

Sustainability in electromobility purchasing

Prioritising raw materials using multi-criteria decision-making

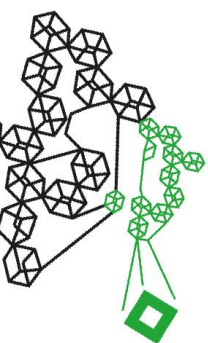


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Management summary

This research is conducted at OEM X in its electromobility purchasing department. This department focuses on purchasing the necessities for developing and delivering OEM X's electric vehicles. This department aims to increase sustainability in three aspects. The strategy focuses on resources, climate and people and is based on the UN Sustainable Development Goals (SDGs). For instance, the goal is to have decarbonised value delivery in 2040. However, concrete plans for raw materials are not on the current sustainability agenda for two segments within the electromobility purchasing department. There is no overview of what raw materials are used precisely, and it is unknown how the developments in the raw material industry influence the usage of raw materials. Therefore, we map the critical raw materials and relevant developments in the Battery Electric Vehicle (BEV) supply chain, focusing on the motor drive system and electrical distribution and charging segments. Recommendations in the form of an action plan are presented on which raw materials OEM X and its supply chain partners should prioritise. Three sections follow this introduction. First, the highlights of the methodology are presented. Second, the results are discussed, and finally, conclusions and recommendations are formulated.

Method

Multiple circular concepts could be applied to a supply chain, as presented by the R-framework (Potting et al., 2017) or Lansink's Ladder (Kemp & van Lente, 2011). Prevention and product reuse are circular concepts preferred over recycling. On the other hand, raw materials are currently in use, and products cannot be reused indefinitely. Thus, this thesis focuses on recycling as the primary circular concept. Furthermore, there are many reasons to prioritise certain raw materials for recycling over others. These reasons include the maturity of the recycling processes, the geopolitical implications and human rights issues related to the raw materials, environmental concerns or economic dependencies. Moreover, these drivers could be conflicting. Therefore, a multi-criteria decision-making analysis is chosen to execute the prioritisation.

The problem consists of nineteen raw materials that are evaluated on twenty-six criteria. Moreover, the perspectives of five different stakeholders are considered. Most of the raw materials are critical in transitioning to a global economy with net-zero emissions and are also used in many booming industries, like the renewable energy industry. The twenty-six criteria are formed following a combination of the criteria already used at OEM X and by executing a literature review following the three Ps: People, Planet, and Profit. The DEMATEL + ANP and PROMETHEE II method has been selected to perform the prioritisation. The pairwise comparison-based method ANP is selected to determine the relative priorities of each criterion since it does not assume independent criteria by modelling the dependencies between criteria. DEMATEL is selected to reduce the number of pairwise comparisons of ANP. Finally, PROMETHEE II is selected since it adheres to the concept of strong sustainability, which means that extremely strong performances in one criterion cannot offset bad performances on other criteria. Moreover, PROMETHEE II can cope with data uncertainty to a certain extent. The use of this hybrid model is validated by comparing the results of this hybrid to less complex and more naïve methods.

Generally speaking, multi-criteria decision-making methods are deterministic. However, the electromobility sector is developing rapidly. Therefore, uncertainty about the direction of performances on one of the twenty-six criteria should be considered. These developments are modelled using a novel hybrid of scenario analysis and Monte Carlo simulations. This method allows for the creation of scenarios to substantiate development directions of performances and to translate this direction into probability distributions used as input for Monte Carlo simulation. Furthermore, judgmental uncertainty is another type of uncertainty relevant for multi-criteria

decision-making. Therefore, a sensitivity-based Monte Carlo Simulation is executed to analyse the sensitivity of the place of the raw materials in the ranking relative to changes in the priorities.

Results

To determine whether the DEMATEL + ANP provides unique prioritisations, it is compared with AHP and naïve weights. PROMETHEE II is compared with MAVT, comparable to calculating a weighted average. Watrobski et al. (2019) presented that different MCDA methods deliver inconsistent results that might not satisfy the needs of all decision-makers. Figure 1 presents how the rankings of the raw materials differ with each methodology.

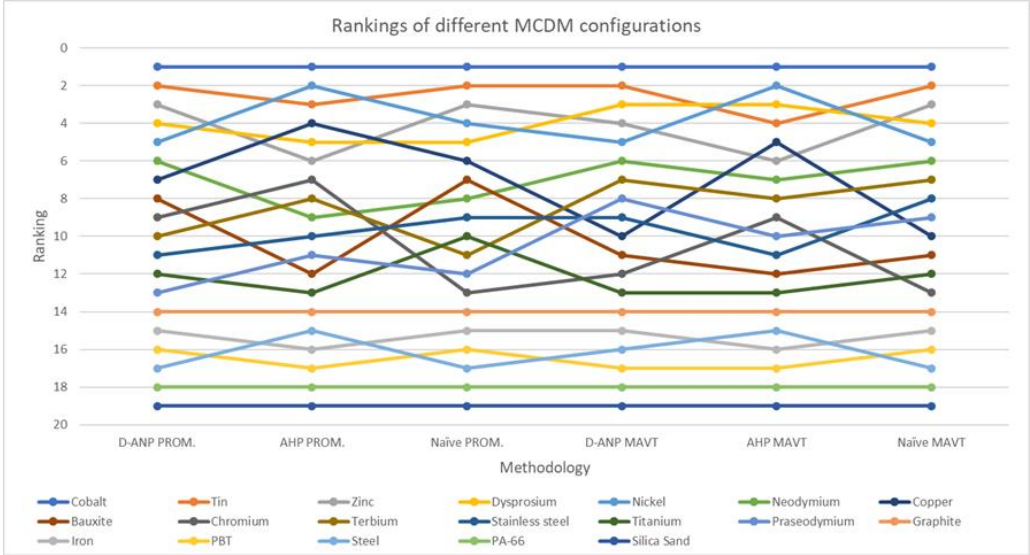


Figure 1: Rankings per configuration. The following abbreviations are used: DEMATEL-ANP is D-ANP, PROMETHEE II is PROM.

In short, it can be concluded that the rankings differ significantly; therefore, the use of DEMATEL-ANP and PROMETHEE II require validation by the stakeholders, which requires the aggregated ranking and the ranking per stakeholder. Figure 2 presents the prioritisation with the rankings visualised in the left graph and the scores visualised in the right graph:

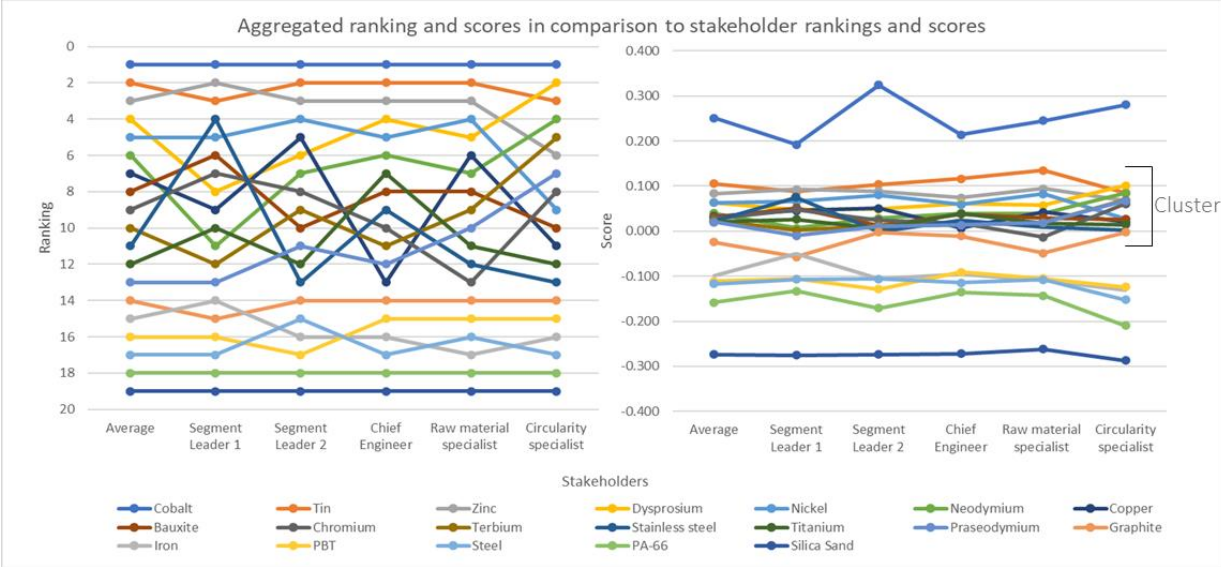


Figure 2: Aggregated results in comparison with stakeholder results for rankings and scores.

It can be observed that the five stakeholders provide different rankings for the raw materials. This means that the rankings differ significantly. Moreover, the scores between the raw material ranked third, zinc, and the raw material ranked fourteenth, graphite, do not differ significantly

between the stakeholders, as shown by the cluster in the right graph of Figure 2. The top five raw materials following the DEMATEL-ANP and PROMETHEE II method are cobalt, tin, zinc, dysprosium, and nickel. These impose the most significant sustainability issues. However, cobalt and dysprosium are currently not viable for recycling as the recycling processes are too immature. Therefore, preventive circular concepts, like rethink, refuse and reduce, should be applied to ensure that Cobalt and Dysprosium do not receive a significant role in the supply chain.

Furthermore, scenario planning based on a PESTEL analysis has been executed to measure the impact of the mapped industry developments on the ranking of raw materials. The developments on four criteria have been measured, namely: market balance, recycle rates, CO₂ emissions and residual end-of-life-waste. Triangular distributions based on the scenario analysis have been created and used as input for a Monte Carlo simulation providing the following distribution in the rankings:

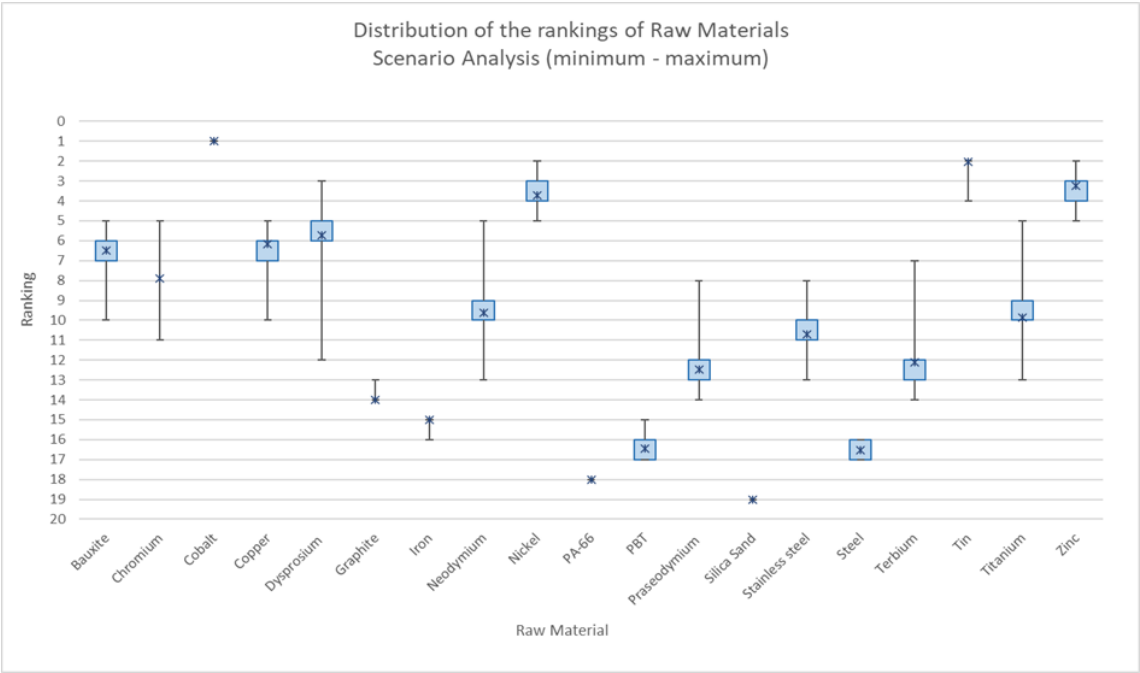


Figure 3: Boxplot of the results of the Monte Carlo simulation when simulating the influence of uncertainty on four different criteria. The whiskers present the range of the rankings. Thus, it presents how the rankings are distributed from the minimum to maximum ranking. The averages are marked with a cross (X).

Figure 3 shows that the positions of the raw materials in the ranking are stable. The interquartile range is either 0 or 1, meaning that the expected developments in these criteria do not influence the rankings significantly. However, long tails are observed for the rare earth elements (REEs), for instance. These long tails are caused by the fact that REEs have the most significant opportunity for improvement. For instance, the CO₂ emissions of REEs per tonne exceed the other raw materials. This room for improvement shows that the lower-ranked REEs have long tails above the box, and the higher-ranked REEs have tails below the box. The triangular distributions cause this behaviour, as the most probable estimates are the same for each raw material. Therefore, some performance combinations would alter the ranking significantly. These are not likely to occur since the interquartile range is small.

Finally, a sensitivity analysis based on a Monte Carlo simulation has been executed to investigate the influence of changing priorities of decision-makers. The priorities are sampled from a uniform distribution since the goal is to evaluate the effects of changes in the weights. Figure 4 presents the distribution of the rankings. The results show that the rankings are susceptible to changes in weights. Thus, there is a reason to focus on most raw materials depending on what the decision-makers prioritise. Furthermore, Figure 2 shows the differences in the priorities of the

stakeholders. Each stakeholder has different priorities due to their background or segment. Concluding, it would be worthwhile to align these priorities to ensure that the rankings are more aligned with the overall strategy of OEM X.

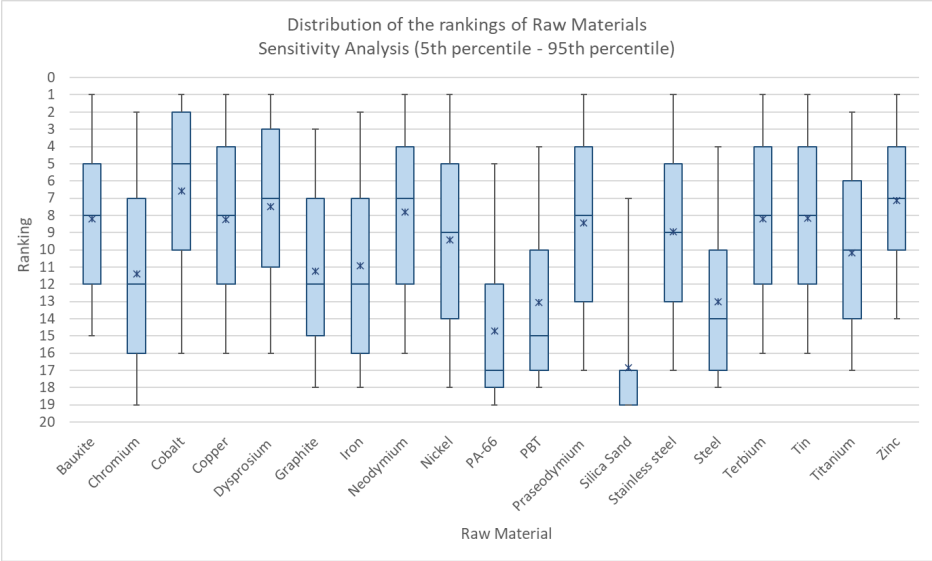


Figure 4: Boxplot of the results of the Monte Carlo simulation when simulating the influence of judgemental uncertainty. The whiskers present the range of the rankings from the 5th to 95th percentile. The averages are marked with a cross (X).

Conclusions and recommendations

The top ten raw materials in the prioritisation are in descending order of significance: cobalt, tin, zinc, dysprosium, nickel, neodymium, copper, bauxite, chromium and terbium. Cobalt and the REEs have significant unsustainable characteristics but are unsuitable for recycling. Therefore, other circular concepts must be introduced. The other raw materials in the top 10, namely: tin, zinc, nickel, copper, bauxite and chromium, have more mature recycling processes. Using a questionnaire, the engineering and purchasing department employees validated these results.

To make the conclusions and recommendations more tangible, synergies are discussed. First, the results should be shared with other segments within OEM X, since, for instance, graphite and cobalt are relevant raw materials for the ESS (Energy Storage Systems) segment. Second, many REEs are critical to the renewable energy industry, as McKinsey & Company (2022) presents. These REEs are critical for the magnets used in, e.g., wind turbines and BEV vehicles. Therefore, these synergies could be exploited, and developments in one of these sectors could prove relevant. Therefore, McKinsey & Company (2022) recommend adapting technology rollout plans to mitigate the effects of the increased demand for raw materials caused by the net-zero transition. The top ten raw materials presented by the MCDM model should be covered in this plan.

Furthermore, OEMs should send clear demand signals and secure raw material supply through off-take agreements or partnerships with raw material suppliers or recyclers. These are essential for BEV OEMs to ensure aggressive growth while becoming increasingly more sustainable regarding people, planet, and profit.

These are all actions that could be implemented in the short term. Therefore, the scenario analysis and Monte Carlo approach should be used to validate the short-term plans by measuring how the rankings might change based on expected shifts in criteria performances. Due to time limitations, only four criteria have been explored. Therefore, it is recommended to use scenario analysis to evaluate more relevant criteria and measure the effects of changes in performances. Finally, the priorities and interdependencies should be re-evaluated regularly due to the sensitivity of the rankings to changes in the priorities. Moreover, aligning these priorities might also prove valuable to ensure one strategy is attained within the segment.

Preface

Hereby I proudly present my thesis marking the end of my Master's in Industrial Engineering and Management. Therefore, I would like to present some acknowledgements.

First, I would like to thank both supervisors of OEM X. They were always available for feedback or answers to my questions. Moreover, I enjoyed the freedom from both supervisors to shape this thesis while they ensured that it delivered value to OEM X. Moreover, I would also like to thank the stakeholders involved in this project. They were all engaged and showed great interest. Finally, I would like to thank my colleagues who helped me throughout the thesis project and made my graduate internship at OEM X very pleasant.

Second, I would like to thank my supervisors from the University of Twente, Eduardo Lalla and Patricia Rogetzer. Eduardo provided great feedback throughout the whole project timeline. I want to emphasise his importance in ensuring this thesis's theoretical and practical relevance, which was especially difficult to define at the start. Moreover, I would like to thank Patricia for her eye for detail, as presented in her perfectly hand-written feedback. Moreover, her knowledge about raw materials and sustainability concepts proved helpful. Finally, I would also emphasise that working with Eduardo and Patricia went smoothly, and there was always room for conversations that were not as important to the thesis but made meetings very enjoyable and resulted in a good synergy between my supervisors and me.

Overall, I have enjoyed my five years at the University of Twente. The university presents the students with the opportunity to shape their studies as the student sees fit. Moreover, proactive behaviour is rewarded, and it presents great learning moments. I had the opportunity to meet many people from many different cultures during my time at the Politecnico di Torino in Italy and Chalmers tekniska högskola in Sweden. I value the insights that I gained there and the friendships that I made. Moreover, I have already got a taste of the working environment by performing two graduate internships. Therefore, the University of Twente ensured that the transition from being a student to starting to work is as smooth as possible. In conclusion, I would like to thank everyone I met throughout this journey who helped me to be where I am right now. This must also be said for my family and high school friends, who have supported me throughout these five years and visited me throughout my periods abroad, for which I am grateful.

I hope you enjoy reading my thesis.

Tobias Lansink,
July 2022

Contents

Management summary	i
Preface.....	v
Contents	vi
List of figures	viii
List of tables.....	ix
Glossary of terms and abbreviations.....	x
1 Introduction.....	1
1.1 OEM X	1
1.2 Problem description	3
1.3 Core problem.....	6
1.4 Research problem.....	7
1.5 Research questions.....	7
2 Context analysis.....	9
2.1 Current situation ED&C and MDS scope	9
2.2 Developments and market evolution analysis	11
2.3 Conclusion	15
3 Literature review	16
3.1 Multi-Actor Multi-Criteria Decision Analysis	16
3.2 Criteria determination	18
3.3 Multi-criteria decision-making methods	22
3.4 Integrating Multi-Criteria Decision-Making and uncertainty modelling	30
3.5 Conclusion	35
4 Solution design	37
4.1 Problem overview.....	37
4.2 Theoretical approach.....	40
4.3 Operationalisation of criteria weights and thresholds.....	51
4.4 Operationalisation of criteria performances.....	51
4.5 Conclusion	53
5 Numerical results.....	54
5.1 Stakeholder priorities	54
5.2 Experimental design	57
5.3 Experiments 1 and 2: parameter tuning.....	61
5.4 Experiment 3: model validation	63
5.5 Experiment 4: deterministic ranking	64
5.6 Experiments 5 and 6: scenario planning and Monte Carlo approach	65

5.7	Experiments 7 and 8: Monte Carlo sensitivity analysis	69
5.8	Conclusion	71
6	Conclusions and recommendations	73
6.1	Conclusion	73
6.2	Discussion	75
6.3	Recommendations and future research.....	76
	Bibliography.....	77
	Appendix A: Description of subsystems ED&C and MDS segment	83
	Appendix B: Sustainability assessment of copper	85
	Appendix C: Workshop design.....	86
	Appendix D: PESTEL methodology	88
	Appendix E: Performance evaluation table.....	89
	Appendix F: Interdependency overview.....	90
	Appendix G: Supermatrix calculations	91
	Appendix H: Results deterministic ranking including criteria groups driving the ranking	94
	Appendix I: Results per segment and rank reversal discussion	95
	Appendix J: Execution of the scenario analysis	96
	Appendix K: Validation of practical contribution	99

List of figures

Figure 1: Rankings per configuration.	ii
Figure 2: Aggregated results in comparison with stakeholder results for rankings and scores.	ii
Figure 3: Boxplot of the results of the Monte Carlo simulation when simulating the influence of uncertainty on four different criteria.	iii
Figure 4: Boxplot of the results of the Monte Carlo simulation when simulating the influence of judgemental uncertainty.	iv
Figure 5: Sustainability strategy OEM X.	1
Figure 6: Business areas of OEM X.	2
Figure 7: Expected market growth of electric truck platform according to internal forecasts for Battery Electric Vehicles (BEV) and Fuel Cell Electric Vehicles (FCEV).	2
Figure 8: Decarbonization goals according to OEM X's sustainability strategy.	3
Figure 9: Framework presenting the timeline concerning the introduction of circularity.	3
Figure 10: R-Framework.	4
Figure 11: Lansink's Ladder.	4
Figure 12: R-Framework in practice for the manufacturing industry.	5
Figure 13: Evolution of the mobility market.	12
Figure 14: Assessment of the economic importance and supply risks per raw material.	15
Figure 15: Overview of MAMCA methodology.	17
Figure 16: Classification tree based on Table 7.	28
Figure 17: Examples of distributions generated according to the Expert-Based Distribution Laws (EBDLs).	34
Figure 18: Problem structure based on the ANP methodology.	39
Figure 19: Theoretical framework and relationships of the different models.	41
Figure 20: Flow-chart of the Monte Carlo simulation used to assess the impact of environmental uncertainty.	49
Figure 21: Flow-chart of the Monte Carlo simulation used to assess the impact of judgmental uncertainty.	50
Figure 22: Center of gravity defuzzification method based on criterion P1 - industry consumption.	52
Figure 23: Interdependencies visualised.	55
Figure 24: Weight distributions representing the priorities of each stakeholder.	56
Figure 25: Corrected weight distributions representing the priorities of each stakeholder considering interdependencies.	56
Figure 26: Results of Experiment 1.	61
Figure 27: Results of Experiment 2.	62
Figure 28: Rankings per configuration.	63
Figure 29: Aggregated ranking in comparison with individual rankings are presented in the left graph.	64
Figure 30: Four scenarios based on the two most significant drivers including a summary of the narratives.	66
Figure 31: Distribution of evaluations for Cobalt on criterion P4.	67
Figure 32: Boxplot of the results of the Monte Carlo simulation when simulating the influence of uncertainty about the environment on four different criteria using triangular distributions.	68
Figure 33: Distribution of weights for criterion P1.	69
Figure 34: Boxplot of the results of the Monte Carlo simulation when simulating the influence of judgemental uncertainty.	70
Figure 35: Electric machine and its subsystems.	83
Figure 36: Electric motor drive and its subsystems.	83
Figure 37: ED&C sub-systems.	84
Figure 38: Example of an overview of the sustainability assessment of raw materials.	85
Figure 39: Overview of sheet that is used as an input form to determine the weights that are not corrected for dependencies.	86
Figure 40: Overview of sheet that is used as an input form to determine the interdependencies.	87
Figure 41: Visualisation of how the original ranking compares to the ranking per segment.	96
Figure 42: Results of the questionnaire visualised by the average and standard deviation.	100

List of tables

Table 1: Overview of the raw materials used per segment.....	9
Table 2: Sustainability assessment based on the Material Change report.	11
Table 3: Raw material and industry synergies.	13
Table 4: MCDA criteria based on the economic bottom line.	19
Table 5: MCDA criteria based on the environmental bottom line.....	20
Table 6: MCDA criteria based on the social bottom line.....	21
Table 7: Literature review covering MCDA methods in similar contexts.....	27
Table 8: Literature review discovering the methods integrated with MCDM to model uncertainty.	32
Table 9: Criterion that should be added to Table 4 based on stakeholders' feedback.	38
Table 10: Scenario analysis perspective considered for this research.	47
Table 11: Scenario creation approach.	47
Table 12: Bounds of the ordinal datapoints for the criterion 'Industry consumption'.	52
Table 13: Summary of the inconsistencies of the pairwise comparisons per cluster.	54
Table 14: Experimental designs.	60
Table 15: Expected output and conclusion for each experiment.	60
Table 16: Absolute differences between different MCDM methods and DEMATEL + ANP and PROMETHEE II.....	63
Table 17: Selected criteria according to scenario analysis combined with the estimates and supporting sources.....	67
Table 18: Performance evaluation table according to the references presented in Table 4, 5, and 6.	89
Table 19: Overview of all the interdependencies. $r(i) - s(i)$ present what criteria are dispatchers or receivers, $r(i) + s(i)$ presents the relative impact of the interdependency.	90
Table 20: Unweighted supermatrix formed by the weights and interdependencies following the structure of Figure 18.....	91
Table 21: The table presents the weighted supermatrix, a column-normalised unweighted supermatrix.	92
Table 22: The limit supermatrix is a matrix presenting the convergence of the weighted supermatrix.	93
Table 23: Rankings of raw materials including the second-level criteria that drive the ranking.....	94
Table 24: Ranking of raw materials per segment including PROMETHEE II score.....	95
Table 25: Elaborated drivers and the PESTEL group that fits best.	96
Table 26: Statements used in the questionnaire following four pillars of the UTAUT theory.	99

Glossary of terms and abbreviations

<i>3TGs</i>	Represent the conflict minerals. It includes tin, tantalum, tungsten and gold.
<i>AHP</i>	Analytical Hierarchy Process
<i>ANP</i>	Analytical Network Process
<i>ASM</i>	Artisanal and Small-scale Mining
<i>BEV</i>	Battery Electric Vehicle
<i>COPRAS</i>	Complex Proportional Assessment
<i>DEA</i>	Data Envelopment Analysis
<i>DEMATEL</i>	DEcision MAKing Trial and Evaluation Laboratory
<i>EBDL</i>	Expert-Based Distribution Law
<i>ED&C</i>	Electrical Distribution and Charging, this is one of the two segments representing this scope.
<i>ELECTRE</i>	Élimination et Choix Traduisant la REalité
<i>EMD</i>	Electric Motor Drive
<i>EM</i>	Electric Machine
<i>ESS</i>	Energy Storage Systems
<i>GRA</i>	Grey Relational Analysis
<i>MAMCA</i>	Multi-Actor Multi-Criteria Analysis
<i>MAVT</i>	Multi-Attribute Value Theory
<i>MCDA</i>	Multi-Criteria Decision Analysis
<i>MCDM</i>	Multi-Criteria Decision-Making
<i>MDS</i>	Motor Drive System, this is one of the two segments representing the scope of this thesis.
<i>OEM</i>	Original Equipment Manufacturer
<i>PA-66</i>	Polyamide 66
<i>PBT</i>	Polybutylene terephthalate
<i>PESTEL</i>	Strategic management tool assessing Political, Economic, Social, Technological, Environmental and Legal factors
<i>PROMETHEE</i>	Preference Ranking Organization METHhod for Enrichment of Evaluations
<i>REEs</i>	Rare Earth Elements, includes the raw materials dysprosium, terbium, neodymium and praseodymium.
<i>RM</i>	Raw Material
<i>SAW</i>	Simple Additive Weighting
<i>SDG</i>	Sustainable Development Goals
<i>SEK</i>	Swedish krona, the official currency of Sweden.
<i>TBL</i>	Triple Bottom Line, representing economic, environmental and social capital.
<i>TOPSIS</i>	Technique for Order of Preference by Similarity to Ideal Solution
<i>UTAUT</i>	Unified Theory of Acceptance and Use of Technology

1 Introduction

The first chapter of this thesis describes the background, problem context and methodology. Section 1.1 describes the company. Section 1.2 discusses the problem context. Then, Sections 1.3 and 1.4 discuss the research problem and research questions. Finally, Section 1.5 presents the research questions.

1.1 OEM X

The thesis is written in collaboration with OEM X. OEM X offers trucks, buses, construction equipment, power solutions for marine and industrial applications, financing and services that increase the customers' uptime and productivity. Moreover, OEM X strives to contribute to developing electrified and autonomous solutions for the benefit of customers, society and the environment. Therefore, according to OEM X (2022a), the mission and vision that summarises the activities and goals is:

'We drive prosperity through transport and infrastructure solutions and our vision is to be the most desired and successful transport and infrastructure solution provider in the world.'

This ambitious mission comes with responsibilities for the environment. Transport accounts significantly for the emission of greenhouse gases, and public opinion considers it as one of the most evident symbols of pollution (Stoycheva et al., 2018). Hence, OEM X defined an overarching sustainability strategy to reduce climate impact, use the world's resources more consciously, and conduct business responsibly. This strategy is based on the United Nations Sustainable Development Goals (SDGs) and consists of three pillars, namely: climate, resources and people, as presented in Figure 5:

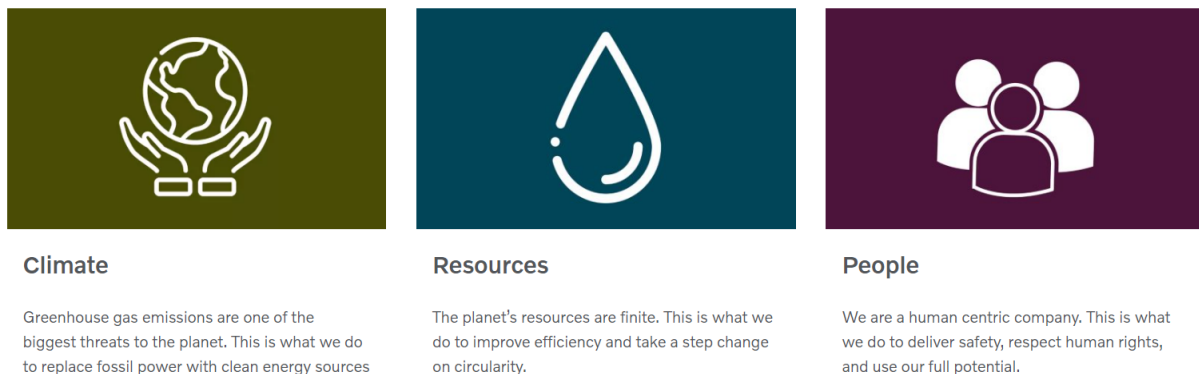


Figure 5: Sustainability strategy OEM X. Source: (OEM X, 2022b)

In combination with the sustainability strategy, the mission and vision apply to all the business areas of OEM X. As presented in Figure 6, there are ten different business areas. Three of those business areas concern trucks. To maintain synergies, the truck business area is split up into three divisions: engineering, operations and purchasing. This thesis is written in close collaboration with the purchasing division.

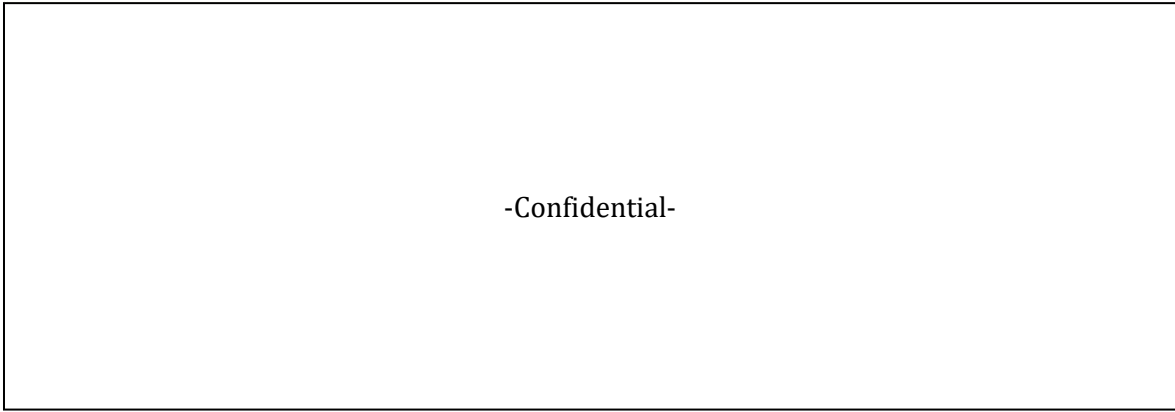


Figure 6: Business areas of OEM X. Source: (OEM X, 2022c)

The purchasing division works together with 36,000 supply network partners, and the purchased parts add up to 200 billion SEK (Swedish krona), which corresponds to roughly 19 billion euros (OEM X, 2015). This amount is used to buy the 6,000 parts that the tier-1 suppliers offer.

The purchasing division is split into multiple departments. This thesis is written in the emerging technologies department, which focuses on purchasing the necessities for developing and delivering OEM X's autonomous solutions, electric vehicles, and hydrogen and fuel cell technology. The focus is on the electromobility branch of the electromobility department. This branch is developing rapidly due to significant sustainable advantages. OEM X presents that electrically powered vehicles achieve zero emissions and significantly reduce noise pollution. Therefore, the market is estimated to grow considerably during the upcoming years, as shown by internal sales estimations presented in Figure 7. Currently, the electric truck is deemed to be in the launch phase. According to OEM X (2022), the growth phase is expected to start in 2024.

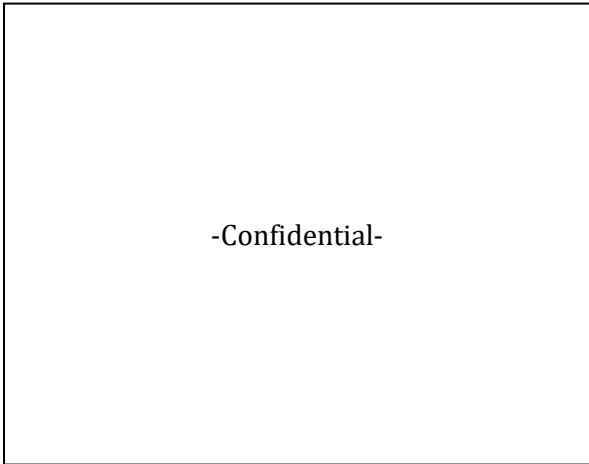


Figure 7: Expected market growth of electric truck platform according to internal forecasts for Battery Electric Vehicles (BEV) and Fuel Cell Electric Vehicles (FCEV). The y-axis presents the number of electric trucks that estimated to be sold for that year.

The MDS (Motor Drive System) and ED&C (Electric Distribution and Charging) segments are the most relevant to this thesis within the electromobility purchasing area. The MDS and ED&C segments are two of the three most significant cost drivers within one electric truck, next to the battery segment. Moreover, the impact of sourcing unsustainably increases significantly during the upcoming years due to the expected increase in sales if changes are not introduced.

In short, the ED&C segment sources the components necessary to ensure that the energy storage system is connected to the energy consumption system safely. Metaphorically, it is considered the glue that keeps the E-mobility system together. This system is complex and consists of many subsystems. Then, the MDS segment consists of two systems: the EMD (Electric Motor Drive) and the EM (Electric Machine). The EM is the electrical motor that could function as a motor and a generator. The EMD, also named the inverter, works as the (speed) controller. An overview of these systems and their subsystems is presented in Appendix A. These subsystems consist of many different raw materials. The focus of this thesis is on these raw materials.

1.2 Problem description

The problem identification presents the context of the problem in Section 1.2.1. The description of the assignment presented by OEM X is given in Section 1.2.2. Finally, a problem cluster is drafted in Section 1.2.3.

1.2.1 Problem context

As presented in Section 1.1, OEM X aims to minimise their environmental impact even though many raw materials are used in the MDS and ED&C supply chain. Therefore, there is an increased interest in introducing circularity in the supply chains of OEM X, because many raw materials involved are finite. According to the internal strategy of the purchasing department, the definition of circularity is as follows: 'Circular economy is a framework for an economy that is restorative and regenerative by design.' The movement toward a more circular economy comes with specific goals that concretise the strategy, as presented in Figure 8:

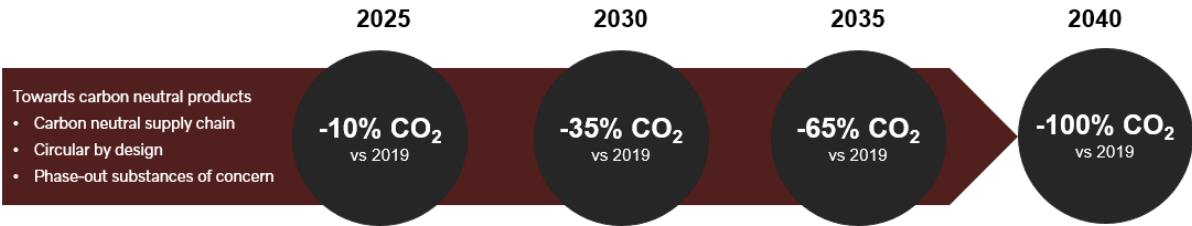


Figure 8: Decarbonization goals according to OEM X's sustainability strategy.

Comparing the goals of Figure 7 and Figure 8, it can be concluded that these goals are conflicting. The expected increase in sales numbers could stagnate the progress towards carbon neutrality. Moreover, the timeline presented in the circular economy strategy, shown in Figure 9, exhibits that circularity should be introduced starting from 2022.

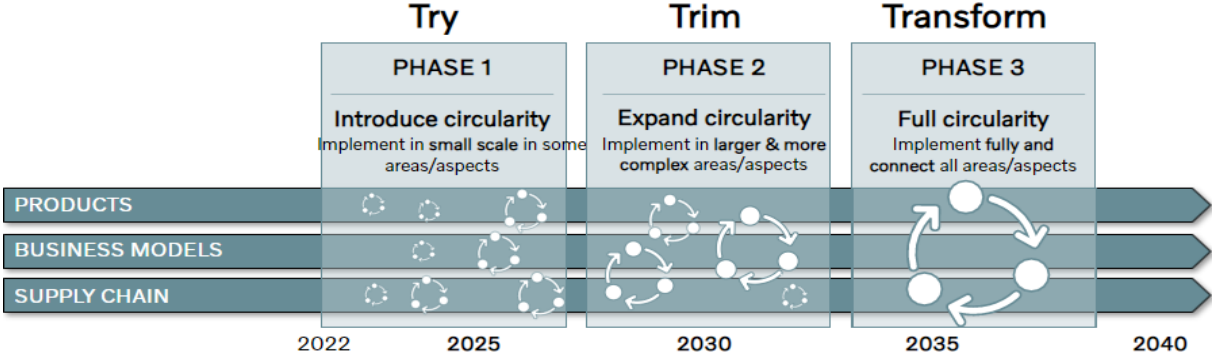


Figure 9: Framework presenting the timeline concerning the introduction of circularity.

This implies that a plan should be ready concerning the introduction of circularity. However, this is not the case for the raw materials available in the supply chain. Therefore, the ambitions are set high, though the road towards reaching the targets remains unclear.

It is clear from an internal and global perspective that introducing circularity is necessary. Bhuyan et al. (2022) present that automobile industry is pushing towards electric mobility for personal and public modes of futuristic urban transportation. Bhuyan et al. (2022) also mention the recycling gap due to various binding factors that range from operational to strategic-level issues, which complies with the sketched scenario at OEM X. Next, Ghadimi et al. (2012) present that the first step to achieving the goal of moving to sustainable manufacturing is to assess the sustainability level of any manufactured product inside the company with great precision.

