

## Multi-Objective approach to the Circular Economy paradigm in the chemical process industry

**Auteur :** Cabo, Virgil

**Promoteur(s) :** Léonard, Grégoire

**Faculté :** Faculté des Sciences appliquées

**Diplôme :** Master : ingénieur civil en chimie et science des matériaux, à finalité spécialisée en Chemical Engineering

**Année académique :** 2023-2024

**URI/URL :** <http://hdl.handle.net/2268.2/21115>

---

### Avertissement à l'attention des usagers :

*Tous les documents placés en accès ouvert sur le site le site MatheO sont protégés par le droit d'auteur. Conformément aux principes énoncés par la "Budapest Open Access Initiative"(BOAI, 2002), l'utilisateur du site peut lire, télécharger, copier, transmettre, imprimer, chercher ou faire un lien vers le texte intégral de ces documents, les disséquer pour les indexer, s'en servir de données pour un logiciel, ou s'en servir à toute autre fin légale (ou prévue par la réglementation relative au droit d'auteur). Toute utilisation du document à des fins commerciales est strictement interdite.*

*Par ailleurs, l'utilisateur s'engage à respecter les droits moraux de l'auteur, principalement le droit à l'intégrité de l'oeuvre et le droit de paternité et ce dans toute utilisation que l'utilisateur entreprend. Ainsi, à titre d'exemple, lorsqu'il reproduira un document par extrait ou dans son intégralité, l'utilisateur citera de manière complète les sources telles que mentionnées ci-dessus. Toute utilisation non explicitement autorisée ci-avant (telle que par exemple, la modification du document ou son résumé) nécessite l'autorisation préalable et expresse des auteurs ou de leurs ayants droit.*

---



# Multi-Objective approach to the Circular Economy paradigm in the chemical process industry

CABO Virgil

Thesis presented for obtaining the Master's degree in  
**Chemical and Materials engineering**

Supervisor:  
**LÉONARD Grégoire**

June 8, 2024

# Acknowledgments

Words cannot express my gratitude to Mr. Espuña and Mr. Léonard for believing in me and for making this journey possible. I am forever grateful for the personal investment they put into my project. I also want to thank them for their valuable advice and guidance. I am delighted to have had the chance to live this enriching experience and to have been able to evolve working on this thesis. I also could not have undertaken this project without the help of Adrián Pacheco López, who generously provided his expertise. His availability and the ease of our exchanges were invaluable.

Furthermore, I want to give my warmest thanks to all the members of the CEPIMA group, who did not only help me with my project but who welcomed me in the best possible way. It has been a pleasure to work with all those inspiring people.

Then, I would be remiss if I did not mention my family and friends, especially my partner Sarah Collignon and my parents who have always believed in me and encouraged me in all my projects. Sarah has been an incredible support, not only during my master's thesis but throughout my entire academic journey. Her unwavering presence in difficult times and her constant willingness to help have been invaluable. I am deeply grateful for her love and support.

Finally, thank you to those who, in one way or another, have contributed to my thesis, my internship and my academic career.

# Abstract

This thesis deals with a multi-objective approach to promote the circular economy in the context of chemical recycling of plastic waste. The main objective of this thesis was to develop a multi-objective decision making tool that could be integrated into the iSMA framework developed by Pacheco-López et al. (2023) to fill an identified gap. The literature review highlighted the growing importance of sustainable plastic waste management, describing current waste management methods and their limitations, as well as the potential of chemical recycling to improve this situation. Chemical recycling, in particular pyrolysis, offers a promising way to convert plastic waste into valuable resources, although challenges remain in terms of efficiency and environmental impact.

The iSMA framework generates Pareto optimal solutions for different recycling paths, but a tool was needed to objectively select the best options. This tool, developed in Python, implements the multi-objective optimization methods TOPSIS and PROMETHEE, and includes a sensitivity analysis module to assess the stability and robustness of alternatives in the face of uncertainty in the weighting of criteria. The results obtained show that the tool is functional and able to provide relevant rankings, although depending on the quality and completeness of the initial data. Future prospects include extending the tool to other areas of environmental sustainability, integrating new optimization methods, and specifying criteria weightings guided by local sustainability policies.



# Résumé

Ce mémoire aborde une approche multi-objectifs pour promouvoir l'économie circulaire dans le cadre du recyclage chimique des déchets plastiques. L'objectif principal de ce travail était de développer un outil de prise de décision multi-objectifs, intégrable dans la structure iSMA développée par Pacheco-López et al. (2023), afin de combler une lacune identifiée. La revue de littérature a mis en évidence l'importance croissante de la gestion durable des déchets plastiques, en décrivant les méthodes actuelles de gestion des déchets et leurs limitations, ainsi que le potentiel du recyclage chimique pour améliorer cette situation. Le recyclage chimique, notamment la pyrolyse, offre une voie prometteuse pour transformer les déchets plastiques en ressources précieuses, bien que des défis subsistent en termes d'efficacité et d'impact environnemental.

Le cadre iSMA génère des solutions Pareto optimales pour divers chemins de recyclage, mais nécessitait un outil pour choisir les meilleures options de manière objective. Cet outil, développé en Python, implémente les méthodes d'optimisation multi-objectifs TOPSIS et PROMETHEE, et intègre un module d'analyse de sensibilité pour évaluer la stabilité et la robustesse des alternatives face à l'incertitude de la pondération des critères. Les résultats obtenus montrent que l'outil est fonctionnel et capable de fournir des classements pertinents, bien que dépendants de la qualité et de l'exhaustivité des données initiales. Les perspectives futures incluent l'extension de l'outil à d'autres domaines relatifs à la durabilité environnementale, l'intégration de nouvelles méthodes d'optimisation, et la spécification de pondérations de critères guidées par des politiques de développement durable locales.

# Contents

<b>Introduction</b>	<b>11</b>
<b>1 Chemical recycling of plastics waste: background, challenges and future directions</b>	<b>15</b>
1.1 Plastic waste management and associated challenges . . . . .	15
1.2 Chemical recycling and circular economy of plastic waste . . .	23
1.3 Ontological frameworks and decision-making tools in environmental sustainability . . . . .	35
1.4 Conclusion . . . . .	41
<b>2 Rationale for this work</b>	<b>43</b>
2.1 Background . . . . .	43
2.2 Description of the iSMA framework . . . . .	44
2.2.1 General presentation . . . . .	44
2.2.2 Framework objectives . . . . .	45
2.2.3 Stage details . . . . .	46
2.3 Case study . . . . .	50
2.3.1 Description of the case study . . . . .	50
2.3.2 Resulting data used for this work . . . . .	52
2.4 Objective for this work . . . . .	54
<b>3 Methodology</b>	<b>58</b>
3.1 Data gathering . . . . .	58
3.2 Normalization method . . . . .	59
3.3 Objective reduction . . . . .	61
3.4 Multi-objective optimization methodologies . . . . .	62
3.4.1 TOPSIS . . . . .	62
3.4.2 PROMETHEE . . . . .	65
3.5 Sensitivity analysis . . . . .	69
3.5.1 Introduction . . . . .	69
3.5.2 Procedure . . . . .	69

3.5.3	Results analysis . . . . .	71
3.5.4	Conclusion . . . . .	72
<b>4</b>	<b>Tool development</b>	<b>73</b>
4.1	Introduction . . . . .	73
4.2	Technologies and tools . . . . .	73
4.2.1	Programming language . . . . .	73
4.2.2	Development environments . . . . .	74
4.2.3	Libraries . . . . .	75
4.3	Tool architecture . . . . .	76
<b>5</b>	<b>Results and discussion</b>	<b>78</b>
5.1	Introduction . . . . .	78
5.2	Results analysis for TOPSIS . . . . .	79
5.2.1	Impact of the normalization method . . . . .	79
5.2.2	Impact of the criteria weighting . . . . .	81
5.2.3	Impact of the weighting uncertainty . . . . .	84
5.3	Results analysis for PROMETHEE . . . . .	86
5.3.1	Impact of the normalization method . . . . .	86
5.3.2	Impact of the criteria weighting . . . . .	88
5.3.3	Impact of the weighting uncertainty . . . . .	91
5.3.4	Impact of the preference function . . . . .	92
5.4	Comparison between TOPSIS and PROMETHEE . . . . .	93
5.5	General discussion . . . . .	97
	<b>Conclusion and perspectives</b>	<b>98</b>
	<b>Bibliography</b>	<b>105</b>

# List of Figures

1.1	Annual plastic production from 1950 to 2019 including polymer resin and fibers. Adapted from (Geyer et al. 2017) and (OECD 2022a).	16
1.2	Distribution of the global plastics production by type in 2021. Adapted from (PlasticsEurope 2022).	16
1.3	Distribution of the global plastics use by application in 2021. Adapted from (PlasticsEurope 2022).	17
1.4	Life cycle and management pathways for plastic waste: from production to end-of-life options.	19
1.5	Share of plastic waste that is recycled, landfilled, incinerated and mismanaged across the world in 2019. Adapted from (OECD 2022b).	22
1.6	Schematic representation of a plastic waste pyrolysis process retrieved from the paper of Maqsood et al. (2021).	27
1.7	Diagram of the main reactions involved in the steam cracking of alkanes retrieved from the review of Gholami et al. (2021).	31
1.8	Infographic describing the circular economy model (European Parliament 2023).	33
1.9	Eisenhower Matrix.	37
1.10	Example of a Pareto front ( <i>Pareto Front</i> n.d.).	39
2.1	Schematic representation of the iSMA framework (Pacheco-López et al. 2023).	44
2.2	Graph created during the initial assessment phase, showing tentative connections (Pacheco-López et al. 2023).	51

2.3	Optimal Pareto solutions within each two-objective space, exploring the balance between profit and the three environmental endpoint indicators (Pacheco-López et al. 2023). Solid dots indicate solutions that are optimal for their specific bicriteria Pareto front, whereas open dots represent projections from optimal solutions in other bicriteria Pareto fronts. The solutions are differentiated by color, corresponding to various configurations as outlined in Table 2.1. A dotted line is used to illustrate hypothetical points along the Pareto front. . . . .	57
3.1	Comparison of data distribution before and after normalization (vector and min-max). . . . .	60
3.2	3-dimensional representation of Pareto optimal solutions, Utopian and Nadir points, with min-max normalization and equal weighting for each criterion. . . . .	63
3.3	Usual, linear and Gaussian preference functions. . . . .	67
3.4	Sampled weights distribution from a normal distribution with an initial weight of 5 and lower and upper confidence limits of 3 and 7, respectively. . . . .	70
3.5	Ridgeline plot resulting from a sensitivity analysis run with PROMETHEE and 10,000 weight sets. All initial weights are equal to 5 and all confidence intervals are between 3 and 7. . .	71
3.6	Percentage of first and top 3 places for the 5 best alternatives in each case. These results were obtained under the conditions described in Figure 3.5. . . . .	72
4.1	Data flow within the tool. . . . .	77
5.1	Comparison of alternative rankings using the two normalization methods for TOPSIS, with equal weighting for each criterion (5, 5, 5). . . . .	79
5.2	Comparison of performance scores distributions obtained through sensitivity analysis using the two normalization methods for TOPSIS, with equal weighting (5, 5, 5) and uncertainty ( $\pm 20\%$ ) for each criterion. . . . .	80
5.3	Comparison of first place percentages of the 5 best alternatives obtained through sensitivity analysis using the two normalization methods for TOPSIS, with equal weighting (5, 5, 5) and uncertainty ( $\pm 20\%$ ) for each criterion. . . . .	81
5.4	Comparison of alternative rankings using two weighting scenarios for TOPSIS, with min-max normalization. . . . .	81

5.5	Comparison of performance scores distributions obtained through sensitivity analysis using two weighting scenarios for TOPSIS, with min-max normalization and equal uncertainty ( $\pm 20\%$ ) for each criterion. . . . .	82
5.6	Comparison of first place percentages of the 5 best alternatives obtained through sensitivity analysis using two weighting scenarios for TOPSIS, with min-max normalization and equal uncertainty ( $\pm 20\%$ ) for each criterion. . . . .	83
5.7	Comparison of performance scores distributions obtained through sensitivity analysis using two uncertainty scenarios for TOPSIS, with min-max normalization and equal weighting (5, 5, 5) for each criterion. . . . .	84
5.8	Comparison of first place percentages of the 5 best alternatives obtained through sensitivity analysis using two uncertainty scenarios for TOPSIS, with min-max normalization and equal weighting (5, 5, 5) for each criterion. . . . .	85
5.9	Comparison of alternative rankings using the two normalization methods for PROMETHEE, with equal weighting for each criterion (5, 5, 5). . . . .	86
5.10	Comparison of net outranking flows distributions obtained through sensitivity analysis using the two normalization methods for PROMETHEE, with equal weighting (5, 5, 5) and uncertainty ( $\pm 20\%$ ) for each criterion. . . . .	87
5.11	Comparison of first place percentages of the 5 best alternatives obtained through sensitivity analysis using the two normalization methods for PROMETHEE, with equal weighting (5, 5, 5) and uncertainty ( $\pm 20\%$ ) for each criterion. . . . .	88
5.12	Comparison of alternative rankings using two weighting scenarios for PROMETHEE, with min-max normalization and Gaussian preference function. . . . .	88
5.13	Comparison of net outranking flows distributions obtained through sensitivity analysis using two weighting scenarios for PROMETHEE, with min-max normalization, Gaussian preference function and equal uncertainty ( $\pm 20\%$ ) for each criterion. . . . .	89
5.14	Comparison of first place percentages of the 5 best alternatives obtained through sensitivity analysis using two weighting scenarios for PROMETHEE, with min-max normalization, Gaussian preference function and equal uncertainty ( $\pm 20\%$ ) for each criterion. . . . .	90

5.15	Comparison of net outranking flows distributions obtained through sensitivity analysis using two uncertainty scenarios for PROMETHEE, with min-max normalization and equal weighting (5, 5, 5) for each criterion. . . . .	91
5.16	Comparison of first place percentages of the 5 best alternatives obtained through sensitivity analysis using two uncertainty scenarios for PROMETHEE, with min-max normalization and equal weighting (5, 5, 5) for each criterion. . . . .	92
5.17	Comparison of alternative rankings using two preference functions for PROMETHEE, with min-max normalization and equal weighting for each criterion (5, 5, 5). . . . .	92
5.18	Comparison of net outranking flows distributions obtained through sensitivity analysis using two preference functions for PROMETHEE, with min-max normalization, and equal weighting (5, 5, 5) and uncertainty ( $\pm 20\%$ ) for each criterion. . . . .	93
5.19	Comparison of alternative rankings using TOPSIS and PROMETHEE, with min-max normalization, Gaussian preference function for PROMETHEE and equal weighting for each criterion (5, 5, 5). . . . .	94
5.20	Comparison of performance scores and net outranking flows distributions obtained through sensitivity analysis using TOPSIS and PROMETHEE, with min-max normalization, Gaussian preference function for PROMETHEE, and equal weighting (5, 5, 5) and uncertainty ( $\pm 20\%$ ) for each criterion. . . . .	95
5.21	Comparison of first place percentages of the 5 best alternatives obtained through sensitivity analysis using TOPSIS and PROMETHEE, with min-max normalization, Gaussian preference function for PROMETHEE, and equal weighting (5, 5, 5) and uncertainty ( $\pm 20\%$ ) for each criterion. . . . .	96

# List of Tables

2.1	For each Pareto solution configuration, the processing level of each Process Step is detailed, displaying values in tons per hour of material input (Pacheco-López et al. 2023). The total quantity of initial mixed plastic waste remains consistent across all configurations. Column headers are color-coded to correspond with configurations shown in Figure 2.3. To facilitate identifying available and unavailable technologies in each configuration, cells are shaded in shades of green or red. . . . .	53
2.2	Pareto-optimal solutions evaluated according to the four objectives (Pacheco-López et al. 2023). This data table serves as a basis for multi-objective optimization. . . . .	55
3.1	Correlation coefficients between criteria. . . . .	61



# Introduction

Global plastics production has increased dramatically in recent decades, reaching unprecedented levels. In 2019, global plastics production exceeded 368 million tons (Geyer et al. 2017), and this trend continues to grow (Lebreton et al. 2019). This rapid increase in production has led to a massive accumulation of plastic waste, which poses serious environmental, economic, and social problems.

Plastic waste is ubiquitous in the environment: it ends up in oceans, soil, and even the air we breathe. Plastics take hundreds of years to decompose, resulting in persistent pollution and significant ecological damage. Microplastics, which result from the degradation of plastics, have been detected in many ecosystems and can enter the food chain, with potentially significant effects on human health (Kumar et al. 2021; Ullah et al. 2023).

Traditionally, plastic waste management has relied on three main methods: landfilling, incineration and mechanical recycling. However, these methods have significant limitations. Landfills take up large amounts of space and can contaminate soil and groundwater (Cook et al. 2020). Incineration, while reducing the volume of waste, releases harmful pollutants into the atmosphere and contributes to greenhouse gas emissions (Nagy et al. 2016; Anshassi et al. 2021). Mechanical recycling, on the other hand, is limited by the type of materials that can be processed, the degradation of the recycled materials, and its economic viability (Schyns et al. 2021).

In this context, it is crucial to find sustainable and efficient solutions for the management of plastic waste. Chemical recycling is emerging as a promising solution capable of transforming plastic waste into valuable resources. Unlike mechanical recycling, chemical recycling breaks down plastics into their basic chemical components, which can then be reused to produce new plastics or other valuable chemicals (Hong et al. 2017). This approach promotes a circular economy in which waste is continuously reintroduced into the production cycle, reducing dependence on virgin raw materials and minimizing environmental impact (Meys et al. 2020).

However, in order to implement chemical recycling on a large scale and

in an efficient way, it is necessary to develop robust tools to evaluate the different technologies and methods available, taking into account economic and environmental aspects. With this in mind, the iSMA framework, developed by Pacheco-López et al. (2023), proposes a holistic methodological approach to generate and evaluate different recycling pathways for plastic waste.

Starting from a set of processes and associated plastic products, this framework generates recycling pathways that are combined into a network that is optimized according to four criteria: economic profit and environmental impact on ecosystems, human health and resources. From this optimized network, Pareto optimal solutions with different trade-offs between the criteria are generated. A selection of these alternatives is then arbitrarily chosen for detailed modeling. This arbitrary selection creates a clear need for a robust and systematic multi-objective decision support tool, capable of objectively selecting the best option from a set of Pareto optimal solutions according to the user’s preferences.

The main objectives of this thesis are as follows:

1. **Development of a multi-objective decision-making tool:** This tool aims to fill the gap identified in the iSMA framework by providing a systematic method for choosing between Pareto optimal configurations. The tool will integrate the TOPSIS and PROMETHEE multi-objective optimization methodologies to provide a complete and objective evaluation of the different alternatives.
2. **Incorporate sensitivity analysis:** A critical aspect of the tool is the ability to assess the stability and robustness of alternatives in the face of uncertainty in the weighting of criteria. This feature allows us to determine whether a solution remains relevant even when conditions vary slightly, ensuring more reliable and robust decisions.
3. **Adapting the tool to different issues:** Although developed specifically for the chemical recycling of plastic waste, the tool needs to be flexible enough to adapt to other environmental sustainability contexts. This means being able to integrate different databases and decision criteria according to the specific needs of each situation.

These objectives translate into the development of a tool capable of ranking Pareto optimal alternatives, assessing their stability and robustness, and integrating with the iSMA framework to promote the circular economy in the chemical recycling of plastic waste.

The development of the multi-objective decision-making tool is based on a rigorous methodology that includes several key steps to ensure its effective-

ness. The two multi-objective optimization methods used are TOPSIS and PROMETHEE.

TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) ranks alternatives according to their relative distance from an ideal solution (best for all criteria) and an anti-ideal solution (worst for all criteria). This method involves normalizing the criteria, calculating the Euclidean distances to the ideal and anti-ideal solutions, and finally ranking the alternatives according to these distances.

The PROMETHEE (Preference Ranking Organization METHod for Enrichment Evaluations) method uses preference functions to compare alternatives in pairs and calculate a net outranking flow for each alternative, allowing alternatives to be ranked. This method involves selecting preference functions, comparing alternatives in pairs, calculating positive and negative outranking flows, and finally ranking alternatives based on the net flow.

The sensitivity analysis module in this tool follows several key steps. It begins with the sampling of random weights from normal distributions constructed using the uncertainties associated with the criteria weights provided by the user. These normal distributions are used to generate a large number of random weightings that reflect possible variations in the user's preferences. Each random weighting is then used in optimization methods (TOPSIS or PROMETHEE) to produce a set of results. By repeating this process with a large number of random weights, the tool generates a distribution of scores for each alternative. These distributions are then analyzed to assess the stability and robustness of the alternatives in the face of weighting uncertainty. This analysis allows us to visualize how the rankings of alternatives vary according to different weightings, providing an in-depth understanding of the robustness of solutions and helping to identify the most stable alternatives.

Developed in Python, the tool is structured in modules to ensure clear organization and smooth execution of the various steps. This modularity allows for efficient data management and results in a tool that can be easily modified and extended.

The thesis is divided into several chapters to guide the reader through the research process and findings.

The first chapter is a detailed literature review. It is divided into three main sections: plastic waste management and associated challenges, chemical recycling and the circular economy of plastic waste, and finally ontological frameworks and decision-making tools in environmental sustainability. This review highlights current challenges and potential solutions for more sustainable plastic waste management.

The second chapter explains the rationale of the thesis by describing in detail the structure of the iSMA framework and the case study of municipal

plastic waste recycling considered. It also presents the objectives of the dissertation.

The third chapter describes the methodology used in this thesis. The multi-objective optimization methods TOPSIS and PROMETHEE are described, as well as the sensitivity analysis module. This chapter also includes a discussion of the objective reduction and the data normalization method, which plays a crucial role in obtaining reliable results.

The fourth chapter focuses on the practical development of the tool in Python. It describes the modular architecture of the tool, the different functions implemented, and the data flow between the modules. This section highlights the structure and functionality of the tool, as well as the technical choices made during its development.

The fifth chapter presents and discusses the results obtained. The performances of TOPSIS and PROMETHEE are compared as a function of different parameters, such as normalization methods, criteria weighting, and preference functions. The results of the sensitivity analysis are also discussed in detail, providing a comprehensive assessment of the robustness of the proposed solutions.

Finally, the conclusion summarizes the main contributions of the thesis, discusses the limitations of the developed tool and proposes prospects for future research. It highlights the importance of the tool in the context of multi-criteria decision making for the chemical recycling of plastic waste, and suggests potential improvements to enhance its applicability and effectiveness.

# Chapter 1

## Chemical recycling of plastics waste: background, challenges and future directions

### 1.1 Plastic waste management and associated challenges

The rise of global plastic production over the past seven decades has been tremendous, leading to a major impact on waste generation and environmental policies. This trend is illustrated in Figure 1.1, which shows the annual plastic production from 1950 to 2019. According to Geyer et al. (2017), production soared from about 2 million tonnes in 1950 to 380 million tonnes in 2015. This growth steadily continued, with annual production reaching over 460 million tonnes in 2019, showing a constant increase in plastic use.

The distribution of plastic production by type, as represented in Figure 1.2, indicates that Polyethylene (PE), Polypropylene (PP), and Polyvinyl Chloride (PVC) together constitute approximately 60% of the global output in 2021. These materials are essential to various applications due to their diverse properties and low cost. PE, with its variants like LDPE and LLDPE, is extensively used for its flexibility and durability, particularly in the packaging industry. PP is often found in automotive parts and consumer goods for its resilience and high-temperature resistance. PVC's rigidity and resistance make it a predominant material in construction industry and medical devices.

The application of these polymers across industries is described in Figure 1.3, which shows the usage of plastics by sector in 2021. The data reveals that the packaging sector accounts for 44% of total plastics use, reinforcing

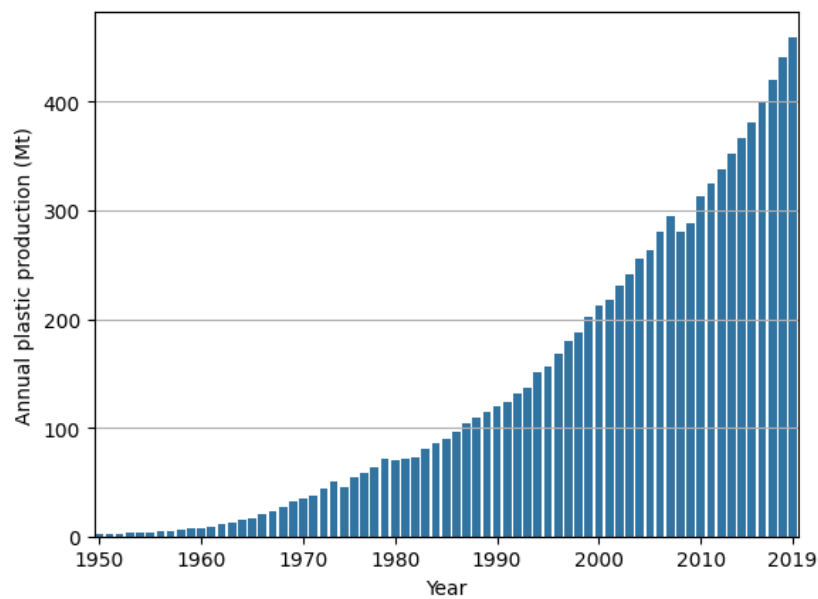


Figure 1.1: Annual plastic production from 1950 to 2019 including polymer resin and fibers. Adapted from (Geyer et al. 2017) and (OECD 2022a).

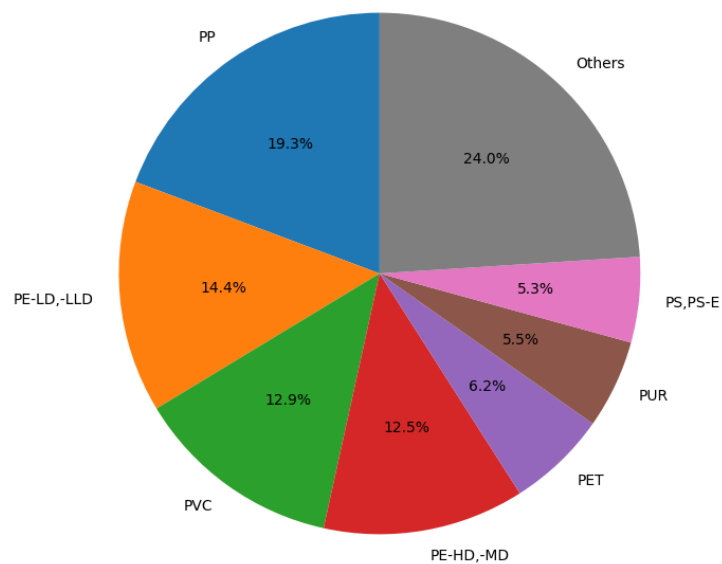


Figure 1.2: Distribution of the global plastics production by type in 2021. Adapted from (PlasticsEurope 2022).

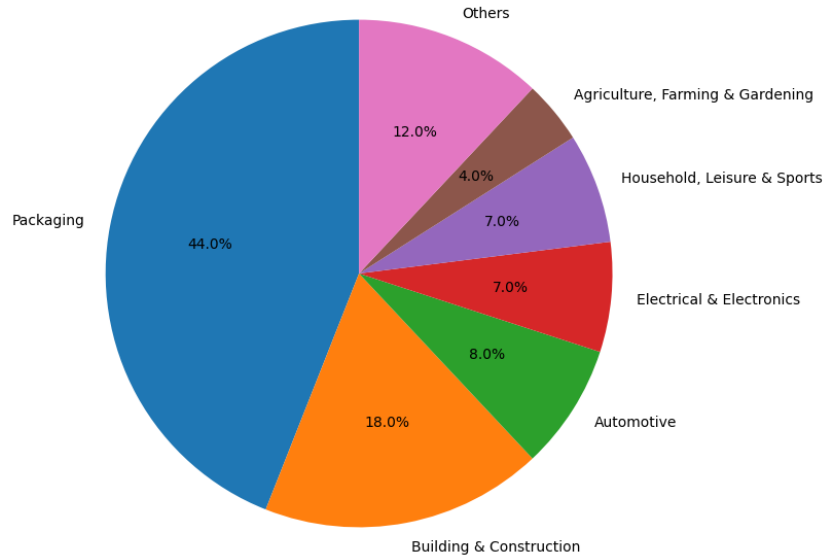


Figure 1.3: Distribution of the global plastics use by application in 2021. Adapted from (PlasticsEurope 2022).

concerns about the extensive use of single-use plastics, as discussed in the work of Ncube et al. (2021). Plastics are also widely used in the construction and automotive sectors, illustrating the widespread use of plastics in more durable applications. However, these applications ultimately add to the generation of waste, highlighting the significance of managing the entire lifecycle of plastics.

Looking ahead, the forecasts for plastic production and waste generation are concerning. According to Lebreton et al. (2019), if current trends continue, it is projected that the amount of plastic waste will increase significantly in the future, further complicating the already challenging task of managing waste effectively. This trend towards increased production and waste generation necessitates an urgent reassessment of our global waste management strategies.

Regarding the current strategies, Figure 1.4 provides a graphical visualization of the lifecycle and various management routes for plastic waste, ranging from its production to potential end-of-life alternatives. The processes depicted in the shaded area of the diagram potentially allow a closed system for the utilization of plastic. Unfortunately a fully closed loop is unattainable, not only because most of plastic waste never enter the recy-

cling stream but also because of the losses and inefficiencies inherent in the recycling methods themselves. Furthermore, considering the increasing demand, it is inconceivable to cease the production of fresh polymers derived from fossil resources.

