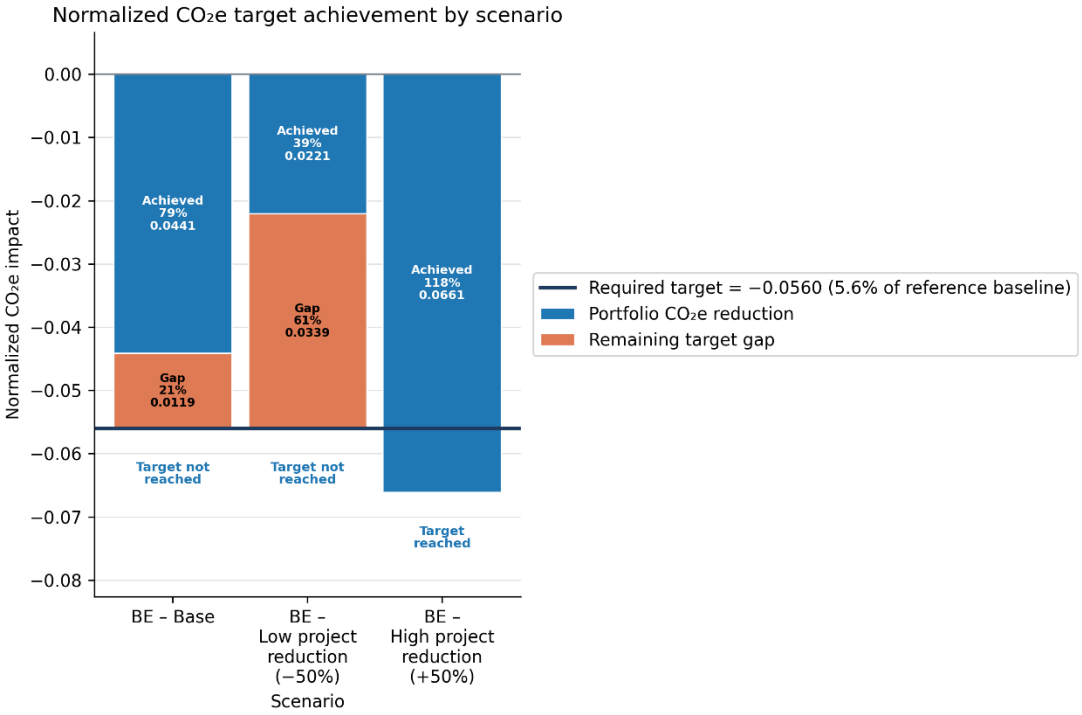

Figure 4.6.3.1: Normalized CO_2e target achievement under project reduction assumptions

