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**D4.3 - MULTICRITERIA CONSIDERATION OF
KEY MODELLING PARAMETERS, RISKS AND
PRIORITIES**

WP4 – Robustification & Socio-Technical Analysis

Toolbox

Version: 1.00

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EC Summary Requirements

1. Changes with respect to the DoA

No changes with respect to the work described in the DoA.

2. Dissemination and uptake

This deliverable aims to serve as a scientific framework for evaluating the transition readiness of countries as well as facilitating the elicitation of stakeholder preferences throughout the PARIS REINFORCE project for better-informed modelling exercises, in work packages WP5-WP7, by co-defining modelling parameters and scenario components. It is therefore aimed at academia, policymakers and other stakeholder groups in different countries in the world.

3. Short summary of results (<250 words)

As a starting point, this report establishes an assessment framework and index for evaluating the readiness of different countries to achieve a sustainable transition, based on social, economic, political/regulatory, and technological criteria; the proposed framework is compared against other respective indicators in the literature and finds that major emitters outside Europe appear to lack capacity for drastic energy transitions. The report then establishes a new software application that implements a framework for group decision-making, coupled with a new consensus measuring model to increase robustness of results. Aside from a pilot case study with stakeholders aiming to assess climate policy risks in the Austrian iron and steel sector, the tool is applied to the first EU regional stakeholder council dialogue of the project, aiming to prioritise SDGs to incorporate in the modelling analysis for Europe; as well as to a national stakeholder workshop in Kenya, aiming to establish both sectoral decarbonisation priorities and sustainability dimensions to consider in WP6 modelling analyses. The first study finds stakeholders prioritise sustainability aspects related to biodiversity and ecosystems as well as responsible resource use and social equalities, as targets to integrate in modelling exercises for climate change and policy, despite the limited representation of these SDGs in models. The second study indicates that modelling efforts should focus on cross-sectoral policies in the residential and agriculture sectors, considering implications for SDGs 7 and 15, while at the same time addressing lack of energy access and use of non-sustainable fuels through demand-side transformations.













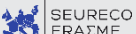





4. Evidence of accomplishment

This report, and the associated scientific papers/chapters.



Preface

PARIS REINFORCE will develop a novel, demand-driven, IAM-oriented assessment framework for effectively supporting the design and assessment of climate policies in the European Union as well as in other major emitters and selected less emitting countries, in respect to the Paris Agreement. By engaging policymakers and scientists/modellers, PARIS REINFORCE will create the open-access and transparent data exchange platform I2AM PARIS, in order to support the effective implementation of Nationally Determined Contributions, the preparation of future action pledges, the development of 2050 decarbonisation strategies, and the reinforcement of the 2023 Global Stocktake. Finally, PARIS REINFORCE will introduce innovative integrative processes, in which IAMs are further coupled with well-established methodological frameworks, in order to improve the robustness of modelling outcomes against different types of uncertainties.

NTUA - National Technical University of Athens	GR	
BC3 - Basque Centre for Climate Change	ES	
Bruegel - Bruegel AISBL	BE	
Cambridge - University of Cambridge	UK	
CICERO - Cicero Senter Klimaforskning Stiftelse	NO	
CMCC - Fondazione Centro Euro-Mediterraneo sui Cambiamenti Climatici	IT	
E4SMA - Energy Engineering Economic Environment Systems Modeling and Analysis	IT	
EPFL - École polytechnique fédérale de Lausanne	CH	
Fraunhofer ISI - Fraunhofer Institute for Systems and Innovation Research	DE	
Grantham - Imperial College of Science Technology and Medicine - Grantham Institute	UK	
HOLISTIC - Holistic P.C.	GR	
IEECP - Institute for European Energy and Climate Policy Stichting	NL	
SEURECO - Société Européenne d'Economie SARL	FR	
CDS/UnB - Centre for Sustainable Development of the University of Brasilia	BR	
CUP - China University of Petroleum-Beijing	CN	
IEF-RAS - Institute of Economic Forecasting – Russian Academy of Sciences	RU	
IGES - Institute for Global Environmental Strategies	JP	
TERI - The Energy and Resources Institute	IN	



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1 Assessing the energy transition readiness at the national level

This study was published in: Neofytou, H., Nikas, A., & Doukas, H. (2020). Sustainable energy transition readiness: A multicriteria assessment index. *Renewable and Sustainable Energy Reviews*, 131, 109988.

1.1 Introduction

Unless appropriate action is taken promptly, next generations will be facing devastating consequences of climate change. Scientists and policymakers alike have deduced that focusing on sustainable development can serve to mitigate climate change and its impacts. Sustainable development regards the enhancement of life, without affecting the environment, and thus constitutes a core priority in policy design (Antanasijević et al., 2017), but largely depends on the massive challenge of energy system transformations. During the last decades, fossil fuel dependence and increasing energy demand have hindered sustainable energy shifts, despite worldwide efforts to decarbonise the energy sector, which accounts for the largest part of greenhouse gas (GHG) emissions: around two-thirds of global GHG emissions stem from energy production and use, putting the energy sector at the core of climate action (Gielen et al. 2019).

Consequently, energy transition is considered among the main drivers of limiting global temperature rise well below 2°C above pre-industrial levels, according to the Paris Agreement. This is why energy transitions have been studied deeply over the past five years (Figure 1), in various wordings across literature, e.g. "sustainable" (Sareen and Haarstad, 2018; Warren et al., 2016; Batinge et al., 2019), "green" (Akermi and Triki, 2017), or "low-carbon" (Guler et al., 2018; Nikas et al., 2020; Antosiewicz et al., 2019).

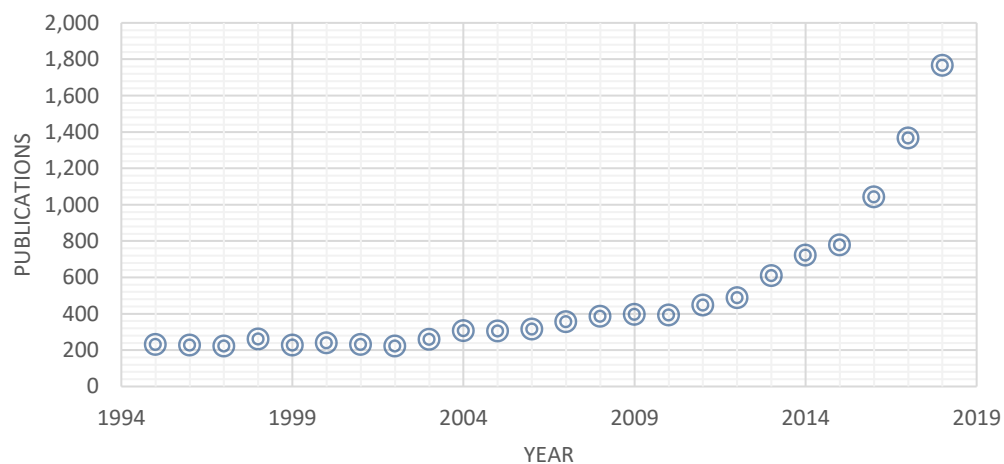


Figure 1: Publications mentioning "energy transition"

Source: Scencedirect¹

¹ <https://www.sciencedirect.com/>



Energy transition constitutes the core objective of every policy aimed at decarbonisation and can be largely achieved by accelerated deployment of renewable energy technologies and energy efficiency measures (Li and Strachan, 2019; Sovacool et al., 2018; Tagliapietra et al., 2019). Both major emitting and less developed countries aim to transform their energy systems, towards ensuring reliable, sustainable and affordable energy supply, which is critical to economic activity, social development and poverty reduction (Bouzarovski, 2018; Nerini et al., 2018a). The question is to what degree countries are potent to make the appropriate changes and achieve respective targets.

A characteristic of today's society is that everything is measured and compared. Decision makers require, among others, numbers and rankings to underpin their strategies or monitor relative 'progress'; the latter appears to be a key-phrase in recent developments in climate policy, constituting the main goal of the global stocktake for informing new climate action pledges (Doukas et al., 2018). There are increasing efforts to quantify aspects of national performances in various fields and compare them against a set of goals or other countries (Surminski and Williamson, 2012), by means of indices, which can be used for highlighting changes over time; assessing progress in respect to national/regional commitments; informing policymakers on trends and gaps; exploring investment opportunities; and enabling forecasts (Bandura, 2005).

As far as development of national and international policies is concerned, policymakers tend to set priorities based on diverse insights. Rankings constitute influencing tools that significantly contribute to policymaking (Meijering et al., 2014), by highlighting success stories and comparison references, and eventually helping outline desired pathways (Araújo, 2014).

This study aims to contribute in this respect, by selecting countries of different profiles and reported progress in the problem domain, and assessing their readiness level to achieve sustainable, socially acceptable, financially viable and technically feasible energy transitions. Countries largely differ from one another in several dimensions that should be considered when delving into national capacity for successful energy transitions. These dimensions include energy mix; potential for diffusing renewable energy; infrastructure, technological innovation and capacity to transform; as well as societal values and political ambition. This multiplicity of factors makes the problem of assessing the global energy transition capacity significantly more complex and cultivates the need for multiple-criteria analyses; as literature suggests, selecting the best solution, or simply evaluating the different alternatives, against a multitude of criteria is a frequently described problem in the complex domain of energy policy (Abu-Taha, 2011; Marinakis et al., 2017a; Wątróbski et al., 2016; Radziejowska and Zima, 2016; Papapostolou et al., 2017a; Nikas et al., 2018a).

The framework developed for the purposes of this analysis draws on the synergistic implementation of two multiple-criteria decision aid models: the Analytical Hierarchy Process (AHP) method, for determining the criteria weights; and PROMETHE II, for ranking the alternatives and subsequently obtaining a sustainable energy transition readiness (SETR) index.

1.2 Literature Overview

Indicators have long been used as a means of expressing and communicating energy issues to policymakers and other stakeholders. Indicatively, in 2000 the Latin American Energy Organisation and the Economic Commission for Latin America and the Caribbean jointly published the principal characteristics of energy transformation processes of the Latin American and Caribbean countries, ranking them against a set of sustainable energy indicators (Pistonesi et al., 2000). In 2005, a set of Energy Indicators for Sustainable Development (EISD) was presented for assessing countries' energy systems and tracking their progress towards nationally defined



sustainable development objectives (International Atomic Energy Agency, 2005). Other examples include the International Energy Agency's (IEA's) Energy Development Index (EDI), which measured a country's progress in shifting to modern fuels and energy services, by means of normalised and averaged household and community indicators but without reference to sustainability based on the country's economic, social or environmental conditions (International Energy Agency, 2012); as well as the Sustainable Energy Development Index (SEDI), which focused on establishing the sustainability level of intra- and inter-generational needs (Iddrisu and Bhattacharyya, 2015).

From a broader perspective, several recent studies on environmental indices can be found. The Environmental Performance Index (EPI) annually ranks 178 countries according to ecological performance comprising twenty-two single variables (das Neves Almeida and García-Sánchez, 2016). The Environmental Sustainability Index (ESI) benchmarks the ability of nations to protect the environment, integrating 76 indicators of environmental sustainability for 146 countries (Michalos, 2014). The Environmental Vulnerability Index (EVI) encompassed risks, intrinsic resilience and health or integrity of the environment, and quantified the vulnerability of the natural environment to damage from natural and anthropogenic hazards for 234 nations (Kaly et al., 1999). The Ecological Footprint (EF) measured consumption of renewable resources by human activities for 52 countries (Loh and Wackernagel, 2004).

Most of these indicators, however, were introduced long before climate change was highlighted as one of the most critical threats to global society (Doukas and Nikas, 2020). Following the Paris Agreement, there emerged several studies to evaluate targets, national progress made towards them, or national capacities to sustain global temperature rise (Tagliapietra et al., 2019; Ari and Sari, 2017; Oliveira et al., 2019; Sferra et al., 2019). Burck et al. (2019) recently introduced the Climate Change Performance Index (CCPI), which tracks 56 countries' and the European Union's (EU's) policy ambition and progress towards a well-below-2°C pathway. CCPI evaluates the countries' 2030 targets based on the weighted average of their scores against fourteen indicators orbiting on emissions, renewable energy, and energy use, incorporating policies defined in their Nationally Determined Contributions (NDCs). Furthermore, Climate Action Tracker (2019) indicates 33 countries' compatibility with the Paris Agreement, by rating (intended) NDCs, 2020 pledges, long-term targets and current policies; it provides a transparent way of comparing NDCs based on the broad and diverse literature on equity in effort-sharing. Climate Action Network Europe (Europe, C.A.N., 2018) ranks EU countries, assessing their energy and climate ambitions, and their progress in reducing emissions and promoting renewables and energy efficiency at home, based on overall performance on climate and energy indicators, progress in 2020 targets, national on top of Community targets, and increased ambition.

Similarly, Ecologic Institute and Climact (2019) recently evaluated the EU Member States' draft National Energy and Climate Plans, through a qualitative analysis of adequacy of national targets, completeness and detail of policy descriptions, and quality and inclusiveness of drafting process; fourteen indicators were used in an assessment tool developed in consultation with stakeholders.

Sachs et al. (2019b) introduced the Sustainable Development Goals (SDGs) Index (SDGI), indicating 162 countries' current performance and trends across all seventeen SDGs of the United Nations 2030 Agenda for Sustainable Development, broken down into 169 detailed targets and means for implementation, of which only twenty regard sustainable energy, resilient cities and climate action. A strict and explicit methodology is implemented to define assumptions, handle missing data, ensure quality of data sources and assign weights, before calculating the index based on arithmetic and geometric means.

There also exist recent studies and reports featuring indices on subjects relevant to, yet not explicitly on, energy transitions (Cherp et al, 2018). For instance, the Energy Trilemma Index (WEC, 2016) ranks the energy performance



of countries, based on a weighted average; one of the IRENA project reports presents a country-by-country analysis, regarding the development of a decarbonisation pathway until 2050 (IRENA, 2017); Ernst & Young (2017) rank countries based on their renewable energy attractiveness. Straying from a national evaluation framework, Marinakis et al. (2017b) present an assessment of rural communities' needs and priorities towards sustainable development, while IEA (2017) unpacks key elements of policy packages for sustainable energy transitions, and Li and Strachan (2019) explore whether and how energy system analysis can be broadened to better encompass the socio-political dimension. Moreover, certain studies focus on a specific country and/or assess countries from a single perspective (Demski et al., 2015; Apostoli, 2016).

The most recent assessment, closely associated with energy transitions, is the World Economic Forum's Energy Transitions Index (ETI) (Singh et al., 2019), which calculates the performance of 115 countries, regarding their energy system performance and transition readiness, thereby falling well within the scope of this study. The ETI is based on the normalisation of various indicators across the economic (growth and development, capital and investment), environmental (sustainability), energy (access security, mix), political (commitment and regulation), institutional (governance, infrastructure, innovation) and human (capital and participation) dimensions. However, the impressive set of 40 variables considered, although operational, do not from a methodological point of view constitute a consistent family of evaluation criteria (Bouyssou, 1990), in that there exist functional relations between the selected criteria, i.e. a change of one indicator cannot be *ceteris paribus*. As such, the family of 40 variables is not legible or minimal, which is necessary for reflecting a discussion basis that allows analysis to assess inter-criteria information and implement an aggregation procedure. This is, also, why the selected computational approach is an equal-weights average, instead of an elaborate MCDA method, which the authors attribute to the lack of empirical evidence on the relative importance of variables within and across the ETI dimensions for the covered countries. The use of a remarkable number of standardised indicators as evaluation criteria is convenient for standardisation of a ranking but may render capacity to align input data for a broader pool of countries difficult, as also reflected in political commitment to the COP21 Paris Agreement: this is dependent on the NDCs of the Parties to the accord, making it difficult to assess countries represented by a supranational body and a collective pledge, like EU member states; while the Climate Action Tracker indicator used to reflect said commitment does not evaluate but a limited number of countries. It should finally be noted that political commitment is necessary for a transition but may reflect ambition more than readiness, as explained by Sachs et al. in the SDGI report (Sachs et al., 2019b).