This realization presents a difficult context for the investigation of current waste disposal techniques. It underscores the necessity for a multifaceted approach that not only seeks to optimize current recycling and reuse strategies but also acknowledges and addresses the limitations of these systems. Before diving into the specific waste management methods, it is essential to realize that the challenge is not just improving recycling techniques, but also ensuring they are utilized to their full potential. As it is, a significant portion of plastic waste is sent to landfill, incinerated, or, in the worst cases, leaked into the environment due to a combination of policy gaps and economic factors. Enhancing the efficiency of recycling is one part of the solution; the other crucial aspect is making sure these practices are adopted widely enough to make a substantial impact.

Landfilling, whether controlled or uncontrolled, shares common challenges in managing plastic waste, although with varying degrees of environmental impact. In both scenarios, the challenges include greenhouse gas emissions, impacts on human health and on ecosystems. Controlled landfills aim to mitigate these impacts by using containers with liner and methane capture technologies. However, they still struggle with issues like leachate contamination and incomplete gas capture. Leachate is described as a contaminated liquid that forms as a result of water passing through a landfill, collecting pollutants, and flowing into underground areas. Uncontrolled dumping amplifies these problems, leading to more direct and severe consequences on human health and ecosystems. Hazardous substances from unregulated landfills can leak into water sources, putting in danger both human health and ecosystems (Cook et al. 2020). Moreover, the greenhouse gases emitted from these sites, mostly methane, significantly contribute to global warming. The global warming potential of methane from landfills is particularly concerning as it is far more potent than carbon dioxide in trapping heat in the atmosphere. To make matter worse, landfills and open dumps are together the third contributor to global human-made methane emissions (Wang et al. 2020).

Incineration allows to reduce the volume of plastic waste and in some cases to recover energy. This process consists of the high-temperature combustion of plastics which reduces waste volume between 70% and 90%. Modern incinerators can recover the energy produced during this process by converting it into electricity or heat. However, the environmental impact of plastic waste incineration raises considerable concerns. The burning of plastics, especially



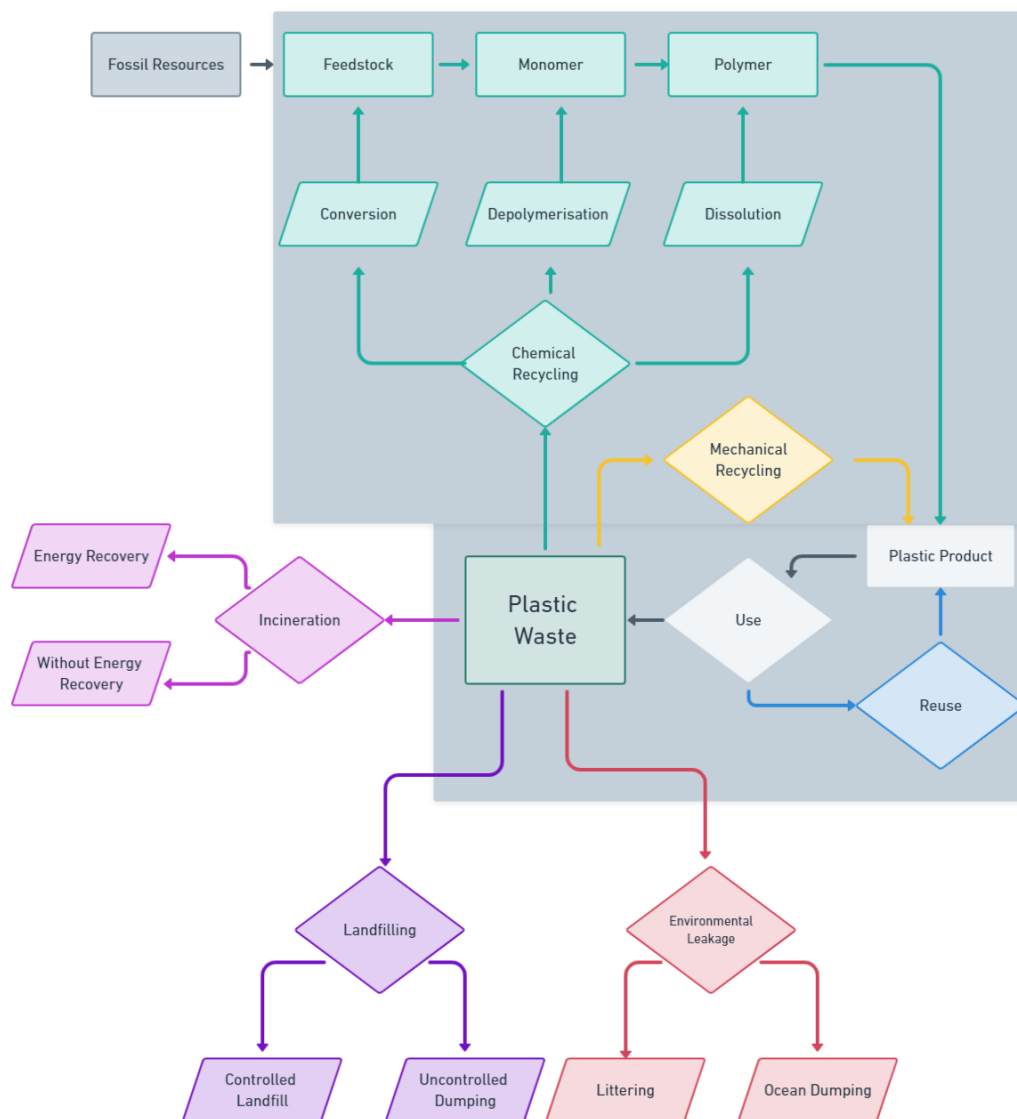


Figure 1.4: Life cycle and management pathways for plastic waste: from production to end-of-life options.

those containing chlorine like PVC, can lead to the emission of dioxins and other harmful pollutants (Nagy et al. 2016). These harmful substances emitted during combustion impose sophisticated filtration systems in incinerators to maintain air quality and to reduce risks to public health. Regarding greenhouse gas emissions, a careful evaluation of the environmental trade-offs is necessary when comparing landfilling with incineration (Anshassi et al. 2021). Indeed the comparison between the direct release of  $CO_2$  during incineration of fossil-based plastics and the slower, but potentially more harmful, methane emissions from landfills is not straightforward. The use of incineration also presents a challenge regarding single-use plastics: it offers a seemingly convenient disposal method that potentially discourage the reduction of plastic production. Thus one should consider each solution in its globality in order to evaluate the best method in a specific context.

The simplest method of plastic recycling is the reuse. Reusing plastic products is a way of extending their lifespan by using them more than once. They can be used in the same way, but also for a different purpose. This approach potentially involves repairs as well as cleaning, particularly when it comes to food containers. Practical examples include plastic bottles and reusable shopping bags. This practice is particularly interesting, as it saves energy and reduces environmental impact in a number of ways. Firstly, reuse avoids the need to produce new products from fresh raw materials. In addition to the above-mentioned advantages, this also has an economic benefit. Secondly, this process avoids the generation of waste and the difficulties associated with it. However, the reuse of plastics has certain limitations such as the degradation of plastic quality over time and the limited reusability of certain types of plastics. It can also presents health and safety concerns, particularly when reused for food storage. Additionally, there are logistical difficulties in gathering and distributing used plastics, and consumer perceptions about hygiene and aesthetics prevent the widespread adoption of plastic reuse.

The most widespread method of recycling plastics is mechanical recycling. This recycling method is a process that transforms plastic waste into reusable materials, thereby reducing the need for virgin plastics. After collection, the waste is first sorted to separate the different types of plastic. Sorting is a crucial step in mechanical recycling. Indeed, this stage, through the potential incompatibility of materials, has a significant impact on the final product quality, as well as on the overall recycling process efficiency. The sorted plastics are then cleaned to remove any impurities or contaminants. Once cleaned, the plastics are shredded into small pieces called flakes. These flakes are then melted and transformed back into granules, which can be used in the production of new plastic products. Mechanical recycling

of plastics offers several key advantages in waste management. Firstly, it reduces the amount of waste destined for landfill and incineration, helping to conserve space and reduce environmental impacts. Secondly, by reusing existing materials, mechanical recycling saves natural resources and reduces dependence on virgin raw materials. In addition, the process supports the circular economy, extending the life of materials and stimulating innovation in the recycling sector. Although it may seem highly advantageous, mechanical recycling suffers from a number of important limitations. Probably the most important is the deterioration in plastic quality. Although degradation mechanisms differ from polymer to polymer, changes in chain length and mechanical properties are a recurring problem (Schyns et al. 2021). Secondly, as mentioned above, the inherent complexity of waste sorting makes this method of recycling very difficult. The process can also be quite costly, making it potentially less attractive than the production of new plastics. This problem is exacerbated by the dependence on market’s demand: if demand for these recycled materials is low, the economic incentive will be weak.

Leaving aside chemical recycling (which will be discussed in detail in Section 1.2), leakage to the environment is the last end-of-life option for plastic waste shown in Figure 1.4. It is a fate that is unfortunately all too common for plastic waste. It has been estimated, for example, that between 0.8 and 2.7 million tonnes of plastic waste are dumped into the ocean via rivers every year, mainly in Asia (Meijer et al. 2021). Environmental leakage also extends to terrestrial ecosystems, including urban and peri-urban areas, forests and wilderness areas, as well as agricultural land. The work of Kumar et al. (2021) highlights the consequences of this leakage, showing a complex and widespread impact on ecosystems and human health. The dispersal of plastic waste in natural environments is leading to an alarming accumulation of microplastics. These fine particles are capable of absorbing and transporting chemical pollutants, and can enter food chains, causing ecological imbalances and health problems in animals and humans. The harmful effects on our health are of particular concern. Microplastics can cross the body’s biological barriers and accumulate in various tissues, posing significant risks of long-term toxicity. Among the chemical pollutants present in these microplastics are numerous endocrine disruptors. These substances cause hormonal imbalances with deleterious consequences for the reproductive system and endocrine organs such as the hypothalamus, pituitary gland and thyroid, to name but a few (Ullah et al. 2023). However, further studies are needed to better understand this topic as well as the damage caused by soil contamination, as the work of Chae et al. (2018) suggests. However, it is quite clear that this contamination also concerns agricultural soils and therefore raises the question of food safety. Moreover, as mentioned earlier

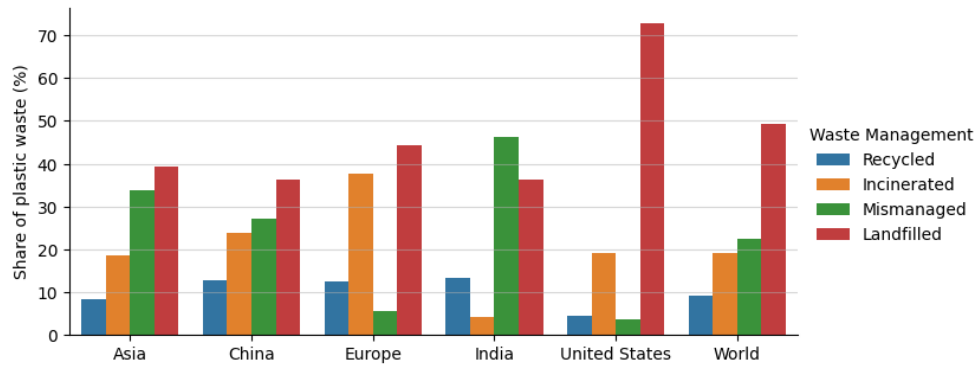


Figure 1.5: Share of plastic waste that is recycled, landfilled, incinerated and mismanaged across the world in 2019. Adapted from (OECD 2022b).

in the discussion on landfill, the degradation of plastics releases greenhouse gases, thereby contributing to global warming.

Having explored the various plastic waste management systems and the difficulties associated with them, as well as the serious consequences associated with environmental leakage, it is worth looking at current strategies on a global scale. Figure 1.5 shows the share of plastic waste that is recycled, landfilled, incinerated and mismanaged in various region of the world in 2019. Mismanaged plastic waste includes materials burned in open pits, dumped into seas or open waters, or disposed of in unsanitary landfills and dumpsites. This chart highlights regional disparities and similarities in waste treatment. A first obvious observation is that, with the exception of India, where most plastic waste is mismanaged, the most common fate for this waste around the world is landfill. In the USA, for example, up to 70% of plastic waste is landfilled. It can also be observed that a very significant proportion of waste is mismanaged in India, China and Asia in general, where the state of plastics management and recycling is highly unsatisfactory. These figures lead us to believe that Asia is a particularly poor performer in this area, but it is absolutely necessary to nuance this statement, given that Asian countries import a huge amount of plastic waste from other countries. Indeed, as the analysis of Liang et al. (2021) on Asia’s plastic waste trade shows, Asia imported 74% of the world’s plastic waste in 2016. These imports mainly concerned China, but since the ban on imports of plastic waste from foreign countries came into force at the beginning of 2018, imports have been transferred to other Asian countries such as Vietnam or Malaysia. It is therefore vital to bear in mind that this is a global problem. Globally, less than 10% of plastic waste is recycled, which is by no means enough, especially given the general inefficiency of current recycling methods.

In the light of the picture painted in this section, it is clear that profound changes are needed to improve the current situation. As the work of Prata et al. (2019) underlines, this issue can only be tackled through a multi-faceted approach that considers all the ins and outs of plastics production, consumption and disposal. The entire life cycle of plastics needs to be improved, and this means applying the four R's rule, in order: reduce, reuse, recycle and recover. The first step is, of course, sobriety, by regulating production and consumption. This includes political efforts to ban single-use plastics and promote sustainable alternatives. Nevertheless, society will continue to produce waste. It is therefore crucial to design products that are more easily recyclable and contain fewer harmful additives. More efficient collection systems are needed to ensure that these products are properly processed. It is vital that these changes are accompanied by improvements in recycling methods. Indeed, technological innovation can play a key role, by developing new methods that are more efficient and less damaging to the environment. These new solutions will promote the circular economy, transforming waste into valuable resources. In this context, Section 1.2 will examine a very promising processing method: chemical recycling. Although this recycling method presents its own challenges and opportunities, it has the potential to radically transform the way plastic waste is managed.

## **1.2 Chemical recycling and circular economy of plastic waste**

The challenges associated with plastic waste management, exacerbated by the constant increase in its production, were explored in detail in Section 1.1. While traditional methods such as landfilling, incineration and mechanical recycling have their own limitations and environmental impacts, chemical recycling stands out as a promising route to more sustainable plastic waste management.

The chemical recycling of plastic waste refers to all technologies that enable this waste to be converted back into valuable products through chemical transformations. These valuable products are purified polymers, monomers, fuels or other chemical substances. These technologies have the advantage of reintegrating plastics into the production cycle, helping to reduce dependence on virgin fossil resources and minimize their ecological footprint (Meys et al. 2020). Unlike mechanical recycling, which is often associated with "downcycling" due to the loss of material quality, chemical recycling offers a pathway to maintain or even improve the quality of recycled materials (Hong et al.

2017).

Chemical recycling encompasses a variety of methods, each characterized by its own specific products and constraints. Among them, conversion generates feedstock in the form of oil or gas, which can be used as fuels or bases for other chemical compounds. Depolymerization, on the other hand, transforms polymers back into monomers, while dissolution focuses on the recovery and purification of the polymers themselves from plastic waste. Each method, responding to specific challenges, contributes in its own way to the circular economy by transforming waste into reusable resources.

Dissolution is particularly relevant for processing industrial plastic waste, such as manufacturing offcuts, which are generally clean and of constant composition. According to Walker et al. (2020), the STRAP (solvent-targeted recovery and precipitation) technique has proved effective in separating industrial multilayer packaging into pure resins with near-perfect material efficiency. However, this efficiency needs to be nuanced, as it applies to uncontaminated post-industrial waste, rather than mixed municipal waste. The dissolution method presents significant challenges, particularly with regard to its large-scale application. The use of chemical solvents imposes significant limitations in terms of cost, availability and post-use management. These constraints, combined with the need for highly selective solvents to effectively dissolve specific types of plastic, complicate the dissolution process. Zhao et al. (2018) also highlight that, despite the production of high-quality plastics, dissolution and supercritical fluid extraction face similar challenges. These techniques require improvement to become more environmentally friendly, economically viable and suitable for large-scale processing of plastic waste.

Depolymerization is a chemical recycling method that involves breaking long polymer chains into their constituent monomers. This approach is particularly effective for recycling polyethylene terephthalate (PET), a polyester whose ester bonds can be easily split by chemical reactions such as hydrolysis, glycolysis or methanolysis. PET’s structure enables efficient recovery of terephthalic acid and ethylene glycol, which can be reused to produce virgin-grade PET (Crippa et al. 2019). Depolymerization offers a solution for recycling PET that is difficult to process by mechanical recycling, particularly when it is heavily colored or soiled. However, this technique presents challenges in terms of technical complexity and high cost, making its large-scale application less practical. Additionally, it is not suitable for all types of plastic. For example, polyethylene (PE) and polypropylene (PP) have chemical structures that do not lend themselves well to depolymerization. Indeed, these polyolefins are long hydrocarbon chains without easily breakable functional groups like PET’s ester bonds. At the same time, research into microbial and enzymatic biodegradation of synthetic plastics is opening

up new prospects for chemical recycling. The work of Mohanan et al. (2020) highlights the use of microorganisms and enzymes to break down plastics into reusable monomers or convert them into valuable bioproducts. Although progress has been made in identifying enzymes capable of degrading PET, research continues to focus on the discovery and characterization of enzymes effective for other types of plastic. The speed of degradation and the specificity of the enzymes remain major obstacles to the wider application of this type of technique.

While dissolution and depolymerization techniques are often more selective and geared towards the recovery of specific materials, thermal processes offer greater flexibility to handle a wide range of plastic wastes and produce a diversity of useful products (Davidson et al. 2021). These thermal methods, particularly gasification and pyrolysis, are better suited to municipal waste management. Indeed, they enable the treatment of large volumes of mixed and contaminated waste that would otherwise end up in landfill or be incinerated (Qureshi et al. 2020). These technologies are based on the application of heat under a controlled atmosphere, transforming the waste into gas, oil and coal (Maqsood et al. 2021). Although the basic concept is simple, practical implementation on an industrial scale can be quite complex. It requires precise control of process conditions, product and by-product management, and advanced systems for emissions treatment (N. Zhou et al. 2021). These challenges, together with questions about energy efficiency and economics, qualify the considerable potential of thermal processes and motivate technological advances (Dogu et al. 2021). Moreover, optimizing these technologies to maximize the quality and utility of end products is an active area of research and development (Solis et al. 2020). It is therefore crucial to explore gasification and in particular pyrolysis in depth to better understand how they work, their advantages and challenges, as well as future prospects.

The gasification of plastic waste is a complex process that takes place in several stages. Initially, the plastics are ground or shredded to a uniform particle size, facilitating their treatment in the reactor. Once prepared, this waste is fed into a gasification reactor, which is generally either a fluidized bed or fixed bed reactor. The fluidized-bed reactor, for example, promotes homogeneous heat distribution and efficient interaction between the waste and the gasifying agent, thanks to a fluidized particle medium (Mastellone et al. 2007). In the reactor, the plastics are exposed to high temperatures, typically between 700°C and 1000°C, generally under atmospheric pressure. The reactor atmosphere is made up of gasifying agents such as water vapor and carbon dioxide, plus a small amount of oxygen or air. The first key stage in the reactor is the pyrolysis of carbonaceous waste. During this stage, volatile particles are released, forming a gas and a solid matrix called char. Next, the

small amount of oxygen introduced generates combustion, releasing heat for the subsequent gasification phase and producing  $\text{CO}_2$ . Then comes the gasification process proper where the carbon contained in the char reacts with steam and carbon dioxide to form carbon monoxide and hydrogen following reactions 1.1 and 1.2 (Janajreh et al. 2020). In addition, the reversible gas phase water-gas shift reaction (1.3) rapidly reaches equilibrium, stabilizing the concentrations of carbon monoxide, steam, carbon dioxide and hydrogen.



The process is designed to produce syngas, a mixture mainly composed of hydrogen and carbon monoxide. The conversion efficiency and quality of this syngas are highly dependent on the reactor’s operating parameters, including temperature, pressure and the proportion of gasifying agent. Recent technological advances focus on optimizing these parameters to improve syngas yield and minimize environmental impacts. Studies such as the one conducted by Abdelrahman et al. 2018 have explored the use of sustainable materials and catalysts to improve gasification efficiency and product quality. In terms of energy applications, syngas is a versatile fuel. It can be burned directly to generate heat and electricity, or used in internal combustion engines and gas turbines. Its high calorific value makes it particularly attractive for power generation. Syngas is also a key raw material in chemical synthesis. It is used to manufacture a variety of chemicals such as methanol and ammonia, and is also the reactive mixture used in the Fischer-Tropsch process for hydrocarbon production. The transformation of CO and  $\text{H}_2$  into a range of chemicals further enhances the value of syngas as a resource (Xu et al. 2010). However, the presence of contaminants such as tars and fine particles in syngas can complicate its use. Research and development efforts aim to improve syngas cleaning methods, removing these impurities and increasing gas purity for downstream applications. These advances are essential to optimize the use of syngas and maximize its economic and environmental potential.

Whereas gasification uses a partially oxygenated environment to transform plastic waste into syngas, pyrolysis is taking place in the total absence of oxygen, thus avoiding any form of combustion. This fundamental difference affects not only the composition of the final products, but also the strategy for managing plastic waste. During the pyrolysis process, polymers are transformed into a mixture of pyrolysis oil, gas and char in varying proportions. The nature of the products obtained and their proportions in the final mix-



ture depend on factors such as temperature, heating rate and residence time (Papuga et al. 2016). Pyrolysis is typically carried out at a temperature between 300°C and 900°C. The selection of temperature and other factors depends on the specific pyrolysis objectives, such as maximizing oil or gas production. Pyrolysis reactors also vary, ranging from fixed-bed reactors to fluidized and rotating beds, each with direct implications for heating rate and residence time, and thus the quality and quantity of pyrolysis products (Anuar Sharuddin et al. 2016).

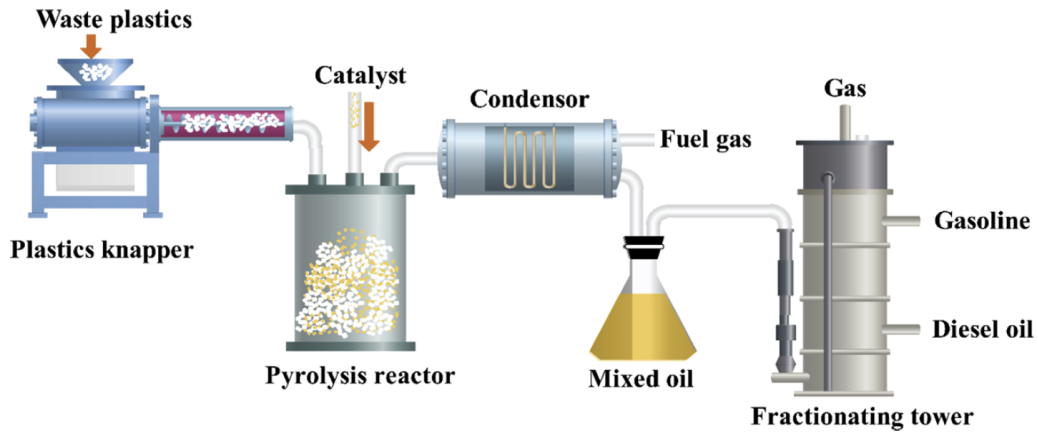


Figure 1.6: Schematic representation of a plastic waste pyrolysis process retrieved from the paper of Maqsood et al. (2021).

Figure 1.6 shows a schematic process of plastic waste pyrolysis, in which the plastic waste is shredded and fed into the reactor. When the plastic is heated and reaches its melting point, it melts and begins to break down into smaller hydrocarbon molecules. This complex physico-chemical transformation results in the breaking of various carbon-hydrogen and carbon-carbon bonds. The work of Hujuri et al. (2011) examines the evolution of polypropylene pyrolysis products as a function of temperature. The way in which process conditions influence the nature and quantity of the products is used to determine the pyrolysis mechanism. A combination of random-scission reactions, intra- and intermolecular hydrogen transfers,  $\beta$ -scissions and radical recombinations produce different types of alkanes and alkenes covering a wide range of chain lengths. These volatile molecules in gaseous form are then sent to a condenser, where they are either condensed into pyrolysis oil, or remain in a gaseous state for those that cannot be condensed.

The use of catalysts in the pyrolysis of plastic waste significantly modifies its thermal decomposition. Catalysts, typically zeolites, act by lowering the temperature required to initiate the pyrolysis reaction and by influencing the

selectivity of the end products. For example, catalysts such as zeolite ZSM-5 can promote the formation of low-molecular-weight aromatic hydrocarbons via Diels-Alder cyclization and aromatization of alkenes and dienes from polyolefin pyrolysis (Onwudili et al. 2019). These catalysts accelerate the fragmentation of polymer chains and facilitate the formation of more volatile compounds. Cracking and molecular rearrangement reactions are more pronounced leading to pyrolysis oils with lower molecular weights and a higher proportion of hydrocarbons in the gasoline range (Ratnasari et al. 2017). In addition, zeolite catalysts modify the distribution of gaseous products by promoting the formation of specific gases such as ethylene and propylene, which can be used as raw materials in the manufacture of polyethylene and polypropylene, thereby reinforcing the circular economy paradigm (Muhammad et al. 2015).

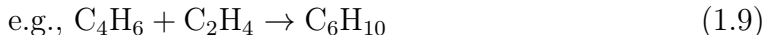
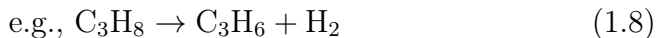
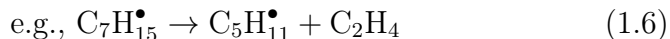
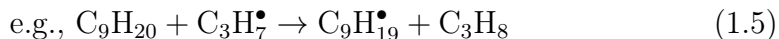
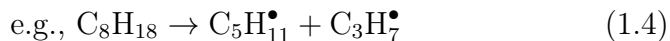
Of the products obtained from the pyrolysis of plastic waste, char is generally the one obtained in the smallest quantities, as it is less valuable than oil or gas. However, there are several ways to use it, the most common being as a substitute for coal as a solid fuel. After activation, it can also be used as a means of extracting heavy metals, odors and toxic gases from waste (Maqsood et al. 2021). The gas obtained during pyrolysis consists of light alkanes and alkenes such as methane, ethane, ethylene, propane, propylene and butane, as well as non-condensable gases such as dihydrogen and carbon mono- and dioxides. The nature of the plastic waste and the reaction temperature play a very important role in the exact composition of the gas mixture. For example, a high proportion of PET increases CO and CO<sub>2</sub> concentration, while an increase in operating temperature enhances H<sub>2</sub> production (Singh et al. 2016). These gaseous products can be used as raw materials for chemical synthesis. In particular, as described above in the context of gasification, the syngas contained in the mixture can be used in a variety of ways. However, this type of valorization requires advanced separation and purification technologies to isolate useful components and remove impurities. More simply, thanks to its high calorific value, pyrolysis gas can be burned to generate electricity via steam turbines, or to produce the heat needed for the pyrolysis process itself.

Pyrolysis oil from plastic waste processing is a key product in the thermo-chemical recycling process, distinguished by its high valorization potential. Compared with the char and gas also produced during pyrolysis, the oil is generally obtained in larger quantities and has greater reuse and processing potential, underlining its central role in plastic waste recycling efforts. The composition of pyrolysis oil varies greatly depending on the conditions under which pyrolysis is carried out, such as temperature, residence time and the use of catalysts. These factors influence not only the quantity but also the

quality of the oil obtained. In terms of physical properties, pyrolysis oil shares similarities with conventional diesel, particularly with regard to its viscosity and calorific value (Miandad et al. 2017). However, its chemical composition can differ significantly. Unlike diesel, which is mainly composed of saturated alkanes and a smaller proportion of aromatic hydrocarbons, pyrolysis oil can have a much higher concentration of aromatic compounds, particularly when it is derived from the pyrolysis of polystyrene-rich mixtures (Miandad et al. 2017). This divergence in composition makes its direct use as a transport fuel problematic without post-pyrolysis treatments to improve its characteristics, such as distillation, refining, or blending with conventional diesel to adjust its composition. Distillation of the pyrolysis oil separates the various hydrocarbon fractions, enabling more targeted use of these components, whether for energy or fuel production, or for the manufacture of new chemicals. The conversion of plastic waste into fuels via pyrolysis is a very active area of research, offering an attractive method for recovering plastic waste while meeting energy needs. The critical review of Li et al. (2022) sheds light on this approach, highlighting the potential for converting plastic waste into various types of fuel using a variety of technologies, including pyrolysis in particular. The use of pyrolysis oil as a fuel is emerging as a particularly attractive avenue for large-scale deployment. This is likely to be a feasible and profitable business that has already been successfully put into practice, although it does involve technical difficulties associated with the composition of pyrolysis oil (Fahim et al. 2021; Faussone 2018). In particular, conversion into fuels such as diesel and gasoline, suitable for use in internal combustion engines, illustrates the potential of this approach to make a significant contribution to the energy mix. However, this strategy raises concerns about its long-term sustainability. Continued reliance on petroleum-based fuels, even when recycled from plastics, can detract from the aims of the circular economy, which aims to reduce consumption of non-renewable resources and promote a more sustainable materials life cycle. In addition, the focus on burning fuels derived from pyrolysis oil could perpetuate emissions of CO<sub>2</sub> and other pollutants, underlining the importance of considering alternative solutions that better align with the principles of emissions reduction and environmental preservation.

