A Techno-Economic Methodology for Decarbonisation Pathway Analysis Under Uncertainty

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Abstract

Decarbonisation in the industrial sector is crucial in limiting global warming to a 1.5°C increase and preventing the severe consequences of climate change. Despite this, with vast uncertainties in companies' emission forecasts and future decarbonisation technology costs, and a funding gap equivalent to half of global corporate profits in 2020, innovative valuation methods and risk mitigations are required. Real Options Analysis is a technique that considers uncertainty in project valuation and the flexible design of infrastructure. This paper proposes a methodology enabling companies to integrate flexibility into strategies used in their decarbonisation pathways, building on existing frameworks and integrating industry insights. A novel concept of a Carbon Target Probability is introduced, which allows the benefit of flexibility to be quantified by considering the probability of attaining emission targets. A case study of an automotive manufacturer to which the methodology is applied shows an improvement in the Expected Net Present Value of 53% by using flexible decarbonisation strategies compared to standard designs and economic valuation processes, as well as a 55% improvement in the Carbon Target Probability. Along with the development of a Decision Support Tool, the paper provides insights into how to reduce risk and improve valuation in the context of decarbonisation pathways.

Keywords: Real Options Analysis, Flexibility in Design, Net-Zero, Industrial Sector, Decarbonisation, Optimisation

1. Introduction

Achieving Net-Zero emissions by 2050 in the interest of limiting global warming to a 1.5°C increase [IPCC, 2018] is critical in avoiding the catastrophic impacts of climate change. An increasing number of governments and companies are committing to accelerating this Net-Zero transition through the implementation of decarbonisation infrastructure such as offshore wind farms, coupled with carbon-negative strategies, notably Direct Air Capture (DAC), that facilitate the sequestration of atmospheric greenhouse gases.

This acceleration and importance is evident in new protocols and legislations including the EU's Emissions Trading System [European Commission, 2022], which allows companies that have spare emission units - emissions permitted to them but not "used" - to sell this excess capacity to companies exceeding their limit. The Science Based Targets Initiative is dedicated to facilitating and promoting science-based target setting [SBTi, 2023], while independently evaluating established goals within corporations.

Existing research however, reveals efforts to date fall short of limiting the 1.5°C increase [Matthews & Wynes, 2022], with global energy emissions increasing by 6% in 2021, and registering a new peak of 321 million tonnes in 2022 [IEA, 2022].

This lack of action can be attributed to two primary factors. The first is the significant financial commitment required for such initiatives. As reported by McKinsey [2022], these climate objectives necessitate an annual investment of $9.2 trillion, a significant rise of $3.5 trillion from current levels and a funding gap equivalent to half of global corporate profits in 2020.

The second factor concerns the uncertainty that project planners face, not only with forecasting future emissions to mitigate in volatile markets but also in technology cost and policy incentives. Technologies such as DAC are still in their infancy, and the cost of extracting CO2 is $250-600 per tonne [Lebling, K., et al., 2022] which when compared to natural gas processing or ammonia methods at around $25 per tonne [Baylin-Stern & Berghout, 2021] is not yet viable. Companies must weigh up deploying strategies early as technology pioneers or wait for policy changes and cost reductions before deployment. The effectiveness of decarbonisation projects may be compromised due to the unpredictable growth trajectories of companies and the corresponding uncertainties in their emission forecasts, with BCG [2022] reporting average errors of 30% in emission measurements. The 2022 Goldman Sachs [2022] Carbonomics Report indicates that cost-of-capital discrepancies between high and low emitters, instigated by uncertainty, are causing systematic underinvestment in industrial sectors. The uncertainties of the industrial sector are further highlighted in a report by the IEA [2022], projecting that technologies that are still in prototype and demonstration phases will contribute up to 60% of the emission reductions in this sector.

The financial value of projects is traditionally determined using capital budgeting, where the net present value (NPV) is calculated by taking into consideration deterministic time value-adjusted costs and revenues over a project's lifetime. This method, however, is largely inaccurate as it doesn't consider uncertainties, or project planners' ability to adjust and defer investment decisions during the project lifetime.

Change is vital in this area to overcome the multifaceted uncertainty and resulting funding gap. Innovative valuation methods and decarbonisation solutions must be proposed to allow decision-makers to make long-term investment decisions.

Flexibility in Design is a paradigm that does consider uncertainty and has the key advantage of deploying adaptable systems that can respond to changing market conditions. It facilitates the allocation of deployment costs across time which, when discounted to their present value, effectively reduces the total expenditure. The additional benefit of using flexibility in the context of Net-Zero, is it encourages resource consumption in a more considerate manner, as deployment is only undertaken if and when required.

To incorporate flexibility into companies' Net-Zero projects, Real Options analysis (ROA) can be used as it considers the real options available to a system, along with relevant uncertainties when determining how to evolve the project during its lifetime.

As an example of real options, in the 1990s, facing market uncertainty, the HCSC building in Chicago was strategically designed with the potential for future expansion. The skyscraper was designed to accommodate 27 additional stories on top of its initial construction if required [Guma, 2009]. Several years later, due to unexpected growth in office space demand, the company decided to utilise this built-in flexibility and added the extra floors. This pre-planned strategy enabled the company to adapt to market changes and expand its office capacity in a timely manner.

ROA focuses on quantifying the value of flexibility (VoF) in irreversible investment projects [Trigerorgis, 1996]. The VoF is a measure of the economic performance difference between a flexible system and a benchmark system. This value represents the maximum amount that one should consider justifiable to invest to achieve such flexibility.

This alternative approach is necessary for considering uncertainty and reducing investment costs in companies' decarbonisation efforts. The following literature review section presents a review of state-of-the-art research on the intersection of decarbonisation and ROA, summarising key developments in these fields.

2. Literature Review

2.1 ROA & Flexibility Methodology

The term 'Real Options' (RO) was first coined by Myers [1977] and was derived from the analytical technique of financial options [Black-Scholes, 1973], which are contractual agreements that grant the holder the right, but not the obligation, to transact a financial asset at an agreed-upon price before or on a set date. Similar to a financial option, integrating flexibility in an engineering system creates a real option, which is a "right but not an obligation" to make future investment decisions to adapt a system based on current conditions, and can involve deferral, acceleration and closure of facilities [de Neufville, 2003].

ROA is a prevalent method for quantifying the VoF and enabling companies to reduce cost and uncertainty in their decarbonisation pathways. This technique has been applied within frameworks, with [Mun, J., 2006] creating one to enable flexibility for companies with several projects. Stages in this framework include listing of potential projects, deterministic baseline design and discounted cash flows for each project, uncertainty recognition, framing RO with techniques such as Decision Rules, simulation and comparison of baseline and RO designs and, then combination of desired projects into a portfolio for analysis on multiple projects. [Cardin, 2015] proposed a ROA methodology that builds on this, by including sensitivity analysis at a project level to ensure the robustness of designs. Using an LNG facility case study, the sensitivity of Economies of Scale (EoS) and Learning Rates was made in the paper between fixed centralised and modular facilities. Results show the robustness of flexible design, providing better value over reasonable EoS and learning rates. Despite both these frameworks offering robust methods for integrating flexibility into a company's projects, due to their generality, they don't consider specific decarbonisation factors. For example, in these frameworks, there is no direct consequence if demand exceeds a facility's capacity, but in a decarbonisation context, if a company's emission targets are missed due to emissions 'demand' not being reduced then direct penalties may need to be levied.

2.2. Flexibility in Net-Zero Applications

There have been applications of ROA in the area of Net-Zero projects, where [Qixin, 2010] examined the flexibility in Carbon Capture and Storage operations, and analysis demonstrated that a cost reduction of 69% compared to fixed plant designs is achievable. There has also been research in the Net-Zero space of renewable energy, [Martínez-Cesena, 2011] investigated the application in a hydropower case study, with results also favouring flexible facility designs.

[Chuan-Chuan Ko, 2019] developed an optimal decision-making model for companies to invest in Net-Zero projects using RO, by modelling the impact of government taxes, as well as subsidies. The presented model, intended to create a win-win situation for companies and governments by providing indicators for firms on when to proceed or delay investment in green projects, is reusable but requires both Net-Zero subsidies and taxes to be applicable.

2.3 Decarbonisation Methodologies

There have been methodologies designed specifically for the analysis of Net-Zero projects such as Photovoltaic systems [Koo, 2013], which concluded could be useful in aiding decision-makers in their analysis. Due to the variability in different sources of uncertainty and flexibility however, the constrained scope of this approach restricts its applicability solely to regional photovoltaic systems analysis and planning. [Melese et al, 2015] devised a methodology for developing RO in Carbon Capture and Storage network design. This analysis proves crucial for transitioning from uncertainty identification to formulating flexible options in Net-Zero projects, and it is relevant to any network-based infrastructure system. Despite this, its limited scope restricts use in various engineering systems and lacks context for company-specific decarbonisation projects.

Some frameworks and methodologies primarily focus on the context of companies and their decarbonisation pathway. [Stavropoulos, 2022] presents a framework for energy-intensive industries looking to decarbonise, by introducing digitalisation and energy-efficient equipment to production lines. The framework applies to companies, and integrates different metrics, both from emissions and cost viewpoints. The framework, however, is focused at a more granular level, rather than considering a company's sum of emissions, with the consideration of uncertainty also missing. The SCORE methodology [Carter, 2022] is aimed at assisting in decarbonisation pathways at a company-wide level. This approach provides guidance to corporations on establishing targets, selecting decarbonisation strategies, forecasting and implementing such strategies. Despite these contributions, it overlooks the inherent uncertainties present in companies' emission forecasts and future technology costs. Consequently, it falls short in integrating flexibility and ROA into its framework.

2.4 Decision Support Tools

Decision Support Tools and Systems (DST & DSS), which integrate methodologies into an interface to allow project planners to be supported in decision-making, can be an important tool in comparing different options available. [Beriro, 2022] developed a DSS for onshore renewable energy projects, and showed the benefit of these systems in their ability to allow non-specialists to appreciate outcomes and used them to inform early-stage decision-making in the context of onshore renewable energy. [Koldo, 2020] examines urban energy planning and outlines key features needed for Decision Support Systems to aid city managers in urban decarbonisation.

Nonetheless, these DSS do not involve the concept of flexibility and focus more on the sustainability aspect. In contrast, [Anderson, 2022] analysed flexible staged deployment for satellite constellations, showing not only a 43.1% decrease in expected life-cycle cost compared to traditional design strategies but also a DSS that conveys the VoF to system engineers using it. Conversely, this DSS is designed purely for satellite deployment analysis, so is limited in its application to decarbonisation analysis.

2.5 Research Gaps

Despite research around ROA in the application of specific types of decarbonisation projects, and general methodologies and DST to convey the VoF to project planners, a gap exists for a specific decarbonisation ROA methodology that companies can follow when planning their Net-Zero strategy. In addition to this, there appears a lack of DST to facilitate project planners in the valuation and decision-making process for decarbonisation projects. Table 1 highlights the gap in the literature across the areas of Net-Zero projects, ROA, decarbonisation methodologies and DST.

Table 1. Showing the research gap in the existing literature

Paper	ROA	Net-Zero Projects	Decarbonisation Methodology	DST
(Cardin, 2015)	✓			
(Ko, 2019)	✓	✓		
(Qixin, 2010)	✓	✓		
(Stavropoulos, 2022)		✓	✓	
(Beriro, 2022)		✓		✓
(Anderson, 2022)	✓			✓
Research Gap	✓	✓	✓	✓

3. Research Aims

To respond to this gap, the paper has three key research objectives. The first is to develop a methodology to embed decarbonisation metrics into ROA models. The scope of this methodology will primarily target the industrial sector, a sector marked by significant uncertainties and potential upside from integrating RO into decarbonisation strategies. The second objective is to use the methodology to uncover the quantitative VoF for the industrial sector's decarbonisation projects. The third is to explore how a Decision Support Tool can aid decision-makers in their early-stage planning and ensure ROA is explainable to these stakeholders. These objectives will contribute to recognising the VoF through ROA in industrial sector Net-Zero pathways, to reduce uncertainty risk and improve valuations of decarbonisation projects.

To achieve these objectives, the paper first investigates current methodologies, supplemented by industry insights on key factors in corporate decarbonisation. The proposed methodology is then detailed through a case study of an automotive manufacturer, allowing the VoF to be quantified. Finally, the paper develops a DST to exhibit how ROA and the VoF can be communicated to project planners.

4. Methodology Design

This section details how the proposed ROA Decarbonisation Methodology was developed, using a combination of metadata analysis of existing decarbonisation and RO methodologies, as well as engaging with stakeholders to gain insights into considerations for the methodology.