Motivated by the discussed knowledge and methodological gaps, our study differs from the literature: it is set in a post-Paris context; explicitly focuses on energy transition; exploits a diverse yet consistent set of social, political, regulatory, economic and technological criteria; highlights progress and transition readiness rather than ambition and willingness; and places energy in the forefront of a sustainability context, rather than being as broad as the diversity of all SDGs, of which energy and climate action are only one; in order to introduce a dedicated SETR index. More importantly, from a methodological point of view, none of these studies, or to the best of our knowledge others in the broader literature, exploit an elaborate multicriteria decision support system for evaluating countries in climate and sustainability dimensions against their capacity to transform their energy systems. Nonetheless, multiple-criteria decision analysis/aid (MCDA) has been widely used in a variety of studies regarding inter alia sustainable energy management (Pohekar and Ramachandran, 2004), evaluation of sustainable energy scenarios in cities (Simoes et al., 2019), and international rankings of energy policies (Siksnylyte et al., 2019), since these domains comprise problems regarding conflicting objectives (Marinakis et al., 2017a; Papapostolou et al., 2017b).

In particular, PROMETHEE—lying at the core of the proposed methodology— has been widely used in environmental and/or energy problems (Diakoulaki et al., 2007; Klauer et al., 2006; Tsoutsos et al., 2009), among



other fields (Behzadian et al., 2010). The synergetic implementation of PROMETHEE and AHP is frequently met in literature for evaluation purposes (Ren et al., 2009; Sennaroglu and Celebi, 2018; Polat et al., 2016). Therefore, this study contributes to the literature and the energy policy-science interface by effectively establishing a decision support framework, based on two well-established techniques for evaluating the energy transition readiness of different countries against multiple criteria, and introducing a respective index.

1.3 Problem Definition

As discussed above, the purpose of this study is to evaluate the extent to which a number of countries stand ready to effectively achieve sustainable energy transitions, while considering their prospects to reduce GHG emissions and contribute to climate action. The decision makers (DM) of this study are thirty-two experts, with many years of experience in the theoretical and practical field of sustainable energy, energy economics and energy policy, including policymakers from the Ministry of Environment and Energy as well as stakeholders from utilities, energy providers, climate-related NGOs, and members of the academic community of the National Technical University of Athens (professors of energy-related courses, and senior research associates working in energy- and climate-related projects). Twenty-six were fully engaged in a survey, while six were contacted via bilateral interviews.

1.3.1 The case study countries (alternatives)

Fourteen countries were selected to assess their capacity to successfully and sustainably achieve the desired transition of their national energy sector: *Austria, Canada, Chile, China, Greece, India, Indonesia, Kenya, Netherlands, Poland, Spain, Sweden, Switzerland, and United Kingdom (UK)*. The selection was based on the nature of the problem, which dictates that different dimensions be considered and thus cultivates the need to evaluate a country pool of diverse economic, political, social and technological profile, as well progress already made towards sustainable development. It is also in line with the highlighted goals of the Paris Agreement that emphasises the importance of the national context in the need for climate action, which differs among major emitters and other less emitting countries. The selection of the countries reflects this need: the pool includes both major emitters (Canada, China and India) and other less emitting countries (Kenya, Chile, Indonesia), with different priorities across the mitigation, adaptation and climate finance axes (Doukas et al., 2018); it also includes the EU, which is both a major emitting supranational body submitting a collective NDC and included though representative major (UK, Spain, Poland) and less (Greece, Netherlands, Sweden, Switzerland) emitting countries, thereby formulating an interesting mix. Further discussion of the selection of this diverse pool of countries can be found in Hanger-Kopp et al., 2019. However, this selection only serves as a case study for the purposes of validating the proposed framework. Some basic details are given to capture their background and give some insights regarding the reasons for selecting them.

In **Austria**, with the iron and steel industry forming 15.5% of total GHG emissions and 38% of total fossil CO₂ emissions (Reiter and Lindorfer, 2015) while contributing only 2% of the country's GDP (Wolkingner et al., 2019), total fossil fuel consumption accounts for more than 60% of total energy consumption (Martins et al., 2018). Moreover, in 2013, about two thirds of national electricity generation was derived from hydropower whereas fossil fuels comprised about 18%; while the country's economic growth rate had been above the EU-28 average (Wagner et al., 2015; Dvoroková, 2014), which is no longer the case. Currently, the economic situation is framed by discussions about strengthening the modest economic growth, mitigating unemployment and reducing bureaucracy in all sectors (BMFWF, 2016).

Canada not only is one of the top emitters globally, contributing 1.63% to global emissions, but also ranks first globally in terms of emission intensity per person (Davis et al., 2018; Elias et al., 2019). It has the third largest oil



reserves in the world, with its oil and gas industry representing approximately 5% of the country's GDP (Odell, 2013; Dissou, 2010), which in turn represents 2.5% of the world economy, making Canada the 12th largest economy worldwide (Bekaert and Harvey, 2017). Indicatively, by 2014 its primary energy mix of the country was crude oil (43%), natural gas (33%), coal (8%), and hydro (7%), with electricity production however being dominated by hydro (59.3%), followed by nuclear (15.9%), oil and gas (10.2%), coal (9.5%) and non-hydro renewables (5.1%) (CANADA N R, 2016).

Chile, on the other hand, is facing increasing energy demands in order to respond to the expected social, environmental and economic welfare of the population. Its primary energy mix depends on oil (32.9%), coal (24.4%), wood and biomass (23.7%) and hydroelectricity (6.4%) (Venegas-Troncoso et al., 2019). The industrial and mining sectors consume 64% of total electricity consumption (Duran et al., 2015). The main sources of electricity generation in Chile, in 2014 were coal (41%), hydro (34%) and natural gas (16%) (Gaete-Morales et al., 2018). Chile's GDP is equivalent to 0.37% of the global economy (IMF, 2016), while almost two thirds of it depends on international trade (sum of exports and imports).

China is the largest energy producer and consumer as well as the largest greenhouse gas emitter in the world with its energy system based on coal, electricity, oil, natural gas and renewable energy (Cohen et al., 2018; You et al., 2018). At the same time, it faces great challenges including among others energy demand pressure; multiple energy supply constraints; severe damage to the ecological environment; lagging energy technology level; and energy security issues. China has "sacrificed" its natural environment in order to attain economic growth and, in order to control its CO₂ emissions, has been establishing stricter emission standards and energy development strategies (Zheng et al., 2019). In 2014, coal consumption accounted for over 70% of the primary energy mix, as the country is the largest coal producer and consumer in the world (Bloch et al., 2012; Zhang et al., 2018), while consumption from renewables accounted for 22% (He et al., 2016). Moreover the energy supply and demand gap is increasing and is currently addressed through imports. Industry is the dominant sector in end-user energy consumption, which equals 70% of total consumption, while contributing 40% of the country's GDP (Ouyang and Lin, 2015).

Greece consumes about 1.6% of the energy consumed totally in the EU (Azam et al., 2016). However, its energy sector heavily depends on oil and lignite, with its primary energy supply to have been the most carbon-intensive among the IEA member countries (Nikas et al., 2019c). Therefore, the country presents large room for increasing use of wind and solar energy, especially given its potential (Ramírez et al., 2017). A distinctive characteristic of Greece's energy system is that it is essentially broken down into a mainland grid and a non-interconnected grid in islands, with the latter being powered mainly by oil-fired plants. Indicatively, in 2016, the country's electricity generation mix was mainly shared between lignite (27%), natural gas (22.6%), oil (8.4%), hydro (8.7%) and other renewables (17.2%); the main reason behind the extended lignite use for power generation lies in the domestic sources, the exploitation of which improves its energy independency (Orfanos et al., 2019).

India is one of the largest global GHG emitters (Nejat et al., 2015) with more than 80% of electricity generated from fossil fuel-based sources (Shearer et al., 2017). However, in its Intended NDC, it appears to aim to decrease its emission intensity of GDP by 33-35% below the 2005 level by 2030, by provisioning non-fossil fuel-based energy, e.g. solar and wind. India ranks third among the highest coal producing countries in the world; this is because of the domestic abundance of this resource, which accounts for 70% of the power generation mix, followed by another 10% of natural gas and diesel oil (Shearer et al., 2017). Industry constitutes the largest consumer over the past years, which can be associated with the economic development of the country (Shahbaz M et al, 2017).



Indonesia is the 7th largest emitter in the world but with fairly low per capita emissions (Harvey et al., 2018). Its recent economic growth was followed by an increase in energy consumption and, in turn, of GHG emissions. Moreover, its policies have been deemed insufficient to meet its NDC trajectory (Climate Action Tracker, 2016). In 2014, the country was the world's largest coal and fifth largest LNG exporter (Dutu, 2016; Kompas and Che, 2016), translating into significant revenues; IEA estimates that as much as 30% of government revenues come from fossil fuels. The indigenous coal and gas reserves represent 2.2% and 1.6% of the world's reserves, respectively (Kurniawan and Managi, 2018; Purwanto et al., 2016).

Kenya is highly dependent on natural resources making its GDP very sensitive to climate change impacts on the natural environment. In 2015, 24% of the country's GDP came from agriculture and forestry, while industry accounted for 15% (Ototo and Vlosky, 2018). In 2014, wood fuel and other biomass —accounted for 68% of total final energy consumption in Kenya, with oil and electricity accounting for 22% and 9% respectively (Sarkodie and Adom, 2018). The residential sector, typically consuming biofuels and waste for cooking, accounts for 75% of total final energy consumption (Stoppok et al., 2018).

The Netherlands was among the first countries to invest in emission reduction projects. More than 90% of energy used in the country is still generated from traditional energy sources such as gas (42%), coal (13%) and oil (36.8%), while renewable energy accounts for the 5.6%, (Ligtvoet et al., 2016; Hölsgens, 2019; Kooij et al., 2018). Dependence on natural gas can be attributed to it being a domestic energy source, which makes the Netherlands the largest natural gas producer in the EU. However, large-scale availability of natural gas has reduced the need in the country to accelerate development and diffusion of renewable energy options (Nikas et al., 2018b).

Poland's total primary energy supply is largely based on coal by more than 80% (Wierzbowski et al., 2017), while renewable energy sources (RES) account only for 1% (Szczerbowski and Ceran, 2017). Coal in the Polish energy mix is considered critical for the country's energy security (Manowska et al., 2017) and economic growth (Antosiewicz et al., 2019), thus there is significant reluctance to reduce its role. Moreover, the large number of unskilled workers in the mining sector as well as the experience of low pace and rates of these miners shifting between sectors in Poland in the '90s constitute some other major barriers that hinder the transition from coal to non-fossil sources (Tyrowicz and van der Velde, 2014). The transition of the Polish economy from central planning to a free market economy provides an interesting example of decoupling between GDP and CO₂ emissions. The growth of GDP in Poland was accompanied by a drop in emissions per capita and this was largely due to the shutting down of old power plants as well as due to structural, legislative and economic changes (Kiulla, 2018).

Spain's primary energy production is mainly based on RES and nuclear with 41% and 43% respectively, whereas the contribution of coal is about 5% (MINETUR, 2014). The role of RES, which is 100% home-generated in the case of solar, wind and geothermal power and more than 95% for biomass and biofuels, is crucial in order to satisfy demand and reduce dependency on oil and natural gas imports. It is estimated that RES contribute to less than 1% of total GDP, peaking in 2012 with a 1.01% (Spanish Renewable Energy Association, 2014). However, despite the increasing trend until 2012, when the contribution of renewables reached its maximum, there reportedly was a decrease in 2013 and 2014; this is due to the new regulatory framework, which reduced the public support devoted to RES and introduced retroactive measures affecting the legal certainty of the sector.

Electricity production in **Sweden**, in 2014, was based solely on RES (63%), dominated by hydropower (Bergek and Mignon, 2017) and nuclear (Qvist and Brook, 2015). Fossil fuels dominate road transport with the 8% to be biodiesel, ethanol and biogas (Larsson et al., 2015). It is also worth mentioning that Sweden was EU's eighth largest economy in absolute terms and had the tenth highest per capita level in 2015 in the Union (Eurostat, 2015). Furthermore, Sweden is a leader in innovation and consistently ranks highly in regional and global indices (Maier,



2018) possibly due to the high investment per unit of GDP in research and development (Freimane and Bāliņa, 2016).

Switzerland is one of the wealthiest economies globally (40th largest economy in the world), and already has an almost carbon-free electricity supply because of its many hydropower plants. Its electricity demand is covered by hydropower (56%), nuclear (38%), fossil fuel, waste and new renewables (6%) (Pattupara and Kannan, 2016).

The UK, being the world’s fifth largest economy (Lee and Werner, 2018), has an energy system on the verge of major transition (Geels et al., 2016), driven by three main factors: the age of electricity generation and network infrastructure, the declining indigenous fossil fuel resources, and the imperative need to reduce GHG emissions. Its total primary energy supply is based on natural gas by 42.8%, oil by 26.9%, electricity by 9.6%, coal by 8.1%, bioenergy and waste by 7.2%, petroleum products by 5% and manufactured fuels by 0.3%. Delving into electricity, the power generation mix comprises 36.8% gas, 16.9% nuclear, 14.9% coal and 13.9% wind and solar (Department of energy and climate change, 2016).

1.3.2 Evaluation criteria

The multicriteria evaluation system, proposed to assess the capacity of the countries to achieve sustainable energy transitions, is based on four evaluation pillars: social, political-regulatory, economic and technological. In particular, based on the need to put together a consistent, operational and legible family of evaluation criteria (Bouyssou, 1990), and drawing from knowledge gaps in the literature discussed throughout Section 1.2, selected pieces of which (Cherp et al., 2018; Markard et al., 2012; Chappin and Ligtoet, 2014) served as a discursive space and basis for exhaustive dialogue with the six interviewed DMs, eight criteria were selected, as shown in Figure 2. Therefore, the process of determining the evaluation criteria included multiple perspectives, but mainly oriented on the dimensions highlighted in the literature and the subjective nature of the DMs’ preferences.