Aligning plastic waste management with the circular economy opens up innovative pathways for its valorization. One of the most promising methods is to convert plastic waste into virgin monomers, which can then be reused to create new polymers. This offers a sustainable solution by closing the plastic life cycle. Steam cracking is a particularly relevant technique in this context. This process enables the production of light alkenes such as ethylene, polypropylene, butene and butadiene, which are essential building blocks for

the manufacture of a variety of polymers. Basically, thermal cracking is the preferred industrial means of obtaining these light olefins. In this process, saturated hydrocarbon chains are broken and converted into smaller, unsaturated hydrocarbons, thanks to a multitude of reactions taking place in a steam-rich environment. Typically, the feedstock for steam cracking includes naphtha cuts or light alkanes. However, the use of heavier cuts, such as pyrolysis oil from waste plastics, is also possible (Kusenberget al. 2022b). Nevertheless, the massive quantities of raw materials required to feed industrial steam crackers far exceed the available volumes of sorted plastic waste. This means that it is unrealistic to expect these plants to operate exclusively on plastic waste. However, it is entirely possible and potentially beneficial to blend pyrolysis oil obtained from plastic waste with fossil feedstocks traditionally used in these reactors (Kusenberget al. 2022b).



The steam cracking process involves a series of complex chemical reactions. However, it is possible to define a number of key stages that transform heavy hydrocarbons into light olefins, highly valuable compounds. The mechanism begins with the homolytic breaking of a carbon-carbon bond, forming two smaller free radicals (Equation 1.4). This step is the initiation reaction, generating highly reactive particles that drive subsequent reactions. The propagation reaction (Equation 1.5) follows, where a free radical interacts with a hydrocarbon to produce a lighter molecule and another free radical, continuing the chain of reactions. A crucial step in this process is illustrated by Equation 1.6, where a free radical can split into a smaller radical and an olefin. This reaction contributes directly to the formation of light olefins such as ethylene and propylene. Finally, termination reactions take place, involving the recombination of two free radicals (Equation 1.7). Beyond this general process, dehydrogenation reactions (Equation 1.8) also take place, where alkanes are transformed into olefins while hydrogen is released. In addition, as shown in Equation 1.9, the Diels-Alder reaction produces cyclohexane derivatives from a diene and an alkene. These cyclohexane derivatives then undergo dehydrogenation reactions to form a benzene derivative, which is a coke precursor.

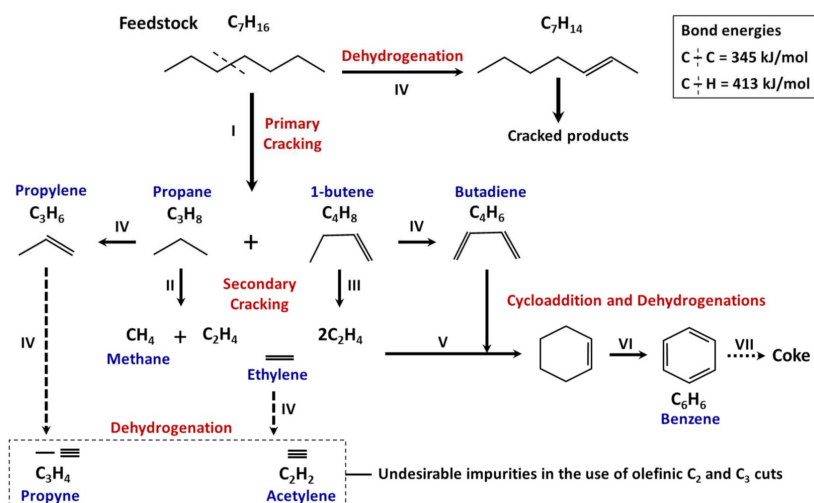


Figure 1.7: Diagram of the main reactions involved in the steam cracking of alkanes retrieved from the review of Gholami et al. (2021).

Figure 1.7 shows a general steam cracking diagram, divided into primary cracking (I) - the splitting of heavy hydrocarbons into lighter compounds - and secondary cracking (II) - the production of even lighter, olefin-rich products. This figure also highlights the risk of unwanted reactive alkyne formation during olefin dehydrogenation (IV).

The success of steam cracking is highly dependent on the quality of the feedstock processed. This sensitivity underlines the importance of careful management of plastic waste even before the pyrolysis process. Contamination of plastic waste can introduce impurities into the resulting pyrolysis oil, originating in particular from additives used in the production of plastics and from dirt accumulated during their use. These impurities include oxygenated, chlorinated and nitrogenous compounds, as well as iron, sodium and silicon (Kusenberget al. 2022a). The presence of these compounds and of alkenes and dienes poses specific challenges for steam cracking. The study by Kusenberget al. (2022b) shows the potential harm caused by these undesirable substances. Compounds with heteroatoms can poison and thus deactivate catalysts and cause corrosion in the pipes, notably via the formation of hydrochloric acid. Alkenes and dienes cause reactor fouling through increased coke formation. These consequences greatly affect the overall efficiency of the cracking process. To overcome these challenges, hydrotreatment appears to be a key step in purifying pyrolysis oil prior to its use in steam cracking. This treatment involves reacting the oil with hydrogen at high pressure and temperature, in the presence of specific catalysts. This technique removes not

only impurities, but also alkenes and dienes that are unsuitable for cracking. The use of cobalt/molybdenum (CoMo) and nickel/molybdenum (NiMo) catalysts supported on alumina has proved effective for the hydrotreatment of a mixture of heavy atmospheric diesel and waste cooking oil, as reported by Bezergianni et al. (2014) in their analysis. This mixture is comparable to the composition of plastic waste pyrolysis oil, opening the door to an interesting solution for the post-treatment of this pyrolysis oil.

This question of the sensitivity of steam cracking to the quality of pyrolysis oil highlights a more general constraint associated with chemical recycling: technical complexity. For example, on paper, the transformation of plastic waste into virgin monomers through a succession of pyrolysis, hydrotreatment and steam cracking processes seems an ideal solution, but this is without taking into account the technical challenges involved in scaling up such a process to industrial scale (Dogu et al. 2021). Each of these stages requires specific operating conditions, advanced equipment and rigorous management. Precise control of these systems is necessary to achieve sufficient yields and ensure the quality of the final products (Solis et al. 2020). Moreover, chemical recycling processes, especially those that use heat as a conversion means such as pyrolysis and gasification, are particularly energy-intensive. This high energy demand, potentially through the use of fossil resources, whether directly or indirectly, strongly qualifies the idea of environmental sustainability. Additionally, the environmental impacts of chemical recycling go beyond energy consumption and greenhouse gas emissions. Processing plastic waste through chemical recycling can generate by-products and emissions that need to be managed responsibly to avoid new types of pollution (Hahladakis et al. 2018). The economic viability of chemical recycling is also an essential consideration. Indeed, it is utopian to imagine that manufacturers would embark on chemical recycling without expecting a return on their investment, especially given the potentially colossal investments involved in this type of technology. Consequently, large-scale adoption of chemical recycling will only be encouraged if the operational costs associated with energy, catalysts and equipment maintenance are more than offset by the profits generated by the sale of recycled products. There are two potential responses to these challenges: technological innovation and the introduction of new policy regulations. Technological innovation appears to be a crucial lever for improving efficiency, reducing costs and minimizing the environmental impact of chemical recycling. The development of more energy-efficient processes, improved catalysts and cleaner treatment methods are all pathways to be explored to make the chemical recycling of plastic waste more sustainable and economically viable. The introduction of new policy regulations also plays a key role. By offering subsidies and tax incentives, governments can encourage



Figure 1.8: Infographic describing the circular economy model (European Parliament 2023).

companies to invest in the necessary infrastructure and innovate in the field of plastic waste processing. Such financial support could offset high initial costs and operational expenses, making chemical recycling more economically attractive. In addition, policy regulations can set clear standards for the quality and safety of products derived from chemical recycling, boosting consumer and industrial confidence in recycled materials. This could open up new markets for chemically recycled products and stimulate demand, creating a virtuous circle. Targeted policies could also encourage research and development by facilitating collaboration between companies, universities and research institutes.

Despite the challenges associated with chemical recycling, the fact remains that it is an essential solution for the development of the circular economy. The circular economy stands as an alternative economic model

that breaks with the traditional linear pattern of "take, make, consume, throw away". Geisendorf et al. (2018) define the circular economy as a system where the reuse, repair, renewal and recycling of materials and products extend their life cycle, thereby reducing resource consumption and waste production. This approach, depicted in Figure 1.8, aims to create a closed loop of materials, optimizing the value of resources throughout their life cycle. Chemical recycling, at the heart of the circular economy, plays a key role in converting plastic waste into monomers or other chemicals that can then be reused to make new plastics. This technology offers an opportunity to significantly reduce the environmental footprint of plastics by reducing the reliance on fossil resources to produce new materials and limiting the amount of plastic waste destined for landfill or incineration. Meys et al. (2020) highlight the potential impact of chemical recycling on improving the environmental sustainability of plastic packaging, providing a viable solution for its integration into circular economy models.

Having highlighted the importance of chemical recycling for the development of the circular economy, despite the challenges involved, it is now time to look to the future and explore methods to effectively manage the complexity of these technologies. Chemical recycling, with pyrolysis at the forefront, is a very active field of study, explored through laboratory work and various simulations. In the case of pyrolysis, for example, this research reveals a wide range of potential configurations that are influenced by the nature of the feedstock, the catalysts used, and the operating conditions. This diversity of methods poses a major challenge: how to identify the most efficient and environmentally friendly recycling methods from an ocean of possibilities? Performing detailed simulations is a critical step prior to actual process development. However, this process is both complex and time-consuming, and cannot be systematically repeated to evaluate the multitude of options available. Ontological structures and decision-making tools are critical at this stage. They provide a structured framework for analyzing and comparing different recycling methods, making it easier to identify and select the most promising strategies for further exploration. Section 1.3 will focus on the importance of ontological frameworks and decision-making tools in moving towards greater environmental sustainability.



### 1.3 Ontological frameworks and decision-making tools in environmental sustainability

Having explored the promises and difficulties associated with chemical recycling, the importance of making informed choices in the face of the multitude of options available becomes essential in the pursuit of more sustainable approaches to plastic waste management. This need highlights the usefulness of ontological frameworks and decision-making tools as effective means of structuring knowledge and facilitating relevant choices in the complex field of plastic waste recycling. Ontologies are key elements of knowledge management because they provide a structured framework for defining the relevant concepts in a given domain and the relationships between these concepts. These structures play an important role in allowing information to be categorized and linked in a structured way, enabling in-depth understanding and analysis. In addition, attributes are associated with these concepts. For example, in the context of plastic waste recycling, ontological frameworks not only define the various processes and products and the links between them, but also allow specific attributes to be associated with each of these processes and products. Typically, a given recycling process or different plastic products would be assigned a cost and an environmental impact, allowing a multi-criteria evaluation of each option. This ability to associate attributes with concepts becomes particularly important when exploring complex decisions related to chemical recycling. As Kumazawa et al. (2014) point out, ontological engineering applied to sustainability science can greatly facilitate the deliberative process that is essential to addressing sustainability issues holistically.

The issue of sustainability and the application of these conceptual frameworks naturally extends to a variety of fields. The work of Muñoz et al. (2013) illustrates how an ontological framework can facilitate the integration of environmental concerns into business decision-making processes. The approach proposed by Hou et al. (2015) uses ontologies and semantic web technologies to optimize structural design in the construction sector, highlighting the importance of considering environmental and economic impacts from the earliest stages of design. This methodology illustrates how ontological frameworks can guide material selection and construction methods that minimize carbon footprints and maximize sustainability. Finally, Upward et al. (2016) vision of highly sustainable business models introduces an extended application of ontological structures and demonstrates how they can be used to rethink business models with the goal of achieving strong sustainability. By integrating environmental, social, and economic considerations

within the framework of a business model ontology, companies can identify strategies that not only reduce their negative impact on the environment, but also contribute positively to society while maintaining profitability. The exploitation of the fundamental principles of ontological structures through these studies reveals a wide range of applications and stresses their importance in promoting sustainable practices. By taking into account the environmental and economic attributes of processes and products, and by carefully organizing the associated information, ontological frameworks emerge as an effective strategy for addressing the challenges inherent in plastic waste recycling. This analysis begins the discussion of decision-making tools and their synergy with ontologies, a key element in the effective implementation of strategies to promote environmental sustainability.

Decision-making is a process in which an individual or a group chooses an option among several alternatives according to specific criteria and objectives. This process involves several key stages: identification of the problem to be solved, evaluation of the various alternatives available, selection of the best option and, finally, implementation of the decision. These stages involve cognitive elements, such as judgment and analysis, as well as emotional factors, underscoring the complexity of decision-making. For example, according to Papadakis et al. (1998), business decisions are influenced by three main factors: the details of the situation, the decision makers, and the overall business context. They point out that decisions are shaped by logic, established rules, communication, and influence. This shows that a decision is not just a matter of rationality, but is greatly influenced by the overall context in which it is made. Decision-making is of paramount importance in a wide range of fields and sectors. Not only does it influence the direction and performance of organizations in industrial environments, but it also plays a key role in social behavior and political governance. Effective and informed decision making is fundamental to solving problems in a variety of complex and changing environments (Wilson et al. 2007).

Various theories and strategies have been developed in the field of strategic decision making. These approaches use both analytical methods, based on data and facts, and more intuitive methods, which take into account personal experience and instinct. According to Ahmed et al. (2014), decision-making is not just about choosing the option that looks best on paper; it involves a thorough evaluation of different options, reflection on potential consequences, and alignment with long-term goals. A good decision has several key elements. It must be informed, considered, aligned, pragmatic, and adaptive. Informed means based on rigorous analysis of relevant data. A well-considered and aligned decision is one that takes into account different future scenarios, uncertainties, and the balance of pros and cons, while being

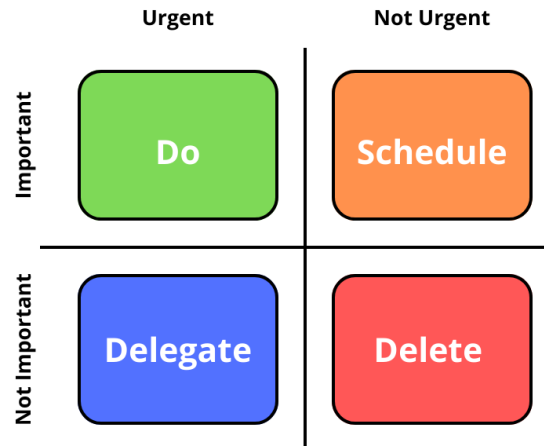


Figure 1.9: Eisenhower Matrix.

aligned with the broader goals of the organization. A good decision must also be achievable within the context of existing resources and constraints, and be adaptable as the situation evolves. This description of a good decision suggests that it's an objective process, but it is important to remember that decision-making is at least partly subjective. This means that the intervention of human expertise and intuition is often necessary. However, in today's complex, data-driven world, the use of specific decision-making tools becomes not only useful, but sometimes essential.

These tools are methods or software that are used to analyze, evaluate, and compare different alternatives or options according to specific criteria in order to make more informed decisions. They can also play an important role in quantifying uncertainty. Decision-making tools can be classified according to whether they are qualitative or quantitative. Qualitative decision-making tools, such as concept maps and decision matrices, help organize thoughts and categorize alternatives. The Eisenhower Matrix, shown in Figure 1.9, is a simple example of a qualitative decision-making tool. It involves distinguishing between tasks that are important or not, and urgent or not, in order to organize and prioritize them. This decision matrix can be applied in a variety of contexts and has been used, for example, to prioritize orthodontic procedures and, therefore, patients on a waiting list (Batra 2017).

Quantitative tools, on the other hand, transform raw data into useful information to support decision-making. There are a variety of methods and techniques for analyzing and processing this data. These mathematical techniques are particularly valuable for their ability to quantify the impact of different options, allowing decision makers to evaluate them objectively. The study by Bagshaw et al. (2019) examines the trend toward quantitative anal-

ysis as a core function in decision-making and highlights that it is an effective tool in today's organizations. One of the most widely used tools in industry is linear programming. This technique is highly valued for its versatility, accessibility, and power. The core of linear programming is the optimization of a linear objective function that represents a measure, such as cost or profit, that aims to be maximized or minimized. This objective function is a linear combination of several parameters called decision variables. Optimization takes place within constraints in the form of equations or inequalities, which are also linear. These constraints may include a limited amount of resources, maximum production capacity, or minimum satisfaction requirements. The search for the optimal solution in the space of feasible solutions is based on the application of mathematical or numerical algorithms. The simplex method, developed by George Dantzig in the 1940s, is the classic algorithm for solving this type of problem. It is a simple, efficient, and robust algorithm that works by systematically moving from one vertex to another along the edges of the space of feasible solutions, each time in a direction that improves the value of the objective function until no further improvement is possible (Kye et al. 2019).

Although linear programming is a powerful technique, many real-world problems don't fit neatly into its framework, where the objective function and constraints are linear and the decision variables are continuous. Two important variants of the method overcome these limitations: mixed-integer linear programming (MILP) and nonlinear programming (NLP). On the one hand, in MILP, one or more decision variables are constrained to take only integer values, which makes it possible to represent elements that cannot be divided, such as people or machines. However, this type of optimization is more complex and requires different types of algorithms. On the other hand, NLP deals with optimization problems where the objective function or some of the constraints are non-linear. Finding an optimal solution for these nonlinear problems is more complex because there are local optimums in addition to the global optimum. There are several specialized solution methods based on different principles, each with its own advantages and disadvantages. The steepest descent method is relatively easy to implement and involves using the gradient to find the direction in which the function increases or decreases most rapidly. Newton's and Quasi-Newton's methods use not only the gradient but also the curvature of the objective function via the Hessian matrix to find the direction to the optimum. This technique is more computationally expensive, but tends to converge faster. Genetic algorithms, for example, apply the principles of natural evolution through selection, mutation, and crossover. The introduction of randomness does not guarantee finding the absolute global optimum, but it does allow the

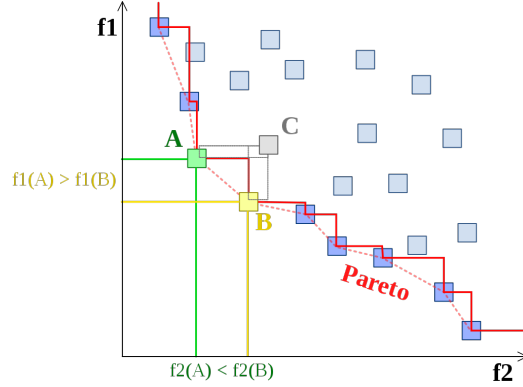


Figure 1.10: Example of a Pareto front (*Pareto Front* n.d.).

exploration of large solution spaces, which proves effective for complex and highly nonlinear problems.

The methods described above are very effective, but they suffer from a major conceptual limitation: they are designed to optimize a single objective function at a time. This fundamental limitation poses a problem when it comes to making a decision in a multifaceted situation with multiple, often conflicting, objectives. It is sometimes possible to convert different objectives into a single measure, but when the criteria are very different in nature, they are not always quantifiable in the same way. For example, how do you directly compare financial costs with environmental impact or employee satisfaction? This is where multi-objective or multi-criteria optimization comes in.

Multi-objective optimization focuses on identifying a set of solutions rather than a single optimal solution. These solutions are called Pareto optimal and represent trade-offs between different objectives, where no objective can be improved without sacrificing another. Thus, the concept of trade-offs is inherent in multi-objective optimization. This set of Pareto optimal solutions is called a Pareto front. An example of a Pareto front, where both objectives  $f1$  and  $f2$  are to be minimized, is shown in Figure 1.10. The Pareto front, represented by the red line, includes all non-dominated solutions in the objective space, unlike the other solutions. For example, point C is strictly dominated by points A and B because the values of both objectives are higher. On the other hand, point A is better than point B with respect to the second objective, and point B is better than point A with respect to the first objective, which means that one is not strictly better than the other, highlighting the idea of compromise.

There are many methods for obtaining Pareto fronts in multi-objective problems, and the  $\epsilon$ -constraint method is one of the most commonly used.

The  $\epsilon$ -constraint method involves optimizing one objective function while treating the other objectives as constraints (Mavrotas 2009). The general form is given by:

$$\begin{aligned} & \text{Minimize} && f_1(x) \\ & \text{Subject to} && f_2(x) \leq \epsilon_2 \\ & && f_3(x) \leq \epsilon_3 \\ & && \vdots \\ & && f_m(x) \leq \epsilon_m \\ & && x \in X \end{aligned}$$

Here,  $f_1(x)$  is the objective function to be minimized,  $f_2(x), f_3(x), \dots, f_m(x)$  are the other objective functions treated as constraints with upper bounds  $\epsilon_2, \epsilon_3, \dots, \epsilon_m$ , and  $X$  represents the feasible set. To obtain the Pareto front, the constraints  $\epsilon_i$  are varied systematically within their respective ranges. The optimization problem is solved repeatedly for different values of  $\epsilon_i$ , generating a set of Pareto optimal solutions.

Evolutionary algorithms are also a well-known method for generating Pareto fronts. These algorithms mimic the processes of natural selection and biological evolution to solve multi-objective optimization problems. They start with an initial population of candidate solutions and use genetic operators such as selection, crossover, and mutation to evolve toward better solutions over generations (A. Zhou et al. 2011). Among the most popular algorithms in this category is the Multi-Objective Genetic Algorithm (MOGA), which uses Pareto dominance-based selection to guide the search toward the Pareto front. Each individual in the population is evaluated according to its performance against different objectives, and individuals that are not dominated by any other are selected to reproduce. Diversity maintenance mechanisms such as crowd distance are often used to ensure a good distribution of solutions on the Pareto front (Deb et al. 2002). Multi-objective evolutionary algorithms (MOEAs) are capable of obtaining the approximate Pareto optimal set in a single run by evolving a population of solutions. Algorithms such as NSGA-II (Non-dominated Sorting Genetic Algorithm II, Deb et al. (2002)) and SPEA2 (Strength Pareto Evolutionary Algorithm 2, Zitzler et al. (2001)) are widely used and have proven effective in many applications. For example, NSGA-II uses non-dominated sorting and crowd distance to maintain solution diversity, while SPEA2 combines strength of dominant solutions and an external archive to preserve the best solutions found.

To conclude the discussion of Pareto frontiers, it is important to mention that there are methods to make a choice from a set of Pareto optimal solutions. Multi-Criteria Decision Making (MCDM) methods such as TOPSIS, PROMETHEE, and VIKOR are particularly relevant in this context. These methods can be used to rank the various Pareto optimal alternatives and thus select the best solution using a quantitative and structured approach. For example, TOPSIS helps identify the solution that is closest to the positive ideal and furthest from the negative ideal. VIKOR is another method for determining a compromise solution as a function of distance from the ideal. The application of these methods often requires human expertise to weight the different criteria. For example, the study by Makan et al. (2020) uses the PROMETHEE method to assess the sustainability of large-scale composting technologies by integrating environmental, economic, social and technical criteria. The weights of the criteria were determined using the judgments of international experts, making it possible to calculate outranking flows for each alternative and identify the most sustainable technologies. Similarly, in the context of multi-site supply chain planning, Felfel et al. (2017) used TOPSIS and VIKOR to select the best solutions from a set of Pareto optimal solutions generated by the epsilon constraint method. These methods helped maximize both profit and product quality by providing decision makers with tools to evaluate and compare the various options available. These examples illustrate the importance and effectiveness of MCDM methods in the decision-making process, particularly in selecting the optimal solution from among several Pareto optimal alternatives.

## 1.4 Conclusion

The literature review presented highlights the many challenges associated with plastic waste management, while emphasizing the importance of chemical recycling and decision-making tools in the context of circular economy. Global plastic production has increased drastically in recent decades, leading to an increase in plastic waste. Traditional waste management methods, such as landfilling, incineration and mechanical recycling, all have significant limitations, and more sustainable and efficient methods need to be explored.

Chemical recycling is a promising method for the sustainable management of plastic waste. Unlike mechanical recycling, chemical recycling offers the opportunity to convert plastic waste back into monomers or other valuable chemicals, making it easier to return them to the production cycle. Among the various chemical recycling methods, pyrolysis and gasification are particularly well suited to treating municipal plastic waste, while dissolution and

depolymerization offer effective solutions for specific types of plastic such as PET.

However, the diversity of chemical recycling methods and the many possible configurations pose a major challenge: How can we identify the most efficient and environmentally friendly methods among a multitude of options? This is where ontological structures and decision support tools come into play. Ontological structures help to structure and organize knowledge about different recycling processes, facilitating in-depth comparative analysis. They associate attributes such as cost and environmental impact with each process, enabling multi-criteria evaluation.

Decision-making tools, meanwhile, play a critical role in selecting the best options from a set of solutions. Multi-objective optimization methods, such as  $\epsilon$ -constraint and evolutionary algorithms, generate Pareto fronts that provide a set of optimal solutions from which to choose. These Pareto fronts represent trade-offs between different objectives, underscoring the importance of considering multiple criteria in the decision-making process.

Multi-criteria decision-making methods, such as TOPSIS and PROMETHEE, are particularly useful for selecting the best solution among Pareto optimal alternatives. These methods often require human expertise to weight the criteria, but they provide a structured, quantitative approach to evaluating and comparing the various options available, making them relevant to the sustainable management of plastic waste.

In conclusion, the integration of ontological structures and decision-making tools in plastic waste management offers a promising way to identify and implement the most efficient and sustainable recycling methods. This not only allows for better management of plastic waste, but also promotes a circular economy by turning waste into valuable resources. The following chapter explores the rationale behind this master's thesis, detailing the objectives and expected contributions of this research.



# Chapter 2

## Rationale for this work

### 2.1 Background

Chapter 1, which focused on a comprehensive literature review and general contextualization, highlighted the seriousness of the plastic waste management problem. This analysis highlighted the catastrophic environmental impact of plastic waste, the urgent need to develop recycling methods that are not only effective but also sustainable, and the need for behavioral change on a global scale. Among the various strategies envisaged, chemical recycling, and in particular thermal decomposition techniques such as pyrolysis, stand out as a particularly promising solution. However, the implementation of these techniques on an industrial scale remains limited due to the complexity of choosing from a multitude of potential variants.

In this context, the work of Pacheco-López et al. (2023) provides a significant breakthrough. By implementing the innovative methodological framework designated iSMA (acronym for integrated Synthesis, Modeling, and Assessment), it is possible to generate and evaluate different recycling paths for plastic waste. This approach, based on a combination of knowledge management, graph theory and optimization algorithms, makes it possible to identify recycling configurations that are both economically viable and environmentally responsible. However, it has one shortcoming: the choice of which of the pareto-optimal options to promote to the last stage of the methodology remains arbitrary.

This is where this work comes in and makes a significant contribution. By developing a multi-objective decision support tool, this project aims to facilitate an informed and objective choice among recycling options, based on specific preferences linked to the context of use of the whole tool. A key aspect of this tool is its ability to assess the robustness of the proposed

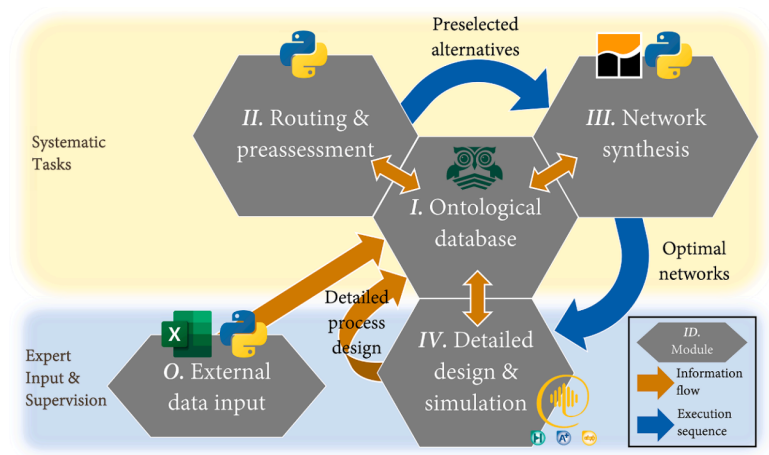


Figure 2.1: Schematic representation of the iSMA framework (Pacheco-López et al. 2023).

solutions in the face of the inherent uncertainty of the user’s preferences, thanks to its built-in sensitivity analysis. This feature ensures the overall relevance of a solution, beyond the specificities of a given context.

Although this tool has been developed specifically for the analysis of chemical recycling paths for plastic waste, its potential application extends to other contexts where selection from a list of Pareto-optimal options is required, and where analysis of the robustness of a solution in the face of uncertainty is crucial. As such, this tool promises to be an interesting contribution to the scientific literature, offering a new perspective on decision making, and in particular in the field of sustainable recycling and waste management.

## 2.2 Description of the iSMA framework

### 2.2.1 General presentation

The iSMA structure represents a holistic methodological framework designed to systematically address the complex issue of chemical recycling of plastic waste. Figure 2.1 illustrates the interconnected and iterative nature of this framework. This architecture highlights how each component interacts and contributes to the overall process of identifying and evaluating the most promising recycling pathways.

The diagram shows a process structured around four main modules. At the heart of the structure is Module I: Ontological database, which serves

as the foundation for knowledge storage and management. This repository centralizes essential data on waste, transformation processes and products, and serves as a reference throughout the assessment process (Pacheco-López et al. 2021).

Next, Module II: Routing & preassessment aims to generate and preliminarily evaluate potential routes for converting waste into resources. This module implicitly generates all possible paths connecting waste sources to final products. These paths are evaluated using a Global Performance Indicator (GPI) that takes into account economic profitability, environmental impact, and technological readiness. The most promising paths are identified using the Bellman-Ford algorithm (Bellman 1954), which constructs and evaluates the shortest paths. In this way, the process effectively narrows the vast range of possibilities down to a manageable selection of routes, while ensuring that different options are selected using assigned weights for each processing node.