Furthermore, it is mentioned that sustainability assessment frameworks are not delivering properly. Stoycheva et al. (2018) present: 'Overall, the literature review results suggest that with minor exceptions, sustainability assessment frameworks and models in the automotive industry fail to deliver tools that can integrate the three pillars of the sustainability agenda in product manufacturing.' Finally, Deleryd and Fundin (2020) present that organisations should embrace a broad definition of quality as societal satisfaction and embark on a sustainable business development strategy. Then, these organisations increase the probability of becoming a market leader in the sustainability race. Thus, organisations will not only contribute to society, customers and the environment, but will also ensure solid financial development that would enable future investments in sustainability.

Thus, circularity should and is one of the focus points of OEM X's strategy. Introducing circularity at OEM X is done according to the so-called 'R-framework' as introduced in the OEM X sustainability structure and based on the literature of Potting et al. (2017). The R-Framework is presented in Figure 10:

CIRCULAR ECONOMY ↑ LINEAR ECONOMY	SMARTER PRODUCT USE & MANUFACTURING	R0 REFUSE	Make product redundant by abandoning its function or replacement by radically different product
		R1 RETHINK	Make product use more intensive (i.e., by sharing products)
		R2 REDUCE	Increase efficiency in product manufacturing or by consuming less natural resources
	EXTEND LIFESPAN OF PRODUCT AND PARTS	R3 REUSE	Reuse of discarded product which is still in good condition and fulfils its original function
		R4 REPAIR	Repair and maintenance of defective product so it can continue to be used with its original function
		R5 REFURBISH	Restore an old product and bring it up-to-date
		R6 REMANUFACTURE	Use (parts of) discarded product in a new product with the same function
		R7 REPURPOSE	Use (parts of) discarded product in a new product with a different function
	USEFUL APPLICATION OF MATERIALS	R8 RECYCLE	Process materials to obtain the same or lower quality
		R9 RECOVER	Incineration of material with energy recovery

Figure 10: R-Framework (Potting et al., 2017).

The R-Framework presents guidelines to shift from a linear economy to a circular economy. Moreover, the arrow shows the impact of the individual Rs on the transition to a more circular economy. The impact is visualised clearer in Figure 11, showing the Lansink Ladder. This framework highlights the impact of circular concepts. The impact on the transition from the linear economy to the circular economy is deemed higher when a concept is higher in the hierarchy for both frameworks. For instance, the prevention option of Lansink's Ladder corresponds to the first three Rs.



Figure 11: Lansink's Ladder. A hierarchy for waste management (Kemp & van Lente, 2011).

In practice, the R-Framework can be applied as follows for the manufacturing industry as presented in Figure 12:

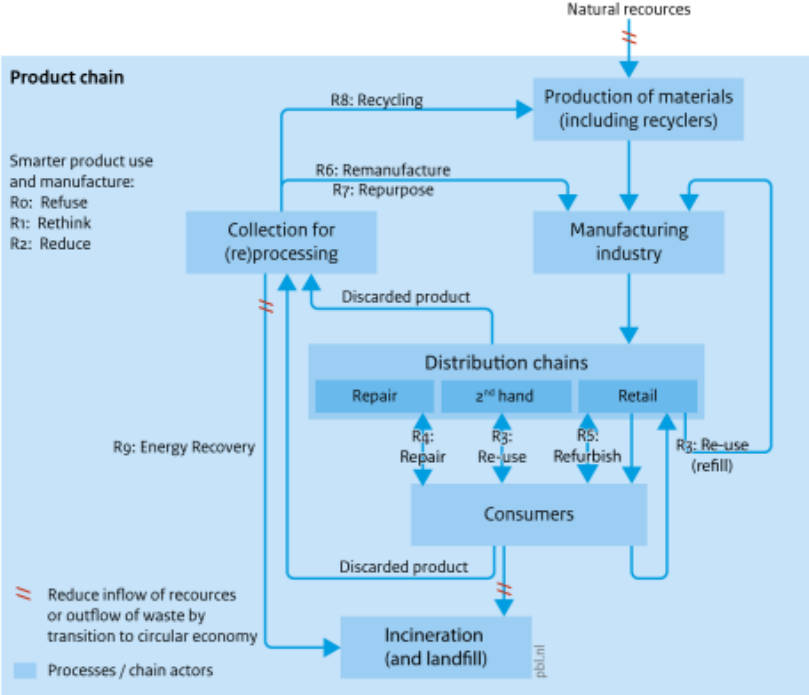


Figure 12: R-Framework in practice for the manufacturing industry (Potting, Worrel, & Hekkert, 2017).

Figure 12 presents how natural resources and waste could be excluded from the complete product chain by keeping products and materials in the loop for as long as possible. The scope of this thesis concerns raw material usage, and recycling is essential for closing the loop as products likely come in a state where re-use is not an option anymore and products are to be recycled (Kalverkamp et al., 2017). The term re-use comprises of the Rs related to extending the lifespan of products and parts of the R-framework. In addition, some public governments have taken the initiative concerning recycling. For instance, China, Korea and Japan have defined targets ranging from 80% to 95% concerning the recycling of automotive products (Morseletto, 2020). These figures imply that recycling automotive products is possible. Thus, the problem considers recycling as its primary focus.

1.2.2 Assignment description

As presented, this thesis focuses on raw material usage in the MDS and ED&C supply chain. Stoycheva et al. (2018) recommend including the three pillars of the sustainability agenda. Therefore, multiple criteria are taken into account when making a decision. Multi-criteria decision analyses are developed to support a decision-maker in choosing the preferable variant from many possible options, considering many criteria characterising the acceptability of individual decision variants (Watrobski et al., 2019). Hildenbrand et al. (2021) present that MCDAs (Multi-Criteria Decision Analysis) addresses the complexity by objectively considering different confliction dimensions. This results in better informed decision-making, enhanced awareness, and empowered communities due to the incorporation of economic, environmental, social and political considerations. Therefore, the thesis will cover a MCDA to address the issues and opportunities discussed in Section 1.2.1.

The assignment description has been formulated as follows:

'Map the critical raw materials and relevant developments in the Battery Electric Vehicle (BEV) supply chain with a focus on the MDS and ED&C segment and present recommendations in the form of an action plan based on Multi-Criteria Decision Analysis (MCDA) on what OEM X and its supply chain partners should prioritise to recycle.'

To concretise the assignment, the expected deliverables of this thesis are discussed. A map of the raw materials and their characteristics, KPIs and other relevant metrics are delivered. Then, it is identified who the stakeholders are. They are considered as the input of the problem. Next, semi-structured interviews were planned and performed. These interviews presented the input of the relevant stakeholders, and valuable input is gained considering the design, criteria and weights of the MCDA, which is another deliverable. The MCDA quantitatively presents the prioritisation concerning the recycling of raw materials. This MCDA is presented in the form of a tool. Furthermore, the highly dynamic environment combined with the request to include short-, medium- and long-term perspectives means that a method is included to present robust solutions to the problem. Finally, a description of the deliverables mentioned above and the steps taken to reach these deliverables are delivered in a report.

1.3 Core problem

Sections 1.1 and 1.2 present the information necessary to derive the overarching action problem that requires solving. This action problem is formulated as follows:

'The current environmental impact of OEM X is too high'.

This action problem has many causes. The main cause requiring solving is the core problem:

'Concrete plans for raw materials are not on the current sustainability agenda for the ED&C and MDS segment.'

The core problem influences all three aspects of OEM X 's sustainability strategy, as presented in Figure 5. By not introducing circularity on a raw material level, OEM X 's goals cannot be reached, and the environment, resources and people aspects might all be influenced depending on the impact of the raw material usage. These are the three aspects on which OEM X 's sustainable impact can be measured as presented in the problem cluster. To concretise the action problem, the three sustainable strategy factors can be explained more in detail and in the context of OEM X:

- Climate perspective: the conclusion has been drawn in Section 1.2.1 that the increased sales of electric trucks will conflict with the emission decrease objective. Though, the introduction of circular initiatives could present a good start. To present an example, a report on recycling metals discusses the following (EuRIC, 2020):
 - o 'Using steel scrap in the production process reduces CO₂ emissions by 58%.' (p.4)
 - o 'Using aluminium scrap, CO₂ emissions can be reduced 92% compared to raw aluminium.' (p.5)

Therefore, the environmental impact could be significantly decreased by creating an action plan to recycle raw materials.

- Resource perspective: The raw materials are available in finite amounts. Moreover, the extraction process is resource-intensive. For instance, some extraction processes rely on using large amounts of water, which might be polluted during the process (Drive sustainability et al., 2018).
- People perspective: The supply chains in OEM X consist of many tiers. Therefore, it is difficult to track human rights throughout the supply chain. For instance, 54% of the

mined cobalt used in magnets is extracted in Congo. Moreover, 90% of the mined Cobalt in Congo is linked to artisanal and small-scale mining, strongly associated with child labour (Drive sustainability et al., 2018). Therefore, human rights can be protected by decoupling the supply chain from using these raw materials by introducing circular concepts.

Overall, mapping and assessing the raw materials used in the MDS and ED&C supply chain is essential to understand the environmental issues and determine where to focus in the short, mid, and long term.

1.4 Research problem

The research problem describes the knowledge that needs to be acquired.

'How can the critical raw materials in the MDS and ED&C supply chain be selected and prioritised for recycling by performing an MCDA?'

There are many raw materials in the MDS and ED&C supply chain. Moreover, many criteria could be used to determine the relevance for OEM X to stimulate circularity in its supply chain concerning areas like global availability, costs, environmental impacts, and geopolitical implications. Moreover, the recommendations are based on short-, medium- and long-term decision-making. Therefore, uncertainty is also introduced to the problem as further explained in Section 1.5. Then, multiple stakeholders are impacted by the decision to start recycling raw materials. Overall, the MCDA tool should be constructed carefully.

1.5 Research questions

Multiple research questions have been formulated to solve the core problem, present answers to the research question, and execute the assignment successfully, as shown in the following list.

1. *How can the raw materials be mapped and assessed?'*
 - a. *'What raw materials should be considered and who are the stakeholders that should be considered?'*
 - b. *'How is the sustainability of raw materials currently being measured?'*
 - c. *'What developments should be considered that might influence the raw material usage?'*

This question is split up into sub-questions. The first goal is to present an overview of the raw materials used in the MDS and ED&C segment combined with the stakeholders involved in the process. Then, it should be discussed how these raw materials are currently assessed from a sustainable perspective. The criteria that are used are presented combined with the measurements. Finally, the rapid developments in the design of electric trucks might result in changes in raw material usage or introduce new raw materials. Furthermore, industries are competing for the same resources. These industries could be mapped to assess whether the market for these raw materials is somewhat balanced. Overall, to ensure that this thesis not only provides a solution for today, the developments of tomorrow need to be considered. These developments could be considered the primary source of uncertainty for this thesis.

2. *'What does the literature propose for solving the MCDM problem?'*
 - a. *'What MCDM methodology fits the current situation at OEM X best?'*
 - b. *'What criteria are used to assess the sustainability of materials in the manufacturing industry?'*

- c. *'What methods are available to solve the MCDM problem?'*
- d. *'How can the uncertainty of the problem context be modelled in the MCDM method?'*

The problem can be defined as a multi-criteria decision-making problem, as stated in Section 1.3. This question tries to answer what methods exist and which one fits the best to the presented problem. The literature review could help determine the assessment criteria and determine how to consider those. What criteria are relevant now and in the foreseeable future, and how can these be determined?

Furthermore, how to include uncertainty based on possible developments could be investigated to present a more robust prioritisation. According to Stewart (2005), MCDM models are based on deterministic evaluations. However, problems arise when risks and uncertainties are as significant as the trade-offs evaluated with the MCDM method. In this case, it might be the case that, for instance, data uncertainty and technological and market developments could result in the insignificance of the prioritisation in the mid- and long term.

- 3. *'How should the multi-criteria decision approach be designed?'*
 - a. *'What is the formal problem description, including the final selection of criteria?'*
 - b. *'What are the requirements for the multi-criteria decision-analysis tool from the stakeholders' perspective?'*
 - c. *'How can the uncertainty modelling be designed in multi-criteria decision-making?'*

First, the criteria can be assessed and further defined based on the stakeholder analysis. Then, the performance of the raw materials can be finalised based on the set of criteria defined in the literature research and further developed based on the answers to question 3.a. Moreover, the requirements of the MCDA tool can be determined throughout the same interview. Finally, the input for the uncertainty modelling can be determined based on the future developments and the method determined in the literature research. The context for the numerical experiments for the scenario analysis according to the literature framework can also be presented in this chapter.

- 4. *'How can a multi-criteria decision analysis tool be used to create a prioritisation concerning recycling raw materials in the MDS and ED&C supply chain?'*
 - a. *'What are the results from testing the multi-criteria decision analysis tool, and how does the uncertain future influence them?'*
 - b. *'What does the proposed action plan look like?'*

Based on the previous chapters, an MCDA tool can be developed. The solution framework that has been chosen in the literature review, in combination with the operationalisation of the criteria, must be combined into a model that can generate the prioritisation. Furthermore, the uncertainty must be included based on the solution framework and the input given by answering research question 3.c. Then, numerical experiments using the MCDA tool can be presented. Moreover, an action plan can be presented based on the numerical results.

- 5. *'What conclusions can be drawn, and what recommendations can be formulated based on the multi-criteria decision analysis?'*

Finally, a functioning MCDA tool has been developed. Then, recommendations can be formulated based on the results of the MCDM analysis if the results are deemed reliable and on the stakeholders' requirements within OEM X. These recommendations could be shaped into an action plan that satisfies the short-, mid-, and long-term needs.

2 Context analysis

This chapter presents a complete overview of the raw materials, the stakeholders, current sustainability measurements, and the developments. This chapter is split up into two sections. Section 2.1 presents the current scenario and an overview of what is known about the raw materials, stakeholders and the method that is currently used to assess the sustainability of raw materials. Furthermore, Section 2.2 presents what is known about the future. The goal is to present an overview of the expected internal changes relevant to raw material usage. Moreover, synergies are discussed. Section 2.3 concludes Chapter 2.

2.1 Current situation ED&C and MDS scope

The information gathered to determine the current situation of raw material usage is done by unstructured interviews, asking specific follow-up questions, and consulting internal reports and databases.

2.1.1 Raw materials

The bills of materials of the subsystems in the ED&C and MDS segments often go one level deeper than the subsystem without specifying what raw materials are used. Therefore, interviews with the engineers have been performed to determine the raw materials based on their expertise. These interviews were unstructured since the engineers took the lead in determining the used raw materials. A summary is presented in Table 1:

Table 1: Overview of the raw materials used per segment.

Raw Material	Available in MDS scope	Available in ED&C scope	Comment
Bauxite	X	X	RM for Aluminium
Chromium	X	X	RM for stainless steel
Cobalt	X		
Copper	X	X	
Dysprosium	X		Rare Earth Element
Graphite	X	X	Carbon (e.g., in SiC)
Iron	X	X	
Neodymium	X		Rare Earth Element
Nickel	X	X	RM for stainless steel
PA-66		X	Thermoplastic
PBT		X	Thermoplastic
Praseodymium	X		Rare Earth Element
Silica Sand	X	X	RM for Silicon (e.g., in SiC)
Stainless steel	X	X	Included in USGS report
Steel	X	X	Included in USGS report
Terbium	X		Rare Earth Element
Tin		X	
Titanium		X	
Zinc		X	

Some limitations need to be addressed. The raw materials and the recyclability of these raw materials depend on the surface treatments used. Surface treatments are applied to different raw materials in different subsystems and components. However, this thesis aims to assess the raw materials from a holistic perspective. Thus, the materials used for these surface treatments, like gold, are not included. Moreover, the thickness of these surface treatments is measured in microns

(1×10^{-6} meter). Therefore, recycling surface treatments will not amount to a significant weight and is thus irrelevant. Moreover, materials in subsystems could be integrated by applying, for instance, thermosetting plastics. This influences recyclability on a component level as well. Potting epoxies prevents subcomponents from being recycled.

The number of different types of used plastics is vast. It is not possible to gather data for each plastic considering the time limitations, and it is also not possible to generalise the plastics due to the vast number of different properties, recycling methods and performances on economic KPIs. Thus, the analysis only includes two plastics, PA-66 (Polyamide 66) and PBT (Polybutylene terephthalate). Therefore, the plastics have been discussed with the segment leaders responsible for the plastic strategy and the choice has been made to include PA-66 and PBT.

Moreover, four Rare Earth Materials (REEs) are used in the MDS scope. These REEs are used in the magnets placed in the electric motor. Moreover, raw materials are generalised to ensure that data is available and limit the number of alternatives used for the MCDA. For instance, the many different plastics are categorised as thermoset and thermoplastic since the latter is recyclable and the first is not. Finally, bauxite, graphite, and silica sand are assessed since those are the raw materials for aluminium, carbon elements, and silicon.

2.1.2 Stakeholders

The definition of a stakeholder is presented according to Macharis et al. (2012): 'A stakeholder is everyone who has a vested interest in a problem in any of the three following ways: 1) by mainly affecting it, 2) by mainly being affected by it and 3) by both affecting it and being affected by it.' Considering these three points, these are the most critical stakeholder groups that should be taken into account:

- Segment leaders: They are responsible for the segment strategy from a purchasing perspective. The sustainability agenda plays an essential part in these segment strategies.
- Engineers: The engineers of both segments are affected by the materials used and have an expert view of the technical requirements that might prove valuable during this research.
- Raw materials team: The raw materials team is responsible for monitoring raw materials from multiple perspectives, including the economic and environmental perspectives.
- The circular operations and solutions team: This team focuses on introducing circular initiatives according to the R-Framework presented in Figure 11.

2.1.3 Sustainability assessment

The final topic covered in this section concerns the assessment of sustainability within OEM X. Section 2.1.2 introduced the raw material and circular operations and solutions teams. Moreover, these teams have experience in assessing raw materials. An example of the assessment of copper is presented in Appendix B. These assessments are based on the Material Change report (Drive sustainability et al., 2018). The report concerns sixteen criteria split up into three groups: material significance, supply significance and association with environmental, social and governance issues, as shown in Table 2.

Overall, these criteria are assessed based on a qualitative scale. Though, sources for each criterion are presented. Therefore, it might be possible to evaluate at least some of the criteria quantitatively. Moreover, the presented data should be re-evaluated since almost every point is based on data from 2017 or earlier.

Table 2: Sustainability assessment based on the Material Change report. Source: (Drive sustainability et al., 2018).

Material significance	Supply significance	Association with environmental, social and governance issues
1. Industry consumption	3. EU dependency on imported material	8. Artisanal and small-scale mining (ASM)
2. Function criticality	4. US dependency on imported material	9. Child labour and forced labour
	5. Recycling rate	10. Countries with weak rule of law
	6. Virgin material consumption	11. Countries experiencing corruption
	7. Estimated rate of depletion	12. Countries experiencing high-intensity conflict
		13. High CO ₂ emissions
		14. Incidences of conflict with indigenous people
		15. Incidences of overlap with areas of conservation importance
		16. Potential for acid discharge to the environment
		17. Potential for harm from hazardous materials and chemicals
		18. Preconditions for radioactive materials in ores and tailings

2.2 Developments and market evolution analysis

The electromobility area is rapidly developing. Currently, it can be witnessed that the transport sector is electrifying. The large-scale deployment of electric vehicles depends on the availability of the relevant raw materials. Moreover, technological developments follow each other up at a rapid pace. Therefore, this section is split into sub-sections, with Section 2.2.1 discussing the internal developments and Section 2.2.2 discussing the external developments. Finally, Section 2.2.3 concludes this sub-section based on the gathered information.

2.2.1 Internal developments

Internal technological developments could influence the use of raw materials by introducing, removing or redesigning parts. Therefore, the developments have to be mapped. The goal of OEM X is to have a fossil-free product range in 2040 where electromobility plays an essential part, represented by battery-electric and fuel cell electric vehicles. These developments have been discussed next to sustainability initiatives influencing raw materials used for both segments.

2.2.1.1 ED&C segment

The general goal for the ED&C segment is to downsize the modules and improve efficiency. This will result in the following developments:

- Removal of the onboard charger. Therefore, the onboard charger is not taken into account in this research.
- The DCDC subsystem will use SiC or GaN. It is confirmed by the chief engineers that SiC will be used in future systems. The confirmation is not given for GaN. Therefore, its use remains unsure but probable.
- The mid-term focus of the segment is on the reduction of housing materials. The housing materials mainly consist of aluminium and stainless steel.

2.2.1.2 MDS segment

For the MDS segment, the primary focus is on the REEs. The developments can be described as follows:

- Ongoing research by OEM X's engineering division aims to evolve the EM design and remove 100% of the magnets. The goal is to have at least 50% removed by 2030.

2.2.1.3 Sustainability initiatives

Finally, developments can be pushed internally by participating in sustainability initiatives. The sustainable minerals program considers conflict minerals, Tin, Tantalum, Tungsten and Gold (3TG) and Cobalt (OEM X, 2020). Moreover, these raw materials are linked to human rights violations in the Democratic Republic of Congo. Therefore, the aim is to:

- Ensure that 3TG minerals are either sourced sustainably or not at all.
- Ensure that cobalt is sourced sustainably or not at all.

Another sustainability initiative that is highly regarded is the material and substance of concern list. Though, this is not relevant due to the strong focus on chemicals.

2.2.2 External developments and trends

The raw materials used in the e-mobility sector are also in demand by other sectors. Therefore, it is relevant to determine how the e-mobility market develops and what industries share the same raw materials.

2.2.2.1 E-mobility market evolution

The overview of the external developments and trends starts with reviewing a report of the European Commission. The report presents a foresight study analysing the use of critical raw materials and considers a timeline until 2050 (European Commission, 2020a). Figure 13 presents that the e-mobility market will increase significantly:

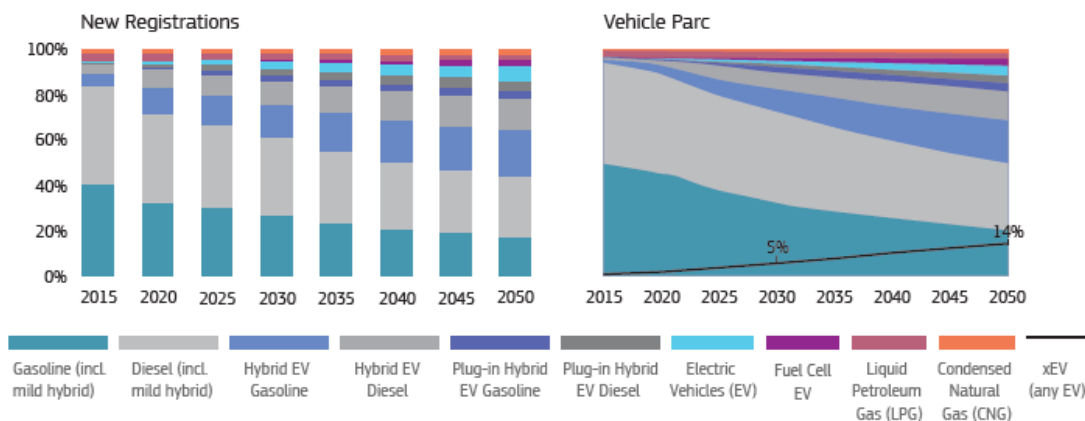


Figure 13: Evolution of the mobility market (European Commission, 2020a).

However, e-mobility is not the most dominant market according to the European Commission, which is not in line with the expectations of OEM X. Though, the representation in Figure 13 covers the entire e-mobility market. The e-mobility market consists of small-sized electronic products, ranging from e-bikes to heavy transport. Therefore, it is not entirely comparable.

2.2.2.2 E-mobility market competition

Moreover, it is interesting to see which markets heavily depend on the same raw materials. Therefore, the European Commission compared the e-mobility sector to the defence, aerospace, and renewable energy sectors (European Commission, 2020a). Additionally, the Material Change

report compares the electromobility sector with the consumer electronics sector (Drive sustainability et al., 2018). Finally, McKinsey & Company (2022) presented the critical raw materials for the net-zero transition. Overall, Table 3 creates an overview of the markets, the raw materials they are competing for and the expected growth:

Table 3: Raw material and industry synergies. [X] represents that there is a significant relevance for the industry, [O] means that there is a moderate, low or even no relevance for the industry, [MD] presents that the data is missing. Input is based on (Drive sustainability et al., 2018); (McKinsey & Company, 2022); (European Commission, 2020a). Different sources substantiate the market size and growth figures, as presented in the footnotes.

Raw Material	Electromobility	Consumer Electronics	Defence and Aerospace	Renewable energy sector
Bauxite	X	O	X	X
Chromium	X	O	X	O
Cobalt	X	X	X	O
Copper	X	X	X	X
Dysprosium	X	X	X	X
Graphite	X	O	O	O
Iron	O	O	X	X
Neodymium	X	X	X	X
Nickel	O	O	X	X
PA-66	O	O	MD	MD
PBT	O	O	MD	MD
Praseodymium	X	X	X	X
Silica Sand	X	O	O	X
Stainless steel	O	O	X	X
Steel	O	O	X	X
Terbium	X	X	X	X
Tin	O	X	X	O
Titanium	O	O	X	O
Zinc	O	X	X	X
Estimated market size (in billions)	\$151.9 ¹	\$1,000 ² , \$1,032 ³	\$452.69 ⁴	\$881.7 ⁵
Estimated compound annual growth rate	22.0% ¹	8.0% ² 1.8% ³	5.8% ⁴	8.4% ⁵

Some raw materials identified for the ED&C and MDS segment are not marked as very relevant for the electromobility sector, since these are assessed in light of the whole electromobility sector.

Moreover, it can be concluded that all industries compete for similar raw materials. Market size and relative raw material consumption could provide valuable leverage when securing certain raw materials. Therefore, the growth of the electromobility sector, which is more in line with OEM X 's expectations than the European Commission's expectations, could result in more leverage in the long term.

Furthermore, it is interesting to highlight the shared interest in raw materials by the renewable energy sector, specifically concerning wind energy (McKinsey & Company, 2022). The MIT (Massachusetts Institute of Technology) confirms this view from an REE perspective. 'Rare Earth

¹ [Precedence Research - 2020 until 2030](#)

² [Global Market Insights - 2020 until 2027.](#)

³ [Statista - 2019 until 2025](#)

⁴ [The Business Research Company - 2021 until 2026](#)

⁵ [Allied Market Research - 2020 until 2030](#)

Elements (REEs) are increasingly integrated into new technologies, especially within the clean energy, military, and consumer electronics sectors (Massachusetts Institute of Technology, 2016). Moreover, the MIT also forecasts growth in all sectors.

2.2.2.3 Market mechanisms

As presented in Section 2.2.2.2, many sectors compete for the same raw materials. Moreover, the transition to a net-zero economy is relevant in all sectors to at least ensure to limit global warming to a maximum of 1.5 °C. This transition will be metal-intensive, and the raw materials will be at the centre of decarbonization efforts and electrification of the economy (McKinsey & Company, 2022). Moreover, McKinsey & Company also characterises the metals and mining industry by having long lead times, being capital intensive, having price fly-ups and finally, being a bottleneck due to demand outstripping supply. Therefore, strategic stockpiles and other means of over-capacitating the system could result in the inability to keep up with the forecasted exponential growth in the short term (5-7 years).

The market balancing mechanisms that can be expected are the following (McKinsey & Company, 2022):

- **Supply responds to prices.** As demand accelerates and prices react, new supply is brought in relatively quickly. The raw material does not become a structural bottleneck even though there might be short term volatility.
- **Material substitution.** Due to the inability of the industry to provide the necessary commodities, technological innovation will lead to material substitution in specific applications. As a result, performance might be comprised.
- **Technology substitution.** The end-user is forced to shift its technology mix, which might result in different bottlenecks. For instance, non-tellurium based solar panels might lack in the performance category. Then, a greater demand for wind-generated power might add pressure on neodymium used for wind turbines.

Material substitution and technology substitution will play a significant role in the sustainability race. It is expected that roughly 46% of the emission reductions to achieve carbon neutrality in 2050 will be enabled by technologies at the demonstration or prototype stage (Trehan, 2022). Moreover, it is presented that behavioural changes only account for around 5% of the reductions.

Overall, it can be concluded that the raw material market is inflexible due to the long lead times even though the demand is increasing significantly due to the net-zero transition and exponential growth of many different sectors. Supply risks might become commonplace. Therefore, the European Commission (2020b) acted and mapped a significant number of raw materials based on their economic importance and the imposed supply risks as presented in Figure 14.

Figure 14 confirms the viewpoint that REEs are supply critical. However, many other raw materials are also considered to be supply critical. Supply risks are calculated based on global supply, sourcing countries mixes, import reliance, supplier countries' governance, trade restrictions and agreements, and availability and criticality of substitutes. Economic importance is based on the importance of a given material in end-use applications and the performance of available substitutes.

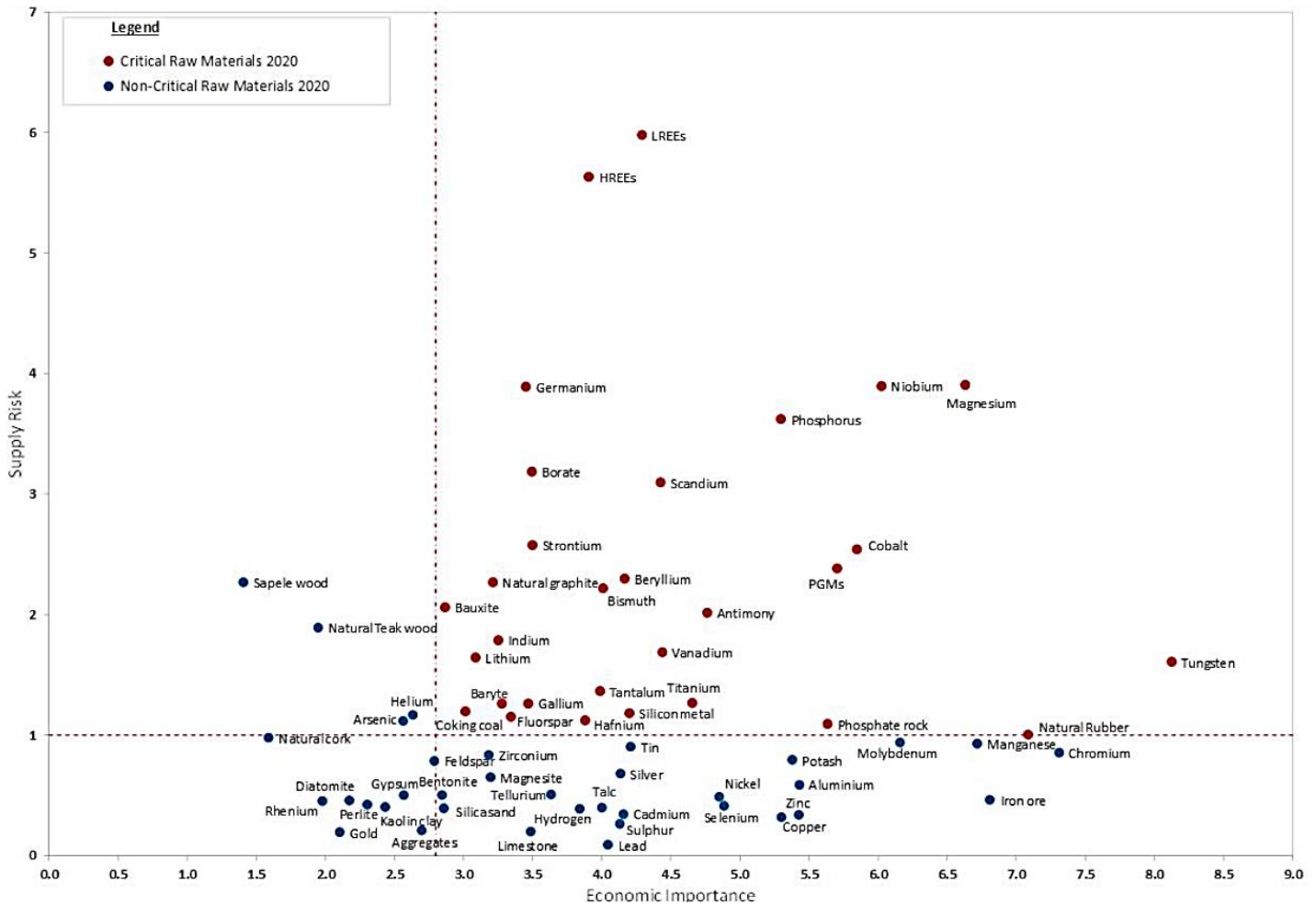


Figure 14: Assessment of the economic importance and supply risks per raw material (European Commission, 2020b).

2.3 Conclusion

Section 2.1 identified nineteen raw materials relevant for this analysis with the help of the engineers. Moreover, four stakeholder groups are identified. Finally, the current assessment of the sustainability of raw materials is discussed by presenting eighteen criteria in Table 2 and by giving an example in Appendix B. Currently, performances of raw materials are assessed. However, comparisons or prioritisations are not made.

Section 2.2 discusses that the raw materials used in the ED&C and MDS segments are essential in the net-zero transition. Moreover, these materials are shared by many industries, as presented in Table 3, partly explaining the supply criticality and economic importance outlined in Figure 14. Three mechanisms have been identified to show how supply will meet demand. Finally, it became clear that there are materials that will be included or phased out during the following years. Cobalt and REEs might, for instance, be phased out, while gallium could be introduced, and the use of silicon might be increased significantly.

Thus, it is clear that the MCDA should be able to cope with these uncertain events. Furthermore, the most significant events include supply risks due to shared raw materials in rapidly growing sectors. However, these might result in synergies, as the renewable energy and electromobility sectors share similar problems, like the supply criticality of the REEs used in the magnets.

3 Literature review

This chapter aims to create a conceptual solution framework based on the context analysis. The problem description of Chapter 2 should be considered:

- Nineteen raw materials are considered, as presented in Table 1.
- OEM X currently uses eighteen criteria shown in Table 2.
- Four stakeholder groups are identified in Section 2.1.2.
- The electromobility sector is developing rapidly and imposes uncertainty. The input for a short-term assessment is provided. However, many input factors become variable when assessed from a long-term perspective. For instance, uncertainty can be caused by shared demand between exponentially growing industries shown in Table 3.

An MCDM method should be chosen that can include perspectives from multiple stakeholders. Therefore, Section 3.1 covers the topic of Multi-Actor Multi-Criteria Decision Analysis. Then, Section 3.2 discusses the criteria used as an input for MCDM. Section 3.3 covers the selection of a suitable MCDA method. The selection of the MCDA method will be performed based on two steps. First, the characteristics of MCDM methods are identified. Second, applications of MCDA in similar contexts will be discussed and classified according to the previously identified characteristics. Then, a well-substantiated choice can be ensured. If the choice is not well-substantiated, the recommendations' quality could decrease as different MCDA methods deliver inconsistent results that might not satisfy the needs of the decision-makers (Watrobski et al., 2019). Furthermore, Section 3.4 discusses how uncertainty can be incorporated into the MCDA. Finally, Section 3.5 discusses the overall theoretical contribution of this literature review.

3.1 Multi-Actor Multi-Criteria Decision Analysis

Therefore, a methodology that fits multiple stakeholders' input is required to solve the problem. This methodology is classified as a Multi-Actor Multi-Criteria Analysis (MAMCA).

The general steps proposed to perform a Multi-Actor Multi-Criteria Analysis are shown in Figure 15 (Macharis et al., 2012); (Huang et al., 2021). Two remarks can be placed with this framework.

- The first three steps are interdependent and could be revisited multiple times to increase the quality of the problem context iteratively.
- Macharis et al. (2012) mention that any MCDA method can assess the different alternatives during step 5, though some methods have been adjusted specifically for the multi-actor situation. In 2012, these adjusted methods included PROMETHEE (Preference Ranking Organization METHhod for Enrichment of Evaluations), AHP (Analytic Hierarchy Process) and ELECTRE (ÉLimation et Choix Traduisant la REalité).

Multi-Criteria Decision Making ensures better-informed decision-making, as presented in the introduction of Chapter 3. However, the results of different MCDM methods are often conflicting, and the decision-maker may make a different decision even when using the same criteria weights and alternatives (Watrobski et al., 2019). To ensure that the MCDA method fits the problem context, other MCDA methods will be discussed next to the three options that have been adjusted to the MAMCA framework. When reflecting on the framework, it can be concluded that the first three steps have been partially conducted. The third step will be assessed by reviewing the literature. Therefore, the next step of the literature research is to determine criteria based on the literature. Afterwards, a suitable MCDA method can be chosen.

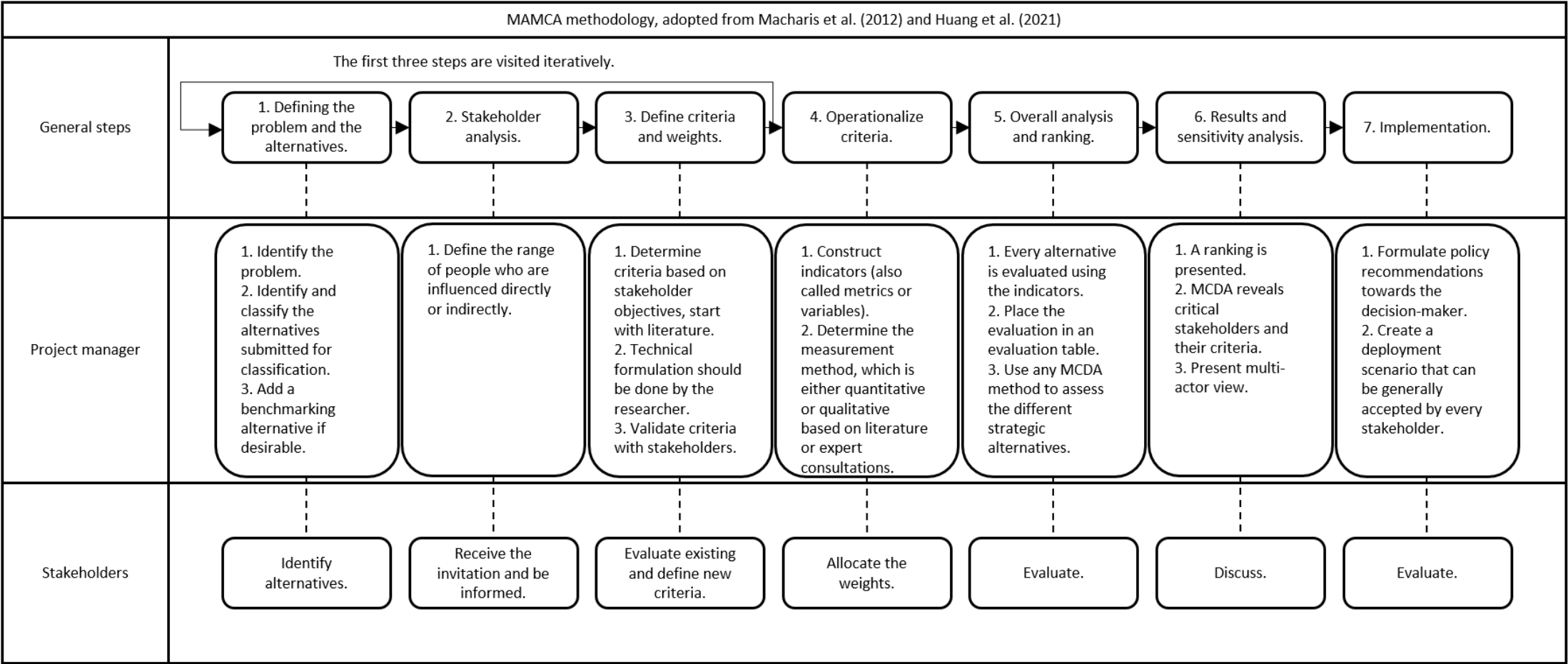


Figure 15: Overview of MAMCA methodology.

3.2 Criteria determination

This section aims to identify the assessment criteria used as input for the MCDA. The next chapter presents a complete assessment of the criteria to map the raw materials and present an overview of all the raw materials.

3.2.1 Triple bottom line

The criteria presented in Chapter 2 follow the overarching strategy provided by OEM X. The strategy introduces sustainability from three perspectives: environment, resources, and people. Stoycheva et al. (2018) present that sustainability is discussed according to environmental, economic and social components of products in the automotive manufacturing context. These three interdependent aspects cover the Triple Bottom Line (TBL). The TBL is a concept introduced by Elkington (1997) and identifies economic, natural and social aspects of sustainability, also known as the 3Ps: People, Planet, and Profit. Sustaining these three aspects of sustainability will result in profitable operations, sound ecology, and social progress and encourage businesses to be more efficient while benefiting society.