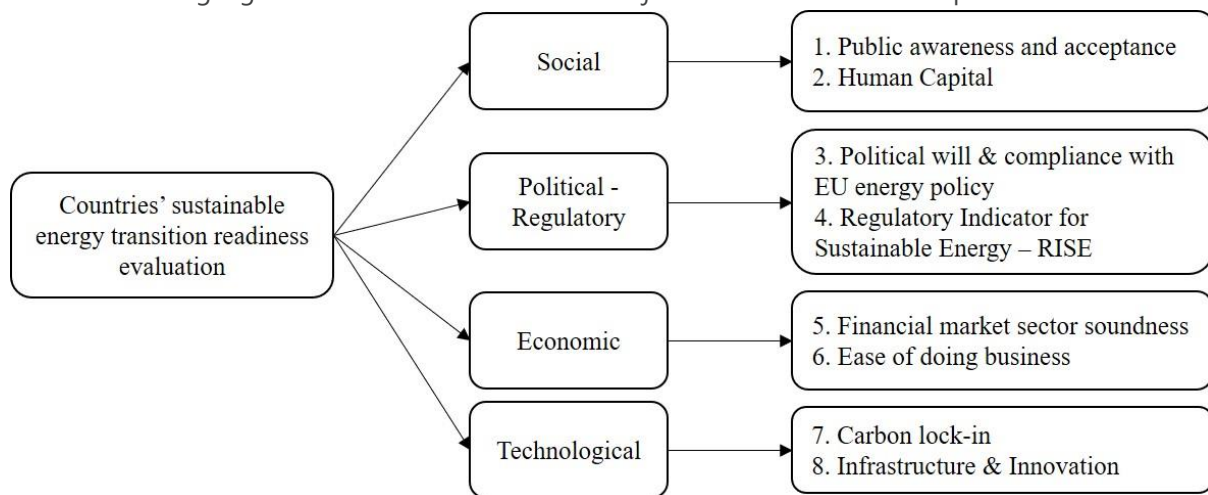


Figure 2: The evaluation system of the SETR Index

A brief presentation of the criteria, their evaluation scales and their data sources is provided in Table 1 below:

Table 1: Evaluation criteria, scales and description

Criterion	Evaluation Scale	Description
g1. Public awareness and acceptance	[0 – 5]	This criterion is a qualitative index which derives from estimations based on information retrieved from the European Barometer (European

		Commission, 2017). It assesses the general attitude of a country's citizens with regard to climate change. Among others, it takes into consideration the awareness of the citizens, to what extent they act individually, so as to mitigate the consequences, and to what degree they are receptive to their governments' policy measures. The barometer's values have resulted from surveys and polls outlining people's objective view of climate change.
g2. Human capital	[4.4 – 6.2]	Human capital indicates each country's average performance on three competitiveness pillars: health and primary education; higher education and training; and labour market efficiency. The data were obtained from the Global Competitiveness Report 2016-2017 (The World Bank, 2018), which presents an extended variety of scores per pillar for each country. It should also be noted that, within this report, competitiveness is defined as the set of institutions, policies, and factors that determine the level of productivity of an economy, which in turn sets the level of prosperity that the country can achieve.
g3. Political will	[0 – 5]	This criterion, drawing from the literature (Hanger-Kopp et al., 2019), is a qualitative index that assesses politicians' attitudes and acts against climate change based on the environmental awareness that the political leadership exhibited in the past, the political strategy followed today, as well as the inner political compassion.
g4. Regulatory Indicator for Sustainable Energy (RISE)	[47 – 92]	RISE, a policy scoreboard by World Bank aimed at helping governments assess if they have a policy and regulatory framework in place to drive progress on sustainable energy, assesses countries' regulatory performances regarding electricity access, energy efficiency and renewable energy (World Economic Forum, 2016).
g5. Financial sector sustainability	[2.5 – 5.3]	This index represents each country's performance on financial development, which includes, among others, the affordability of financial services, the ease of access to loans, the sustainability of banks, etc. (The World Bank, 2018).
g6. Ease of doing business	[79 – 8]	World Bank's ease of doing business rank measures bureaucracy and constitutes a qualitative criterion (Business, D., 2020). It represents a country's ranking based on how easy it makes it for people to start, operate and expand a business in the country.
g7. Carbon lock-in	[4.55 – 0]	Carbon lock-in assesses the dependence on fossil fuel-based energy systems, which essentially hinder the adoption of alternative energy technologies. The index is based on the domestic fossil fuel reserves and the existence of newly-built fossil fuel-powered plants. Its calculation was based in Eq. (1): $CarbonLockIn = \sqrt{Age * FFshare}$ <p>where FFshare: share of fossil fuels (namely coal and oil) in the power generation mix.</p>

		<p>Age: the age of the fossil fuel generation fleet, based on (Papapostolou et al., 2017a) and adapted to current year (2019) and to deal with missing data on the year of latest rehabilitation/renovation of a unit, as in Eq. (2):</p> $Age = \frac{\sum_{i=1}^n Cap_i [(Constr.Year_i + 40) - 2019]}{\sum_{i=1}^n Cap_i}$ <p>where Capi: capacity of coal- or oil-powered unit i; n: total number of coal- and oil-powered units of a country; and Constr.Yeari: year of construction of unit i; and</p> <p>The construction years are provided by Global Energy Observatory (2019). According to IEA, coal- and oil-powered plants are assumed to have a lifetime of 40 years (OECD, 2010).</p>
g8. Infrastructure & Innovation	[3.55 – 6]	<p>This criterion shows each country's average performance on the extend and efficiency on efficient infrastructures, such as modes of transport, electricity supplies and telecommunication network and the capacity to promote innovative activities, through investments in R&D, adapting to new technologies (The World Bank, 2018).</p>

1.3.3 Methodological framework

Due to its wide application in this field (Pohekar and Ramachandran, 2004; Nikas et al., 2018a), PROMETHEE II (Preference Ranking Organisation Method for Enriching Evaluation II) was selected as the basis of the proposed framework. While PROMETHEE I calculates the extent to which an alternative is preferable over the others (positive outranking flow), and the extent to which it is outranked by the rest of the alternatives (negative outranking flow) (Brans et al., 1986), PROMETHEE II is commonly employed for reaching a complete ranking of the alternatives (net outranking flow) based on impacts, weights, and preference functions. In this study, the Visual PROMETHEE2 software is used to reach numerical and visual results. The entire methodological framework of PROMETHEE is described in detail in Appendix A.

Drawing from its flexibility and capacity to provide the DMs with a simple and comprehensible procedure to express their perceived relative importance of one criterion over another, the AHP (Saaty, 1980) method is implemented to assign weights to the evaluation criteria. The AHP method is a well-organised technique based on comprehensive mathematical principles where the relative priority of each criterion with respect to each of the others is derived by a pairwise comparison using a numerical scale (Saaty, 1987). The AHP methodological framework is described in detail in Appendix B.

2 <http://www.promethee-gaia.net/visual-promethee.html>



1.4 Application of the model

1.4.1 Data collection

First, the values of each of the fourteen countries for the eight criteria should be determined. As discussed in Table 1, g1 and g3 constitute qualitative criteria, the quantification of the scores of each alternative against which draws on the literature. Then, g2, g4, g5, g6 and g8 are based on available indices in the literature, while g7 is calculated by the authors. It should be mentioned that PROMETHEE is found to effectively address qualitative criteria derived from surveys, by means of thresholds, in order to mitigate possible error margins in the final results; thus, using the 'generalised' criterion functions, the uncertainty in the criteria performance values can be considered (Hyde et al., 2003; Balali et al., 2014; Shakey, 2006; Ghazinoory et al., 2013; Albadvi et al., 2007; Rogers et al., 2004).

Public awareness and acceptance (g₁)

This is a qualitative criterion, the values for which have been determined based on the authors' interpretation of information found in the literature, including the Eurobarometer (for European countries) and other research and/or reports for non-European countries.

Austria: 3.5

In Austria, climate change is considered to be a rather serious problem by 68% of the population, whereas only 31% believe that action constitutes personal responsibility; 60% also appear to have recently participated in at least one environmental activity. (European Commission, 2017)

Canada: 4.0

95% of the Canadian population are aware of climate change, which is considered to be a serious threat by 74% (Pugliese and Ray, 2009); 75% are in favour of national climate change mitigation planning and of the establishment of the minimum carbon pricing scheme (Harrison, 2012). Moreover, 63% of the population are willing to pay for more expensive and environment-friendly products, despite acknowledging that climate action could lead to job losses.

Chile: 1.0

Only 1% of the entire Chilean population find climate change to be a significant environmental problem (Ministerio de Medio Ambiente de Chile, 2015); however, citizens appear open to RES, but their behaviour is unpredictable and often contradictory (Carrasco and Cerda, 2019).

China: 1.5

In China, only two thirds of the population are aware of climate change and just 21% believe it poses a serious threat (Pugliese and Ray, 2009).

Greece: 3.0

Climate change is considered to be a very serious problem by 85% of Greeks, with only 17% believing action is a personal responsibility: social resistance to clean energy projects and the not-in-my-backyard (NIMBY) phenomenon still pose a threat to further diffusion of renewables (Nikas et al., 2019b).

India: 2.0

About a third of the population are aware of the changing climate and even less acknowledge it as a significant issue (Pugliese and Ray, 2009); this lack of environmental awareness can be partly attributed to poverty and access



to energy, especially in rural areas (Bhattacharyya, 2006). Big city residents, on the other hand, are generally willing to pay carbon taxes for transportation (Gupta, 2016).

Indonesia: 2.0

39% of the Indonesian population are aware of climate change but significantly less know how it can be tackled (Pugliese and Ray, 2009). The socio-cultural context is also interesting, given that some renewable options are deployed but opposed to by certain communities, such as biogas production and Muslim communities (Ali, 2006).

Kenya: 2.5

More than half of Kenyans are aware of climate change, as a serious multifaceted threat (Pugliese and Ray, 2009). However, about as many live below the poverty line (Njuguna and Muruka, 2017); combined with limited education and access to modern energy services, environmental awareness is scarce or not prioritised.

Netherlands: 3.0

78% of the Dutch population find climate change to be a very serious problem, and the majority generally engage in environmental actions (European Commission, 2017). However, citizens have frequently voiced NIMBY objections to RES installations, with the exception of solar projects (Nikas et al., 2018b), which have largely been considered as profitable investments (Sijmons and Van Dorst, 2012).

Poland: 2.5

Climate change in Poland is considered to be a serious problem by 58% of population, but less than a third have personally participated in related activities recently (European Commission, 2017). More importantly, more than half prioritise growth and job creation instead (Antosiewicz et al., 2019), indicating past negative experiences of economic transformation in Poland (World Value Survey, 2015).

Spain: 3.5

The vast majority of the Spanish population acknowledge climate change as a critical threat (European Commission, 2017). Renewables are also seen as an opportunity to alleviate unemployment (Sociological Research Center, 2016), but recent regulatory changes have made citizens more reserved (Sorman et al., 2019).

Sweden: 4.5

Four out of five Swedes find climate change to be serious and engage in related activities, while a remarkable 59% believe that action constitutes a personal responsibility (European Commission, 2017).

Switzerland: 3.0

57% of the Swiss population believe climate change is a serious threat to humans and the environment. Environmental awareness levels had remained relatively stable since 1994, but lately stronger environmental behavior has been observed, such as in the acceptance of economic constraints in favour of environmental protection (Bonfadelli, 2016). However, the Swiss are quite attached to their landscapes and recognise their value in terms of tourism (Niță et al., 2015) and thus find it difficult to accept large-scale RES installations.

UK: 3.0

More than 60% of the UK population characterise climate change as a very serious problem, but only 14% find climate action to also constitute a personal responsibility (European Commission, 2017). 75% of the population applaud reductions in electricity use and efforts to reduce dependence on fossil fuels (Demski et al., 2015; Parkhill et al., 2013), but the current sociopolitical context of Brexit-related uncertainties across all aspects of life and activities impacts sustainability awareness (Ziv et al., 2018).



Human capital (g₂)

The Global Competitiveness Index (GCI) was introduced by the World Economic Forum (The World Bank, 2018), for 138 countries. GCI is a weighted average of 114 indicators or other aspects of competitiveness. These indicators are categorised in twelve pillars and the pillars in three sub-indices that stand as weights based on each country's development, since the pillars affect different economies in different ways. In our study, human capital has been calculated as the average of the following three GCI pillars of competitiveness: a) health and primary education; b) higher education and training; and c) labour market efficiency. In Table 2 the first three columns present the indices for each of the studied countries; the last column presents the calculated average.

Table 2: Human capital

	Health and primary education	Higher education and training	Labour market efficiency	Human capital (Average)
Austria	6.4	5.8	4.5	5.6
Canada	6.6	5.5	5.3	5.8
Chile	5.7	5.2	4.4	5.1
China	6.2	4.6	4.5	5.1
Greece	6.1	4.9	3.8	4.9
India	5.5	4.1	4.1	4.6
Indonesia	5.3	4.5	3.8	4.5
Kenya	4.7	3.9	4.6	4.4
The Netherlands	6.7	6.1	5.1	6.0
Poland	6.2	5.0	4.1	5.1
Spain	6.3	5.1	4.2	5.2
Sweden	6.4	5.6	4.9	5.6
Switzerland	6.6	6.0	5.9	6.2
The United Kingdom	6.5	5.5	5.5	5.8

Political will (g₃)

As with g₁, this is a qualitative criterion, the values for which have been determined based on the authors' interpretation of information found in the literature (e.g. Hanger-Kopp et al, 2019).

Austria: 2.0

Despite having signed international treaties and committing to community targets, Austria was reportedly the worst performing Member State on EU targets in 2009 (European Environment Agency, 2014). For long, economic policy had focused on growth, tackling unemployment and bureaucracy but not environmental problems; since 2010, however, energy efficiency and RES have been the pillars of the Austrian Energy Policy (BMWWF, 2016), but most political parties still refrain from discussing and promoting climate change issues, in fear of deindustrialisation (Wolkinger et al., 2019). Another barrier is industry being regulated by the energy and telecommunications service, while transport and buildings by local authorities, leading to conflicts of interest or incoordination.

Canada: 3.5

Recent measures announced by both the government and regional authorities indicate a positive tendency towards tackling climate change (Beale et al., 2015; Leach et al., 2015); however, conflicting federal and provincial policies or agendas and industry lobbying are considered to be strong political barriers to an energy transition



(Virla et al., 2019).

Chile: 3.5

Energy policy is at the heart of public policies in Chile, aimed at lowering prices, reducing energy use and increasing the share of renewable energy in the country's energy mix. Chile, in the context of the Paris Agreement, has also imposed taxes on industry and transport to reduce GHGs (Carrasco and Cerda, 2019). However, the government is committed to achieving the environmental targets only if coupled with economic growth (Mardones and Flores, 2018).

China: 4.0

Under the National Energy Management blueprint for the period 2016-2020, \$361 billion are being channeled into RES, creating thirteen million new jobs (Liu and Chu, 2019). These actions reflect China's effort to tackle climate change, but at the same time shield its economy from the absence of carbon that has been dominating growth for many years. In a recent assessment of stakeholder-perceived risks to decarbonisation, the political axis was not discussed, due to China's political system being stable over the past decades and to policy support from the central government to push forward decarbonisation efforts (Song et al., 2019).

Greece: 2.5

Greece has achieved its national GHG emission targets for 2020 (Ministry of Environment and Energy, 2018). However, despite the recognition of the problem of climate change by the government, all political parties prioritise tackling economic recession over a sustainable energy transition (Nikas et al., 2019b).

India: 3.0

The country's political leadership recognises the need to reorganise the nation's energy system and, in the framework of India's participation in the Paris Agreement, it presented a very ambitious plan for energy and climate. However, the lack of synergy between central and local governments hinders the formulation of clear policy towards achieving the objectives and discourages investors from new energy technology investments (Ghosh and Ghosh, 2016).

Indonesia: 3.5

In the context of the Paris Agreement, Indonesia has set ambitious goals and formed policies to increase RES in its energy mix (UNFCCC, 2017). Moreover, the installation of a center for clean energy is considered as a significant commitment to sustainable development. However, the simultaneous need to tackle structural problems in the country, as well as efforts to secure economic growth often lead to conflicting policies (Wibisono and Badruzzaman, 2018).

Kenya: 3.0

In collaboration with the African Union (Union A., 2014), Kenya focuses on the enforcement of environmental taxes, carbon pricing and the integration of RES into energy production, while responsible bodies have also been set up at national level to research new energy technologies. Although Kenya defined sustainable development goals in its new constitution, regional authorities seek to exploit local oil and coal deposits and use power supply funds for other purposes (AfDB/OECD/UNDP, 2016).

Netherlands: 2.5

The Dutch climate policy is primarily an implementation of EU directives and its government is usually passively supportive. The country takes a variety of measures to achieve its targets but they seem to be insufficient (Caymaz,



2013; Nikas et al., 2018b), while there is currently little policy support for sustainable energy actions at the local scale (de Bruyn-Szendrei et al., 2019).