Module III: Network synthesis represents an advanced optimization phase in which the pre-selected alternatives are synthesized into a superstructure. This superstructure is then optimized using a mathematical model developed by Somoza-Tornos et al. (2021) to determine optimal process networks that effectively balance economic objectives with environmental criteria.

Finally, Module IV: Detailed design & simulation is dedicated to the technical realization of the selected configurations. The most promising alternatives are developed through detailed simulations with a view to their potential implementation on an industrial scale.

Completing the structure, Module 0: External data input represents the manual addition of new external data by experts, allowing the database to be enriched and improved by the addition of new technologies or better data on existing technologies.

### 2.2.2 Framework objectives

The main objective of the iSMA structure is to build a decision-making tool that goes beyond traditional approaches to chemical recycling of plastic waste. The structure aims to provide an overview that not only identifies and evaluates potential recycling routes, but also steers these routes towards concrete, optimized implementation while respecting environmental and economic constraints.

The goal of iSMA is threefold:

1. **Resource Optimization:** Identify the most efficient recycling routes to turn plastic waste into valuable resources, with a focus on minimizing

environmental impact while maximizing economic benefit.

2. **Informed decision making:** Provide decision-makers with analytical tools that allow them to choose from a wide range of recycling options based on rigorous scientific data and multi-criteria assessments. This ensures that decisions made are both viable and consistent with sustainable development goals.
3. **Adaptability and robustness:** Design a flexible, scalable structure that can adapt to different contexts and integrate new data or technologies as they emerge. The robustness of the iSMA structure is essential to ensure its long-term relevance and effectiveness in the face of evolving industry standards and environmental concerns.

The in-depth case study by Pacheco-López et al. (2023) provides a concrete demonstration of iSMA’s ability to synthesize and evaluate complex recycling configurations. This framework represents a significant step forward in promoting the circular economy.

### 2.2.3 Stage details

#### Knowledge management (module I)

This module serves as a central repository for collecting, managing, and structuring knowledge related to plastic waste recycling processes. It uses a predefined ontological framework to represent and classify a variety of transformation processes, waste types, and resulting products.

Through the adaptation of the OntoCAPE ontology dedicated to the field of Process Systems Engineering (PSE) (Marquardt et al. 2010), this module assimilates information from the scientific literature into a formal database. This information includes material characteristics and process performance parameters such as raw material characteristics, processing capacities, yields, process temperatures, as well as economic data and environmental impact indicators. Materials are modeled as p.states (process states) and processes as p.steps (process steps). All this information is encoded in a natural machine-understandable language to ensure efficient knowledge management and to facilitate queries performed by humans and logical inference by reasoners. Any entity or relationship between entities can be queried from the ontology.

The power of this module lies in its ability to represent processes and products using a well-defined relational database, where concepts are related to each other with different properties relationships (axioms). It enables the construction of processing paths by mapping waste, available processing

technologies and valuable products. This modeling serves as the basis for the generation and preassessment of recycling paths, which are then evaluated and optimized in subsequent modules of the iSMA framework.

The practical implementation of this module was done using the Protégé ontology editor (Musen 2015), which integrates an inference engine capable of validating data consistency and generating new conceptual relationships. The result is an organized, hierarchical representation of knowledge.

### **Path generation and pre-assessment (module II)**

The second module of the iSMA framework plays a crucial role in the creation and preliminary evaluation of plastic waste recycling routes. This module, which has been described in detail in another paper of Pacheco-López et al. (2021), uses the ontological database built in Module I to perform these tasks, focusing on two main activities: network construction and route evaluation.

An input-output matching algorithm is developed to link wastes, processes and products. Using data from the ontology, a graph is built in steps: starting from a waste (p.state), the algorithm searches for processes (p.steps) that use this state as input. For each process step, all outputs are retrieved and the process is repeated for each new process state, building branches that end when no marketable product can be obtained or when the process step has no output, indicating an end-of-life alternative such as incineration or landfilling.

A tree-like graph is created with all potential branches using a state-task network approach, where operations and processes are categorized as "tasks" and raw, intermediate, and final materials as "states." This bipartite graph connects two types of nodes which are process steps and material states, storing their corresponding information on economic, environmental, and behavioral aspects. After the graph is constructed, the algorithm identifies all possible paths from the initial node, representing the waste to be processed, to all potential final products, thus enabling further evaluation based on the total weight of each path.

The paths assessed by the shortest path algorithm are analyzed according to three main criteria: economic, environmental and technological maturity. A global performance indicator (GPI) is calculated using the following system of equations, where index  $i$  represents the different process steps, index  $j$  represents the process states, and index  $k$  represents the complete paths.

$$\text{Profit}_i^{eco} = \sum_{j \in \text{outputs}_i} x_{i,j}^{out} \cdot \text{Price}_j - \sum_{j \in \text{inputs}_i} x_{i,j}^{in} \cdot \text{Price}_j - \text{Cost}_i \quad (2.1)$$

$$\text{Profit}_i^{env} = \sum_{j \in \text{outputs}_i} x_{i,j}^{out} \cdot \text{EI}_j^{p.state} - \sum_{j \in \text{inputs}_i} x_{i,j}^{in} \cdot \text{EI}_j^{p.state} - \text{EI}_i^{p.step} \quad (2.2)$$

$$\text{Profit}_k^{eco,path} = \sum_{i \in \text{path}_k} \text{Profit}_i^{eco} \quad (2.3)$$

$$\text{Profit}_k^{env,path} = \sum_{i \in \text{path}_k} \text{Profit}_i^{env} \quad (2.4)$$

$$\text{Profit}_k^{total,path} = \text{Profit}_k^{eco,path} + \text{Profit}_k^{env,path} \quad (2.5)$$

$$f_k^{eco} = \frac{\text{Profit}_k^{eco,path} - \min_k \{\text{Profit}_k^{eco,path}\}}{\max_k \{\text{Profit}_k^{eco,path}\} - \min_k \{\text{Profit}_k^{eco,path}\}} \quad (2.6)$$

$$f_k^{env} = \frac{\text{Profit}_k^{env,path} - \min_k \{\text{Profit}_k^{env,path}\}}{\max_k \{\text{Profit}_k^{env,path}\} - \min_k \{\text{Profit}_k^{env,path}\}} \quad (2.7)$$

$$f_k^{TRL} = \frac{\text{TRL}_k - \min_k \{\text{TRL}_k\}}{\max_k \{\text{TRL}_k\} - \min_k \{\text{TRL}_k\}} \quad (2.8)$$

$$\text{GPI}_k = \text{Profit}_k^{total,path} \cdot f_k^{eco} \cdot f_k^{env} \cdot f_k^{TRL} \quad (2.9)$$

Equation 2.1 determines the economic profit of a process by calculating the difference between the sum of the outputs price multiplied by their corresponding fractions in the output of the process and the sum of the inputs price multiplied by their fractions in the input of the process, while subtracting process costs. Equation 2.2 follows the same principle to evaluate environmental profit, using the monetized environmental impacts of p.states and p.steps rather than their price and processing cost, respectively. Equations 2.3 and 2.4 add the economic and environmental profits of all the processes that make up a given path. Equation 2.5 calculates the total profit by adding the results of Equations 2.3 and 2.4. Equations 2.6, 2.7, and 2.8 generate weighting factors to favor paths with high economic and environmental benefits as well as superior technological maturity (TRL) over less profitable, environmentally favorable or mature alternatives. Finally, according to Equation 2.9, the global performance indicator (GPI) for a path is calculated by multiplying the total profit for that path by the corresponding weighting factors.

The different paths are ranked according to their GPI. Only a limited number of options are promoted for the next step, while ensuring that a diverse set of technologies is included. This diversity is ensured by the in-

formation provided by the ontology, which defines the type of technology for each path.

### **Superstructure optimization (module III)**

The third module focuses on the optimization of a process superstructure, forming an optimized network that exploits the waste recycling paths identified in the previous module. This optimization is based on the mathematical model developed by Somoza-Tornos et al. (2021), which is a tool that aims to determine the most appropriate process networks according to economic profit and three environmental indicators: impacts on human health, ecosystems and resources.

Using mixed-integer linear programming (MILP) optimization, this tool aims to link different recycling technologies with waste sources and raw material requirements, combining recycling paths derived from the previous module. First, the superstructure is optimized to maximize/minimize each objective and then identifies robust anchor points for each pair of bi-objective criteria, evaluating each environmental objective against economic profit. Next, the  $\epsilon$ -constraint method (Mavrotas 2009) is used to generate a set of Pareto optimal solutions. For each environmental objective, the maximum and minimum values are known. The interval between these values is then divided into several sub-intervals, for example, into ten parts. For each specific value within this interval, the model maximizes the economic profit while taking this value as a constraint. This is how the Pareto optimal solutions are obtained.

The different resulting configurations are represented by bi-criteria Pareto fronts, which show the best possible solutions according to the two criteria evaluated. Each point on a Pareto front corresponds to a specific configuration of the superstructure that is considered optimal, since neither objective can be improved without compromising the other. Each configuration is characterized by the processes used, the amount of material processed in each, the products and by-products generated, and the residual waste or by-products sent to incineration or landfill.

On the basis of these configurations, a summary table is created showing the evaluation of each configuration according to the four criteria discussed: economic profit and the three environmental indicators. These data form the basis of the multi-objective analysis carried out in the present work.

## Process design and optimization (module IV)

The final module of the iSMA framework focuses on the detailed simulation and optimization of one or more selected processes using Aspen Plus software. This phase involves complex operations such as heat integration, energy recovery, and  $CO_2$  capture, with the goal of fine-tuning and optimizing the configurations developed in the previous phases.

The main objective is to build a rigorous model of the identified optimal configurations, which requires considerable human expertise. This stage requires extensive technical knowledge to make strategic decisions about equipment, utilities, and operating parameters such as pressure and temperature. This is a particularly time-consuming part of the process for which automation has not yet provided effective solutions.

Currently, the selection of options to be simulated from the Pareto optimal solutions is arbitrary. The multi-objective decision tool developed in this project aims to fill this gap. This tool allows for a more systematic and justified approach to selecting configurations for further investigation, finding the most adequate trade-off optimal solution to a particular decision-making situation.

## 2.3 Case study

### 2.3.1 Description of the case study

The case study presented focuses on the processing of mixed plastic waste from municipal sorting centers, consisting of 40% polyethylene (PE), 35% polypropylene (PP), 18% polystyrene (PS), 4% polyethylene terephthalate (PET), and 3% polyvinyl chloride (PVC). Figure 2.2 illustrates the complex network of tentative pathways, or connections, created during the first module of the iSMA framework. This visualization shows intermediates, final products, and treatment processes, including end-of-life options such as incineration and landfilling.

The processes considered include several pyrolysis methods operating at temperatures ranging from 350°C to 1000°C and using different catalysts. In addition to pyrolysis, the network also includes a gasification process at 850°C. The conversion steps can be followed by separation, which is essential to isolate and purify the end products, making them suitable for various industrial uses or as new raw materials to produce new plastics. Pyrolysis products can also be used directly as fuels without the need for purification.

The case study is based on the processing of 32.71 tons of plastic waste per hour, which corresponds to the amount of post-consumer plastic waste



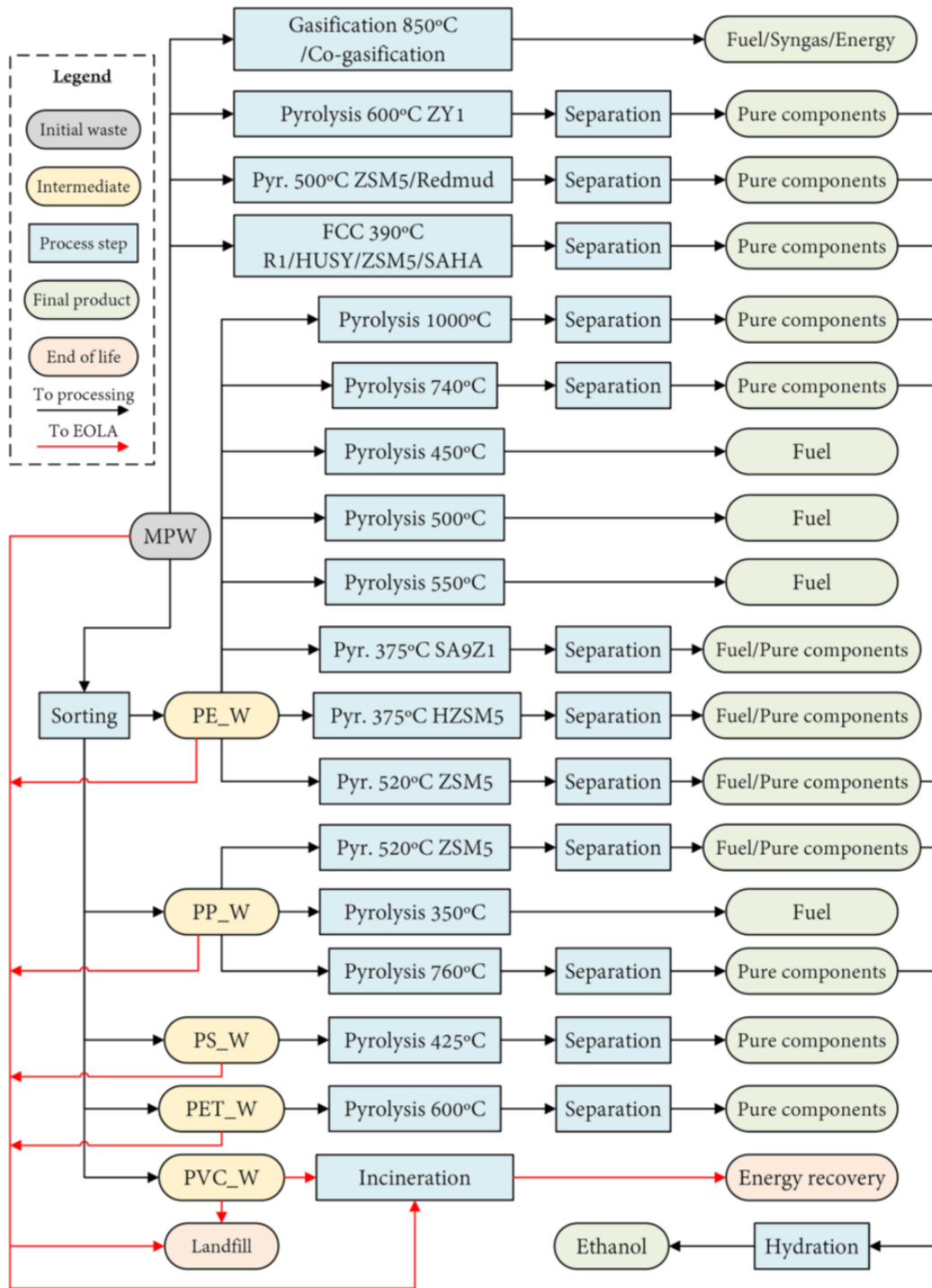


Figure 2.2: Graph created during the initial assessment phase, showing tentative connections (Pacheco-López et al. 2023).

collected in the European Union in 2018 (29.1 million tons), scaled down to an area the size of the province of Barcelona, with a population of around 5 million.

### 2.3.2 Resulting data used for this work

Table 2.1 from the third module of the iSMA framework shows the resulting Pareto optimal configurations, each defined by a specific set of processes. Each configuration indicates the amount of material processed by the different processes, expressed in tons per hour. As mentioned above, the total amount of plastic waste mix processed is set to 32.71 tons per hour for all configurations.

Configurations are color-coded to indicate the use of similar technologies. Configurations of the same color use the same technologies, but in different proportions. For example, configurations 1 to 4 and 14 to 16 include a sorting stage for the mixed plastic waste and therefore use pyrolysis technologies adapted to each type of waste. Furthermore, configurations 7 to 13 are distinguished by the inclusion of a separation stage for the gases produced during the pyrolysis of the initial mix, a feature not present in the other alternatives.

The Pareto fronts generated in the third module of the iSMA structure, shown in Figure 2.3, are a graphical representation of the evaluation of the different configurations according to the four considered criteria: economic profit, environmental impact on human health, environmental impact on ecosystems, and environmental impact on resources. Three bi-criteria Pareto fronts are presented because economic profit is evaluated against each of the three environmental impacts. Pareto-optimal configurations are those where none of the criteria can be improved without worsening at least one other criterion. These fronts help visualize the trade-offs between economic and environmental objectives.

Economic profit is measured in Euros per hour (€/h) and represents the net profitability of the configurations, calculated by subtracting operating and investment costs from the revenues generated by the end products. The environmental impact on human health is measured in Disability Adjusted Life Years per hour (DALY/h). DALY measure the difference between an ideal situation, in which everyone lives to the standard life expectancy in perfect health, and the actual situation. This measure combines years of life lost (YLL) due to premature mortality and years of life lost due to disability (YLD) from living with a disease or its consequences:  $DALY = YLD + YLL$  (Salwa et al. 2020).

Environmental impact on ecosystems is measured in species lost per year

Table 2.1: For each Pareto solution configuration, the processing level of each Process Step is detailed, displaying values in tons per hour of material input (Pacheco-López et al. 2023). The total quantity of initial mixed plastic waste remains consistent across all configurations. Column headers are color-coded to correspond with configurations shown in Figure 2.3. To facilitate identifying available and unavailable technologies in each configuration, cells are shaded in shades of green or red.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Pyrolysis MPW 500°C	19.70	0.00	0.00	0.00	10.89	26.30	32.71	32.71	32.71	32.71	23.23	12.56	1.38	0.00	0.00	0.00
Separation Gas Pyr. MPW 500°C	0.00	0.00	0.00	0.00	0.00	0.00	1.51	4.72	7.92	11.12	7.90	4.27	0.47	0.00	0.00	0.00
Separation Oil Pyr. MPW 500°C	12.84	0.00	0.00	0.00	7.10	17.15	21.33	21.33	21.33	21.33	15.14	8.19	0.90	0.00	0.00	0.00
Pyrolysis MPW 500°C / REDMUD /	0.00	25.96	28.76	31.11	21.82	6.41	0.00	0.00	0.00	0.00	9.48	20.15	31.33	30.70	28.40	26.23
Separation Gas Pyr.RM. MPW 500°C	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	3.92	8.32	12.94	12.68	11.73	10.83
Separation Oil Pyr.RM. MPW 500°C	0.00	14.80	16.39	17.73	12.44	3.65	0.00	0.00	0.00	0.00	5.40	11.49	17.86	17.50	16.19	14.95
Sorting MPW	13.01	6.75	3.95	1.60	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	2.01	4.31	6.48
Pyrolysis PE 740°C	5.20	2.70	1.58	0.64	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Separation Gas Pyr. PE 740°C	0.00	1.59	0.93	0.38	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Separation Oil Pyr. PE 740°C	2.03	1.05	0.62	0.25	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Pyrolysis PE 1000°C	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.80	1.72	2.59
Separation Gas Pyr. PE 1000°C	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.80	1.71	2.57
Pyrolysis PP 760°C	0.00	0.00	0.00	0.56	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.70	1.51	2.27
Separation Gas Pyr. PP 760°C	0.00	0.00	0.00	0.29	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.36	0.77	1.16
Separation Oil Pyr. PP 760°C	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.33	0.71	1.07
Pyrolysis PET 600°C	0.52	0.27	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.26
Separation Oil Pyr. PET 600°C	0.31	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Pyrolysis PS 425°C	2.34	1.21	0.71	0.29	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.36	0.78	1.17
Separation Oil Pyr. PS 425°C	2.27	1.18	0.69	0.28	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.35	0.75	1.13

per hour (species·yr/h) and reflects damage to natural ecosystems, including biodiversity loss and habitat degradation. Environmental Impact on Resources, measured in USD2013 per hour, represents the additional monetary costs associated with the need to produce materials to compensate for what was not obtained through recycling (*SimaPro database manual Methods library* 2022). This measure includes the additional costs associated with raw material extraction, production and depletion of natural resources. In other words, the unit USD2013 evaluates the expenditure required to produce materials in the conventional way, taking into account the environmental and economic impacts of that production.

These environmental criteria are endpoint indicators resulting from the combination of several midpoint environmental indicators. These indicators result from the application of the *ReCiPe2016* life cycle assessment methodology described in the work of Huijbregts et al. (2017). Table 2.2 presents the numerical evaluations of each configuration according to the four criteria, which are the starting point for the multi-objective analysis developed in this work.

## 2.4 Objective for this work

This master’s thesis aims to fill a gap identified in the iSMA structure. Although this framework is very useful for generating and evaluating different recycling configurations, it has a limitation: the arbitrary choice of Pareto-optimal configurations to be modeled in detail. Therefore, the main objective of this work is to design and develop a systematic and robust decision making tool for selecting, among the Pareto-optimal configurations, those that need to be studied in more detail, by integrating the multi-objective optimization methods TOPSIS and PROMETHEE.

This decision-making tool is designed to select one or more configurations based on the user’s specific preferences. In fact, the ideal weighting of criteria varies according to the user’s context and priorities. Consequently, the tool must be flexible and adaptable to different decision environments and contexts. In addition, the tool must be applicable and adaptable to different types of problems, not only those related to sustainability or chemical recycling of plastic waste.

Another important goal of this tool is to integrate sensitivity analysis functionality. Since users have to determine their preferences for criteria, intrinsic uncertainty is inevitable. It is therefore essential to assess how different solutions behave in the face of this uncertainty. The tool must be able to analyze the stability and robustness of proposed solutions, ensuring

Table 2.2: Pareto-optimal solutions evaluated according to the four objectives (Pacheco-López et al. 2023). This data table serves as a basis for multi-objective optimization.

Point	Profit (€/h)	Impact on Human Health ( $DALY/h$ ) $\times 10$	Impact on Ecosystems ( $species \cdot yr/h$ ) $\times 10^4$	Impact on Resources ( $USD2013/h$ ) $\times 10^{-4}$
1	566.37	2.474	5.532	4.082
2	2701.83	2.496	5.576	4.094
3	4223.16	2.518	5.625	4.124
4	5381.57	2.539	5.674	4.156
5	6091.79	2.561	5.720	4.192
6	6221.99	2.583	5.766	4.214
7	6271.55	2.605	5.814	4.220
8	6272.59	2.626	5.862	4.213
9	6273.62	2.648	5.910	4.205
10	6274.65	2.670	5.958	4.198
11	5843.28	2.640	5.890	4.151
12	5324.84	2.624	5.853	4.103
13	4575.07	2.606	5.811	4.056
14	3815.92	2.594	5.785	4.008
15	3002.12	2.582	5.760	3.961
16	2227.80	2.571	5.734	3.914

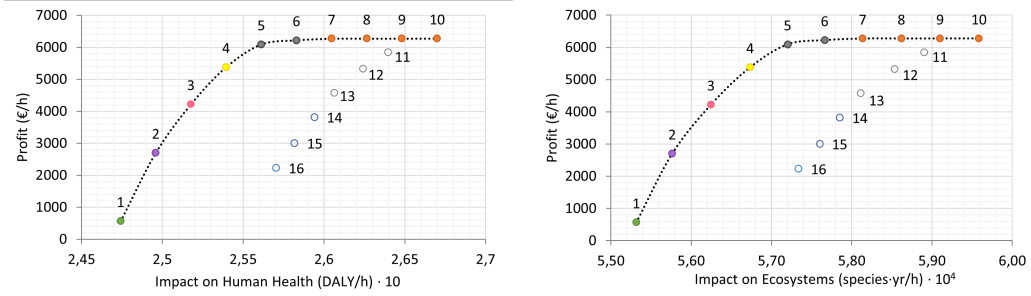
that a solution remains relevant even if the weighting of the criteria varies slightly. This ensures that the chosen solution is not only optimal in a highly specific context, but also retains its relevance and reliability in a variable context.

In summary, the objective of this work is to develop a tool that:

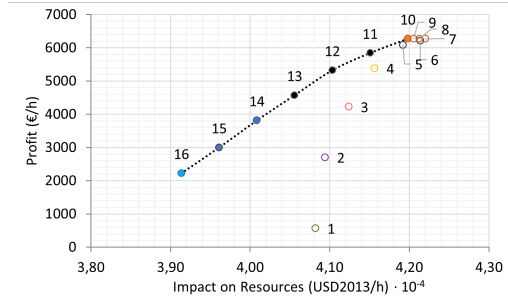
- From a data table containing the Pareto optimal options evaluated according to all the criteria considered and the user’s preferences, produces a ranking of these options.
- Evaluate the stability and robustness of these options with respect to the uncertainty of the user’s weighting.

The decision making tool is designed to be integrated within the iSMA framework and be applicable to other contexts. By providing a simple, systematic, effective and robust method, this tool will help decision makers in

the complex field of sustainable recycling and contribute to the promotion of the circular economy.



(a) Profit against environmental impact on human health. (b) Profit against environmental impact on ecosystems.



(c) Profit against environmental impact on resources.

Figure 2.3: Optimal Pareto solutions within each two-objective space, exploring the balance between profit and the three environmental endpoint indicators (Pacheco-López et al. 2023). Solid dots indicate solutions that are optimal for their specific bicriteria Pareto front, whereas open dots represent projections from optimal solutions in other bicriteria Pareto fronts. The solutions are differentiated by color, corresponding to various configurations as outlined in Table 2.1. A dotted line is used to illustrate hypothetical points along the Pareto front.

# Chapter 3

## Methodology

### 3.1 Data gathering

The data collection process begins with importing the decision matrix, which is a table containing the various Pareto-optimal solutions and their evaluations according to the considered criteria. This data is provided in the form of a CSV or Excel file. Following this, user inputs are gathered. These inputs include the nature of each criterion, the weighting of the criteria, and the chosen normalization method.

- **Nature of Criteria:** The nature of a criterion refers to whether it is beneficial or non-beneficial. A beneficial criterion is one that should be maximized, while a non-beneficial criterion is one that should be minimized. This step ensures adaptability to various data sets. For instance, in the case study considered in this work, the profit criterion is beneficial because it should be maximized, whereas the environmental impacts are non-beneficial as they should be minimized.
- **Criterion Weighting:** Users must enter their preferences for each criterion by assigning a value from 1 to 10, where 1 indicates the least important and 10 the most important criterion. These assigned values are then normalized so that their sum equals 1.
- **Normalization Method:** Users can choose between three normalization options: no normalization, vector normalization, and min-max normalization.

This data gathering part ensures that the tool can systematically handle different datasets and accommodate user preferences.



## 3.2 Normalization method

The choice of data normalization method is a crucial step in multi-objective analysis. In fact, this choice can have a significant impact on the final results (Sałabun et al. 2020). Therefore, it is imperative to make a conscious and informed choice of the normalization method to be used. In this work, we focus on two normalization methods: vector normalization and min-max normalization, since these are the ones offered to the user in the tool.

Vector normalization consists of dividing each element of the decision matrix by the square root of the sum of the squares of the elements in the same column. Formally, for an element  $x_{ij}$  of the decision matrix, the normalized value  $n_{ij}$  is calculated as follows:

$$n_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^m x_{ij}^2}} \quad (3.1)$$

This method preserves the original distribution of the data.

Min-max normalization consists in adjusting the values of a column so that they lie between 0 and 1. For an element  $x_{ij}$ , the normalized value  $n_{ij}$  is calculated as follows:

$$n_{ij} = \frac{x_{ij} - \min(x_j)}{\max(x_j) - \min(x_j)} \quad (3.2)$$

This method imposes a range of values from 0 to 1, regardless of the initial distribution of the data.

The distinction between beneficial and non-beneficial criteria is made at this stage of normalization. For non-beneficial criteria, the normalized element is obtained by subtracting the normalized value from 1 to invert the scale. This approach simplifies the interpretation of the normalized values: the higher the value, the better, regardless of the criterion.

The two normalization methods differ fundamentally in how they treat the data. Vector normalization preserves the relative distribution of the data, while min-max normalization can radically alter that distribution. This is illustrated in Figure 3.1 by the data tables before and after normalization. It can be seen that the min-max method significantly changes the distribution of the values for the three environmental criteria, but not for profit. This difference is explained by the relative differences between the values of the environmental criteria, which are low, and those of the profit criterion, which are high.

This can have important implications for multi-objective analysis. For example, with vector normalization, the environmental criteria will be much

Alternatives	Profit	Human Health	Ecosystems	Resources
1	566,37	2,474	5,532	4,082
2	2701,83	2,496	5,576	4,094
3	4223,16	2,518	5,625	4,124
4	5381,57	2,539	5,674	4,156
5	6091,79	2,561	5,720	4,192
6	6221,99	2,583	5,766	4,214
7	6271,55	2,605	5,814	4,220
8	6272,59	2,626	5,862	4,213
9	6273,62	2,648	5,910	4,205
10	6274,65	2,670	5,958	4,198
11	5843,28	2,640	5,890	4,151
12	5324,84	2,624	5,853	4,103
13	4575,07	2,606	5,811	4,056
14	3815,92	2,594	5,785	4,008
15	3002,12	2,582	5,760	3,961
16	2227,80	2,571	5,734	3,914

(a) No normalization.