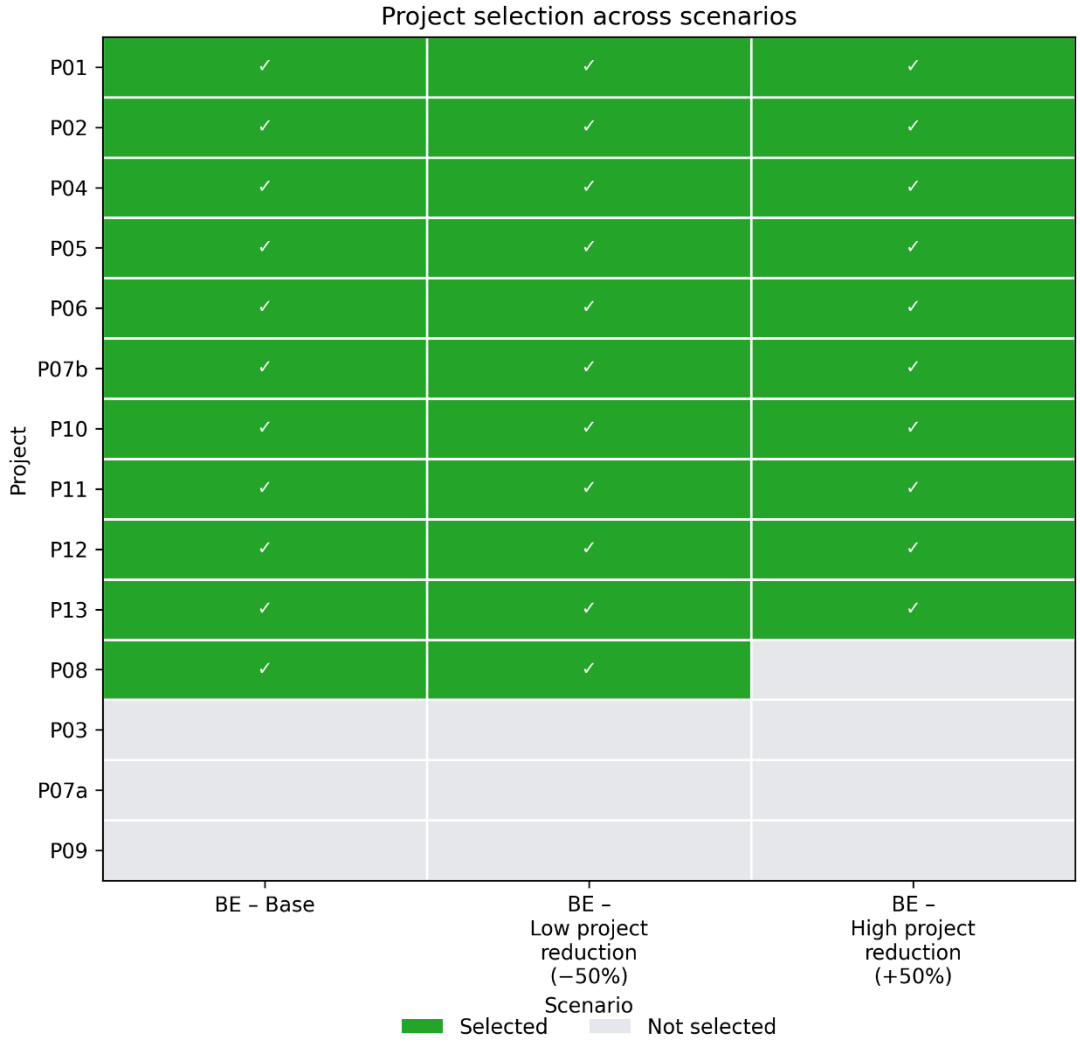

Figure 4.6.3.2: Project selection under different project reduction assumptions

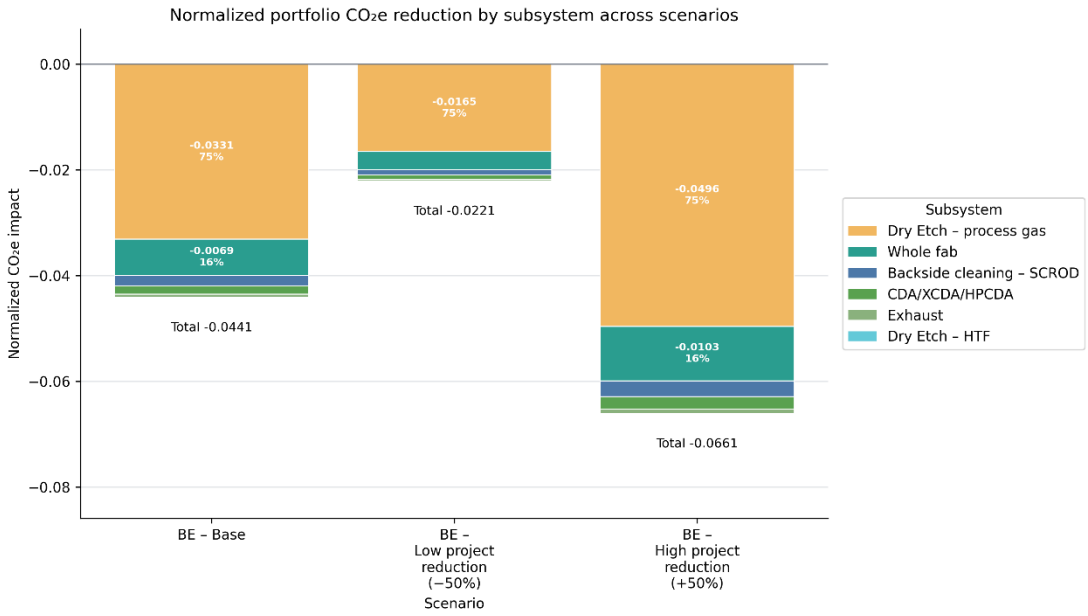

Figure 4.6.3.3: Normalized portfolio CO2e reduction by subsystem under different project reduction assumptions

5 Discussion

5.1 Portfolio composition

The results of the four main scenarios show that scenarios within the same location produced identical CO_2e reductions and selected the same projects. In contrast, the total CO_2e reduction differed between Belgium and Taiwan. Figure 4.3.3 shows that P01, P02, P04, P05, P06, P07b, P10, P11, P12, and P13 were selected in all four main scenarios. Although project selection was highly similar across the main scenarios, the selected projects did not contribute equally to the total CO_2e reduction.