Poland: 1.5

The government formally recognises EU requirements and the Paris Agreement (UNFCCC, 2017) and urges the modernisation of the coal industry. Actions to achieve the latter goal include plans to build more efficient coal-fired power plants, closing oldest plants and voluntary exit programs for miners to shrink the industry. However, these efforts are not socially accepted and all parties indirectly support the mining sector. Thus, significant dependence on coal makes the Polish government appear reluctant to act (Mardones and Flores, 2018), which can be reflected in the heated debate in the country (Antosiewicz et al., 2019).

Spain: 3.0

The government has formulated a strategy with specific targets for the period up to 2030. Regulatory frameworks have been developed, while the government has committed itself to specific rates for improving energy consumption and efficiency. National and local authorities are working in this direction, but political instability, poor prioritisation and overall volatile agendas of political parties (Sorman et al., 2019) have a diverse impact on the budget channeled towards sustainable energy (Tirado and Jiménez Meneses, 2016).

Sweden: 4.5

The government plans to reduce oil imports, optimise the use of bioenergy for heating and develop an electric vehicle fleet, aiming to become fully independent from fossil fuels by 2040. Efforts are being made through a government-industry partnership, and supporting technological development. Traditionally governments in Sweden spend a significant part of the budget towards research and development (European Commission, 2016; Global Innovation Index, 2016).

Switzerland: 2.5

Energy is not a top priority in Switzerland, as political will is strongly intertwined with societal acceptance, due to its political system of direct democracy ('People's Initiatives'); many sustainable energy projects therefore end up being blocked in referendums (van Vliet, 2019), while many referendums on carbon use and taxation have never passed the federal level; however, the government has provided support programs for hydroelectric power generation and following the decision on nuclear phase-out, it aims to replace them with imported renewable electricity (Lilliestam and Hanger, 2016).

UK: 3.5

The UK is the only dominant European economy that has formulated a legally binding plan for gradual total carbon independence. However, due to Brexit, there is strong uncertainty about its future relationship with the EU, whether it will comply with its directives and how it will replenish EU funding for energy innovation (Hepburn and Teytelboym, 2017).

Regulatory Indicator for Sustainable Energy (RISE) (g₄)

RISE is a global inventory of policies and regulations in support of SDG7 progress, indicating 133 countries' performance across electricity access, energy efficiency and renewables. It measures how close to or far from offering an attractive policy and regulatory environment a country is. SETR uses RISE global scores for measuring the regulatory framework relevant for the transition readiness, presented in Table 5, as all three sub-indices contain relevant aspects (Foster, V. et al., 2018).



Financial sector sustainability (g₅)

Scores in this criterion were determined by the financial market development pillar from the Global Competitiveness Report (World Economic Forum, 2016). Scores are presented in Table 5.

Ease of doing business (g₆)

The World Bank publishes a report ranking 190 countries against twelve areas of business regulation, including starting a business, dealing with construction permits, paying taxes, enforcing contracts, and so on, by measuring procedures, times and costs. Ranks are interpreted as criterion values, as presented in Table 5.

Carbon lock-in (g₇)

After determining the active power plants, their capacity and the year of their construction, we used Eq. (1) and Eq. (2), as discussed in Table 2. To illustrate this, the case of Austria is presented below. Table 3 provides a list of power plants and their specifications necessary to calculate the country's carbon lock-in (Papapostolou et al., 2017a).

Table 3: Austria's carbon lock-in

Power Plants	Capacity (MWe)	Construction Year	C=Constr.Year + 40 - 2019	Capacity* C
Mellach CHP Power Plant Austria	246	1986	7	1722
Duernrohr CHP Power Plant Austria	405	1985	6	2430
	352	1985	6	2112
Lenzing Thermal Power Plant Austria	38	1999	20	760
Theiss Thermal Power Plant Austria	180	2000	21	3780
	250	2003	24	6000

The calculated age of Austria's fossil fuel generation fleet is 11.42. Electricity production from coal and oil sources in Austria's energy mix was found to be 9.64% (Trading Economics, 2015). Therefore, Austria's carbon lock-in is 1.05. The values of all countries are provided in Table 5. It should be also noted that Sweden and Switzerland have no coal or oil power plants and therefore their carbon lock-in equals zero.

Infrastructure & innovation (g₈)

Similar to g₂, scores against the infrastructure & innovation criterion has been calculated as the average of two GCI competitiveness pillars (World Economic Forum, 2016): a) infrastructure, and b) innovation.

Table 4: Infrastructure & Innovation

	Infrastructure	Innovation	Average
Austria	5.8	5.0	5.4
Canada	5.7	4.6	5.2
Chile	4.7	3.4	4.1
China	4.7	4.0	4.4



Greece	4.8	3.3	4.1
India	4.0	4.0	4.0
Indonesia	4.2	4.0	4.1
Kenya	3.3	3.8	3.6
The Netherlands	6.4	5.4	5.9
Poland	4.3	3.4	3.9
Spain	5.9	3.8	4.9
Sweden	5.6	5.5	5.6
Switzerland	6.2	5.8	6.0
The United Kingdom	6.0	5.0	5.5

1.4.2 Multicriteria analysis

Having calculated all the criteria values for each country, the evaluation table is developed as shown in Table 5.

Table 5: Alternative scores for each criterion

Countries	g ₁	g ₂	g ₃	g ₄	g ₅	g ₆	g ₇	g ₈
Austria	3.5	5.6	2.0	79	4.5	27	1.14	5.40
Canada	4.0	5.8	3.5	90	5.3	23	0.99	5.15
Chile	0.5	5.1	3.5	77	4.8	59	3.28	4.05
China	1.5	5.1	4.0	80	4.2	31	4.47	4.35
Greece	3.0	4.9	2.5	81	2.5	79	2.61	4.05
India	1.5	4.6	3.0	75	4.4	63	4.55	4.00
Indonesia	2.0	4.5	3.5	47	4.3	73	4.17	4.10
Kenya	2.5	4.4	3.0	61	4.2	56	2.27	3.55
The Netherlands	3.0	6.0	2.5	89	4.5	42	3.07	5.90
Poland	2.5	5.1	1.5	65	4.2	40	2.90	3.85
Spain	4.0	5.2	3.0	79	4.0	30	1.24	4.85
Sweden	4.5	5.6	4.5	83	5.2	10	0.00	5.55
Switzerland	3.0	6.2	2.5	85	5.3	36	0.00	6.00
The United Kingdom	3.0	5.8	3.5	92	4.9	8	1.25	5.50

The criteria weights were extracted by means of the AHP method (Appendix B), based on the DMS' collective preference model. Table 6 presents the pairwise comparison of the assessment The Consistency Ratio (CR) (Saaty, 1980) was found 8.8%.



Table 6: Pairwise comparison of elements in AHP

Criterion	g ₁	g ₂	g ₃	g ₄	g ₅	g ₆	g ₇	g ₈
Public Awareness and acceptance (g ₁)	1.00	0.25	0.20	0.20	0.33	0.33	0.13	0.25
Human Capital (g ₂)	4.00	1.00	0.25	0.33	0.25	3.00	0.20	0.50
Political Will and compliance with the EU energy policy (g ₃)	5.00	4.00	1.00	3.00	2.00	5.00	0.33	3.00
Regulatory Indicator for Sustainable Energy – RISE (g ₄)	5.00	3.00	0.33	1.00	0.20	4.00	0.20	2.00
Financial market sector soundness (g ₅)	3.00	4.00	0.50	5.00	1.00	4.00	0.33	5.00
Ease of doing business (g ₆)	3.00	0.33	0.20	0.25	0.25	1.00	0.14	0.33
Carbon lock-in (g ₇)	8.00	5.00	3.00	5.00	3.00	7.00	1.00	5.00
Infrastructure & Innovation (g ₈)	4.00	2.00	0.33	0.50	0.20	3.00	0.20	1.00
Criteria weights based on AHP	0.03	0.06	0.19	0.10	0.18	0.04	0.34	0.07

In a further step, the preference functions as well as the criteria thresholds for the PROMETHEE II method were defined (Table 7), after discussing with the DMs and gaining insights from other surveys (Brans et al., 1986; Sultana and Kumar, 2012; Mohamadabadi et al., 2009; Sola et al., 2011). As part of this study, two different types of criteria preference functions were modelled: level and linear (Figure 3). PROMETHEE provides the option to use thresholds to further capture the preferences (Appendix A).

Table 7: Criteria characteristics

	g ₁	g ₂	g ₃	g ₄	g ₅	g ₆	g ₇	g ₈
Preference function	level	linear	level	level	linear	level	linear	linear
Indifference threshold – q	0.5	0.2	0.5	5	0.3	5	0.50	0.20



Preference threshold – p	1.0	0.5	1.0	10	0.6	10	0.80	0.50
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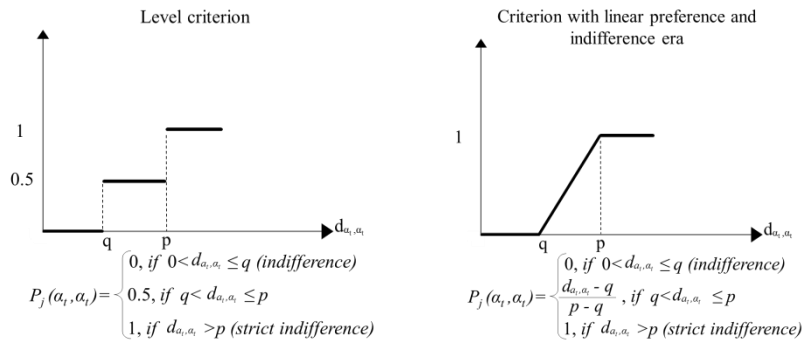


Figure 3: The level and linear criteria preference functions

PROMETHEE II was finally implemented and the net outranking flows of the alternatives were calculated. Table 8 illustrates the net outranking flows of the fourteen countries, as extracted by Visual PROMETHEE.

Table 8: Countries’ ranking and net outranking flows

Ranking	Country	Net outranking flows
1	Sweden	0.761
2	Switzerland	0.534
3	Canada	0.519
4	The United Kingdom	0.492
5	Spain	0.111
6	Austria	0.083
7	The Netherlands	-0.035
8	Chile	-0.107
9	China	-0.261
10	Kenya	-0.283
11	Greece	-0.390
12	Poland	-0.453
13	India	-0.464
14	Indonesia	-0.508

Results indicate that, among these countries, Western European countries and Canada appeared to perform higher, with the others showing that significant progress is still to be made. Particularly, Sweden ranks first by far, outranking the second (Switzerland) by 43%. Between the top four countries and the bottom ten there is an evident gap, with the UK (4th) outranking Spain (5th) by 342%. This could be attributed to the fact that the top four feature the lowest carbon lock-in and stronger political will (two criteria with the highest importance, according to the DMs), compared to the other ten countries. We also observe that Canada and Poland only slightly differ from the UK and India, meaning that changing some of the problem’s parameters (e.g. thresholds) could result in a different ranking.



Weight sensitivity was explored by calculating the stability intervals. These represent the range of weights, for each of the criteria, for which the ranking remains unchanged. A large interval indicates more stability and robustness against larger changes in criteria weights. Figure 4 shows the assigned weights as well as the lower and upper limits for each criterion.

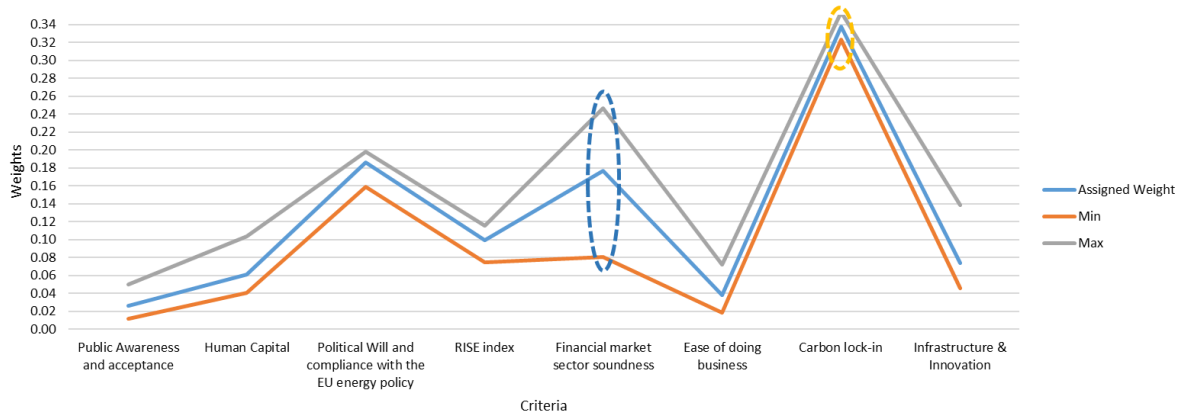


Figure 4: Stability intervals

The blue and orange circles in Figure 4 indicate the wider and narrower intervals respectively. *Ceteris paribus* changes in assigned weights within the respective intervals will not alter the ranking of alternatives; overall results appear to be sensitive to the weights, since the intervals are mainly small. It is also evident that, among the weights assigned by the DMs, the carbon lock-in has the greatest impact on the final ranking.

Results (in a range of [-1, 1]) are further normalised in a range of [0, 1] using Eq. (3):

$$x' = \frac{x + 1}{2} \quad (3)$$

Where x is the attribute value to be normalised.

The SETR index for each country is presented below:

Table 9: SETR index of the fourteen countries

Country	SETR [0, 1]
Sweden	0.881
Switzerland	0.767
Canada	0.759
The United Kingdom	0.746
Spain	0.556
Austria	0.542
The Netherlands	0.482
Chile	0.447
China	0.369
Kenya	0.359
Greece	0.305
Poland	0.274



India	0.268
Indonesia	0.246

1.4.3 Comparative analysis

CCPI (Burck et al., 2019), SDGI (Sachs et al., 2019b) and ETI (Singh et al., 2019) are selected to compare the outputs of this study with existing indices and indicate whether and to what extent they are aligned (Table 10). The four indices include different aspects of measurements as well as different methodological approaches. Through this comparison, we seek to validate the proposed SETR index, understand the resulting differences for the selected countries, and potentially gain insights for future research.