Alternatives	Profit	Human Health	Ecosystems	Resources
1	0,0283	0,7607	0,7602	0,7523
2	0,1352	0,7585	0,7583	0,7515
3	0,2113	0,7564	0,7562	0,7497
4	0,2692	0,7544	0,7541	0,7478
5	0,3047	0,7522	0,7521	0,7456
6	0,3112	0,7501	0,7501	0,7442
7	0,3137	0,7480	0,7480	0,7439
8	0,3138	0,7459	0,7459	0,7443
9	0,3138	0,7438	0,7438	0,7448
10	0,3139	0,7417	0,7418	0,7452
11	0,2923	0,7446	0,7447	0,7481
12	0,2664	0,7461	0,7463	0,7510
13	0,2289	0,7479	0,7481	0,7538
14	0,1909	0,7490	0,7493	0,7567
15	0,1502	0,7502	0,7503	0,7596
16	0,1114	0,7513	0,7515	0,7625

Alternatives	Profit	Human Health	Ecosystems	Resources
1	0,0000	1,0000	1,0000	0,4510
2	0,3741	0,8878	0,8967	0,4118
3	0,6406	0,7755	0,7817	0,3137
4	0,8435	0,6684	0,6667	0,2092
5	0,9680	0,5561	0,5587	0,0915
6	0,9908	0,4439	0,4507	0,0196
7	0,9995	0,3316	0,3380	0,0000
8	0,9996	0,2245	0,2254	0,0229
9	0,9998	0,1122	0,1127	0,0490
10	1,0000	0,0000	0,0000	0,0719
11	0,9244	0,1531	0,1596	0,2255
12	0,8336	0,2347	0,2465	0,3824
13	0,7023	0,3265	0,3451	0,5359
14	0,5693	0,3878	0,4061	0,6928
15	0,4267	0,4490	0,4648	0,8464
16	0,2911	0,5051	0,5258	1,0000

(b) Vector normalization.

(c) Min-max normalization.

Figure 3.1: Comparison of data distribution before and after normalization (vector and min-max).

less important than the profit criterion, regardless of the weighting, because their variations are very small. Conversely, min-max normalization puts all criteria on an equal footing, making the weighting more relevant and balanced.

This is particularly relevant for the case study presented here. Initially, the vector method was used for TOPSIS and the min-max method for PROMETHEE, resulting in very different rankings. The TOPSIS method systematically favored high-profit options, even with a weighting that favored environmental criteria. To avoid this disproportionate influence of the profit criterion, the min-max method is recommended, as it ensures a balanced weighting of the criteria, regardless of their initial values.

### 3.3 Objective reduction

Objective reduction is an important step in multi-objective optimization, as it aims to simplify the problem by reducing the number of criteria to be considered without losing necessary information (Yurdakul et al. 2009). A correlation analysis revealed that two of the environmental criteria considered were almost perfectly correlated, making one of them redundant.

Pearson’s correlation coefficient was used to identify this redundancy. This coefficient measures the strength of the linear relationship between two variables. It is calculated as follows:

$$r = \frac{\sum(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum(x_i - \bar{x})^2 \sum(y_i - \bar{y})^2}} \quad (3.3)$$

where  $x_i$  and  $y_i$  are the values of the variables and  $\bar{x}$  and  $\bar{y}$  are their respective means. A correlation coefficient of +1 indicates a perfect positive correlation, -1 indicates a perfect negative correlation, and 0 indicates no correlation.

Table 3.1: Correlation coefficients between criteria.

/	Profit	Human Health	Ecosystems	Resources
Profit	1,0000	0,7087	0,7192	0,7692
Human Health	0,7087	1,0000	<b>0,9997</b>	0,2857
Ecosystems	0,7192	<b>0,9997</b>	1,0000	0,3070
Resources	0,7692	0,2857	0,3070	1,0000

Table 3.1, which contains the Pearson’s coefficients for each pair of criteria, shows that the coefficient between the environmental impact on human health and that on ecosystems is 0.9997, which is almost a perfect correlation. This high correlation indicates that these two endpoint environmental indicators depend on the same midpoint indicators, or that the indicators they do not share do not have a significant influence in this case study.

The human health criterion was arbitrarily removed to simplify the problem and avoid double counting or double optimization of certain underlying parameters.

## 3.4 Multi-objective optimization methodologies

### 3.4.1 TOPSIS

#### Introduction of the TOPSIS method

TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) is a multi-criteria optimization method that ranks and selects the best alternatives from a set of choices according to their proximity to an ideal solution (Çelikbilek et al. 2020). This method identifies two hypothetical solutions: an ideal solution and an anti-ideal solution. The first corresponds to a solution that has the best possible values for each criterion (Utopian point), and the second corresponds to a solution that has the worst possible values for each criterion (Nadir point). For each alternative, the relative distance to the ideal and anti-ideal solutions is calculated. Based on these distances, a performance score is determined and used to generate a ranking.

#### Steps for implementing TOPSIS

The first step is to normalize the decision matrix using one of the two normalization methods described in Section 3.2. The normalized decision matrix is then weighted according to the user's preferences. The weighted values  $v_{ij}$  are obtained by multiplying each normalized value by the normalized weight corresponding to the criterion:

$$v_{ij} = w_j \cdot n_{ij} \quad (3.4)$$

where  $w_j$  is the normalized weight of the criterion  $j$ .

The Utopian (U) and Nadir (N) points are determined from the weighted decision matrix:

$$U = \{v_1^+, v_2^+, \dots, v_n^+\}, \quad N = \{v_1^-, v_2^-, \dots, v_n^-\} \quad (3.5)$$

where

$$v_j^+ = \max(v_{ij}), \quad v_j^- = \min(v_{ij}) \quad (3.6)$$

The distance from each alternative to the Utopian ( $D_i^+$ ) and Nadir ( $D_i^-$ ) points is calculated using the Euclidean distance:

$$D_i^+ = \sqrt{\sum_{j=1}^n (v_{ij} - v_j^+)^2}, \quad D_i^- = \sqrt{\sum_{j=1}^n (v_{ij} - v_j^-)^2} \quad (3.7)$$

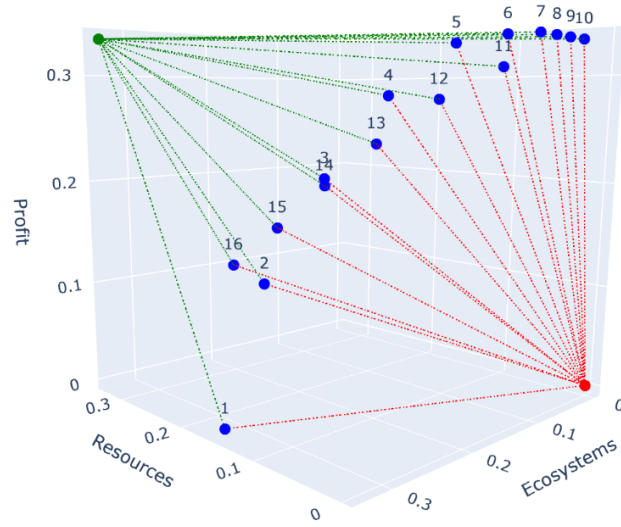


Figure 3.2: 3-dimensional representation of Pareto optimal solutions, Utopian and Nadir points, with min-max normalization and equal weighting for each criterion.

Figure 3.2 shows a 3-dimensional visualization of the different points and the distance between them. The blue dots represent the different alternatives, the green dot represents the Utopian point, and the red dot represents the Nadir point. This representation was obtained using a min-max normalization and considering equal weighting for each of the criteria. The Utopian point is effectively placed at coordinates  $(\frac{1}{3}, \frac{1}{3}, \frac{1}{3})$  because these are the best values  $(1, 1, 1)$  obtained after min-max normalization multiplied by a normalized weight of  $\frac{1}{3}$ , which is identical for each criterion. Similarly, the nadir point is placed at coordinates  $(0, 0, 0)$ .

The performance score  $P_i$  for each alternative is then determined as follows:

$$P_i = \frac{D_i^-}{D_i^+ + D_i^-} \quad (3.8)$$

A higher score indicates an alternative that is closer to the Utopian point and further from the Nadir point. Alternatives are ranked according to their  $P_i$  performance scores. The alternative with the highest  $P_i$  score is considered the best.

The resulting data includes the performance score and ranking position for each alternative.

## Advantages

- **Simplicity and ease of use:** TOPSIS is a relatively simple and straightforward method, making it easy to implement and understand. It does not require complex calculations, which means it can be used on large datasets and facilitates its use in a variety of contexts and by users with different levels of technical expertise.
- **Flexibility:** TOPSIS can be used with different types of criteria and is adaptable to a variety of decision situations. It can easily integrate user preferences in the form of criteria weighting, allowing the analysis to be adapted to the specific priorities of each case study.
- **Clear visualization:** TOPSIS results can be easily visualized by ranking alternatives according to their proximity to the ideal solution. This visualization helps to understand and interpret the results and facilitates decision making.

## Limitations

- **Sensitivity to normalization:** TOPSIS results can be strongly influenced by the normalization method used. As discussed in Section 3.2, vector normalization and min-max normalization can produce very different distributions of the data, which can affect the final ranking of the alternatives.
- **Dependence on weighting:** The method depends on the weights assigned to the criteria. If these weights are not rigorously or objectively defined, they can introduce significant subjectivity into the results. Determining weights can be difficult and subjective which requires careful consideration and possibly consultation with experts or stakeholders.
- **Linearity assumption:** TOPSIS uses Euclidean distance to calculate the closeness of alternatives to ideal solutions. This implies a linear relationship between criteria, i.e. the method assumes that variations between criteria are proportional. In contexts where the relationships between criteria are non-linear, this assumption may limit the accuracy of the evaluation. Complex interactions or threshold effects are not accounted for by a simple linear distance.
- **Handling outliers:** TOPSIS can be sensitive to extreme data (outliers), which can disproportionately influence both positive and negative ideal solutions. This can bias computed distances and thus alter native rankings.

- **Interactions between criteria:** The method treats each criterion independently and does not consider possible interdependencies between criteria. In situations where criteria are correlated or interdependent, this can result in less accurate or relevant scores.

### 3.4.2 PROMETHEE

#### Introduction of the PROMETHEE method

Like TOPSIS, PROMETHEE (Preference Ranking Organization Method for Enrichment Evaluations) is a multi-criteria decision support method for ranking and selecting the best alternatives from a set of choices according to multiple criteria. However, it is based on a very different principle: pairwise comparison of alternatives and evaluation of their relative preferences using preference functions (Maadi et al. 2014). For each criterion, a preference relationship is established between each pair of alternatives. This relationship is determined by a preference function that quantifies the intensity of preference for one alternative over another. Preferences are then aggregated to obtain outranking flows, which are used to compare alternatives. There are several versions of the PROMETHEE method, and the tool developed in this master's thesis uses version II, which provides a complete ranking of alternatives, ordering all alternatives from best to worst.

#### Steps for implementing PROMETHEE

As with the TOPSIS method, the first step is to normalize the values of the decision matrix to make the criteria comparable.

For each pair of alternatives  $(A_i, A_j)$  and for each criterion  $k$ , the difference  $d_{ij}^k$  is calculated as follows:

$$d_{ij}^k = f_k(A_i) - f_k(A_j) \quad (3.9)$$

where  $f_k(A_i)$  represents the value of the alternative  $A_i$  for the criterion  $k$ .

The next step is to choose a preference function for each criterion. In the PROMETHEE method, these functions are used to quantify the degree of preference of one alternative over another, based on the difference between their evaluations for a given criterion. The tool proposed in this work allows the user to choose between three of the most common types of preference functions: usual, linear and Gaussian. The usual preference function, described by Equation 3.10, is the simplest. It only considers whether one of the alternatives is strictly better than the other. If the difference between the two alternatives is positive, the preference is 1, i.e., total, otherwise it

is 0. This function does not require any additional parameters and is useful when considering a binary decision, a qualitative or critical criterion where the slightest difference is very important.

$$P_k(d_{ij}^k) = \begin{cases} 0 & \text{if } d_{ij}^k \leq 0 \\ 1 & \text{if } d_{ij}^k > 0 \end{cases} \quad (3.10)$$

Equation 3.11 defines the linear preference function, which takes into account a preference proportional to the deviation. This function uses two threshold parameters,  $q$  and  $p$ . If the deviation is less than  $q$ , there is no preference. If the deviation is greater than  $p$ , there is full preference. Between these two thresholds, the preference increases linearly with the difference. These thresholds allow the sensitivity of the function to be adjusted, making this approach relevant when it is critical to accurately determine a preference based on the difference between values.

$$P_k(d_{ij}^k) = \begin{cases} 0 & \text{if } d_{ij}^k \leq q \\ \frac{d_{ij}^k - q}{p - q} & \text{if } q < d_{ij}^k < p \\ 1 & \text{if } d_{ij}^k \geq p \end{cases} \quad (3.11)$$

Finally, the Gaussian preference function described by Equation 3.12 uses a bell curve to model preference. It is defined by a constant,  $\sigma$ , which represents the standard deviation and controls the width of the curve. In this tool, this constant is set to 0.3. This preference function is of similar interest as the linear function, except that here it is possible to give greater importance to small differences.

$$P_k(d_{ij}^k) = 1 - \exp\left(-\frac{(d_{ij}^k)^2}{2\sigma^2}\right) \quad (3.12)$$

Figure 3.3 provides a visual representation of the three preference functions available in the tool.

Once a preference function  $P_k(d_{ij}^k)$  is chosen for each criterion, it is applied to each difference. Aggregate preference indices  $\pi(A_i, A_j)$  are then calculated by weighting the preferences for each criterion by the normalized weight  $w_k$  of the criterion:

$$\pi(A_i, A_j) = \sum_{k=1}^n w_k \cdot P_k(d_{ij}^k) \quad (3.13)$$

This index indicates how much alternative  $A_i$  is preferred to alternative  $A_j$ , taking all criteria into account.



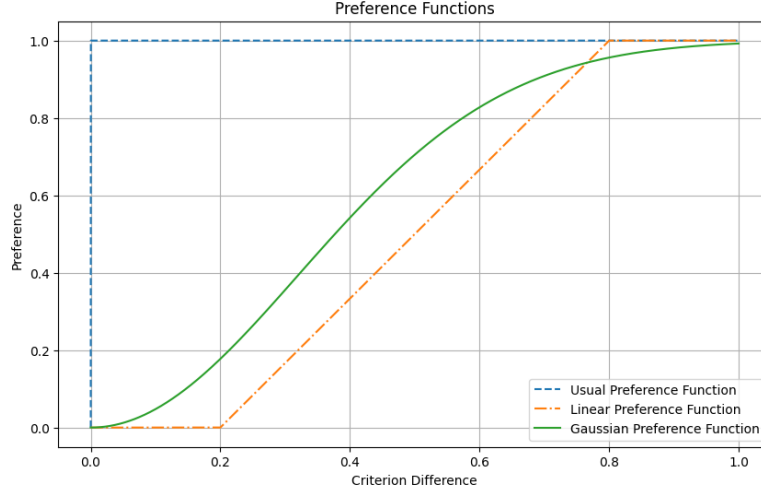


Figure 3.3: Usual, linear and Gaussian preference functions.

Next, positive ( $\phi^+$ ) and negative ( $\phi^-$ ) outranking flows are calculated for each alternative. The positive outranking flow  $\phi^+(A_i)$  measures the superiority of alternative  $A_i$  over all the others, while the negative outranking flow  $\phi^-(A_i)$  measures the inferiority of the alternative over all the others:

$$\phi^+(A_i) = \frac{1}{m-1} \sum_{j=1, j \neq i}^m \pi(A_i, A_j) \quad (3.14)$$

$$\phi^-(A_i) = \frac{1}{m-1} \sum_{j=1, j \neq i}^m \pi(A_j, A_i) \quad (3.15)$$

Finally, the net outranking flow  $\phi(A_i)$  is obtained by subtracting the negative flow from the positive flow:

$$\phi(A_i) = \phi^+(A_i) - \phi^-(A_i) \quad (3.16)$$

Alternatives are ranked according to their net outranking flows  $\phi(A_i)$ . An alternative with a higher net preference flow is considered better.

The resulting data includes the net outranking flow and ranking position for each alternative.

### Advantages

- **Flexibility and advanced consideration of user preferences:** PROMETHEE allows advanced personalization by integrating user

preferences through preference functions and criteria weighting. The increased flexibility provided by these preference functions allows modeling complex preferences that cannot be captured by simpler methods such as TOPSIS.

- **Pairwise comparison:** The pairwise comparison principle used by PROMETHEE captures fine nuances between alternatives. This approach is particularly useful when alternatives are very close in terms of performance. TOPSIS, on the other hand, which relies on global distances to ideal solutions, may not always reflect the subtle differences between alternatives.
- **Interpretability:** Positive, negative and net outranking flows are intuitive measures that facilitate the interpretation of results. This makes it easier for decision makers to understand why one alternative is preferred over another, improving the transparency and acceptability of decisions.

## Limitations

- **Complexity of implementation and need for expertise:** The implementation of PROMETHEE can be complex, especially when it comes to defining appropriate preference functions for each criterion. This complexity requires specific expertise to properly parameterize the method, which may limit its accessibility to users.
- **Sensitivity to weighting:** Like TOPSIS, PROMETHEE is sensitive to the weights assigned to the criteria. Poorly defined weights can introduce subjectivity and bias the results.
- **Handling outliers:** PROMETHEE can be affected by extreme values (outliers), which can distort the final rankings. This sensitivity is similar to that of TOPSIS.
- **High computational cost:** Due to the large number of pairwise comparisons required to evaluate alternatives, PROMETHEE can be very computationally expensive, especially for datasets with many alternatives. This can increase the computational time and resources required, making the method less practical for large-scale problems.
- **Interactions between criteria:** Like TOPSIS, PROMETHEE does not explicitly consider interactions between criteria. In situations where criteria are highly interdependent, this may limit the accuracy of the evaluation.

## 3.5 Sensitivity analysis

### 3.5.1 Introduction

Sensitivity analysis is used to evaluate the robustness of alternatives in the face of uncertainty associated with the weighting of criteria. As mentioned in Section 3.4, TOPSIS and PROMETHEE multi-objective optimization methods are sensitive to criteria weighting. Determining an ideal weighting for a given context is a complex and subjective task that introduces intrinsic uncertainty. It is crucial to account for this uncertainty when selecting the best alternative to ensure that it performs not only under specific conditions, but also in variable situations.

### 3.5.2 Procedure

The first step in sensitivity analysis is to generate weight ranges for each criterion, sampled from normal distributions constructed based on user-defined confidence intervals. The user provides a lower and upper bound for each criterion, defining a 95% confidence interval. From these bounds, a standard deviation is calculated for each criterion.

The standard normal distribution  $\mathcal{N}(0, 1)$  has a mean  $\mu$  of 0 and a standard deviation  $\sigma$  of 1. The probability density for a variable  $Z$  following this distribution is given by:

$$f(z) = \frac{1}{\sqrt{2\pi}} e^{-\frac{z^2}{2}} \quad (3.17)$$

The cumulative distribution function of the standard normal distribution, denoted  $\Phi(z)$ , gives the probability that the variable  $Z$  is less than or equal to  $z$ :

$$\Phi(z) = P(Z \leq z) = \int_{-\infty}^z \frac{1}{\sqrt{2\pi}} e^{-\frac{t^2}{2}} dt \quad (3.18)$$

For a 95% confidence interval, the quantile of the standard normal distribution  $z$  is such that:

$$\Phi(z) = 0.975 \quad (3.19)$$

The value 0.975 is used because it indicates that 97.5% of the values in the distribution are below the quantile  $z$ , and because of the symmetry of the normal distribution, 2.5% of the values are below  $-z$ . Calculating the value of  $z$  is usually done using numerical methods, and it is found that  $z \approx 1.96$ .

For a normal distribution with mean  $\mu$  and standard deviation  $\sigma$ , 95% of the values are between  $\mu - 1.96\sigma$  and  $\mu + 1.96\sigma$ . Assuming a lower bound  $a$  and an upper bound  $b$ , it can be written that:

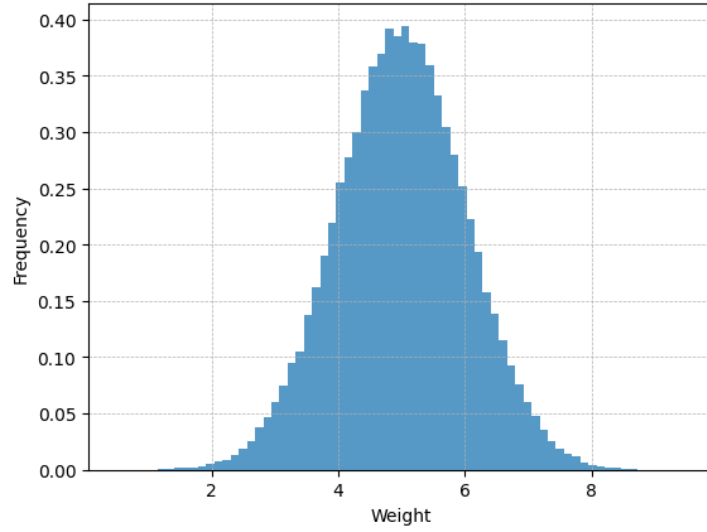


Figure 3.4: Sampled weights distribution from a normal distribution with an initial weight of 5 and lower and upper confidence limits of 3 and 7, respectively.

$$\mu - 1.96\sigma = a \quad (3.20)$$

$$\mu + 1.96\sigma = b \quad (3.21)$$

Subtracting the first equation from the second equation gives:

$$(\mu + 1.96\sigma) - (\mu - 1.96\sigma) = b - a \quad (3.22)$$

$$3.92\sigma = b - a \Rightarrow \sigma = \frac{b - a}{3.92} \quad (3.23)$$

Once the standard deviations have been calculated, normal weight distributions are constructed for each criterion, centered on their initial weight. Lists of randomly sampled weights are generated, one per criterion, with a size of 100,000 elements. Figure 3.4 shows an example of a weight distribution sampled from a normal distribution with an initial weight of 5 and lower and upper confidence limits of 3 and 7, respectively.

These lists are then randomly combined to form a desired number of weight sets.

These weight sets are first normalized and then used to generate performance scores and rankings through the application of TOPSIS and PROMETHEE multi-objective optimization methods. The resulting data is stored as two matrices: one containing all the scores and the other containing all the rankings.

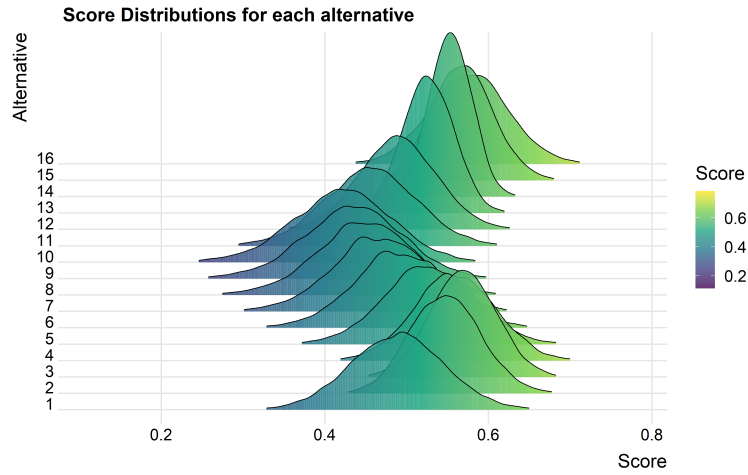


Figure 3.5: Ridgeline plot resulting from a sensitivity analysis run with PROMETHEE and 10,000 weight sets. All initial weights are equal to 5 and all confidence intervals are between 3 and 7.

### 3.5.3 Results analysis

From the matrix of scores, a score distribution is generated for each alternative. Figure 3.5 shows an example of a ridgeline plot that shows the score distributions of all alternatives, allowing them to be compared with each other. The position and width of these distributions indicate the average performance and stability of each alternative. A broad peak means that performance is strongly influenced by variations in weighting, indicating a degree of instability. Conversely, a narrow peak indicates that the alternative is stable in the face of weighting uncertainty.

Rankings indicate the frequency with which alternatives reach a particular position. These frequencies are calculated by simply counting the number of times a particular position appears for each alternative in the ranking matrix. The sensitivity analysis module determines the frequency with which each alternative receives the top position or a position in the top three. In both cases, the top five alternatives are filtered and a histogram is generated. Examples of these histograms are shown in Figure 3.6. This identifies the most robust and frequently performing alternatives and provides a more complete view of their relative stability.

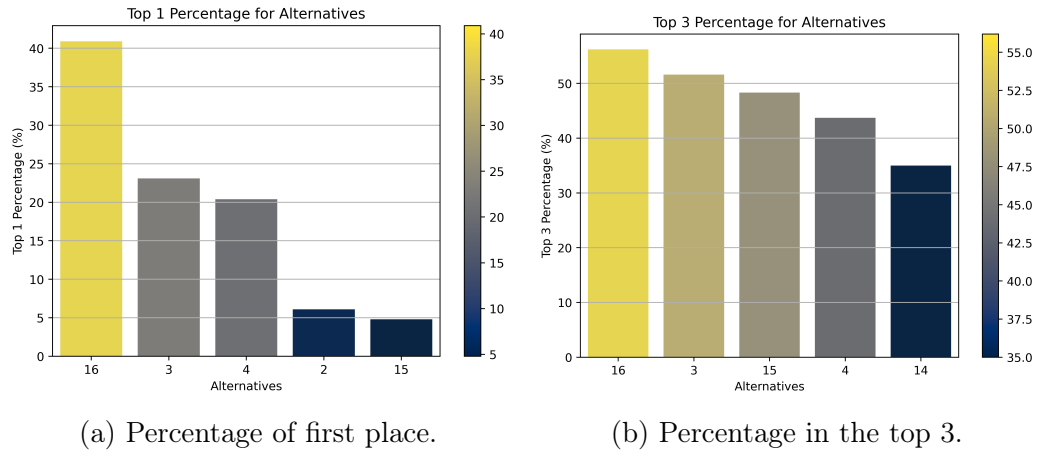


Figure 3.6: Percentage of first and top 3 places for the 5 best alternatives in each case. These results were obtained under the conditions described in Figure 3.5.

### 3.5.4 Conclusion

Sensitivity analysis is essential for assessing the robustness of decisions made using TOPSIS and PROMETHEE multi-objective optimization methods. By taking into account the uncertainty associated with the weighting of criteria, this analysis ensures that the alternatives selected are not only optimal under certain conditions, but also stable and efficient under different weightings. This increases the reliability of decisions and helps decision-makers make informed choices even in the presence of uncertainty.

# Chapter 4

## Tool development

### 4.1 Introduction

The development of the multi-objective decision-making tool required the practical implementation of the theoretical methodologies described in Chapter 3. This chapter describes how these methodologies were translated into a functional tool, highlighting the technologies used and the code architecture. The main goal is to provide a clear overview of the tool's structure and functionalities, while explaining the technical choices made to ensure its efficiency and robustness.

The tool consists of several modules, each dedicated to a specific function. These modules include data collection and preparation, implementation of the TOPSIS and PROMETHEE optimization methods, sensitivity analysis, visualization of results, and storage of results. This modular structure is designed to facilitate the use and modification of the tool.

### 4.2 Technologies and tools

#### 4.2.1 Programming language

The multi-objective decision-making tool was developed primarily in Python. This programming language was chosen for several reasons.

First, the iSMA framework described in Chapter 2, from which the development project for this tool was born, is also developed in Python. This ensures consistency and compatibility between the different components of the project, making it easier to integrate the tool into the existing framework.

Second, Python offers many advantages for the development of scientific and technical tools. It has a large number of useful libraries that facilitate

the implementation of complex tasks. These libraries significantly reduce development time by providing pre-built, optimized functions for various operations.

Python also benefits from a very large user community. This active community contributes to rich documentation and rapid support through various forums and online platforms. This facilitates problem solving and learning new techniques, making the development process more efficient and less restrictive.

Finally, Python's syntax is clear and expressive, making it easy to write readable and maintainable code. This is critical in a collaborative project where multiple developers may be working on the same code. Python's simplicity also enables rapid prototyping, which is essential for testing and validating ideas before they are fully implemented.

Thus, the choice of Python as the programming language for the development of the tool is based on its consistency with the existing ontological structure, the richness of its libraries, the support of a large community, and the clarity of its syntax.

## 4.2.2 Development environments

### Jupyter Notebook

Jupyter Notebook is used for rapid prototyping and experimentation with different algorithms and techniques. This interactive environment combines executable code, visualizations, and textual explanations in a single document. This facilitates iterative development by allowing immediate visualization of results and interactive data exploration. Key benefits of Jupyter Notebook include:

- **Instant visualization:** Calculation results can be immediately visualized in the form of built-in graphs, helping to understand and adjust algorithms in real time.
- **Flexibility:** Notebooks can be run cell by cell, providing great flexibility to develop and test small segments of code before integrating them into a larger structure.

### Visual Studio Code

Visual Studio Code (VS Code) was used for the final development and organization of the code into modules. VS Code is a lightweight yet powerful source code editor that integrates many of the features essential to software development. Key benefits of VS Code include:



- **Extensions and plugins:** An extensive library of extensions allows to add additional functionality, such as support for different programming languages, integration with version control systems like Git, and code formatting tools.
- **Version management:** Native integration with Git makes it easy to manage code versions and track changes.
- **Jupyter Notebook integration:** VS Code also supports Jupyter notebooks, making it easy to switch between interactive prototyping and more structured, modular development.

### 4.2.3 Libraries

The development of the tool is based on several essential Python libraries. These tools simplify and optimize data manipulation and result visualization.

#### NumPy and Pandas

NumPy (Numerical Python) is a fundamental library for scientific computing in Python. It provides powerful data structures and optimized functions for performing mathematical operations on them. NumPy is used for fast, efficient computations that are critical for optimization algorithms and sensitivity analysis.

Pandas is a data manipulation and analysis library that provides flexible, expressive data structures, DataFrames, and Series. This library facilitates data manipulation, making the development of mathematical algorithms faster and more intuitive. DataFrames are tabular data structures with axis labels (rows and columns), while Series are one-dimensional data structures with index labels. These data structures are powerful because they offer several advantages:

- **Indexing and selection:** Quickly access specific rows and columns using index labels. For example, it is easy to extract an entire column to perform calculations.
- **Vectorized operations:** Apply mathematical operations to entire columns without the need for explicit loops. For example, a column can be normalized in a single line of code.
- **Join and merge:** Combine multiple DataFrames using join and merge operations, simplifying the handling of complex data sets.