4.1 Metadata analysis

Existing Net-Zero frameworks have been developed to help companies plan their decarbonisation pathway, and generally include three key stages:

1. Auditing emissions and setting decarbonisation targets.
2. Planning how to reach targets set i.e., what decarbonisation strategies will be used.
3. Executing the plan, alongside ongoing monitoring.

Figure 1 shows an example of existing high-level frameworks for companies to follow. Alongside the importance of defining targets and having an accurate audit, existing frameworks also show the importance of using a combination, or 'portfolio' of decarbonisation strategies.

The key component missing from existing decarbonisation frameworks is the consideration of uncertainty in the planning stage, and how it should be mitigated. Figure 2 shows an example of a flexible ROA methodology designed in the context of an LNG plant case study to help consider uncertainty and realise the VoF in these systems. The importance of ideating flexible designs and corresponding decision rules, comparing fixed designs alongside flexible designs as well as performing sensitivity analysis are all aspects to include in the ROA Decarbonisation Methodology.

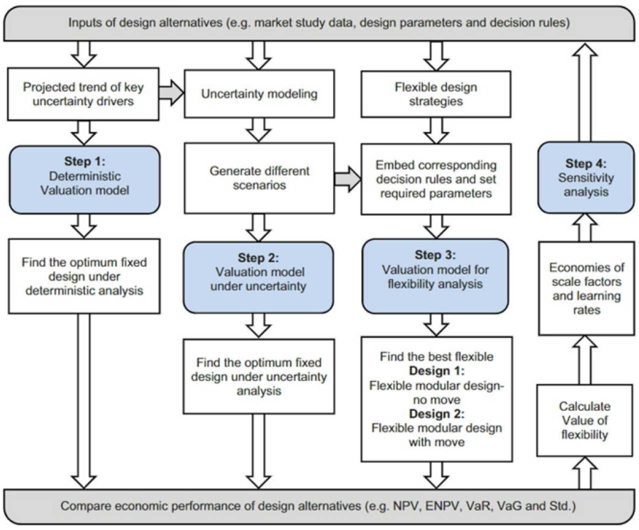

Figure 2. Example methodology to evaluate flexible designs against uncertainty [Cardin, 2015]

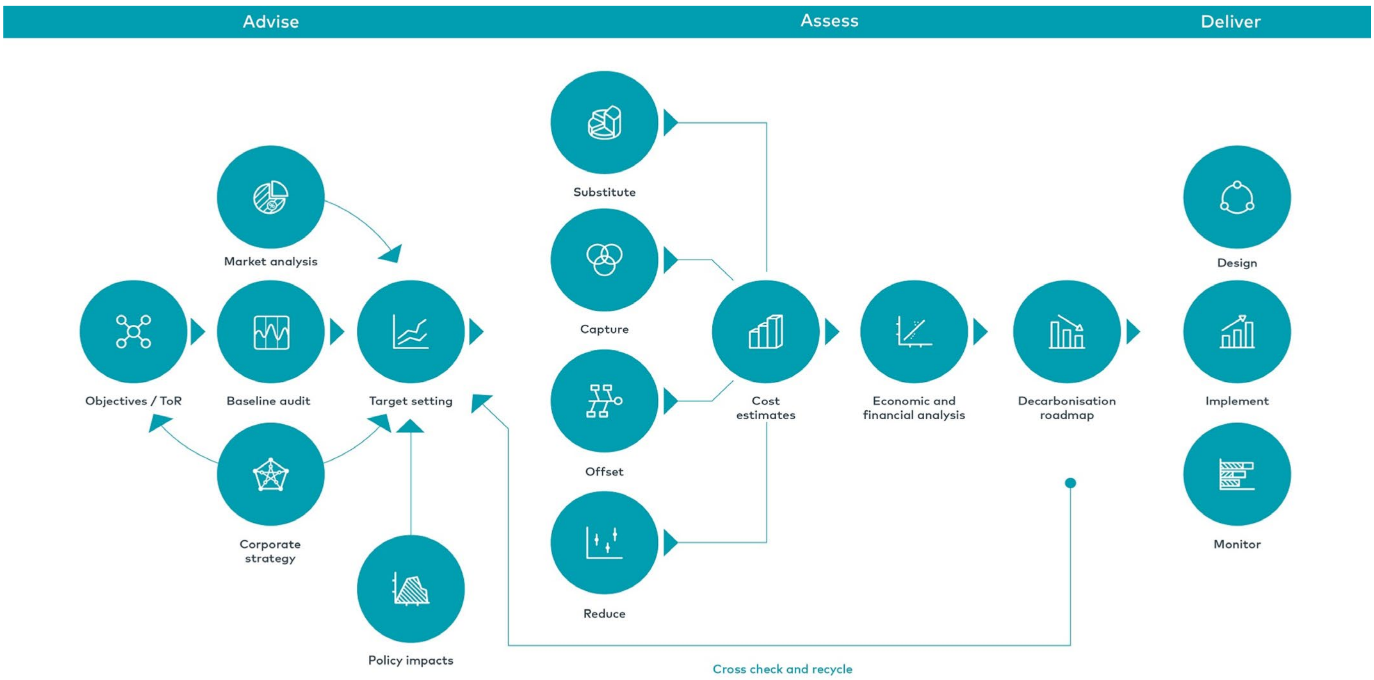

Figure 1. SCORE decarbonisation framework [Carter, 2022].

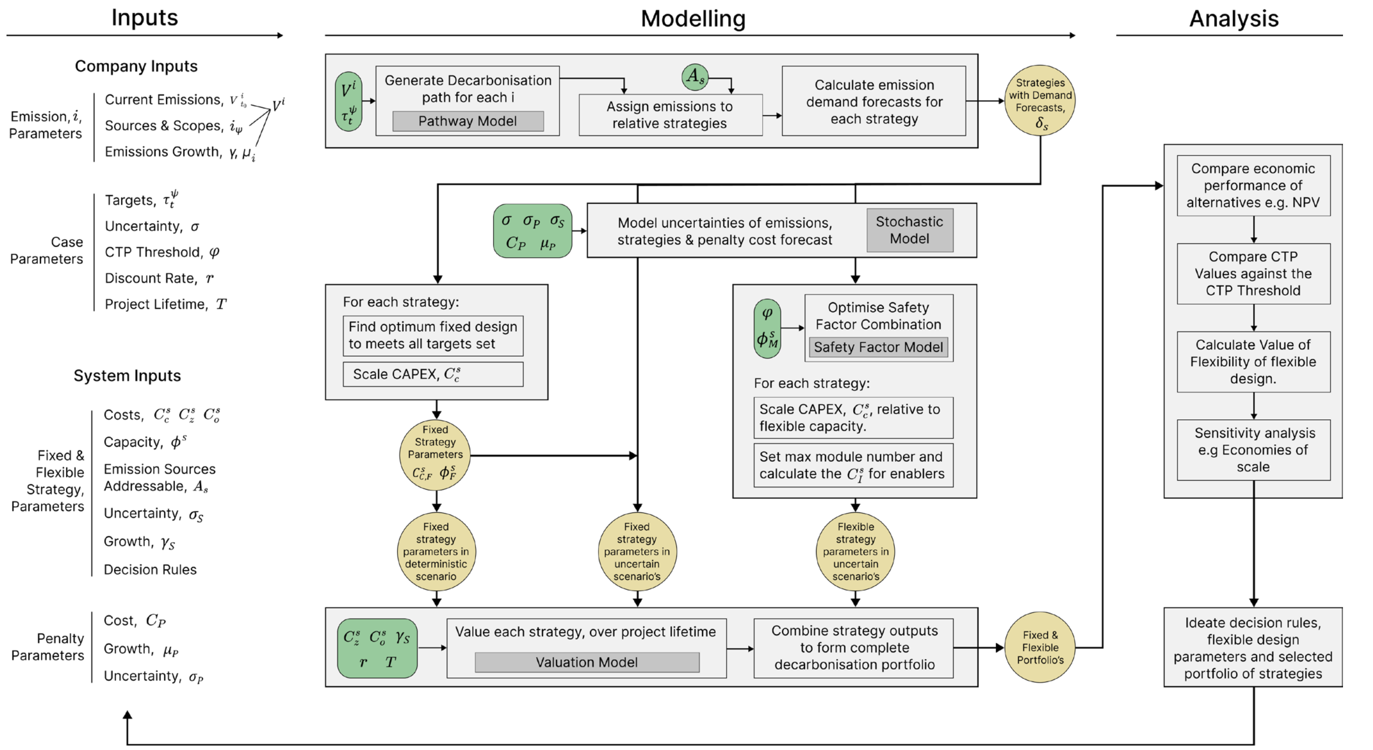

Figure 3. Proposed ROA Decarbonisation Methodology

4.2 Stakeholder Exploration

Informal interviews and discussions were conducted with sustainability consultancies and industrial sector companies involved in decarbonisation to gather insights on the specific aspects of decarbonisation pathways that were important to them.

While the participants reinforced aspects of Net-Zero Frameworks, there were also important additional insights to integrate into the ROA decarbonisation methodology. Three repeated insights are key to consider:

1. Although targets may be set every 20 years, companies aim for a linear reduction in emissions year on year:
   "With improvements we make to our manufacturing process a large emissions decrease can happen at once, but in general we'd aim to consistently reduce emissions each year to stay on track for our targets." - Automotive OEM employee
2. Where possible, carbon offsets should be avoided, and should be used as a last resort to meet targets:
   "Companies prefer to reduce emissions through tangible assets, before buying external offsets." - Sustainability Consultant
3. Companies wish to have different targets for different scopes of their emissions:
   "To an extent, we have more control over our scope 1 and 2 emissions so can set more ambitious targets" - Automotive OEM

Based on the metadata analysis and stakeholder insights, the ROA decarbonisation methodology displayed in Figure 3 was developed combining decarbonisation and ROA methodologies as well as insights on key requirements from interviews.

5. Application of Methodology: A Case Study

This section demonstrates how the proposed methodology can be used to analyse a system of interest. One type of industrial company that faces challenges in its decarbonisation is automotive manufacturers. Despite the shift to electric vehicles (EVs) and gradual decarbonisation of the energy grid, there are still high emissions from vehicle production and other sources such as logistics and end-of-life vehicle treatment.

The case study analysed an automaker that produces 14,161 EVs, the same number as Jaguar Land-Rover did in 2022 [JLR, 2022] with forecasted average sales growth of 4% YoY in line with global vehicle sales [Luman, O.S, 2023].

5.1 Company Emissions Inputs

The first step in the methodology involves defining company inputs. To obtain accurate values for this study, emission levels and categories were calculated by stating emissions per vehicle based on a standard vehicle, and then multiplying these by annual vehicle sales.

Table 2. Vehicle Specifications & emission volumes [Qiao, Q., 2019]

Sold Vehicle Parameters	Vehicle (ex-Battery)	Battery
Weight (kg)	1300	188.7
Battery Capacity (kWh)		27
Materials Extraction & Refining (tCO2)	5.87	1.78
Production Logistics (tCO2)	1.44	0.45
Component Manufacturing (tCO2)	1.71	0.74
Lifetime Mileage (km)	150,000	
Electricity Production for Use Phase (tCO2)	15	
End-of-Life Disposal (tCO2)	1.39	0.66

It was assumed that the companies' emissions were predominantly from the vehicles produced and that other emissions such as employee travel were negligible.

Table 3 shows the overall annual company emissions for the year 2023, as well as categorising each emission source, i, into a scope. The external growth parameter for each source, μ_i, is to be used alongside the overall emissions growth, γ, to help forecast the annual growth rate of each source of emissions, V^i_t, given by:

$$V^i_t = V^i_{t_0} * \mu_i * \gamma \qquad (1)$$

For example, electricity production is expected to decrease at a rate of 9% a year as the electricity grid decarbonises [BEIS, 2018], which is an external factor that a manufacturer cannot control. Figure 4 shows the deterministic emission forecast, without uncertainty, based on $V^i_{t_0}$, μ_i and γ.

Table 3. Annual company emission sources and scope, see Appendix A2 for μ_i calculations.