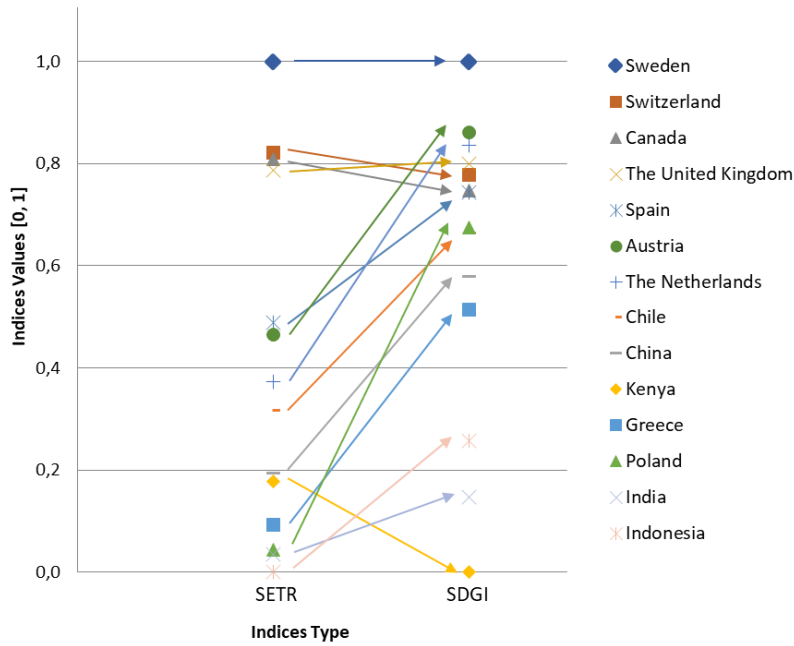
Table 10: Comparison between SETR, SDGI, CCPI and ETI

Country	SETR	SDGI	CCPI	ETI
Sweden	0.881	85.0	75.77	74.9
Switzerland	0.767	78.8	60.61	74.3
Canada	0.759	77.9	31.01	61.0
The United Kingdom	0.746	79.4	69.80	70.2
Spain	0.556	77.8	46.03	63.5
Austria	0.542	81.1	44.74	70.7
The Netherlands	0.482	80.4	50.89	68.5
Chile	0.447	75.6	62.88	63.0
China	0.369	73.2	48.16	49.6
Kenya	0.359	57.0	no data	52.1
Greece	0.305	71.4	52.59	56.2
Poland	0.274	75.9	39.98	51.4
India	0.268	61.1	66.02	51.2
Indonesia	0.246	64.2	44.65	54.6

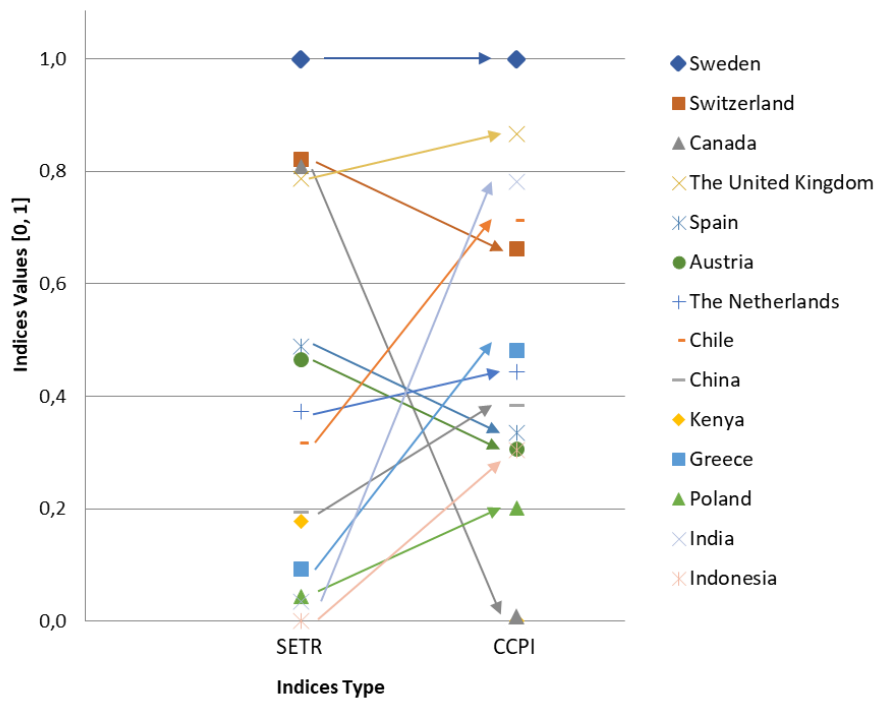
Figure 5 illustrates the rankings and highlights the differences between SETR-SDGI, SETR-CCPI and SETR-ETI, with all scores normalised in the entire [0, 1] range for comparability using Eq. (5):

$$x' = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (5)$$

Where x is the attribute value to be normalised.

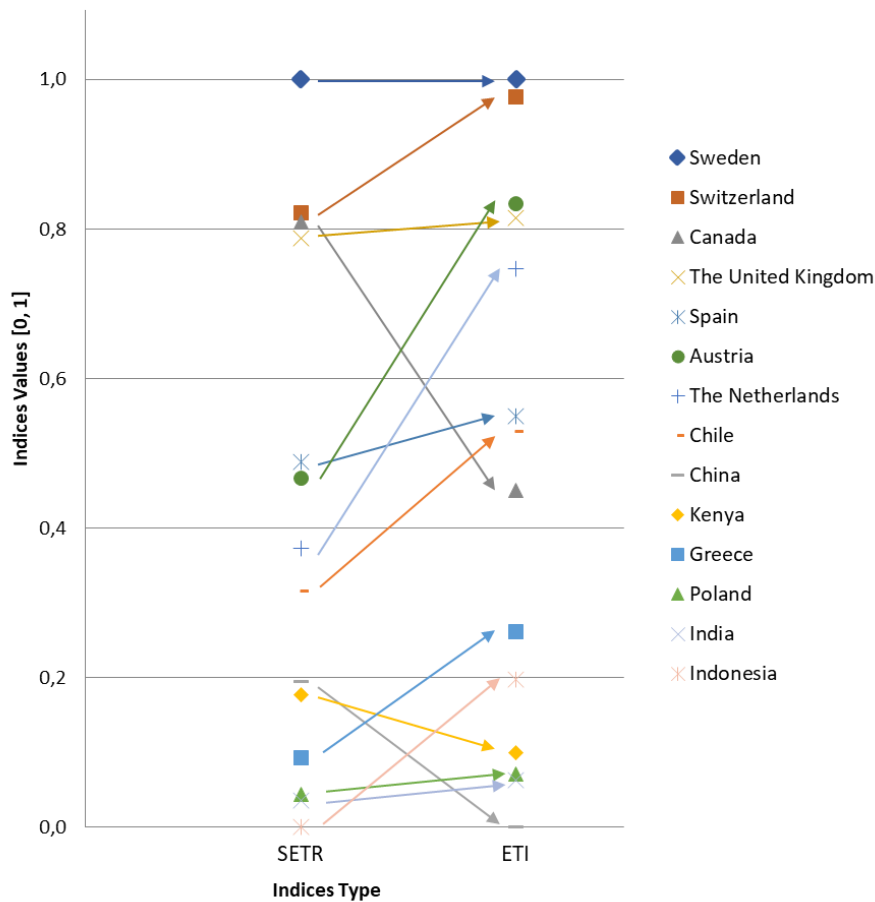


(a)



(b)





(c)

Figure 5: Comparison between (a) SETR & SDGI, (b) SETR & CCPI, and (c) SETR & ETI

In most cases, SETR does not coincide with the SDGI (Figure 5a), with Sweden, Switzerland, UK and Austria ranking high in both cases and one country group remaining comparable: Spain, Chile, China, Greece appear with the same sequence in the middle. This can be largely attributed to the fact that SDGI considers the sum of seventeen SDGs, while SETR focuses on sustainable energy. It is also noteworthy that Poland does fairly better in SDGI than in SETR, meaning that Poland appears to lag behind in the energy sector but thrives in other dimensions of sustainable development. Kenya, on the other hand, ranks relatively low in terms of sustainable energy transition readiness but performs the worst in terms of overall sustainable development.

SETR is also compared to CCPI (Figure 5b), which however does not cover Kenya, again with large differences. Sweden ranks top in both cases. Switzerland and the UK rank high in both cases, while Spain and Austria hold their relative ranks but lower in the CCPI chart. Canada and India constitute the extreme cases. Canada ranks the worst in climate change performance among the thirteen countries, while having larger capacity to transform its energy system, according to SETR; this could be due to the country implementing its coal-fired power plant phase-out, yet in clear need to take more climate action, as emissions are projected to still be above 1990 levels beyond 2030, far from its Paris Agreement target (Climate Action Tracker, 2019). India has the second worst performance in SETR but appears in the 3rd place in CCPI; this is an expected finding, given that the country appears to be on



a 2°C-compatible pathway, but has not abandoned plans to build new coal-fired power plants (Climate Action Tracker, 2019).

Finally (Figure 5c), despite some differences, SETR and ETI present more evident similarities. To begin with, Sweden and Switzerland rank first and second, respectively. These are followed, in both cases, by a group of countries with average performances, with similar rankings: UK, Spain, Canada, Netherlands and Chile. The remaining six countries present the worst performances. Pairwise comparisons between Greece and Indonesia as well as Poland and India are similar in both cases. Expectedly, among the three benchmark indices, SETR resembles ETI the most, as they share the same objective. However, they also differ from each other, since ETI incorporates environmental sustainability, through energy intensity, CO₂ per capita etc.; energy security; energy mix, instead of conventional fuel lock-ins; and numerous other aspects. SETR, in contrast, does not measure political commitment via NDCs but qualitatively, with broader considerations, and captures public awareness; more importantly, it does not apply an equal weighting method and features a detailed mathematical approach underpinning its framework. A discussion on the core methodological differences between the two, and possible explanation of the differences between the resulting rankings, can be found in Section 1.2.

1.5 Conclusions

The study presented in this paper addresses the assessment of sustainable energy transition readiness, introducing a respective assessment index, based on a multi-criteria evaluation system oriented on the AHP and PROMETHEE II methods. The model provides a ranking of countries exploiting societal, political, economic and technological indicators that are perceived to be drivers of energy transition. Taking everything into consideration, Sweden appears to have by far the most favourable conditions to transform its energy system to a more sustainable one, followed by Western Europe and Canada. Results were compared against three other indicators in the literature, on progress in the entire SDG framework, the narrower climate action front, and the broader energy transition. Our analysis is relevant to both global agendas, since it offers insights into the strengths and weaknesses of a country regarding energy needs and requirements towards drastic energy transformations, which are central to climate mitigation efforts but also constitute a major pillar of overall sustainability, without disregarding other relevant socio-political and techno-economic dimensions. From an empirical point of view, it is also noteworthy that, among the examined countries, it primarily is major emitting countries to be found in dire need of improvements. The proposed model also enables the development of tailored assessments, since the evaluation process is an independent procedure that allows decision makers to specify their own preference models on weights, thresholds and functions.

The SETR evaluation system can be used to inform policymakers and help plan the future national low-carbon transition pathways. Consequently, a comprehensive future perspective of this study lies in the extension of the evaluation system to broaden the country pool, as well as in its establishment as a yearly benchmark, further supporting analysts and policymakers in keeping track of the progress made, and identifying key areas in which each country is lagging behind and must therefore focus on improving. It should be noted that the group of engaged stakeholders in the analysis of the selected country pool is not intended to be exhaustive, as Section 1.4 is only a validation framework of the proposed methodology, aimed at showcasing the real-world applicability potential of the framework; as such, the engagement of only thirty-two experts is an acknowledged limitation of this study.

Last but not least, enhancing the framework with further robustness analyses and relevant indices is meaningful and can potentially add significant value, towards assessing whether and to what extent differentiations over the final ranking emerge, with respect to changes in the DMs' preference model(s).



2 APOLLO: A Fuzzy Multi-criteria Group Decision-Making Tool in Support of Climate Policy

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2.1 Introduction

Decision-making (DM) problems range from the most common situations in human beings' daily lives (e.g., what film to see at the cinema) to much more complex ones that may affect larger social units, including communities (a new policy to reduce pollution in a city center), nations (a financial incentive to boost technological innovation), regions (sectoral coverage of the European Union's Emissions Trading System), or the globe (effort sharing in mitigating climate change). A DM problem always comprises a set of alternatives or possible solutions for the problem, and often a group of experts with different attitudes, who evaluate these alternatives in order to collectively select the "best" one. More often than not, the evaluation of the alternatives is based on several criteria, leading to *multi-criteria decision-making* (MCDM) (Kacprzyk, 1986; Ishizaka and P. Nemery 2013).

However, in many MCDM problems, complexity significantly increases, with conflicts emerging among alternatives' performances across the evaluation criteria and reaching one optimal solution not being a straightforward process (Forouli et al., 2019). Furthermore, combined with the lack of information related to the alternatives, this complexity often implies the apparition of uncertainty. In this situation, modeling uncertainty is not a trivial task, since experts are usually unable to express it by using exclusively discrete assessments. To overcome the latter limitation, *linguistic variables* (Zadeh, 1975) have been used successfully (Rodriguez et al., 2010). By means of such variables, experts can express their opinions by using linguistic terms, such as *good* or *very bad*, *high*, or *insignificant*, etc., which are closer to their way of thinking. Under these conditions, MCDM becomes *linguistic decision-making* (LDM) (Martínez et al., 2009).

The classical resolution scheme for MCDM problems considers only the aggregation of the experts' opinions over the alternative actions in order to obtain a ranking of these actions and select the best one (Roubens, 1997). This could often lead to situations where the possible disagreements that may emerge in the group are ignored or not reflected in the aggregate preferential model (Nikas et al., 2017). Consequently, some experts might not agree with the solution achieved and feel outside of the decision process. To increase the robustness of the chosen solutions, a consensus level of the experts can be measured (Bender and Simonovic, 1997) to identify sources of proximity and disagreement.

Nowadays, many of the most important real-world MCDM problems are related to sustainability issues (Neofytou et al., 2020). The effects of global environmental change are becoming increasingly obvious and its impacts on our societies, economies, and environment, today and in the near future, constitute one of the main concerns worldwide. This is why nations have long set out to address this challenge (e.g., the Kyoto Protocol and, recently, the Paris Agreement), in a globally coordinated and cooperative manner (Doukas et al., 2018).

The enormous complexity of problems associated with climate change and action, especially in the context of an all-inclusive, participatory, and transparent dialogue, based on the principles of Talanoa (Sorman et al., 2020), makes experts often come up with a series of assumptions that fail to reflect the real-world constraints, in order to reduce such complexity. MCDM has long been used to address challenges and resolve problems associated with environmental, energy, and climate policy (Doukas and Nikas, 2020). Respectively, decision support systems,



i.e., software tools used to support decisions, judgements, and courses of action, have recently been developed, featuring the capacity to solve climate change-related MCDM problems from the perspective of multiple stakeholders (e.g., Nikas *et al.*, 2018a; Jeong, 2018), without however aiming to improve consensus.

In this direction, this research aims to make an important qualitative contribution within the climate change policy research area by presenting a new fuzzy decision support system, *A group decision fuzzy TOOL in support of climate change policy making* (APOLLO). The main aim of APOLLO is to facilitate a consensus measuring process of a group of individuals toward reaching the best decision for an MCDM problem related to climate change and policy issues. Additionally, the software has the ability to analyze the conflicts (or disagreements) that emerge among the experts. Furthermore, in order to validate it and showcase its usefulness, APOLLO is presented and stress-tested in a real-world case study that was carried out in Austria, in the context of assessing the risks embedded in pathways for decarbonizing the country's iron and steel sector.

From a methodological point of view, this paper seeks to contribute to the literature by establishing a new decision support system that focuses on dealing with problems related to climate change adaptation and mitigation policy issues. It takes into account the challenges of engaging with multiple actors from various stakeholder groups and thereby increases ownership of decisions, while introducing a new consensus analysis method, drawing from the literature.

The rest of the paper is organized as follows: Section 2.2 reviews several basic concepts toward facilitating the understanding of proposed method and tool. Section 2.3 introduces both the resolution process and the architecture of APOLLO. Section 2.4 describes the real-world case study on evaluating risks associated with the decarbonization of Austria's iron and steel sector, showcasing the performance of the APOLLO decision support tool. Finally, in Section 2.5 some conclusions and prospects of our research are drawn.

2.2 Methods and Tools

This section describes the proposed methods and tools that will be implemented in APOLLO. First, the choice of linguistic variables is facilitated through the review of LDM and the presentation of the 2-tuple linguistic model. Second, the 2-tuple Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) model that APOLLO uses to solve group DM problems is described. Finally, the new consensus measuring framework is introduced.

2.2.1 Linguistic Decision-Making

Human beings are continuously faced with decision problems; what to eat, what mobile phone to buy, or what shoes to wear today are common examples of this type of problems. As the problematic, along with the impacts of a decision to address it, shifts from individuals to larger social units (e.g., policymaking), the decision-making process requires ownership of a collectively acceptable solution and therefore entails the engagement of more than one decision maker. Formally, in these cases, the DM problem is formed by a set of experts, $E = \{e_1, \dots, e_k\}$, who evaluate different alternatives, $A = \{a_1, \dots, a_m\}$, and choose the best one(s) as solution(s) to the problem, by evaluating them against a set of different conflicting criteria, $C = \{c_1, \dots, c_n\}$ (Nikas *et al.*, 2018a).