- **Mathematical operations:** Mathematical operations between DataFrame and Series are greatly facilitated by row and column indexing. This indexing automatically applies operations between the correct rows and columns, eliminating the need to write complex loops to ensure data alignment.

## Matplotlib and Seaborn

Matplotlib is a basic library for creating graphs in Python. It is highly flexible and can be used to create a wide range of visualizations, from line graphs to complex 3D visualizations.

Seaborn is a data visualization library based on Matplotlib. It provides more sophisticated statistical visualizations and aesthetic themes by default. Seaborn is used to create more complex and aesthetically pleasing graphs, making results easier to interpret.

## 4.3 Tool architecture

The tool is structured in modules to ensure a clear organization and smooth execution of the various steps. The data flow, shown in Figure 4.1, begins with the collection of data about the alternatives and the user's preferences, performed by the data collection module. This data is then processed by optimization methods. After processing, a sensitivity analysis is performed. The results of this analysis are then analyzed and visualized, and finally stored for future use.

The tool is coordinated by two main executable files, one for TOPSIS and one for PROMETHEE. Each main file successively calls the main function defined within each module, allowing the execution of the different stages of the tool.

Each module contains several functions, each of which models a specific step, such as performing a mathematical operation, displaying a graph, or saving a particular set of data. These functions are aggregated into a main function within each module. This main function is then called in the corresponding main file (TOPSIS or PROMETHEE).

The main file for TOPSIS, *TOPSIS\_main.py*, successively calls the main functions of the different TOPSIS-specific modules to compose the complete tool. Similarly, the main file for PROMETHEE, *PROMETHEE\_main.py*, coordinates the steps specific to the PROMETHEE method by calling the main functions of the corresponding modules.

There are five types of modules in the tool:

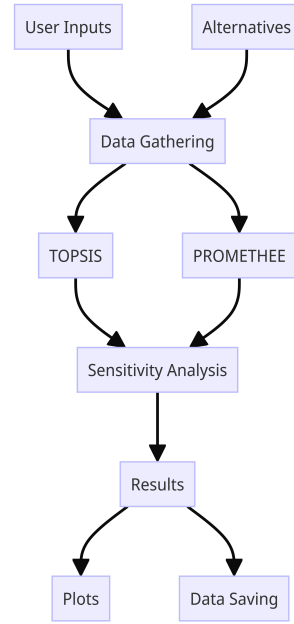


Figure 4.1: Data flow within the tool.

- **Data gathering:** This module collects data on alternatives and user input and normalizes the data set.
- **Optimization methods:** This type of module has two versions, one for TOPSIS and one for PROMETHEE, each implementing the steps specific to their respective algorithms.
- **Sensitivity analysis:** This module performs sensitivity analysis, with specific versions for TOPSIS and PROMETHEE.
- **Plotting results:** This module uses visualization libraries to display results.
- **Saving results:** This type of module saves results in CSV files.

This modular structure ensures clear organization and easy adaptation of the tool to different contexts and needs, while facilitating maintenance and future extensions. The complete code of the tool, including all source files, is available on GitHub. The repository can be browsed at: [GitHub - MODM tool](#).

# Chapter 5

## Results and discussion

### 5.1 Introduction

This chapter analyzes the results obtained with the multi-objective decision-making tool by varying different parameters: the normalization method, the criteria weighting as well as the uncertainty associated, and the preference functions for the PROMETHEE method. The aim is to understand how these parameters influence the final results and to compare the performance of the different alternatives using the TOPSIS and PROMETHEE methods.

The analysis first examines the impact of the normalization method on the results for each optimization method. Next, the impact of the weighting of the criteria on the results is studied by comparing different weighting scenarios. For PROMETHEE, the impact of preference functions is also analyzed by comparing the usual function and the Gaussian function. Finally, a global comparison is made between TOPSIS and PROMETHEE using a fixed normalization method, balanced weighting, and preference function. This comparison also includes a study of different degrees of uncertainty for the sensitivity analysis in order to assess the robustness of the solutions.

## 5.2 Results analysis for TOPSIS

### 5.2.1 Impact of the normalization method

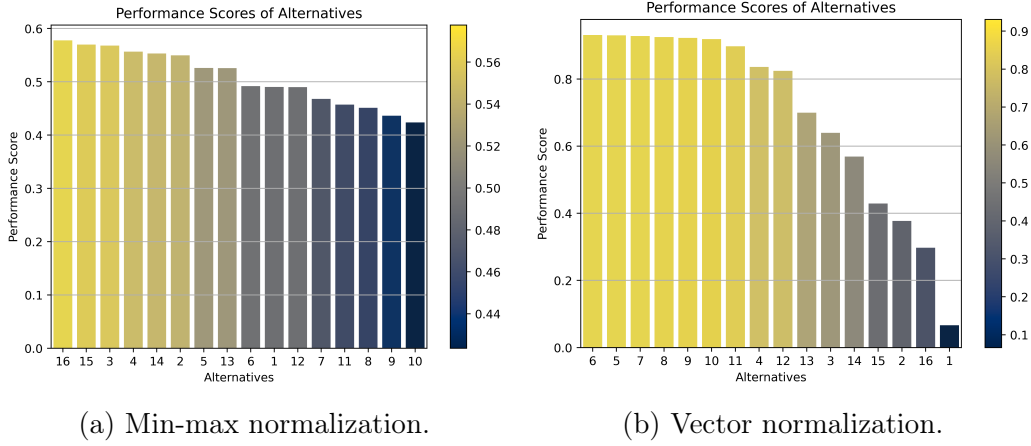


Figure 5.1: Comparison of alternative rankings using the two normalization methods for TOPSIS, with equal weighting for each criterion (5, 5, 5).

Figure 5.1 shows that vector normalization systematically favors high-profit alternatives by placing them at the top of the ranking. The 6 best alternatives, 6, 5, 7, 8, 9, and 10, are relatively indistinguishable from each other, as they have fairly similar performances for all criteria. Alternative 1, on the other hand, with its very good environmental performance, is ranked by far last, as it has the lowest profit of all the alternatives.

Min-max standardization, on the other hand, represents a much more balanced approach to the consideration of different criteria. High profit alternatives tend to be ranked lower because they do not offer significant improvement in environmental criteria compared to the small additional economic gain. This trend is reflected in the bottom ranking of Alternative 10, which has the highest economic benefit. On the other hand, Alternative 16 is ranked first, despite having the second lowest profit, because it offers very good environmental performance, especially in terms of resource impact, where it is the best.

These observations are consistent with the discussion in Section 3.2, which concluded that the min-max normalization method takes into account the different criteria in a balanced way, regardless of the initial distribution of the values associated with these criteria, which is not the case with vector normalization.

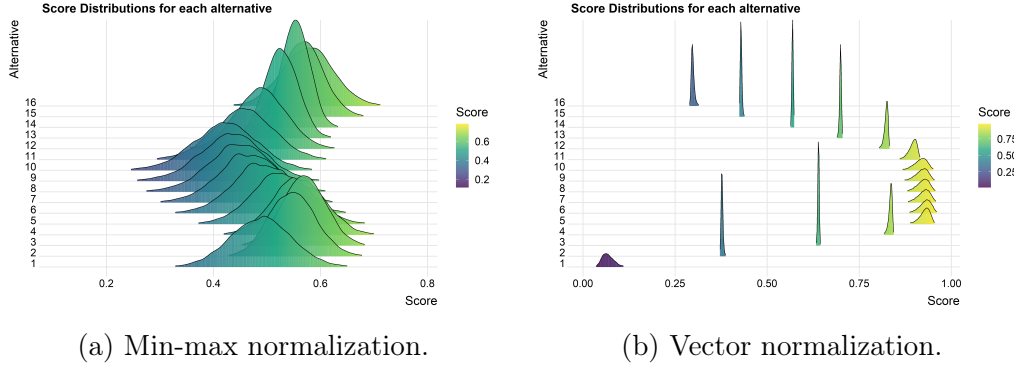


Figure 5.2: Comparison of performance scores distributions obtained through sensitivity analysis using the two normalization methods for TOPSIS, with equal weighting (5, 5, 5) and uncertainty ( $\pm 20\%$ ) for each criterion.

Figure 5.2 shows a clear difference between the score distributions according to the normalization method. The vector normalization shows a wider spread of the scores obtained by the alternatives, ranging from almost 0 to almost 1, while producing distributions at well-defined positions. Again, alternatives 5, 6, 7, 8, 9, and 10 are almost indistinguishable. The narrowness and precise positioning of the distributions show that the influence of the criteria weighting is virtually null when vector normalization is used.

In contrast, the min-max normalization method produces much broader distributions with closer mean values. This shows that the results obtained are highly dependent on the weighting used. The wider distributions indicate that each criterion has a more balanced weight in the final calculation, reflecting better the diversity of the criteria evaluated.

Finally, Figure 5.3 shows that a dominant alternative can be identified for both normalization methods. However, this dominance is more relative for min-max normalization, where alternative 16 ranks first in about 40% of the simulations. On the other hand, for vector normalization, alternative 6 is the best in more than 60% of the cases. It can also be noted that the first place is globally shared between 5 alternatives for min-max normalization, while alternatives 6 and 5 account for almost 100% of the first places in the case of vector normalization.

The analysis shows that the normalization method has a significant impact on the TOPSIS results. Vector normalization strongly favors high-profit alternatives, systematically placing them at the top of the ranking. Min-max normalization, on the other hand, offers a more balanced approach, taking better account of the different criteria and allowing a fairer distribution of the top positions among the alternatives. The choice of normalization method

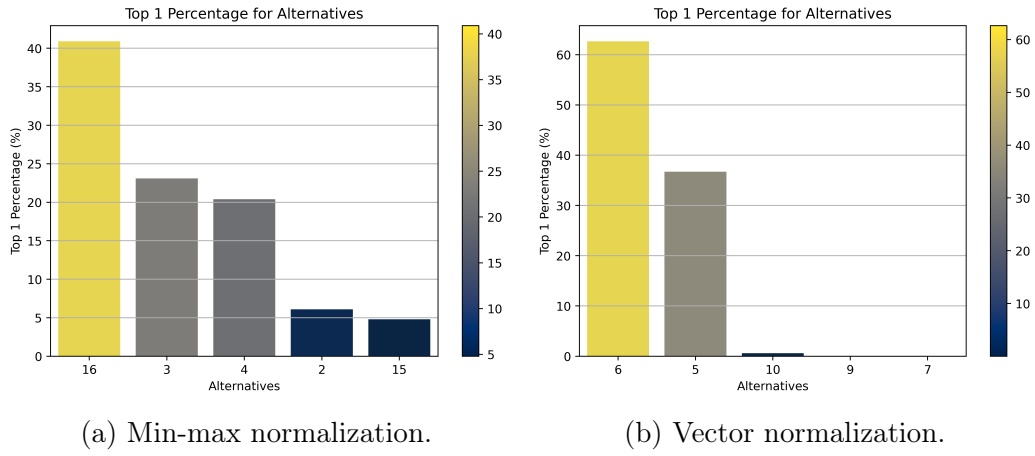


Figure 5.3: Comparison of first place percentages of the 5 best alternatives obtained through sensitivity analysis using the two normalization methods for TOPSIS, with equal weighting (5, 5, 5) and uncertainty ( $\pm 20\%$ ) for each criterion.

must therefore be made according to the specific objectives of the analysis and the criteria to be evaluated.

## 5.2.2 Impact of the criteria weighting

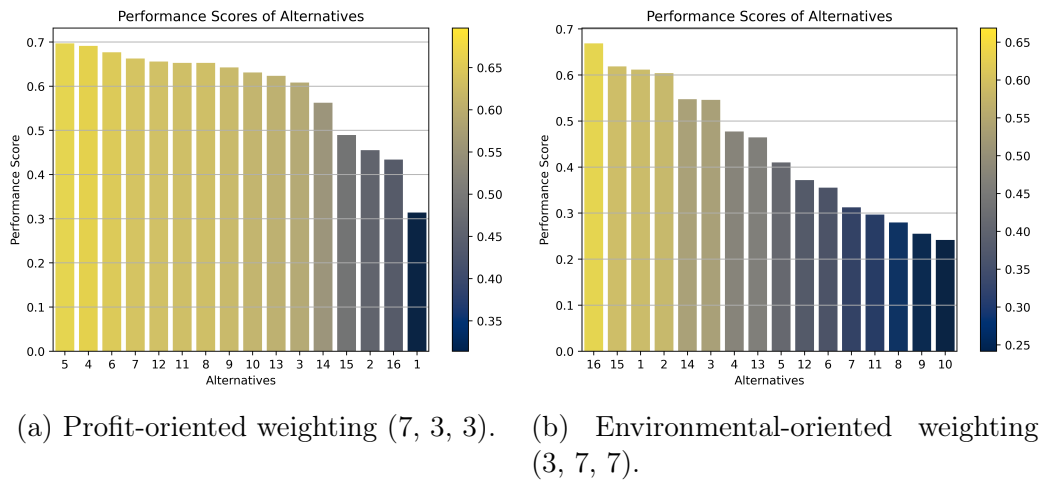


Figure 5.4: Comparison of alternative rankings using two weighting scenarios for TOPSIS, with min-max normalization.

In the profit-oriented scenario (Figure 5.4a), the alternatives with the best economic scores are generally preferred. Alternatives 5, 4, 6, 7, 12, and 11 occupy the top positions in the ranking. However, some high-profit alternatives, such as alternatives 8, 9, and 10, are ranked behind alternatives with slightly lower profits, such as alternative 4. This is because this weighting does not give absolute importance to profit, as it also takes environmental criteria into account, although in a more moderate way. The alternatives with the highest profits, such as Alternative 10, do not offer an ideal compromise between profit and environmental impact.

In the environmentally-oriented scenario (Figure 5.4b), alternatives with better environmental performance are favored. Alternative 16, with the second lowest profit but the best performance in terms of impact on resources, is in first place. Alternatives 15, 1, 2 and 14 follow, highlighting the increased importance of environmental criteria in this weighting scenario. Note that even with a significant relative importance for the profit criterion (3 for profit vs. 7 for environmental criteria), the high-profit alternatives are systematically ranked at the bottom.

These results show that the weighting of criteria has a strong influence on the ranking of alternatives. By adjusting the weights to reflect different priorities, decision-makers can steer the choice towards solutions that better meet their specific objectives, whether economic or environmental. Alternatives that offer a better compromise among the three criteria are highlighted, demonstrating the flexibility of the method to adapt to different scenarios.

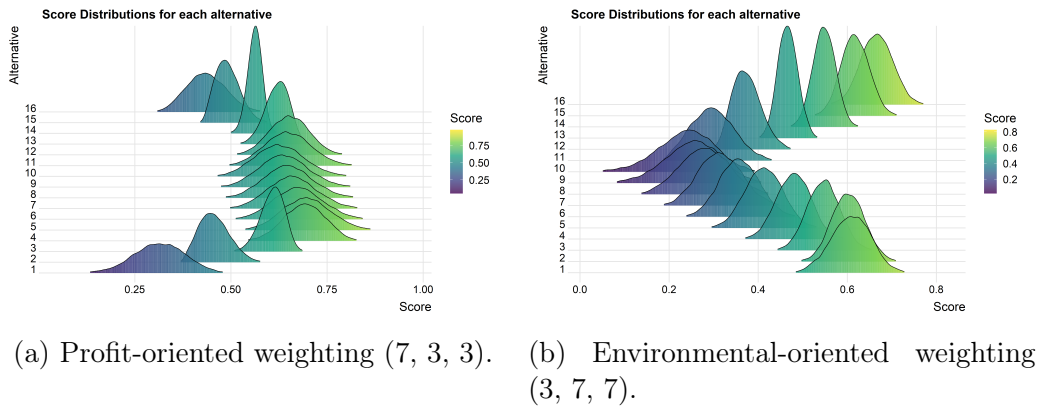


Figure 5.5: Comparison of performance scores distributions obtained through sensitivity analysis using two weighting scenarios for TOPSIS, with min-max normalization and equal uncertainty ( $\pm 20\%$ ) for each criterion.

Figure 5.5 compares the performance score distributions obtained from the sensitivity analysis.



In the profit-oriented scenario (Figure 5.5a), the high-profit alternatives, such as 5, 4, 6, 7, and 12, are ranked ahead of the others and have broader overall distributions with relatively close average performances. This indicates that these alternatives, although favored by their profit, show greater variability in their scores in response to weighting uncertainty.

Moving to the environmental scenario (Figure 5.5b), the difference between average performance of the distributions becomes clearer. Alternatives with higher environmental performance, such as 16, 15, 1, 2, and 14, are now ahead of those with higher profits. It can be seen that, with the exception of Alternative 16, the more environmentally oriented alternatives tend to have narrower peaks, demonstrating greater stability in the face of weighting uncertainty.

One particular observation can be made for Alternative 1. When we move from the profit-oriented scenario to the environmental-oriented scenario, a gain in stability is noticed. The fact that Alternative 1 is the worst from a profit perspective and one of the best from an environmental perspective suggests that the stability of an alternative depends not only on its intrinsic performance, but also on the initial weighting. This observation underlines the importance of the weighting of criteria in the evaluation of alternatives, which influences not only their ranking but also their robustness in the face of uncertainties.

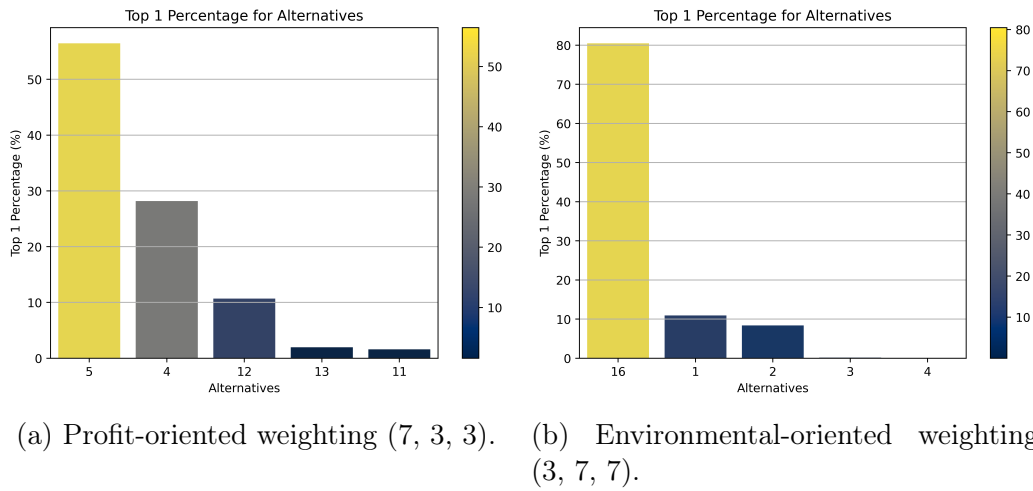


Figure 5.6: Comparison of first place percentages of the 5 best alternatives obtained through sensitivity analysis using two weighting scenarios for TOP-SIS, with min-max normalization and equal uncertainty ( $\pm 20\%$ ) for each criterion.

Figure 5.6 compares the first-place percentages of the five best alternatives

obtained from the sensitivity analysis.

In the profit-oriented scenario (Figure 5.6a), Alternative 5 clearly dominates, taking the top spot in over 50% of the simulations. Alternatives 4, 12, 13, and 11 follow with significantly lower percentages, with alternative 4 taking about 30% of the top spots and the other alternatives sharing the remaining 20%. This shows that even with uncertainty in the weightings, Alternative 5 remains widely preferred when high profit is prioritized.

In the environmentally-oriented scenario (Figure 5.6b), Alternative 16 becomes largely dominant, ranking first in nearly 80% of simulations. Alternatives 1 and 2 share the remaining top spots with much lower percentages. This reflects a strong preference for Alternative 16 when environmental criteria are weighted more heavily.

These results demonstrate the significant impact of criteria weighting on the ranking of alternatives. An alternative can go from dominant to marginal depending on the priorities defined by the weighting. The min-max normalization method brings out this variation clearly, showing that the preferences of the decision makers strongly influence the results obtained by TOPSIS.

### 5.2.3 Impact of the weighting uncertainty

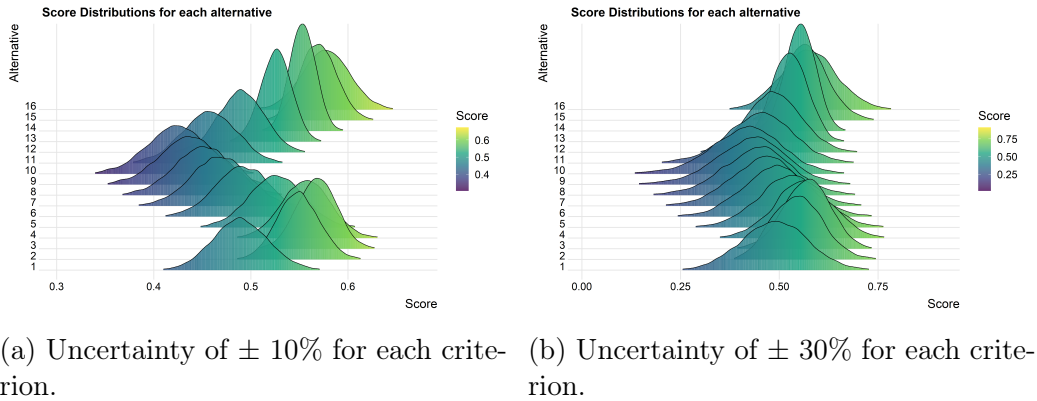


Figure 5.7: Comparison of performance scores distributions obtained through sensitivity analysis using two uncertainty scenarios for TOPSIS, with min-max normalization and equal weighting (5, 5, 5) for each criterion.

Figure 5.7 compares the score distributions obtained from the sensitivity analysis for two uncertainty scenarios. As expected, increasing the uncertainty of the weights from  $\pm 10\%$  (Figure 5.7a) to  $\pm 30\%$  (Figure 5.7b) has the effect of broadening the score distributions. This broadening of the distributions reflects the greater variability of the scores due to the increased

uncertainty. It is important to note that although the distributions are wider in the increased uncertainty scenario, the overall average performance of the alternatives remains unchanged. This is visible despite the difference in scale on the x-axis: the distributions range from 0.4 to 0.6 in Figure 5.7a, while they range from 0.25 to 0.75 in Figure 5.7b.

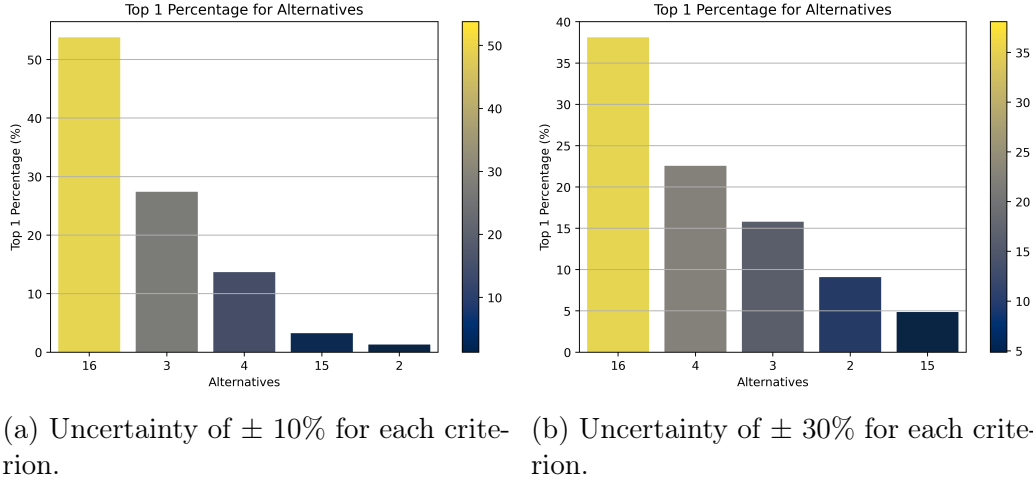


Figure 5.8: Comparison of first place percentages of the 5 best alternatives obtained through sensitivity analysis using two uncertainty scenarios for TOPSIS, with min-max normalization and equal weighting (5, 5, 5) for each criterion.

Figure 5.8 compares the ranked percentages of the top 5 alternatives obtained through sensitivity analysis for two uncertainty scenarios. In both scenarios, the top 5 alternatives remain the same, with alternative 16 holding the top position. However, the order of the next 4 alternatives changes slightly. Alternative 16, while remaining in first place, achieves a higher percentage of first places in the lower uncertainty case ( $\pm 10\%$ ), reaching almost 55% of the simulations. When the uncertainty increases to  $\pm 30\%$ , this percentage decreases to about 35%. These observations show that although increasing uncertainty affects the relative dominance of Alternative 16, it remains the best option overall.

## 5.3 Results analysis for PROMETHEE

### 5.3.1 Impact of the normalization method

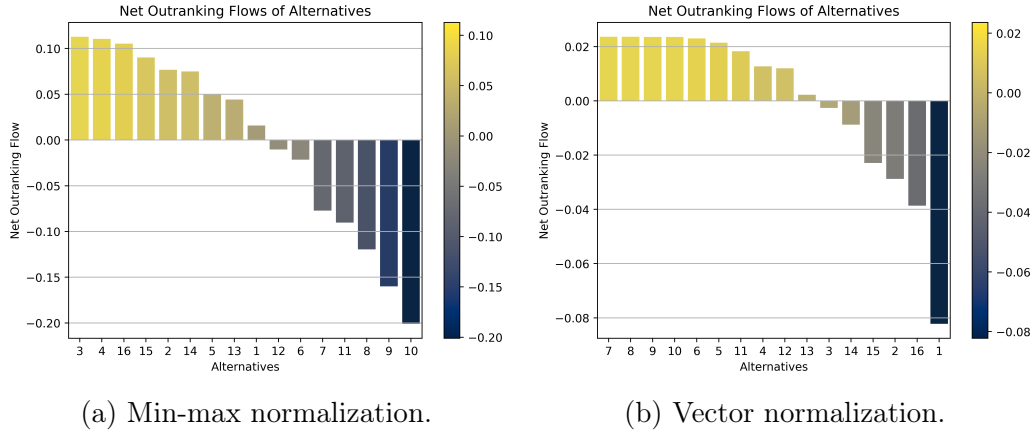


Figure 5.9: Comparison of alternative rankings using the two normalization methods for PROMETHEE, with equal weighting for each criterion (5, 5, 5).

Figure 5.9 shows that the min-max normalization method favors a balance between the criteria, placing alternatives with good environmental performance (such as Alternatives 3, 4, and 16) at the top. Alternative 10, with the best profit, is ranked last. On the other hand, vector normalization favors alternatives with high profits (such as alternatives 7, 8, and 9) and relegates ecologically efficient alternatives to lower positions. This shows that, as with TOPSIS, the normalization method has a significant impact on the rankings obtained with PROMETHEE.

Figure 5.10 shows a clear difference between the distributions of net outranking flows depending on the normalization method, similar to the observations made for TOPSIS. Vector normalization produces very narrow distributions, indicating low sensitivity to criteria weighting and favoring high-profit alternatives. In contrast, min-max normalization produces broader distributions, reflecting greater sensitivity to weighting. Compared to TOPSIS, for PROMETHEE, the differences between the distributions are more pronounced for min-max normalization, while they are slightly less pronounced for vector normalization.

Finally, Figure 5.11 shows that a dominant alternative can be identified for both normalization methods in PROMETHEE. However, this dominance is more relative for the min-max normalization, where alternative 16 ranks first in about 40% of the simulations. In contrast, for the vector normal-

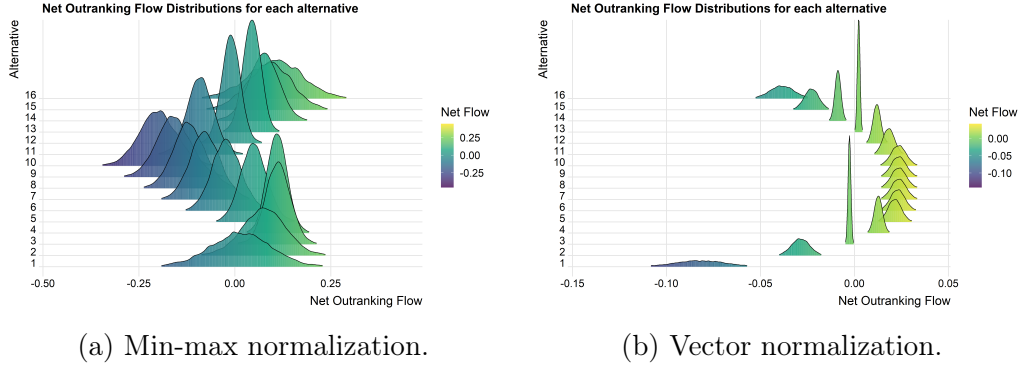


Figure 5.10: Comparison of net outranking flows distributions obtained through sensitivity analysis using the two normalization methods for PROMETHEE, with equal weighting (5, 5, 5) and uncertainty ( $\pm 20\%$ ) for each criterion.

ization, alternative 7 is the best in almost 100% of the cases. This pattern is similar to observations made with TOPSIS, where min-max normalization allows for more balanced competition between alternatives, while vector normalization strongly favors a single alternative.

In conclusion, the choice of normalization method has a significant impact on the results obtained with PROMETHEE. The min-max normalization favors a more balanced evaluation of the alternatives, better reflecting the diversity of the criteria. On the other hand, the vector normalization tends to heavily favor certain alternatives, especially those with higher profits. This behavior is consistent with the observations made for TOPSIS and emphasizes the critical role of normalization in multi-criteria decision-making.