Sources	Volume, $V_{t_0}^i$ (tCO2)		External Drift, μ_i
	Scope 1&2	Scope 3	
Materials Extraction & Refining (body)		83,072	-1%
Materials Extraction & Refining (battery)		25,243	0%
Production Logistics (body)		20,448	-6%
Production Logistics (battery)		6,311	-6%
Component Manufacturing (body)	24,283		-6%
Component Manufacturing (battery)	10,518		-6%
Electricity Production		212,415	-9%
End-of-Life Disposal (body)		19,684	-6%
End-of-Life Disposal (battery)		9,431	-6%

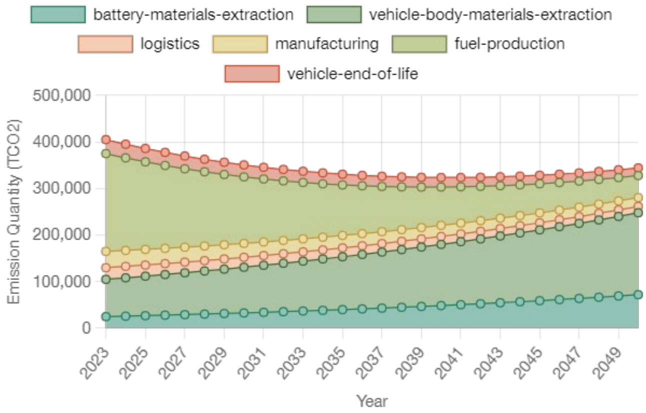

Figure 4. Deterministic forecast of emissions.

5.2 Strategy & Penalty Inputs

Out of all the possible decarbonisation strategies, this study proposes that the company constructs its decarbonisation 'portfolio' by selecting 3 real strategies, s, to deploy: DAC, Lithium-Ion Battery Recycling, and Vehicle Body Recycling.

DAC reduces emissions by removing CO2 directly from the air, so this can be used to reduce any of the companies' sources of emissions. However, for Body Recycling, this reduces emissions by recovering the required materials from end-of-life vehicles, used for producing new vehicle bodies rather than extracting raw materials. This can therefore only be used to reduce emissions from the Body Materials Extraction & Refining source. This is similar for Battery Recycling where it can only reduce the emissions from Battery Materials Extraction & Refining.

However, due to the size of the current and forecasted emission volumes from both Extraction & Refining sources, these recycling strategies will still be significant.

Table 4. Sources assigned to each strategy.

Source	Emissions Addressable By		
	DAC	Battery Recycling	Body Recycling
Materials Extraction & Refining (body)			✓
Materials Extraction & Refining (battery)		✓	
Production Logistics	✓		
Component Manufacture	✓		
Electricity Production	✓		
End-of-Life Disposal	✓		

The system inputs can then be defined which includes the parameters of each of the three strategies considered in this case study. Quantitative data on the parameters of the strategies were obtained from studies and market research, as seen in Table 5. The parameters for the fixed plants and modular plants used in the study are scaled from these values. The recycling plants' capacities were converted from kt/yr to ktCO2/yr using conversion factors detailed in Appendix A3.

Table 5. Real Data used in the study. See Appendix A3 for sources

Strategy	Capacity (ktCO2/yr)	CAPEX ($ million)	OPEX ($/tCO2)	Savings ($/tCO2)	Drift (%)
DAC	10	8.5	89	-	-5
Battery Recycling	126	165	238	340	-2.6
Body Recycling	76	6.7	117	161	-1.5

Unlike standard ROA, if emission reduction demand cannot be met, there must be a direct 'penalty' to ensure that targets are still met for the company. In this case study, the penalty required the company to pay for EU Carbon Permits which are used if a company has higher emissions than permitted as part of the EU Emissions Trading Scheme. The cost per tCO2 of the penalty, C_P, was modelled with a drift of $\mu_P = 8.4\%$, volatility, $\sigma_P = 4.5\%$, and at a cost, C_P=\$88 at $t = 0$ based on historic data (see appendix A4).

5.3 Emissions Pathway Generation

In this study, the company sets decarbonisation targets, τ_t^ψ where ψ is the scope, of a 55% reduction of scope 1 & 2 emissions and a 50% reduction of scope 3 emissions by 2030, and to reach Net-Zero (100% reduction) by 2050 in all 3 scopes. These are similar to global vehicle manufacturers such as Jaguar Land Rover [JLR, 2022].

Using $V_{t_0}^i$ assigned to each strategy, along with the targets, an emission pathway for each strategy can be developed. This pathway dictates the allowable emission level per year for i assigned to each strategy. Each i can have its pathway modelled as follows; for each τ_t^ψ, if $\tau_\psi = i_\psi$, multiply V_0^i by τ_t^ψ, and add it to i pathway array in the index t. After the target years have been populated in this array, linear interpolation is used to fill in the remaining empty entries of the array between the established target values. This follows the insights from the interviews suggesting that emission paths should be linear in-between targets and is also suggested by Faria [2019] as part of a target-setting method.

With each i assigned to a strategy, by summing their pathways, an overall pathway for each strategy can be seen in Figure 5.

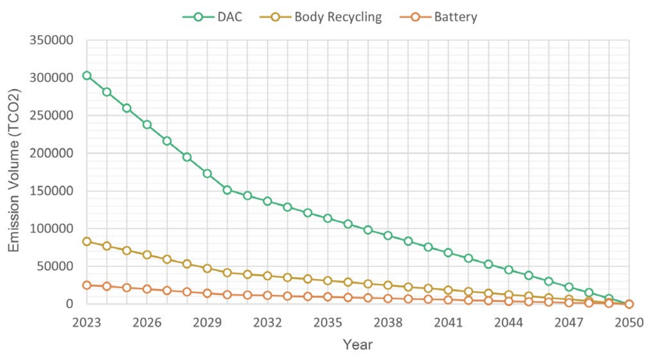

Figure 5. Annual emissions targets for each strategy

By calculating the difference between V_t^i assigned to each strategy, and τ_t^s each year, the emissions 'demand', δ_s, that each strategy was expected to reduce each year could be obtained as seen in Figure 6.

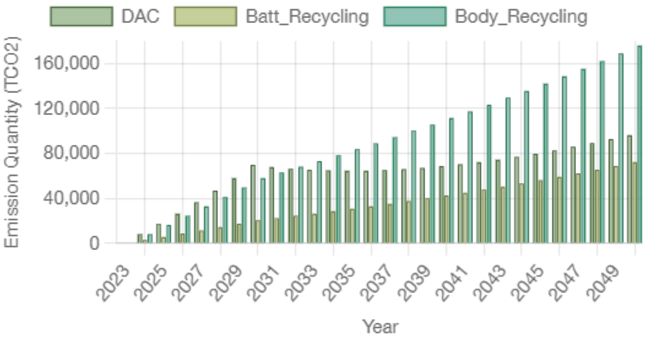

Figure 6. Annual emissions (demand) for each strategy

For the study, the Project Lifetime, T, equals 27 years to simulate the time between 2023 and 2050. t to construct plants for any of the strategies was assumed to be one year, based on historic DAC and recycling facility construction [Judge, P., 2021] [Macmillan, 2021] and the discount rate, r, for the study, was set at 10%. r accounts for the time value of money and allows the present value of costs incurred over the project lifetime to be calculated by:

$$PV(C) = \frac{C}{(1+r)^t} \tag{2}$$

5.4 Deterministic Analysis (Fixed Designs)

With the δ_s and project parameters defined, the next stage is to perform a deterministic study. The optimal capacity, ϕ_F^s, of each strategy's plant for the deterministic demand of emissions should then be determined. Each strategy's ϕ_F^s should ensure that all forecasted emissions are reduced without the need to use Carbon Permits, and therefore the fixed plant designs for each strategy in the analysis have ϕ_F^s to meet the full demand of the deterministic emissions, δ_s over T. The parameters can be seen in Table 7. CAPEX is obtained by linearly scaling real data from Table 6. OPEX and savings are assumed constant per tCO2 regardless of the ϕ_F^s.

Table 6. Fixed design parameters.

Fixed Plant	Capacity, ϕ_F^s (ktCO2/yr)	CAPEX, $C_{C,F}^s$ ($ million)	OPEX, C_O^s ($/tCO2)	Savings, C_Z^s ($/tCO2)
DAC	100	85	89	-
Battery Recycling	75	97	238	340
Body Recycling	200	17.7	117	161

5.5 Uncertainty Analysis (Fixed Designs)

The volatility parameter, σ, in the companies' forecasted emissions for vehicle sales, which affects the emissions produced each year by the manufacturer and allows uncertain scenarios to be modelled was set at $\sigma = 8.5\%$ based on historic Jaguar Land Rover sales [JLR, 2022]. The realised growth rate for each emission source per year, φ_t^i, can be modelled with Geometric Brownian motion:

$$\varphi_t^i = \left(\gamma \cdot \Delta t + \sigma \cdot \varepsilon \cdot \sqrt{\Delta t}\right) \cdot (\mu_i) \tag{3}$$

Where Δt is the time step (1 year in this study) and ε captures the Wiener process based on a standard normal distribution. As seen in Figure 7 where 25 realised scenarios are graphed using Monte Carlo simulation, the deviations between best and worst-case scenarios capture the volatile nature of long-term emission forecasts.

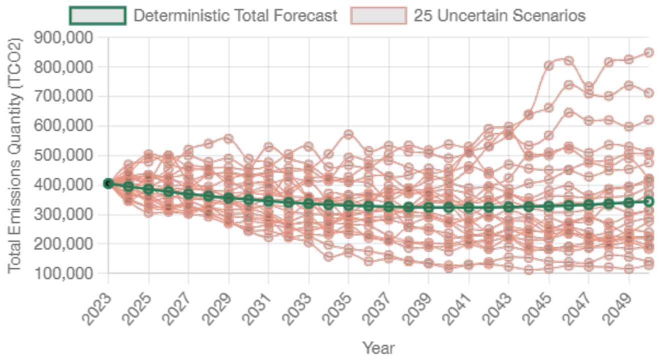

Figure 7. Deterministic and uncertain forecasts of total emissions.

There is also strategy uncertainty, σ_S, modelled into each strategy's future CAPEX and OPEX, with 9% for DAC, 5% for battery recycling, and 3% for body recycling (see appendix A5 for calculation).

For each fixed strategy plant, $N = 2000$ scenarios were run in a Monte Carlo simulation to determine the average Expected Net Present Value (ENPV) of each strategy compared to the deterministic analysis. The ENPV is defined as:

$$ENPV = \frac{1}{N}\sum_{s=1}^{N} NPV_s \tag{4}$$

The results in Table 7 show that for every strategy, the ENPV is lower with uncertainty.

Table 7. Comparing deterministic and uncertainty

Strategy	NPV Deterministic ($ mil)	ENPV Uncertain ($ mil)	Strategy CTP
DAC	-109	-124	0.56
Body Recycling	22.7	12.1	0.60
Battery Recycling	-60.9	-65.1	0.58

5.6 Carbon Target Probability

An important and novel system input that should be considered with uncertainty is a Carbon Target Probability Threshold (CTPT). This is not currently a standardised measurement used by companies when setting Science Based Targets, as uncertainty is not considered in the SBTI's Target Validation Protocol [SBTi, 2023], which reviews whether a company's emission targets are achievable. However, with future uncertainty in decarbonisation strategy cost, and forecast emissions, there is not only financial risk but the risk of not meeting official emissions targets that are set and approved.

Therefore, this paper proposes that policymakers or companies themselves set a CTPT. This is the probability that over the Monte Carlo scenarios, emissions targets set are achieved by the strategies deployed by the company. Stakeholder exploration emphasised minimising the use of carbon offsets to compensate for missed targets, and this risk is reduced by setting a CTPT.

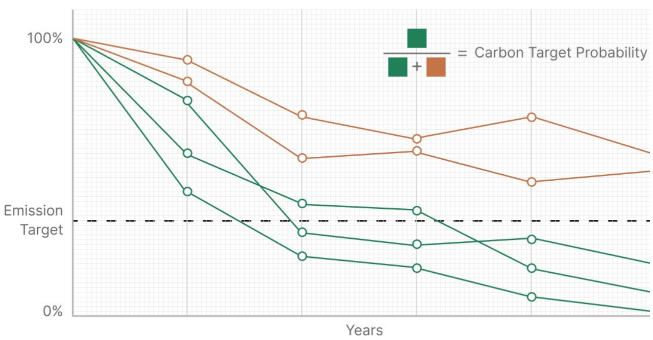

Figure 8. Example representation of the CTP concept

For this study, the CTPT, $\varphi = 0.8$, meaning the company requires an 80% probability of reaching the emission targets set without using carbon offsets.

It is important to note that in deterministic analysis, as the capacity is larger than the emissions demand for all strategies, it is assumed that the targets will therefore be met. With uncertainty however, the CTP for every strategy in Table 7 shows that is a significant probability (~40%) that both targets will be missed due to a lack of capacity to reduce higher volumes than forecast of emissions. When these strategies are combined, the CTP further decreases to 0.53. This is because all six targets (three strategies, and two targets in 2030 & 2050) must be met in the same simulated scenario for the portfolio to have met the overall targets. Therefore, to meet φ at a portfolio level, ϕ_F^s would have to be significantly larger.