The subsystem contribution results show that P07b was the dominant contributor across the four main scenarios. P07b alone provided 75% and 54% of the total reductions in the Belgium and Taiwan cases, respectively. It was selected in all four scenarios. The destruction and removal efficiency (DRE) of the P07b abatement improvement project was high. In addition, the relatively large subsystem baseline allowed the project to achieve a large reduction in process gas emissions. Therefore, its large absolute reduction and low CAPEX of approximately €10K were the main reasons for its repeated selection. As P07b was the main contributor, adding or removing projects with lower contributions had a relatively limited effect on the total CO_2e reduction. However, the selected project combination still changed across scenarios and sensitivity cases.

Some projects were selected only under certain assumptions, and the sensitivity analysis showed that their selection changed for different reasons. In the three Belgium budget cases shown in Figure 4.4.3, P05 was not selected in the 75% budget case, while P02 was still selected at 75% but was removed in the 40% budget case. This shows that P05 was more sensitive to budget reduction than P02. Based on the cost sensitivity analysis,

Figure 4.5.3 shows that P03 was selected only when the project cost was reduced by 50%. P03 had a CAPEX of €1M, which was almost the full €1.004M budget and therefore limited the number of other projects that could be selected together with it.

In the Belgium base case, P08 had a slightly positive annualized net cost of approximately €1.1K/year. Nevertheless, it was selected because the target was infeasible and the model prioritized additional CO_2e reduction. In the target and project reduction sensitivity cases, P08 was removed when the target could be reached because its additional reduction was not needed and removing it lowered the annualized net cost. P09 was not selected in any tested scenario. P09, the installation of a centralized compressor island, required a high CAPEX of approximately €3M, which exceeded the available budget in the tested cases. The project was therefore infeasible for selection.

As shown in Figure 4.3.2, projects affecting the whole fab made the second largest combined contribution to the total CO_2e reduction. Although not all of these projects were selected, most involved adjustments to CDA, or the optimization of pumps, MAUs, and FFUs. These projects had much lower CAPEX values than the major infrastructure project. Although each project contributed much less than P07b, their lower CAPEX allowed several projects to fit within the available budget. Therefore, the total reduction depended more on the contribution of each project than on the number of projects selected.

The model compared project reductions, CAPEX, annualized net cost, targets, and budget constraints simultaneously rather than ranking projects based on a single parameter. It also showed which projects were repeatedly selected and which projects were selected only under certain conditions. The model helped identify P07b as the dominant project and compare the remaining projects under different assumptions and constraints.

5.2 Regional and economic drivers

Regional environmental and economic inputs affected different aspects of the model results. For direct Scope 1 projects, the CO_2e reduction was based on the affected emissions baseline and the reduction rate or DRE of each project. The physical electricity savings and grid carbon intensity determined the Scope 2 reduction. Financial inputs such as electricity price, carbon price, CAPEX, OPEX, and discount rate, determined the economic performance.

5.2.1 Grid carbon intensity

Grid carbon intensities of 0.22 and 0.57 tCO_2e/MWh were used in the model for Belgium and Taiwan, respectively. Taiwan's grid carbon intensity was approximately 2.59 times Belgium's. The large difference in grid carbon intensity allowed the Taiwan scenarios to achieve greater calculated CO_2e savings from the same electricity saving projects.

The physical electricity savings depended on the affected baseline and the reduction rate of each project. Grid carbon intensity does not affect direct Scope 1 reductions because it is only used to convert electricity savings into CO_2e reductions. Consequently, P07b had the same normalized CO_2e reduction of 0.0331 across all four main scenarios, as shown in Figure 4.3.2. Grid carbon intensity explained the difference between the Belgium and Taiwan scenarios, but it did not change the fact that P07b was the largest contributor.

The normalized model annual reduction target was fixed at 0.0560. The Taiwan scenarios achieved 110% of the target, while the Belgium scenarios achieved 79%. This difference in target achievement determined which optimization objective was applied. Because the target could be reached in Taiwan, the model minimized the annualized net cost. In Belgium, the target could not be reached, so the model maximized CO_2e reduction within the budget and selected the additional project P08.