3.2.2 Identification of criteria through literature review

Criteria need to be determined to map the raw materials in the MDS and ED&C supply chain. A criterion in the context of the MCDA presents a tool that is constructed to evaluate and compare potential actions according to the point of view that must be well-defined Figueira et al. (2005).

The criteria should follow the rationale of the triple bottom line. Thus, Section 3.2.1 focuses on the economic bottom line, Section 3.2.2 focuses on the environmental bottom line, and Section 3.2.3 focuses on the societal bottom line. Multiple sources are used to create a list of the available criteria and represent the database or report where it can be found. These sources range from other MCDA problems to sustainability reports to ensure that the criteria are formulated from multiple perspectives. These sources will be represented in the tables of Section 3.2.1, Section 3.2.2 and Section 3.2.3 by a number shown in the following list:

1. Drive sustainability et al. (2018)
2. Jasinski et al. (2018)
3. Calabrese et al. (2016)
4. Noci (1995)
5. IVL Swedish Environmental Research Institute (2020)
6. Govindran et al. (2013)
7. Stoycheva et al. (2018)

The criteria of all three sustainability aspects will be presented in the same format. The first column presents in which source the literature is found. The second column presents the criteria, which are then described in the third column. The description is combined with a criteria-specific code used for the sole purpose of being a reference to the criterion. Then, the fourth column explains the objective, whether it should be minimised or maximised. The assessment might not be intuitive in some cases. The MCDA aims to prioritise raw materials for recycling. Therefore, it is likely that a raw material with the most significant negative environmental impact ranks first, thus maximising the scores on those criteria. Moreover, a particular raw material will also receive a higher ranking when it is feasible for recycling.

3.2.2.1 Economic bottom line

First of all, criteria are constructed based on the economic bottom line as presented in Table 4:

Table 4: MCDA criteria based on the economic bottom line.

Author(s)	Criteria	Description	Objective
1, 3	P1 Industry	The criterion presents the relative amount consumption of raw material used by the automotive industry.	Minimisation
1, 2	P2 EU import reliance	Presents the percentage that the EU imports from non-EU countries.	Maximisation
1, 2	P3 US import reliance	Presents the percentage that the US imports from foreign countries since the US are a significant market for OEM X.	Maximisation
2	P4 Market balance (supply risk)	Determines whether the supply is expected to match demand.	Maximisation
5	P5 Market price-based allocation	The allocation can be based on the scrap's market value compared to the virgin material's market value. The metric concerns an index.	Minimisation
1	P6 Function criticality	It measures the degree to which the material is critical and cannot be replaced while maintaining similar quality or functionality according to current-day technologies.	Maximisation
4	P7 Recycling viability	Technical viability. It presents the technical ability to recycle raw materials according to current-day technologies.	Maximisation
2	P8 Recycle rate	Economic viability. What percentage of the generated waste is recycled by industries?	Maximisation
4, 5	P9 Quality level	Presents the relative quality of the recycled raw material compared to the virgin counterpart. It could concern the purity of metals, for instance.	Maximisation

3.2.2.2 Environmental bottom line

Table 5 presents the criteria found in the literature:

Table 5: MCDA criteria based on the environmental bottom line.

Author(s)	Criteria	Description	Objective
1	E1 Estimated rate of depletion	It describes the estimated number of years it takes for the material to become depleted.	Minimisation
1, 4, 6	E2 CO ₂ emissions	The impact of raw materials extraction and processing on the environment concerning CO ₂ emissions.	Maximisation
1, 7	E3 Incidences of overlap with areas of conservation importance	Describes whether the raw material is linked to incidences of mining sites overlapping with areas of conservation importance. This has the potential to hurt biodiversity conservation.	Maximisation
1, 6	E4 Potential for acid discharge to the environment	Describes whether there is a potential for acid discharge to the environment. Acid-mine drainage might occur if the material is found in acidic sulphide ores.	Maximisation
1	E5 Preconditions for radioactive materials in ores and tailings	This concerns the likelihood of the material extracted from ores being linked to radioactive exposure.	Maximisation
3, 4, 6	E6 Water consumption	The amount of water used for extraction and processing of raw material.	Maximisation
1	E7 Virgin material consumption	The percentage of mined material used as input to production compared to the usage of secondary material. Opposite of recycling input rate.	Maximisation
1	E8 Residual end-of-life waste	End-of-life post-consumer waste that is not recycled for the automotive industry.	Maximisation
4, 5	E9 Environmental impact recycling process	The relative impact of the recycling of raw materials on the environment compared to the extraction and processing of virgin raw materials. Measures by how much the energy usage decreases when recycling compared to the traditional virgin material industry.	Minimisation

3.2.2.3 Societal bottom line

Table 6 presents the criteria found in the literature:

Table 6: MCDA criteria based on the social bottom line.

Author(s)	Criteria	Description	Objective
1, 3, 7	S1 Countries experiencing corruption	The criterion is based on the top 5 producing countries based on the perceptions of corruption in a country.	Minimisation
1, 3, 7	S2 Countries with weak rule of law	The criterion is based on the top 5 producing countries based on their ability to abide by the rules of society, like contract enforcement, property rights, the police, and the courts.	Minimisation
1, 6	S3 Countries experiencing high-intensity state conflict	Criterion is based on the top 5 producing countries and discusses whether a country is associated with high intensity, inter or intra-state conflict.	Maximisation
1	S4 Artisanal & small-scale mining (ASM)	Describes the percentage of global production reportedly attributable to artisanal and small-scale mining. It is more likely that the raw material is violated with the violation of human rights when mining is done on a small scale.	Maximisation
1, 3	S5 Child labour and forced labour	The criterion rates whether the material is globally associated with child labour or forced labour.	Maximisation
1, 3, 6, 7	S6 Harm done to communities	Assesses the harm done to local communities, like the indigenous people that live close to the mining sites.	Maximisation
1, 6, 7	S7 Potential for harm from hazardous materials and chemicals	Does the extraction of the raw material pose severe health and safety threats for workers and surrounding communities?	Maximisation

3.3 Multi-criteria decision-making methods

Since a complete overview of the different criteria has been given, it can be determined what multi-criteria decision-making methods could be used to solve the problem. Therefore, the characteristics of MCDM problems are discussed. Moreover, literature is then reviewed to determine what MCDM methods have been used in a similar context. Finally, the most appropriate methods can be further analysed, and a decision can be made.

3.3.1 Taxonomy of Multi-Criteria Decision-Making problems and methods

Multi-criteria problems in the most basic form consist of the following data (Guitouni et al., 2000); (Rowley et al., 2012):

- A set of n decision alternatives $A = \{a_1, \dots, a_n\}$.
- A set of m criteria $C = \{c_1, \dots, c_m\}$.
- An m by n evaluation matrix E , also named performance table, that presents the evaluation e_{nm} of each alternative a_n on each criterion c_m .

The problems can generally be split up into four different categories (Watrobski et al., 2019):

- Selection problematic. Select a single best option out of the available alternatives.
- Sorting problematic. Categorise the alternatives in predefined groups.
- Ranking problematic. Rank alternatives from best to worst.
- Description problematic. Describe the alternatives and their consequences.

This thesis covers the ranking problematic, as one of the defined deliverables concerns prioritising the identified raw materials. However, MCDA methods that cover the ranking problematic often can be used for the selection problematic as presented by Ishizaka and Nemery (2013), since the best option is presented by ranking the alternatives. Ishizaka and Nemery (2013) present nine methods that can be applied for both the selection and ranking problematic, confirming the similarity of the ranking problematic and sorting problematic MCDA methods.

Overall, multiple characteristics could be discussed when selecting an MCDA method. Rowley et al. (2012) present a selection of characteristics with a focus on sustainability, and therefore, the characteristics of that paper are assessed. The discussed characteristics are performance evaluation methods, importance evaluation methods, compensation mechanisms, and measurement scales:

- Performance evaluation methods present how the distinguishment can be made between decision alternatives based on their performance given by the evaluation matrix.
- Importance evaluation methods present how the performance evaluations can be aggregated to evaluate the importance of a decision alternative.
- Compensation mechanisms ensure or prevent the poor performance of decision alternatives on specific criteria might be compensated by very high performance on one or more criteria, ensuring that all the three TBL sustainability aspects are evaluated equally.
- Measurement scales are discussed to discuss how performance data can be presented. MCDM methods are dependent on the input data. Therefore, input data is classified.

3.3.1.1 Different performance evaluation methods

As Watrobski et al. (2019) presented, multi-criteria problems and methods can be further characterised. Multi-criteria problems can be split up into continuous and discrete problems. The continuous problems can be solved by, for instance, multi-criteria linear programming. Moreover, the discrete problems are often solved by methods based on, for instance, utility or value functions, which aggregate the discrete measurements using a specific evaluation method, or by

outranking approaches. Moreover, multi-criteria linear programming is also applicable to discrete problems. The problem considered in this thesis is discrete, as most data presented in Chapter 2 is discrete.

The utility and value theory approaches, also named the full aggregation approach or single criterion approach, distinguish two types of relationships between variants, indifference ($a_i I a_j$) and preference ($a_i P a_j$). Outranking methods expand the set of relationships with the weak preference relationship ($a_i Q a_j$) and the incomparability relationship ($a_i R a_j$). The latter is used when for instance, data is unavailable. Overall, these preferential relationships can then be used to determine the final outranking relationship ($a_i S a_j$). This outranking relationship can incorporate indifference, strict and weak preferences.

Moreover, outranking methods use preference scenarios that are related to different thresholds. These are indifference (q), preference (p) and veto (v) thresholds (Watrobski et al., 2019):

- A set of m indifference thresholds $T = \{q_1, \dots, q_m\}$ where $m \in C$.
- A set of m preference thresholds $U = \{p_1, \dots, p_m\}$ where $m \in C$.
- A set of m veto thresholds $V = \{v_1, \dots, v_m\}$ where $m \in C$.

These thresholds are explained according to the formulations in this section and Section 3.3.1.2.

Three performance evaluation methods can be distinguished (Rowley et al., 2012). First, an MCDA method is called a true-criterion method when the thresholds are not used. The following formulation holds based on the relationships presented in Equation (3.1):

$$\begin{cases} a_i P a_j \leftrightarrow e_{im} > e_{jm} \\ a_i I a_j \leftrightarrow e_{im} = e_{jm} \end{cases} \quad \forall a_i, a_j \in A, \forall e_{im}, e_{jm} \in E \quad (3.1)$$

The formulation presents that alternative a_i is preferred over alternative a_j when the performance of alternative a_i is better than a_j on criterion c_m as presented by the performance evaluation matrix. However, alternative a_i is deemed to be indifferent compared to alternative a_j if and only if the performance is the same.

The major disadvantage of this model is that arbitrariness or uncertainty in data is unaccounted for. For instance, when CO₂ emissions are used as a criterion and alternative a_i is evaluated with 99.9kg of CO₂ emissions compared to alternative a_j with 100kg, a strict preference is modelled. However, this might be caused by data input uncertainty or arbitrariness. Therefore, the quasi-criterion model has been proposed to cope with this disadvantage by using the indifference threshold q_m for criterion c_m , which is modelled as follows:

$$\begin{cases} a_i P a_j \leftrightarrow e_{im} - e_{jm} > q_m \\ a_i I a_j \leftrightarrow |e_{im} - e_{jm}| \leq q_m \end{cases} \quad \forall a_i, a_j \in A, \forall e_{im}, e_{jm} \in E, \forall q_m \in T \quad (3.2)$$

The formulation differs slightly from the true-criterion model since the range where the indifference range is increased from 0 to $|e_{im} - e_{jm}|$. The tunable parameter q_m determines when alternative a_i is preferred over alternative a_j or whether the pair of alternatives perform indifferently on the criterion c_m .

This model increases the range where indifference should be considered. Though, there is still a strict border between the strict preference and indifference relationship. Therefore, the preference threshold can be introduced to define a buffer zone between the strict preference and indifference relationship. This model is named the pseudo-criterion model, which is modelled as follows by adding the preference threshold p_m for criterion c_m :

$$\begin{cases} a_i P a_j \leftrightarrow e_{im} - e_{jm} > p_m \\ a_i Q a_j \leftrightarrow q_m < e_{im} - e_{jm} \leq p_m \\ a_i I a_j \leftrightarrow |e_{im} - e_{jm}| \leq q_m \end{cases} \quad \forall a_i, a_j \in A, \forall e_{im}, e_{jm} \in E, \forall q_m \in T, \forall p_m \in U \quad (3.3)$$

The weak preference is modelled as an area between the indifference area and the strict preference area with the boundaries presented by q_m and p_m .

These different models all have their advantages and disadvantages. The pseudo-criterion model copes best with the arbitrariness of data and offers the most flexibility at the cost of being a more data-intensive model. The quasi-criterion model can be placed between the pseudo-criterion and true-criterion models. The true-criterion model is the least data-intensive and, thus, easier to operationalise.

3.3.1.2 Importance evaluation methods

The previous section introduced how performances could be evaluated on a single criterion. However, a problem is rarely assessed on one criterion. Moreover, a distinguishment can be made between the importance of certain criteria. There are three types of importance evaluation methods to determine the relative importance of the criteria, according to Rowley et al. (2012):

- Utilise veto thresholds.
- Design a hierarchical structure of criteria.
- Assign weights to the criteria.

The first option utilises veto thresholds, as presented in the previous section. These thresholds are used as a reference point. The alternative is not feasible if the criterion performs worse than the reference point. Furthermore, the purely hierarchical structure establishes an order in the criteria from most important to least important. Then, the hierarchy is followed, and the alternatives are assessed against each other. It is not possible to make trade-offs between criteria. For instance, if economic performance is deemed more important than environmental performance, a more environmentally friendly alternative cannot be chosen if it is economically inferior. To be able to make the trade-offs, weights can be introduced by introducing a numerical value for every criterion as follows:

- A set of m weights $W = \{w_1, \dots, w_m\}$ where $m \in C$.

These weights can represent the assignment of either importance coefficients or substitution rates to the criteria. Importance coefficients present the perceived importance of one criterion towards the other as judged by the decision-making committee. Substitution rates manifest a quantitative trade-off relationship where the outcome depends on the evaluation matrix. Moreover, the sustainability assessment community advises that the weighting set should be independent of the decision alternatives and favours the importance coefficients over the substitution rates (Rowley et al., 2012).

3.3.1.3 Compensation mechanisms

Finally, MCDA methods can be classified based on criteria compensation. Cinelli et al. (2014) and Figueira et al. (2005) explain the concept of compensation. Three types of compensation are used to differentiate methods. These are full (total), partial, and no compensation. The concept of compensation is defined as the ability to offset a disadvantageous criterion with an advantageous criterion. This is, for instance, not possible when a purely hierarchical criteria structure is used. Partial compensation can, for instance, be achieved when thresholds are used, allowing some criteria to be compensated if the thresholds are not triggered. Since the definition of partial

compensation is rather vague, the term high and low compensation is used. Then, models including thresholds are classified as low compensation methods.

3.3.1.4 Measurement scales

MCDA methods are different and require different types of input. The data that can be used as the input for an MCDA can be measured according to the following scales (Figueira et al., 2005); (Watrobski et al., 2019):

- Cardinal scale. The cardinal scale is a quantitative scale referring to a precise, concrete, defined quantity in a way that gives meaning. It is split up into two different groups, namely:
 - o Interval scale. Data is presented according to a measurement scale that has order. Moreover, the difference between the two variables is meaningful and equal. The presence of zero is arbitrary.
 - o Ratio scale (relative). Data is presented in relation to other data. For instance, the weight of criterion one is three times more important than the weight of criterion two.
- Ordinal scale. The ordinal is a qualitative scale and split up into two different groups, namely:
 - o The verbal scale presents pairs of consecutive degrees that reflect equal preference differences all along the scale.
 - o A numerical scale presents pairs of consecutive degrees that reflect equal preference differences, but a numerical value always separates these differences. The numbers are assigned as labels.

Furthermore, the data can be discerned into deterministic (crisp) or uncertain data. The latter can be evaluated according to some kind of distribution that can be either continuous, discrete, or in fuzzy form. There are two types of fuzzy representations (Figueira et al., 2005):

- Represent an imprecisely known but well-defined concept. The fuzzy numbers represent an ordinal distribution of uncertainty presented as a formula.
- Represent a linguistic variable. These fuzzy numbers represent a multi-valued logic where semantics allow values in the interval $[0,1]$.

3.3.2 Multi-criteria decision-making methods selection

The selection of a multi-criteria decision-making method could be considered a multi-criteria decision-making problem. Multi-criteria decision-making methods have their limitations, particularities, hypotheses and perspectives, and there is a significant diversity of alternatives (Ishizaka & Nemery, 2013). Moreover, relatively limited attention has been paid to the appropriate selection for the given decision problem compared to the development and improvement of MCDAs.

3.3.2.1 MCDM method literature review

To determine what MCDA method will be used, the sustainability perspectives of Cinelli et al. (2014) and Rowley et al. (2012) are considered. One of the essential constructs mentioned by Cinelli et al. (2014) is related to the degree of compensation. The constructs are '*strong sustainability*' and '*weak sustainability*'. Weak sustainability refers to the interchangeability of the performance on a TBL aspect. For instance, that study refers to the interchangeability of one of the three TBL aspects meaning that environmental performance can be compensated by economic performance. The exchangeability is limited in a strong sustainability concept, where the performance on specific aspects of the TBL cannot be compensated. Overall, weak sustainability

coincides with a low level of compensability, and strong sustainability coincides with a high degree of non-compensability.

To present an overview of the relevant literature, Table 7 is created. This table shows papers that use MCDM methods to solve similar problems like the one posed in this thesis. The literature is collected by systematically searching for 'multi-criteria decision-making methods' or synonyms in problem contexts similar to this one, like sustainable supplier selection and material selection.

Then, the first column of Table 7 presents the reference. Then, the second column shows the MCDA method used with the problem size in the third column. The following five columns present the input data that is used based on the respective problem context, available binary relationships, the weighting methods and the level of compensation according to the taxonomy presented in Section 3.3.1. Finally, the problem context and relevant comments about the method are placed in the final two columns. The problem context has to cover either the automotive or manufacturing industry, sustainable decision-making, or material selection. The material selection problem often ranks the materials to choose the best option, as presented in Section 3.3.1. Therefore, the concept 'material selection' suffices when searching for MCDA methods that fit the problem context of this thesis.

Multiple conclusions can be drawn based on the literature review.

- Most methods are only able to model indifference and preference relationships. This seems logical when the rankings are based on numeric evaluations. The evaluation of two alternatives is either the same, resulting in indifference, or different, resulting in strict preference. Moreover, it appeared that quasi-criterion models were not used. Preference thresholds are always included when indifference thresholds are incorporated into an MCDM model.
- Weighting is the primary importance evaluation method. Veto thresholds are used once in combination with weighting, and finally, the purely hierarchical model is not used. Some methods use a hierarchy, but the hierarchy is then translated into weights as in AHP, for instance. Furthermore, the level of compensation is mainly high due to the weighting importance evaluation method. Therefore, not many concepts adhere to the strong sustainability concept.
- Some topics are covered in the comments that were not included in the taxonomy section. These are rank reversal and modelling interdependencies. These topics are covered in the following two subsections.

Based on the conclusions and the information provided by the literature research, a decision tree can be drawn to present how methods structurally differ according to the most significant characteristics. These findings are presented in Figure 16. Most true-criterion methods do not suffer from rank reversal or consider interdependencies. However, both concepts are important for this problem. Thus, the classification tree does not continue to distinguish these MCDM methods.

Table 7: Literature review covering MCDA methods in similar contexts. The binary relationship can be interpreted as follows: [I] = Indifference, [P] = Preference, [Q] = Weak Preference, [R] = Incomparability, [S] = Outranking relationship.

Reference (alphabetical order)	MCDA method	Problem size	Input data types	Availability of binary relationship					Performance evaluation method			Importance evaluation method			Level of Compensation	Problem context	Comments	
				I	P	Q	R	S	T	Q	P	V	H	W				
(Buyukzkan & Cifci, 2012)	Fuzzy ANP + Fuzzy TOPSIS	- Theoretical model	Ratio, Qualitative	X	X					X					X	High	Green supplier selection, Automotive industry	Due to the incorporation of ANP, the MDCDA method can deal with criteria dependencies. Though, the method is complex. Rank reversal might occur, as explained in Section 3.3.2.2.
(Chatterjee et al., 2011)	COPRAS	- 4 Criteria - 6 Alternatives	Interval	X	X					X					X	High	Material selection, manufacturing industry	COPRAS is computationally inexpensive, transparent and straightforward. However, it only copes with quantitative information.
(Figueiredo et al., 2021)	Fuzzy AHP	- 5 Criteria - 4 Alternatives	Interval	X	X					X					X	High	Material selection, TBL, Construction Industry	Although AHP is quite simple, it does require many pairwise comparisons if the criteria set is expanded. Moreover, AHP suffers from rank reversal. Fuzzy logic is implemented to deal with the subjectivity of choices made by the decision-makers. Therefore, the uncertainty of the decision-makers is accounted for. Input data is fuzzified.
(Ghadimi et al., 2021)	Fuzzy AHP	- 21 Criteria - Theoretical model	Qualitative, interval	X	X					X					X	High	Product sustainability assessment, TBL, Automotive Industry	The same comments hold for this source as the previous source.
(Govindran et al., 2013)	Fuzzy TOPSIS	- 12 Criteria - 4 Alternatives	Qualitative	X	X					X					X	High	Supplier selection, TBL	Able to handle vast numbers of criteria and alternatives, in contrast to ELECTRE and AHP.
(Hatefi et al., 2021)	ARAS	- 25 Criteria - 6 Alternatives	Qualitative	X	X					X					X	High	Material selection, TBL, Construction Industry	ARAS uses the entropy of a random variable to determine the uncertainty of the information. The variables are measured using fuzzy linguistics, and the decision-makers' confidence is used to determine the entropy. Rank reversal is often prevented, but cannot be excluded.
(Luthra et al., 2017)	AHP + VIKOR	- 22 Criteria - 5 Alternatives	Qualitative	X	X					X					X	High	Sustainable supplier selection, Automotive industry	The major downside of AHP concerns rank reversal. Input data only consist of ordinal data presented by linguistic variables. However, input data is not restricted to qualitative data.
(Mousavi-Nasab & Sotoudeh-Anvari, 2018)	COPRAS + TOPSIS + SAW	Theoretical framework with examples	Interval	X	X					X					X	High	Sustainable material selection	This method is specifically developed to counter the rank reversal problem. It includes COPRAS + TOPSIS. Moreover, SAW will be included in the methodology if an alternative is added or removed to counter rank reversal.
(Peng & Xiao, 2013)	ANP + PROMETHEE II	- 19 Criteria - 4 Alternatives	Interval, Qualitative	X	X	X								X	X	Low	Material selection	Preference functions instead based on thresholds are used, which is computationally expensive. Interdependencies can be modelled. PROMETHEE uses indifference and preference thresholds.
(Stoycheva et al., 2018)	MAVT	- 15 Criteria - 5 Alternatives	Interval	X	X					X					X	High	Material selection, TBL, Automotive Industry	MAVT is a simple method. However, it is very data-intensive and requires accurate data to present robust results. It does not present information on how to determine weights or normalise performance. Rank reversal is not a problem.
(Vahabzadeh et al., 2015)	Fuzzy VIKOR	- 5 Criteria - 6 Alternatives	Qualitative	X	X					X					X	High	Green decision-making model, reverse logistics	Fuzzy VIKOR suffers from the rank reversal phenomenon.
(Vinodh & Girubha, 2012)	PROMETHEE II	- 16 Criteria - 3 Alternatives	Interval, Qualitative	X	X	X								X	X	Low	Manufacturing industry, selecting sustainable concepts	PROMETHEE competes with ELECTRE, though ELECTRE is computationally more expensive. PROMETHEE uses indifference thresholds.
(Yu & Hou, 2016)	AHP	- 14 Criteria - 5 Alternatives	Interval	X	X					X					X	High	Green supplier selection, automotive industry	Significant downsides of AHP still hold. Though, the ease of use and understandability is presented in the paper.
(Zak & Weglinski, 2014)	ELECTRE IV	- 9 Criteria - 10 Alternatives	Interval, Ratio				X	X			X	X	X	X	X	Low	Logistics Centre Location Selection, TBL	ELECTRE IV is able to include incomparability. Moreover, the final binary relationship can model weak, strict and incomparable relationships. However, it often results in partial rankings.
(Zhang et al., 2017)	DEMATEL + ANP + GRA + TOPSIS	- 14 Criteria - 5 Alternatives	Interval	X	X					X					X	High	Sustainable material selection, manufacturing industry	The method combines different aspects of different MCDA methods. ANP is used to model interdependencies. Crisp and reliable data is necessary for this alternative. DEMATEL is used to model the interdependencies, significantly decreasing the number of pairwise comparisons.

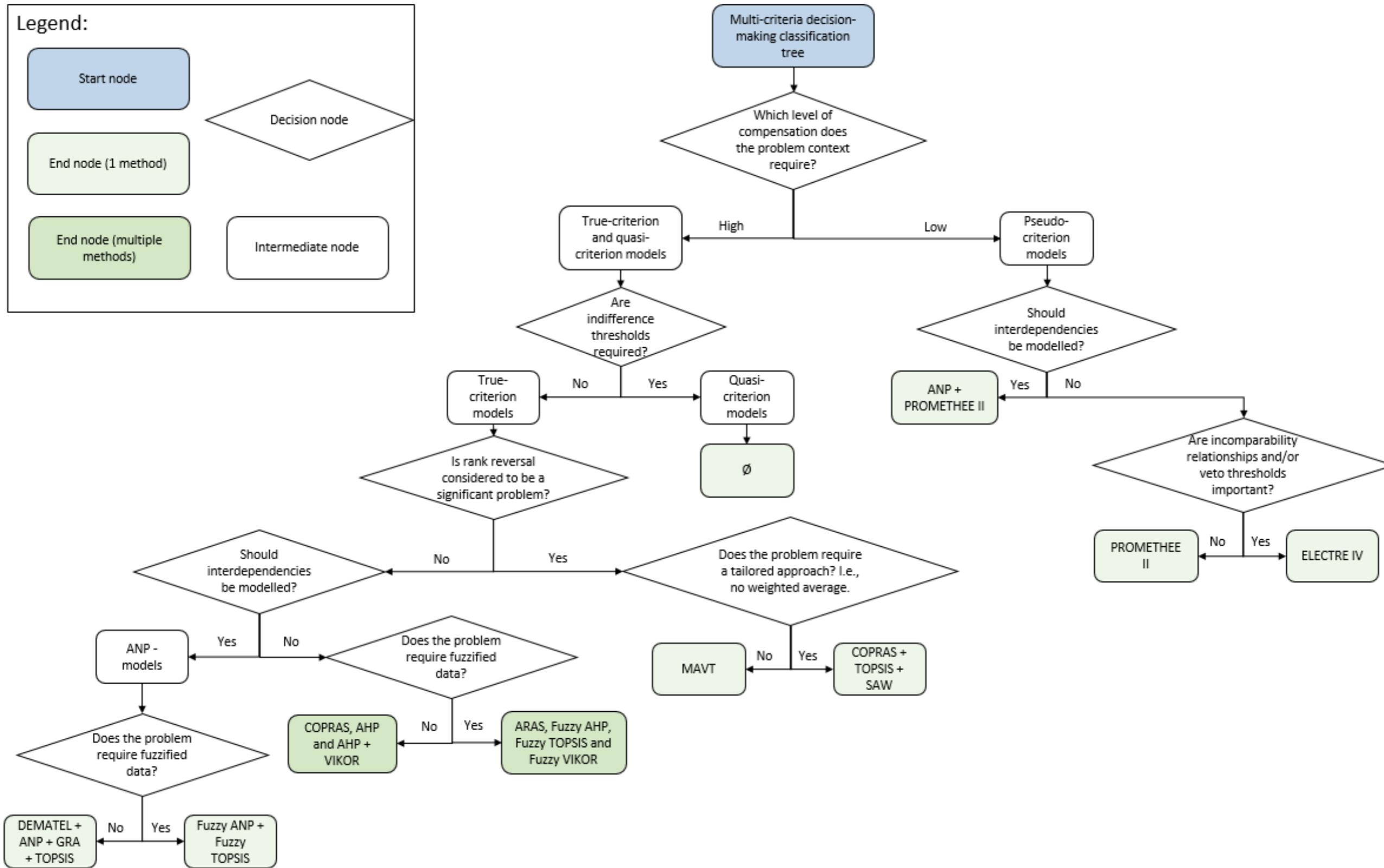


Figure 16: Classification tree based on Table 7. The figure presents an overview of the identified methods and how these methods can be distinguished based on the characteristics deemed most important.

3.3.2.2 Rank reversal

Rank reversal is an issue that appears when re-evaluating a decision. Rank reversal is a problem of MCDM techniques that results in an inversion in the rank of alternatives when alternatives are added or removed. This means that the positions of two decision alternatives are influenced by a third one (Mousavi-Nasab & Sotoudeh-Anvari, 2018). The problem with rank reversal is that it could be unexplainable for the decision-makers, implying unreliability of the decision-making process. The rank reversal problem occurs in popular outranking methods like ELECTRE, PROMETHEE II, AHP, TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution), SAW (Simple Additive Weighting), DEA (Data Envelopment Analysis), ANP (Analytic Network Process) and GRA (Grey Relational Analysis).

3.3.2.3 Interdependencies

The methods suggested in Table 7 include hybrid MCDM methods using ANP to model interdependencies. MCDM methods assume that the criteria are independent. However, dependencies can arise between any elements of the decision problem, like the criteria, sub-criteria and the goal. Therefore, some criteria are weighted relatively more critical due to existing dependencies with other criteria. For instance, the criteria based on the geopolitical situation cannot be considered independent.

3.3.2.4 MCDM method selection

Three methods are selected for further comparison based on the previously drawn conclusions and Figure 16. The first choice consists of the ANP and PROMETHEE II hybrid approach by Peng and Xiao (2013). This method can deal with data uncertainty based on the inclusion of indifference thresholds and can model interdependencies in criteria due to the inclusion of ANP. Additionally, the hybrid method adheres to the strong sustainability concept by using preference thresholds. The disadvantages of the method include many pairwise comparisons and rank reversal.

Furthermore, the other two included methods can cope with the rank reversal phenomenon. The first method combines TOPSIS, COPRAS (Complex Proportional Assessment) and SAW. Moreover, the second method is MAVT (Multi-Attribute Value Theory). Regarding the hybrid approach, rank reversal often happens when applying TOPSIS and COPRAS but rarely when applying SAW (Mousavi-Nasab & Sotoudeh-Anvari, 2018). The TOPSIS, COPRAS and SAW hybrid approach is based on the following three statements:

- Using multiple MCDM methods results in a more confident and safer decision.
- Rank reversal is common in the TOPSIS and COPRAS methods. However, it is uncommon when applying SAW.
- SAW is an MCDM method that can benchmark the results presented by MCDM methods.

Therefore, rank reversal cannot be excluded entirely, and the method cannot model interdependencies. Furthermore, the methodology differs based on whether alternatives are added or removed compared to the initial decision. This makes the process less clear for the decision-makers. Finally, the hybrid approach is technically not a fundamental hybrid approach since the methods are executed independently. Providing multiple rankings might make the decision process slightly more subjective since the decision-maker has to choose which ranking is the most relevant, especially if the decision-maker is unfamiliar with the exact mathematical procedures. Therefore, this method seems inferior to the ANP and PROMETHEE II hybrid.

Furthermore, MAVT calculates the ranking based on a simple weighted average, and the proposed method does not present details on weighting, normalisation, and how to deal with minimisation and maximisation differences. Therefore, it is also inferior to the ANP and PROMETHEE II hybrid.

Overall, the ANP and PROMETHEE II hybrid seem to be the most suitable method for the material ranking problem in OEM X. However, the large number of pairwise comparisons remains a downside. The number of pairwise comparisons is decreased by using DEMATEL (Decision Making Trial and Evaluation Laboratory) to model the interdependencies, as Zhang et al. (2017) demonstrated. Moreover, Si et al. (2018) concluded that it is common to combine ANP with DEMATEL, as 154 examples were presented. Finally, a weakness of ANP is that the concept of reciprocity is used to determine the dependencies. However, DEMATEL does not model interdependencies according to reciprocity (Buyukozkan & Guleryuz, 2016). The two models differ based on the following analogy:

To determine the influence of criteria A on criteria B, the following question is asked:

'Given criteria A and B, how much does criterion A influence criterion B?'

However, ANP would have required the following question based on three criteria:

'Given criterion C and comparing criteria A and B, which of the two criteria influences criterion C more?'

The first method following the DEMATEL logic requires $n \times n - n$ assessments. The second method requires $\frac{n \times n - n}{2} \times n$ assessments. The transitivity of the pairwise comparisons of the ANP methodology explains the division by two.

3.4 Integrating Multi-Criteria Decision-Making and uncertainty modelling

As concluded in Section 2.3, uncertain factors influence the decision-making process. For instance, the expected increase in supply risks due to the demand for certain raw materials by multiple industries caused by the net-zero transition should influence the prioritisation.

Furthermore, the data gathered based on the criteria in Tables 4, 5 and 6 are from a holistic perspective, which might impose uncertainty. It cannot be assumed that the data presented by those sources is crisp. Moreover, there is subjectivity imposed by the decision-makers by determining the weights themselves. Therefore, uncertainty should be considered carefully.

3.4.1 Uncertainty classes

The first step is to classify the different types of uncertainty and assess which types are relevant for this thesis. The literature of Stewart (2005) is used for the classification. The classification splits the concept of uncertainty up into two types, 'internal uncertainty' and 'external uncertainty'.

- Internal uncertainty covers both the structure of the adopted model and the judgemental input required by these models.
 - o The structure relates to ambiguity in the meaning of criteria or when stakeholders generate large sets of different criteria.
 - o The imprecision of human judgements occurs when specifying their preferences or assessing the consequences of actions.
- External uncertainty also covers two types of uncertainty.
 - o The core uncertainty about the environment concerns uncertainty that the decision-maker cannot influence. This includes a lack of understanding or knowledge about decision areas and randomness inherent in processes or decision areas.

- Uncertainty about related decision areas concerns the impact of related decision-making problems. The outcome of one multi-criteria decision-making problem might impact another multi-criteria decision problem since these two are interconnected.

Structural uncertainty is not considered. Appropriate structuring of the decision problem already limits the availability of internal uncertainty since it is one of the main strengths of ANP. The uncertainty considering the judgmental inputs is relevant since it is impossible to exclude it entirely, and it has to be considered to determine the robustness of the prioritisation. A sensitivity analysis assesses the imprecision of human judgements (Buyukozkan & Guleryuz, 2016).

Furthermore, the most relevant type of uncertainty is the uncertainty about the environment. Uncertainty imposed by multiple decision areas is not considered since the scope of this thesis limits it. PROMETHEE II partly tackles uncertainty about the environment since indifference thresholds are used to cope with the uncertainty of the individual data points in the evaluation performance table. However, the internal and external developments are not taken into account. Thus, coping with uncertainty about the environment should be investigated further.

3.4.2 Uncertainty modelling in MCDM literature review

A second literature review is presented to see what methods can be used to cope with uncertainty about the environment. An overview is presented in Table 8. This overview is concept-oriented instead of reference-oriented since it provides an overview of methods generally combined with MCDM analyses. The first column presents the method, and the second column presents the reference. The third and fourth columns present the type of uncertainty it could deal with. Judgmental uncertainty is included due to the inclusion of stakeholder input. The final three columns explain the method, its advantages and disadvantages. Moreover, the selection of methods is not restricted to the application area since the combination of uncertainty modelling and MCDM concerns a niche.

3.4.3 Uncertainty modelling method selection

The Monte-Carlo simulation approaches and scenario planning are the two methods suitable for modelling environmental uncertainty. These methods are discussed in Section 3.4.3.1. The other models have disadvantages that are too significant:

- Probabilistic models: The method can only be applied to utility functions.
- Pairwise comparisons of probability functions: This method is only valid when criteria are stochastically independent and is widely used for risk aversion. The assumption that criteria are stochastically independent cannot be made. Moreover, risk aversion is irrelevant to this thesis.
- Risk measures as surrogate criteria: The method only suits goal programming and utility functions.
- Bayesian network: First, it is computationally one of the most expensive methods. Second, it requires training and validation. Training and validation data are not available.
- Fuzzy numbers: Ranking methods might provide unreasonable results. PROMETHEE II is classified as a ranking method.
- Sensitivity analysis: The traditional sensitivity analysis cannot assess interactions between performances on multiple criteria.

Next, the traditional sensitivity analyses and the Monte-Carlo simulation methods are considered to assess judgmental uncertainty. Distance-based analyses are not taken into account due to the complexity of the method, and fuzzy numbers need to be incorporated into the model, while the aim is to assess the sensitivity parallel to the ranking methods.

Table 8: Literature review discovering the methods integrated with MCDM to model uncertainty. 'U1' represents uncertainty about the environment, 'U2' represents judgmental uncertainty.

Method	Reference(s)	U1	U2	Elaboration	Advantages	Disadvantages
Probabilistic Models	(Stewart, 2005); (Durbach & Stewart, 2012)	X		Treat uncertainty by developing probability distribution so that the decision requires a comparison of probability distributions.	- Most thoroughly axiomatised mathematical treatment of uncertainty.	- Only useful in combination with utility functions. - Large number of parameters that need to be fitted, far from trivial.
Pairwise Comparisons of Probability Functions	(Stewart, 2005); (Durbach & Stewart, 2012)	X		Execute pairwise comparisons to see whether alternatives dominate each other stochastically. The fact that pairwise preferences exist on criteria level under uncertainty means that some outranking approaches should be able to aggregate the different probability functions.	- Exact probability functions do not need to be created.	- Concordance measures determined by the model are entirely based on risk aversion. - Strong interdependence assumptions are made because the approach is only valid when criteria are stochastically independent.
Risk Measures as Surrogate Criteria	(Stewart, 2005); (Durbach & Stewart, 2012)	X		Risk measures assume that uncertainty can be broken down into value and risk components. Value components concern expected values, and risk components concern variances, ranges and quartiles.	- Very useful for single attribute problems. This attribute can then be decomposed into the value and risk components.	- Applications are only found for goal programming and value function (utility) methods in literature in the case of MCDM.
Scenario Planning	(Stewart, 2005); (Durbach & Stewart, 2012)	X		Identify uncertain and uncontrollable factors. Scenario planning could be defined as a process of organizational learning emphasising explicit and ongoing consideration of multiple futures.	- Pragmatic approach that is not data intensive. Scenario planning does not require the use of probability theory. - Good results might be obtained when including 3-5 scenarios.	- The inclusion of many scenarios is deemed impractical. - Ignorance of events or certain scenarios might give the decision-maker the illusion of a robust solution even though this is not the case. - Some advocates of scenario planning prefer to avoid formal quantitative modelling.
Monte Carlo Simulation	(Durbach & Stewart, 2012); (Mosadeghi et al., 2013); (Baudry et al., 2018) (Balezentis & Streimikiene, 2017); (Butler et al., 1997)	X	X	Generate evaluations using probability distributions and use those as input for the decision model. In the case of judgmental uncertainty, random numbers can be drawn to measure the sensitivity of the ranking. In the case of uncertainty about the environment, it can be combined with scenario planning to determine the relevant drivers.	- Provide statistical sampling and present approximate solutions to the decision problem, useful for modelling uncertainty about the environment. - Assuming a uniform distribution, it can be easily applied to determine the sensitivity of the judgmental input. - Is capable of measuring interactions between performances on criteria and the judgmental input. - Useful in high-dimension applications.	- Depends on the ability to derive probabilistic functions to model the stochastic variables. - Relatively simple probability distributions might not represent reality well.
Fuzzy Numbers	(Durbach & Stewart, 2012); (Mosadeghi et al., 2013)	X	X	The idea is to model uncertain elements using fuzzy sets and fuzzy numbers. Recall that fuzzy numbers represent a multi-valued logic where semantics are allowed.	- Many decision models can use fuzzy numbers since (almost) all operations used in MCDM have been fuzzified. - Applicable when the following uncertainty arises: (i) unquantifiable information, (ii) Incomplete information, (iii) nonobtainable information and (iv) partial ignorance.	- Fuzzy numbers use relatively inaccurate data and inputs. - Ranking methods might not always provide reasonable outcomes. - In both uncertainty cases, it should be incorporated in the model.
Sensitivity Analysis	(Mosadeghi et al., 2013); (Hyde et al., 2005)	X	X	Sensitivity analyses systematically vary one or more criteria weights over their entire range while fixing the other parameters.	- Easy to implement. - Presents robustness and stability of the results obtained by the MCDM method. - A large number of methods ensure that there is probably one that fits the problem context.	- Combined changes in multiple parameters cannot be determined due to the fixation of the other parameters. - Sensitivity analyses are very method dependent.
Bayesian Network	(Mosadeghi et al., 2013); (Roobahani et al., 2018)	X		A Bayesian Network consists of nodes representing alternatives, attributes and external factors leading to the uncertainty of the data. A probability function accompanies each node.	- Bayesian networks provide a conceptual system. - Bayesian networks are competent in modelling uncertainties based on conditional probabilities and the ability to determine causal relationships.	- Bayesian networks need to be trained and validated using input data. Therefore, it is a very data-intensive process.
Distance-based Analysis	(Mosadeghi et al., 2013); (Hyde et al., 2005)		X	The distance-based analysis presents the minimum Euclidean distance for each pair of alternatives. A small Euclidean distance presents that the alternatives are sensitive to change, presenting the weakest comparisons.	- This model can model critical factors and combined changes due to the complete assessment of all parameters.	- This method is applicable to measure the robustness of the criteria weights. It could be applicable to measure what happens when changes in the evaluation criteria occur. - Requires non-linear optimization to determine the distances.