5.7 Flexibility Analysis (Flexible Designs)

Flexible plant designs for each strategy aim to improve the overall portfolio ENPV, as well as the ability to meet φ by mitigating uncertainty risk. The flexible plant designs were created by running workshops with experts in each technology field. This follows the 'Explicit Training and Prompting' technique [Cardin, 2014] where experts are introduced to flexibility, and then partake in structured prompting sessions to support flexible strategy generation. Workshop slides can be seen in Appendix A6.

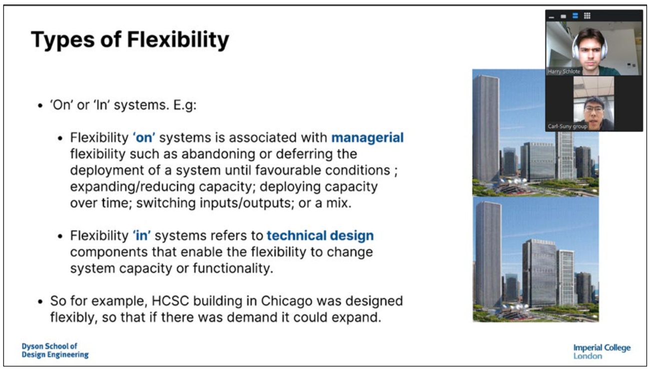

Figure 9. Workshop with SUNY Group to identify flexible Battery Recycling plant designs.

From these workshops, several ideas and corresponding enablers, decision rules and constraints were ideated to allow each strategy to expand to meet realised demand.

A Pugh Chart Analysis was completed to rank the ideas for each strategy as seen in Appendix A7 tables. From the highest scoring ranking options, they all favour ideas that expand capacity in a modular manner while integrating existing facilities, rather than building completely new facilities.

This means that while additional CAPEX may be higher to allow for infrastructure and space for expansion e.g., DAC plant having enough energy supply for an expanded facility rather than starting capacity, the cost and time to add additional capacity will be lower than building new facilities from the ground up.

Figure 10-12 shows how the three strategies can be designed to enable this modular expansion. The DAC plant can connect additional modules to existing energy, sorbent, and sequestration pipelines, and for the recycling plants, additional machinery lines can be purchased and added to the existing plant, given there are enough supporting facilities such as floor space and storage.

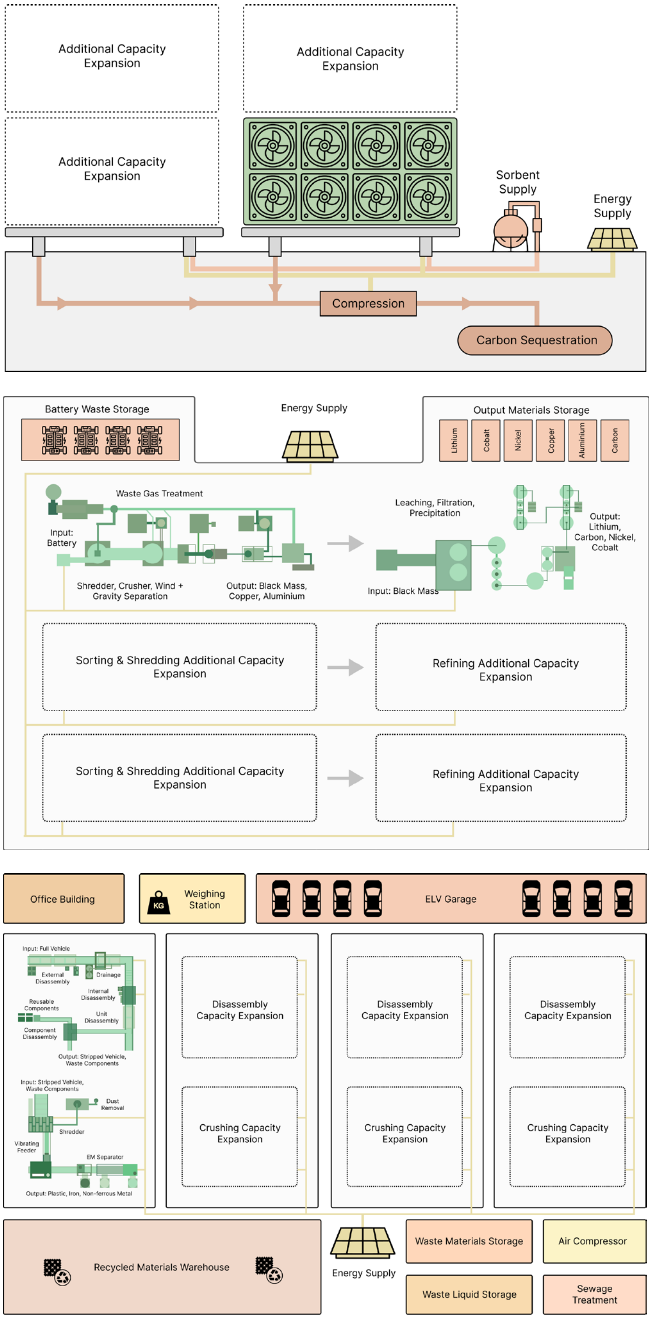

Figure 10-12. High-level DAC, Battery Recycling (top-down view), Body Recycling plant design (top-down view) for Modular Capacity Expansion

The capacity of the modular designs, ϕ_M^s, was parameterised at 10% of ϕ_F^s. As the three strategies' flexible designs all use a modular expansion plan, all three follow the same decision rule format:

- IF "the product of demand and χ_s is larger than the current facilities capacity,"
- THEN "expand the capacity of by adding the number of modules/machinery lines to match the product of demand and χ_s,"
- ELSE "do nothing."

χ_s can be thought of as a safety factor for each strategy. If it is too small, then there is a risk of not having enough capacity, not meeting emission targets, and getting penalised. If it is too large however, there is a risk of building too much capacity without it being utilised. Ideally χ_s would be as small as possible while ensuring that φ is met.

When running the Monte Carlo simulation with the flexible strategies, Figure 13 shows that with this threshold, χ_s for DAC should be at least 1.3, and for both recycling strategies it should be at least 1.2 to meet the CTPT for each strategy.

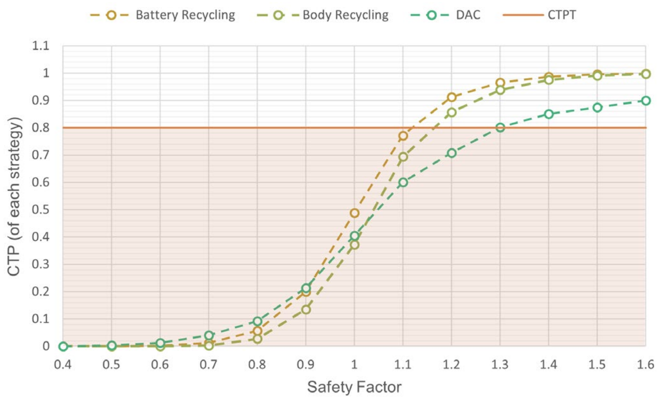

Figure 13. graph of χ_s against CTP in 2000 flexible scenarios

Although, as discussed φ is a portfolio level parameter, not strategy level and by using the safety factors from Figure 10, the portfolio CTPT = 0.75. Therefore χ_s must be adjusted to meet φ.

This is achieved by running smaller sample-sized Monte Carlo Simulations for each strategy, at a range of χ_s between 1.0 and 2.0 in 0.1 increments. Then, using optimisation, the combination of χ_s that maximises the NPV while meeting the φ constraint can be found. Figure 14 highlights the trade-off between a higher CTP (through using a larger χ_s) and higher NPV with the pareto front shown in red. The optimisation found the favourable values of χ_s = 1.4 for both recycling strategies, and 1.3 for DAC.

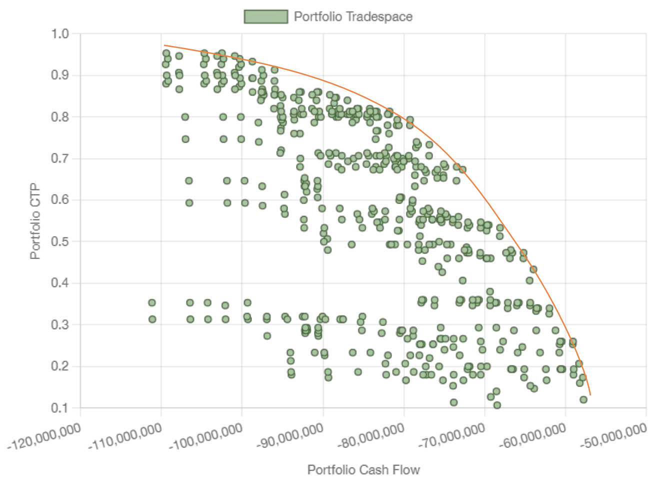

Figure 14. Each point on the graph is a different combination of χ_s to make up the portfolio.

For modular designs, there are enablers which allow this modularity. A summary of the enablers for the flexibility analysis can be seen in Table 8.

Table 8. Each strategies enablers and costs

Strategy	Enablers
DAC	Sufficient sorbent & energy supply, and sequestration space
Battery Recycling	Sufficient storage space, floor space & energy supply
Body Recycling	Sufficient storage space, floor space, energy supply and sewage treatment

With each of these enablers, there will be an upfront investment cost, C_I^s so that the modules can then be installed over the project's lifetime. The size and therefore C_I^s, e.g., size of floor space invested in year 0, depends on what the maximum number of modules, $N_{M,max}^s$, is likely to be.

With the capacity and χ_s set for each flexible strategy, $N_{M,max}^s$ needed in the 2000 scenarios could be determined. As seen in Table 9, $N_{M,max}^s$ is far larger than the average modules required, due to the few scenarios where there are exceptionally high emissions. If the 95th percentile of modules required is taken however, $N_{M,max}^s$ is much lower as seen in Figure 15. So, despite not catering for the 5% of scenarios, C_I for the enablers will be far lower.

Table 9. Modular design parameters with CAPEX and capacity scaled from the real data in table 6.

Strategy	Average Modules Needed,	Max Modules,	Max Modules (95% scenarios),
DAC	15	69	27
Battery Recycling	9	41	17
Body Recycling	13	45	23

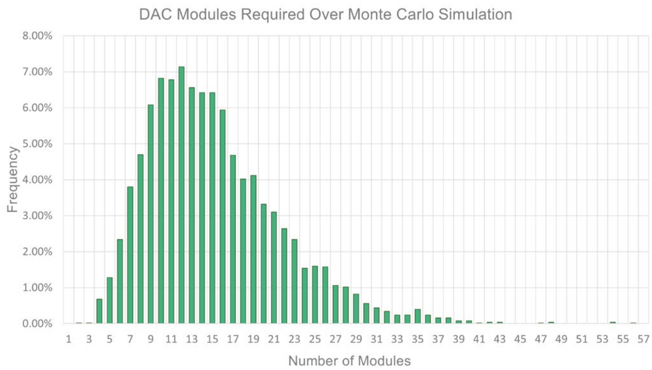

Figure 15. Histogram of DAC modules used over 2000 scenarios (see Appendix A8 for Battery & Body Recycling histograms)

With $N_{M,max}^s$ defined, the enablers must cater for this number of modules. The initial investment cost, C_I^s, in the enablers is defined for each strategy as:

$$C_I^s = N_{M,max}^s * C_{C,F}^s * \frac{\phi_M}{\phi_F} * \omega \tag{5}$$

Where $C_{C,F}^s$ is the CAPEX for the fixed design and ω is the Modular Infrastructure Factor, the percentage of a module's CAPEX invested in the enablers and is assumed to be 5% for this study. To calculate the CAPEX of each flexible module, $C_{C,M}^s$:

$$C_{C,M}^s = C_{C,F}^s * \frac{\phi_M^s}{\phi_F^s} * (1-\omega) \tag{6}$$

Table 10 shows the financial parameters for this ROA. OPEX and savings are assumed to be the same as in the fixed design per tCO2.

Table 10. Parameters for ROA

Strategy	Initial Costs, C_I^s (\$ million)	Module Capacity, ϕ_M^s (ktCO2/yr)	Module CAPEX, $C_{C,M}^s$ (\$ million)
DAC	11.5	10	8
Battery Recycling	8.3	7.5	9.3
Body Recycling	2	20	1.7

5.8 Comparative Analysis

From the ROA using the defined variables, the VoF of the flexible strategies, where the fixed designs are the benchmark, can be seen in Table 11.