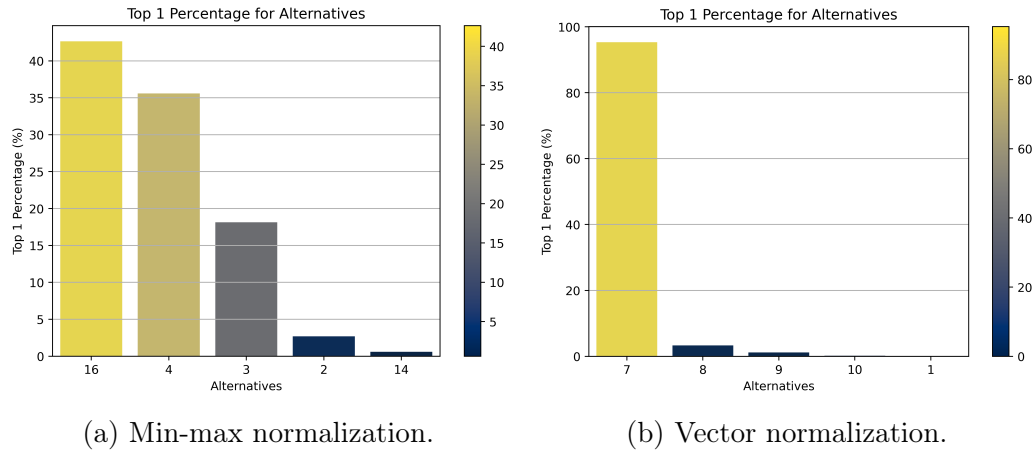


Figure 5.11: Comparison of first place percentages of the 5 best alternatives obtained through sensitivity analysis using the two normalization methods for PROMETHEE, with equal weighting (5, 5, 5) and uncertainty ( $\pm 20\%$ ) for each criterion.

### 5.3.2 Impact of the criteria weighting

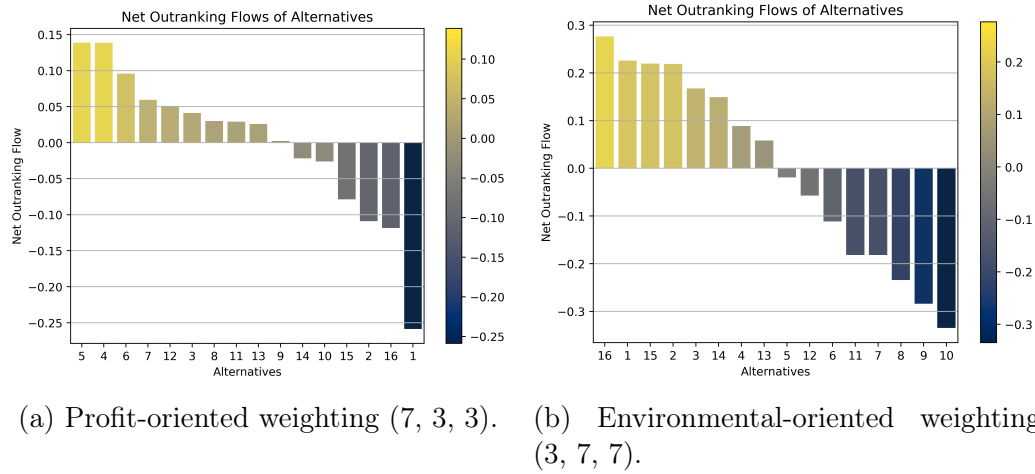


Figure 5.12: Comparison of alternative rankings using two weighting scenarios for PROMETHEE, with min-max normalization and Gaussian preference function.

The results shown in Figure 5.12 for PROMETHEE are consistent with the observations made for TOPSIS. In the scenario with profit-oriented weighting (7, 3, 3), alternatives with higher profit values, such as alternatives 5, 4 and

6, are ranked among the best. However, even in this scenario, Alternative 10, which has the highest profit, is ranked among the bottom five alternatives. This indicates that alternatives with a better balance of criteria are favored.

Switching to the weighting scenario in favor of environmental criteria (3, 7, 7), alternatives with better environmental performance, such as alternatives 16, 1, and 15, move to the top positions. This shift demonstrates the significant impact of weighting on the ranking of alternatives and highlights the flexibility and responsiveness of PROMETHEE to different prioritization schemes.

Overall, the rankings between TOPSIS and PROMETHEE are not perfectly identical, but the general trends are similar.

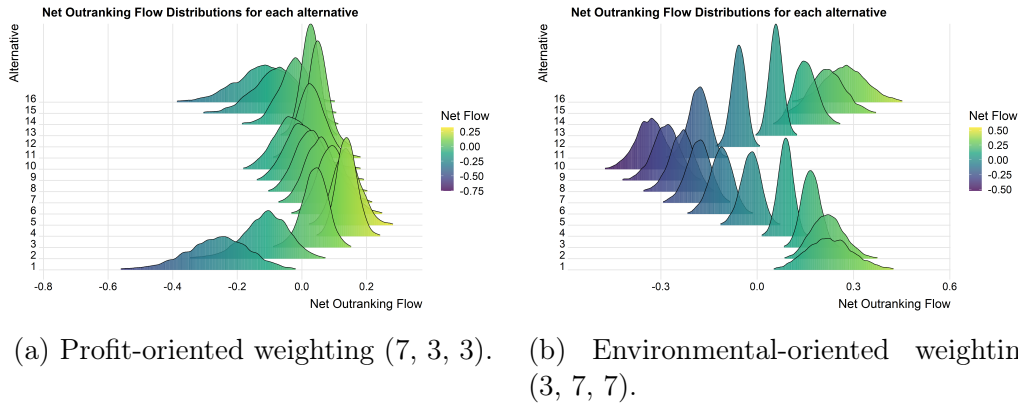


Figure 5.13: Comparison of net outranking flows distributions obtained through sensitivity analysis using two weighting scenarios for PROMETHEE, with min-max normalization, Gaussian preference function and equal uncertainty ( $\pm 20\%$ ) for each criterion.

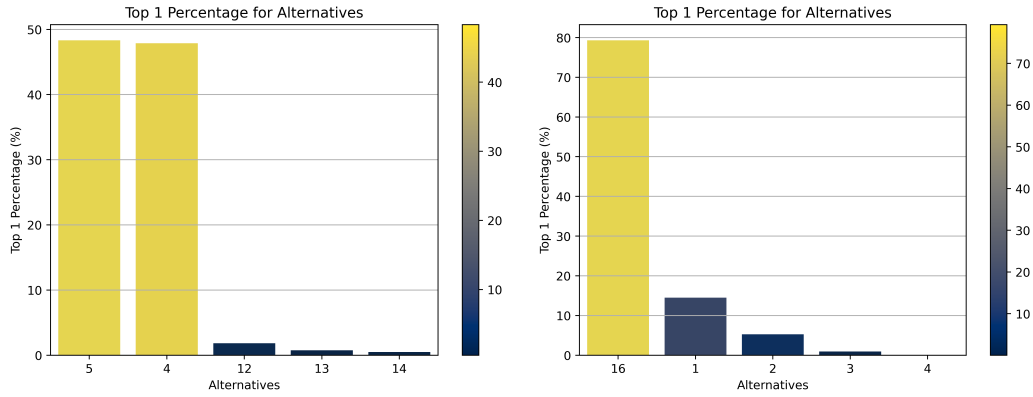
Figure 5.13 shows the distributions of net outranking flows obtained by sensitivity analysis with the PROMETHEE method, using two different weighting scenarios. The observations made for TOPSIS apply here as well. A notable difference is that the stability gain observed for Alternative 1 when moving from the profit to the environmental scenario can be extended to alternatives that perform well on environmental criteria.

In fact, the distributions of alternatives 14, 15, 16, 1, and 2 narrow when moving from one scenario to the other. There is little or no evidence of this for the alternatives that perform well according to the profit criterion. This can be explained by the fact that there is a single profit criterion and two environmental criteria. When switching from the profit to the environmental scenario, greater importance is simultaneously given to both environmental criteria, which can have a significant impact.

Statistically, the random weights generated by the sensitivity analysis favor a certain stability for alternatives that perform well in terms of environmental criteria. If one of the two environmental criteria has a lower importance, the other can compensate by having a higher importance. Although the two environmental criteria are not identical and therefore not perfectly correlated, alternatives with low or even moderate profit tend to perform acceptably in both environmental criteria. This double-weighting dynamic provides a form of compensation that contributes to the increased stability of these alternatives.

On the other hand, this behavior cannot be observed for the profit criterion, since it is unique. Consequently, the profit-oriented alternatives show no significant change in stability between the different weighting scenarios. This is due to the lack of dynamic compensation, which explains why these alternatives show no significant change in stability between the two scenarios.

In summary, the environmental alternatives gain stability as the environmental weighting increases, thanks to the dynamic compensation provided by the double weighting. This observation is less pronounced for the profit-oriented alternatives, since they do not benefit from this dynamic compensation.



(a) Profit-oriented weighting (7, 3, 3). (b) Environmental-oriented weighting (3, 7, 7).

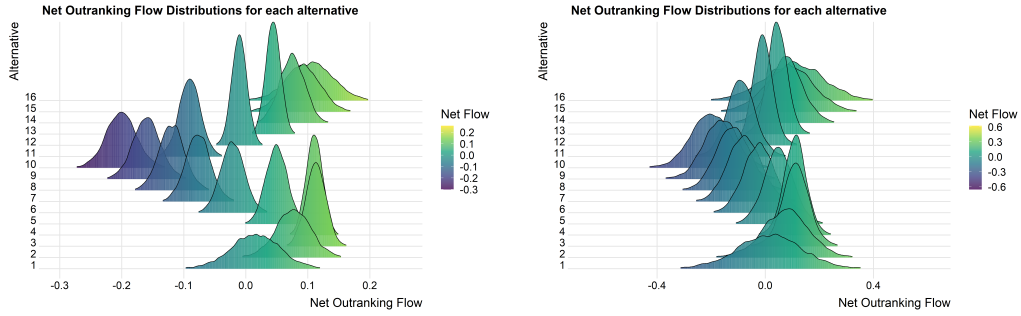
Figure 5.14: Comparison of first place percentages of the 5 best alternatives obtained through sensitivity analysis using two weighting scenarios for PROMETHEE, with min-max normalization, Gaussian preference function and equal uncertainty ( $\pm 20\%$ ) for each criterion.

Figure 5.14 shows that, as with TOPSIS, Alternative 16 is widely preferred in the environmental weighting scenario, ranking first in almost 80%



of the simulations. In contrast, in the profit-oriented weighting scenario, alternatives 5 and 4 share the top rankings with almost identical percentages, each reaching about 50% of the top spots.

### 5.3.3 Impact of the weighting uncertainty



(a) Uncertainty of  $\pm 10\%$  for each criterion. (b) Uncertainty of  $\pm 30\%$  for each criterion.

Figure 5.15: Comparison of net outranking flows distributions obtained through sensitivity analysis using two uncertainty scenarios for PROMETHEE, with min-max normalization and equal weighting (5, 5, 5) for each criterion.

Figure 5.15 shows similar results to TOPSIS. The increase in uncertainty due to weighting spreads the distributions without affecting the average performance of the alternatives. As with TOPSIS, it is important to note that the scale of the x-axis has changed. The distributions range from about -0.3 to 0.2 for an uncertainty of  $\pm 10\%$  (Figure 5.15a), while they range from -0.4 to 0.4 for an uncertainty of  $\pm 30\%$  (Figure 5.15b).

Figure 5.16 shows that in the lower uncertainty case, alternatives 2 and 1 have a zero percentage of first places, meaning that alternatives 16, 4, and 3 all share the first places in the simulations. When moving to a higher uncertainty scenario, Alternatives 2 and 1 receive a low percentage of first places, demonstrating that greater uncertainty increases the likelihood that other alternatives will be ranked first. The percentages given to alternatives 2 and 1 are mainly due to the 10% lost by alternative 3. Alternative 16, on the other hand, actually increases its percentage of firsts slightly, demonstrating its ability to perform very well in variable situations.

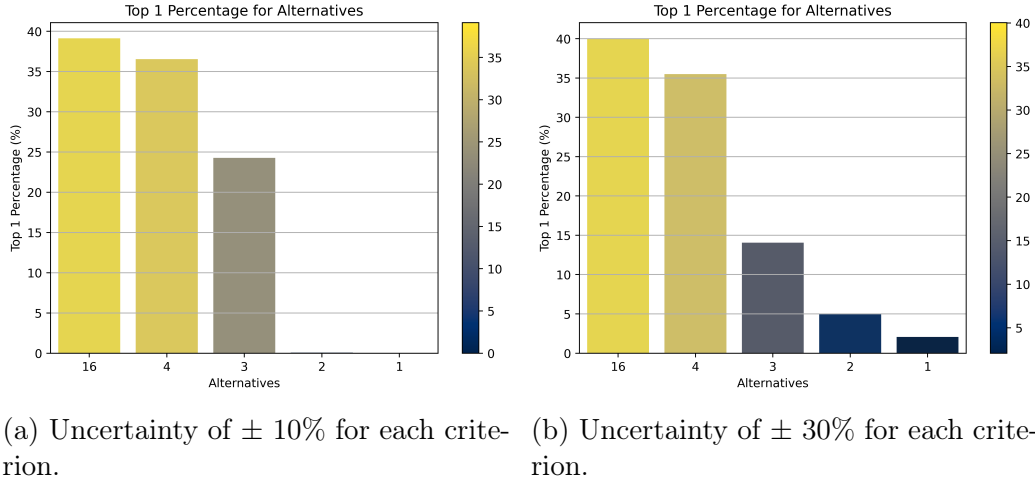


Figure 5.16: Comparison of first place percentages of the 5 best alternatives obtained through sensitivity analysis using two uncertainty scenarios for PROMETHEE, with min-max normalization and equal weighting (5, 5, 5) for each criterion.

### 5.3.4 Impact of the preference function

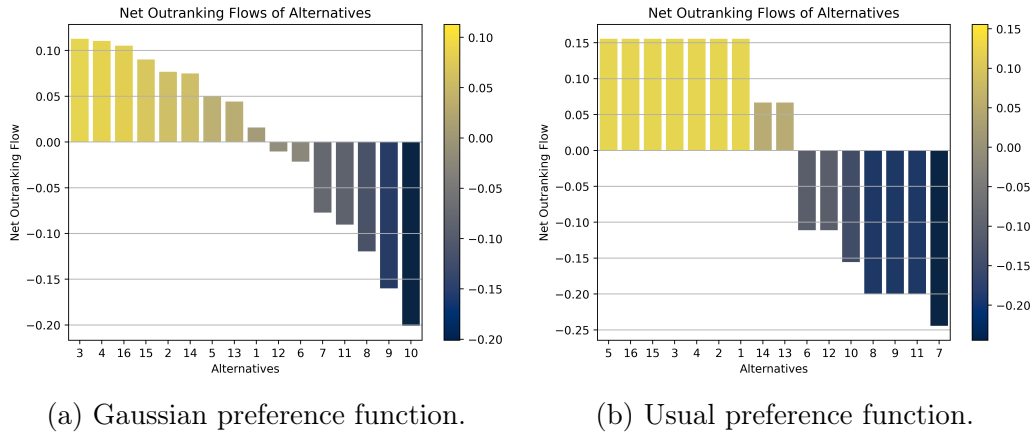


Figure 5.17: Comparison of alternative rankings using two preference functions for PROMETHEE, with min-max normalization and equal weighting for each criterion (5, 5, 5).

Figure 5.17 shows that the usual preference function tends to form a ranking with groups of alternatives that are indistinguishable from each other. In contrast, the Gaussian preference function assigns a unique net outranking

flow to each alternative, producing a unique ranking. This distinction stems from the fact that the usual preference function is simpler and only considers either an overall preference or no preference at all. It is not capable of fine-grained evaluation of the preference of one alternative over another, unlike the Gaussian preference function, which provides a precise preference value based on the difference in evaluation between the alternatives. In the context of ranking Pareto optimal solutions resulting from trade-offs between different criteria, the usual function does not seem relevant.

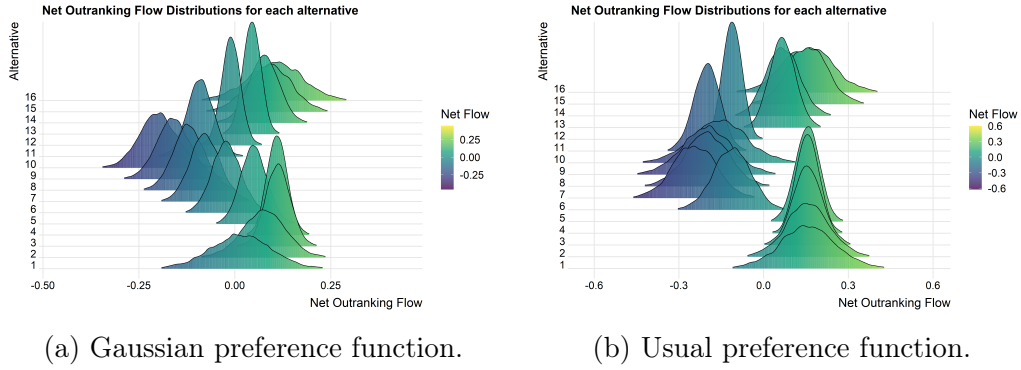


Figure 5.18: Comparison of net outranking flows distributions obtained through sensitivity analysis using two preference functions for PROMETHEE, with min-max normalization, and equal weighting (5, 5, 5) and uncertainty ( $\pm 20\%$ ) for each criterion.

Figure 5.18 shows that the distributions obtained with the usual preference function support the idea of alternative grouping. Alternatives tend to group into clusters with similar average net outranking flow values. However, it is still possible to assess the relative stability of the different alternatives within each cluster. In comparison, the Gaussian preference function provides a better distinction between alternatives in terms of net outranking flow, resulting in less clustered and more individualized distributions. This confirms that the Gaussian function provides greater precision in assessing preferences between alternatives.

## 5.4 Comparison between TOPSIS and PROMETHEE

Comparing the TOPSIS and PROMETHEE methods allows to identify differences in the results obtained by these two approaches. The aim is to check whether the methods agree on the ranking of alternatives, which reinforces the robustness of the decisions taken.

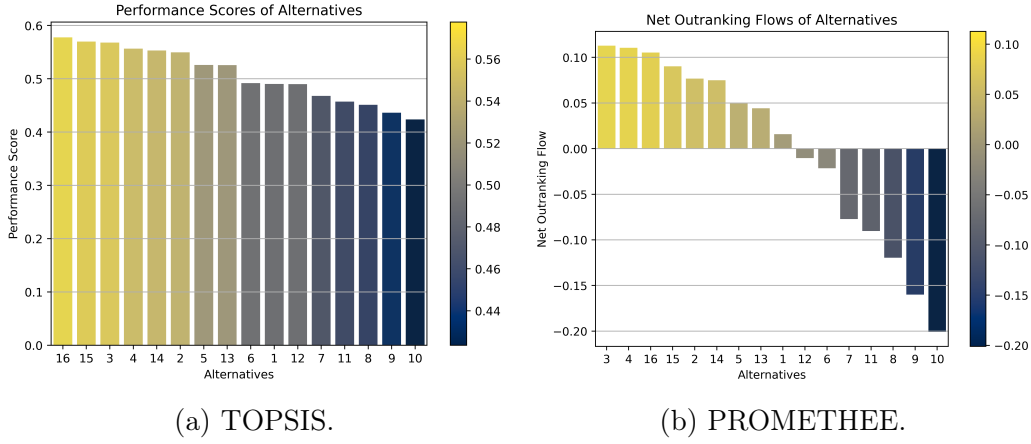


Figure 5.19: Comparison of alternative rankings using TOPSIS and PROMETHEE, with min-max normalization, Gaussian preference function for PROMETHEE and equal weighting for each criterion (5, 5, 5).

The two methods were compared using the min-max normalization method, the Gaussian preference function for PROMETHEE, and a balanced weighting of all criteria. The rankings obtained with the two methods, although not perfectly identical, are very similar as it can be seen on Figure 5.19.

First, in both cases, the five worst alternatives are alternatives 7, 11, 8, 9, and 10, always in that order. Then, the two multi-objective optimization methods seem to agree on the worst alternatives, which are systematically those with the highest profits. This shows that these high-profit alternatives do not offer a very attractive trade-off in terms of environmental criteria. In fact, the small economic gain does not compensate for the significant environmental losses.

However, Alternative 5 remains an exception as it offers a high profit with an acceptable environmental performance. This alternative, together with alternatives 14, 2, 13, 6, 1 and 12, forms the middle of the table, which is again very similar between the two methods. Finally, alternatives 3, 4, 15, and 16 are considered the bests by both methods. Alternatives 3 and 4 are in the upper middle range for the profit and for the environmental impact on ecosystems, and in the lower middle range for resource impacts. Alternatives 15 and 16, on the other hand, are the best in terms of impact on resources, while they are average in terms of impact on ecosystems and quite weak in terms of profit. TOPSIS prefers alternatives 16 and 15, while PROMETHEE prefers alternatives 3 and 4.

In summary, these observations show that the TOPSIS and PROMETHEE methods tend to agree on which are the best and worst alternatives, while

producing rankings that are not perfectly identical.

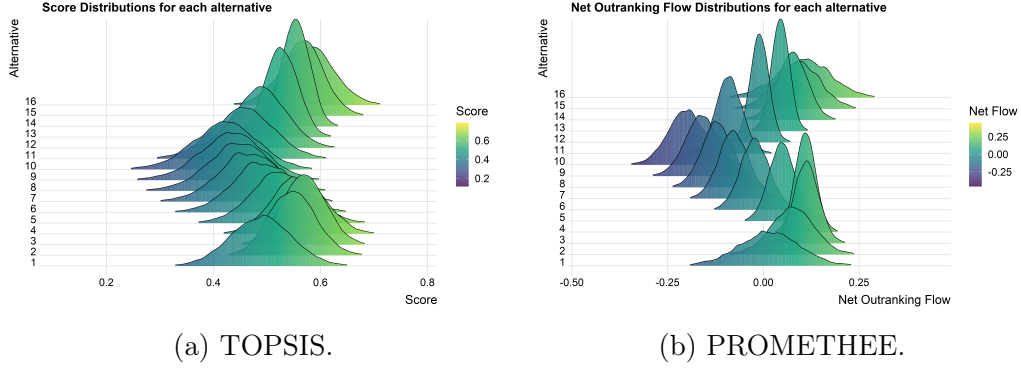


Figure 5.20: Comparison of performance scores and net outranking flows distributions obtained through sensitivity analysis using TOPSIS and PROMETHEE, with min-max normalization, Gaussian preference function for PROMETHEE, and equal weighting (5, 5, 5) and uncertainty ( $\pm 20\%$ ) for each criterion.

Figure 5.20 shows that the relative positioning of the distributions of the different alternatives is fairly equivalent from one method to another. However, the differences between the distributions are clearer for PROMETHEE, mainly due to the greater width of the distributions obtained with TOPSIS. A very interesting observation can then be made: the differences in width between the distributions are more pronounced for PROMETHEE than for TOPSIS. For example, alternatives 1 and 4 show comparable peak widths with TOPSIS, whereas this is absolutely not the case with PROMETHEE, where alternative 4 has a much narrower distribution than 1. This suggests that PROMETHEE is better suited to assess the differences in stability between the alternatives.

Let's focus on the distributions obtained with PROMETHEE and consider alternatives 4 and 16, both of which have a high and almost identical average performance. The distribution of Alternative 16 is much wider, which means that its performance is largely influenced by the weighting of the criteria. Under certain conditions, Alternative 16 will excel and largely dominate all others. Under other conditions, it will perform much poorly and find itself at the bottom of the table. For Alternative 4, the analysis is different. Thanks to its narrow peak, it is very stable and will therefore almost always be among the best. However, this stability is achieved at the expense of potentially very high performance.

The choice between a good, stable alternative and one that is excellent under some conditions and average under others depends not only on the risk

aversion of the decision-makers, but also on the degree of certainty given to the weighting. If the weighting is absolutely certain, it makes sense to choose the alternative that is excellent under those conditions, no matter how unstable it may be in other situations. On the other hand, if the exact conditions are relatively unknown, then the right choice is to select an alternative that performs well while remaining stable.

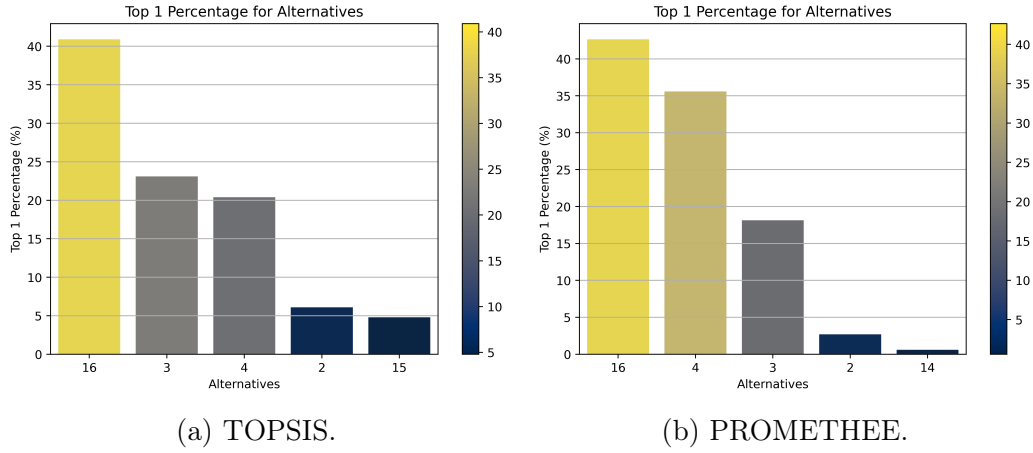


Figure 5.21: Comparison of first place percentages of the 5 best alternatives obtained through sensitivity analysis using TOPSIS and PROMETHEE, with min-max normalization, Gaussian preference function for PROMETHEE, and equal weighting (5, 5, 5) and uncertainty ( $\pm 20\%$ ) for each criterion.

Figure 5.21 shows that Alternative 16 is relatively dominant for both methods. For PROMETHEE, Alternative 4 is almost equally dominant. In light of the above observations, it is important to qualify the dominance of Alternative 16. Indeed, as we have seen, it has a wide distribution of scores and is therefore relatively unstable in the face of uncertainty in the weighting of the criteria.

Thus, although it is often favored in certain situations, as shown by the 40% of first places obtained, there are many other situations where it does not dominate, resulting in a very average performance and a lower ranking. Alternative 4, on the other hand, is more stable, obtaining 20% dominance for TOPSIS and 35% for PROMETHEE, which is still quite high, although slightly lower than the 40% of Alternative 16. However, it could be argued that the 20% and 35% of Alternative 4 are potentially more valuable due to its greater stability, offering a more consistent and reliable performance across different weightings.

## 5.5 General discussion

The comparative analysis of TOPSIS and PROMETHEE presented in this chapter reveals several key insights regarding their application in multi-criteria decision-making for chemical recycling of plastic waste. The study carefully varied several parameters, including normalization methods, criteria weighting, uncertainty levels, and preference functions, to examine how these factors influence the results obtained with the tool.

Both the TOPSIS and PROMETHEE methods showed a significant impact of the normalization method on the results. The min-max normalization provided a more balanced evaluation by reflecting the diversity of the criteria, while the vector normalization specifically favored alternatives with higher profits, resulting in narrower distributions of scores and less sensitivity to criteria weighting.

When examining the impact of criteria weighting, it was clear that the choice of weights strongly influenced the ranking. In both methods, profit-oriented weighting scenario placed high-profit alternatives at the top, while environmentally-oriented weighting favored alternatives with better environmental performance. This shift underscores the flexibility of both methods to accommodate different prioritization scenarios and the critical role of criteria weighting in multi-criteria decision-making.

The analysis also highlighted the importance of stability in the face of weighting uncertainty. PROMETHEE’s ability to distinguish between alternatives based on their stability was particularly noteworthy. Alternatives with broader distributions under PROMETHEE, such as Alternative 16, were shown to be highly sensitive to weighting changes, resulting in significant variability in performance. Conversely, alternatives with narrower distributions, such as Alternative 4, showed greater stability, making them more reliable choices under uncertain conditions.

The choice of preference function in PROMETHEE further underscored its capacity for finer evaluation. The Gaussian preference function provided precise preference values and resulted in less clustered and more individualized distributions compared to the usual preference function, which tended to form indistinguishable groups of alternatives.

Overall, while both TOPSIS and PROMETHEE generally agreed on the best and worst alternatives, they produced slightly different rankings, reflecting their inherent methodological differences. PROMETHEE’s nuanced assessment of stability and sensitivity to criteria weighting and preference functions provided a more detailed understanding of the trade-offs involved in the decision-making process.

In conclusion, this comprehensive analysis demonstrates that both TOP-

SIS and PROMETHEE are valuable tools for multi-criteria decision-making in the context of chemical recycling of plastic waste. Their comparative use can provide robust insights and support informed decision making, ensuring that the alternatives chosen are well aligned with the specific priorities and constraints of the decision-makers. The results highlight the need for careful consideration of normalization methods, criteria weighting, and preference functions to achieve optimal and sustainable outcomes in complex multi-criteria decision contexts.



## Conclusion and perspectives

This thesis deals with a multi-objective approach to promote the circular economy through the chemical recycling of plastic waste. The main objective of this work was to develop a multi-objective decision-making tool to be integrated into the iSMA framework developed by Pacheco-López et al. (2023), in order to fill an essential gap within this structure.

The underlying reasons for the need to develop and improve such a tool have been detailed in a rigorous literature review. This review is divided into three main sections: plastic waste management and associated challenges, chemical recycling and the circular economy of plastic waste, and finally ontological frameworks and decision-making tools in the context of environmental sustainability. The first section highlights the growing production of plastics and the current management of plastic waste. Among others, the methods of landfilling, incineration and mechanical recycling are described, highlighting their limitations, especially from an environmental point of view. This section concludes by acknowledging that major changes are needed to improve the current situation. These changes are of various kinds and include a global change in our behaviour, political efforts, the improvement and optimal use of existing waste treatment technologies, but also innovation and the development of efficient and sustainable recycling methods. Chemical recycling, and in particular thermal techniques such as gasification and pyrolysis, are presented as a promising solutions that needs to be explored in depth.