A short description of scenario planning to provide substantiation of choice is presented in the following sub-section. Then, section 3.4.3.2 describes traditional sensitivity analyses and Monte-Carlo-based sensitivity analyses.

3.4.3.1 Integration of scenario planning and range-based Monte-Carlo simulations

Scenario analysis is a method utilised when strategic decision problems characterised by increasingly complex and interrelated uncertainties need to be solved (Durbach & Stewart, 2012). Measures like probabilities, belief functions or fuzzy numbers might become challenging to comprehend and difficult to validate. In this case, scenario planning proves helpful as multiple narratives are constructed to describe what the future might look like. Each narrative is an internally consistent scenario and presents futures that do not have contradictory elements. The primary goal is to provide a structured method that sensitises decision-makers to external and uncontrollable uncertainties and creates an understanding of the uncertainties. Moreover, scenario planning helps compensate for the usual decision-making errors: overconfidence and tunnel vision (Schoemaker, 1995).

The scenarios can be modelled using a value tree based on the number of scenarios. A set of scenarios S can be added:

- A set of h scenarios $N = \{n_1, \dots, n_h\}$ where $h \in N$.

Then, the evaluation matrix E can be adjusted to a three-dimensional table that is scenario dependent according to the following notation:

- An m by n by h evaluation matrix E , also named performance table, that presents the evaluation e_{nmh} of each alternative a_n on each criterion c_m in each scenario n_h .

Aggregation over the scenarios using ‘*scenario weights*’ is not recommended since it is impossible to include the whole probability space. Moreover, that would require the decision-makers to model the probability that a particular scenario will happen. Applying swing weights could be considered to be an option. However, it is also appropriate to use scenarios as an exploration method by not aggregating the results of the different scenarios.

Concerning the application of scenario planning in multi-criteria decision-making, Stewart et al. (2013) propose a hypothetical example where all the aspects of scenario planning are discussed. Moreover, the combination has been used to assess the exit strategies of a provincial broker to determine which strategy would be the most suitable (Montibeller et al., 2006). Montibeller et al. (2006) also present the integration of scenario planning and multi-criteria decision-making applied to whether the location of a warehouse should be changed and, if so, where it should be located. Therefore, scenario planning in multi-criteria decision-making concerns a niche characterised by high uncertainty. Moreover, both topics have received significant attention in the literature. However, the combination remains novel.

The limitation of using only the scenario-planning approach concerns that only a limited number of performances on the performance evaluation table can be assessed. Therefore, it can be combined with a Monte-Carlo simulation. Baudry et al. (2018) present a method to integrate Monte-Carlo simulations with Multi-Actor Multi-Criteria Analysis based on ‘*exploratory scenario approaches*’. A range of possible futures driven by underlying and evolving socio-economic conditions are generated based on expert-based distribution laws (EBDL). These EBDLs are determined based on three performances forecasted by an expert, a most probable performance, an optimistic performance, and a pessimistic performance. According to Baudry et al. (2018), this is the most critical part of the integrated method. Therefore, the structure of scenario planning

can then be used to determine those three forecasts profoundly. Figure 17 presents how the three performances can be aggregated into a distribution.

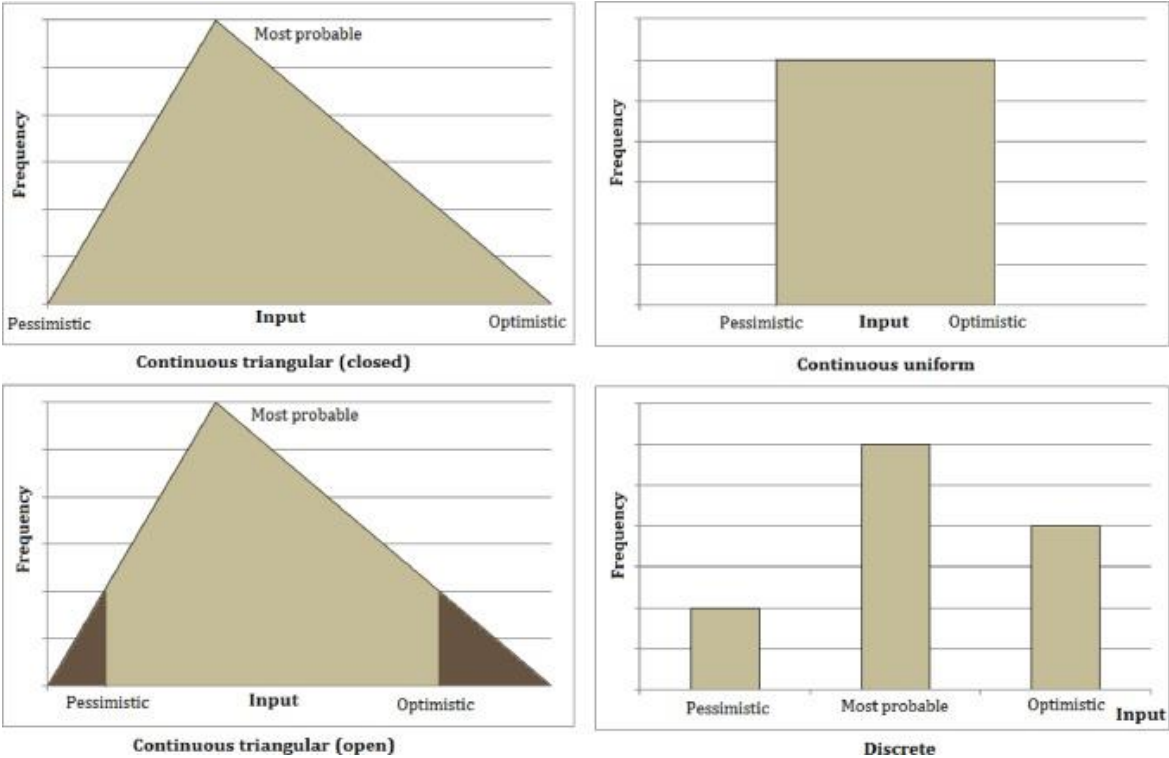


Figure 17: Examples of distributions generated according to the Expert-Based Distribution Laws (EBDLs).

The combination of scenario planning and EBDLs overcome the difficulty of comprehending the probability functions and can be used to explore future scenarios. The interaction between the scenario planning method and the EBDLs is used to validate the probability functions because the distributions should follow the logic of the scenarios. Then, Monte Carlo simulations can capture the full range of performances of the decision alternatives using the EBDLs according to the following three steps:

1. Define the probability distributions of the alternative impacts for each criterion according to the EBDLs.
2. Pick a set of alternative performances randomly and create a performance evaluation matrix E based on the probability distributions.
3. Execute the MCDM method.

This process can then be repeated to model the expected performance ranges and the rankings that follow accordingly.

3.4.3.2 Sensitivity analyses

As proposed by Hyde et al. (2005), a sensitivity analysis aims to determine the relationship between changes in the criteria weights and the subsequent alterations to check whether judgmental uncertainty could have a significant influence. Different sensitivity analysis methods are used to assess the impact of uncertainty in criteria weights. This section discusses the 'classical sensitivity analysis' and the 'simulation-based sensitivity analyses'.

The first method concerns the classical sensitivity analysis. The classical sensitivity analysis aims to find the minimum quantity (δ) that a criteria weight (w_j) needs to be changed to reverse the ranking of a pair of alternatives (a_i) and (a_k).

Furthermore, it might not always provide a feasible solution since changing the rank between two criteria based on one criteria weight could be impossible. The critical criteria are then identified as the criteria that require the smallest relative change in the criteria weight (w_j) to change the ranking of a pair of alternatives. In this way, the primary purpose is to highlight areas of interest.

Although the classical sensitivity analysis has been used widely, it does not prove helpful for this situation due to the large dimension of the problem and the inability to model interactions. Therefore, Butler et al. (1997) and Balezentis and Streimikiene (2017) used Monte Carlo simulations to model the sensitivity. The Monte Carlo simulation allows the decision-makers to review the results of the ranking by exploring a vast number of different sets $W = \{w_1, \dots, w_j\}$ that differ depending on the Monte Carlo simulation trial. These sets can be generated using a uniform distribution since the goal is to evaluate all possible weight combinations. The use of a uniform distribution is supported by the literature of Butler et al. (1997) and Balezentis and Streimikiene (2017).

Overall, sensitivity analyses based on the Monte-Carlo simulation approach will be used. The method is suitable for finding dominating and dominated alternatives and assessing an alternative's robustness.

3.5 Conclusion

This chapter started with identifying the methodology that fits the current situation at OEM X best. The MAMCA (Multi-Actor Multi-Criteria Analysis) is chosen since it allows for multiple stakeholders. Moreover, twenty-five criteria are identified to assess the raw materials on sustainability based on the perspectives of people, planet, and profit.

The method that has been selected to execute the prioritisation is the DEMATEL-ANP and PROMETHEE II hybrid. The pairwise comparison-based method ANP is selected to determine the weights of the criteria by determining the priorities of the stakeholders and correcting these for dependencies. DEMATEL is added to reduce the number of pairwise comparisons since ANP demands many. Furthermore, PROMETHEE II is selected since it adheres to the concept of strong sustainability, which means that extremely strong performances in one criterion cannot offset bad performances on other criteria. PROMETHEE II can also cope with data uncertainty to a certain extent due to incorporating indifference thresholds.

Next, two types of uncertainty are identified. These are uncertainty about the environment and judgemental uncertainty. The first type of uncertainty is mitigated by performing a scenario analysis and Monte Carlo simulation using triangular distributions. The scenario planning provides a structured methodology to determine in what directions performances of raw materials on criteria might be developing. Based on these scenarios, probability distributions can be developed using a most probable, optimistic, and pessimistic estimate. These are then used as input for the Monte Carlo simulation. Then, judgemental uncertainty is mitigated using a sensitivity analysis based on a Monte Carlo simulation. Classical sensitivity analyses require one-factor-at-a-time changes to measure the sensitivity of criteria weights. However, this method negates interactions between changes in weights and requires many calculations due to the fact that twenty-five criteria have been identified. Thus, the Monte Carlo sensitivity analysis is used to overcome the two aforementioned problems with classical sensitivity analyses.

Then, the theoretical contribution is discussed. The theoretical contribution is twofold. Moreover, the theoretical contribution covers developments or advancements in the existing theories used in this literature review.

First, this literature review provides a complete overview of all relevant criteria related to modelling the sustainability and recyclability of raw materials. Sources of multi-criteria decision-making analyses in similar areas and research groups assessing the general sustainability of raw materials, like the Dragonfly Initiative and the Swedish Environmental Research Institute, are combined to ensure that this research objectively prioritises raw materials based on a holistic perspective.

Furthermore, multi-criteria decision-making methods have been classified first before a selection is made based on methods applied in similar decision contexts. Although this is not the first time MCDM methods are classified before a suitable method is selected, it often does not occur. For instance, the work of Zak and Weglinski (2014) is the only source where a method is elaborately classified based on multi-criteria decision-making attributes. However, it is not as elaborate as the classification presented in Section 3.3.1 since it only highlights attributes relevant to the ELECTRE III/IV method. Therefore, this paper presents an elaborate classification to ensure that a suitable method is chosen, preventing the decision makers' needs from not being satisfied.

Then, the combination of DEMATEL-ANP and PROMETHEE II has not been applied to material ranking or selection problems. Therefore, assessing the sustainability of raw materials using the hybrid method is also novel. Overall, the hybrid approach does suit the problem context. ANP allows the modelling of interdependencies to come as close to reality as possible at the cost of many pairwise comparisons. The addition of DEMATEL ensures a significant reduction in pairwise comparisons, making the method useful in elaborate problem contexts with many criteria. Moreover, PROMETHEE II adheres to the strong sustainability concept by having preference thresholds. Additionally, the indifference thresholds are valuable to cope with data uncertainty in the evaluation performance table to a certain extent.

The final theoretical contribution concerns the integration of scenario planning in range-based Monte Carlo simulations. Baudry et al. (2018) mention that the most critical part of range-based simulations concerns constructing the EBDLs. The method that currently has been proposed consists of two steps. First, the type of distribution is chosen based on Figure 17. Second, experts need to be consulted to discuss and validate the EBDLs. However, there have not been any guidelines on determining the estimates. Therefore, this thesis proposes including the scenario planning approach to identify what criteria are relevant for a range-based analysis as the first step. Then, these criteria can be assessed based on the different scenarios to evaluate what the optimistic, pessimistic, and most probable estimates are.

Overall, this thesis has an elaborate theoretical contribution to many aspects of multi-criteria decision-making. The determination of the criteria, the selection of the suitable MCDM method, the application of the chosen method in the given problem context and the assessment of the results concerning uncertainty have all been discussed in this section.

4 Solution design

This chapter consists of five sections. Section 4.1 discusses the problem. Section 4.2 presents the conceptual model. Then, Section 4.3 discusses the operationalisation of criteria as advised by the methodology presented in Figure 15. Section 4.4 presents how the data is prepared to fit the multi-criteria decision-making model. Finally, Section 4.5 concludes Chapter 4.

4.1 Problem overview

The problem is presented by first describing by combing the assignment description of Chapter 1, the problem context of Chapter 2 and the literature review of Chapter 3.

4.1.1 Problem description

As introduced in Section 1.2.2, the problem is considered an MCDM problem. This MCDM problem is a ranking problem. This ranking aims to determine which raw materials should be focused on concerning recycling. The ranking can be driven by the maturity of the recycling processes and the unsustainable practices linked to a specific raw material.

The DEMATEL-ANP and PROMETHEE II MCDM method has multiple inputs. These inputs concern n decision alternatives $A = \{a_1, \dots, a_n\}$, m criteria $C = \{c_1, \dots, c_m\}$, an m by n evaluation performance table presented in matrix E filled with performances e_{nm} for every decision alternative and criteria combination. This problem consists of the nineteen decision alternatives in Table 1. Moreover, twenty-six criteria are identified based on Tables 4, 5, and 6 and stakeholder feedback. Based on this information, the MCDM model evaluates the raw materials based on $19 \times 26 = 494$ performances stored in matrix E . Moreover, all m criteria require a priority determined by the stakeholders. These stakeholders can be added to PROMETHEE II using the MAMCA extension by adding the set S as Schar and Gelermann (2021) explain:

- A set of r stakeholders $S = \{1, \dots, r\}$

This means that the set of weights is two-dimensional in the form of a r by m matrix filled with weights w_{rm} . Finally, the sets of indifference thresholds T and preference thresholds U are used to ensure the stakeholders' preferences are modelled accurately for all m criteria. Figure 15 presents that these weights should already have been executed in step 3. However, the literature review reveals that defining weights is too dependent on the chosen MCDM method. Therefore, the criteria weights will be determined in parallel with the operationalisation of the criteria performed in step 4 of Figure 15.

The model's output consists of global net flows ϕ , which presents a score between -1 and 1 for every raw material. Ordering these global net flows from high to low results in the final ranking.

Then, the scenario analysis aims to understand the influence of uncertainty about the environment on the position of raw materials in the ranking. Input for this analysis concerns the EBDLs and the number of Monte Carlo trials t_1 . The output used for further analysis is presented in a t_1 by n matrix and presents a ranking for every trial.

Finally, the Monte Carlo sensitivity analysis aims to understand the influence of judgemental uncertainty on the position of raw materials in the ranking. The Monte Carlo analysis is performed by executing t_2 trials. Adjusted input for this analysis includes a randomised set of weights in a two-dimensional t_2 by m matrix. The output analysis is done based on a similar matrix as the scenario analysis and Monte Carlo analysis with a size of t_2 by n . Section 4.2 will discuss how input parameters can be attained and how the output is calculated.

The problem structure can be visualised based on Chapter 2, Chapter 3, and the problem description, resulting in Figure 18. This figure presents the three criteria levels and how these

relate to the goal. Moreover, it presents how the decision alternatives are related to the criteria. The references to the criteria in Tables 4, 5 and 6 increase readability.

Figure 18 and the problem description present that there are twenty-six criteria. One criterion is added following stakeholder evaluations. This criterion, with reference 'P10' presents the relative usage of the material in the two segments for a Battery Electric Vehicle (BEV). The MAMCA framework in Figure 15 shows that stakeholders should validate the criteria. The stakeholders have all been asked to review the criteria to check for ambiguities, unclarities and wordiness. Moreover, it should be ensured that the criteria are inclusive. The following addition should be made to Table 4 based on the feedback of stakeholders:

Table 9: Criterion that should be added to Table 4 based on stakeholders' feedback. Therefore, the Author(s) column is not applicable [N.a.].

Author(s)	Criteria	Description	Objective	Potential data collection method or source
N.a.	P10 Relative usage	The criterion presents the relative amount of raw material used to create one truck based on the modules used in the ED&C and MDS segments.	Maximisation	Bill of materials, interviews with cost engineers.

Moreover, this problem has a single goal: modelling the sustainability of raw materials from a recycling perspective. The first- and second-level criteria are used to split up the problem for two purposes:

- It significantly reduces the number of pairwise comparisons.
- It ensures that pairwise comparisons are only made when criteria are comparable due to similarities in the context. For instance, the criteria 'Child Labour and Forced Labour' is not compared directly with 'Industry Consumption'. That comparison could be biased due to ethical considerations.

4.1.2 Limitations

The general requirements concerning solving the problem can be formulated as follows based on the guidelines presented in Chapter 3:

- The model has to present a complete ranking of raw materials. Partial rankings are not allowed.
- The model must present the influence of judgmental uncertainty through a sensitivity analysis.
- The model must check the solution for robustness by comparing the deterministic solution to the range of solutions generated by the scenario analysis and Monte Carlo approach.

Then, the segment leaders also presented requirements concerning the model's input and output. These include the following:

- For each raw material, the main drivers of the ranking have to be visible. The question: "Which second level criteria group has the most significant contribution to the ranking of a raw material?" has to be answered.
- Present the low-hanging fruits. Low-hanging fruits can be defined as raw materials that are most relevant in the short term due to high recycling feasibility.
- The tool should be able to present the ranking of the raw materials based on whether a single or both segment(s) is/are considered.
- The methodology should be reproducible.

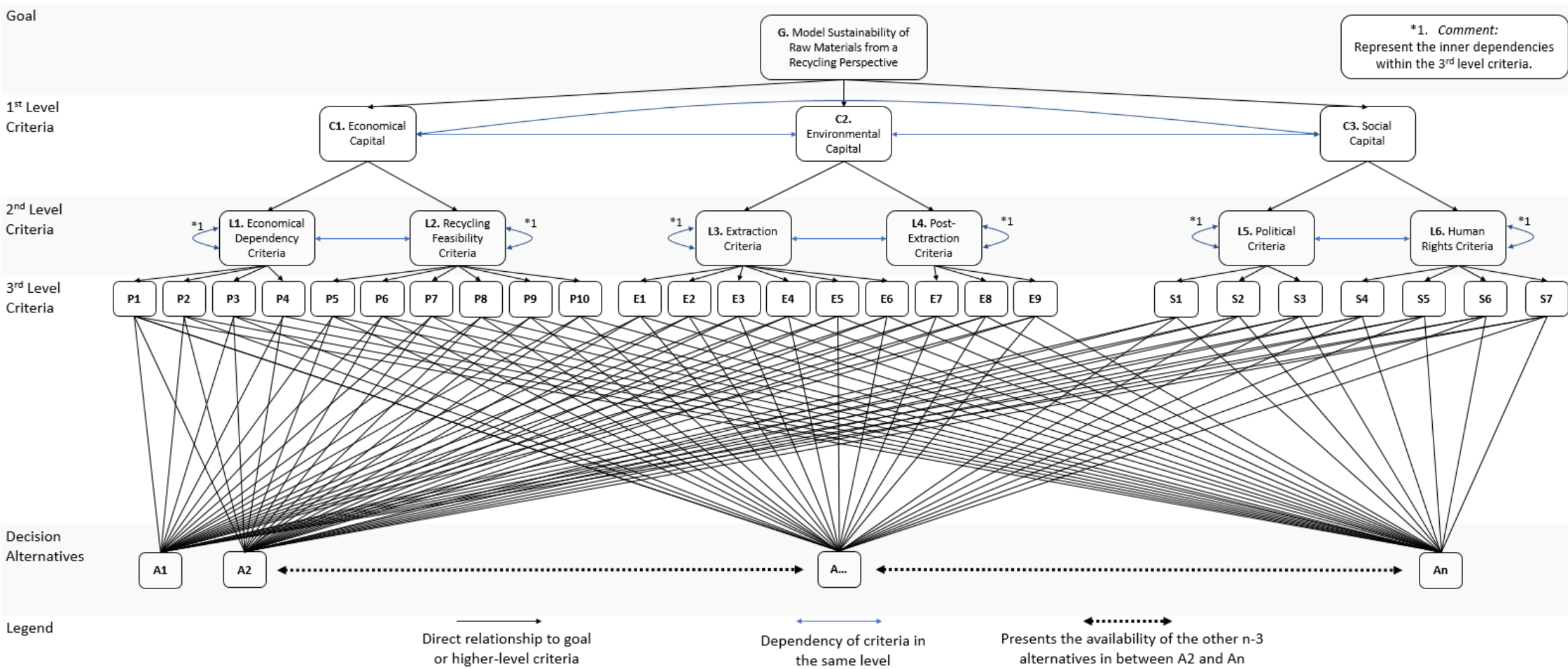


Figure 18: Problem structure based on the ANP methodology.

4.2 Theoretical approach

As presented in the literature review, the primary benefit of including ANP is the ability to model interdependencies. Additionally, DEMATEL is included to decrease the number of pairwise comparisons. Moreover, PROMETHEE II can cope with the data uncertainty using indifference and preference thresholds and behaves as low-compensatory. A formal explanation of DEMATEL-ANP, and PROMETHEE II follows to understand how the hybrid approach behaves. Moreover, the methods to cope with uncertainty about the environment and judgemental uncertainty are discussed. Finally, a flowchart is created to present how the individual methods interact based on the literature review and Section 4.1. This flowchart is presented in Figure 19. The bottom right part of Figure 19 presents the input to PROMETHEE II and why it should be evaluated.

4.2.1 DEMATEL-ANP method

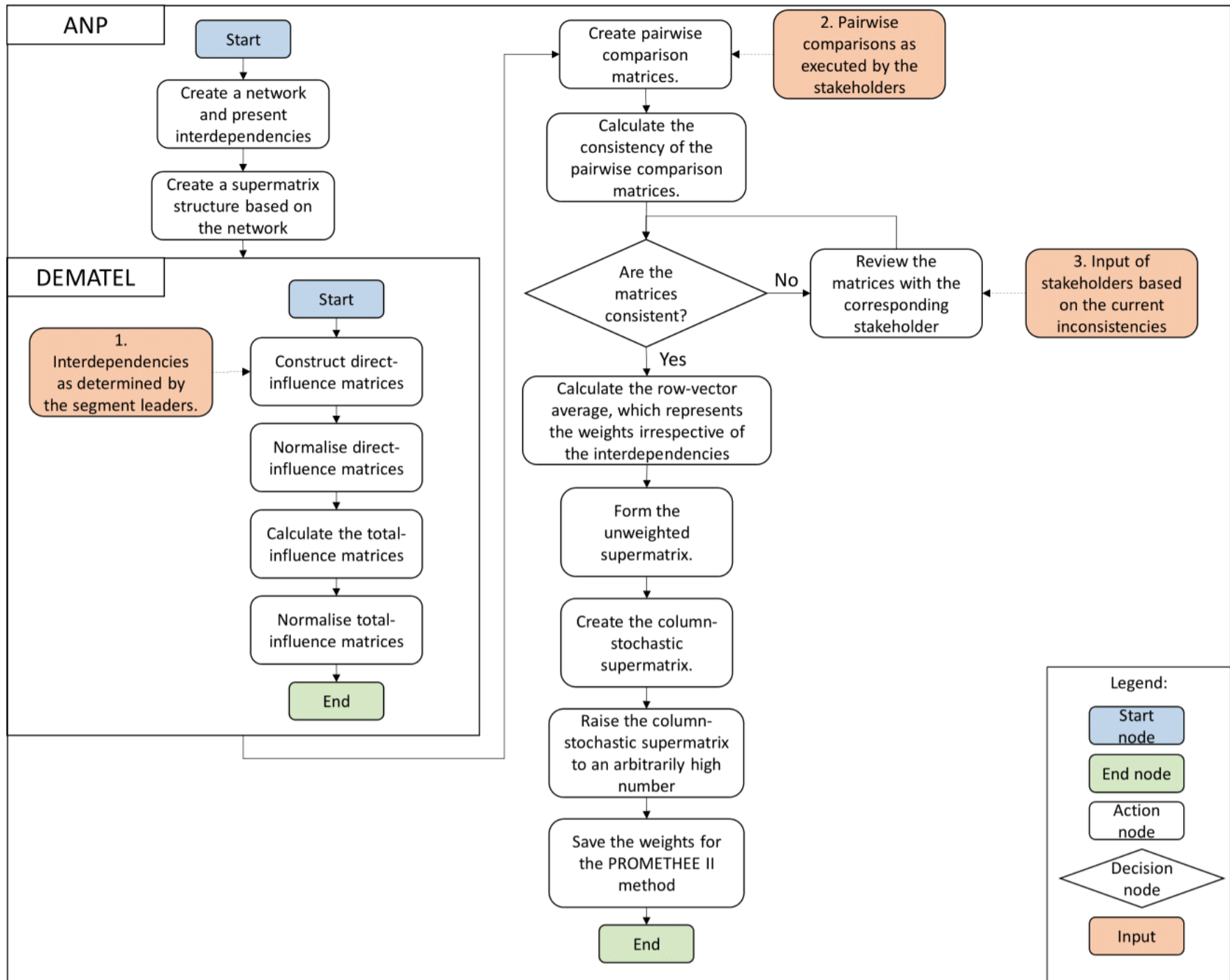
Five sources have been used to describe the DEMATEL-ANP methodology formally (Chung et al., 2005); (Si et al., 2018); (Ishizaka & Nemery, 2013); (Bongo et al., 2018); (Buyukozkan & Guleryuz, 2016):

ANP generalises AHP by replacing the hierarchies of AHP with networks. In AHP, a problem is decomposed into components and hierarchies of criteria are built. Then, the goal influences the criteria categories, which influences each criterion. These feedback loops can be modelled in a 'supermatrix' by representing inner or outer dependencies. The supermatrix can be presented as follows and is based on the problem structure in Figure 18:

$$\text{Supermatrix} = \begin{array}{l} \text{Goal} \\ \text{First level criteria} \\ \text{Second level criteria} \\ \text{Third level criteria} \end{array} \begin{array}{l} (G) \\ (1^{st}) \\ (2^{nd}) \\ (3^{rd}) \end{array} \begin{array}{c} G \quad 1^{st} \quad 2^{nd} \quad 3^{rd} \\ \left[\begin{array}{cccc} 0 & 0 & 0 & 0 \\ \omega_{21} & \omega_{22} & 0 & 0 \\ 0 & \omega_{32} & \omega_{33} & 0 \\ 0 & 0 & \omega_{43} & \omega_{44} \end{array} \right] \end{array} \quad (4.1)$$

The input for the matrix for this problem can be defined as follows. ω_{21} is a column vector representing the first level criteria's potential to satisfy the goal. In more informal terms, the column vector presents the weights of the three TBL aspects. ω_{22} represents a matrix that represents the inner dependence within the level of the problem hierarchy. Moreover, ω_{32} and ω_{43} represent a similar column vector compared to ω_{21} at lower levels of the problem structure and ω_{33} and ω_{44} represent a similar matrix compared to ω_{22} presenting inner dependencies on lower levels. Furthermore, outer dependencies concern dependencies between layers, which might be slightly harder to grasp. For instance, the criterion weights could be influenced by the availability of particular alternatives. For instance, buying a piece of clothing could be an MCDM problem with the criteria costs, quality and colour. Then, the criterion colour could have different weights based on whether the favourite colour is available. These outer dependencies are not considered, explaining the zeroes in the supermatrix.

Concerning the goal, in this case, the goal is to model the sustainability of each alternative. The criteria concern the economic, environmental, and social aspects and the sub-criteria concern the individual criteria as presented in Table 4, Table 5, and Table 6.



5. Weights per stakeholder adjusted for interdependencies

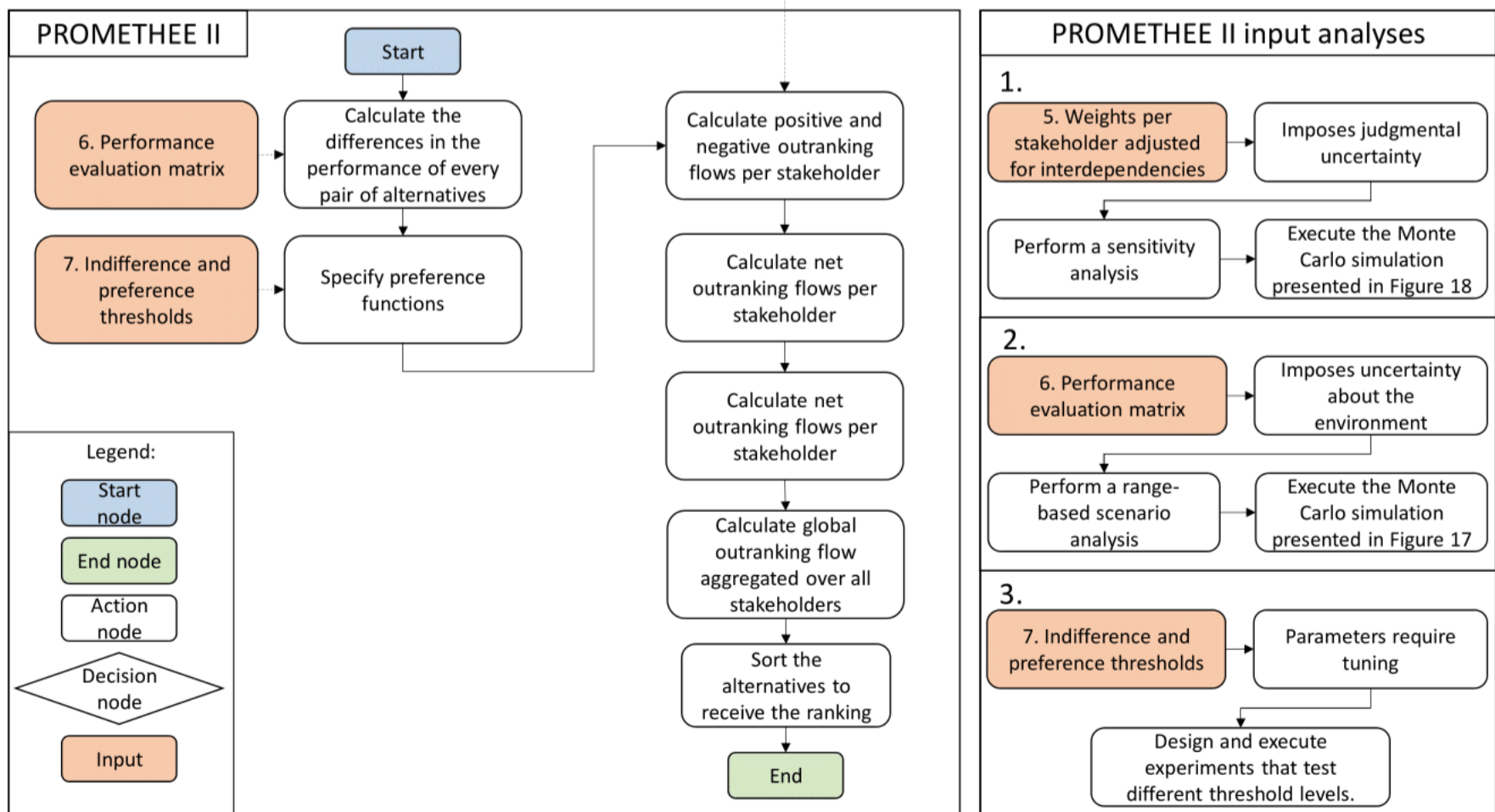


Figure 19: Theoretical framework and relationships of the different models. The bottom right part presents the input to PROMETHEE II and why it should be analysed further. Moreover, it is explained how the further analysis can be executed in one sentence.

DEMATEL is used to determine the interdependencies as presented in ω_{22} , ω_{33} and ω_{44} for each level. Then, the ANP method can be followed by first determining the weights presented by the vectors ω_{21} , ω_{32} and ω_{43} . Then, the supermatrix can be constructed. The complete application of DEMATEL-ANP is as follows:

Step 1: Construct a model and structure the problem. This step clearly defines the problem by decomposing it into a network. The structure can be obtained through brainstorming or other appropriate methods. In this case, the structure is created iteratively by discussing with the segment leaders and visualised in Figure 18.

Step 2: Construct the direct-influence matrix $Z = [z_{ij}]_{n \times n}$. These are squared matrices modelling the different interdependencies z_{ij} according to an ordinal scale of 'no influence (0)', 'low influence (1)', 'medium influence (2)', 'high influence (3)' and 'very high influence' (4). Multiple stakeholders can be included by taking the average of the results. However, these dependencies do not represent an opinion since the dependencies should be objective. Therefore, this would not require many respondents.

Step 3: Construct the normalised direct-influence matrix $X = [x_{ij}]_{n \times n}$ using Equation (4.2) and Equation (4.3):

$$X = \frac{Z}{s} \quad (4.2)$$

$$s = \max \left(\max_{1 \leq i \leq n} \sum_{j=1}^n z_{ij}, \max_{1 \leq j \leq n} \sum_{i=1}^n z_{ij} \right) \quad (4.3)$$

The elements x_{ij} in matrix X adhere to $0 \leq x_{ij} \leq 1$, $0 \leq \sum_{j=1}^n x_{ij} \leq 1$. Moreover, it is ensured that there is at least one i such that $\sum_{j=1}^n z_{ij} \leq s$. The positive scalar s represents the maximum of the largest direct effect given by criteria i or the largest direct effect received by criteria i .

Step 4: Construct the total-influence matrix T . The normalised direct-influence matrix X is used as presented by Equation (4.4):

$$T = \lim_{h \rightarrow \infty} (X + X^2 + X^3 + \dots + X^h) = X(I - X)^{-1} \quad (4.4)$$

In this equation, I represents the Identity matrix. The column-normalised total-influence matrix T represents the inner-dependence matrix that will fit the position of ω_{22} , ω_{33} and ω_{44} in the supermatrix based on the cluster that is assessed and after column-normalisation. From a mathematical perspective, it is assumed that that X^h converges to a zero matrix. This assumption, formally presented in Equation (4.5), does not hold if columns of matrix X sum to unity or less than one:

$$\lim_{h \rightarrow \infty} (X^h) = [0]_{n \times n} \quad (4.5)$$

If the assumption is violated, DEMATEL is proven infeasible. Therefore, Lee et al. (2013) provided a slight adjustment to Equation (4.3). By adding ε , a very small positive number, like 10^{-5} , the assumption in Equation (4.5) holds:

$$s = \max \left(\max_{1 \leq i \leq n} \sum_{j=1}^n z_{ij}, \varepsilon + \max_{1 \leq j \leq n} \sum_{i=1}^n z_{ij} \right) \quad (4.6)$$

The complete derivations are presented by Lee et al. (2013).

Step 5: The final step is to analyse the results presented by DEMATEL. The sum of the rows and columns of the total-influence matrix are the vectors R and S as calculated by Equation (4.7) and Equation (4.8), respectively.

$$R = [r_i]_{nx1} = \left[\sum_{j=1}^n t_{ij} \right]_{nx1} \quad \text{where } i \in [1, \dots, n] \quad (4.7)$$

$$S = [s_j]_{1xn} = \left[\sum_{i=1}^n t_{ij} \right]_{1xn} \quad \text{where } j \in [1, \dots, n] \quad (4.8)$$

r_i denotes the sum of the i th row of the direct-influence matrix and s_j denotes the sum of the j th column of the direct-influence matrix. Then, the vector S can be transposed using $[s_j]_{1xn}^T = [s_i]_{nx1}$ for comparison purposes. The significance of a single criterion regarding the dependencies is presented by adding the respective numerical position in both vectors ($r_i + s_i$). Then, the distinguishment between 'receiver criteria' and 'dispatcher' criteria can be determined by subtracting the respective numerical position in both vectors ($r_i - s_i$). Finally, the influential network relations map can be obtained by plotting the data set of ($r_i + s_i, r_i - s_i$). Moreover, many methods, like the one proposed by Buyukozkan and Guleryuz (2016), propose to use a threshold to determine whether the dependency is significant enough to be mapped in a network relations map. However, it would reduce the accuracy of modelling the problem as realistic as possible. Moreover, it requires an extra parameter that should be tuned. Therefore, Peng & Xiao (2013) do not use the threshold.

Step 6: Execute the final step of the DEMATEL methodology, column-normalise the total-influence matrix T , ensuring that all the columns sum to one.

Step 7: The following steps are according to the ANP methodology. Perform pairwise comparisons between every level in the decision hierarchy. The relative importance values are determined similarly to AHP using pair-wise comparisons on the Saaty Scale of 1 to 9, where 1 indicates equal importance between two elements and 9 indicates extreme importance of one element to another. A reciprocal value will then be assigned to the inverse comparison. The final step after the pairwise comparisons concerns determining the consistency ratio (CR) that can be calculated according to Equations (4.9) and (4.10):

$$CI = \frac{\lambda_{max} - n}{n - 1} \quad (4.9)$$

$$CR = \frac{CI}{RI} \quad (4.10)$$

The consistency index (CI) is calculated using the maximal eigenvalue λ_{max} and the order of the square pairwise comparison matrix n . Finally, the consistency ratio is calculated using the random index (RI), which presents the average CI of 500 randomly filled matrices. The consistency ratio should be less than 10% to be deemed consistent. I.e., the matrix is more consistent than 10% of 500 randomly filled matrices.

Moreover, λ_{max} is calculated using the following approximation (Yeh & Huang, 2014):

$$\lambda_{max} = \frac{1}{m} \sum_{i=1}^m \frac{(AW)_j}{W_j} \quad \text{where } j \in C \quad (4.11)$$

W represents a matrix with the approximate weights for the criteria, and A represents the matrix with the original pairwise comparisons. W can be calculated by using the row-vector average method shown in Equation (4.12):

$$W_i = \frac{\sum_{j=1}^n \left(\frac{\alpha_{ij}}{\sum_{i=1}^n \alpha_{ij}} \right)}{n} \text{ where } i \in C \quad (4.12)$$

The variable α_{ij} presents an entry in the pairwise comparison matrix A .

Step 7: Moreover, the relative weights presented in ω_{21} , ω_{32} and ω_{43} are also calculated using the row-vector average method of Equation (4.12). These are weights that are not adjusted according to the interdependencies of ω_{22} , ω_{33} and ω_{44} .

Step 8: Form the unweighted supermatrix by creating a partitioned matrix with the column-normalised matrices and vectors ω_{21} , ω_{22} , ω_{32} , ω_{33} , ω_{43} and ω_{44} as its components according to Equation (4.1). The priorities can then be calculated using a Markov chain process presented in the following two steps.

Step 9: Transform the supermatrix to make it stochastic. The stochastic supermatrix is named the weighted supermatrix. The weighted supermatrix is created by column normalizing the unweighted supermatrix.