The higher target achievement in the Taiwan scenarios does not mean that the projects saved more electricity. The physical electricity savings were the same. However, the calculated Scope 2 CO_2e reduction was larger in Taiwan. As a result, physical electricity savings and calculated CO_2e reductions should be considered separately when evaluating the projects. If grid carbon intensity decreases in the future, the calculated CO_2e benefit of electricity saving projects will also decrease, even if their physical electricity savings remain unchanged.

5.2.2 Electricity price, carbon price and discount rate

Electricity price, carbon price, and discount rate affected different parts of the annualized net cost. These financial inputs did not directly change the physical electricity savings, project reduction rates, or calculated CO_2e reduction of individual projects. In the tested cases, changes in these three inputs changed the annualized net cost without affecting target achievement or project selection.

The electricity price increased from €125 to €162.50/MWh, a 30% increase, in the Taiwan high electricity price scenario. The annualized net cost of the Taiwan scenario changed from –€1.93M/year to –€2.51M/year. However, the physical electricity savings,

target achievement, and project selection remained unchanged. The higher electricity price increased the financial value of the selected project portfolio. Because both Taiwan scenarios reached the target, annualized net cost was used to select the portfolio. Although electricity price could affect project selection in the Taiwan scenarios, the tested increase was not sufficient to favor a different project combination.

The same pattern was observed between the Belgium base and high carbon price scenarios. The carbon price approximately doubled and changed the annualized net cost from –€3.18M/year to –€4.22M/year. The higher carbon price increased the avoided carbon value and made the annualized net cost more negative, but it did not change the reduction contribution or CAPEX of any project. Since the Belgium target could not be reached, the model prioritized CO_2e reduction within the same budget. Consequently, the higher carbon price changed the annualized net cost, but the project selection remained the same. P08 had a slightly positive annualized net cost in the Belgium base scenario, but this became negative in the high carbon price scenario. It was selected in both scenarios to provide additional CO_2e reduction.

Lastly, the discount rate did not affect CO_2e reduction, target achievement, or project selection. The annualized net cost changed only slightly, from –€3.20M/year to –€3.15M/year, when the discount rate increased from 4% to 12%. The discount rate changed the annualized CAPEX but did not change the initial CAPEX or the CO_2e reduction of each project. Since the target remained infeasible in all three cases, project selection continued to be based on CO_2e reduction within the budget.

Within the tested ranges, electricity price and carbon price had a greater impact on the annualized net cost than the discount rate, but the tested financial inputs did not change project selection. Since project selection remained unchanged under the tested assumptions, the electricity or carbon price at which the portfolio would change could not be identified.

5.3 Effects of assumptions and constraints

The sensitivity analysis showed that the available budget, project costs, reduction target, and project reduction assumptions affected the portfolio results in different ways. Budget and project costs mainly changed the selection of the projects. The project reduction assumptions directly changed the calculated CO_2e reduction and therefore had a strong effect on target achievement.

5.3.1 Budget and project cost

In the case with 40% of the base budget, the available budget decreased by 60%, while target achievement decreased by only 4 percentage points, from 79% to 75%. P07b remained selected and provided more than 70% of the portfolio reduction. The additional budget available in the base case allowed P02 and P05 to be selected, but their combined reduction contribution was relatively small. Consequently, within the tested budget range, the total CO_2e reduction was not proportional to the available budget. The case with the lower budget used approximately 80% of its available budget, compared with 97% in the base case. Projects could only be selected or not selected, and the model could not select part of a project. The remaining budget was insufficient to fund another project for further reduction. The tested cases showed that increasing the budget resulted in smaller additional CO_2e reductions. After the projects with the largest reduction contributions were selected, additional budget was used for projects with smaller contributions. This information can support decisions on whether the additional CO_2e reduction justifies a higher investment budget.

Reducing project costs by 50% increased target achievement from 79% to 89% and increased the number of selected projects from 11 to 12, with P03 selected. The lower CAPEX allowed P03 to fit within the budget and contribute a large reduction. In contrast, increasing project costs by 50% reduced target achievement by only 2 percentage points, from 79% to 77%, although the number of selected projects decreased from 11 to 8. The projects removed from the high-cost case had relatively small reduction contributions. Therefore, project costs had a clear effect on the exact project combination, but the reduction contribution of the selected projects was more important than the number of projects. This suggests that cost reduction efforts should focus on projects with large CO_2e reduction potential. Making one such project fit within the budget may improve target achievement more than keeping several projects with smaller contributions.