The following section focuses on the study of chemical recycling and its potentially great importance in promoting the circular economy of plastics. The main chemical recycling methods are discussed in turn: dissolution, depolymerization, gasification and finally pyrolysis.

Dissolution and depolymerization are interesting methods due to their selectivity and efficiency. However, they suffer from significant limitations in terms of cost and industrial scale implementation. Moreover, they are not suitable for municipal waste, which is often a mixture of different types of contaminated plastics. This leads to the discussion of thermal processes

capable of treating large volumes of contaminated waste.

Gasification primarily produces synthesis gas, which is used to generate heat and electricity, but also serves as a feedstock for methanol and ammonia synthesis. Pyrolysis, on the other hand, produces mainly gas and oil. Pyrolysis oil is particularly interesting because it can be used as a fuel or processed and purified to produce a variety of valuable chemicals. In addition, when pyrolysis is combined with hydrotreatment and steam cracking, it is possible to synthesize monomers that can be used to produce new virgin-grade plastics.

The production of new raw materials, whether monomers, fuels, or any other type of chemical compound, clearly demonstrates the impact of chemical recycling on the circular economy of plastics by turning waste into valuable resources.

However, chemical recycling, and pyrolysis in particular, is not without its shortcomings. Thermal chemical recycling processes are particularly energy intensive and can have a significant environmental impact. In addition, economic viability is an important consideration. For these reasons, pyrolysis has been extensively studied and numerous variants have been described in the literature. Most of these variants remain at pilot or even laboratory scale. The desire to intensify chemical recycling raises the question of which methods are preferable, in terms of efficiency and environmental friendliness.

This need to make an informed and reasoned choice from an ocean of possibilities introduces ontological frameworks and decision support tools. On the one hand, ontological frameworks are key elements of knowledge management. They enable the definition of concepts within a given domain, along with the relationships between them and the attributes associated with them. For example, in the context of plastic waste recycling, processes and associated plastic products can be associated with costs and environmental impacts, allowing a multi-criteria evaluation of each option.

On the other hand, decision-making tools generally refer to optimization methods that either determine the ideal parameters of a system or identify one or more optimal solutions to a given problem. In the case of optimizing a system with a single objective function, there are many powerful mathematical methods, such as linear programming and its derivatives. However, when we want to use a multifaceted approach, considering multiple and often conflicting objectives, other methods are required. This is known as multi-objective optimization. These methods produce a set of optimal solutions rather than a single solution. These solutions, known as Pareto optimals, together form a Pareto front, representing the trade-offs between different objectives, where no criterion can be improved without worsening another.

There are various methods to generate these Pareto fronts, among which

the  $\epsilon$ -constraint method and evolutionary algorithms are commonly used. When it comes to selecting a particular option from these Pareto optimal solutions, multi-criteria decision-making methods are used. These methods provide a structured, quantitative approach to evaluating and comparing the various alternatives available. Based on preferences related to the context of the decision, translated into specific weightings of the various criteria, these methods produce a ranking of alternatives.

As mentioned above, the main objective of this thesis was to develop a multi-objective decision-making tool for integration into the iSMA framework. This holistic methodological framework aims to promote the circular economy in the context of chemical recycling of plastic waste. The major shortcoming identified in the iSMA framework was the lack of a systematic and objective method for selecting the Pareto optimal solutions to be modeled in detail. The developed tool uses TOPSIS and PROMETHEE methods to rank these solutions according to the user's preferences, taking into account economic and environmental criteria.

Another key objective of this thesis was to integrate a robust sensitivity analysis into the decision-making tool. This sensitivity analysis makes it possible to assess the robustness of proposed solutions by taking into account the uncertainty associated with the user's weighting of the criteria. Indeed, the weighting of criteria can vary according to the user's specific preferences or the context in which the decision is made. Sensitivity analysis ensures that proposed solutions remain relevant and stable even when weightings vary. This ensures that recommended solutions are not only optimal in a very specific context, but also retain their relevance in slightly different situations.

It was also important to ensure that the tool developed was not only effective for the specific case of chemical recycling paths for plastic waste, but also versatile and adaptable to other contexts. In other words, the tool had to be flexible enough to be applied to a variety of sustainability issues that require decision-making among a set of Pareto optimal solutions.

In terms of practical implementation, the tool was coded in Python, taking advantage of its rich libraries and clear syntax. To ensure a clear organization and smooth execution of the different steps, the tool is structured in modules. The data flow starts with the collection of data about user alternatives and preferences, which is performed by the data collection module. This information is then processed by optimization methods before a sensitivity analysis is performed. The results of this analysis are then analyzed, visualized and stored for future use.

The tool is coordinated by two main executable files, one for TOPSIS and one for PROMETHEE. Each main file successively calls the main function defined in each module, thus allowing the ordered execution of the different

steps of the tool. Each module contains several functions, each of which models a specific step, such as a mathematical operation, the display of a graph or the acquisition of specific data. These functions are combined into a main function within each module. The complete code of the tool is available on GitHub, providing full transparency and the possibility of community use and improvement. The GitHub repository can be accessed via the following link: MODM\_tool.

The results obtained in this thesis can be divided into two main categories: the validation of the developed tool and the detailed analysis of the solutions generated by this tool.

The first and most important result is that the developed multi-objective decision-making tool is functional. This thesis is mainly a methodological work aimed at describing the reasons behind and the process of developing this tool. The final objective was to create a tool capable of objectively ranking Pareto optimal alternatives according to the user's preferences, and this was successfully achieved.

The results obtained reveal several key elements regarding the application of TOPSIS and PROMETHEE methods to multi-criteria decision making for the chemical recycling of plastic waste. The study carefully examined several parameters, including normalization methods, criteria weighting, uncertainty levels, and preference functions, in order to assess the influence of these factors on the results generated.

The TOPSIS and PROMETHEE methods showed that the normalization method had a significant impact on the results. Min-max normalization provided a more balanced evaluation by reflecting the diversity of the criteria, while vector normalization specifically favored alternatives with higher profit. This resulted in narrower score distributions and less sensitivity to criteria weighting.

Looking at the impact of criteria weighting, it is clear that the choice of weighting strongly influenced the ranking. In both methods, the profit-oriented weighting scenario placed high-profit alternatives in the lead, while the environment-oriented weighting favored alternatives with better environmental performance. This change underscores the flexibility of both methods to adapt to different prioritization scenarios and the essential role of criteria weighting in multi-criteria decision-making.

The analysis also highlighted the importance of stability in the face of weighting uncertainty. PROMETHEE's ability to discriminate between alternatives based on their stability is particularly noteworthy. Alternatives with wider distributions in PROMETHEE, such as Alternative 16, proved to be highly sensitive to changes in weighting, resulting in significant variability in performance. Conversely, alternatives with narrower distributions, such

as Alternative 4, showed greater stability, making them more reliable choices under uncertain conditions.

The choice of preference function in PROMETHEE further emphasized its ability to perform a more refined evaluation. The Gaussian preference function provided precise preference values and resulted in less clustered, more individualized distributions than the usual preference function, which tended to form indistinguishable clusters of alternatives.

Overall, while TOPSIS and PROMETHEE generally agree on the best and worst alternatives, they produce slightly different rankings, reflecting their inherent methodological differences. PROMETHEE's nuanced assessment of stability and sensitivity to criterion weighting and preference functions has led to a better understanding of the trade-offs involved in the decision process.

In conclusion, this comprehensive analysis shows that both TOPSIS and PROMETHEE are valuable tools for multi-criteria decision-making in the context of chemical recycling of plastic waste. Their comparative use can provide solid information and support informed decision-making, ensuring that the alternatives chosen are well aligned with the specific priorities and constraints of the decision-makers. The results highlight the need for careful consideration of normalization methods, criteria weighting and preference functions to achieve optimal and sustainable results in complex multi-criteria decision contexts.

Although the tool developed in this thesis is reliable and robust by design, it has certain inherent limitations. The main limitation lies in its total dependence on the quality of the data supplied to it. Indeed, if the initial data is inaccurate, incomplete or biased, the final ranking of alternatives will inevitably be compromised and may prove to be unusable. In addition to quality, the tool is currently unable to handle missing data. If there are gaps in the initial database, the tool cannot estimate or complete these missing data, which could limit its effectiveness and applicability in contexts where information is incomplete.

The results obtained and the observations made in this thesis open several interesting perspectives for future research and potential improvements of the tool.

First, due to its flexibility and adaptability, the tool could be applied to other databases related to environmental sustainability. By broadening its scope, it would be possible to fully exploit the tool's capabilities in a variety of multi-criteria decision contexts.

Second, the inclusion of new optimization methods would extend the analysis capabilities and provide an even more comprehensive evaluation of available alternatives. This could include additional multi-criteria decision

methods or more advanced algorithms to handle even more complex problems.

Another important perspective would be to enable the tool to handle missing data. By integrating data imputation techniques or advanced statistical methods, the tool could estimate missing values and thus improve its robustness and applicability in situations where data are incomplete.

It would also be useful to improve the sensitivity analysis module by providing quantified data on the stability of each of the alternatives. This would allow decision makers to better understand the impact of their choices and make more informed decisions.

Finally, defining a weighting of the criteria based on local sustainable development policies could make the tool even more relevant and adapted to specific contexts. By incorporating weightings that reflect local priorities, the tool could provide recommendations that are aligned with the goals and constraints of local decision-makers.

In conclusion, this work has highlighted the importance of a multi-criteria decision-making tool in the context of chemical recycling of plastic waste. The results obtained demonstrate the robustness and effectiveness of the TOPSIS and PROMETHEE methods for evaluating and comparing alternatives. Although there is still room for improvement, the developed tool represents a step forward in promoting the circular economy and environmental sustainability. Future research perspectives offer numerous opportunities to perfect the tool and broaden its scope of application, thus contributing to a more efficient and sustainable plastic waste management.

# Bibliography

- Abdelrahman, A. et al. (May 2018). “Studying and Evaluating Sustainable Materials for Converting Plastic Waste to Fuel”. In: *Energy and Environment Research* 8.1, p. 73. ISSN: 1927-0569. DOI: 10.5539/eer.v8n1p73.
- Ahmed, A. H. et al. (June 2014). “Strategic Decision Making: Process, Models, and Theories”. In: *Business Management and Strategy* 5.1, p. 78. DOI: 10.5296/bms.v5i1.5267.
- Anshassi, M., H. Sackles, and T. G. Townsend (Nov. 2021). “A review of LCA assumptions impacting whether landfilling or incineration results in less greenhouse gas emissions”. In: *Resources, Conservation and Recycling* 174. ISSN: 18790658. DOI: 10.1016/j.resconrec.2021.105810.
- Anuar Sharuddin, S. D. et al. (May 2016). *A review on pyrolysis of plastic wastes*. DOI: 10.1016/j.enconman.2016.02.037.
- Bagshaw, K. B. and K. L. Nissi (2019). “Trend in Viewing Quantitative Analysis as a Primary Function Involving Decision Making in Organisations”. In: *American Journal of Industrial and Business Management* 09.06, pp. 1492–1505. ISSN: 2164-5167. DOI: 10.4236/ajibm.2019.96099.
- Batra, P. (2017). *Eisenhower Box for Prioritising Waiting List of Orthodontic Patients*. Tech. rep. URL: <https://www.researchgate.net/publication/352005944>.
- Bellman, R. (1954). *THE THEORY OF DYNAMIC PROGRAMMING*. Tech. rep.
- Bezergianni, S., A. Dimitriadis, and G. Meletidis (June 2014). “Effectiveness of CoMo and NiMo catalysts on co-hydroprocessing of heavy atmospheric gas oil-waste cooking oil mixtures”. In: *Fuel* 125, pp. 129–136. ISSN: 00162361. DOI: 10.1016/j.fuel.2014.02.010.
- Çelikkilek, Y. and F. Tüysüz (Apr. 2020). “An in-depth review of theory of the TOPSIS method: An experimental analysis”. In: *Journal of Management Analytics* 7.2, pp. 281–300. ISSN: 23270039. DOI: 10.1080/23270012.2020.1748528.

- Chae, Y. and Y. J. An (Sept. 2018). *Current research trends on plastic pollution and ecological impacts on the soil ecosystem: A review*. DOI: 10.1016/j.envpol.2018.05.008.
- Cook, C. R. and R. U. Halden (Jan. 2020). “Ecological and health issues of plastic waste”. In: *Plastic Waste and Recycling: Environmental Impact, Societal Issues, Prevention, and Solutions*. Elsevier, pp. 513–527. ISBN: 9780128178805. DOI: 10.1016/B978-0-12-817880-5.00020-7.
- Crippa, M. and B. Morico (2019). “PET depolymerization: A novel process for plastic waste chemical recycling”. In: *Studies in Surface Science and Catalysis* 179, pp. 215–229. ISSN: 01672991. DOI: 10.1016/B978-0-444-64337-7.00012-4.
- Davidson, M. G., R. A. Furlong, and M. C. McManus (Apr. 2021). *Developments in the life cycle assessment of chemical recycling of plastic waste – A review*. DOI: 10.1016/j.jclepro.2021.126163.
- Deb, K. et al. (2002). *A Fast and Elitist Multiobjective Genetic Algorithm: NSGA-II*. Tech. rep. 2.
- Dogu, O. et al. (May 2021). *The chemistry of chemical recycling of solid plastic waste via pyrolysis and gasification: State-of-the-art, challenges, and future directions*. DOI: 10.1016/j.pecs.2020.100901.
- European Parliament (May 2023). *Circular economy: definition, importance and benefits*. URL: <https://www.europarl.europa.eu/topics/en/article/20151201ST005603/circular-economy-definition-importance-and-benefits#:~:text=The%20circular%20economy%20is%20a,cycle%20of%20products%20is%20extended..>
- Fahim, I., O. Mohsen, and D. Elkayaly (Mar. 2021). “Production of fuel from plastic waste: A feasible business”. In: *Polymers* 13.6. ISSN: 20734360. DOI: 10.3390/polym13060915.
- Faussone, G. C. (Mar. 2018). “Transportation fuel from plastic: Two cases of study”. In: *Waste Management* 73, pp. 416–423. ISSN: 18792456. DOI: 10.1016/j.wasman.2017.11.027.
- Felfel, H., O. Ayadi, and F. Masmoudi (July 2017). “Pareto optimal solution selection for a multi-site supply chain planning problem using the ViKOR and TOPSIS methods”. In: *International Journal of Service Science, Management, Engineering, and Technology* 8.3, pp. 21–39. ISSN: 19479603. DOI: 10.4018/IJSSMET.2017070102.
- Geisendorf, S. and F. Pietrulla (Sept. 2018). “The circular economy and circular economic concepts—a literature analysis and redefinition”. In: *Thunderbird International Business Review* 60.5, pp. 771–782. ISSN: 15206874. DOI: 10.1002/tie.21924.
- Geyer, R., J. R. Jambeck, and K. L. Law (2017). *Production, use, and fate of all plastics ever made*. Tech. rep. URL: <https://www.science.org>.



- Gholami, Z. et al. (Dec. 2021). “A review on the production of light olefins using steam cracking of hydrocarbons”. In: *Energies* 14.23. ISSN: 19961073. DOI: 10.3390/en14238190.
- Hahladakis, J. N. et al. (Feb. 2018). *An overview of chemical additives present in plastics: Migration, release, fate and environmental impact during their use, disposal and recycling*. DOI: 10.1016/j.jhazmat.2017.10.014.
- Hong, M. and E. Y. Chen (2017). *Chemically recyclable polymers: A circular economy approach to sustainability*. DOI: 10.1039/c7gc01496a.
- Hou, S., H. Li, and Y. Rezgui (June 2015). “Ontology-based approach for structural design considering low embodied energy and carbon”. In: *Energy and Buildings* 102, pp. 75–90. ISSN: 03787788. DOI: 10.1016/j.enbuild.2015.04.051.
- Huijbregts, M. A. et al. (Feb. 2017). “ReCiPe2016: a harmonised life cycle impact assessment method at midpoint and endpoint level”. In: *International Journal of Life Cycle Assessment* 22.2, pp. 138–147. ISSN: 16147502. DOI: 10.1007/s11367-016-1246-y.
- Hujuri, U., A. K. Ghoshal, and S. Gumma (Feb. 2011). “Temperature-dependent pyrolytic product evolution profile for polypropylene”. In: *Journal of Applied Polymer Science* 119.4, pp. 2318–2325. ISSN: 00218995. DOI: 10.1002/app.32904.
- Janajreh, I., I. Adeyemi, and S. Elagroudy (June 2020). “Gasification feasibility of polyethylene, polypropylene, polystyrene waste and their mixture: Experimental studies and modeling”. In: *Sustainable Energy Technologies and Assessments* 39. ISSN: 22131388. DOI: 10.1016/j.seta.2020.100684.
- Kumar, R. et al. (Sept. 2021). *Impacts of plastic pollution on ecosystem services, sustainable development goals, and need to focus on circular economy and policy interventions*. DOI: 10.3390/su13179963.
- Kumazawa, T. et al. (2014). “Initial design process of the sustainability science ontology for knowledge-sharing to support co-deliberation”. In: *Sustainability Science* 9.2, pp. 173–192. ISSN: 18624057. DOI: 10.1007/s11625-013-0202-z.
- Kusenberg, M. et al. (Mar. 2022a). “A comprehensive experimental investigation of plastic waste pyrolysis oil quality and its dependence on the plastic waste composition”. In: *Fuel Processing Technology* 227. ISSN: 03783820. DOI: 10.1016/j.fuproc.2021.107090.
- Kusenberg, M. et al. (Feb. 2022b). *Opportunities and challenges for the application of post-consumer plastic waste pyrolysis oils as steam cracker feedstocks: To decontaminate or not to decontaminate?* DOI: 10.1016/j.wasman.2021.11.009.

- Kye, K. and M. Lecturer (2019). *Simplex Method for Solving Maximum Problems in Linear Programming*. Tech. rep., pp. 410–411. URL: [www.ijsea.com410](http://www.ijsea.com410).
- Lebreton, L. and A. Andrady (Dec. 2019). “Future scenarios of global plastic waste generation and disposal”. In: *Palgrave Communications* 5.1. ISSN: 20551045. DOI: 10.1057/s41599-018-0212-7.
- Li, N. et al. (Feb. 2022). *Conversion of plastic waste into fuels: A critical review*. DOI: 10.1016/j.jhazmat.2021.127460.
- Liang, Y. et al. (Jan. 2021). “An analysis of the plastic waste trade and management in Asia”. In: *Waste Management* 119, pp. 242–253. ISSN: 18792456. DOI: 10.1016/j.wasman.2020.09.049.
- Maadi, M. and M. Soltanolkottabi (2014). *Extension of PROMETHEE method for solving multi objective optimization problems*. Tech. rep. 11, pp. 975–8887.
- Makan, A. and A. Fadili (July 2020). “Sustainability assessment of large-scale composting technologies using PROMETHEE method”. In: *Journal of Cleaner Production* 261. ISSN: 09596526. DOI: 10.1016/j.jclepro.2020.121244.
- Maqsood, T. et al. (Oct. 2021). “Pyrolysis of plastic species: A review of resources and products”. In: *Journal of Analytical and Applied Pyrolysis* 159. ISSN: 01652370. DOI: 10.1016/j.jaap.2021.105295.
- Marquardt, W. et al. (2010). *OntoCAPE*. RWTHedition. Berlin, Heidelberg: Springer Berlin Heidelberg. ISBN: 978-3-642-04654-4. DOI: 10.1007/978-3-642-04655-1. URL: <https://link.springer.com/10.1007/978-3-642-04655-1>.
- Mastellone, M. L. et al. (2007). *Devolatilization and Gasification of Plastic Wastes in a Fluidized Bed Reactor*. Tech. rep.
- Mavrotas, G. (July 2009). “Effective implementation of the  $\epsilon$ -constraint method in Multi-Objective Mathematical Programming problems”. In: *Applied Mathematics and Computation* 213.2, pp. 455–465. ISSN: 00963003. DOI: 10.1016/j.amc.2009.03.037.
- Meijer, L. J. J. et al. (2021). *More than 1000 rivers account for 80% of global riverine plastic emissions into the ocean*. Tech. rep. URL: <https://www.science.org>.
- Meys, R. et al. (Nov. 2020). “Towards a circular economy for plastic packaging wastes – the environmental potential of chemical recycling”. In: *Resources, Conservation and Recycling* 162. ISSN: 18790658. DOI: 10.1016/j.resconrec.2020.105010.
- Miandad, R. et al. (Apr. 2017). “Effect of plastic waste types on pyrolysis liquid oil”. In: *International Biodeterioration and Biodegradation* 119, pp. 239–252. ISSN: 09648305. DOI: 10.1016/j.ibiod.2016.09.017.

- Mohan, N. et al. (Nov. 2020). *Microbial and Enzymatic Degradation of Synthetic Plastics*. DOI: 10.3389/fmicb.2020.580709.
- Muhammad, C., J. A. Onwudili, and P. T. Williams (May 2015). “Catalytic pyrolysis of waste plastic from electrical and electronic equipment”. In: *Journal of Analytical and Applied Pyrolysis* 113, pp. 332–339. ISSN: 01652370. DOI: 10.1016/j.jaap.2015.02.016.
- Muñoz, E. et al. (2013). “Considering environmental assessment in an ontological framework for enterprise sustainability”. In: *Journal of Cleaner Production* 47, pp. 149–164. ISSN: 09596526. DOI: 10.1016/j.jclepro.2012.11.032.
- Musen, M. A. (June 2015). “The protégé project”. In: *AI Matters* 1.4, pp. 4–12. DOI: 10.1145/2757001.2757003.
- Nagy, Á. and R. Kuti (Dec. 2016). “The Environmental Impact of Plastic Waste Incineration”. In: *Academic and Applied Research in Military and Public Management Science* 15.3, pp. 231–237. ISSN: 2498-5392. DOI: 10.32565/aarms.2016.3.3.
- Ncube, L. K. et al. (Mar. 2021). “An overview of plasticwaste generation and management in food packaging industries”. In: *Recycling* 6.1, pp. 1–25. ISSN: 23134321. DOI: 10.3390/recycling6010012.
- OECD (2022a). *Global Plastics Outlook*. URL: [https://stats.oecd.org/viewhtml.aspx?datasetcode=PLASTIC\\_USE\\_10&lang=en](https://stats.oecd.org/viewhtml.aspx?datasetcode=PLASTIC_USE_10&lang=en).
- (2022b). *Global Plastics Outlook*. URL: [https://stats.oecd.org/viewhtml.aspx?datasetcode=PLASTIC\\_WASTE\\_5&lang=en](https://stats.oecd.org/viewhtml.aspx?datasetcode=PLASTIC_WASTE_5&lang=en).
- Onwudili, J. A., C. Muhammad, and P. T. Williams (Oct. 2019). “Influence of catalyst bed temperature and properties of zeolite catalysts on pyrolysis-catalysis of a simulated mixed plastics sample for the production of upgraded fuels and chemicals”. In: *Journal of the Energy Institute* 92.5, pp. 1337–1347. ISSN: 17460220. DOI: 10.1016/j.joei.2018.10.001.
- Pacheco-López, A. et al. (Oct. 2021). “Synthesis and assessment of waste-to-resource routes for circular economy”. In: *Computers and Chemical Engineering* 153. ISSN: 00981354. DOI: 10.1016/j.compchemeng.2021.107439.
- Pacheco-López, A. et al. (July 2023). “Integrated synthesis, modeling, and assessment (iSMA) of waste-to-resource alternatives towards a circular economy: The case of the chemical recycling of plastic waste management”. In: *Computers and Chemical Engineering* 175. ISSN: 00981354. DOI: 10.1016/j.compchemeng.2023.108255.
- Papadakis, V. M., S. Lioukas, and D. Chambers (1998). *STRATEGIC DECISION-MAKING PROCESSES: THE ROLE OF MANAGEMENT AND CONTEXT*. Tech. rep., pp. 115–147.

- Papuga, S. V., P. M. Gvero, and L. M. Vukić (2016). “Temperature and time influence on the waste plastics pyrolysis in the fixed bed reactor”. In: *Thermal Science* 20.2, pp. 731–741. ISSN: 03549836. DOI: 10.2298/TSCI141113154P.
- Pareto Front* (n.d.). URL: [https://en.wikipedia.org/wiki/Pareto\\_front](https://en.wikipedia.org/wiki/Pareto_front).
- PlasticsEurope (Oct. 2022). *Plastics - the Facts 2022*. Tech. rep. Brussels: PlasticsEurope.
- Prata, J. C. et al. (July 2019). *Solutions and integrated strategies for the control and mitigation of plastic and microplastic pollution*. DOI: 10.3390/ijerph16132411.
- Qureshi, M. S. et al. (Nov. 2020). “Pyrolysis of plastic waste: Opportunities and challenges”. In: *Journal of Analytical and Applied Pyrolysis* 152. ISSN: 01652370. DOI: 10.1016/j.jaap.2020.104804.
- Ratnasari, D. K., M. A. Nahil, and P. T. Williams (Mar. 2017). “Catalytic pyrolysis of waste plastics using staged catalysis for production of gasoline range hydrocarbon oils”. In: *Journal of Analytical and Applied Pyrolysis* 124, pp. 631–637. ISSN: 01652370. DOI: 10.1016/j.jaap.2016.12.027.
- Saġabun, W., J. Watróbski, and A. Shekhovtsov (Sept. 2020). “Are MCDA methods benchmarkable? A comparative study of TOPSIS, VIKOR, COPRAS, and PROMETHEE II methods”. In: *Symmetry* 12.9. ISSN: 20738994. DOI: 10.3390/SYM12091549.
- Salwa, H. N. et al. (Nov. 2020). “Life cycle assessment of sugar palm fiber reinforced-sago biopolymer composite takeout food container”. In: *Applied Sciences (Switzerland)* 10.22, pp. 1–21. ISSN: 20763417. DOI: 10.3390/app10227951.
- Schyns, Z. O. and M. P. Shaver (Feb. 2021). *Mechanical Recycling of Packaging Plastics: A Review*. DOI: 10.1002/marc.202000415.
- SimaPro database manual Methods library* (2022). Tech. rep.
- Singh, R. K. and B. Ruj (June 2016). “Time and temperature depended fuel gas generation from pyrolysis of real world municipal plastic waste”. In: *Fuel* 174, pp. 164–171. ISSN: 00162361. DOI: 10.1016/j.fuel.2016.01.049.
- Solis, M. and S. Silveira (Mar. 2020). *Technologies for chemical recycling of household plastics – A technical review and TRL assessment*. DOI: 10.1016/j.wasman.2020.01.038.
- Somoza-Tornos, A. et al. (Jan. 2021). “Process screening framework for the synthesis of process networks from a circular economy perspective”. In: *Resources, Conservation and Recycling* 164. ISSN: 18790658. DOI: 10.1016/j.resconrec.2020.105147.

- Ullah, S. et al. (Jan. 2023). *A review of the endocrine disrupting effects of micro and nano plastic and their associated chemicals in mammals*. DOI: 10.3389/fendo.2022.1084236.
- Upward, A. and P. Jones (Mar. 2016). “An Ontology for Strongly Sustainable Business Models: Defining an Enterprise Framework Compatible With Natural and Social Science”. In: *Organization and Environment* 29.1, pp. 97–123. ISSN: 15527417. DOI: 10.1177/1086026615592933.
- Walker, T. W. et al. (2020). *Recycling of multilayer plastic packaging materials by solvent-targeted recovery and precipitation*. Tech. rep. URL: <https://www.science.org>.
- Wang, Y., J. W. Levis, and M. A. Barlaz (Feb. 2020). “An Assessment of the Dynamic Global Warming Impact Associated with Long-Term Emissions from Landfills”. In: *Environmental Science and Technology* 54.3, pp. 1304–1313. ISSN: 15205851. DOI: 10.1021/acs.est.9b04066.
- Wilson, C. and H. Dowlatabadi (2007). “Models of decision making and residential energy use”. In: *Annual Review of Environment and Resources* 32, pp. 169–203. ISSN: 15435938. DOI: 10.1146/annurev.energy.32.053006.141137.
- Xu, C. et al. (2010). *Recent advances in catalysts for hot-gas removal of tar and NH<sub>3</sub> from biomass gasification*. DOI: 10.1016/j.fuel.2010.02.014.
- Yurdakul, M. and Y. Tansel Iç (Jan. 2009). “Application of correlation test to criteria selection for multi criteria decision making (MCDM) models”. In: *International Journal of Advanced Manufacturing Technology* 40.3-4, pp. 403–412. ISSN: 02683768. DOI: 10.1007/s00170-007-1324-1.
- Zhao, Y. B., X. D. Lv, and H. G. Ni (Oct. 2018). *Solvent-based separation and recycling of waste plastics: A review*. DOI: 10.1016/j.chemosphere.2018.06.095.
- Zhou, A. et al. (2011). *Multiobjective evolutionary algorithms: A survey of the state of the art*. DOI: 10.1016/j.swevo.2011.03.001.
- Zhou, N. et al. (Aug. 2021). “Catalytic pyrolysis of plastic wastes in a continuous microwave assisted pyrolysis system for fuel production”. In: *Chemical Engineering Journal* 418. ISSN: 13858947. DOI: 10.1016/j.cej.2021.129412.
- Zitzler, E. ; et al. (2001). “SPEA2: Improving the strength pareto evolutionary algorithm”. In: DOI: 10.3929/ethz-a-004284029. URL: <https://doi.org/10.3929/ethz-a-004284029>.