Step 10: Finally, the limit supermatrix can be created using the Markov chain concept. This limit matrix is calculated by raising the weighted supermatrix by an arbitrarily large number k . Then the weights in every column will stabilize, and the final weights can be obtained.

4.2.2 PROMETHEE II method

Two sources are used to formally describe the PROMETHEE II methodology (Athawale et al., 2012); (Ishizaka & Nemery, 2013):

Step 1: Normalise the evaluation performance matrix by determining r_{ij} for every criterion. The evaluation can be dependent on individual stakeholders. However, that does not apply to this research because the performance evaluation table concerns objective data independent of the stakeholders. In case of maximisation, Equation (4.13) is applied:

$$r_{ij} = \frac{e_{ij} - \min(e_{ij})}{\max(e_{ij}) - \min(e_{ij})} \text{ where } i \in A, j \in C \quad (4.13)$$

In case of minimisation, Equation (4.14) is applied:

$$r_{ij} = \frac{\max(e_{ij}) - e_{ij}}{\max(e_{ij}) - \min(e_{ij})} \text{ where } i \in A, j \in C \quad (4.14)$$

Step 2: Calculate the difference d_{ikj} between two evaluations for every alternative:

$$d_{ikj} = r_{ij} - r_{kj} \text{ where } i, k \in A, j \in C \text{ and } i \neq k \quad (4.15)$$

Step 3: Specify a preference function $y_j(d_{ikj})$ for each criterion that translates d_{ikj} for every criterion in a preference degree ranging from 0 to 1. This preference degree presents how preferred alternative a_i is to a_k on a specific criterion. Linear preference functions can be used based on the indifference threshold (q_j), and preference threshold (p_j) according to Equation (4.16):

$$y_j(d_{ikj}) \begin{cases} 0 & \text{if } d_{ikj} \leq q_j \\ \frac{d_{ikj} - q}{p - q} & \text{if } q_j < d_{ikj} < p_j \\ 1 & \text{if } d_{ikj} \geq p_j \end{cases} \quad \text{where } i, k \in A, j \in C, l \in S \text{ and } i \neq k \quad (4.16)$$

The model can be simplified and less data-intensive when q and p are set to 0 and 1, respectively. The model can then be classified as a true-criterion model. However, the model would adhere less to 'strong sustainability' and data uncertainty is not accounted for. Although these are not recommended, the thresholds can be determined using elicitation methods. Another method is to experiment with different sets and the behaviour of the ranking based on the different sets. Then, stakeholder preferences and the experiments can be combined to tune the parameters. Recall that the goal of the MAMCA methodology is to ensure stakeholder acceptance concerning the decision to be taken.

Finally, the preferences can be aggregated per criteria group to determine the main driver groups as requested by the segment leaders. The driver groups are the second level criteria.

Step 4: Define the outranking relation π for every alternative for every stakeholder by adding the weights per stakeholder as determined by the ANP method:

$$\pi_{ikl} = \sum_{j=1}^m w_{jl} y_j d_{ikj} \quad \text{where } i, k \in A, l \in S \text{ and } i \neq k \quad (4.17)$$

Step 5: Determine the positive outranking flow representing the relative strength of alternative a_i . This is determined by calculating how alternative a_i is outranking all the other alternatives.

$$\phi_i^+(a_i) = \frac{\sum_{k=1}^m \pi_{ikl}}{n - 1} \quad \text{where } i \in A, l \in S \text{ and } i \neq k \quad (4.18)$$

Step 6: Determine the negative outranking flow representing the relative weakness of alternative a_i . The negative outranking flow is determined by calculating how alternative a_i is outranked by all the other alternatives:

$$\phi_{il}^- = \frac{\sum_{k=1}^m \pi_{kil}}{n - 1} \quad \text{where } i \in A, l \in S \text{ and } i \neq k \quad (4.19)$$

Step 7: Calculate the net outranking flow per stakeholder:

$$\phi_{il} = \phi_{il}^+ - \phi_{il}^- \quad \text{where } i \in A, l \in S \quad (4.20)$$

Step 8: Calculate the global net flow ϕ_i by taking the weighted average of the individual outranking flow per stakeholder. Introduce the weight per stakeholder as ω_l .

$$\phi_i = \sum_{l=1}^r \phi_{il} \omega_l \quad \text{where } i \in A \quad (4.21)$$

Moreover, Equation (4.22) should ensure that the outranking flows per stakeholder are appropriately aggregated. Moreover, Schar and Geldermann (2021) highlight that it is recommended to apply equal weights for the stakeholders to ensure stakeholder acceptance according to the MAMCA methodology.

$$\sum_{l=1}^r \omega_l = 1 \quad (4.22)$$

The ranking is finalised by ordering the alternatives from the highest net outranking flow to the lowest net outranking flow.

4.2.3 Rank reversal

Furthermore, the major downside of the solution design as presented in this chapter concerns rank reversal as presented in Section 3.3.2.4. Therefore, it would be insightful to understand when rank reversal occurs to determine the significance of its impact. Section 3.3.2.4 also stated that rank reversal occurs when an alternative, in this case a_x , is added or removed. Therefore, rank reversal materialises based on the following relationships (Mareschal et al., 2009):

Assume that alternative a_i is preferred to a_j ($\phi_i - \phi_j > 0$) then, the outranking flows for a_i and a_j in case of the removal or addition of a_x can be formulated as follows:

$$\phi_i^x - \phi_j^x > 0 \text{ where } i, j, x \in A \text{ and } i \neq x \neq j \quad (4.23)$$

Equation (4.23) is applicable if Equation (4.24) is true.

$$\phi_i - \phi_j > \frac{(\pi_{ix} - \pi_{xi}) - (\pi_{jx} - \pi_{jx})}{n - 1} \text{ where } i, j, x \in A \text{ and } i \neq x \neq j \quad (4.24)$$

Therefore, rank reversal only materialises when:

$$0 < \phi_i - \phi_j < \frac{(\pi_{ix} - \pi_{xi}) - (\pi_{jx} - \pi_{jx})}{n - 1} \text{ where } i, j, x \in A \text{ and } i \neq x \neq j \quad (4.25)$$

Recall that the preference coefficients are formulated as numbers between 0 and 1. Therefore, rank reversal will not occur when:

$$\phi_i - \phi_j > \frac{2}{n - 1} \text{ where } i, j \in A \text{ and } i \neq j \quad (4.26)$$

Concluding, rank reversal occurs when the outranking flows between two different alternatives are sufficiently small. Moreover, many alternatives are assessed. Therefore, significant implications for the decision-makers and the decision-making process are not expected.

4.2.4 Modelling uncertainty about the environment

As presented, most multicriteria decision analyses are deterministic, which means that for a specific decision alternative (a_i), a performance (e_{ij}) is determined with the goal of reconciling the conflicts between the criteria. However, it is questionable whether the performances are deterministic. Therefore, Section 3.4.3 identified scenario planning and Monte Carlo simulations as the methods to cope with the uncertain environment. Moreover, Stewart et al. (2013) believe that the synergies between scenario planning and quantitative decision modelling can be exploited in addressing complex decision contexts. Moreover, Monte Carlo simulations can be applied to explore a vast range of performances generated according to the narratives of scenario planning. Thus, the first sub-section discusses scenario planning and the second sub-section discusses the Monte Carlo simulation.

4.2.4.1 Scenario planning

To include the uncertain nature of decision-making, the following guidelines are considered for constructing scenarios in multi-criteria decision analysis (Stewart et al., 2013):

1. About 4-6 scenarios need to be constructed.
2. The scenarios must be defined in terms of exogenous drivers.

3. The scenarios need to cover ranges of expected outcomes and key associations between variables.
4. In circumstances where there are substantial differences between the fundamental values of stakeholders, there may be an advantage in using scenarios that represent different ideal worlds.

Moreover, four perspectives considering the usage of scenarios have been identified. The perspective that is most suitable for this research is the 'external situations affecting consequences of policy actions' shown in Table 10 (Stewart et al., 2013):

Table 10: Scenario analysis perspective considered for this research.

Concept	Context	Purpose	Role of Formal Decision Analysis
External situations affecting the consequences of policy actions	Emphasis on external uncertainties and future states; policy components excluded	To provide a strategic conversation between stakeholders, with consideration of the robustness of alternatives	No formal methods of evaluation used

More specifically, this scenario perspective aims to provide the means to consider today's policies and decision-making processes in light of potential future developments. Table 10 does present that no formal decision analysis methods are used. However, the different potential performances will be aggregated using the Monte Carlo analysis. The Monte Carlo simulation aims to explore different performances and understand how the rankings are distributed based on the exogenous drivers. Therefore, the scenarios are used to provide a strategic conversation and review the robustness of the deterministic ranking.

Next, it remains unclear how to develop the scenarios. Therefore, the application of Siebelink et al. (2016) is used as presented in Table 11:

Table 11: Scenario creation approach (Siebelink et al., 2016).

Step	Elaboration
1. Scope definition	Determine the scope of the scenarios based on the firm's corporate strategy.
2. Driving force exploration	Driving forces can be gathered through standard strategic management tools.
3. Determine development direction	Choose the two most important driving forces to create two development directions per driving force.
4. Develop scenario themes	Use the four combinations of the development directions to generate the scenario themes.
5. Develop rough and plausible narratives	For every scenario theme, develop rough and plausible narratives based on the other key driving factors representing the envisioned business environment.
6. Evaluate and use the scenarios	Evaluate the scenarios.

The strategic management tool used is PESTEL, according to the guidelines presented in Appendix D. Moreover, the evaluation of the scenarios will be done according to the EBDLs and the Monte Carlo simulation shown in Section 4.1.5.2.

4.2.4.2 Monte Carlo Simulation

At this point, four narratives are constructed based on exogenous drivers. These exogenous drivers and the corresponding narratives present the input for determining the distributions according to the EBDLs. Moreover, twenty-six criteria are used as input for the model. However, not all criteria might be impacted in the short-, mid- or long-term, which can be confirmed based on the formulated drivers. For instance, the drivers might not impact the estimated rate of depletion. The estimated depletion rate could remain unchanged during the next five to twenty years. Therefore, it should be determined first what criteria are impacted by the drivers. Moreover, due to time limitations, developing probability distributions for all criteria and alternative pairs is impossible. It would require $26 \times 19 = 494$ different distributions.

The probability distributions can be distinguished based on the characteristics visualised in Figure 17.

1. Is the distribution skewed or symmetric? I.e., is the distribution uniform or not?
2. Is the distribution discrete or continuous?
3. Is the distribution open or closed? I.e., does the pessimistic or optimistic estimate correspond to the bounds of the distribution? Or are errors expected?

Baudry et al. (2018) recommended that triangular distributions are most suitable for sustainability assessments. The open distribution can be used if the probability that the actual value might be lower than the most pessimistic evaluation or higher than the most optimistic evaluation. The discrete distribution could prove helpful for ordinal data. Three out of four distributions presented in Figure 17 might be used. Only the continuous uniform distribution can be excluded since it is not reasonable to assume equal probabilities for the entire performance range.

Finally, the formal representation of the probability distribution remains undiscussed. The segment leaders determine the pessimistic performance, most probable performance and optimistic performance. Their role is to formulate the long-term strategy for the segments. Therefore, the segment leaders should be able to estimate performances for different criteria. Then, the samples need to be taken from the defined distributions. Equation (4.27) presents the triangular distribution. Note that the triangular distribution represents both the open and closed triangular distribution. The difference is that the optimistic (a_1) and pessimistic (a_3) estimates are adjusted for errors in the case of an open-triangular distribution. Moreover, the most probable estimate is represented by a_2 . The probability density function $f(x)$ for a triangular distribution of a random variable X on the interval (a_1, a_3) given $X \sim Tri(a_1, a_2, a_3)$ is (Kotz & Dorp, 2004):

$$f_X(x) = \begin{cases} \frac{2(x - a_1)}{(a_3 - a_1)(a_2 - a_1)} & \text{if } a_1 < x \leq a_2 \\ \frac{2(a_3 - x)}{(a_3 - a_1)(a_3 - a_2)} & \text{if } a_2 < x < a_3 \end{cases} \quad (4.27)$$

Based on Equation (4.27), the cumulative distribution function can be calculated according to Equation (4.28):

$$F_X(x) = \begin{cases} \frac{(x - a_1)^2}{(a_3 - a_1)(a_2 - a_1)} & \text{if } a_1 < x \leq a_2 \\ 1 - \frac{(a_3 - x)^2}{(a_3 - a_1)(a_3 - a_2)} & \text{if } a_2 < x < a_3 \end{cases} \quad (4.28)$$

The cumulative distribution can be used to generate the random evaluation x by generating a random number between 0 and 1 which represents $F(x)$. Every Monte Carlo trial can reproduce these computations for the triangular and discrete distribution. In contrast, the discrete distribution is more time-intensive to model. The discrete distribution requires a probability to accompany every estimate. Then, the sum of these probability functions should add up to 1. Therefore, Section 4.4 discusses the quantification of ordinal data. Overall, the scenario analysis and Monte Carlo simulation process is summarised in the following flow-chart:

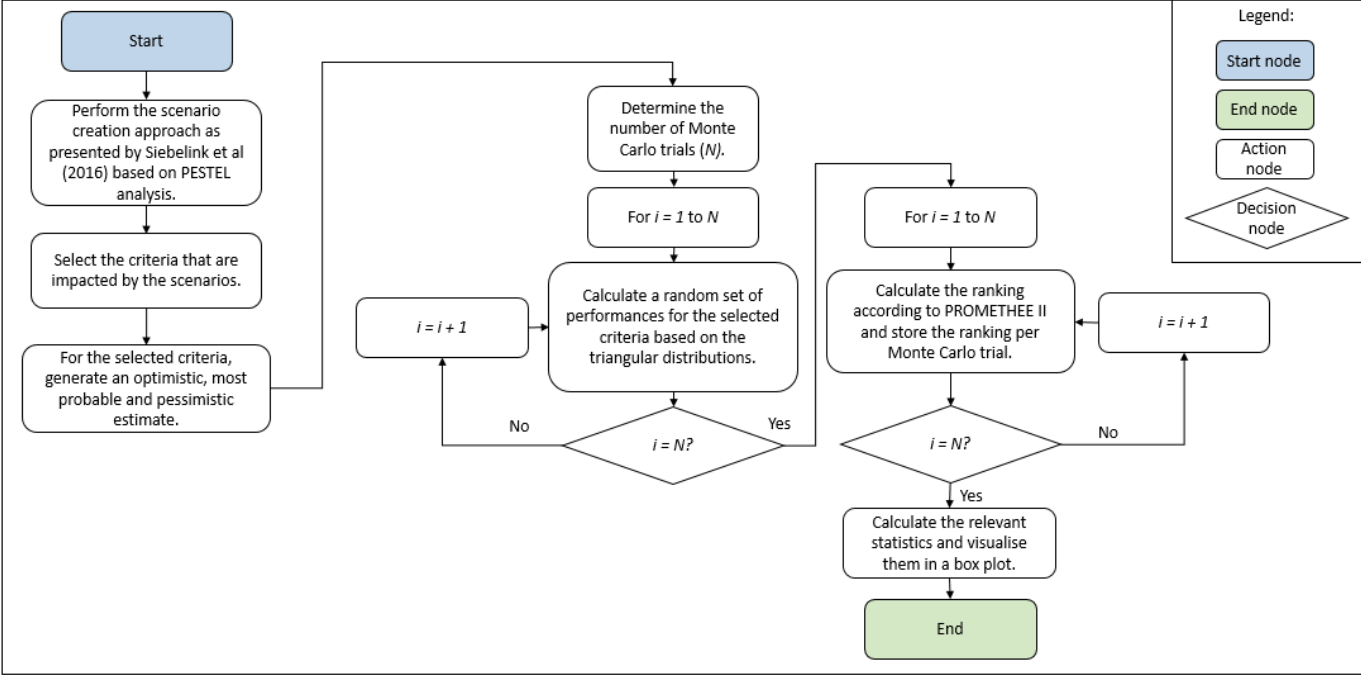


Figure 20: Flow-chart of the Monte Carlo simulation used to assess the impact of environmental uncertainty.

4.2.5 Sensitivity analysis

The final topic of the solution design concerns the sensitivity analysis. The solution design for the Monte Carlo-based sensitivity analysis is based on the methods proposed by Butler et al. (1997) and Balezentis and Streimikiene (2017). As presented in Section 3.4.3.2, the sensitivity analysis should be able to model interactions between different criteria and explore a vast range of different weight combinations.

Butler et al. (1997) propose three methods to determine the weights, (i) random weights, (ii) rank order weights, and (iii) response distribution weights. The first approach assumes that there is no knowledge about the relative importance of criteria. The advantage of this method concerns the determination of structural dominance of specific alternatives due to the unbiased weight generation. The second method assumes that it is unreasonable to assign weights randomly if some objectives are deemed more important than the others and that it is questionable whether it is possible to assign exact weights to criteria. Therefore, different hierarchies of criteria are assessed by the simulation approach. Finally, the third method assumes that variation in response errors obtained from the responses used to determine the weights can be modelled according to a gamma distribution. This method exposes the criteria most sensitive to relatively small weight changes.

Balezentis and Streimikiene (2017) use the first method as input for the Monte Carlo simulation to determine whether perturbations in the weights can impact the stability of the results. Moreover, random weights can be used to determine structural dominances between specific alternatives, which might remain uncovered in case of a biased sensitivity analysis. Therefore, the

first method is chosen. The random weights will be drawn based on the following methodology (Butler et al., 1997):

Step 1: Draw $m - 1$ random numbers r according to a uniform distribution, where r is independently and identically distributed according to a uniform distribution:

$$r_j \sim U(0,1) \text{ where } j \in \{1, \dots, m - 1\} \quad (4.29)$$

Step 2: Rank the numbers from large to small, including the bounds (0,1). These numbers can be ranked according to Equation (4.30):

$$1 > r_{(m-1)} \geq \dots \geq r_{(2)} \geq r_{(1)} > 0 \quad (4.30)$$

Step 3: Calculate the first differences k_m of the ranked numbers, including the bounds following Equation (4.31):

$$\begin{aligned} k_m &= 0 - r_{(m-1)} \\ k_{m-1} &= r_{(m-1)} - r_{(m-2)} \\ &\vdots \\ k_1 &= r_{(1)} - 0 \end{aligned} \quad (4.31)$$

Following these three steps, the results present a set of numbers $\{k_1, \dots, k_m\}$ that sum to 1 and are uniformly distributed. Moreover, these three steps can be repeated for every Monte Carlo trial to create many different sets of weights to assess the judgmental uncertainty by analysing the distribution of the different rankings. Overall, the Monte Carlo simulation is performed according to the flow-chart presented in Figure 21:

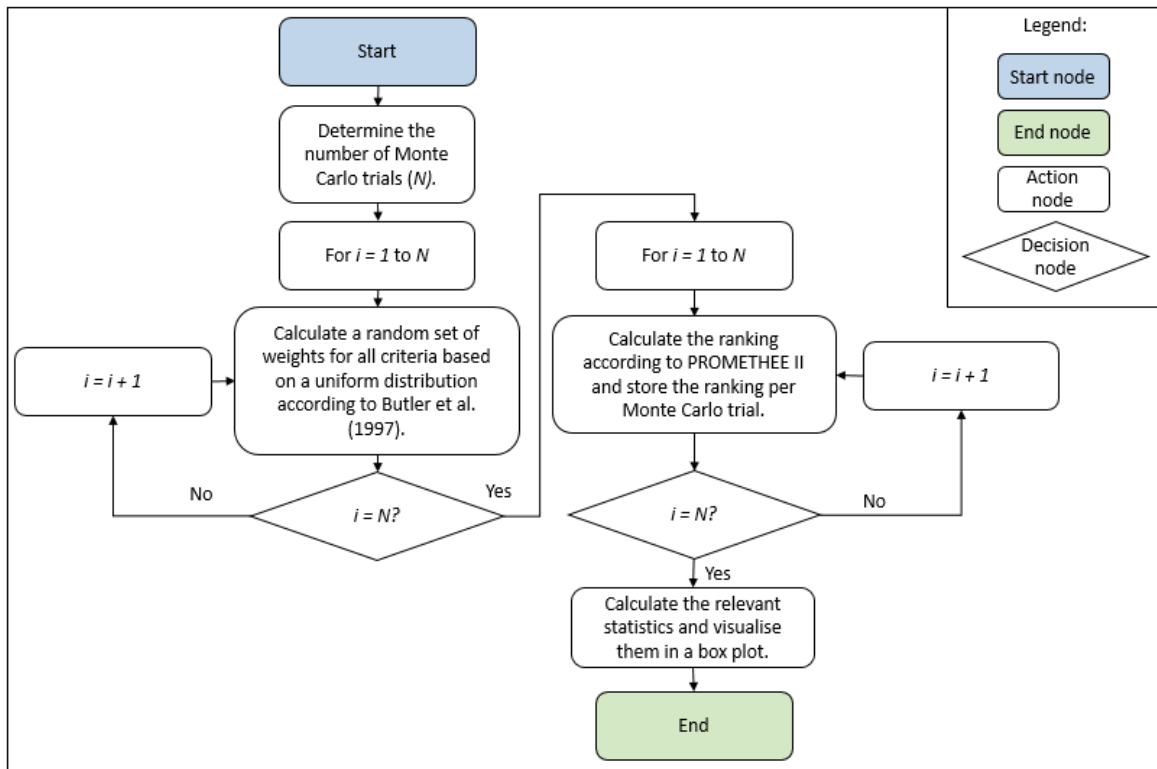


Figure 21: Flow-chart of the Monte Carlo simulation used to assess the impact of judgmental uncertainty.

4.3 Operationalisation of criteria weights and thresholds

This section will provide some highlights and methodological challenges concerning criteria weights in Section 4.3.1 and thresholds in Section 4.3.2.

4.3.1 Criteria weights

The criteria weights are determined based on the DEMATEL-ANP hybrid, as presented in the previous section. The input that is required to determine the weights are gathered through individual workshops. These workshops are held according to the guidelines presented in Appendix C.

4.3.2 Preference and indifference thresholds

The determination of the preference and indifference thresholds is discussed in this section. The indifference thresholds present a level of uncertainty expected within a dataset. It is unknown what the level of uncertainty is. Therefore, this is one of the first experiments executed in Chapter 5.

Furthermore, the preference thresholds present the point after which difference results in strict preferences. These thresholds should be set based on the preferences of the decision-makers. The decision-makers have presented that there is only one criterion that should be taken into account concerning preference thresholds. This is “E1 – Estimated rate of depletion”. Differences larger than 250 years are deemed irrelevant. The choice to include only one preference threshold can be explained by the relevance of other extreme performances, like supply risks and CO₂ emissions for the rare earth elements. These large evaluations are relevant and are not considered positive evaluations that compensate for unsustainable practices. Finally, the indifference threshold should be tuned based on the preference threshold. In this case, 250 years account for 0.45% of the complete data range. Therefore, an indifference threshold of 5% of the complete data range would result in complete indifference for that criterion. Therefore, the preference threshold should always be higher than the indifference threshold.

4.4 Operationalisation of criteria performances

The evaluation performance table includes multiple scales to assess the raw materials on different criteria. The input data is measured on one of four scales, an interval scale, a ratio scale, an ordinal scale or a binary scale. Normalising performances based on the interval or ratio scale does not result in problems as Equations (4.13) and (4.14) can be applied. Evaluations on the binary scale, represented by “yes” or “no” evaluations, can be normalised without problems. Normalisation is unnecessary since the criteria are already based on a zero-to-one scale. Additionally, the preferences are calculated without problems as well. A difference of 1 results in modelling the strict preference relationship. A difference of 0 would result in modelling the indifference relationship.

The difficulty of data preparation lies with normalising ordinal data. The Material Change report presents data qualitatively according to a 4-point ordinal scale (Drive sustainability et al., 2018). However, equal distances between the bounds of each ordinal measurement cannot be assumed. Though, the report does present the bounds of each ordinal data point. For example, the criterion ‘*Industry Consumption*’ is assessed by the scale presented in Table 12:

Table 12: Bounds of the ordinal datapoints for the criterion 'Industry consumption'.

Ordinal ranking	Assessment of criteria
Low	Less then 5%
Moderate	From 5% to 10%
High	From 10% to 30%
Very High	More than 30%

The translation can be made using a process called defuzzification. To know what fuzzy function is applicable, the distribution of crisp measurements within the bounds of an ordinal measurement should be known. However, since only the bounds are presented, the assumption is made that the data in between the bounds of an ordinal measurement is uniformly distributed.

The bounds of the ordinal data are exact. Therefore, overlap is not allowed. This means that a datapoint fits one of the four points. Moreover, it is not possible that a datapoint has a probability of 75% to be associated with the score low and 25% to be associated with the score moderate. The function presenting how the datapoints are related to a qualitative measurement is called a membership function. Following this logic, the ordinal data has to be presented as a rectangular membership function. Thus, a visualisation of the ordinal ranking can be made based on Table 12 and an example from Fatemi et al. (2018). Note that this figure presents the membership functions and not the data distribution within the bounds.

Then, there are multiple methods to perform defuzzification. One of the most accessible and intuitive methods is the Centre Of Gravity (COG) method, as used by, Talon and Curt (2017). Figure 22 presents the defuzzification of "Very High". This method is computationally inexpensive since a uniform distribution is assumed. the crisp representation is the average of the two bounds.

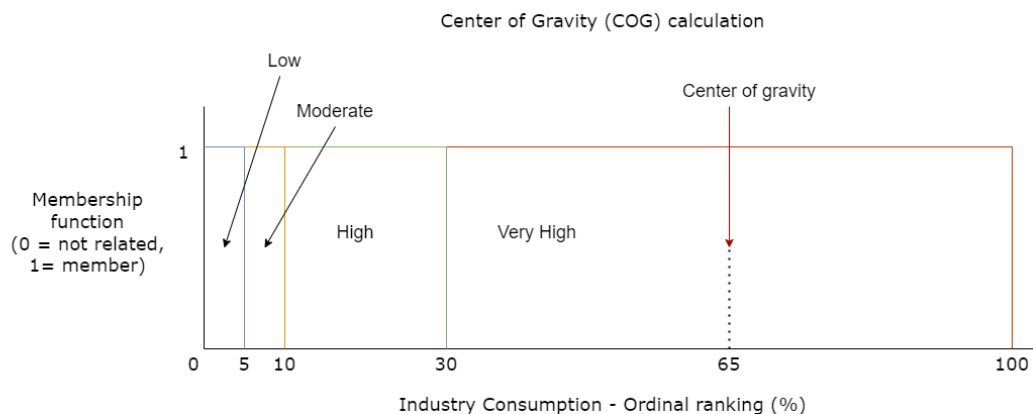


Figure 22: Center of gravity defuzzification method based on criterion P1 - industry consumption.

Finally, some estimates had to be made based on the unavailability of data. However, these estimates account for less than 2% of all the evaluations in the evaluation performance table. For instance, water consumption was not available for natural graphite, chromium and tin. Then, the average is taken for all raw materials except for the rare earth elements, since water consumption of rare earth elements is not comparable to the others. Moreover, numerical values for function criticality and supply risk were unavailable for PA-66 and PBT. An estimate is determined by a plastics specialist. The final example concerns the price indices. Some raw materials, like rare earth elements, do not have a global price index. Then, a value of 1 is given to the measurement, since scrap prices are usually lower than the virgin raw material price. This is caused by the fact that virgin raw materials are ready to be used, and secondary scrap needs to be processed.

Overall, the entire performance evaluation table is presented in Appendix E.

4.5 Conclusion

Chapter 4 started with a formal and lean problem description. Then, the problem has been structured into a hierarchy including dependencies, as presented in Figure 18. This figure contains one extra criterion added based on stakeholder feedback. Therefore, twenty-six criteria are considered in total. Then, limitations are discussed based on the literature review and stakeholder requirements. The stakeholder requirements mostly consider interpretation requirements since low-hanging fruits have to be presented based on the main drivers of the ranking. The second-level criteria are chosen as driver categories.

Chapter 4 answers the research question '*How should the multi-criteria decision approach be designed?*' by presenting the complete problem description and discussing the theoretical approach of DEMATEL-ANP and PROMETHEE II based on this problem description of Section 4.1. A detailed description of DEMATEL-ANP and PROMETHEE II is presented. Moreover, the scenario analysis and Monte Carlo simulation method, and the Monte Carlo based sensitivity analysis are discussed. These two processes are visualised according to the flow charts in Figures 20 and 21. Chapter 4 ends by discussing the operationalisation of the criteria and data preparation. The weights for the criteria are determined according to the workshop as described in Appendix C. Moreover, some criteria are evaluated on an ordinal scale. These ordinal datapoints should be translated into crisp numbers. These numbers are determined based on the centre-of-gravity defuzzification method.

5 Numerical results

Chapter 5 presents the results based on the conceptual model of Chapter 4. First, the results of determining the stakeholders' priorities are presented in Section 5.1. Second, experiments are executed to tune parameters and present results that contribute to fulfilling the assignment as described in Section 1.2.2. These experiments are explained in detail in Section 5.2. Overall, four sets of results can be presented based on the experiments. First, the indifference and preference thresholds are tuned in Section 5.3. Second, the results of the DEMATEL-ANP and PROMETHEE II method based on the stakeholder input are shown in Section 5.4. Third, the results of the scenario planning and Monte Carlo approach, including the scenario narratives, are shown in Section 5.5. Finally, the results of the sensitivity analysis are presented in Section 5.6. The results can be summarised in tangible actions in Section 5.7.

5.1 Stakeholder priorities

The results of the priority workshops are accumulated and presented in this section. The workshop is executed for five stakeholders according to the workshop description in Appendix C. Five individual sessions were planned, since it was impossible to schedule the sessions simultaneously. Moreover, a follow-up session to validate and improve the inconsistencies is scheduled after the first session. The stakeholders included two segment leaders, a chief engineer, a raw material specialist and a circularity specialist. The segment leaders are responsible for developing the strategy for the purchasing department for their segment. The chief engineer is responsible for developing the technological roadmap for the segment. Then, the raw material specialist ensures that the purchasing department is supported on all topics related to raw materials, especially from a business controlling perspective. Finally, the circularity specialist pushes the use of circular concepts and investigates the possibilities concerning the currently used technology and the technology in development. The weights for the five stakeholders are checked for consistencies according to Equations (4.9) and (4.10) for each cluster. A cluster concerns a specific part of Figure 18. Figure 18 shows, for instance, two clusters on the third criteria level that represent economic criteria. Table 13 presents the inconsistencies.

Table 13: Summary of the inconsistencies of the pairwise comparisons per cluster. The cluster number corresponds to a set of pairwise comparisons following the structure of Figure 18 as presented in the first two columns.

TBL aspect	Criteria level	Matrix number (cluster)	Segment leader 1	Segment leader 2	Chief engineer 1	Raw material specialist	Circularity specialist
All	1 st	M1	0.000	0.000	0.000	0.000	0.000
Economic	2 nd	M2	0.000	0.000	0.000	0.000	0.000
Environmental	2 nd	M3	0.000	0.000	0.000	0.000	0.000
Social	2 nd	M4	0.000	0.000	0.000	0.000	0.000
Economic	3 rd	M5	0.025	0.058	0.058	0.079	0.000
Economic	3 rd	M6	0.075	0.097	0.082	0.097	0.062
Environmental	3 rd	M7	0.038	0.093	0.005	0.098	0.068
Environmental	3 rd	M8	0.000	0.033	0.000	0.033	0.000
Social	3 rd	M9	0.000	0.056	0.000	0.000	0.000
Social	3 rd	M10	0.048	0.091	0.000	0.059	0.000

Moreover, the criteria can be evaluated based on their interdependency ratings, presenting whether the criteria are receivers (effect-criteria) or dispatchers (cause-criteria) according to Equations (4.7) and (4.8) in combination with the logic presented below the equations. These evaluations present how criteria influence other criteria and how significant the influence is. The

whole table is presented in Appendix F. Moreover, a visualisation based on the social criteria is shown in Figure 23.

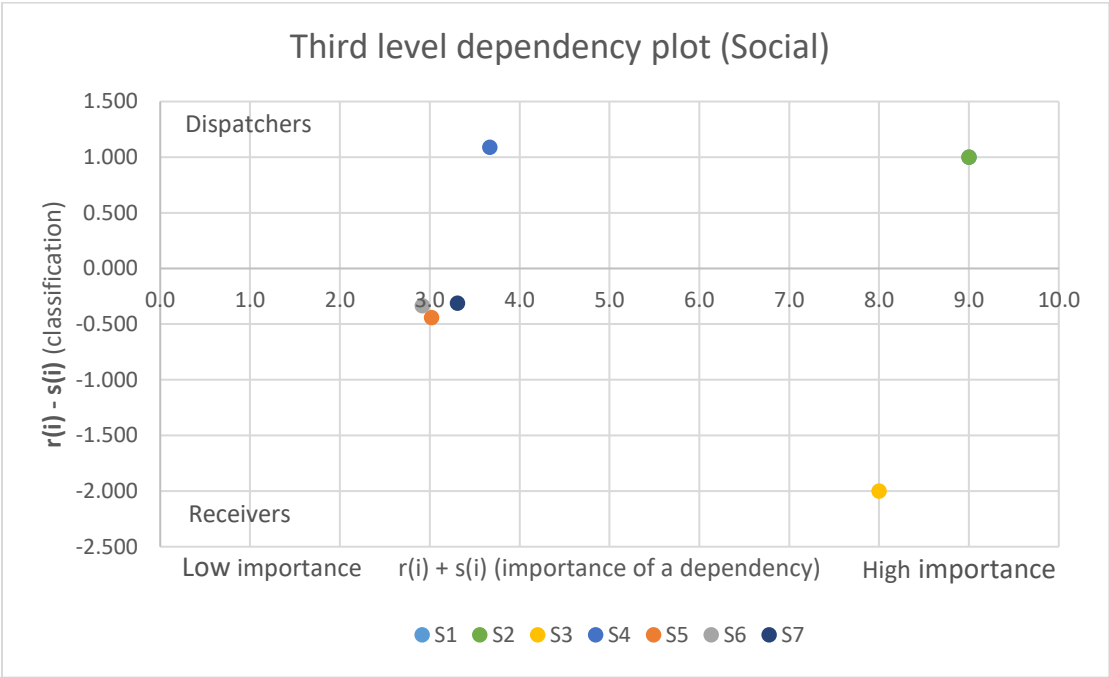


Figure 23: Interdependencies visualised. $r(i) + s(i)$ presents the importance of a dependency; the larger the number, the more significant the dependency is. $r(i) - s(i)$ presents whether the criterion can be classified as a receiver (<0) or a dispatcher (>0). The criteria are described according to the references presented in Table 6. Finally, S1 and S2 have the same score, resulting in overlapping markers in the graph.

Figure 23 represents the two clusters of third-level criteria representing the social aspect of the triple bottom line. The first cluster, M9, concerns the following criteria: countries experiencing corruption (S1), countries with a weak rule of law (S2) and countries experiencing a high-intensity state of conflict (S3). The second cluster, M10, corresponds to artisanal & small-scale mining (S4), child labour and forced labour (S5), harm done to communities (S6), and potential for harm from hazardous materials and chemicals (S7).

It can be concluded that S3, S5, S6, and S7 are receivers. S1, S2, and S4 are dispatchers. The reasoning behind this division in, for instance, cluster M10 is that a high percentage of the population working in artisanal and small-scale mining might indicate a higher probability of child and forced labour occurring. Artisanal and small-scale mining is significantly more challenging to regulate than large-scale mining. Community harm and effects of hazardous materials and chemicals are also harder to regulate in artisanal and small-scale mining. Therefore, if the raw material is unsustainable from an artisanal and small-scale mining perspective, the issues with criteria S5, S6 and S7 are probably more significant according to the input of the stakeholders.

The consistent pairwise comparisons are calculated into weights, and the interdependencies are included. Figure 24 presents the weight distributions, excluding the dependencies and Figure 25 presents the weights, including the dependencies. Figure 25 is calculated using the DEMATEL-ANP methodology. The results in Figure 24 are calculated by determining the row-vector average. For the complete numerical elaboration, Appendix G can be studied.

Figure 24 presents that the viewpoints of the stakeholders differ significantly. Moreover, out of 26 criteria, some criteria receive significant importance based on stakeholders' viewpoints. For instance, criteria S5, representing child and forced labour, is weighted significantly since the occurrence violates the most basic human rights. The logic of the previous paragraph is visualised

in these Figure 24 and Figure 25. Thus, the preference for S5 is decreased. Simultaneously, the interdependencies increase S4 to account for the dispatching behaviour of S4 and the receiving behaviour of S5.

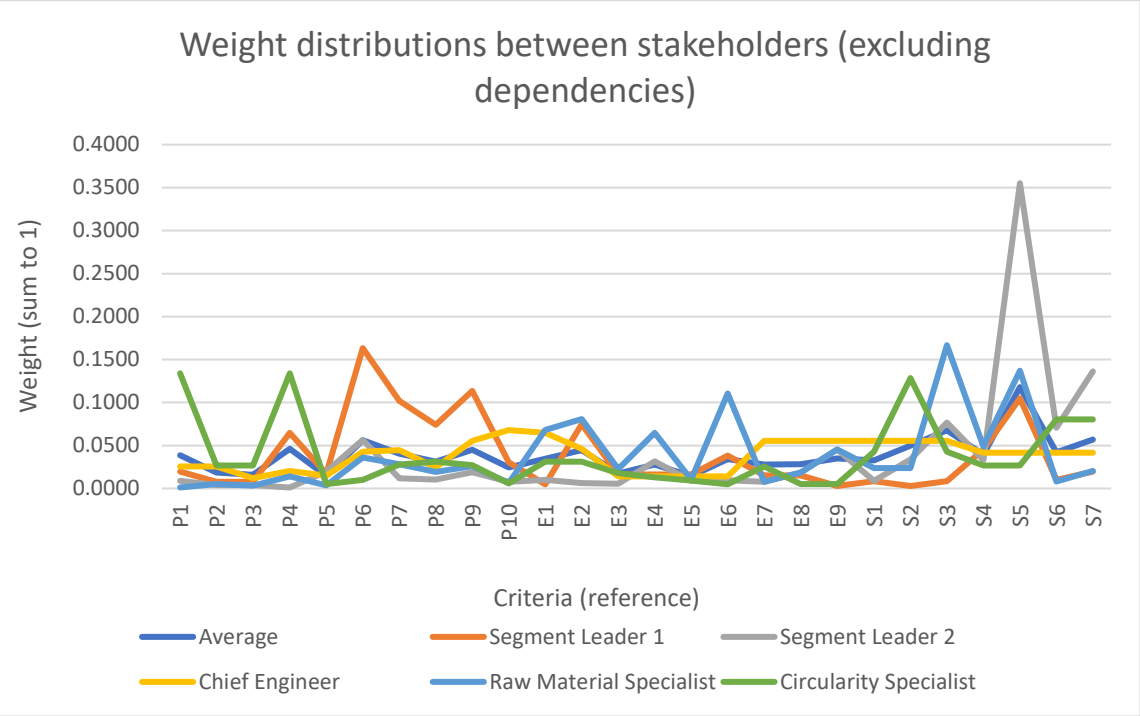


Figure 24: Weight distributions representing the priorities of each stakeholder. These weights are not corrected for dependencies.