Table 11. Improvement of Performance Metrics

		DAC	Battery Recycling	Body Recycling
Fixed	ENPV ($ millions)	-124	-65	12
	$VaR_{5\%}$ ($ millions)	-213	-81	-17
	$VaG_{95\%}$ ($ millions)	-87	-47	33
Flexible	ENPV ($ millions)	-96	-11	29
	$VaR_{5\%}$ ($ millions)	-189	-26	11
	$VaG_{95\%}$ ($ millions)	-27	5	52
ENPV Improvement (%)		23	83	142
$VaR_{5\%}$ Improvement (%)		11	68	165
$VaG_{95\%}$ Improvement (%)		69	110	58

Figure 16 captures the strategy level VoF for the DAC strategy. The flexible design provides less downside risk as seen on the lower left-hand side of the graph, and higher upside potential, seen on the top right quadrant of the graph, due to its ability to expand to higher demand and save on CAPEX if demand is lower than expected.

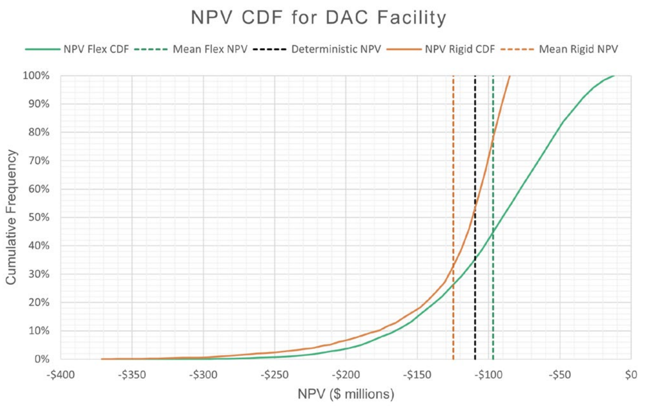

Figure 16. Target Curves for the fixed and flexible DAC design over the 2000 scenarios (see Appendix A8 for recycling distributions)

Having constructed models for the fixed and flexible strategies for reducing the company's emissions, the next step is to combine them into a portfolio so that the VoF in the company's overall decarbonisation pathway can be assessed. This portfolio is essentially a sum of the strategies' NPV. It therefore differs from standard financial portfolios, as the strategies value dictates their percentage share of the portfolio each year. Figure 17 visualises the increased upside and decrease downside once these three strategies are combined into the portfolio.

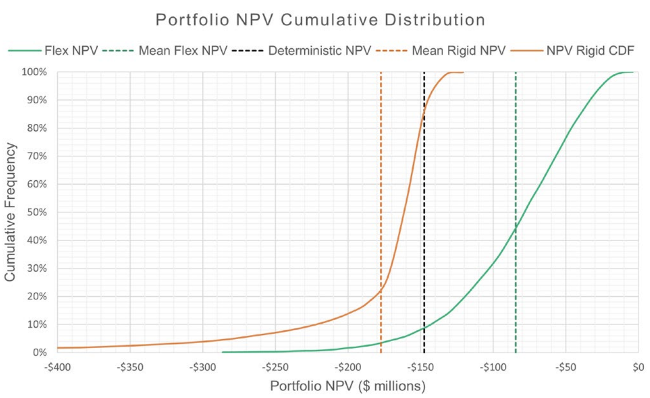

Figure 17. Target Curves for the fixed and flexible portfolio of strategies over 2000 scenarios

Table 12 shows that the flexible designs have a 54% improvement in their ENPV, as well as having less downside risk, and better upside potential as shown in the Value at Risk and Gain improvements.

Table 12. Comparison of fixed and flexible portfolios

	Fixed ($ millions)	Flexible ($ millions)	Improvement (%)
ENPV	-176	-82	53
$VaR_{5\%}$)	-273	-165	39
$VaG_{95\%}$	-141	-25	82
CTP	0.53	0.82	55

5.9 Sensitivity Analysis

Sensitivity analysis is crucial to check for robustness in the choice of strategy designs and is the last step in the methodology.

The first sensitivity analysis investigated the effect of learning rates and economies of scale, α. From the analysis up to this point, both have been equal to 1. α dictates that the larger that plants are built, the lower the cost per unit of capacity. For each strategy the relationship between CAPEX, $C^s_{C,F}$, and ϕ^s_F is given by:

$$C^s_{C,F} = \kappa \cdot {\phi^s_F}^{\alpha} \tag{7}$$

Where κ is a constant for each strategy. The learning rate, LR, assumes that as modules are built, the company can then produce the next one more efficiently. It is expressed by the relationship:

$$C^s_{C,M_i} = C^{s,}_{C,M_1} * i^B \tag{8}$$

Where, C^s_{C,M_1} and C^s_{C,M_i} is the CAPEX of the first and i^{th} module respectively and:

$$B = \log(100\% - LR\%)\,/Log(2) \tag{9}$$

LR was investigated between 0% to 20%, and an α between 0.7 to 1. Figure 18 shows a combination of the two, and the VoF when comparing the flexible design to the fixed designs ENPV. It is evident that LR increases, the VoF increases to counterbalance the fact that while the α decreases, the VoF decreases.

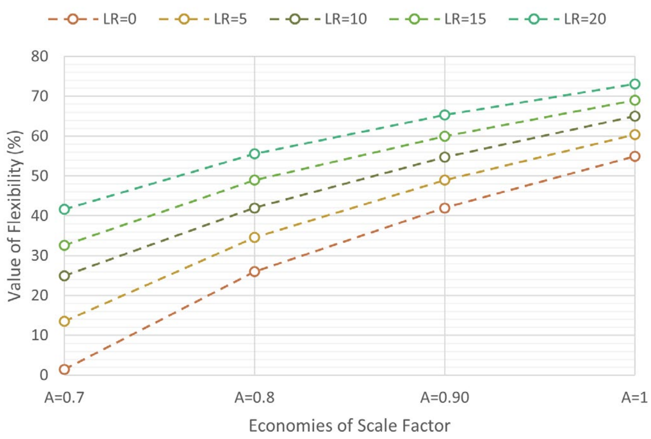

Figure 18. Varying LR and α to calculate the VoF.

It is also important to test the sensitivity of r, as well as σ, and C^s_I that allows modular capacity to later be built. Figure 19 shows the sensitivity of the flexible strategies ENPV, with higher C_I decreasing the ENPV, but as the bottom graph shows, the VoF is still positive while varying these parameters.

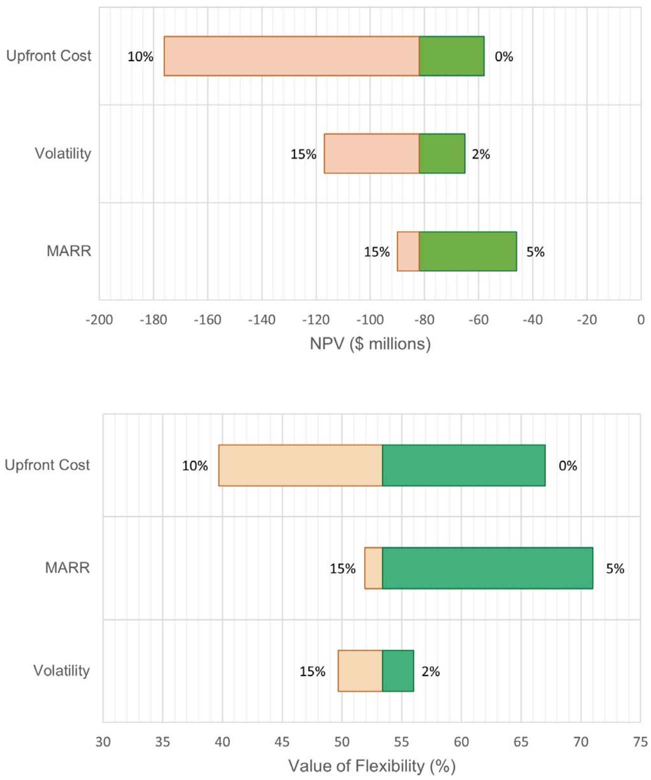

Figure 19. Tornado diagrams showing the effects of varying parameters.

Due to the parameters of the three strategies used to reduce the company's emissions, r has a complex effect on the ENPV of the designs as seen in Figure 20. When r is very low, future cash flows are not heavily discounted, so savings from the recycling strategies increases the ENPV. For the fixed design, as r increases, these revenues are discounted but the high CAPEX for the fixed designs in year 0 are not, hence the ENPV for the fixed design remains low for all higher r. For the flexible design however, as the r increases, the ENPV first decreases due to future revenues being discounted but then increases again as the modules constructed in the mid-term future have their CAPEX discounted.

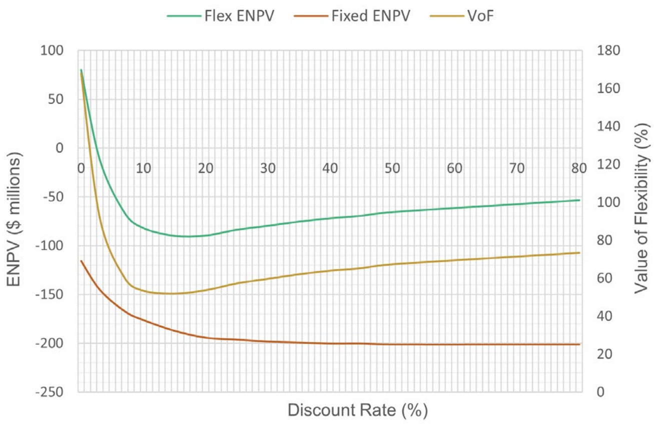

Figure 20. Analysing variation of r on fixed and flexible designs.

Through this sensitivity analysis, where key parameters were varied, the robustness of using flexible modular design in decarbonisation strategies for the industrial sector is evident.

6. Decision Support Tool

Despite the VoF being evident through using this methodology, it is crucial to convey this value to project planners who may have limited expertise in ROA. As discussed in the literature review, effective Decision Support Tools (DST) have been created by integrating the RO model, and a Graphical User Interface (GUI).

The DST was developed as a web-application allowing users to input data, run the model in the background, and display the outcomes. The DST was named DATRO (Decarbonisation-Analysis-through-Real-Options) and was developed with over 3000 lines of code based on the ROA Decarbonisation methodology (see Appendix B1 for web-app and code). Figure 21 gives an overview of the user interaction flow for DATRO, with Figures 22 & 23 showing the GUI of the tool.

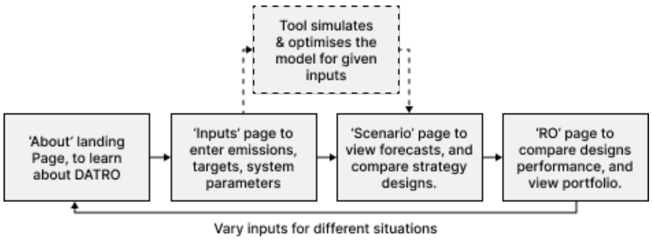

Figure 21. User Interaction flow

1. *About:* gives users with no experience in ROA background information, along with general instructions on the tool's capabilities, and how to use it.
2. *Your Inputs*: there are 3 main sections on this page. The first allows users to input different emission sources, and their corresponding quantity, scope, and forecast growth. The user can also input overall emissions/company growth and the level of volatility in forecasts. The second section is for study parameters such as the start and end years, the CTPT, and r. The third section is to input targets and corresponding scope which is important for companies that have different targets for different scopes. There is also an autofill button which allows the section to be filled with the data used in this case study.
3. *Scenario Analysis:* this page shows the best strategies to reduce emissions, as well as the forecasts of emissions and volumes assigned to each strategy based on the targets. It also visualises uncertainty in forecasts and suggests flexible design alternatives for each strategy to mitigate this risk.
4. *Real Options:* after viewing the scenario and strategies, this page compares the economic performance of the fixed and flexible strategies, as well as the CTP differences. It also displays the trade-space for the different combinations of strategy χ_s, and shows the trade-off between ENPV or greater CTP.
5. *Loading Screen:* Due to the complexity of the model, this screen notifies the user of the expected wait time and indicates when the simulations have finished running.

To ensure that the tool was usable for non-specialist decision-makers, in addition to the 'About' page, the tool also includes 'Info Tooltips' which when hovered over, provide information to the user about every feature in the tool.

DATRO has also been developed with the potential to run offline without the requirement of online servers, eliminating concerns about data privacy that companies may have when inputting confidential data into the tool.