None of the three cost cases reached the target, although target achievement increased as project costs decreased. Overall, the project cost assumptions affected the exact portfolio more than target achievement.

5.3.2 Target feasibility and project reduction assumptions

The target sensitivity tested reduction targets of 2.8%, 5.6%, and 8.4%. Each reduction target produced a different target achievement rate of 157%, 79%, and 53%, respectively. However, the normalized portfolio reduction remained approximately 0.0441 in all three cases. The low target case selected 10 projects. The base and high target cases selected 11 projects. As the target was achieved in the 2.8% case and no additional reduction was needed, only one project, P08, was removed. Changing the target affected whether the

target could be reached and which model objective was used. However, it did not change the project reduction rates or physical savings of individual projects.

The project reduction sensitivity changed the calculated CO_2e reduction of the projects. The 0.5 times project reduction assumption lowered target achievement to 39%, compared with 79% in the base case and 118% under the 1.5 times project reduction assumption. The project reduction assumptions substantially affected both target achievement and annualized net cost. Overall, the budget and project cost cases produced smaller changes in target achievement than the project reduction cases. The tested discount rates did not change target achievement. The project reduction values should therefore be carefully verified before project investment decisions are made.

6 Conclusion

6.1 Summary of findings

The thesis developed a techno-economic framework to support preliminary planning and decision-making for the selection of fab decarbonization projects. The framework was demonstrated using a simulated N28 fab and evaluated 14 fab improvement projects based on CO_2e reduction and annualized net cost. Targets and budgets were set as constraints, and regional conditions were used to model different scenarios. The findings are summarized to explain how they support the application of the framework by answering research questions.

6.1.1 Main research question

Which improvement projects should a semiconductor fab prioritize under local conditions and budget limits to meet its CO_2e reduction target?

Ten projects were commonly selected in all four main scenarios, and P07b made the largest contribution to CO_2e reduction. Based on whether the target could be reached, the model used different objectives. In the Belgium scenarios, the model maximized CO_2e reduction within the budget because the target could not be reached. In the Taiwan scenarios, the model minimized annualized net cost because the target could be reached. Project selection depended on target feasibility, scenario conditions, project costs, and the available budget. The modeling was based on 14 candidate projects and a simulated N28 fab under the tested assumptions. The results only represent this simulated environment and are not exact portfolio recommendations for a real fab.

6.1.2 Supporting research question 1

Which combination of projects can meet the CO_2e reduction target at the lowest annualized net cost?

The model results indicated that both Taiwan scenarios reached 110% of the model annual reduction target. The portfolio of P01, P02, P04, P05, P06, P07b, P10, P11, P12, and P13 met the CO2e reduction target at the lowest annualized net cost. Taiwan base had an annualized net cost of −€1.93M/year, and Taiwan high electricity price had −€2.51M/year. Because the target was reached, the model minimized annualized net cost. In contrast, both Belgium scenarios reached only 79% of the model annual reduction target. The Belgium scenarios instead maximized CO2e reduction within the budget and selected one additional project, P08. The Taiwan portfolio results are based on the tested regional inputs, two different electricity prices, the 5.6% target, the €1.004M budget, and the 14 candidate projects.

6.1.3 Supporting research question 2

How much of the CO_2e reduction target can be achieved under different budget constraints?

Belgium base achieved 79% of the model annual reduction target. The case with 75% of the base budget achieved 78%. Target achievement decreased by 1 percentage point. Target achievement decreased further by 3 percentage points to 75% in the case with 40% of the base budget. P05 was removed when the budget decreased to 75% of the base budget, and P02 was further removed when the budget decreased to 40% of the base budget. Both projects had relatively small reduction contributions. The main contributor, P07b, remained selected in all three cases and contributed around 75% to 79% of the portfolio reduction. Therefore, most of the reduction was maintained despite the lower budget. This shows the importance of identifying the main reduction contributor under lower-budget conditions. These results are based on the Belgium conditions, the two lower-budget cases, the 5.6% target, and the 14 candidate projects.

6.1.4 Supporting research question 3

How do local conditions, including electricity price, grid carbon intensity, and carbon price, affect the selected portfolio and model results?

The higher grid carbon intensity in Taiwan resulted in a greater calculated Scope 2 CO_2e reduction, while the physical electricity savings remained unchanged. The Taiwan scenarios therefore reached 110% of the model annual reduction target, compared with 79% in the Belgium scenarios. Because Taiwan reached the target, the model minimized annualized net cost. Belgium did not reach the target, so the model maximized CO_2e reduction within the budget and selected the additional project P08.