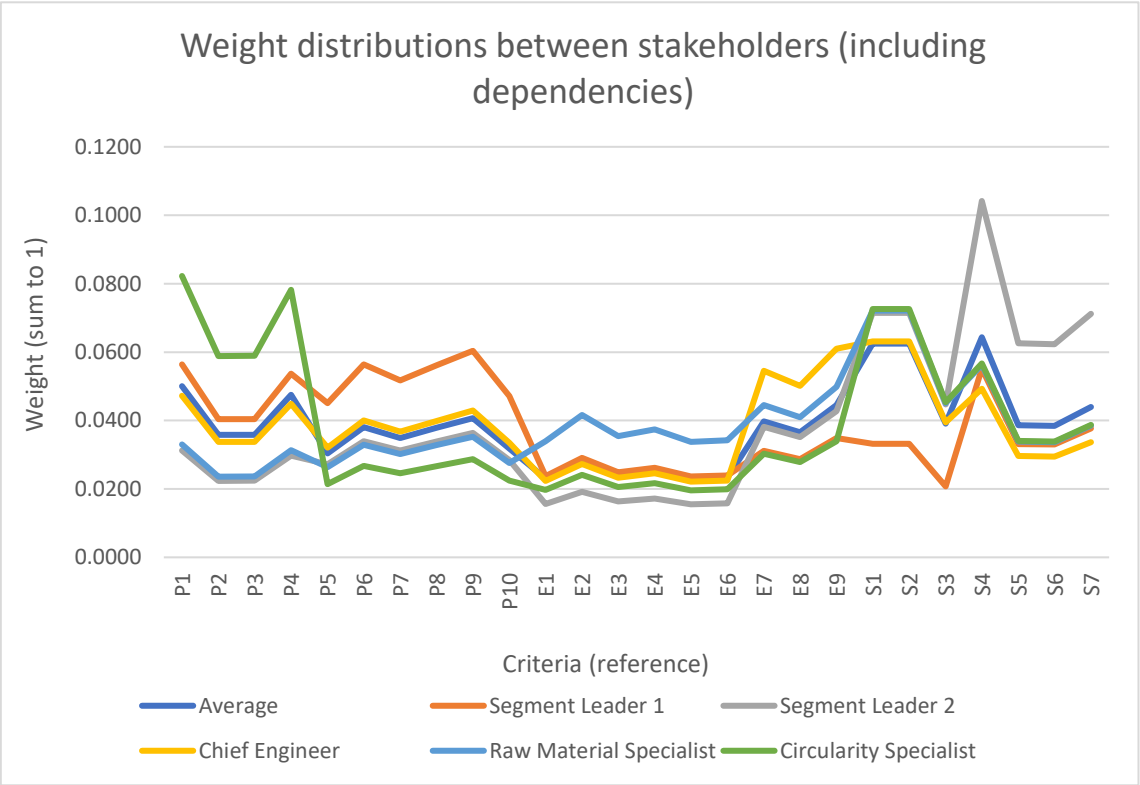


Figure 25: Corrected weight distributions representing the priorities of each stakeholder considering interdependencies.

Other observations include the moderate viewpoint of the chief engineer. The chief engineer's priorities are the closest to the average of all five stakeholders. It could be explained by the chief engineer's pragmatic and solution-oriented approach, which results in more evenly divided priorities. Next, the two segment leaders seem to be divided on the priority of economic and social perspectives while both are working in the same department and should follow the same strategy. Overall, the most significant focus is placed on the social criteria, represented by the criteria ranging from S1 to S9, followed by the economical performances. The environmental priorities are deemed the least important. These observations confirm the current issues with the geopolitical situation and supply chain disruptions. Furthermore, structural human rights violations could be devastating to supply chains.

5.2 Experimental design

All experiments are performed on a computer with an i5-1145G7 processor of 2.60 GHz and 16.0 GB RAM. All experiments should be reproducible on similar devices.

Concerning the design of the experiments, it must be determined which parameters are tuneable and what input data can be used to perform experiments. Section 4.2 showed that the indifference and preference parameters required tuning. Moreover, the number of Monte Carlo iterations for both simulations need to be tuned. Finally, the numerical experiments are designed to find the deterministic ranking and determine the influence of uncertainty about the environment and judgemental uncertainty on the position of the raw materials in the ranking. Figures 15, 16 and 17 and Sections 3.3.1 and 4.1.1 present the following parameters and sets:

- A set of n decision alternatives $A = \{a_1, \dots, a_n\}$. The set differs based on the scope.
- A set of m criteria $C = \{c_1, \dots, c_m\}$.
- An m by n evaluation matrix E , also named performance table, that presents the evaluation e_{nm} of each alternative a_n on each criterion c_m .
- A set of m weights $W = \{w_1, \dots, w_m\}$ where $m \in C$. This set can be extended based on whether multiple stakeholders are considered. Then, the set is expanded according to Section 4.1.
- A set of m indifference thresholds $T = \{q_1, \dots, q_m\}$ where $m \in C$.
- A set of m preference thresholds $U = \{p_1, \dots, p_m\}$ where $m \in C$.
- The number of Monte Carlo trials for the scenario planning and Monte Carlo method (t_1)
- The estimates for the triangular distributions according to the expert-based distribution laws (EBDLs)
- The number of Monte Carlo trials for the sensitivity analysis (t_2)

Due to the problem's structure, it is complicated to quickly change the number of criteria by including or excluding a criterion. Then, the complete problem structure has to be adjusted, requiring new pairwise comparison and interdependency assessments. The mathematical procedures in Sections 4.2.1 and 4.2.2 must be executed again if adding or removing a criterion is desired. Each experiment will have one question that needs answering. Overall, these experiments are summarised in Tables 14 and 15. These tables present how the input is manipulated, how the output can be presented and what conclusions have to be drawn. The input either remains constant, is not applicable, is altered based on a range with increments or is drawn from a distribution.

Two remarks have to be made before explaining the experiments. The raw materials of a segment used for the experiments, which either includes both the ED&C and MDS segment or a single segment, is based on the purpose of the experiment. Both scopes are assessed together and individually in the case of the deterministic ranking. Moreover, the estimates of the EBDLs are not

manipulated. Finally, the set W is based on the stakeholder priorities for all experiments, except for experiments 7 and 8, since the weights are randomised.

- **Experiments 1 and 2: parameter tuning**

The purpose of experiments 1 and 2 is to understand the model's results after following the DEMATEL-ANP and PROMETHEE II methods, as seen in Section 4.2 regarding the preference and indifference thresholds. The indifference threshold concerns the range where a slight difference in performance is deemed negligible and caused by the arbitrariness of the data. The preference thresholds define a buffer zone between the strict preference and indifference relationship. Moreover, the normalisation method presented in Equations (4.13) and (4.14) ensures that differences are calculated on a -1 to 1 scale. The indifference thresholds are varied based on a percental difference. The following question is the basis for this experiment:

'How does the MCDM model react to changes in the indifference thresholds?'

Then, the preference thresholds are determined by the segment leaders based on the criteria's scale. However, the segment leaders only considered one preference threshold. Therefore, this preference threshold will be tuned individually to see whether the threshold fits the model and to see how the model reacts to different preference thresholds:

'How does the MCDM model react to changes in preference thresholds?'

Thresholds can be selected after the behaviour has been studied to understand the impact of using a certain threshold.

- **Experiment 3: model validation**

The third experiment forms the basis to validate the usage of the relatively complex DEMATEL-ANP methodology. This combination is computationally expensive compared to a naïve set of weights or AHP. The naïve set can be represented by giving each criterion the same weight. PROMETHEE II is a straightforward method proven in similar contexts, as shown in Table 7. Therefore, PROMETHEE II does not necessarily require model validation. However, it can be compared to MAVT, which resembles a weighted average and is simple to implement.

Overall, the question worth answering is as follows:

'Does ANP, DEMATEL and PROMETHEE II fulfil the needs of the decision-makers better than naive methods?'

The differences in the rankings should be explainable to the use of DEMATEL-ANP. Moreover, if rankings prove to be similar, the added complexity and computations of the DEMATEL-ANP method are not worth the effort. For PROMETHEE II, the same reasoning holds.

- **Experiment 4: deterministic ranking**

Then, the ranking of the raw materials can be calculated. Experiment 4 provides the deterministic ranking without considering judgmental uncertainty and uncertainty about the environment. The thresholds, weights, and performance evaluations remain constant. Moreover, both scopes have shared raw materials. Therefore, it can be simultaneously investigated what the influence of rank reversal is on this problem by calculating the deterministic ranking for both the ED&C and MDS segments. The question that is answered is the following:

'What are the rankings for both segments and individual segments concerning the current data set and stakeholder preferences?'

- **Experiments 5 and 6: scenario planning and Monte Carlo approach**

Next, it should be understood how uncertainty about the environment influences the rankings. Experiments 5 and 6 investigate how the position of the raw materials in the ranking alters based on the uncertainty about the environment. The determined EBDLs are input for the Monte Carlo simulation. Therefore, the number of Monte Carlo iterations has to be determined. An experiment will be executed where the number of iterations is variable to see how the distributions of the EBDLs materialise when performing the Monte Carlo simulation. An answer to the following question should be presented:

‘What is an appropriate number of Monte Carlo iterations to ensure that the distribution of the EBDLs resembles the triangular distribution as presented in Figure 17?’

Then, if the triangular distribution is modelled correctly, boxplots can be formed to see how those EBDLs influence the rankings. Thus, showing how exogenous drivers can influence rankings presents how robust the current solution presented in experiment 3 is. This understanding shows how uncertainty about the environment influences the decision-making process:

‘How does uncertainty about the environment influence the robustness of the ranking of the raw materials?’

- **Experiments 7 and 8: Monte Carlo sensitivity analysis**

The final experiments that are executed concern the assessment of judgmental uncertainty. As presented in Section 5.1, stakeholder priorities differ. Thus, it is important to measure the impact of judgmental uncertainty on raw material’s position in the ranking. As with the previous experiment, the number of Monte Carlo iterations must be determined first. The number of iterations will be determined empirically based on the distribution of the weights of the criteria by answering the following question:

‘What is an appropriate number of Monte Carlo iterations to ensure that the distribution of the random weights resembles a consistent distribution curve?’

The output is presented in a boxplot to determine how changes in the weights could influence the stability of the ranking. The visualisations present an answer to the following question:

‘How does judgemental uncertainty influence the robustness of the ranking of the raw materials?’

Table 14: Experimental designs. The table presents what parameters are manipulated and what is remained constant, [-] presents that the input is not considered in the experiment.

Experiment number	Input								
	A	C	E	W	T	U	t_1	EBDLs	t_2
1	{Both scopes}	Fixed	Fixed	Fixed	{0; 0.005; 0.01; 0.025; 0.05; 0,10; 0.25}	Fixed (=max)	-	-	-
2	{Both scopes}	Fixed	Fixed	Fixed	Fixed (= output Exp. 1)	{None; 1000; 500; 250; 100}	-	-	-
3	{Both scopes}	Fixed	Fixed	{Naïve, AHP, DEMATEL-ANP}	Fixed (= output Exp. 1)	Fixed (= output Exp. 2)	-	-	-
4	{Both scopes; ED&C; MDS}	Fixed	Fixed	Fixed	Fixed (= output Exp. 1)	Fixed (= output Exp. 2)	-	-	-
5	{Both scopes}	Fixed	$\sim Tri(a, b, c)$	Fixed	Fixed (= output Exp. 1)	Fixed (= output Exp. 2)	{500; 5000; 10,000; 15,000}	Fixed	-
6	{Both scopes}	Fixed	$\sim Tri(a, b, c)$	Fixed	Fixed (= output Exp. 1)	Fixed (= output Exp. 2)	Fixed (= output Exp. 5)	Fixed	-
7	{Both scopes}	Fixed	Fixed	$\sim U(0,1)$	Fixed (= output Exp. 1)	Fixed (= output Exp. 2)	-	-	{500; 5,000; 10,000; 15,000}
8	{Both scopes}	Fixed	Fixed	$\sim U(0,1)$	Fixed (= output Exp. 1)	Fixed (= output Exp. 2)	-	-	Fixed (= output Exp. 7)

Table 15: Expected output and conclusion for each experiment.

Experiment number	Output	Expected conclusion
1	Rankings are visualised per set of indifference thresholds.	Show the (in)stability of the ranking, and choose an indifference threshold.
2	Rankings are visualised per set of preference thresholds.	Show the (in)stability of the ranking, and choose preference thresholds.
3	Rankings visualised per methodology.	Validate the use of DEMATEL-ANP and PROMETHEE II.
4	Present total ranking and the ranking per segment.	Shows the results based on the stakeholder preferences and current data.
5	Visualise how the EBDLS are dependent on iterations.	Choose the suitable number of iterations for experiment 6.
6	Present boxplots showing the impact of the exogenous drivers.	Present the influences of uncertainty about the environment.
7	Visualise the dependency of distribution of weights on iterations.	Choose the suitable number of iterations for experiment 7.
8	Present boxplots showing the impact of judgemental uncertainty.	Present the robustness of the solution concerning stakeholder preferences.

5.3 Experiments 1 and 2: parameter tuning

This paragraph provides results for experiments 1 and 2. First, the indifference thresholds are tuned, and second, the preference thresholds are tuned. The tuning is based on the model's behaviour. Table 14 presents how the tuning is performed. All input parameters remain fixed except for the parameter that is tuned. This parameter is altered based on the range presented in Table 14. Then, the rankings and scores of the raw materials are presented, and the behaviour on the different thresholds is analysed.

5.3.1 Indifference thresholds

The results of the model can be analysed twofold. The influence of the indifference thresholds can be analysed based on the effect of the ranking and the effect on the accompanying scores. Figure 26 presents the effect of the different indifference thresholds on rankings and scores in the left and right graphs, respectively. Moreover, the indifference threshold of 0.25, representing an uncertainty level of 25%, is included to understand the MCDM model's behaviour and is considered an irrelevant threshold for further experiments.

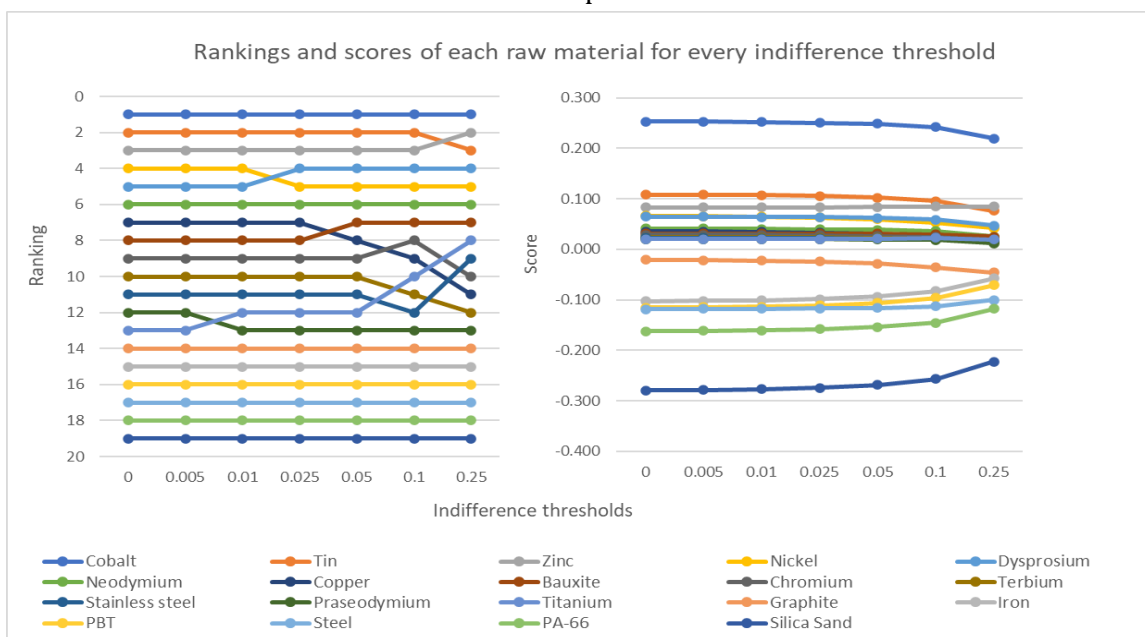


Figure 26: Results of Experiment 1. The graph on the left presents the influence of the indifference thresholds on the ranking, while the graph on the right presents the influence on the global outranking flow calculated in Equation (4.21).

First, it can be concluded that the scores converge when indifference thresholds increase. This is expected, since the sum of the results of the preference function of Equation (4.16) decreases due to an increased range where indifference relationships are modelled. Note that an indifference threshold of 1 would result in complete indifference. Moreover, it can be observed that the top six and bottom five ranked raw materials remain relatively unchanged due to the significant differences in scores. Therefore, the critical range lies between the top six and bottom five raw materials. The most significant changes occur from in between the thresholds of 0.05 and 0.1, which represent data uncertainty of 5% to 10% percent. This means that a few slight differences influence the net outranking flow of the raw materials. Next, a 10% difference significantly influences the data of criteria P1 and S5. The defuzzification and 0.1 indifference threshold result in the indifference of the low/weak and moderate datapoints. This is not desirable. Furthermore, indifference thresholds of 0.005 and 0.01 are too slim to measure indifferences between rounded ratio data. For instance, a supply risk of 0.15 and 0.16 should be rated indifferent, since it is hard to substantiate the difference of 0.01. However, due to the normalisation of Equation (4.13) and Equation (4.14), an indifference threshold of 0.01 is insufficient. The first threshold that models

indifference relationships between those two datapoints and with the lowest probability of interfering with the ordinal data is 0.025. Therefore, this indifference threshold is chosen.

5.3.2 Preference thresholds

The decision-makers have provided that the only relevant preference threshold is the one for the estimated rate of depletion. The preference threshold provided by the segment leaders is 250, meaning that a difference larger than 250 would result in modelling the strict preference relationship. Tuning of this threshold is required to measure the impact of this decision and to understand how the model behaves when applying different preference thresholds. Therefore, different values for the estimated rate of depletion have been tested to present how these thresholds hold. These are presented in Figure 27:

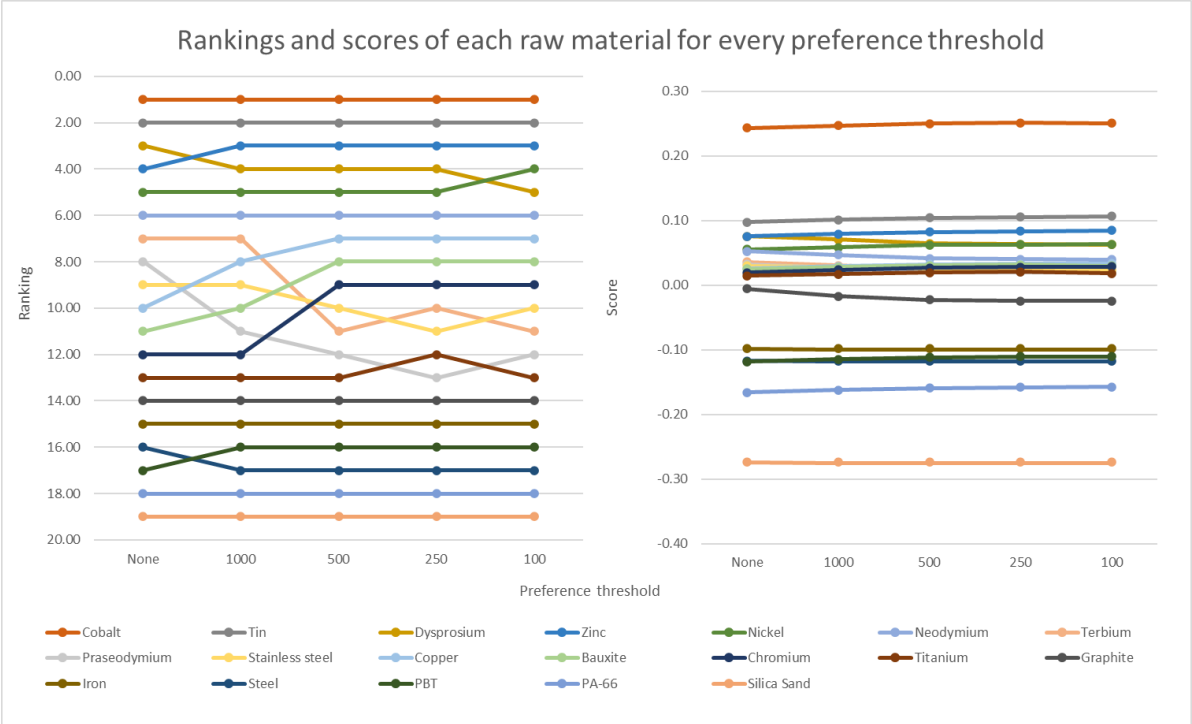


Figure 27: Results of Experiment 2. The graph on the left presents the influence of the preference thresholds on the ranking, while the graph on the right presents the influence on the global outranking flow calculated in Equation (4.21).

Figure 27 shows that this preference threshold does have a relatively significant influence on the rankings, as presented in the left graph of Figure 27. The difference is the largest where the global outranking flows lie closest to each other, with ranks seven until thirteen as the critical range. Moreover, the preference levels for each raw material on criteria E2 can only remain the same or increase due to the linear relationship and the increased area where a strict preference is modelled, which is the opposite of the indifference threshold. Therefore, the scores in the right graph that increase when the preference threshold decreases are caused by raw materials outranking other raw materials on this criterion. These outranking raw materials have relatively lower estimated rates of depletion. Examples are chromium, zinc, bauxite and copper. However, this preference is relatively small due to the large estimated rate of depletions of silicon and iron, for instance. Therefore, the raw materials in the critical range with the largest rates of depletions, like the REEs, are increasingly unfavoured as the preference threshold decreases.

Considering the threshold of 250 that the decision-makers proposed, it seems to be a threshold that suits their preferences. The model follows the rationale that the raw materials that deplete in the upcoming centuries should be considered critical. Many changes in the ranking occur between the range of 500 and 250, which might not fulfil the decision-makers' preferences. Moreover, the range of 250 and 100 presents balanced rankings. Therefore, a threshold of 250 is used.

5.4 Experiment 3: model validation

As presented in Chapter 4 and the previous sections, the DEMATEL-ANP and PROMETHEE II method is complex and requires input from the stakeholders to determine weights, interdependencies, indifference thresholds and preference thresholds. This method aims to fit and tune the method to model the preferences of the decision-makers as accurate as possible. To determine whether the results in the upcoming sections are valid and worth the time and effort, different configurations of MCDM methods are tested, as presented in Section 5.2. Figure 28 presents the results of experiment 3:

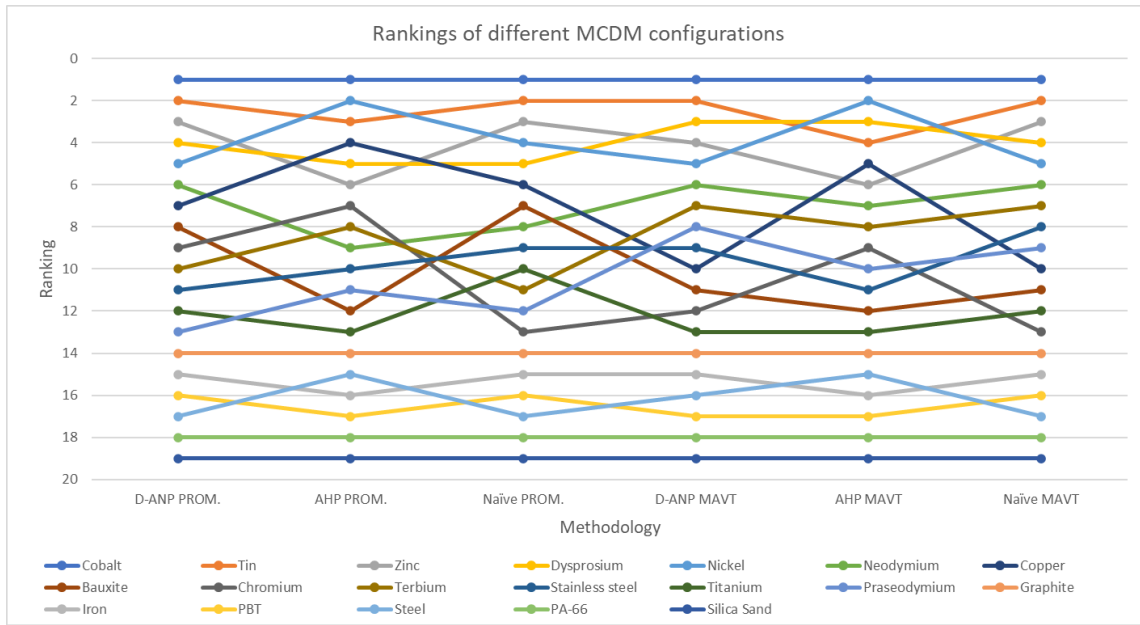


Figure 28: Rankings per configuration. The following abbreviations are used: DEMATEL-ANP is D-ANP, PROMETHEE II is PROM.

The first observation is that cobalt, graphite, PA-66 and silica sand are indifferent to the choice of MCDM methods. As presented in Figures 26 and 27 of the parameter tuning experiments, the scores of these raw materials are isolated for the DEMATEL-ANP and PROMETHEE II methods. Therefore, this method would have been too computationally expensive when this specific problem would have fit the selection problematic, since cobalt is ranked first in every methodology. However, this is a ranking problematic, and it can be concluded that the rankings differ significantly. The absolute differences in the rankings are presented in Table 16. These differences are large considering that four raw materials are relatively isolated based on their scores.

Table 16: Absolute differences between different MCDM methods and DEMATEL + ANP and PROMETHEE II.

Method:	AHP PROM.	Naïve PROM.	D-ANP MAVT	AHP MAVT	Naïve MAVT
Absolute differences in ranking:	30	16	24	26	20

The AHP and PROMETHEE II method shows the most significant differences between the DEMATEL-ANP and PROMETHEE II method. An absolute difference of 30 is relatively large, considering this is measured over the fifteen raw materials, which would result in an average difference of two rankings. This can be explained by the fact that both PROMETHEE II, AHP and DEMATEL-ANP require a large amount of input from the decision-makers. Section 5.1 also presented the differences between the uncorrected and corrected weights, which are large. Moreover, a difference of 16 could also be considered large. For instance, if a top 5 needs to be determined and there are raw materials, like titanium in this case, that differ four places, that

could provide a different top 5 and could result in the fact that decision-makers' preferences are not fulfilled. Thus, the different methods result in significantly different results.

The statement in the introduction of Chapter 3; “... as different MCDA methods deliver inconsistent results ...”, holds true. Chapter 6 discusses the validation of the model further by analysing the results of a questionnaire. Overall, it can be concluded that the methodology is worth the complexity since the stakeholder preferences are considered as much as possible while modelling the interdependencies between the criteria.

5.5 Experiment 4: deterministic ranking

The goal of this thesis is to provide a prioritisation of raw materials in the form of a ranking. At this stage, the parameters are tuned, and the model is validated to a certain extent. The ranking can be calculated based on the current performance evaluation table and stakeholder priorities. The results of the DEMATEL-ANP and PROMETHEE II method per stakeholder are presented in Figure 29:

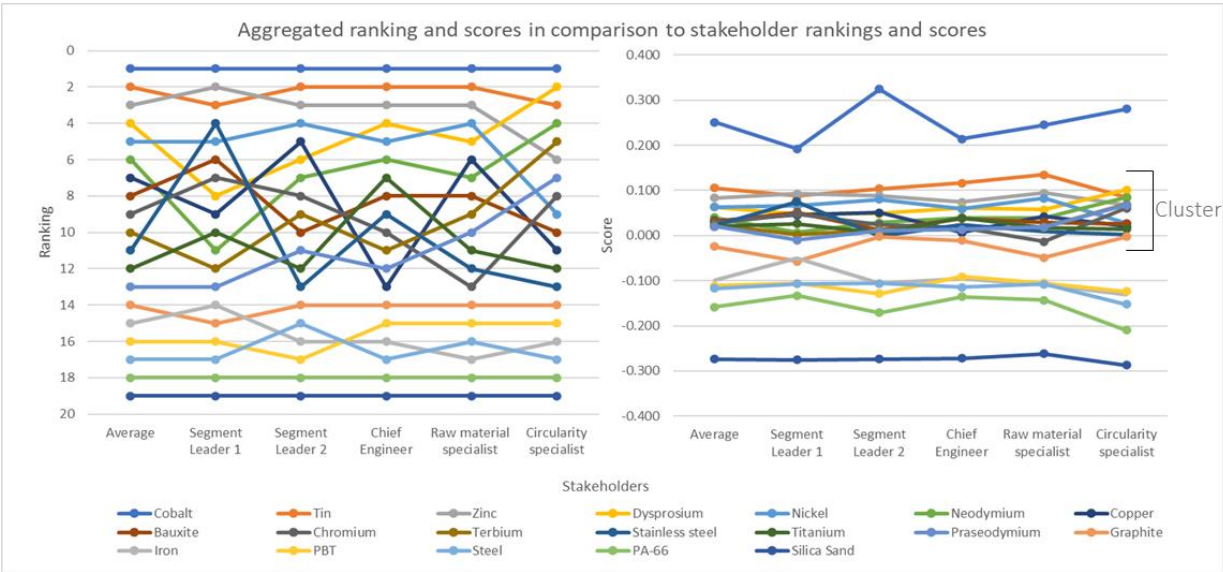


Figure 29: Aggregated ranking in comparison with individual rankings are presented in the left graph. The aggregated scores compared to stakeholder scores are presented in the rights graph.

The global top ten consists of cobalt, tin, zinc, dysprosium, nickel, neodymium, copper, bauxite, chromium and terbium. Cobalt is a clear number 1, as shown in the right graph of Figure 29. Moreover, it can be concluded that silica sand, PA-66, steel, PBT, iron and graphite are the most sustainable or least fit for recycling. Moreover, significant differences in stakeholder preferences can be observed, specifically between ranks two and fourteen. Therefore, the global ranking can be considered an average over significantly different priorities.

The divisive rankings do not provide insights into why Cobalt, for instance, is ranked first. Therefore, it is difficult to translate these rankings into an action plan. Is cobalt ranked first because it is unsustainable? Moreover, if so, how economically, environmentally, or socially unsustainable is cobalt? Additionally, is the recyclability of cobalt considered to be a driver?. To present an answer to these questions, six driver groups are analysed, and the average preference of the raw material on those criteria is calculated on a scale of 0 to 1. These driver groups are the second-level criteria presented in Figure 18. The complete table can be found in Appendix H. The main takeaways from this table can be summarised as follows:

- Cobalt’s number 1 ranking is caused by the social unsustainability and outranks all other raw materials on the geopolitical and human rights criteria.

- The rare earth elements score high on economic dependency and extraction. This can be explained by the expected shortages and monopoly that China has, which is presented by the supply risk criterion, in combination with the dependence of sustainable technologies on those REEs. Moreover, the extraction of REEs is unsustainable due to high water consumption and CO₂ emissions. Dysprosium is the most significant of the four due to higher function criticality and expected supply risks. However, the REEs are not fit for recycling currently.
- Zinc, nickel and copper each have their unsustainable issues. That is why they are ranked in the top next to cobalt and the REEs. However, these raw materials have in common that recycling seems feasible since it drives their ranking to a certain extent.
- The plastics and silicon materials seem relatively sustainable compared to their metal counterparts. However, the recycling processes seem immature compared to the processes of stainless steel and copper.
- Finally, the raw materials driven the most by the 'recycling feasibility' criteria, like bauxite, iron and chromium, are relatively sustainable. Recycling seems to be feasible. Therefore, these materials can be considered as low hanging-fruits. These low hanging-fruits could have a significant contribution, even though recycling a kilogram of raw materials will not have as significant contributions to becoming more sustainable compared to the materials in the top 5. Moreover, these materials seem to be the materials that are used most in the ED&C and MDS scope.

Overall, the ranking combined with the explanation of how these rankings are established provides insightful results. Moreover, it is interesting to see the division between the individual stakeholders. Furthermore, the results per segment and a discussion on rank reversal are presented in Appendix I. The results per segment are similar to the overall ranking, and rank reversal is not a significant issue, as explained from a theoretical perspective in Section 4.2.3.

5.6 Experiments 5 and 6: scenario planning and Monte Carlo approach

This section discusses the influence of uncertainty about the environment on the multi-criteria decision-making problem. Scenario planning is executed in Section 5.6.1. Then, the Monte Carlo process is executed in Section 5.6.2 based on the scenarios created in Section 5.6.1.

5.6.1 Scenario description and implementation

In short, the scenario themes are created according to the two most significant drivers of the segment strategies as identified by the PESTEL analysis. Then, the narratives are formulated by identifying the effects of the development directions on the remaining drivers, like CO₂ emissions, legal obligations, and technology adoption. The complete narratives can be found in Appendix J. Moreover, the development directions and scenario themes including an itemised summary of the narratives that should be created according to steps 2, 3 and 4 of Table 11, are summarised in Figure 30.

The final step is to use the scenario themes. These scenario themes can be used by selecting criteria that are expected to change based on these scenarios. Moreover, the possible evaluations can be estimated based on the criterion and the triangular distributions in Figure 17. Following the segment leaders, four criteria have been chosen. The developments of the context analysis and additional sources have been used to estimate possible directions where the criteria could move towards.

Four distinct scenario themes

X-axis: Level of progressiveness of political organs

Y-axis: Level of supply risk

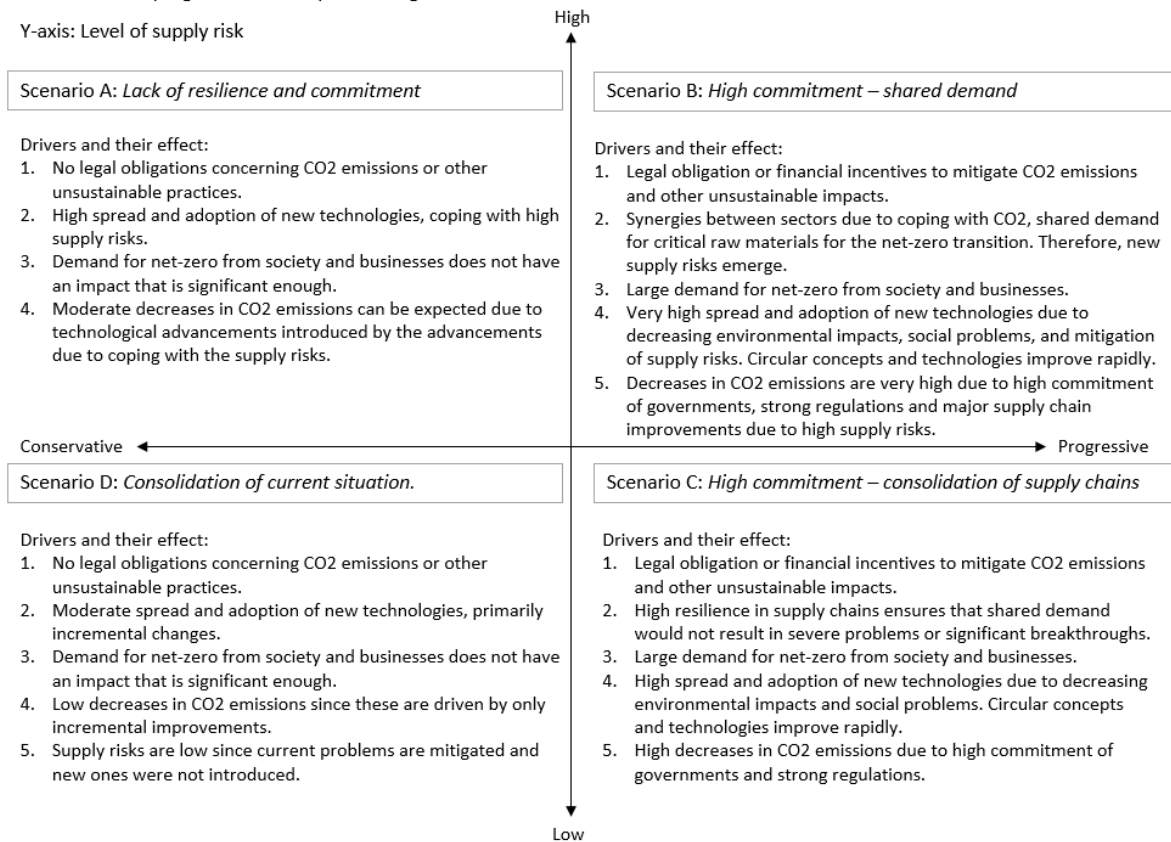


Figure 30: Four scenarios based on the two most significant drivers including a summary of the narratives.

Then, these scenarios presented above can be used to select some criteria that can be adjusted to these scenarios. The following criteria have been selected:

- Supply risks (“P4”): Supply risks are expected due to them becoming commonplace and the shared demand for critical raw materials for the net-zero transition.
- Recycle rates (“P8”): The shared demand for critical raw materials necessary for the net-zero transition, combined with the already existing supply risks for some of these materials, might result in technological advancements and an increased need for recycled materials. Moreover, progressive governmental policies might demand better recycling rates.
- CO₂ emissions (“E2”): CO₂ emissions are currently the most significant KPI to measure a company's sustainability. Therefore, this criterion will be altered according to the scenarios.
- Residual end-of-life waste (“E8”): The inclusion of the residual end-of-life waste is added for the same reasoning as “P8”. However, this criterion is specified for the automotive industry. Therefore, recycling rates concern data of all industries. However, the residual end-of-life waste concerns data for the automotive industry.

Then, the performances per alternative are altered according to Table 17. A distinguishment is made between raw materials and net-zero critical raw materials. McKinsey & Company (2022) lists these net-zero critical raw materials.

Table 17: Selected criteria according to scenario analysis combined with the estimates and supporting sources.

Criterion	Pessimistic estimate	Most probable estimate	Optimistic estimate	Main source for estimates
P4 – Supply risks	- +100% for net-zero critical raw materials - +50% for other raw materials	- +50% for net-zero critical raw materials - +25% for other raw materials	- +10% for net-zero critical raw materials - +0% for other raw materials	(McKinsey & Company, 2022)
P8 – Recycle rate	- Remains the same	- Add 25% points where possible	- Add 50% points where possible	(Fact.MR, 2020)
E2 – CO ₂ emissions	- Remains the same	- -30% (2030)	- -50% (2030)	(McKinsey & Company, 2020)
E8 – Residual end-of-life waste	- Remains the same	- Decreases 1 level where possible	- Decrease two levels where possible	(Fact.MR, 2020)

Finally, some measurements are not possible to improve. For instance, suppose that the recycling rate is 90%, then it is impossible to increase it by more than 10%. However, if supply risks are normalised on a 0-1 scale, then the estimates could exceed one and be normalised again to fit the PROMETHEE II method. In the case of ordinal data points, increasing or decreasing a datapoint might also not be possible. This is indicated in Table 17.

5.6.2 Monte Carlo simulation results

The scenarios and accompanying estimates are determined. Thus, the Monte Carlo Simulation can be executed. First, the number of Monte Carlo trials has to be determined. Equations (4.27) and (4.28) are followed, and a random number is drawn between the optimistic and pessimistic estimations. This will be done t_1 times for each criterion. Figure 31 presents the distributions that result from the completion of Experiment 5:

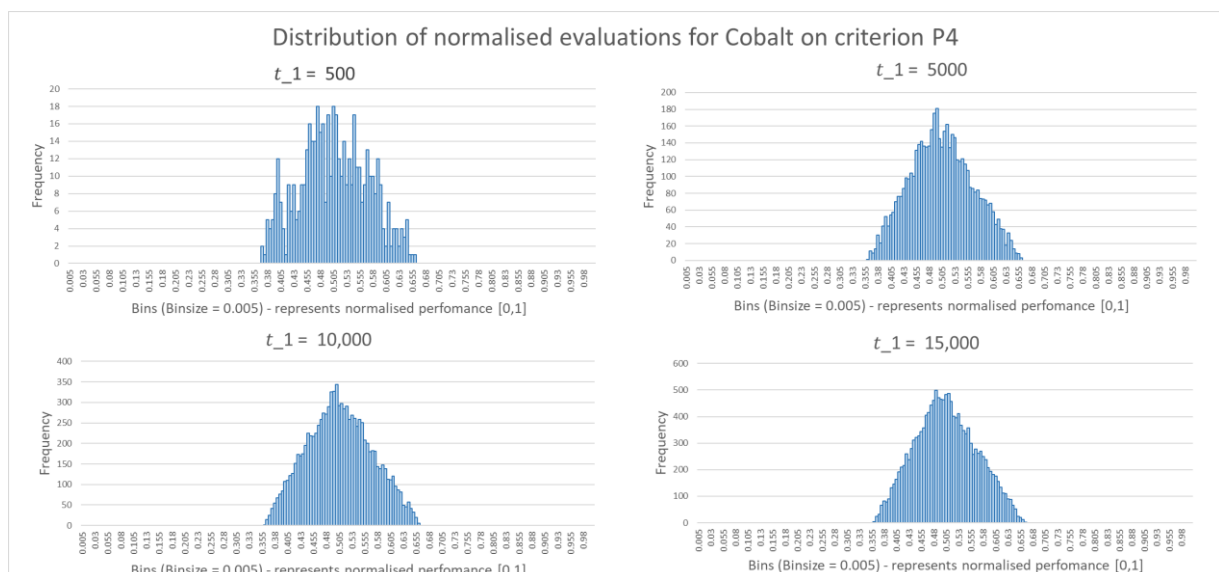


Figure 31: Distribution of evaluations for Cobalt on criterion P4. Number of Monte Carlo iterations is varied to determine how many iterations of Monte Carlo should be run.