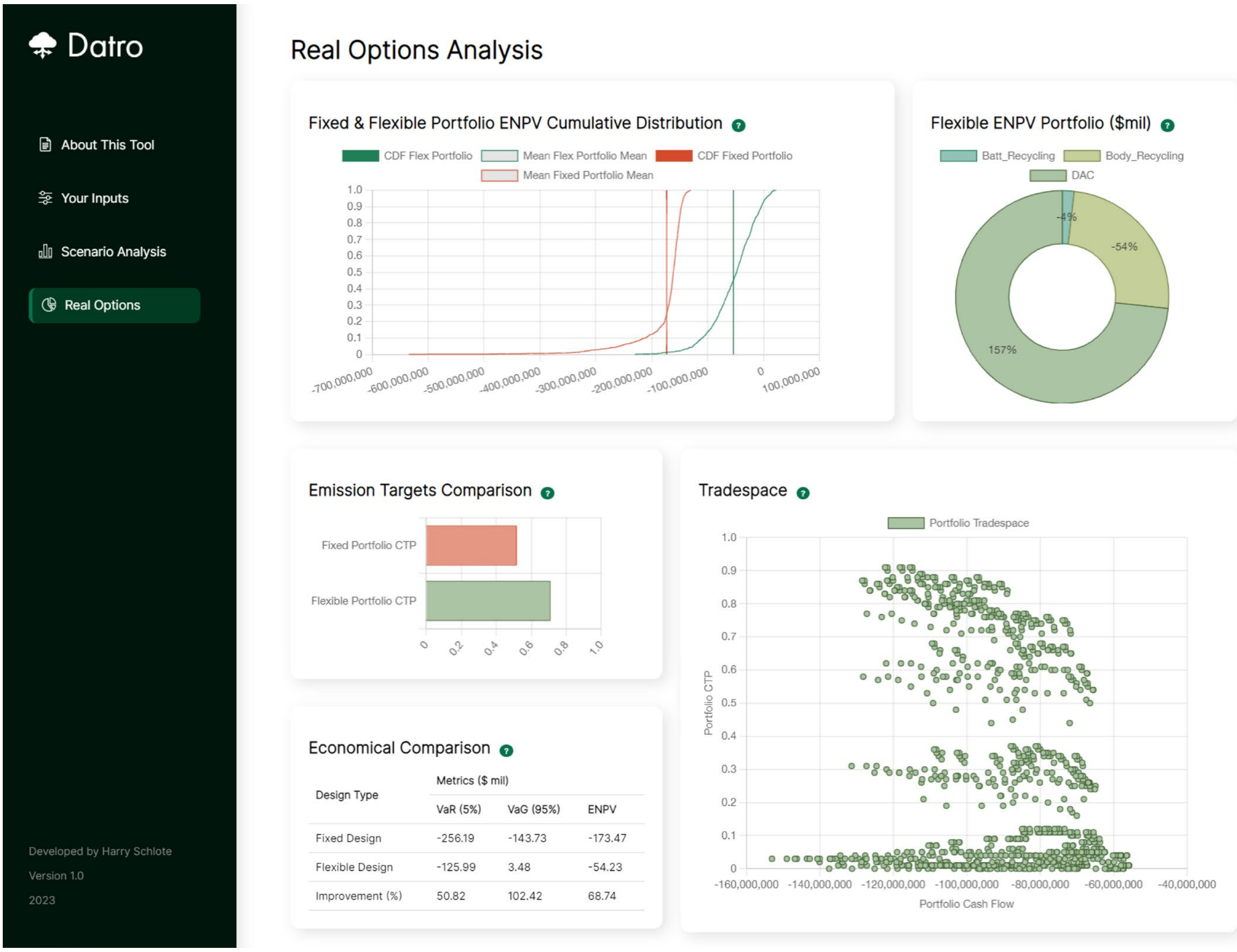

Figure 22. 'Real Options' page after a simulation has run.

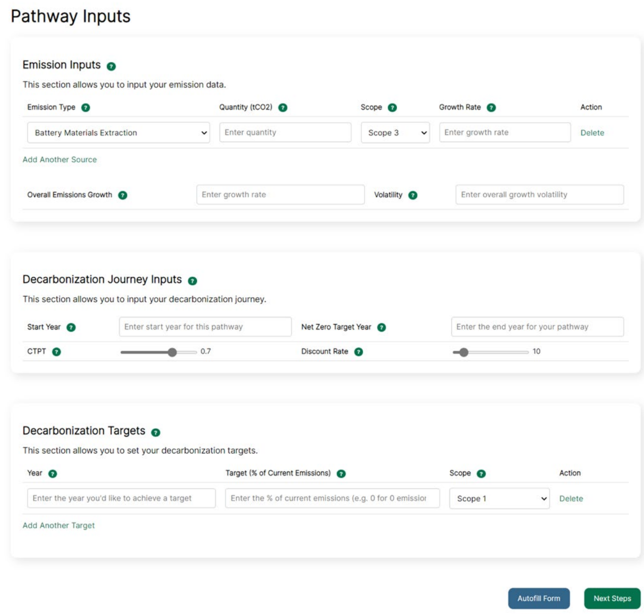

Figure 23. 'Your Inputs' page for the DATRO DST

To validate that this tool was of use to companies in early-stage planning, and helpful in visualising the VoF, initial testing sessions were held with a small number of stakeholders from sustainability consultancies and industrial sector corporations. The feedback was positive with employees describing the platform as a "very visual way to engage with complexity around decarbonisation", and that "as a storytelling tool it's also very compelling".

Feedback on how to further improve the platform focused most on the range of possible inputs, such as the remark that it "would be useful to have more industry-specific emission sources", as there are only a limited number of emissions source choices and strategy suggestions in the prototype version of DATRO.

7. Discussion & Conclusion

7.1 Study Limitations

The case study does have several limitations. The first is that the method for finding the optimal safety factors is computationally expensive, as it requires Monte Carlo Simulations for each combination across the strategies. Another limitation is the lack of consideration for more niche costs involved for each strategy, such as transporting vehicles to be recycled. Due to the analysis of three strategies, these were not explored in the study but could be integrated as additional costs in further developments. σ was also only explored as affecting the sum of emissions, whereas in practice each emission source is likely to have varying degrees of volatility, but this would be possible to integrate with further studies.

From a methodology-level perspective, another key limitation is the fixed assignment of emissions to each strategy. There was no consideration for how strategies could be flexible in reducing emissions initially assigned to other strategies, e.g. DAC reducing battery material extraction emissions if the Battery Recycling facility lacks the capacity in a specific year. It is also important to highlight that the strategies involved must be 'real', i.e. tangible assets. Much of the industrial sector such as automakers will decarbonise with incremental efficiency improvements in design, or material selection, so it would not be realistic to apply RO strategies to every decarbonisation aspect of a company, although it does still have great value where tangible assets are required.

Regarding the DST, it is only in its prototype phase and may still contain bugs, hence not carrying out extensive testing and iterations. It is limited in the detail of strategies it can offer to users, e.g., providing detailed advice on how and where to deploy the strategies, but does still serve its purpose in offering a high-level insight into the value of using ROA in decarbonisation.

7.2 Further Work

One exciting potential advancement of this research is to investigate the flexibility of emission assignment over the simulation period. For example, with a source such as logistics, rather than assigning 100% of the forecasted emission demand to DAC, the optimum ratios of emission assignment to more than one strategy could be determined, depending on uncertain factors such as strategy cost per unit capacity.

As discussed in the limitations, individual emission source volatility could be integrated, and more detailed costs and savings for each strategy could be considered, as well as adding more variation of strategies and emission source inputs into the DST. Further testing and iterations of the DST to ensure the benefits of ROA can be seen not only by project planners, but anyone learning about decarbonisation would be valuable, as well as ensuring the methodology and DST are designed responsibly, and any unintended consequences on the companies used it, or wider stakeholders are mitigated.

The novel concept of a CTP should also be explored further, potentially setting different thresholds for different scopes of emissions, and exploring how it could be applied in decarbonisation policy to ensure a greater chance of meeting targets.

7.3 Overview & Contributions

With a funding gap of $3.5 trillion for decarbonisation projects [McKinsey, 2022], and technologies that are still in prototype phases expected to contribute up to 60% of the emission reductions in the industrial sector [IEA, 2022], innovative valuation methods and risk mitigation is required to achieve global Net-Zero emissions and limit global warming to a 1.5°C increase [IPCC, 2018].

This paper proposes a ROA decarbonisation methodology that not only improves valuation, but additionally increases companies' probability of meeting their Net-Zero targets. Using a case study of an electric vehicle manufacturer, the value of adopting flexibility in a portfolio of decarbonisation strategies can improve the ENVP by 53%, improve upside potential with an 82% increase of Value at gain at 95% confidence, and reduce downside risk with a 39% improvement in the Value at Risk at a 5% confidence interval.

While improving the valuation of the company's decarbonisation pathway, through optimisation of the safety factors in the flexible strategies decision rules, a 55% improvement in the CTP is also achievable. The methodologies application in the case study achieves the research aim of developing a methodology to embed decarbonisation metrics into ROA models, and results from the simulations answers the secondary aim of uncovering the VoF.

By developing DATRO, the DST enables non-specialist decision-makers and project planners to understand ROA and realise the VoF, the tertiary objective is also achieved. These contributions provide valuable tools for decision-makers to consider in decarbonisation projects, with the aspiration of empowering companies to accelerate their emission reduction efforts and contribute to the realisation of a Net-Zero planet.

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Nomenclature

t	Current Time (years from pathway beginning)
T	Project Lifetime (years)
r	Discount Rate (%)
τ_t^{ψ}	Emission Targets (%)
ψ	Scope Category
i	Emission Source
V_t^i	Individual Emissions Volume
ξ_i	Project Lifetime Emissions Forecast
γ	Overall Emissions Drift (%)
σ	Overall Emissions Volatility (%)
μ_i	Individual Emissions Drift (%)
μ_P	Penalty Drift (%)
σ_P	Penalty Volatility (%)
C_P	Penalty Cost ($)
S_F, S_M	Strategy (Fixed, Modular)
δ_s	Strategy Emission Demand
ϕ_F^s, ϕ_M^s	Strategy's Plant Capacity (Fixed, Modular)
$C_{C,F}^s, C_{C,M}^s$	Strategy's CAPEX (Fixed, Modular) ($)
C_I^s	Modular Infrastructure Capital Costs ($)
C_o^s, C_z^s	Strategy Cost Components (OPEX, Savings) ($)
γ_S	Strategy CAPEX & OPEX Drift (%)
σ_S	Strategy CAPEX & OPEX Volatility (%)
χ_s	Safety Factor
$N_{M,max}^s$	Max Strategy Module Capacity
ω	Modular Infrastructure Factor
φ	Carbon Target Probability
α	Economies of Scale Factor
LR	Learning Rate Factor

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Appendix

Drifts calculated in the appendix use the Compound Annual Growth Rate Formula (CAGR) where V_{final} is the final value, V_{begin} is the beginning value, and t is the time between the data points:

$$CAGR = \left(\frac{V_{final}}{V_{begin}}\right)^{\frac{1}{t}} - 1 \tag{10}$$

Appendix A1

The Cradle to Gate (CTG) emissions specified by [Qiao, 2019] were not granular enough. By splitting these emissions into ratios given by [McKinsey, 2020] and [McKinsey, 2023], emissions were more assignable.

Tables 13 & 14. Vehicle Emission Calculations

Body Manufacture Source	Ratio [McKinsey, 2020]	TCO2
Material Mining, refining & processing	65%	5.87
Logistics	16%	1.44
Manufacturing	19%	1.71
Total	100%	9.02

Battery Manufacture Source	Ratio [McKinsey, 2023]	TCO2
Material Mining, refining & processing	60%	1.78
Logistics	15%	0.45
Manufacturing	25%	0.74
Total	100%	2.97

Appendix A2

Table 15. Emission Sources for Growth Rate Calculations.

Sources	External Drift, μ_i	Calculation & Source
Materials Extraction & Refining (body)	-1%	$\left(\frac{100}{140}\right)^{\frac{1}{45}} - 1$ [IEA, 2019]
Materials Extraction & Refining (battery)	0%	-
Production Logistics	-6%	$\left(\frac{62}{91}\right)^{\frac{1}{7}} - 1$ [McKinsey, 2023]
Component Manufacture	-6%	See Production Logistics
Electricity Production	-9%	Average of values from Table 14
End-of-Life Disposal	-6%	See Production Logistics

Table 16. Forecast Decarbonisation of Energy Grid [BEIS, 2018]

Year	Grid Carbon Factors	Annual Growth (%)
2018	173	
2019	144	-20
2020	136	-6
2021	115	-18
2022	108	-6
2023	111	3
2024	111	0
2025	108	-3
2026	98	-10
2027	105	7
2028	100	-5
2029	91	-10
2030	85	-7
2031	76	-12
2032	64	-19
2033	60	-7
2034	51	-18
2035	41	-24

Appendix A3

Table 17. Detailing the sources or equations for DAC

Parameters	Calculation	Value	Source
Capacity (ktCO2/yr)	*Not applicable*	10	[McQueen, 2020]
CAPEX ($ million)	*Not applicable*	8.5	[McQueen, 2020]
OPEX ($/tCO2)	*Not applicable*	89	[McQueen, 2020]
Savings ($/tCO2)	*Not applicable*	-	-
Drift (%)	*Not applicable*	-5	Table 18

From [Buberger, 2022], the emissions saved using recycled body materials equates to 2.93 kgCO2/kg, and for the battery, this equated to 48.4 kgCO2/kWh which for a 27kWh and 188.7kg battery was equivalent to 6.93 kgCO2/kg.