As complexity of a DM problem increases, with decision makers not knowing all of the information required to make a decision about the problem, uncertainty and vagueness are present. Under these circumstances, the classical probabilistic models cannot be used to obtain a solution and a different approach to deal with these problems is necessary. The *fuzzy linguistic approach* and *fuzzy variables* (Zadeh, 1975) have been widely used in the DM area in order to model the inherent uncertainty that appears in many decision situations, giving place to LDM (Martínez *et al.*, 2009). In an LDM problem, the group of engaged individuals provide their opinions by using linguistic expressions, which are considered closer to the way in which human beings express their ideas.



Due to experts using linguistic expressions to give their opinions, it is essential to carry out computations with such linguistic information in order to provide consistent solutions for the LDM problems. Furthermore, these results should also be represented linguistically to promote understanding from the decision makers' point of view. The *Computing with Words* (CWWs) methodology (Doukas et al., 2010; Martinez et al., 2010; Martinez and Herrera, 2014) tries to mimic the reasoning process of human beings, by obtaining linguistic outputs from the linguistic inputs provided by the stakeholders. Many DM methods follow this methodology to solve an LDM problem. In this research, we focus on an extension of the TOPSIS, based on the 2-tuple linguistic model.

2.2.2 The 2-Tuple Linguistic Model

The 2-tuple linguistic computational model (Martinez and Herrera, 2012) is a symbolic model that was introduced as an improvement of other linguistic modeling approaches (Rodríguez and Martínez, 2013). It carries out linguistic computational processes in an easy and comprehensive manner, without losing information, using a continuous linguistic domain, and outputs results that are expressed in the same linguistic domain (Nikas et al., 2018a).

To represent linguistic information, the 2-tuple model uses a pair of values that is called linguistic 2-tuple (s, a) , where s is a linguistic term and a is a numeric value representing a symbolic translation.

Let $S = \{s_0, \dots, s_g\}$ be a linguistic term set and $\beta \in [0, g]$ be the result of a symbolic aggregation operation, where $g + 1$ is the cardinality of S . Let $i = \text{round}(\beta)$ and $\alpha = \beta - i$ be two values, such that $i \in [-0.5, 0.5]$; then α is called a symbolic translation. The symbolic translation of a linguistic term s_i is a numerical value within $[-0.5, 0.5]$ indicating the difference of the information between the calculated value $\beta \in [0, g]$, and its closest element within $\{s_0, \dots, s_g\}$ indicating the content of the closest linguistic term S ($i = \text{round}(\beta)$).

In essence, the 2-tuple linguistic representation model extends the use of indexes modifying the fuzzy linguistic approach, by adding a symbolic translation that represents the linguistic information by means of a linguistic 2-tuple.

$$a = \begin{cases} [-0.5, 0.5), & \text{if } s_i \in \{s_1, s_2, \dots, s_{g-1}\} \\ [0, 0.5), & \text{if } s_i = s_0 \\ [-0.5, 0), & \text{if } s_i = s_g \end{cases} \quad (1)$$

Finally, for a linguistic term set $S = \{s_0, \dots, s_g\}$ and a value supporting the result of a symbolic aggregation operation $\beta \in [0, g]$, the 2-tuple expressing the equivalent information to β is calculated:

$$\Delta: [0, g] \rightarrow S \times (-0.5, 0.5)$$

$$\Delta(\beta) = (s_i, \alpha), \text{ with } \begin{cases} s_i & i = \text{round}(\beta) \\ \alpha = \beta - i & \alpha \in [-0.5, 0.5) \end{cases} \quad (2)$$

Evidently, the conversion of a linguistic term into a linguistic 2-tuple consists of adding a value 0 as symbolic translation: $s_i \in S \Rightarrow (s_i, 0)$.

2.2.3 The 2-Tuple TOPSIS Model

TOPSIS (Hwang and Yoon, 1981) is an MCDM method based on the idea that the best alternative is the closest to a positive ideal solution and the farthest from a negative ideal solution. Initially, TOPSIS was proposed as an MCDM method that can deal with numerical assessments and has been found to be relevant in the climate policy domain (Nikas et al., 2018a); but, as already discussed, uncertainty often appears in many DM problems and, consequently, the need for linguistic information emerges. Several fuzzy TOPSIS methods have been proposed both in the broader literature as well as in climate policy support research (Doukas and Nikas, 2020).

Here, we build on the 2-tuple TOPSIS approach introduced in Sohaib et al. (2019), which makes use of the 2-tuple linguistic model (Martínez et al., 2015) and a new distance function that allows to obtain more precise and interpretable results than other models. However, instead of aggregating the initial input from the stakeholders using average values and then perform the 2-tuple TOPSIS, we follow the methodology established by Krohling



and Campanharo (2011) where the fuzzy TOPSIS was used in the experts' preference to create a global model and then another round of fuzzy TOPSIS was performed to acquire the global solution with the experts' individual solutions acting as the criteria. Nikas *et al.* (2018a) expanded the concept of using a double round of TOPSIS in group DM by using behavioral instead of fuzzy TOPSIS. The 2-tuple TOPSIS method to be used on this study consists of the following steps:

Defining a weight vector $U_t = (u_j^t)_{1 \times n}^T$, where $u_j^t \in U$ is the linguistic preference by stakeholder e_t for criterion c_j and U is a linguistic term set, with $U = \{u_1, u_2, \dots, u_p\}$ transformed into a 2-tuple linguistic decision matrix $U_t = (u_j^t, 0)_{1 \times n}^T$.

Calculating the normalized 2-tuple weight vector $U_t^N = (\bar{u}_j^t, \bar{\beta}_j^t)_{1 \times n}^T$ for each stakeholder e_t as

$$(\bar{u}_j^t, \bar{\beta}_j^t) = \Delta_u \left(\frac{\Delta_u^{-1}(u_j^t, 0)}{T_U - 1} \right), \quad (3)$$

$j = 1, 2, \dots, n$ and T_U is the cardinal of set U .

Normalizing with the cardinal of the linguistic scale instead of the maximum value, as suggested in the original method, is preferred to avoid exaggerating the differences between the responses.

Defining the decision matrix $X_t = (r_{ij}^t)_{m \times n}$, where $(r_{ij}^t) \in S$ is the linguistic value preference provided by stakeholder e_t for alternative a_i over criterion c_j , and S is the linguistic term set, with $S = \{s_1, s_2, \dots, s_t\}$ transformed into a 2-tuple linguistic decision matrix $X_t = (r_{ij}^t, 0)_{m \times n}$.

Calculating the weighted decision matrix $\bar{X}_t = (\bar{r}_{ij}^t, \bar{a}_{ij}^t)_{m \times n}$ for each stakeholder e_t , with

$$(\bar{r}_{ij}^t, \bar{a}_{ij}^t) = \Delta_S \left(\Delta_u^{-1}(\bar{u}_j^t, \bar{\beta}_j^t) \cdot \Delta_S^{-1}(r_{ij}^t, 0) \right), \quad (4)$$

$i = 1, 2, \dots, m, j = 1, 2, \dots, n$.

Calculating the positive and negative ideal solutions for each stakeholder e_t as:

$$(r_1^{t,+}, \alpha_1^{t,+}) = \{(r_1^{t,+}, \alpha_1^{t,+}), (r_2^{t,+}, \alpha_2^{t,+}), \dots, (r_n^{t,+}, \alpha_n^{t,+})\} \text{ and}$$

$$(r_1^{t,-}, \alpha_1^{t,-}) = \{(r_1^{t,-}, \alpha_1^{t,-}), (r_2^{t,-}, \alpha_2^{t,-}), \dots, (r_n^{t,-}, \alpha_n^{t,-})\}, \text{ where}$$

$$(r_j^{t,+}, \alpha_j^{t,+}) = \max_i \{(\bar{r}_{ij}^t, \bar{a}_{ij}^t) \mid c_j \in B\} \text{ or } \min_i \{(\bar{r}_{ij}^t, \bar{a}_{ij}^t) \mid c_j \in B'\} \text{ and}$$

$$(r_j^{t,-}, \alpha_j^{t,-}) = \min_i \{(\bar{r}_{ij}^t, \bar{a}_{ij}^t) \mid c_j \in B\} \text{ or } \max_i \{(\bar{r}_{ij}^t, \bar{a}_{ij}^t) \mid c_j \in B'\}, \text{ where}$$

$i = 1, 2, \dots, m, j = 1, 2, \dots, n$ and where B and B' are the benefit and cost criteria sets respectively.

Determining the distance of each alternative from the positive and negative ideal solutions for each stakeholder e_t as

$$(\xi_i^{t,+}, \eta_i^{t,+}) = \Delta_{S'} \left(\frac{1}{n} \sum_{j=1}^n \frac{(T_{S'} - 1)}{(T_S - 1)} \cdot (|\Delta_S^{-1}(\bar{r}_{ij}^t, \bar{a}_{ij}^t) - (r_j^{t,+}, \alpha_j^{t,+})|) \right) \quad (5)$$

and



$$(\xi_i^{t,-}, \eta_i^{t,-}) = \Delta_{S'} \left(\frac{1}{n} \sum_{j=1}^n \frac{(T_{S'} - 1)}{(T_S - 1)} \cdot (|\Delta_S^{-1}(\tilde{r}_{ij}^t, \tilde{a}_{ij}^t) - (r_j^{t,-}, \alpha_j^{t,-})|) \right) \quad (6)$$

where $S' = \{s'_1, s'_2, \dots, s'_{t'}\}$ is the linguistic term set for the distances, T_S and $T_{S'}$ the cardinals of sets S and S' respectively.

Calculating the relative closeness degree of each alternative from the positive ideal solution for each stakeholder e_t as

$$(\xi_i^t, \eta_i^t) = \Delta_{S'} \left(\left(\frac{\Delta_S^{-1}(\xi_i^{t,-}, \eta_i^{t,-})}{\Delta_S^{-1}(\xi_i^{t,+}, \eta_i^{t,+}) + \Delta_S^{-1}(\xi_i^{t,-}, \eta_i^{t,-})} \right) \cdot (T_S - 1) \right), \quad i = 1, 2, \dots, m \text{ and } T_S \text{ the cardinal of set } S. \quad (7)$$

In the current form the results are expressed in the linguistic scale S used by the stakeholders to increase interpretability. The results could have been displayed in the scale S' which was defined explicitly to express distances; however, presenting the results in the new terms, despite being considered more appropriate, might confuse the stakeholders.

Computing the collective 2-tuple linguistic decision matrix $X = (\tilde{r}_{it}, \tilde{\alpha}_{it})_{m \times k}$, where $(\tilde{r}_{it}, \tilde{\alpha}_{it}) = (\xi_i^t, \eta_i^t)$, $i = 1, 2, \dots, m, t = 1, 2, \dots, k$. In this step the stakeholders are considered equally weighted. By adjusting steps 1–4, the new matrix X could be calculated to also include weights for the expert.

Calculating the positive and negative ideal collective as

$$(r^+, \alpha^+) = \{(r_1^+, \alpha_1^+), (r_2^+, \alpha_2^+), \dots, (r_k^+, \alpha_k^+)\} \text{ and}$$

$$(r^-, \alpha^-) = \{(r_1^-, \alpha_1^-), (r_2^-, \alpha_2^-), \dots, (r_k^-, \alpha_k^-)\}, \text{ where}$$

$$(r_t^+, \alpha_t^+) = \max_i \{(\tilde{r}_{it}, \tilde{\alpha}_{it}) \mid c_j \in B\} \text{ or } \min_i \{(\tilde{r}_{it}, \tilde{\alpha}_{it}) \mid c_j \in B'\} \text{ and}$$

$$(r_t^-, \alpha_t^-) = \min_i \{(\tilde{r}_{it}, \tilde{\alpha}_{it}) \mid c_j \in B\} \text{ or } \max_i \{(\tilde{r}_{it}, \tilde{\alpha}_{it}) \mid c_j \in B'\}, \text{ where}$$

$i = 1, 2, \dots, m, t = 1, 2, \dots, k$ and B and B' are the benefit and cost criteria sets respectively.

Determining the distance of each alternative from the positive and negative ideal solutions for each stakeholder t as $(\xi_i^+, \eta_i^+) = \Delta_{S'} \left(\frac{1}{k} \sum_{t=1}^k \frac{(T_{S'} - 1)}{(T_S - 1)} \cdot (|\Delta_S^{-1}(\tilde{r}_{it}, \tilde{\alpha}_{it}) - (r_t^+, \alpha_t^+)|) \right)$

and $(\xi_i^-, \eta_i^-) = \Delta_{S'} \left(\frac{1}{k} \sum_{t=1}^k \frac{(T_{S'} - 1)}{(T_S - 1)} \cdot (|\Delta_S^{-1}(\tilde{r}_{it}, \tilde{\alpha}_{it}) - (r_t^-, \alpha_t^-)|) \right)$, where

$S' = \{s'_1, s'_2, \dots, s'_{t'}\}$ is the linguistic term set for the distances, T_S and $T_{S'}$ the cardinals of sets S and S' respectively.

Finally, calculating the relative closeness degree of each alternative from the positive ideal solution as

$$(\xi_i, \eta_i) = \Delta_{S'} \left(\left(\frac{\Delta_S^{-1}(\xi_i^-, \eta_i^-)}{\Delta_S^{-1}(\xi_i^+, \eta_i^+) + \Delta_S^{-1}(\xi_i^-, \eta_i^-)} \right) \cdot (T_S - 1) \right), \quad i = 1, 2, \dots, m \text{ and } T_S \text{ is the cardinal of set } S. \quad (8)$$



The results could have been displayed in the distance scale S' , but instead they are converted to the scale the stakeholders provided their answers in for clarity of results, needed in the next steps.

2.2.4 Consensus Measuring

MCDM methods allow to obtain a solution for a DM problem. In certain occasions, however, the solutions obtained do not satisfy all of the engaged stakeholders participating in the decision-making process. For this reason, Kacprzyk (1987) suggests measuring a realistic and "human-consistent" degree of consensus to calculate these differences, softening the concept of complete agreement by introducing the "soft" consensus degree (Kacprzyk, 1986; Kacprzyk and Fedrizzi, 1986; Kacprzyk and Fedrizzi, 1988). Kuncheva (1994) identifies five metrics for consensus measuring based on comparisons between the experts' evaluations, which capture either common ground among the answers or sources of disagreement (Bender and Simonovic, 1997). Many studies used such metrics to extract consensus level information from comparing the experts' preference data (Bryson, 1996; Herrera et al., 1996). However, Herrera-Viedma *et al.* (2002) argue that these methods can withhold information or underestimate consensus, since different evaluations may lead to similar solutions. To avoid this bias, they propose an alternative approach, which is based on comparing the rankings of the experts' assessments with a global solution instead of each other's preferences. Boroushaki and Malczewski (2010) adapted the model to integrate geographical information systems with MCDA, while Ben-Arieh and Chen (2006) also considered the degree of importance of each expert.