As expected, the distribution becomes smoother when the number of Monte Carlo iterations increases. $t_1 = 500$ and $t_1 = 5000$ is not accurate enough compared to $t_1 = 10,000$ and $t_1 = 15,000$, which seem to be similar. Therefore, $t_1 = 10,000$ is chosen since it provides slightly quicker results compared to $t_1 = 15,000$, and it is used in the experiments performed by Baudry et al. (2018).

Then, the Monte Carlo simulation can be performed. The results of the simulation are presented in the boxplot presented in Figure 32:

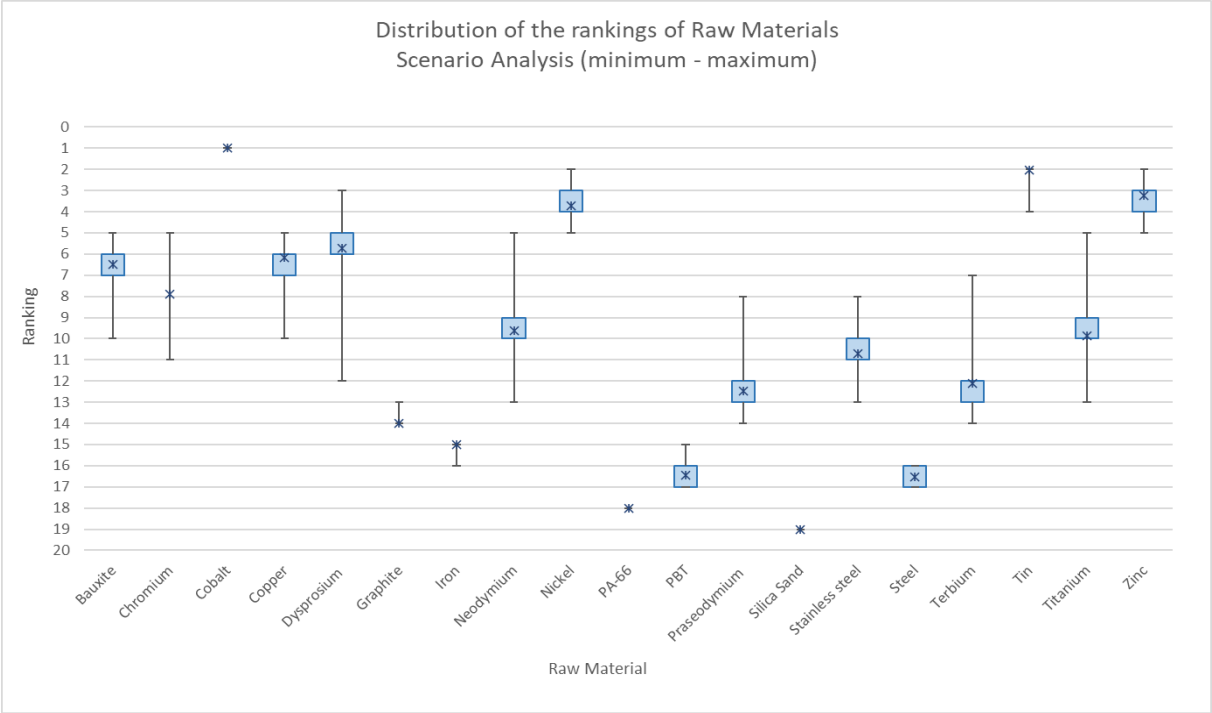


Figure 32: Boxplot of the results of the Monte Carlo simulation when simulating the influence of uncertainty about the environment on four different criteria using triangular distributions. The whiskers present the range of the rankings. Thus, it presents how the rankings are distributed from the minimum to maximum ranking. The averages are marked with a cross (X).

The goal of this Monte Carlo simulation was to combat uncertainty about the environment. The results can be used to achieve this goal by measuring how the rankings change based on the triangular distributions. In this case, all interquartile ranges are either 0 or 1, resulting in a stable ranking. However, the distribution of rankings of the REEs and titanium have long whiskers, meaning there exist some combinations of evaluations that would change their ranking significantly. Considering the four criteria, the REEs had the most significant changes in the rankings. Therefore, the most significant changes occurred in the range considered the most critical in Figure 29. Furthermore, the REEs and Titanium had the worst performances on the four criteria. The room for improvement for these four raw materials is the largest, resulting in large tails. The top five and bottom six raw materials were barely influenced by the change in criteria. Therefore, it can be concluded that uncertainty about the environment does not influence the ranking significantly in this case.

It can be argued that the evaluations have been altered relatively. This would mean that the rankings would remain the same according to relative evaluations. The downside of this method causes this; for 19 raw materials and 26 criteria, 1482 estimations should be made. This is not possible due to time limitations. However, the method is promising, and the inclusion of scenario analysis made it possible to derive the estimates logically.

5.7 Experiments 7 and 8: Monte Carlo sensitivity analysis

Finally, judgemental uncertainty is a type of uncertainty that is relevant in every methodology where input from stakeholders is requested, primarily if it covers preferences. Therefore, a sensitivity analysis is executed according to Experiments 7 and 8. The random weight distributions are generated based on Equations (4.29), (4.30) and (4.30). To determine how many iterations are necessary to provide reliable results, four different levels for the number of iterations t_2 are tested and visualised in Figure 33:

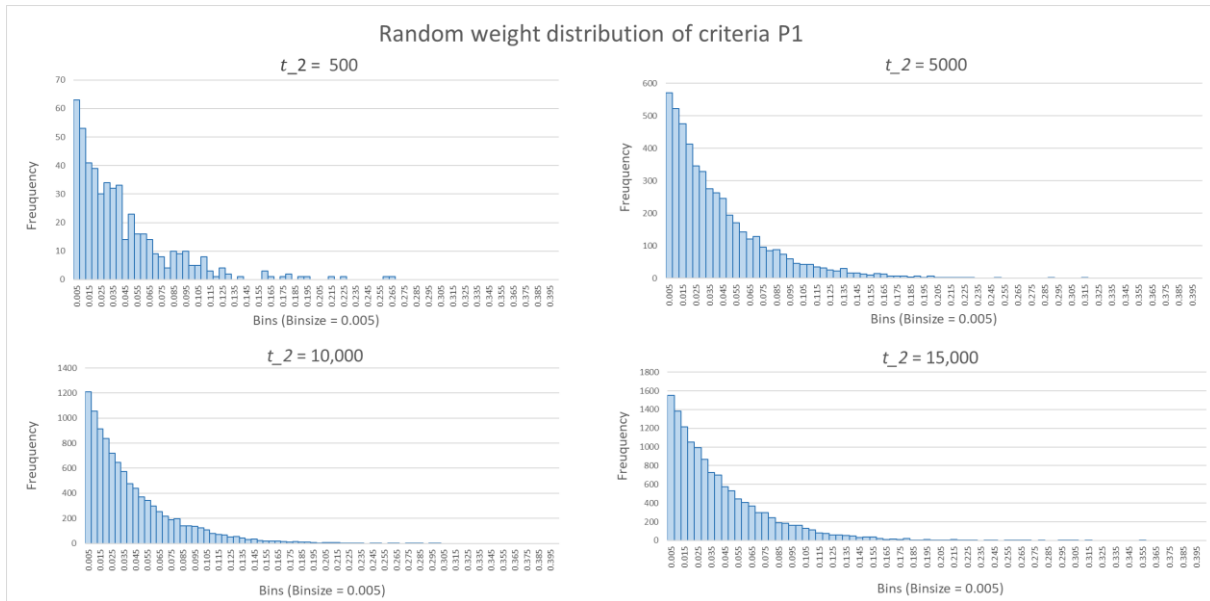


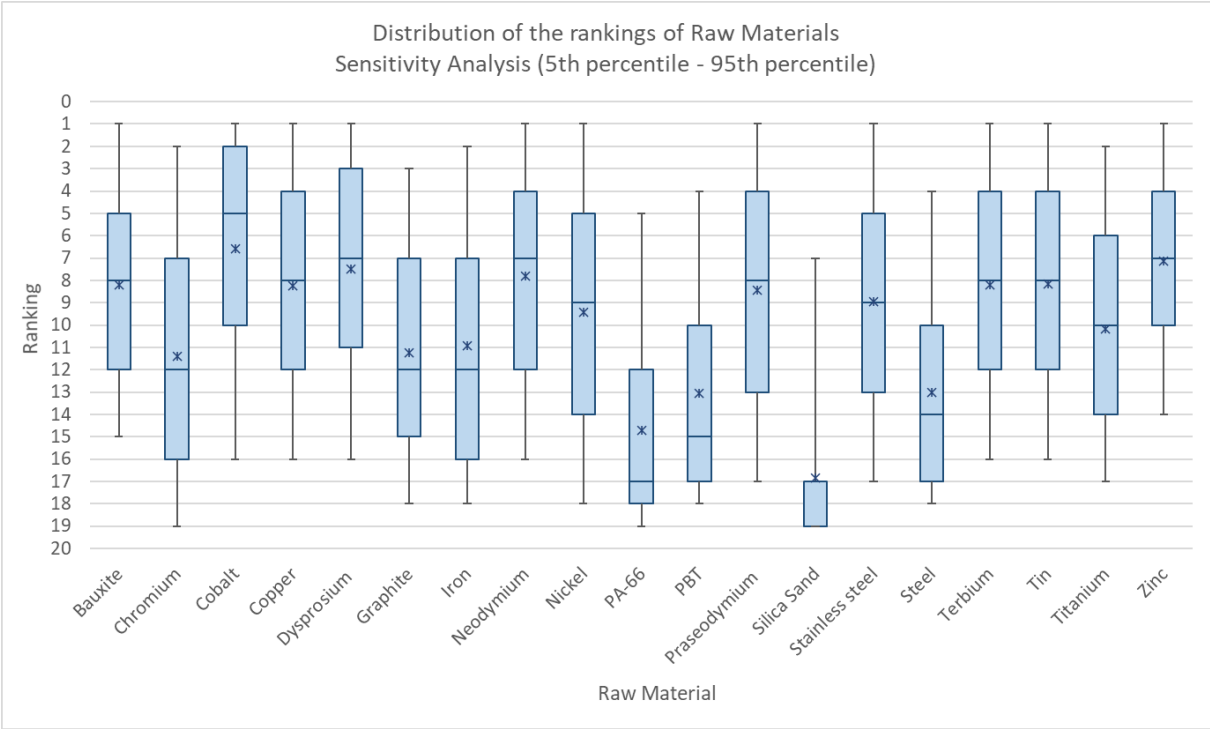
Figure 33: Distribution of weights for criterion P1. Number of Monte Carlo iterations is varied to determine how many iterations of Monte Carlo should be run.

The shape of the distribution can be explained by the fact that random numbers are drawn from a uniform distribution, and the actual weights are determined by taking the difference between these random numbers. Moreover, the sets of weights are relatively similar, as shown by the significance frequencies around $1/26 \approx 0.039$, which is the naïve weight. Moreover, extremes are also investigated, as presented by the long tail. Finally, the fact that the modulus is very low and not close to 0.039 can be explained by the fact that relatively large weights, e.g. weights above $2 \times 0.039 = 0.078$, have to be compensated by more than one criterion.

Furthermore, $t_2 = 500$ and $t_2 = 5000$ are not accurate enough compared to $t_2 = 10,000$ and $t_2 = 15,000$, which seem to be similar. Thus, $t_2 = 10,000$ is chosen since it provides slightly quicker results compared to $t_2 = 15,000$. The rationale presented in this section is similar to the determination of t_1 in Section 5.6.2.

Figure 34 presents the results of the Monte Carlo simulation in the form of a boxplot:

Figure 34: Boxplot of the results of the Monte Carlo simulation when simulating the influence of judgemental uncertainty.



The whiskers present the range of the rankings from the 5th to 95th percentile. The averages are marked with a cross (X).

The boxplots show a vast range of rankings that could result from the MCDM analysis. Therefore, the influence of judgemental uncertainty should not be underestimated. Moreover, Section 5.5 presented significant differences in the rankings per stakeholder. These differences have a significant impact on the ranking. Every stakeholder has a different background and therefore, different priorities and ideas about what sustainability of raw materials entails. The priorities represent what the stakeholders value today. However, priorities change. Therefore, the priority workshop should be executed regularly. Moreover, it can even be argued that the level of interdependencies between criteria changes. Therefore, it might also be worthwhile to re-evaluate the interdependencies as well.

Considering the ranking and recommendations to the OEM X, it can be concluded that there are weight combinations for every raw material that would result in a top ten ranking or even a first-place ranking for some raw materials. Therefore, there are reasons to start recycling or introducing other circular concepts of the 9R-Framework or Lansink’s Ladder for each raw material. The raw materials that receive the first-place ranking in more than 5% of the iterations are bauxite, cobalt, copper, the REEs, stainless steel, tin, titanium, and zinc. Furthermore, of the materials most suitable for recycling, bauxite and stainless steel seem to be the most suitable, and thus are the low-hanging fruits.

5.8 Conclusion

Eight experiments have been performed to fulfil eight individual questions. The results of these experiments contribute to answering the research question:

'What conclusions can be drawn, and what recommendations can be formulated based on the multi-criteria decision analysis?'

The first conclusion that is drawn concerns the deterministic ranking. The global top ten consists of cobalt, tin, zinc, dysprosium, nickel, neodymium, copper, bauxite, chromium and terbium, which each deserve focus. The fact that the model ranks cobalt and tin as first and second, while these receive significant interest in the OEM X sustainability strategy as shown in Section 2.2.1.3, is validation that the model fits the decision-makers' preferences. Moreover, only tin, zinc, nickel, copper, bauxite and chromium are suitable for recycling. One major indicator of the feasibility is that scrap prices are available, which are used to calculate the market-price-based allocation. The other raw materials, cobalt and the REEs, are ranked high while currently being infeasible for recycling. This means that other circular concepts should be applied. Primarily, the "smarter product use" of the R-Framework of Figure 11 should be prioritised, which concerns the refuse, rethink, and reduce concepts. These ensure that these raw materials do not enter the supply chain. Moreover, reading that there are sustainability initiatives to mitigate cobalt and tin in Section 2.2.1.3 seems fitting. Additionally, reducing the dependability on REEs by reducing the usage of these REEs for the MDS segment, as stated in Section 2.2.1.2, seems a logical choice.

Furthermore, the refuse, rethink, and reduce strategies could be generalised to make the results even more relevant. For instance, as McKinsey and Company (2022) and Table 3 show, many REEs are critical to the renewable energy industry. These REEs are critical for the magnets used in wind and the electromobility industries. Therefore, these synergies could be exploited, and developments in one of these sectors could prove relevant in the other sector. Moreover, one of the three mechanics mentioned in Section 2.2.2.3 is likely to play out, especially material substitution and technology substitution. Therefore, McKinsey & Company recommend adapting technology rollout plans to mitigate the effects of the increased demand for some raw materials caused by the net-zero transition. The top ten raw materials presented by the MCDM model should be covered in this plan.

Furthermore, OEMs should send clear demand signals and secure raw material supply through off-take agreements or partnerships with raw material suppliers or recyclers. These are essential for BEV OEMs to ensure aggressive growth while becoming increasingly more sustainable regarding the economic, environmental and social sustainability aspects. This is especially important for raw materials that score high on the economic dependency criteria, like the REEs. Therefore, these aspects could be added to the segment business plans next to the mentioned points in Chapter 2.

Moreover, the plastics and silica sand, the raw material for silicon applications, score very low. There are not many issues from a sustainability perspective, but these materials do not score well on the recycling feasibility criteria. However, a conversation with a sustainability engineer focused on plastics mentioned that PA-66, for instance, can be mechanically recycled. Therefore, it might be worthwhile to investigate the possibilities of recycling business models around these plastics. Recycled plastics might prove helpful when decarbonizing supply chains.

The conclusions that have just been made focus primarily on the deterministic results. For the mid- and long-term it has been evaluated what the effects are of changing four of the twenty-six criteria according to identified scenarios. The results proved to be stable. Further research is needed to see the distribution of rankings if all 1482 estimations on all criteria were done by raw

material experts in combination with elaborate scenarios. These results would be relevant for the technology rollout plan to see where technology or material substitution can be expected or where it is most needed. Moreover, it could be used for the off-take agreements as an evaluation tool. For instance, an off-take agreement for sustainably sourced cobalt would prove incredibly useful. However, its relevance for titanium is discussable due to the large tails for the potential rankings. For this study, however, the most obvious changes in criteria have been evaluated, and the position of raw materials in the ranking remains stable. Therefore, potential off-take agreements and technology rollout plans could include the top-ten raw materials determined by the MCDM method.

Finally, a more significant issue in both the mid- and long-term concerns the stakeholder priorities. The ranking presented in Figure 29 already shows significant differences in stakeholder alignment. The priorities might be different for the different functions and segments. For instance, priorities for one segment leader might be different compared to the other since cobalt and REEs are not used in that segment. Figure 34 presents that the misalignment of priorities could result in significantly different results. Therefore, priorities and maybe the interdependencies should be re-evaluated regularly. Otherwise, the results would not fit the preferences of the decision-makers properly. Off-take agreements and technology rollout plans should be created cross-functionally since these would influence multiple stakeholders. Therefore, aligning first between the stakeholders and then re-evaluating the results is recommended.

6 Conclusions and recommendations

The final chapter aims to summarise the research findings and draw general conclusions. Moreover, theoretical and practical contributions are provided. Then, a short discussion is provided to discuss some limitations. Finally, recommendations and future research are covered.

6.1 Conclusion

This research has been performed for OEM X in the ED&C and MDS segments to present recommendations on increasing the sustainability of their components from a raw material perspective. The assignment is formulated as follows:

'Map the critical raw materials and relevant developments in the Battery Electric Vehicle (BEV) supply chain with a focus on the MDS and ED&C segment and present recommendations in the form of an action plan based on Multi-Criteria Decision Analysis (MCDA) on what OEM X and its supply chain partners should prioritise to recycle.'

This assignment has been completed successfully. The critical raw materials according to industry and developments in the BEV supply chain are presented in Chapter 2. Moreover, the MCDA analysis has been performed, and the DEMATEL-ANP and PROMETHEE II method is implemented to fit the strong sustainability concept. Moreover, the assumption that criteria are independent does not hold when using the twenty-six criteria. ANP solves that issue. Finally, the hybrid copes with uncertain data to a certain extent by using indifference thresholds. The only issue that remains is rank reversal. However, it has been argued, both in theory in Section 4.2.3 and practically in Appendix H, that rank reversal does not have major implications since major rank cases of rank reversal are not found when comparing the results of the analysis for the raw materials of both segments with the results of the single segment analyses. Moreover, two cases of uncertainty have been identified: uncertainty about the environment and judgemental uncertainty. These are mitigated using the scenario analysis and Monte Carlo simulation approach, and the sensitivity analysis based on a Monte Carlo analysis.

Furthermore, the results of the DEMATEL-ANP and PROMETHEE II method and the Monte Carlo simulations are summarized by using the results of the analyses and fitting these results into the context of the decarbonization of supply chains. This combination results in a more concrete action plan consisting of tangible actions. These actions include that the raw materials that are most unsustainable, which are cobalt and the REEs, prove to have recycling processes that are not mature. Therefore, other concepts of the 9R-Framework or Lansink's Ladder must be introduced. The other raw materials in the top ten, tin, zinc, nickel, copper, bauxite and chromium, are more suitable for recycling. However, the design for circularity approach would also be recommended for these raw materials, as preventive measures rank higher in Lansink's Ladder. Finally, technology rollout plans, a suggestion by McKinsey & Company (2022), could include benchmarks of other sustainable technologies, like renewable energy and electromobility technologies. Both technologies share the same critical raw materials, and both the electromobility and renewable energy sectors aim to decarbonize industries.

The practical relevance is two-fold. First, the model results could increase the sustainability of the ED&C and MDS segments. Aggressive growth is expected for the sales of battery electric vehicles. Therefore, increasing the sustainability of a truck might not provide significant results in the short term compared to what the results could be in the long term. Every improvement that is made now to make a battery-electric truck more sustainable will benefit the long-term sustainability of OEM X significantly. For instance, social sustainability is violated using cobalt and economic and environmental sustainability is violated by using REEs if OEM X does not reduce, rethink or refuse the usage of cobalt and the REEs. Moreover, OEM X can continue using the other raw materials in

the ED&C and MDS segment. However, OEM X and its supply chain partners should push the use of recycled materials, especially for the top ten raw materials tin, zinc, nickel, copper, bauxite and chromium. Moreover, the focus on recycled materials should coexist with the other circular concepts presented in the R-Framework and Lansink's Ladder as proposed, since there is no single solution to solve the unsustainable issues related to the raw materials.

Second, the model can also be generalised and utilised in not only the ED&C and MDS segments but also in other segments of the OEM X, like the ESS (Energy Storage Systems) segment, which covers, for instance, many critical raw materials used in batteries, like Lithium and Cobalt. The DEMATEL-ANP and PROMETHEE II method seems suitable for the sustainability assessment of raw materials. Using the hybrid method in different segments could achieve the same practical relevance for the ED&C and MDS segments.

Furthermore, the practical relevance for the ED&C and MDS segments has been assessed using a questionnaire. This questionnaire and the results are presented in Appendix K. The nine statements in the questionnaire were formulated based on the Unified Theory of Acceptance and Use of Technology (UTAUT) by Vinkatesh et al. (2003). This questionnaire did not focus on technology usage, but on the relevance of the results provided by the MCDM methods and further analyses. Nine respondents presented their views on a scale of one (strongly disagree) to five (strongly agree). The averages ranged from 4.11 to 4.56. To give an example, the statement 'I intend to use the results during the next six months' had an average of 4.44, presenting that these results of this thesis are used throughout the next six months.

Then, the theoretical contribution of the literature review is discussed in detail in Section 3.5. The theoretical contribution of the whole thesis is as follows. The reproducibility of the methodology is ensured by providing detailed descriptions of the methods used and emphasizing the reasoning behind the choices made in this thesis. The most significant contributions concern the first implementation of DEMATEL-ANP and PROMETHEE II in material selection, let alone sustainable material selection. Again, the method adheres to the strong sustainability concept, models interdependencies and allows for data uncertainty by the indifference thresholds. Moreover, the following case study has proven that it provides results that differ significantly compared to other methods, like AHP and PROMETHEE II, as shown in Section 5.4. The positive results of the questionnaire strengthen the reasoning that the DEMATEL-ANP and PROMETHEE II method is able to meet the needs of the decision-makers better compared the alternatives that were tested.

Furthermore, using both the scenario planning and Monte Carlo simulation approach and the sensitivity analysis using the Monte Carlo approach is shown to work well in practice. Especially the inclusion of the scenario analysis of Siebelink et al. (2018) is helpful since the two segment leaders could determine how the evaluations in the performance evaluation table might be developing without having in-depth knowledge about each raw material on each criterion, especially since Baudry et al. (2018) mentioned that the determination of the Expert-Based Distribution Laws (EBDLs) is the most critical. It can be concluded that the scenario planning approach bridges the gap between the Monte Carlo simulation and the MCDM (multi-criteria decision-making) method.

Finally, rank reversal is a concept that is sometimes discussed when outranking approaches are used. However, this research also provides theoretical and practical substantiation that it does not pose significant problems in this ranking problem. Rank reversal could pose a threat, however, when a selection has to be made, instead of a ranking. Though, the output of this research is a prioritisation based on the ranking problematic.

Overall, this research ensures that the focus is shifted towards the right raw materials in the ED&C and MDS segments to mitigate unsustainable practices. The detailed methodology ensures that the DEMATEL-ANP and PROMETHEE II hybrid can be replicated with the two Monte Carlo simulations. The practical relevance and theoretical novelty summarise the relevance of this thesis.

6.2 Discussion

The previous section made it seem that there were no limitations or drawbacks to the methodology. This section aims to provide a critical note to the previously drawn conclusions. Moreover, it serves as a basis for the recommendations and suggestions for future research.

Multi-criteria decision-making methods rely on the input of stakeholders. Following the workshop presented in Appendix C, the weight generation method was generally well-received. However, there were some critical notes:

- The method of determining inconsistencies favours moderate opinions. There is a difference in the outspokenness of people. Moreover, inconsistencies are calculated based on multiplicative calculations. Therefore, moderation would result in less significant deviations. Thus, people who are less expressive in giving their opinion have been more consistent in this research. This rationale might be generalisable since it seems logical.
- The random indices used in Equation (4.10) to calculate the consistency of the pairwise comparisons are presented for matrices ranging from a 2x2 size to a 10x10 size. The two largest matrices that have been used in this research, had a size of 6x6. In practice, not a single stakeholder could fill this in consistently. The stakeholders could all see the inconsistencies in their judgments and provide the proper feedback to account for them. However, if the Multi-Actor Multi-Criteria Analysis (MAMCA) framework is used for large stakeholder groups, having decision matrices that exceed four or five criteria might not be recommended. Then, creating a hierarchy to decrease the number of pairwise comparisons should present more consistent results.

Furthermore, the use of PROMETHEE II has been well documented in the literature. However, the literary sources fail to describe elaborate methods to derive the best-tuned preference and indifference thresholds that fit the decision makers' preferences. This thesis has provided a simple method to tune the thresholds by incorporating the decision-makers' preferences into numerical experiments.

Then, a critical note has to be placed on using MCDM methods to measure sustainability. Rowley et al. (2012) mention that it is important to recognise that an MCDA introduces subjectivity through the incorporation of subjective values since the preferences of stakeholders are considered, and through the analyst's methodological choices at each stage of the process. In this case, it should be acknowledged that the analyst's methodological choices might have introduced some subjectivity. However, the methodological choices have been well-substantiated, as the introduction of Chapter 3 explains. Therefore, the implicit subjectivity has been combatted as much as possible.

Finally, there were some limitations during the research. The most obvious limitation concerns the available time. For instance, it has not been possible to derive three estimates for more criteria and alternative combinations. Although the scenario planning approach made it easier to determine relatively accurate estimations, it was not possible to include more. Moreover, another limitation concerns data quality. The dependency on publicly available data resulted in some missing datapoints. Therefore, some datapoint in the evaluation performance table have been derived based on other datapoints or have been estimated by professionals.

6.3 Recommendations and future research

This section is split up into two perspectives. First, the perspective of OEM X is discussed to increase the practical relevance by providing directions. Second, the literary aspect is discussed.

The results provided in Chapter 5 have already been presented in the form of recommendations that could be implemented in the segment business plans in Section 5.8 and Section 6.1. These results could also be used to find further synergies in industries battling unsustainable practices, like the renewable energy industry. These industries could provide new insights and feedback on the results, which could iteratively improve the results and the decision-making process.

Moreover, the quality of the results of the methods can be improved by investing more time in increasing the data quality. This entails that the data in the performance evaluation table could be improved. Next, time should be allocated to increase the quality of the estimates and the number of criteria assessed for the scenario analysis and Monte Carlo simulation. Furthermore, the conclusion is drawn that the changes in priorities influence the MCDM method's outcomes significantly. Therefore, stakeholders should align and re-evaluate these priorities consistently. Then, changing priorities are accounted for.

Next, the literary perspective is discussed. This thesis provided some theoretical contributions, and therefore, these contributions could be further researched. For instance, it would be interesting to see a continuation in the study of combining scenario analysis with Monte Carlo simulations in the context of MCDM. Another case study would increase the theoretical significance of this model and consolidate that it can be used to battle uncertainty about the environment.

Furthermore, there are no guidelines for determining indifference and preference thresholds while valuing the stakeholders' preferences, except for asking for the thresholds directly or applying elicitation methods. Therefore, it would be valuable for future researchers using PROMETHEE II to know how to determine these thresholds based on the available data and the stakeholders' preferences.

Overall, this thesis does not only provide relevant results and conclusions, it also proposes opportunities for further research. The combination of theoretical and practical research opportunities might fit the interests of another thesis student.

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Appendix A: Description of subsystems ED&C and MDS segment

The ED&C and MDS segments' subsystems are presented in Figures 35, 36, and 37.

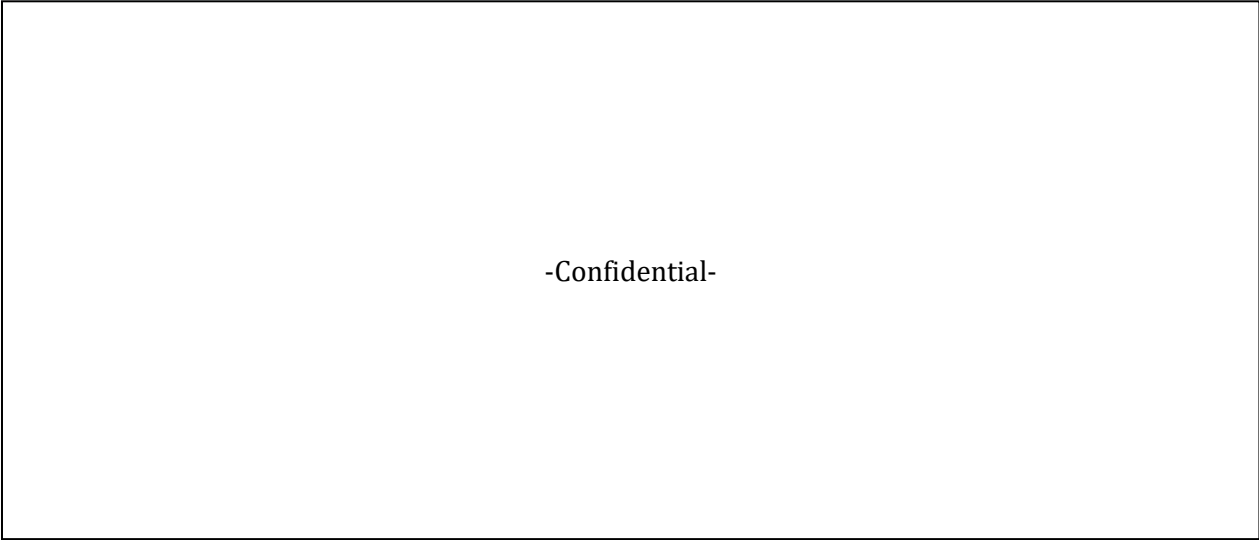


Figure 35: Electric machine and its subsystems.

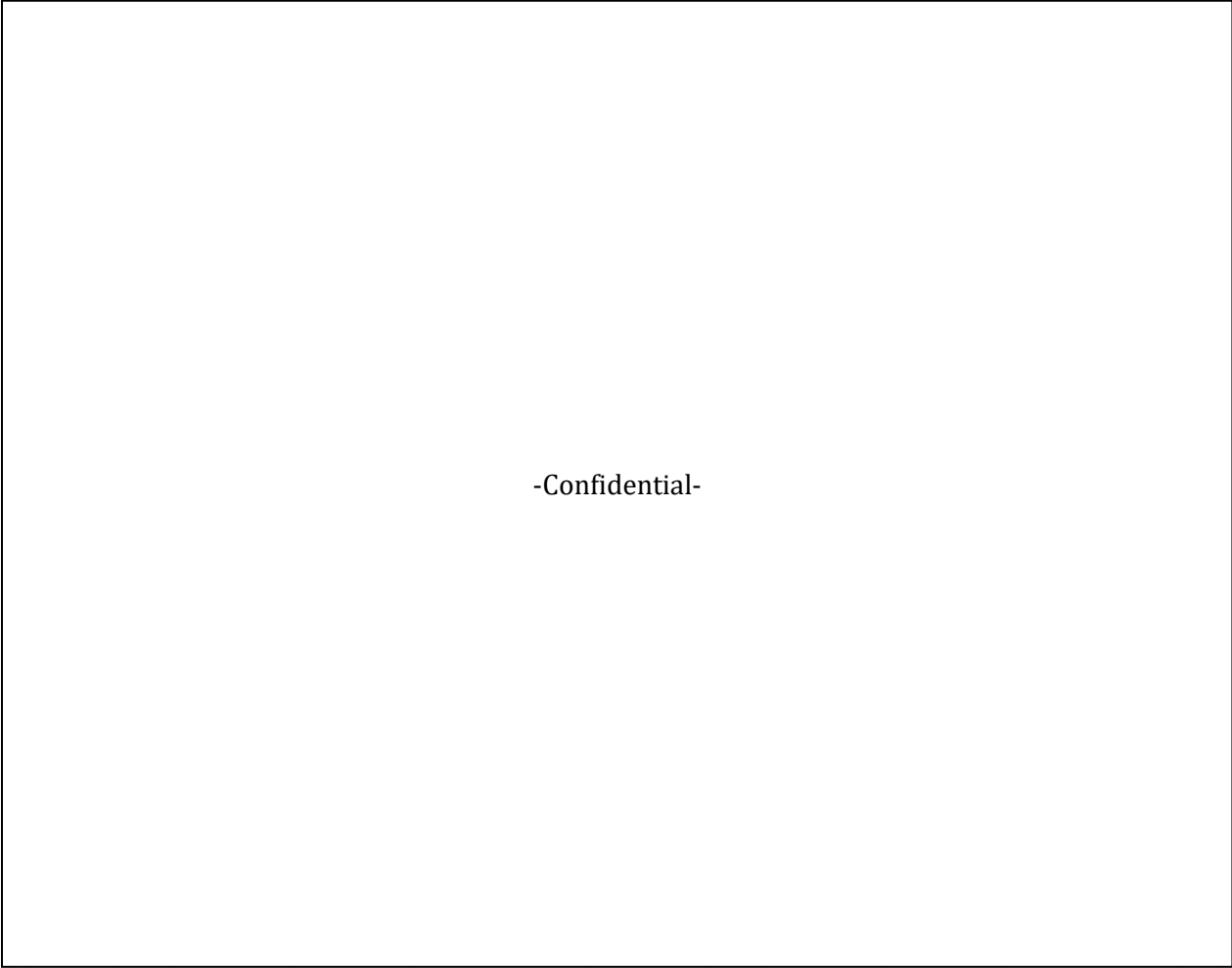


Figure 36: Electric motor drive and its subsystems.

-Confidential-

Figure 37: ED&C sub-systems

Appendix B: Sustainability assessment of copper

Figure 38 provides an overview of how OEM X currently assesses raw materials.

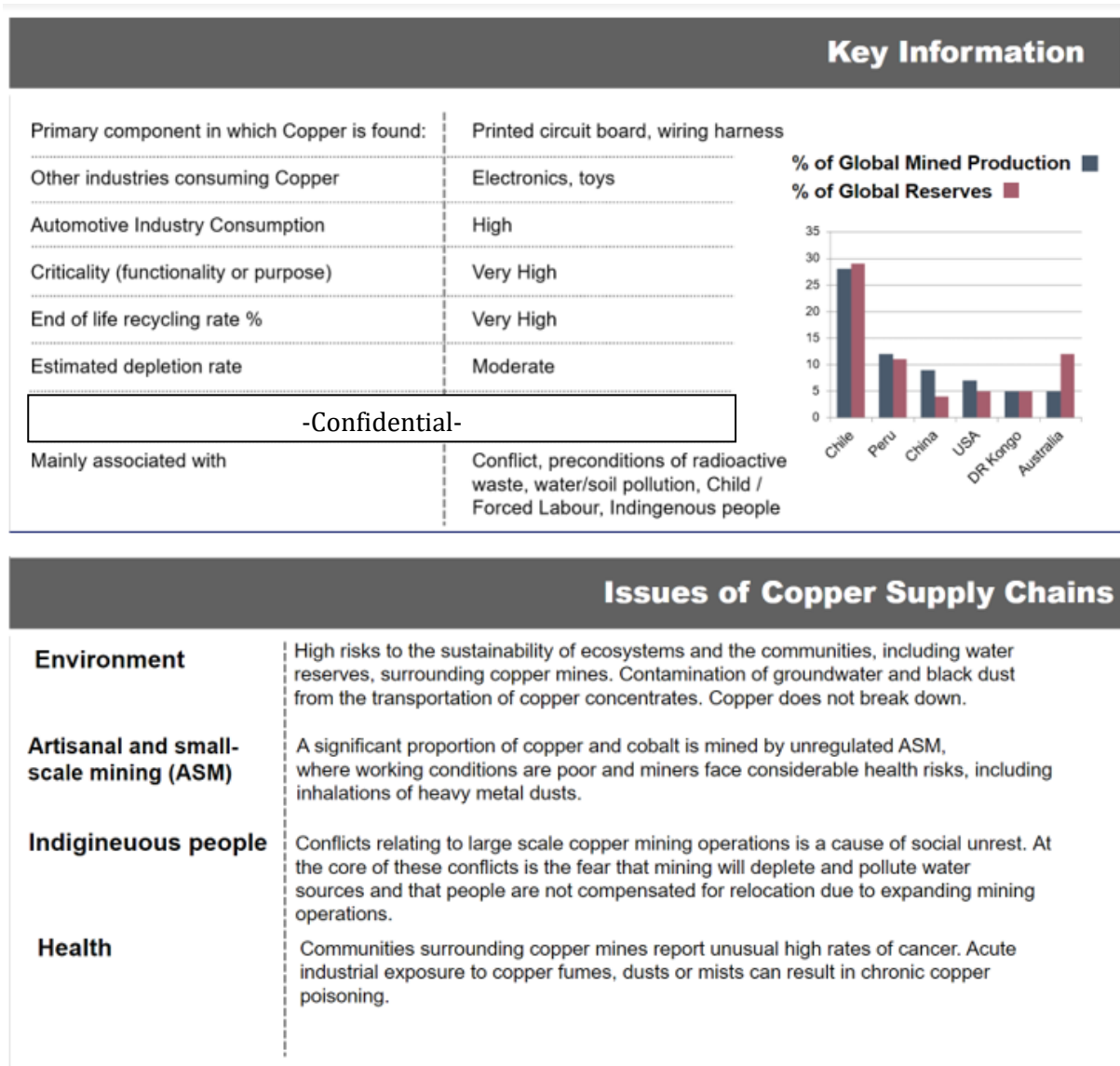


Figure 38: Example of an overview of the sustainability assessment of raw materials, retrieved from OEM X (2020).

Appendix C: Workshop design

The workshop is designed according to Macharis et al. (2012). Step 3 of the framework discusses the definition of criteria and weights. The first step is developing a hierarchical criteria tree, as presented in Figure 18. Moreover, the criteria should be created based on literature and reviewed by stakeholders for completeness, conciseness and ambiguities. Therefore, the first question that will be asked is:

‘Are all criteria concisely and unambiguously defined and all criteria combined all-encompassing?’

Every criterion is read individually by the stakeholder to ensure that the criteria are interpreted correctly. Based on their feedback, additional criteria might be added or removed.

Then, the DEMATEL-ANP methodology is applied. The interdependencies are objective measures presenting the relationships between certain criteria. These are only determined using the input of the segment leaders according to the following template:

Scale:	Meaning	Score	
	No influence	0	
Low influence	1		
Medium influence	2		
High influence	3		
Very high influence	4		

Example	Criteria	L5	L6
	L5. Geopolitical influences	0	4
L6. Human rights	1	0	

Interpretation: Geopolitical influences a have very high influence on human rights.
 Interpretation: Human rights have a low influence on geopolitical influences.

Below follow the Tables with 108 cells that need to be filled. Only the cells within the table that are empty need to be filled in.

1st Level:	Criteria	C1	C2	C3
	C1. Economical capital	0		
C2. Environmental Capital		0		
C3. Social Capital			0	

2nd Level:	Criteria	L1	L2
	L1. Economical dependency	0	
L2. Recycling feasibility		0	

2nd Level:	Criteria	L3	L4
	L3. Extraction influence	0	
L4. Post-Extraction influence		0	

2nd Level:	Criteria	L5	L6
	L5. Geopolitical influences	0	
L6. Human rights		0	

3th Level:	Criteria	P1	P2	P3	P4
	P1. Industry consumption	0			
P2. EU import reliance		0			
P3. US import reliance			0		
P4. Market balance (supply risk)				0	

Figure 39: Overview of sheet that is used as an input form to determine the weights that are not corrected for dependencies.

Then, the weights are determined by all stakeholders. Before the pairwise comparisons are made according to the ANP framework, the concept of inconsistency is explained in combination with the hierarchical structure presented in Figure 18. The overall methodology is presented in a short outline. The pairwise comparisons are executed according to Figure 40:

The Table below presents an example on how it could be filled in with an interpretation of the assessment.

	Criteria 1	Extreme importance (9)	Very strong importance (7)	Strong importance (5)	Moderate importance (3)	Equal importance (1)	Moderate importance (3)	Strong importance (5)	Very strong importance (7)	Extreme importance (9)	Criteria 2
Example	Geopolitical influences										Human rights
	Interpretation:	"Geopolitical influences are of strong importance compared to human rights."									
	Geopolitical influences										Human rights
	Interpretation:	"Human rights are of moderate importance compared to geopolitical influences."									
	Geopolitical influences										Human rights
	Interpretation:	"Geopolitical influences are of equal importance compared to human rights."									