Table 18. Detailing the sources or equations for Battery Recycling

Parameters	Calculation	Value	Source
Capacity (ktCO2/yr)	$18250 \cdot \left(\frac{(41.1 + 55.7)}{2} \cdot \frac{27}{188.7}\right)$	126	[Critical Metals, 2021]
CAPEX ($ million)	*Not applicable*	165	[Critical Metals, 2021]
OPEX ($/tCO2)	$\frac{1650}{\left(48.4 \cdot \frac{27}{188.7}\right)}$	238	[Critical Metals, 2021] [Buberger, 2022]
Savings ($/tCO2)	$\frac{238}{0.7}$	340	[BCG, 2020]
Drift (%)	$\left(\frac{1200}{1650}\right)^{\frac{1}{12}} - 1$	-2.6	[Critical Metals, 2021] [Assured UAM, 2021]

Table 19. Detailing the sources or equations for Body Recycling

Parameters	Calculation	Value	Source
Capacity (ktCO2/yr)	$20000 * 1300 * 0.00293$	76	[Xia, 2016] [Buberger, 2022]
CAPEX ($ million)	*Not applicable*	6.7	[Xia, 2016]
OPEX ($/tCO2)	$\frac{8960000}{76000}$	117	[Xia, 2016]
Savings ($/tCO2)	$\frac{12290000}{76000}$	161	[Xia, 2016]
Drift (%)	*Not applicable*	-1.5	[Assured UAM, 2021]

Table 20 & 21. conversion formulas are shown as units used for calculations in Tables 18 & 19

Battery Recycling	Source Units	Conversion Formula	Useful Units
Capacity	1500 (T/yr)	(T/yr)*(TCO2/T)	10400 (TCO2/yr)
OPEX	1650 ($/T)	($/T)/(TCO2/T)	238 ($/TCO2)
Money Saved	OPEX 70% of revenue	OPEX/0.7	340 ($/TCO2)

Body Recycling	Source Units	Conversion Formula	Useful Units
Capacity	20000 cars	(cars)*(kg per car) *(kgCO2/kg)	76200 (TCO2/yr)
OPEX	8.96 million ($/yr)	($/yr)/(capacity in TCO2/yr)	117.6 ($/TCO2)
Money Saved	12.29 million ($/yr)	($/yr)/(capacity in TCO2/yr)	161.33 ($/TCO2)

Table 22. Data to calculate DAC drift, μ using CAGR [Young, 2022]

	Case 1	Case 2	Case 3	Case 4	Case 5	Average,
2020	639.4	543.4	463.5	507	503.7	
2025	336.4	174.4	147.6	156.1	159.3	
2030	324.8	147.6	119	124.7	128.9	
2040	335.5	130.6	98.1	102.4	107.2	
2050	358.9	125.2	88.8	92.5	97	
Drift, μ	-1.9%	-4.8%	-5.4%	-5.5%	-5.3%	-5%

Appendix A4

Table 23. Emission Penalty Data and Sources

Parameter	Calculation	Value	Source
Starting Penalty Cost, C_P (\$/TCO2)	*Not applicable*	88	[Investing, 2023]
Drift, μ_P (%)	$\left(\frac{88}{26}\right)^{\frac{1}{15}}-1$	8.4	[Investing, 2023]
Volatility, σ_P (%)	*Not applicable*	4.5	[Gollier, 2022]

Appendix A5

Table 24. Drifts for data in Table 21 to calculate DAC volatility

Growth (%)	Case 1	Case 2	Case 3	Case 4	Case 5
2020	-	-	-	-	-
2025	-12.1	-20.3	-20.5	-21.0	-20.6
2030	-0.7	-3.3	-4.2	-4.4	-4.1
2040	0.3	-1.2	-1.9	-2.0	-1.8
2050	0.7	-0.4	-1.0	-1.0	-1.0

To calculate strategy uncertainty, σ_S, for DAC growth rates between each timestep for the data in Table 24 were calculated. Then for each case in [Young, 2022], the standard deviation was estimated:

$$\sigma = \sqrt{\frac{\sum(x-\bar{x})^2}{(n-1)}} \quad (11)$$

where x is the sample mean and n is the sample size. The volatility for each case was then averaged as seen in table 25.

Table 51. DAC average volatility value

(%)	Case 1	Case 2	Case 3	Case 4	Case 5	Avg
$\boldsymbol{\sigma}$	6	9	9	9	9	**9**

As the σ_S was approximately half of μ for DAC, this relationship for the recycling strategies was also assumed. With Battery Recycling $\mu = -2.6$ and Body Recycling $\mu = -1.5$, their respective volatilities were assumed to be $\sigma_S = 5$ and $\sigma_S = 3$

Appendix A6

View workshop slides: Here

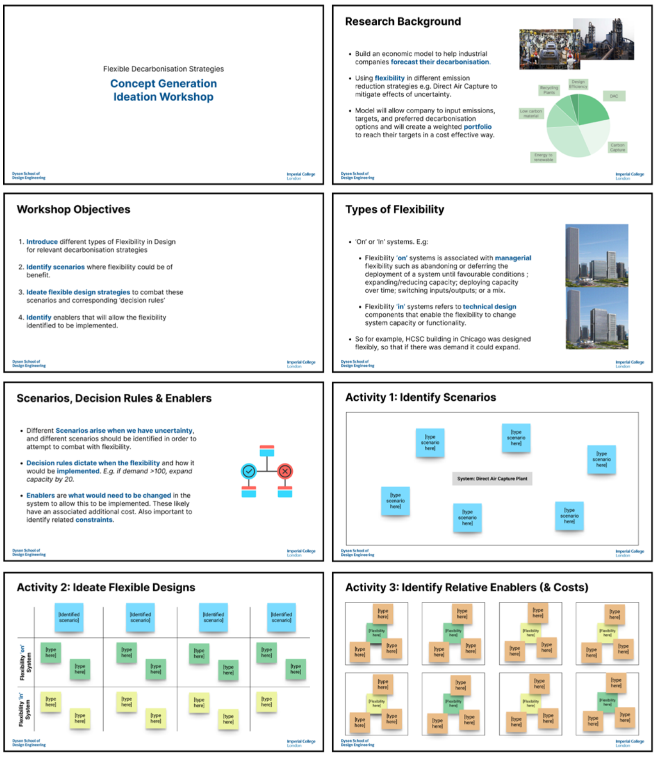


Figure 24. Slides used in the Concept Generation Workshops

Appendix A7

Table 26. Pugh Analysis for Battery Recycling flexibility ideas

Evaluation criteria	Weight factor	Increase z-tunnels and pipe size for each line		Increase operating hours of the facility.		Rent capacity from other plants		Expand number of recycling lines in existing facility	
Deployment Time	2	0	0	1	2	1	2	0	0
Longevity	3	1	3	-1	-3	-1	-3	1	3
Feasibility	2	1	2	0	0	1	2	1	2
Cost	3	0	0	1	3	0	0	1	3
Score			**5**		**2**		**1**		**8**

Table 27. Pugh Analysis for DAC flexibility ideas

Evaluation criteria	Weight factor	Connect additional modular capacity to plant		Upgrade technology for higher efficiency		Construct a new plant in a new location		Rent capacity from other plants	
Deployment Time	2	1	2	0	0	0	0	1	2
Longevity	3	1	3	1	3	1	3	-1	-3
Feasibility	2	1	2	1	2	1	2	1	2
Cost	3	0	0	0	0	-1	-3	0	0
Score			**7**		**5**		**2**		**1**

Table 28. Pugh Analysis for Body Recycling flexibility ideas

Evaluation criteria	Weight factor	Construct New Body Recycling Facility		Rent capacity from other plants		Add extra dismantling & crushing lines to the facility.		Increase operating hours of the facility	
Deployment Time	2	0	0	1	2	0	0	1	2
Longevity	3	1	3	-1	-3	1	3	-1	-3
Feasibility	2	1	2	1	2	1	2	0	0
Cost	3	0	0	0	0	1	3	1	3
Score			**5**		**1**		**8**		**2**

Appendix A8

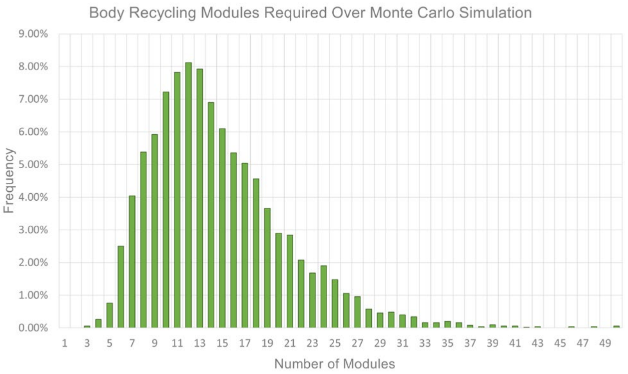


Figure 25. Histogram for the number of Body Recycling modules required over the Monte Carlo simulation

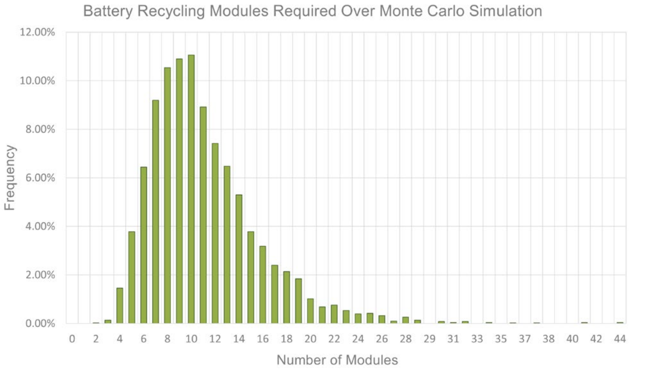


Figure 26. Histogram for the number of Battery Recycling modules required over the Monte Carlo simulation

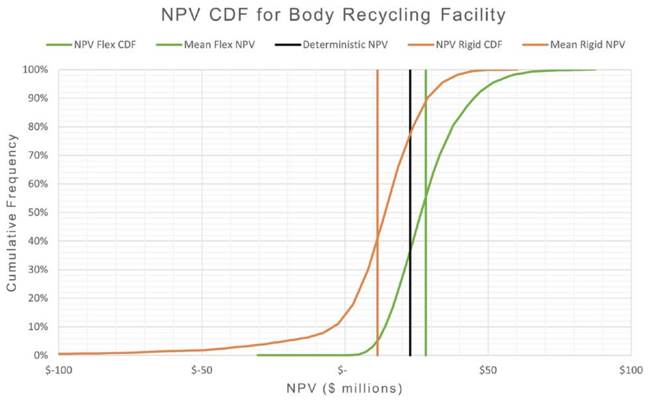


Figure 27. Cumulative Distribution for the fixed and flexible Body Recycling facility designs over the Monte Carlo simulation