However, in this approach, alternatives with similar evaluations in the global solution may result in huge differences in the rankings, which will subsequently lead to exaggerations of dissimilarity, if only the rankings are taken into account. Here, we build on Herrera-Viedma *et al.* (2002) by applying a consensus measuring model that is similarly based on the comparison of a global solution with the experts' assessments but takes advantage of the 2-tuple TOPSIS evaluations provided by the distance function instead of the rankings. The model is described below:

The dissimilarity of each expert for each alternative $p_i(x_j)$ is calculated by comparing the distance between the result of the 2-tuple TOPSIS of that alternative in the experts' individual solution and in the collective one as follows:

$$p_i(x_j) = p(R^i, R^c)(x_j) = \left(\frac{|R_j^c - R_j^i|}{T - 1} \right)^b \quad (9)$$

$\in [0,1], b \geq 0$

where i stands for each expert, j stands for each alternative, b can be in the range of $(0, 1)$ to control the rigorousness of the model, R_j^c is the result of the 2-tuple TOPSIS of the alternative j in the group solution, R_j^i is the result of the 2-tuple TOPSIS of the alternative j in expert's i solution, and T is the cardinal of the linguistic term set, used to normalize the dissimilarity values. With this approach, the evaluation of the group solution and the expert is compared for each alternative instead of the positions in the ranking, enabling us to capture the full information provided by the stakeholders.

Next, we calculate the consensus degree of all experts on each alternative x_j using the following expression:

$$C(x_j) = 1 - \sum_{i=1}^m \frac{p_i(x_j)}{m} \quad (10)$$

where m stands for the total number of experts.

Finally, we calculate the consensus measure over the set of alternatives, called C_X :

$$C_X = \frac{\sum_{j=1}^k C(x_j) * R_j^c}{\sum_{j=1}^k R_j^c} \quad (11)$$



where k is the total number of alternatives. In the original model, the aggregation of the consensus degree of each alternative into the final consensus measure was performed by using the S-OWA OR LIKE operator (Yager and Filev, 1994). Through this process the set of alternatives was split in a set of solutions and a set of remaining alternatives, where the former is given an increased weight, leading to the dependence of the consensus measure on the choice of the OWA operator. To avoid this issue, in our approach, the aggregation is performed through a weighted average formula, where the evaluation of the 2-tuple TOPSIS of the global solution for each alternative is used as the weight of the consensus degree over this alternative.

Applying a similar approach with the consensus measure, the proximity of i -th expert to the global solution can be calculated:

$$P_X^i = \frac{\sum_{j=1}^k (1 - p_i(x_j)) * R_j^C}{\sum_{j=1}^k R_j^C} \quad (12)$$

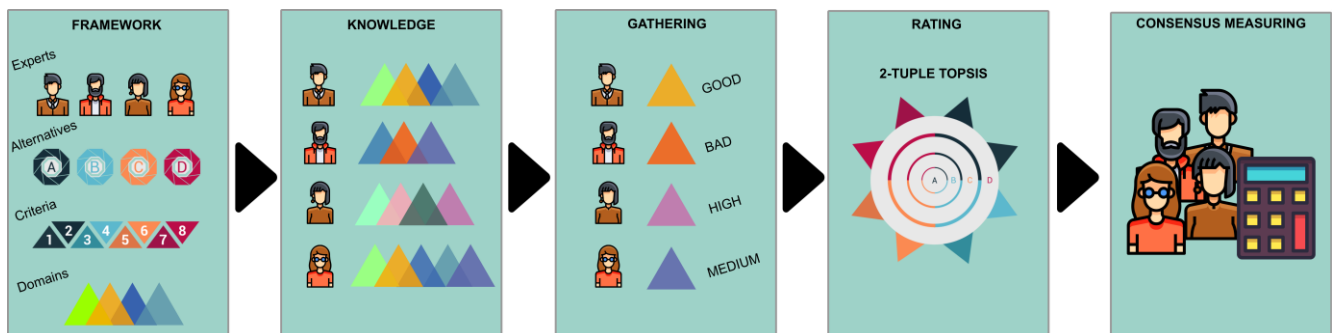


Figure 6: A group decision fuzzy tool in support of climate change policy making's (APOLLO) resolution scheme.

2.3 APOLLO

This section introduces a fuzzy MCDM group decision tool, APOLLO, to solve multicriteria problems under uncertainty, related to climate change and policy. First, we discuss the different steps that describe the resolution scheme of the introduced software, and then we present its architecture.

2.3.1 Resolution Scheme

APOLLO has been developed with the aim of solving LDM problems related to climate change issues, fully aligned with policy developments, such as the Paris Agreement and the Talanoa dialogue, as well as with emerging scientific paradigms in support of these developments (e.g., Doukas *et al.*, 2018; Weitzel *et al.*, 2019). Furthermore, due to the complexity and importance usually linked to these kinds of problems and in the aim of maximizing governance (of science, risks, and policy), our goal is to also provide solutions in which the majority of stakeholders (and stakeholder groups) participating in the decision process agree with one another. Hence, it is necessary to propose a specific LDM solving process that, on one hand, allows using MCDM methods in order to provide solutions for the decision problem and, on the other hand, guarantees that such solutions satisfy the largest part of the group of engaged individuals as much as possible, mitigating potential disagreements. APOLLO's resolution scheme is composed by different steps that are described in the following subsections (see Figure 6).

2.3.1.1 Problem definition (Framework)

This step allows defining the MCDM problem. Stakeholders, criteria, alternatives, and the expression domains that the stakeholders use to provide their preferences. In this application, we consider that stakeholders use linguistic expressions in order to facilitate the preference elicitation process, thus the expression domains are represented



by fuzzy linguistic term sets, the label numbers of which can be selected by the user/analyst.

2.3.1.2 Knowledge domain assignment (Knowledge)

Although linguistic expression domains are created in the previous step, it is essential to match these domains to each participating stakeholder. In doing so, several linguistic scales can be defined, each one tailored to the knowledge/preference of each engaged decision maker.

2.3.1.3 Preference elicitation (Gathering)

At this stage, stakeholders provide their assessments by using linguistic expressions. In this version, stakeholders may use expressions represented by single linguistic terms, such as *Good*, *Bad*, *High*, or *Very Low*.

2.3.1.4 Multi-criteria solution (Rating)

This phase carries out the resolution of the MCDM problem. This version of APOLLO uses the 2-tuple TOPSIS method to solve the defined MCDM problem by following the steps introduced in Section 2.2.3.

2.3.1.5 Consensus measuring

This step allows us to measure the consensus and proximity level of the solution found in the previous stage. APOLLO calculates consensus based on the model presented in Section 2.2.4

If desired, a consensus reaching process (CRP) (Labella et al., 2018; Rodríguez et al., 2018) can be applied to bring the experts' assessments closer with one another and achieve an acceptable level of agreement in the group (consensus control) (Saint and Lawson, 1994). The initial experts' preferences would then be modified through iterative rounds and used to obtain a consensual solution for the problem (feedback process), to conclude the CRP cycle (Palomares et al., 2014).

2.3.2 Architecture

APOLLO has been developed using an Eclipse Rich Client Platform (RCP) developed by IBM and created for building desktop applications with richer functionality. The main advantage of this technology is the capability to extend, modify, and reuse the applications easily in different operative systems thanks to the components-based architecture. Components or also so-called plugins are small pieces of software interconnected with each other that compose the whole RCP application. The use of plugins allows connecting them to other RCP applications and increase their functionality without the need to have a full understanding of how the application works. APOLLO is composed by several plugins classified into different categories:

User interface: the plugins which belong to this category are used to visualize the user interface of the application (buttons, plots, etc.).

MCDM: the plugins included in this category represent all the information related with the MCDM problems and their resolution. Here we can find plugins to represent the different elements of the problems, for instance, experts, alternatives, criteria, or expressions domains. In addition, the MCDM models to solve the problem are also classified in this category. For this version of APOLLO, the 2-tuple TOPSIS is the selected MCDM method but others can be added.

Consensus: APOLLO solves MCDM problems by using MCDM methods but also incorporates plugins that measure the consensus level. In this way, the selection of the best alternatives is accompanied by a consensus level to obtain a more robust solution.



The APOLLO's architecture is represented in Figure 7.

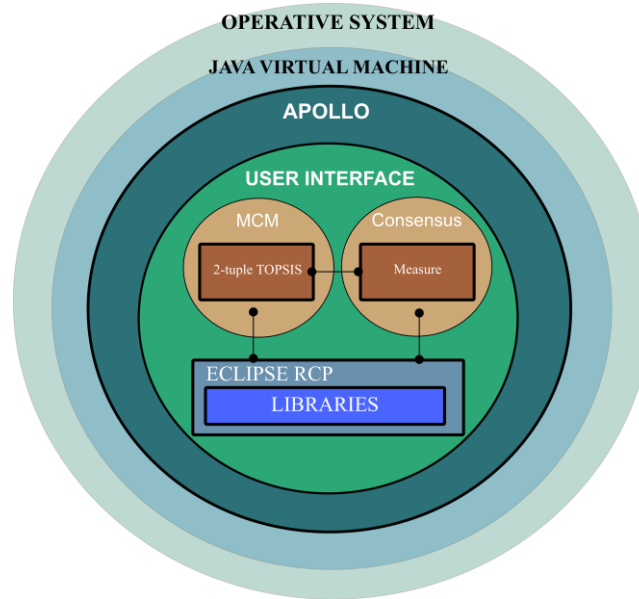


Figure 7: A group decision fuzzy tool in support of climate change policy making's (APOLLO) architecture.

2.4 Case Study

In order to show the usefulness of APOLLO, we use it to solve a real MCDM problem related to the decarbonization of iron and steel production in Austria.

2.4.1 Background Information

Iron and steel is considered an energy-intensive industry (Gerres et al., 2019), accounting for 4%–7% of the industrial CO₂ emissions in the EU (Pardo and Moya, 2013), while in 2017 contributed almost 16% of the industrial and 1.5% of the total GHG emissions (UNFCCC, 2017). In Austria, these shares are even higher, with iron and steel producing 65% of the industrial and 14% of the total GHG emissions in 2017, according to the UNFCCC Inventory, highlighting the importance of decarbonization of the sector as part of the country's emissions mitigation targets. As seen in Figure 8, the emissions of the sector do not only represent a high share, but they steadily increased through time, despite the fluctuation of the total emissions and the obvious decrease from the 2005 level, even rebounding from the decrease caused by the economic crisis in 2008.

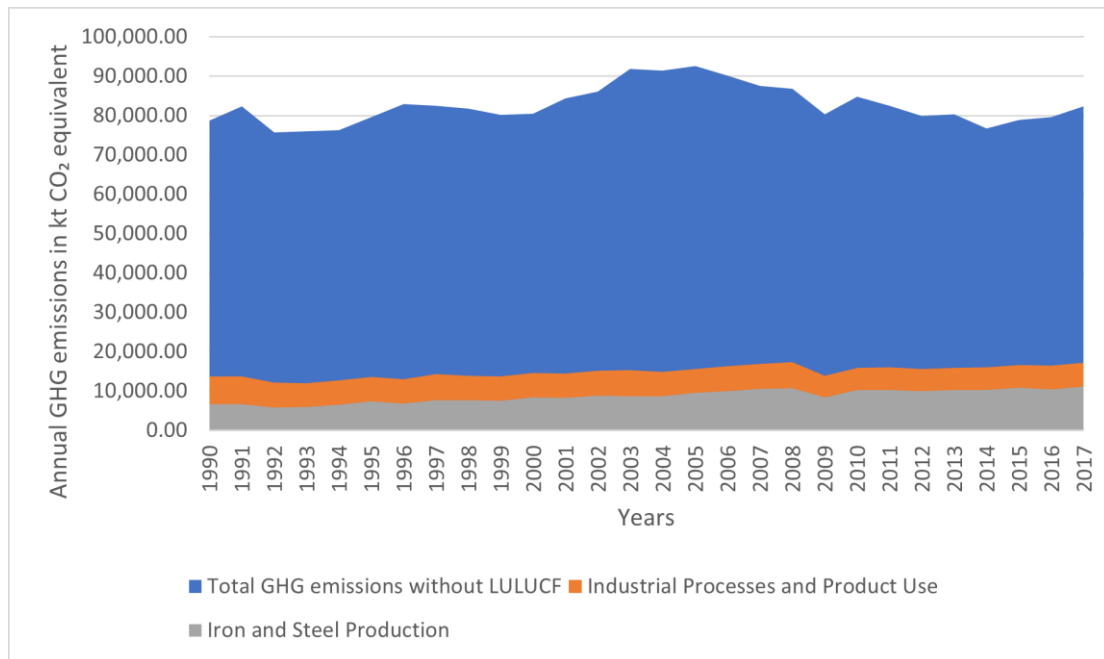


Figure 8: Total, Industrial and Iron and Steel greenhouse gas (GHG) emissions in Austria.

Source: UNFCCC (2017), own elaboration.

Part of the intensity of the iron and steel industry can be attributed to technological reasons for the production process. The dominant process for primary production is the energy-intensive Blast Furnace/Basic Oxygen Furnace route (BF-BOF), where iron ores are reduced to iron, using coke as a reducing agent (Arens et al., 2017). The secondary steelmaking process is the Electric Arc Furnace (EAF) route which produces steel from recycled scrap, requiring a third of the energy needed in the BF/BOF route (Arens et al., 2012).

In Austria the majority of iron and steel produced is based on the BF/BOF route (Mousa et al., 2016). The dominance of BF-BOF compared to other European regions makes Austria one of the most sensitive countries to CO₂ prices in the EU (Bachner et al., 2020). Therefore, radical innovations need to be implemented in the sector to be able to adapt to deep decarbonization strategies (Lechtenböhrer et al., 2016), since simple solutions like the Best Available Techniques have limitations (Fischedick et al., 2014). Such cutting-edge technologies include hydrogen-based production that could drastically reduce emissions intertwined with renewable energy production (Vogl et al., 2018). However, actors are usually skeptical about large-scale transitions out of fear of the cost and risk associated with the adoption of radical innovations (Wesseling et al., 2017). These fears need to be considered during the development of policies, since actively engaging stakeholders in the process could provide valuable insights on their point of view towards a “greener” industry (Bachner et al., 2020). This background constitutes the motivation of our study, showcasing why the Austrian iron and steel sector was selected as a case study.

2.4.2 Alternatives and Evaluation Criteria

In order to facilitate the transition pathway of the Austrian iron and steel industry, risks associated with this transition are prioritized through the engagement of stakeholders in an iterative co-creative process that will provide insights into what key actors of the system fear the most.

In our study, we focus on risks that cut across a number of dimensions, such as energy infrastructure, the political and institutional status, environmental issues related to end-use acceptance, financial markets, and technological innovation (Table 11), adapting from the clustering of risks performed in Bachner *et al.* (2020) and Wolking *et al.* (2019).



Most risks are intertwined with the need to achieve wide-scale diffusion of centralized and decentralized renewable energy sources, in order to support green hydrogen production to be used in industry. This is evident in the infrastructure cluster, where the challenges posed to the stability of the grid due to the increase of renewable generation (Wang and Blaabjerg, 2018) and storage limitations are analyzed. Importance is also given to the institutional level to manage policy-related risks and financially support technological innovation that will pave the way for a just transition that will be acceptable by the society despite lock-ins in the dominant regimes (Nikas et al., 2020b). The list of risks is not exhaustive, given the multiplicity of the various risks that can hinder the envisaged transition pathway, but was considered by the stakeholders to be representative of the risks decelerating the energy transition.

The identified risks are evaluated against four criteria: (a) their likelihood to manifest; (b) the level of the perceived impact that they can have on the climate mitigation policy framework; (c) lack of state/societal capacity to mitigate them; and (d) level of concern.

Table 11: Risk classification and evaluation criteria.