Below follow the 54 comparisons that need to be made. Every empty row within the Table presents a choice and one of the options presented by the scale need to be chosen.

	Criteria 1	Extreme importance (9)	Very strong importance (7)	Strong importance (5)	Moderate importance (3)	Equal importance (1)	Moderate importance (3)	Strong importance (5)	Very strong importance (7)	Extreme importance (9)	Criteria 2
3th Level:	P1. Industry consumption										P2. EU import reliance
	P1. Industry consumption										P3. US import reliance
	P1. Industry consumption										P4. Market balance (supply risk)
	P2. EU import reliance										P3. US import reliance
	P2. EU import reliance										P4. Market balance (supply risk)
	P3. US import reliance										P4. Market balance (supply risk)

	Criteria 1	Extreme importance (9)	Very strong importance (7)	Strong importance (5)	Moderate importance (3)	Equal importance (1)	Moderate importance (3)	Strong importance (5)	Very strong importance (7)	Extreme importance (9)	Criteria 2
3th Level:	P5. Market price-based allocation										P6. Function criticality
	P5. Market price-based allocation										P7. Recycling yield (Technically viable)
	P5. Market price-based allocation										P8. Recycling rate (Economically viable)
	P5. Market price-based allocation										P9. Quality level recycled material
	P5. Market price-based allocation										P10. Relative usage (MDS and ED&C scope)
	P6. Function criticality										P7. Recycling yield (Technically viable)
	P6. Function criticality										P8. Recycling rate (Economically viable)
	P6. Function criticality										P9. Quality level recycled material
	P6. Function criticality										P10. Relative usage (MDS and ED&C scope)
	P7. Recycling yield (Technically viable)										P8. Recycling rate (Economically viable)
P7. Recycling yield (Technically viable)										P9. Quality level recycled material	
P7. Recycling yield (Technically viable)										P10. Relative usage (MDS and ED&C scope)	
P8. Recycling rate (Economically viable)										P9. Quality level recycled material	
P8. Recycling rate (Economically viable)										P10. Relative usage (MDS and ED&C scope)	
P9. Quality level recycled material										P10. Relative usage (MDS and ED&C scope)	

Figure 40: Overview of sheet that is used as an input form to determine the interdependencies.

After the comparisons are completed, the consistency is assessed, and a second meeting is scheduled to discuss the outcomes and improve on inconsistencies. This is done in 30-minute meetings.

Finally, feedback about the process is asked in combination with requirements concerning the outcome of the project.

Appendix D: PESTEL methodology

The PESTEL methodology is a relatively simple strategic management tool useful for structurally scanning the macro-environment. PESTEL is an acronym for the following aspects (De Sousa & Castaneda-Ayarza, 2022):

- 'P' – Political: The political policies that influence the company and its environment is understood.
- 'E' – Economic: The factors considered for the economic analysis consist of its status, prices, rates, correlations and local and global indices.
- 'S' – Social: Demographic issues are mainly discussed for the social aspect. Examples are income, economic class, behaviours, culture, working conditions, and the healthcare system.
- 'T' – Technological: Technological factors concern the development and spread of new technologies.
- 'E' – Environmental: This segment includes sustainability issues from an ecological perspective.
- 'L' – Legal: The final part of the framework considers all relevant regulations, from labour to data protection.

These different segments are assessed individually and result in qualitative answers, each of which can be considered a driver. The input for the analysis consists of documentary research and literary research. De Sousa and Castaneda-Ayarza (2022) provide an example of a PESTEL analysis within the electromobility sector. This research is not specified on raw material usage, but more on the general commercialisation and development of electric and hybrid vehicles.

Appendix E: Performance evaluation table

This appendix presents the performance evaluation table used as input for the MCDM hybrid.

Table 18: Performance evaluation table according to the references presented in Table 4, 5, and 6.

Raw material	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	E1	E2	E3	E4	E5	E6	E7	E8	E9	S1	S2	S3	S4	S5	S6	S7
Bauxite	High	87	75	0.15	0.90	44	Yes	30	100	Very High	82	14.37	Yes	No	Yes	20	88	Low	92	0.26	0.30	2.13	1.43	Weak	0.12	Moderate
Chromium	Very High	23	80	0.51	0.49	76	Yes	20	100	High	15	1.6	No	No	No	219	79	Low	58	-0.07	0.07	3.01	0.20	Weak	0.11	Very High
Cobalt	High	86	76	0.63	1.00	54	Yes	24	100	Low	54	11.73	Yes	Yes	No	258	65	High	45	-1.46	-1.29	4.64	3.68	Very High	63.38	High
Copper	High	44	45	0.22	0.90	70	Yes	32	100	High	43	3.83	Yes	Yes	Yes	97	45	Low	65	0.33	0.34	3.26	1.72	Moderate	9.95	Very High
Dysprosium	Moderate	100	90	0.94	1.00	100	Yes	0	90	Low	500	87.78	No	No	Yes	1805	100	Very High	45	0.19	0.19	2.86	1.64	Weak	33.33	Moderate
Graphite	Moderate	98	100	0.16	1.00	30	Yes	0	100	Low	828	5.3	No	No	No	219	100	Very High	70	-0.14	-0.15	3.19	2.22	Weak	1.04	Moderate
Iron	Moderate	72	0	0.04	0.95	57	Yes	85	100	Very High	55921	2.19	Yes	No	Yes	29	76	Low	58	0.68	0.62	2.10	0.67	Weak	0.06	Weak
Neodymium	Moderate	100	90	0.94	1.00	41	Yes	0	90	Low	500	87.78	No	No	Yes	1805	99	Very High	58	0.19	0.19	2.86	1.64	Weak	33.33	Moderate
Nickel	Moderate	28	48	0.04	0.32	62	Yes	52	100	Moderate	38	13.3	Yes	Yes	No	907	66	Low	90	-0.25	-0.31	3.12	0.23	High	7.17	Very High
PA-66	Moderate	0	0	0.10	0.54	30	Yes	28	100	Moderate	40	6.1	Yes	No	No	525	95	High	70	1.32	1.38	1.88	0.00	Weak	0.19	Weak
PBT	Moderate	14	95	0.10	1.00	30	Yes	28	100	Low	40	2.9	Yes	No	No	72	95	High	70	0.87	0.66	2.26	0.00	Weak	0.19	Weak
Praseodymium	Moderate	100	90	0.89	1.00	41	Yes	0	90	Low	500	87.78	No	No	Yes	1805	90	Very High	45	0.19	0.19	2.86	1.64	Weak	33.33	Moderate
Silica Sand	High	0	0	0.03	1.00	38	Yes	0	90	Low	55921	4.6	Yes	Yes	No	19	88	Low	58	1.28	1.21	1.89	0.10	Weak	0.47	Weak
Stainless steel	High	66	0	0.51	0.40	76	Yes	85	100	Very High	15	4.2	Yes	No	Yes	75	79	Low	58	0.22	0.15	2.93	0.37	Weak	0.07	Moderate
Steel	Moderate	0	0	0.04	0.95	57	Yes	85	100	Moderate	55921	2.19	Yes	No	Yes	29	76	Low	58	0.08	0.03	3.04	0.67	Weak	0.03	Weak
Terbium	Moderate	100	90	0.89	1.00	63	Yes	0	90	Low	500	87.78	No	No	Yes	1805	78	Very High	45	0.19	0.19	2.86	1.64	Weak	33.33	Moderate
Tin	Moderate	0	78	0.46	0.26	36	Yes	23	100	Low	19	2.5	Yes	Yes	Yes	219	68	High	99	-0.47	-0.41	3.31	1.86	High	11.36	Weak
Titanium	Low	100	90	0.09	0.22	63	Yes	0	100	Low	87	16.96	No	No	Yes	220	81	Very High	81	0.17	0.18	2.73	1.25	Weak	2.44	Weak
Zinc	Moderate	60	76	0.32	0.56	38	Yes	60	100	Low	21	4.48	Yes	Yes	Yes	373	69	Moderate	76	0.30	0.23	2.52	1.71	Weak	5.92	Very High

Appendix F: Interdependency overview

Table 19 provides a complete overview of all interdependencies.

Table 19: Overview of all the interdependencies. $r(i) - s(i)$ present what criteria are dispatchers or receivers, $r(i) + s(i)$ presents the relative impact of the interdependency.

Interdependencies						
Level	Criteria	$r(i)$	$s(i)$	$r(i) + s(i)$	$r(i) - s(i)$	Group
1st Level	C1	2.500	1.500	4.000	1.000	Dispatcher
	C2	1.500	2.000	3.500	-0.500	Receiver
	C3	1.500	2.000	3.500	-0.500	Receiver
2nd Level	L1	3.667	2.667	6.333	1.000	Dispatcher
	L2	2.667	3.667	6.333	-1.000	Receiver
	L3	2.000	3.000	5.000	-1.000	Receiver
	L4	3.000	2.000	5.000	1.000	Dispatcher
	L5	3.000	2.000	5.000	1.000	Dispatcher
	L6	2.000	3.000	5.000	-1.000	Receiver
3rd Level	P1	4.685	4.222	8.907	0.463	Dispatcher
	P2	3.315	3.464	6.779	-0.149	Receiver
	P3	3.315	3.697	7.012	-0.382	Receiver
	P4	4.426	4.358	8.784	0.068	Dispatcher
	P5	5.055	6.157	11.213	-1.102	Receiver
	P6	6.365	6.367	12.732	-0.002	Receiver
	P7	5.815	6.750	12.565	-0.934	Receiver
	P8	6.332	6.550	12.882	-0.219	Receiver
	P9	6.832	6.541	13.373	0.291	Dispatcher
	P10	5.363	3.397	8.760	1.967	Dispatcher
	E1	5.030	5.298	10.328	-0.268	Receiver
	E2	6.186	5.488	11.674	0.698	Dispatcher
	E3	5.247	5.952	11.199	-0.705	Receiver
	E4	5.545	5.537	11.082	0.008	Dispatcher
	E5	5.012	4.797	9.809	0.215	Dispatcher
	E6	5.073	5.021	10.094	0.052	Dispatcher
	E7	5.895	6.658	12.553	-0.763	Receiver
	E8	5.441	5.895	11.336	-0.453	Receiver
	E9	6.706	5.489	12.195	1.217	Dispatcher
	S1	5.000	4.000	9.000	1.000	Dispatcher
	S2	5.000	4.000	9.000	1.000	Dispatcher
S3	3.000	5.000	8.000	-2.000	Receiver	
S4	2.376	1.289	3.665	1.088	Dispatcher	
S5	1.289	1.728	3.017	-0.440	Receiver	
S6	1.289	1.624	2.913	-0.336	Receiver	
S7	1.497	1.809	3.306	-0.312	Receiver	

Appendix G: Supermatrix calculations

The supermatrix calculations are conforming Section 4.2.1. The unweighted supermatrix for stakeholder one is presented in Table 20:

Table 20: Unweighted supermatrix formed by the weights and interdependencies following the structure of Figure 18.

		Unweighted SuperMatrix stakeholder 1																																								
		G	C1	C2	C3	L1	L2	L3	L4	L5	L6	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	E1	E2	E3	E4	E5	E6	E7	E8	E9	S1	S2	S3	S4	S5	S6	S7					
Goal	G	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0			
1st Level	C1	0.600	0.333	0.500	0.500	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0			
	C2	0.200	0.333	0.200	0.300	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		
	C3	0.200	0.333	0.300	0.200	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
2nd Level	L1	0	0.167	0	0	0.500	0.636	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0			
	L2	0	0.833	0	0	0.500	0.364	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0			
	L3	0	0	0.833	0	0	0	0.333	0.500	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		
	L4	0	0	0.167	0	0	0	0.667	0.500	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		
	L5	0	0	0	0	0.100	0	0	0	0	0.500	0.667	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		
	L6	0	0	0	0.900	0	0	0	0	0.500	0.333	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		
3th Level	P1	0	0	0	0	0.196	0	0	0	0	0	0.250	0.322	0.318	0.307	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0			
	P2	0	0	0	0	0.078	0	0	0	0	0	0.224	0.180	0.204	0.228	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		
	P3	0	0	0	0	0.078	0	0	0	0	0	0.224	0.205	0.180	0.228	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
	P4	0	0	0	0	0.647	0	0	0	0	0	0.303	0.293	0.298	0.237	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
	P5	0	0	0	0	0	0.034	0	0	0	0	0	0	0	0	0.124	0.145	0.141	0.145	0.148	0.149	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
	P6	0	0	0	0	0	0.327	0	0	0	0	0	0	0	0	0.178	0.157	0.186	0.183	0.183	0.181	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
	P7	0	0	0	0	0	0.204	0	0	0	0	0	0	0	0	0.164	0.171	0.143	0.167	0.167	0.167	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
	P8	0	0	0	0	0	0.148	0	0	0	0	0	0	0	0	0.181	0.180	0.185	0.156	0.182	0.180	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
	P9	0	0	0	0	0	0.227	0	0	0	0	0	0	0	0	0.200	0.195	0.194	0.198	0.168	0.192	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
	P10	0	0	0	0	0	0.061	0	0	0	0	0	0	0	0	0.153	0.152	0.151	0.152	0.152	0.132	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	E1	0	0	0	0	0	0	0.028	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.136	0.163	0.160	0.157	0.160	0.165	0	0	0	0	0	0	0	0	0	0	0	0		
	E2	0	0	0	0	0	0	0.449	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.201	0.167	0.192	0.199	0.197	0.203	0	0	0	0	0	0	0	0	0	0	0	0	0	
	E3	0	0	0	0	0	0	0.098	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.169	0.163	0.142	0.174	0.172	0.164	0	0	0	0	0	0	0	0	0	0	0	0	0	
	E4	0	0	0	0	0	0	0.098	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.178	0.182	0.179	0.150	0.174	0.173	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	E5	0	0	0	0	0	0	0.098	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.157	0.156	0.165	0.162	0.135	0.158	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	E6	0	0	0	0	0	0	0.230	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.159	0.170	0.161	0.158	0.161	0.137	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	E7	0	0	0	0	0	0	0	0	0.455	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.294	0.344	0.348	0	0	0	0	0	0	0	0	0	0
E8	0	0	0	0	0	0	0	0	0.455	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.315	0.272	0.317	0	0	0	0	0	0	0	0	0	0	0	
E9	0	0	0	0	0	0	0	0	0.091	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.391	0.384	0.335	0	0	0	0	0	0	0	0	0	0	0	
S1	0	0	0	0	0	0	0	0	0	0.429	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.333	0.417	0.400	0	0	0	0	0	0		
S2	0	0	0	0	0	0	0	0	0	0.143	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.417	0.333	0.400	0	0	0	0	0	0		
S3	0	0	0	0	0	0	0	0	0	0.429	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.250	0.250	0.200	0	0	0	0	0	0		
S4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.251	0.391	0.379	0.421	0	0		
S5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.584	0.242	0.136	0.220	0.212	0	0	
S6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.056	0.242	0.215	0.136	0.212	0	0	
S7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.109	0.264	0.258	0.265	0.156	0	0	
Sum:		1	2	2	2	2	2	2	2	2	2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1		

The dark-blue cells are automatically copied from the unadjusted weights and interdependencies. Moreover, the light-blue cells are all 0 due to the clustering of the supermatrix conforming to the structure in Figure 18 and the assumption that outer dependencies are not considered. This supermatrix is column-normalised to retrieve the weighted supermatrix as presented in Table 21:

the hierarchy with cluster sinks. In that case, the first column presents how the criteria in the cluster sinks relate to the goal. Moreover, the second, third, and fourth columns present how each third-level criterion relates to each first-level criterion due to the interdependencies modelled at that level. The fifth until the tenth column presents how each third-level criterion relates to each second-level criterion. Note that the first zeroes appear since the hierarchy differentiates these criteria due to their relation to the first level criteria. Finally, the remaining columns present how the probabilities are divided according to the Markov chain principle. The criteria in the cluster sinks all emit and receive priorities. Therefore, these clusters will converge according to the general ANP methodology, where rows present a single priority. Finally, the first ten rows present zeroes since the third level does not emit priorities to the second- or first-level criteria.

Table 22: The limit supermatrix is a matrix presenting the convergence of the weighted supermatrix. The green cells present how the individual criteria are related to the goal.

		Limit SuperMatrix stakeholder 1																																							
Goal	G	C1	C2	C3	L1	L2	L3	L4	L5	L6	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	E1	E2	E3	E4	E5	E6	E7	E8	E9	S1	S2	S3	S4	S5	S6	S7					
1st Level	G	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0					
	C1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0				
	C2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0				
	C3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0			
2nd Level	L1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0				
	L2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0				
	L3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0			
	L4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0			
	L5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0			
	L6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0			
	3th Level	P1	0.056	0.077	0.026	0.026	0.226	0.088	0	0	0	0	0.296	0.296	0.296	0.296	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		
P2		0.040	0.055	0.018	0.018	0.162	0.063	0	0	0	0	0.211	0.211	0.211	0.211	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		
P3		0.040	0.055	0.018	0.018	0.162	0.063	0	0	0	0	0.212	0.212	0.212	0.212	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
P4		0.054	0.073	0.024	0.024	0.215	0.084	0	0	0	0	0.281	0.281	0.281	0.281	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
P5		0.045	0.061	0.020	0.020	0.033	0.100	0	0	0	0	0	0	0	0	0	0.142	0.142	0.142	0.142	0.142	0.142	0.142	0.142	0.142	0.142	0.142	0.142	0.142	0.142	0.142	0.142	0.142	0.142	0.142	0.142	0.142	0.142	0.142	0.142	
P6		0.056	0.077	0.026	0.026	0.042	0.125	0	0	0	0	0	0	0	0	0	0.178	0.178	0.178	0.178	0.178	0.178	0.178	0.178	0.178	0.178	0.178	0.178	0.178	0.178	0.178	0.178	0.178	0.178	0.178	0.178	0.178	0.178	0.178	0.178	
P7		0.052	0.071	0.024	0.024	0.038	0.115	0	0	0	0	0	0	0	0	0	0.163	0.163	0.163	0.163	0.163	0.163	0.163	0.163	0.163	0.163	0.163	0.163	0.163	0.163	0.163	0.163	0.163	0.163	0.163	0.163	0.163	0.163	0.163	0.163	
P8		0.056	0.077	0.026	0.026	0.041	0.124	0	0	0	0	0	0	0	0	0	0.177	0.177	0.177	0.177	0.177	0.177	0.177	0.177	0.177	0.177	0.177	0.177	0.177	0.177	0.177	0.177	0.177	0.177	0.177	0.177	0.177	0.177	0.177	0.177	0.177
P9		0.060	0.082	0.027	0.027	0.045	0.134	0	0	0	0	0	0	0	0	0	0.191	0.191	0.191	0.191	0.191	0.191	0.191	0.191	0.191	0.191	0.191	0.191	0.191	0.191	0.191	0.191	0.191	0.191	0.191	0.191	0.191	0.191	0.191	0.191	0.191
P10		0.047	0.064	0.021	0.021	0.035	0.105	0	0	0	0	0	0	0	0	0	0.149	0.149	0.149	0.149	0.149	0.149	0.149	0.149	0.149	0.149	0.149	0.149	0.149	0.149	0.149	0.149	0.149	0.149	0.149	0.149	0.149	0.149	0.149	0.149	0.149
E1		0.024	0.015	0.060	0.014	0	0	0.109	0.036	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		
E2		0.029	0.018	0.074	0.017	0	0	0.133	0.044	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		
E3		0.025	0.016	0.063	0.015	0	0	0.113	0.038	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		
E4		0.026	0.016	0.066	0.016	0	0	0.120	0.040	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
E5		0.024	0.015	0.060	0.014	0	0	0.108	0.036	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		
E6		0.024	0.015	0.061	0.014	0	0	0.110	0.037	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		
E7		0.031	0.019	0.079	0.019	0	0	0.101	0.253	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		
E8		0.029	0.018	0.073	0.017	0	0	0.093	0.233	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		
E9		0.035	0.022	0.088	0.021	0	0	0.113	0.283	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0		
S1		0.033	0.021	0.020	0.084	0	0	0	0	0.293	0.117	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.381	0.381	0.381	0	0	0	0	0		
S2		0.033	0.021	0.020	0.084	0	0	0	0	0.293	0.117	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.381	0.381	0.381	0	0	0	0	0		
S3	0.021	0.013	0.012	0.052	0	0	0	0	0.183	0.073	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.238	0.238	0.238	0	0	0	0			
S4	0.055	0.035	0.033	0.140	0	0	0	0	0.080	0.240	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.347	0.347	0.347	0.347	0.347			
S5	0.033	0.021	0.020	0.084	0	0	0	0	0.048	0.144	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.208	0.208	0.208	0.208	0.208			
S6	0.033	0.021	0.020	0.083	0	0	0	0	0.048	0.144	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.207	0.207	0.207	0.207	0.207			
S7	0.038	0.024	0.022	0.095	0	0	0	0	0.055	0.164	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.237	0.237	0.237	0.237	0.237				
Sum:	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1				

Appendix H: Results deterministic ranking including criteria groups driving the ranking

Each raw material is assessed based on six second-level driver groups, as presented in Figure 18. The most significant driver groups are presented in the primary driver column. Then, the relevance decreases when the column number increases. Moreover, recycling feasibility is marked green, since it does not pose issues but presents the opportunity for recycling. Cobalt, for instance, is not fit for recycling at all.

Table 23: Rankings of raw materials including the second-level criteria that drive the ranking.

Raw materials	Ranking	Score	Primary drivers	Secondary drivers	Tertiary drivers	Quaternary drivers	Second least relevant drivers	Least relevant drivers
Cobalt	1	0.251	Human Rights Criteria 0.66	Geopolitical Criteria 0.60	Extraction 0.27	Economical Dependency 0.26	Post-Extraction 0.12	Recycling Feasibility 0.08
Tin	2	0.105	Post-Extraction 0.32	Extraction 0.32	Geopolitical Criteria 0.22	Recycling Feasibility 0.17	Human Rights Criteria 0.12	Economical Dependency 0.11
Zinc	3	0.083	Extraction 0.33	Human Rights Criteria 0.22	Recycling Feasibility 0.17	Post-Extraction 0.15	Economical Dependency 0.13	Geopolitical Criteria 0.05
Dysprosium	4	0.063	Economical Dependency 0.34	Extraction 0.34	Post-Extraction 0.28	Human Rights Criteria 0.14	Recycling Feasibility 0.11	Geopolitical Criteria 0.07
Nickel	5	0.063	Extraction 0.31	Human Rights Criteria 0.24	Recycling Feasibility 0.23	Geopolitical Criteria 0.17	Post-Extraction 0.16	Economical Dependency 0.05
Neodymium	6	0.040	Extraction 0.34	Economical Dependency 0.34	Post-Extraction 0.29	Human Rights Criteria 0.14	Geopolitical Criteria 0.07	Recycling Feasibility 0.00
Copper	7	0.033	Extraction 0.32	Human Rights Criteria 0.24	Recycling Feasibility 0.15	Economical Dependency 0.11	Geopolitical Criteria 0.09	Post-Extraction 0.04
Bauxite	8	0.031	Post-Extraction 0.22	Recycling Feasibility 0.21	Extraction 0.21	Economical Dependency 0.18	Human Rights Criteria 0.05	Geopolitical Criteria 0.04
Chromium	9	0.028	Economical Dependency 0.34	Recycling Feasibility 0.21	Human Rights Criteria 0.18	Geopolitical Criteria 0.10	Extraction 0.09	Post-Extraction 0.04
Terbium	10	0.024	Extraction 0.34	Economical Dependency 0.33	Post-Extraction 0.19	Human Rights Criteria 0.14	Geopolitical Criteria 0.07	Recycling Feasibility 0.03
Stainless steel	11	0.022	Recycling Feasibility 0.42	Extraction 0.18	Economical Dependency 0.15	Geopolitical Criteria 0.07	Post-Extraction 0.04	Human Rights Criteria 0.02
Titanium	12	0.021	Post-Extraction 0.30	Recycling Feasibility 0.19	Economical Dependency 0.19	Extraction 0.16	Geopolitical Criteria 0.06	Human Rights Criteria 0.03
Praseodymium	13	0.020	Extraction 0.34	Economical Dependency 0.33	Post-Extraction 0.23	Human Rights Criteria 0.14	Geopolitical Criteria 0.07	Recycling Feasibility 0.00
Graphite	14	-0.024	Post-Extraction 0.33	Economical Dependency 0.21	Geopolitical Criteria 0.15	Human Rights Criteria 0.09	Recycling Feasibility 0.04	Extraction 0.03
Iron	15	-0.098	Recycling Feasibility 0.31	Extraction 0.12	Economical Dependency 0.06	Post-Extraction 0.04	Geopolitical Criteria 0.02	Human Rights Criteria 0.01
PBT	16	-0.111	Post-Extraction 0.25	Extraction 0.14	Economical Dependency 0.10	Recycling Feasibility 0.06	Geopolitical Criteria 0.02	Human Rights Criteria 0.00
Steel	17	-0.117	Recycling Feasibility 0.18	Extraction 0.12	Geopolitical Criteria 0.10	Post-Extraction 0.04	Human Rights Criteria 0.01	Economical Dependency 0.00
PA-66	18	-0.158	Post-Extraction 0.25	Extraction 0.16	Recycling Feasibility 0.13	Economical Dependency 0.00	Geopolitical Criteria 0.00	Human Rights Criteria 0.00
Silica Sand	19	-0.274	Extraction 0.18	Post-Extraction 0.07	Economical Dependency 0.03	Recycling Feasibility 0.00	Geopolitical Criteria 0.00	Human Rights Criteria 0.00

Appendix I: Results per segment and rank reversal discussion

The results per segment are presented in Table 24:

Table 24: Ranking of raw materials per segment including PROMETHEE II score.

Average (ALL)			Average (MDS)			Average (ED&C)		
Raw materials	Ranking	Score	Raw materials	Ranking	Score	Raw materials	Ranking	Score
Cobalt	1	0.251	Cobalt	1	0.251	Tin	1	0.245
Tin	2	0.105	Nickel	2	0.062	Nickel	2	0.178
Zinc	3	0.083	Dysprosium	3	0.058	Zinc	3	0.135
Dysprosium	4	0.063	Neodymium	4	0.036	Copper	4	0.111
Nickel	5	0.063	Bauxite	5	0.031	Chromium	5	0.070
Neodymium	6	0.040	Copper	6	0.028	Bauxite	6	0.067
Copper	7	0.033	Chromium	7	0.021	Stainless steel	7	0.058
Bauxite	8	0.031	Titanium	8	0.018	Graphite	8	0.031
Chromium	9	0.028	Stainless steel	9	0.018	Steel	9	-0.107
Terbium	10	0.024	Terbium	10	0.018	Iron	10	-0.119
Stainless steel	11	0.022	Praseodymium	11	0.014	PBT	11	-0.144
Titanium	12	0.021	Graphite	12	-0.029	PA-66	12	-0.199
Praseodymium	13	0.020	Iron	13	-0.109	Silica Sand	13	-0.325
Graphite	14	-0.024	Steel	14	-0.128			
Iron	15	-0.098	Silica Sand	15	-0.289			
PBT	16	-0.111						
Steel	17	-0.117						
PA-66	18	-0.158						
Silica Sand	19	-0.274						

Moreover, the results can be visualised according to their relationship with the original ranking. If rank reversal did not occur, the lines connecting the ranking points would not cross. Two crossing lines would mean that the rank of the two raw materials is reversed. Thus, the addition or removal of a raw material influenced the ranking. The rankings are visualised in Figure 41:

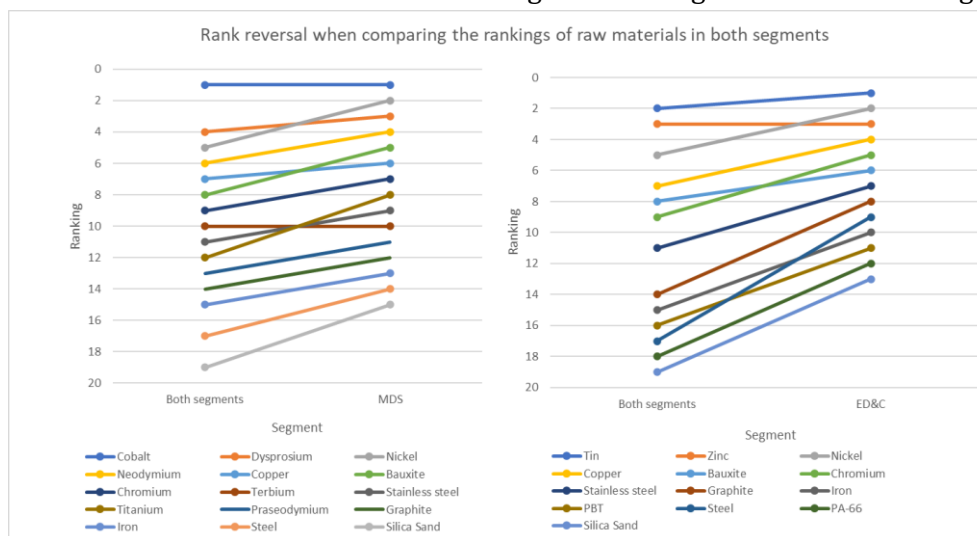


Figure 41: Visualisation of how the original ranking compares to the ranking per segment.

As shown, rank reversal occurred quite often. In the worst case, raw material changed ranks with a raw material two places higher. However, as Section 4.3.2 presented, rank reversal can only occur if the differences between outranking flows are significantly small. Therefore, these raw materials are closely related. To summarise, the absolute differences in the rankings are 7 and 8 for the MDS and ED&C segments, respectively, if only the order and not the actual rankings are considered. This is half of the number of the method that came closest to the ranking of DEMATEL-ANP and PROMETHEE II. Overall, the issue of rank reversal is not very significant, but it has to be noted and taken into account to understand the model's behaviour properly.

Appendix J: Execution of the scenario analysis

The complete execution of the scenario analysis is described in this appendix according to the steps presented in Table 11.

Step 1: Scope definition

The first step of the scenario analysis, according to Table 11, concerns defining the scope. The scope of this thesis should be based on the firm's corporate strategy. However, the segment business plans of the segment leaders are more applicable to the scope of the scenario analysis. The net-zero transition remains an integral part of the segment business plan. Thus, it will play a significant part in the scenario analysis.

Step 2: Driving force exploration using PESTEL

The driving forces are explored using the PESTEL methodology, and the following table can be created:

Table 25: Elaborated drivers and the PESTEL group that fits best.

Driver group	Elaboration
Political	Governmental organisations can commit to the net-zero transition and apply progressive policies. The focus can lie on CO ₂ emissions, the energy mix, waste management and the introduction of circular concepts or the electrification of transportation and industry.
Economic	The net-zero transition offers new business opportunities related to waste management and circular concepts, the net-zero transition or digitalisation. However, the risks of overestimation due to speculation are significant. Moreover, high entry barriers might affect the viability of newcomers.
Economic	The net-zero transition results in a shared demand for critical raw materials as shown in Table 3. Significant supply risks are forecasted, especially since supply chain disruptions became commonplace in the past years due to, e.g. COVID and the European war.
Social	Communities and businesses demand net-zero products, which could be emphasized by the level of progressiveness of the political situation.
Technological	Technological advancements or material substitution could alter the use of certain raw materials. If the business case proves profitable, the adoption can be assumed to work out well. Technological advancements to increase circular concepts are expected.
Technological	Incremental improvements resulting in increasing efficiency could result in reducing (or obsolescence) of specific raw materials.
Environmental	The level of CO ₂ emissions has a significant environmental impact and is used to measure sustainability.
Environmental	Resource scarcity and geographic concentration of raw materials might result in supply risks or social issues.
Legal	Incentives and regulations might be placed around the net-zero transition. Measures like CO ₂ taxes, subsidies for sustainable programs and stricter pollution laws might be applied. Regulations for waste management and the introduction of circular concepts might change companies' approaches.
Legal	Stricter control and better legislation could impact certain raw materials, like cobalt or tin, that pose environmental and social risks.
Legal	Mining quotas influence the supply of REEs significantly.

Step 3: Determine development direction

The most significant development directions are marked grey in Table 25. These drivers have been chosen since political organisations can shape the net-zero transition using, for instance, the measures presented in the legal section. Moreover, supply risks have significantly impacted the formulation of the segment business plans. The influences of COVID and the European war, for instance, have impacted supply chains significantly. Therefore, the level of supply risks has to be taken into consideration.

Step 4: Develop scenario themes

The scenario themes are based on the two drivers mentioned in step 3. These two drivers can be placed on the x-axis and y-axis to create four quadrants representing a scenario. The summary of each scenario is found in Figure 30 of Chapter 5. The political driver ranges from a conservative approach where initiative is not taken to a progressive approach where governments force companies to adhere to the science-based targets. The supply risks can be measured on a simple scale ranging from low to high. Then, there are four scenario combinations:

- Scenario A: Conservative governments and high supply risks
- Scenario B: Progressive governments and high supply risks
- Scenario C: Progressive governments and low supply risks
- Scenario D: Conservative governments and low supply risks.

Step 5: Develop rough and plausible scenario narratives

The four developed scenario themes are formulated based on the remaining drivers of step 2. Moreover, the scenarios received a title to summarize the narrative.

- Scenario A: *Lack of resilience and commitment*

The first scenario concerns conservative governments. Therefore, legal actions are barely undertaken. Moreover, community demands to transition to a net-zero ecosystem are not significant enough to ensure a large transition. For instance, lobbying the governments has not worked. However, new supply chain risks appeared, resulting in a high spread and adoption of new technologies to cope with the increased supply risks, as we have seen throughout the COVID pandemic. Then, a relatively moderate decrease in CO₂ emissions can be expected.

- Scenario B: *High commitment – shared demand*

In this scenario, governments are committed to the net-zero transition. However, that means that certain raw materials, especially those critical for the net-zero transition, might experience severe supply risks, as presented in Table 3 and Figure 14. Moreover, the progressiveness of the government fuels the demand from society and businesses to become net-zero and the other way around. Therefore, to mitigate the supply risks and achieve the net-zero transition goals, a very high spread and adoption of new technologies can be expected, mitigating both environmental and social impacts. Circular concepts will be influenced significantly by these technologies. Overall, very high decreases in CO₂ emissions can be expected due to the high commitment of governments, strong regulations, and major supply chain improvements due to high supply risks.

- Scenario C: *High commitment – consolidation of supply chains*

The third scenario also presents a committed government which uses regulations to increase the pace of the net-zero transition. The relation between the communities, businesses and the government remain similar. Supply risks are low due to an environment where the number of supply chain disruptions has decreased or where supply chains have successfully become

resilient. Therefore, the shared demands would not necessarily result in high supply risks. The spread and adoption can be assumed high to meet the net-zero transition goals. Circular concepts and technologies can then be expected to improve rapidly as well. Therefore, high CO₂ decreases are expected due to the high commitment of governments and robust regulations, which result in substantial technological advancements.

- Scenario D: *Consolidation of the current situation*

The final scenario concerns conservative governments again. Therefore, there are no legal requirements or incentives to achieve sustainability goals. Lobbying by society and organisations has failed to work. However, incremental changes to current-day technologies can be expected, thus resulting in a moderate spread and adoption of new technologies. Low decreases in CO₂ emissions since the incremental improvements only cause these. The supply risks are low since the current ones are mitigated, and new ones did not appear.

Step 6: Evaluate and use the scenario themes

Overall, these scenario themes can be evaluated. The evaluation is done by discussing the scenarios with the segment leaders. Then, the scenario themes can be used to see which criteria are most subjective to change based on these scenarios.

Appendix K: Validation of practical contribution

A questionnaire is created to substantiate the practical relevance of the results provided in this thesis. This questionnaire is created based on the principles of UTAUT (Unified Theory of Acceptance and Use of Technology) (Venkatesh et al., 2003). The UTAUT theory is based upon eight pillars. These are performance expectancy, effort expectancy, attitude towards using technology, social influence, facilitating conditions, self-efficacy, anxiety and behavioural intention to use the system.

Not all pillars are relevant for validating the results of the MCDM method. Social influence, facilitating conditions, self-efficacy, and anxiety are excluded since these pillars focus mainly on technology usage instead of whether the results would provide benefits. Therefore, the questionnaires focus mainly on performance expectancy, effort expectancy and behavioural intention to use the system. The last pillar has been adjusted to the 'behavioural intention to use the results'. Finally, one question about the attitude towards using technology is posed. This question is reformulated to measure the attitude towards the results. The example presented in the work of Venkatesh et al. (2013) is used to formulate the statements.

The questionnaire is presented at the end of the presentation showing the results to OEM X. To motivate people to fill in the questionnaire, the aim is to ensure that people can complete the questionnaire within five minutes. Therefore, only nine statements have been provided, assessed based on a five-point Likert scale. This scale consists of the verbal terms 'strongly disagree', 'disagree', 'neutral', 'agree', and 'strongly agree'. Moreover, the questionnaire's introduction emphasized that these statements should be considered in the context of the results of this thesis. Table 26 presents the relevant pillar, the reference to the statement and the complete statement:

Table 26: Statements used in the questionnaire following four pillars of the UTAUT theory.

UTAUT pillar	Reference	Statement
Performance expectancy	PE-1	I find the results useful for my job.
Performance expectancy	PE-2	I could push for sustainability quicker, given the results.
Performance expectancy	PE-3	I have increased my understanding of how to prioritise raw materials for sustainability.
Performance expectancy	PE-4	My job can be performed better concerning sustainability.
Effort expectancy	EE-1	The results are clear and understandable.
Effort expectancy	EE-2	I could reproduce and reuse the results in my job.
Attitude towards using technology	AT-1	Working with these results would improve the satisfaction I would get from my job.
Behavioural intention to use the results	BI-1	I intend to use the results during the next six months.
Behavioural intention to use the results	BI-2	I intend to prioritise undiscussed raw materials during the next six months.

Following the statements, it can be concluded that there is a strong focus on the relevance and the usage of the results. For instance, the final two statements focus on whether the results of the thesis will be used throughout the next six months. The period of six months has been chosen since business plans are presented twice a year.

The results can be visualised based on scores ranging from 1 to 5, each representing a verbal point. A score of 1 would represent strongly disagree and a score of 5 would represent strongly agree. The average results per statement are visualised in Figure 42:

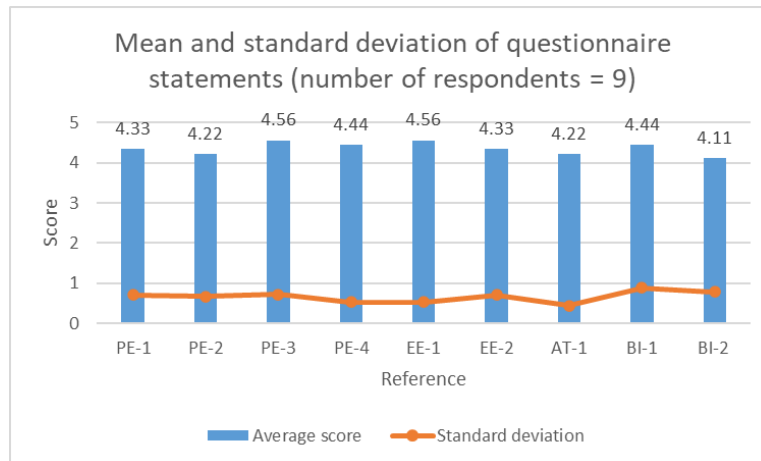


Figure 42: Results of the questionnaire visualised by the average and standard deviation

Four out of five stakeholders answered the questionnaire. Only the ED&C segment leader was not able to respond. Moreover, five other employees responded: two engineers and three buyers. Figure 42 shows the positive reflections of the respondents. Since the answers do not differ significantly and to maintain the privacy of the respondents, all answers are aggregated.

The responses ranged from neutral to strongly agree. The semantics 'strongly disagree' and 'disagree' have not been used. This could imply confirmation bias, since these results are desirable. One respondent answered 'strongly agree' on all statements, which could be assessed as the most significant case of confirmation bias. However, removing these results would not alter the ranking significantly. The standard deviation on each statement is below 1, presenting that stakeholders' answers are comparable. There is also a probability that this person strongly agrees with all statements. For instance, the answer of 4.44, between 'agree' and 'strongly agree', to the statement 'I intend to use the results during the next six months' is logical since Chapter 1 provided that there is no plan for increasing the sustainability of the raw materials.

Overall, all results can be placed between the semantics 'agree' and 'strongly agree'. Therefore, the practical relevance is validated.