Increasing the electricity price and carbon price made the annualized net cost more negative, but project selection remained the same. In Belgium, the model prioritized maximizing CO_2e reduction because the target was not feasible. Therefore, project selection remained unchanged despite the change in annualized net cost. In Taiwan, the higher electricity price made the annualized net cost more negative, but the increase was not enough to change the selected portfolio.

The conclusions are based on the tested assumptions in Belgium and Taiwan. The analysis only tested the selected electricity and carbon price increases and did not identify the price level needed to change the selected portfolio.

6.2 Contribution and practical value

The model is a decision-support framework intended to provide a systematic and transparent way to select improvement projects for achieving fab CO_2e reduction targets. Improvement projects are applied to different fab subsystems and have different costs, savings, and emissions impacts. Fab energy, facilities, and sustainability teams have different responsibilities in project planning and selection. Comparing improvement projects and identifying their contributions to the overall target requires considerable work and collaboration between these teams.

The framework can support project selection and prioritization, budget review, planning, and evaluation of portfolio performance against a defined target. Semiconductor companies could adapt the model to compare projects across fab locations with different electricity and carbon prices, budgets, and CO_2e reduction targets. By changing the fab baseline and project inputs, the framework is intended to be adaptable to fabs of different sizes and technology nodes.

6.3 Model limitations

Due to confidentiality, the data required for this thesis were often incomplete or unavailable. Information is also scattered among different teams. As a result, only a limited number and range of project types were included. They may not represent the full range of projects for an actual fab. A larger project set would require a more suitable optimization solver. Furthermore, the project sources did not always clearly report the reduction rates. The reduction impacts of many projects were calculated using estimated values. Exact CAPEX, OPEX, and lead time data were unavailable or could not be shared, so proxy values were used. Published sources were used as relative benchmarks. The proxy values do not represent official vendor quotations or exact project costs.

These data are highly project-specific and depend on the fab, vendors, and technology. In the model, the project reduction rates were assumed to be applicable to the simulated fab and were kept fixed within each scenario. Because the model was demonstrated using a simulated fab, the available budget was also based on an assumed value. This thesis mainly demonstrates how the framework can be applied to compare projects and analyze portfolio options. Therefore, the results are intended only for preliminary planning and project selection under the tested assumptions.

Additional CO_2e emissions or energy consumption might be generated by improvement projects. The model did not consider these additional impacts and focused only on the savings. The 5.6% target used in the main scenarios was a modeling assumption applied once to the combined Scope 1 and Scope 2 baseline for 2024. The model evaluates annual portfolio performance and does not track year-by-year emission reductions up to the target year 2030. In an actual fab, the baseline and target may change over time because of changes in production, technology, or policy.

The sensitivity analysis changed one input at a time and only tested the selected values. It did not test changes in multiple inputs or identify the exact value at which the selected portfolio would change.

6.4 Future work

Future work could improve the model to better reflect real-world conditions and increase accuracy.

First, improving the quality and availability of the input data can lead to more accurate analysis and decision-making. Collaboration and alignment among fab facilities, sustainability and finance teams, as well as vendors, could help achieve this and ease the data collection process. Using verified project reduction values and actual economic data, such as CAPEX and OPEX, could improve the practical application of the model.

Second, since only a limited number of candidate projects are used to represent the whole fab, the results may not fully represent the range of possible improvements. Adjusting the scope to a smaller area, such as an individual process area, could simplify data collection, improve data availability, and make project comparison more manageable.

Third, the model currently considers Scope 1 and Scope 2 CO_2e reductions together. The framework could be adapted to evaluate an individual impact separately, such as Scope 1 emissions, Scope 2 emissions, water consumption, waste generation, or chemical use. These impacts could be analyzed separately based on fab targets, local regulations, and resource constraints.

Fourth, depending on whether the target can be reached, the current model uses different selection objectives. In future work, a multi-objective MILP method could be applied to examine the trade-off between annualized net cost and CO_2e reduction. The model could minimize annualized net cost under different minimum CO_2e reduction requirements. The results could identify the portfolio switching points and the corresponding annualized net costs to guide decisions on how to balance cost and CO_2e reduction.

Finally, the model could compare scenarios with different fab capacities and changing electricity prices over time. As the demand for more advanced semiconductors surges, fab energy consumption in the model could be scaled with fab capacity growth. Electricity prices could also vary by year or season instead of using one fixed value within each scenario. Future work could also test combined changes in multiple inputs.

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