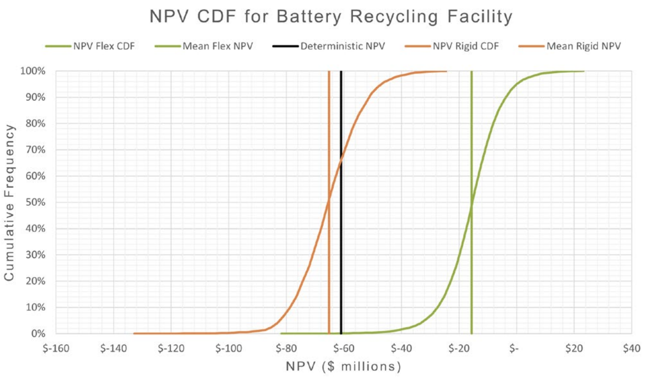
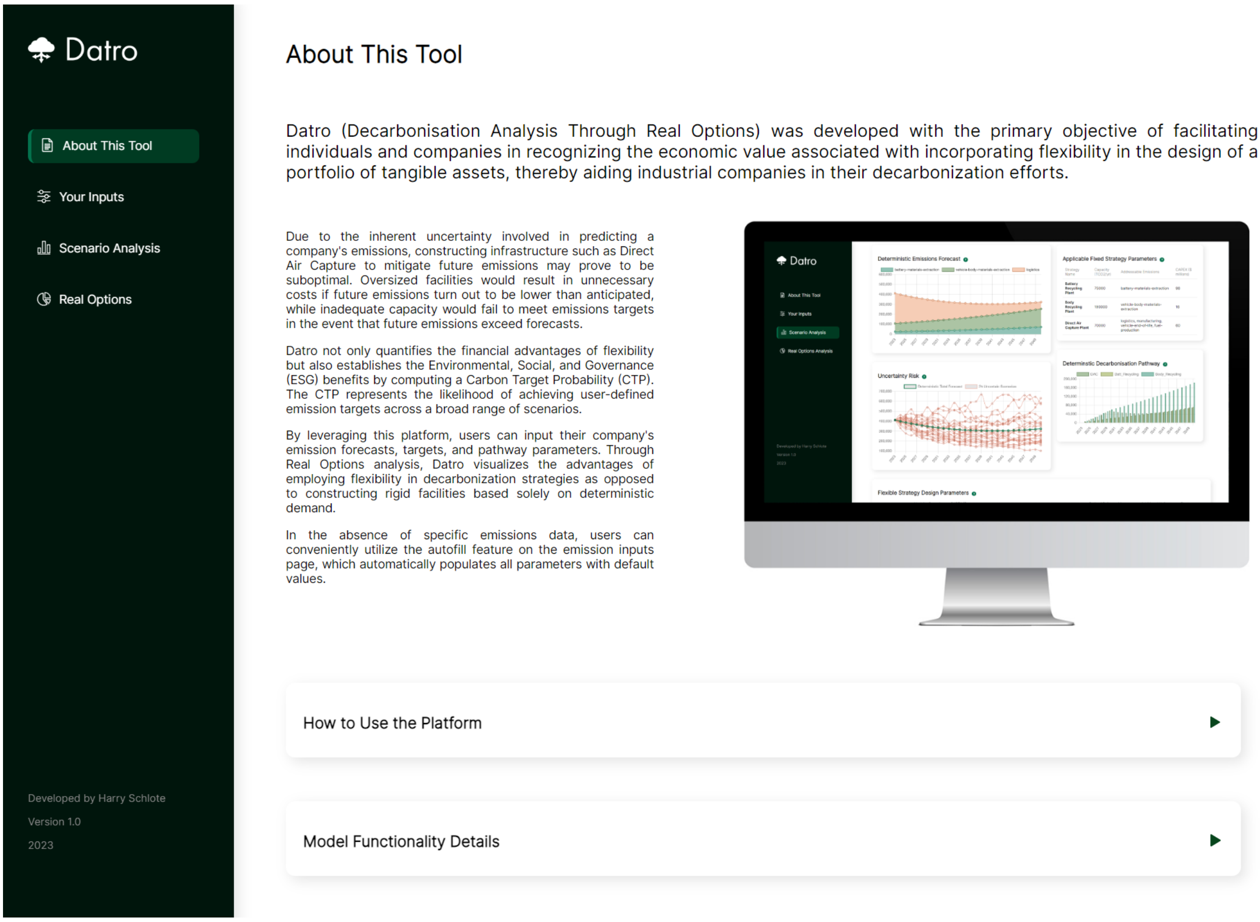
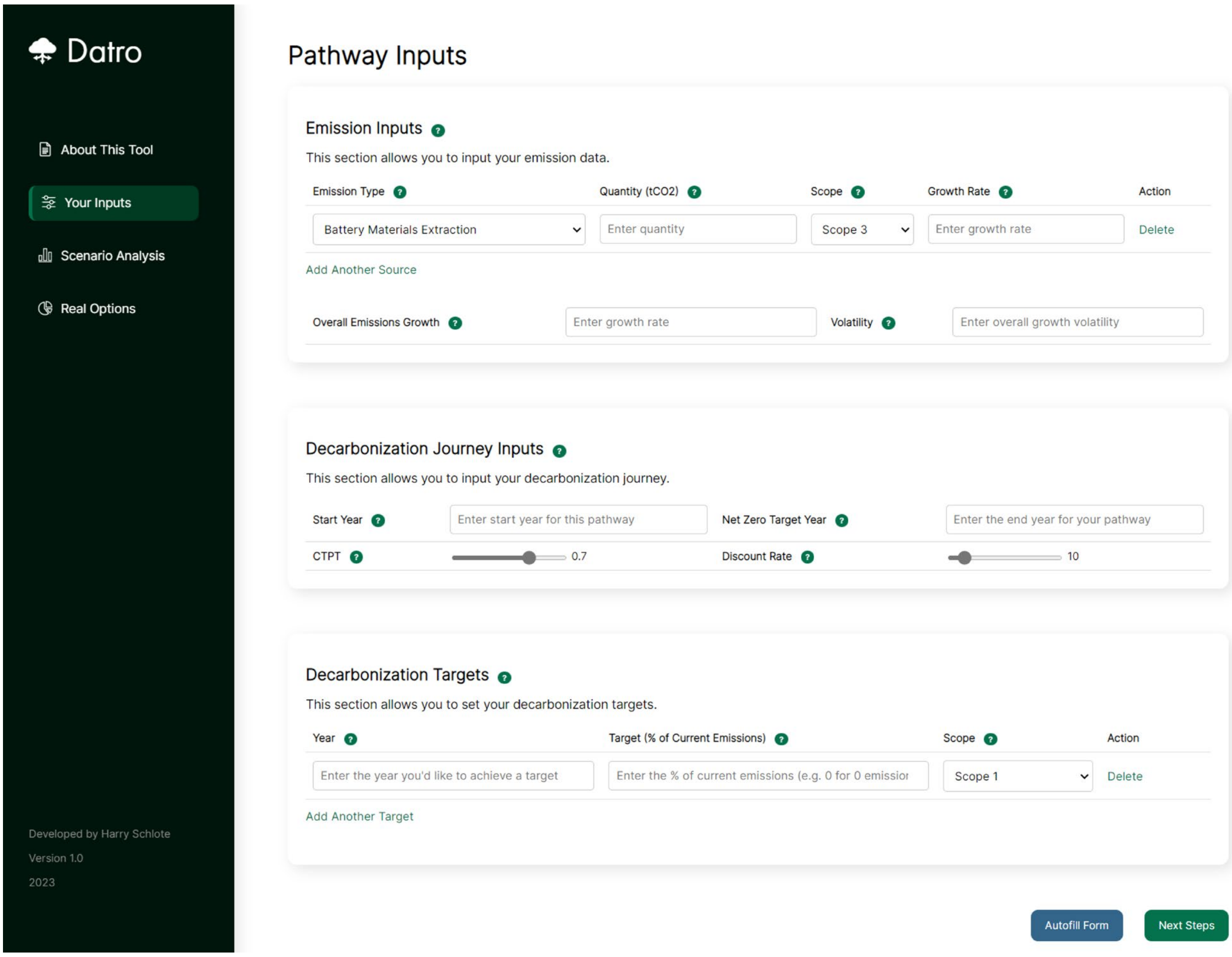


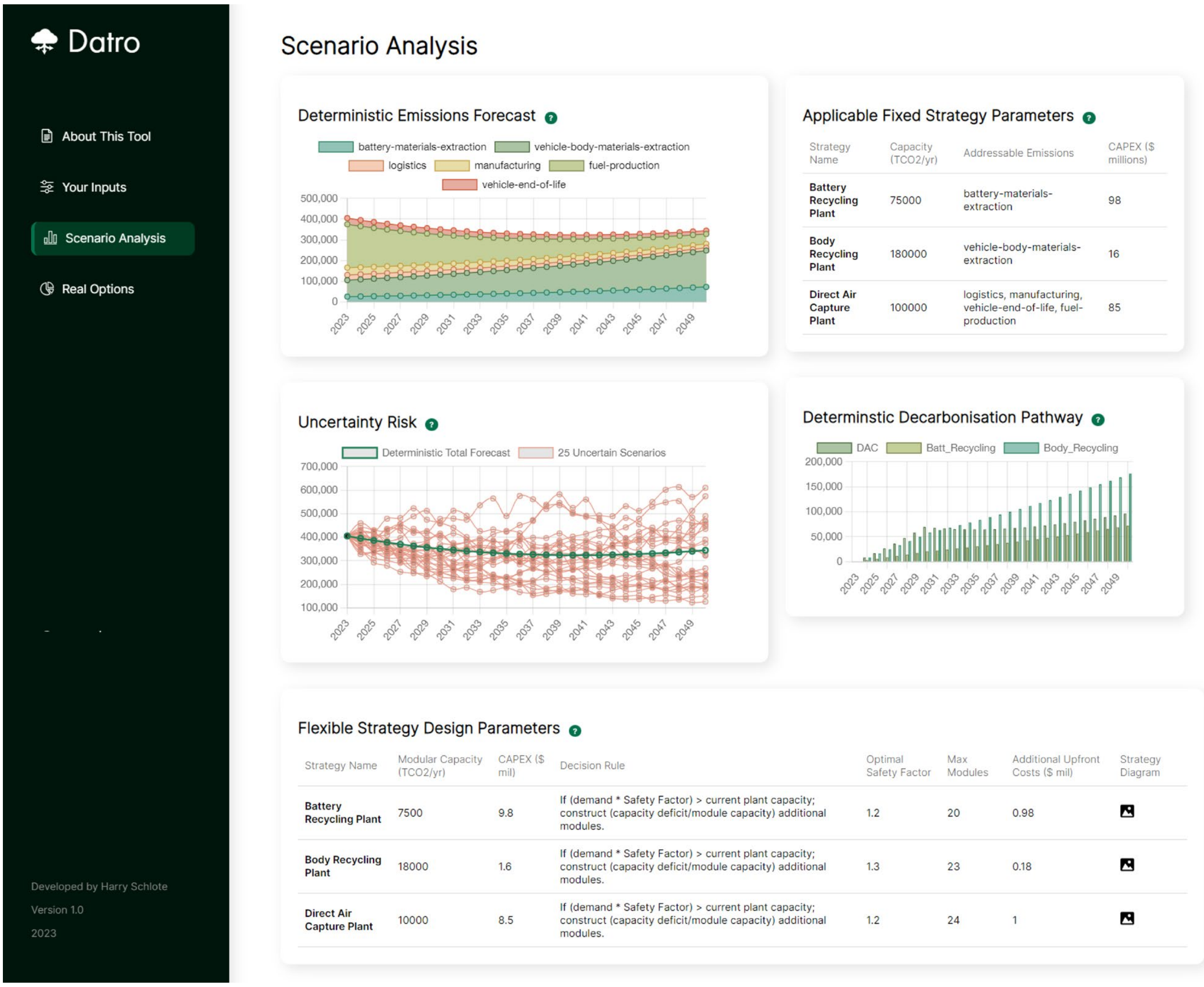
Figure 28. Cumulative Distribution for the fixed and flexible Battery Recycling facility designs over the Monte Carlo simulation

Appendix B1

Link to the prototype webapp: DATRO
Link to web-app code: Here






Datro
About This Tool
Your Inputs
Scenario Analysis
Real Options
Developed by Harry Schlote
Version 1.0
2023
Scenario Analysis
Deterministic Emissions Forecast
battery-materials-extraction
vehicle-body-materials-extraction
logistics
manufacturing
fuel-production
vehicle-end-of-life
Applicable Fixed Strategy Parameters
Strategy Name
Capacity (TCO2/yr)
Addressable Emissions
CAPEX ($ millions)
Battery Recycling Plant
75000
battery-materials-extraction
98
Body Recycling Plant
180000
vehicle-body-materials-extraction
16
Direct Air Capture Plant
100000
logistics, manufacturing, vehicle-end-of-life, fuel-production
85
Uncertainty Risk
Deterministic Total Forecast
25 Uncertain Scenarios
Determinstic Decarbonisation Pathway
DAC
Batt_Recycling
Body_Recycling
Flexible Strategy Design Parameters
Strategy Name
Modular Capacity (TCO2/yr)
CAPEX ($ mil)
Decision Rule
Optimal Safety Factor
Max Modules
Additional Upfront Costs ($ mil)
Strategy Diagram
Battery Recycling Plant
7500
9.8
If (demand * Safety Factor) > current plant capacity; construct (capacity deficit/module capacity) additional modules.
1.2
20
0.98
Body Recycling Plant
18000
1.6
If (demand * Safety Factor) > current plant capacity; construct (capacity deficit/module capacity) additional modules.
1.3
23
0.18
Direct Air Capture Plant
10000
8.5
If (demand * Safety Factor) > current plant capacity; construct (capacity deficit/module capacity) additional modules.
1.2
24
1