Group	Alternatives	Evaluation Criteria
<i>Energy infrastructure</i>	R1. Lack of transparency	C1. Likelihood to manifest
	R2. Grid Instability	C2. Impact on policy
	R3. Lack of storage capacity	C3. Lack of mitigation capacity
	R4. Complicated investment procedures	C4. Level of concern
<i>Environmental/acceptability</i>	R5. Social injustices	
	R6. Insufficient consideration of lifestyles	
	R7. Resource consumption overlooked	
	R8. Social resistance against investments	
	R9. Lack of investment framework	
<i>Political/institutional framework</i>	R10. Non-evidence-based regulatory framework	
	R11. Short-sighted energy/climate planning	
	R12. Market distortions	
	R13. Lack of political leadership	
	R14. Fluctuation of CO ₂ prices	
<i>Financial</i>	R15. Non-coordination at the EU level	
	R16. Uneven distribution of transition costs	
	R17. Non-engaging/unstable markets	
	R18. Narrow consideration of competition	
	R19. Price risks due to new technologies	
<i>Innovation and technology</i>	R20. Limited funding capacity	
	R21. Bad timing of new industry technologies	

	R22. Technological lock-ins in iron and steel	
	R23. Little integration across multiple sectors	
	R24. Lack of information flows	
	R25. Imperfect picture of transition	

2.4.3 Stakeholder Input

Based on the stakeholder dialogue format described in (Bachner et al., 2020), ten stakeholders (E1...E10) from the Austrian iron and steel sector were engaged in the process through bilateral interviews and workshops.

Initially the stakeholders were asked to assess the importance of the four evaluation criteria, using a 5-term linguistic scale {None (N), Low (L), Medium (M), High (H), Extreme (E)}. The evaluations are presented in Figure 9.

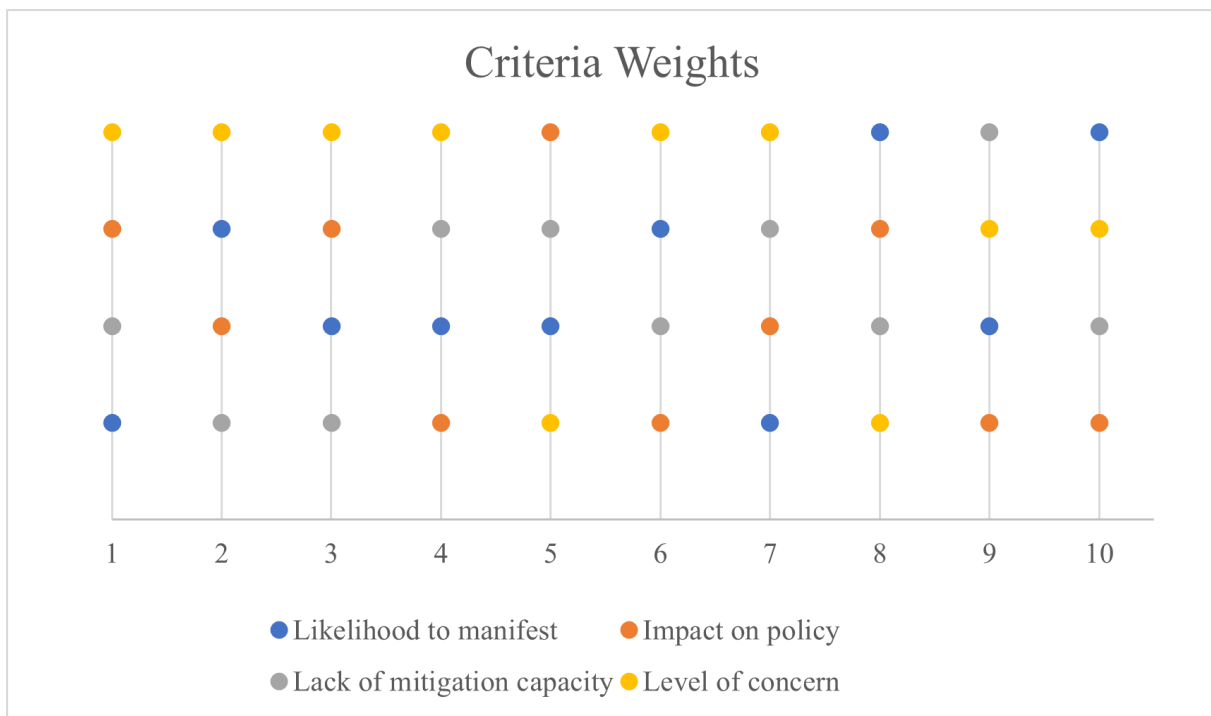


Figure 9: Criteria weights assigned by the ten stakeholders.

Despite significant variance in the responses, the majority of the stakeholders consider the level of concern over each risk to be an important evaluation factor, with six of them weighting concern with extreme importance, two with high importance and only two considered it of low importance.

In the next step, stakeholders were asked to evaluate each alternative/risk against these criteria answering to the questions in Table 12.

Table 12: Questions asked to the stakeholders for the evaluation of each risk against the four criteria.

Evaluation Criteria	Question	Linguistic Scale of the Answers
C1. Likelihood to manifest	What is the likelihood for the following risks to occur?	{Very unlikely, Unlikely, As likely as not, Likely, Very Likely}

<i>C2. Impact on policy</i>	If the following risks were to occur, what would be the extent of their impact?	{Limited, Considerable, Great, Extreme, Catastrophic}
<i>C3. Lack of mitigation capacity</i>	If the following risk were to occur, how would you estimate the capacity of relevant actors to mitigate them?	{None, Low, Medium, High, Extreme}
<i>C4. Level of concern</i>	How worried are you about following risks?	{Not worried, A little worried, Somewhat worried, Very worried, Extremely worried}

The responses of the stakeholders are then converted in the same scale used for the weights, {None, Low, Medium, High, Extreme}, while the answers for Criteria 3 are appropriately adjusted to reflect the lack of capacity.

Based on the adjusted answers, the distribution of the assessments for each term of the linguistic scale is presented in Figure 10. Most of the experts' answers are concentrated around medium and neighboring terms.

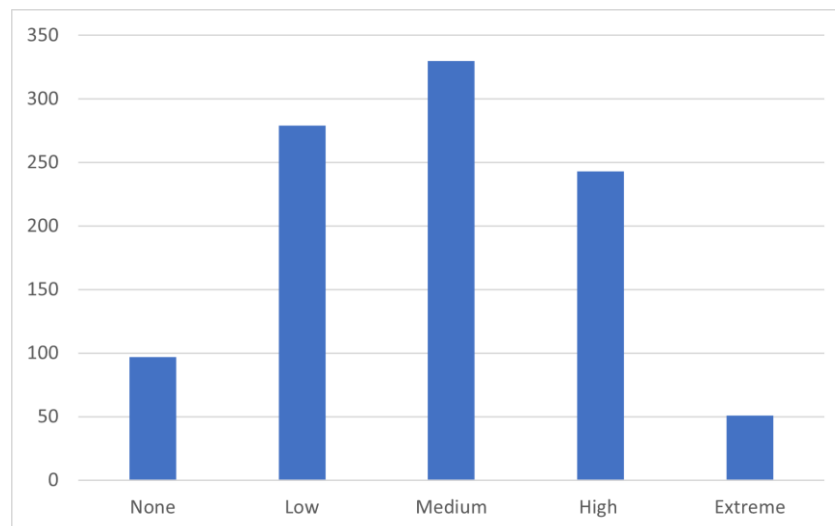


Figure 10: Distribution of the experts' assessments for each linguistic term.

However, the experts seemed more reluctant to use the higher scales, since "none" received almost double the answers of "extreme," while "low" received a higher number of responses than "high." This indicates that the experts showcased a moderate behavior being less willing to use stricter terms.

2.4.4 Results

2.4.4.1 Experts' individual solutions

After initial assessments, the 2-tuple TOPSIS model described in Section 2.2.3 is applied to the answers of each expert independently, in order to calculate the rank and the score of each alternative. In Table 13, the assessments and results of 2-tuple TOPSIS are presented for Expert 1; a similar process is followed for the rest of the experts.

Table 13: Assessments and results for Expert 1.

C1	C2	C3	C4	Results
----	----	----	----	---------

Weights	L	H	M	E	
R1	M	L	L	L	0.92
R2	E	H	L	M	2.77
R3	H	M	N	M	1.85
R4	H	H	M	M	2.92
R5	H	L	N	L	0.77
R6	H	L	N	L	0.77
R7	M	L	L	L	0.92
R8	H	H	L	M	2.62
R9	E	H	L	H	3.38
R10	M	M	M	M	2.31
R11	H	L	M	M	2.00
R12	L	N	L	L	0.31
R13	H	M	L	H	2.77
R14	H	M	M	M	2.46
R15	H	H	L	H	3.23
R16	H	M	M	M	2.46
R17	H	M	M	M	2.46
R18	H	M	H	M	2.77
R19	H	L	L	M	1.69
R20	M	M	M	M	2.31
R21	H	H	L	M	2.62
R22	M	L	L	L	0.92
R23	H	M	L	H	2.77
R24	E	H	M	M	3.08
R25	H	M	M	M	2.46

In Figure 11, the results of the 2-tuple TOPSIS for each expert are presented. Despite general similarities among the results, significant differences between individual choices exist. For example, Expert 4 considers alternative R22 “Lock-ins due to capacity mechanisms” to be the most important risk with an evaluation of (Extreme, -0.19), while Expert 3 considers it to be the risk with the lowest importance and a score of (Low, -0.45). These differences illustrate that the stakeholder pool is well diversified, mitigating possible biases in the collective solution.



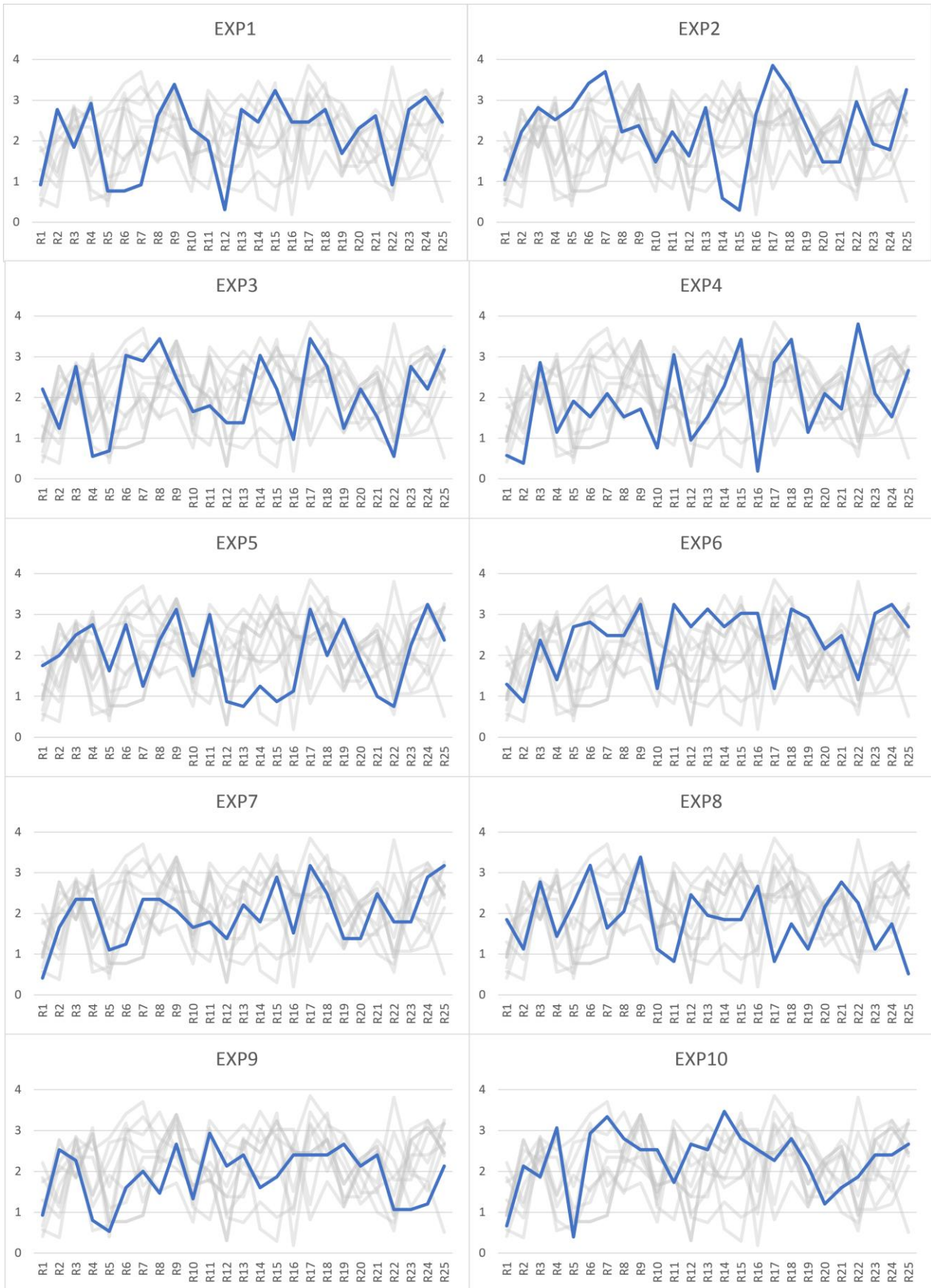


Figure 11: Results of 2-tuple Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) for each individual expert.



2.4.4.2 Collective solution

The results for each individual expert are used to create the new matrix to be used to calculate the collective solution of the group. In that case, the experts will play the role of equally weighted criteria. The 2-tuple TOPSIS is then run again to the new matrix (Table 14) to assess the importance of each alternative as a collective group.

Table 14: New decision matrix for the collective solution.

	E1	E2	E3	E4	E5	E6	E7	E8	E9	E10
R1	0.92	1.04	2.21	0.57	1.75	1.30	0.41	1.85	0.93	0.67
R2	2.77	2.22	1.24	0.38	2.00	0.86	1.66	1.13	2.53	2.13
R3	1.85	2.81	2.76	2.86	2.50	2.38	2.34	2.77	2.27	1.87
R4	2.92	2.52	0.55	1.14	2.75	1.41	2.34	1.44	0.80	3.07
R5	0.77	2.81	0.69	1.90	1.63	2.70	1.10	2.26	0.53	0.40
R6	0.77	3.41	3.03	1.52	2.75	2.81	1.24	3.18	1.60	2.93
R7	0.92	3.70	2.90	2.10	1.25	2.49	2.34	1.64	2.00	3.33
R8	2.62	2.22	3.45	1.52	2.38	2.49	2.34	2.05	1.47	2.80
R9	3.38	2.37	2.48	1.71	3.13	3.24	2.07	3.38	2.67	2.53
R10	2.31	1.48	1.66	0.76	1.50	1.19	1.66	1.13	1.33	2.53
R11	2.00	2.22	1.79	3.05	3.00	3.24	1.79	0.82	2.93	1.73
R12	0.31	1.63	1.38	0.95	0.88	2.70	1.38	2.46	2.13	2.67
R13	2.77	2.81	1.38	1.52	0.75	3.14	2.21	1.95	2.40	2.53
R14	2.46	0.59	3.03	2.29	1.25	2.70	1.79	1.85	1.60	3.47
R15	3.23	0.30	2.21	3.43	0.88	3.03	2.90	1.85	1.87	2.80
R16	2.46	2.67	0.97	0.19	1.13	3.03	1.52	2.67	2.40	2.53
R17	2.46	3.85	3.45	2.86	3.13	1.19	3.17	0.82	2.40	2.27
R18	2.77	3.26	2.76	3.43	2.00	3.14	2.48	1.74	2.40	2.80
R19	1.69	2.37	1.24	1.14	2.88	2.92	1.38	1.13	2.67	2.13
R20	2.31	1.48	2.21	2.10	1.88	2.16	1.38	2.15	2.13	1.20
R21	2.62	1.48	1.52	1.71	1.00	2.49	2.48	2.77	2.40	1.60
R22	0.92	2.96	0.55	3.81	0.75	1.41	1.79	2.26	1.07	1.87
R23	2.77	1.93	2.76	2.10	2.25	3.03	1.79	1.13	1.07	2.40
R24	3.08	1.78	2.21	1.52	3.25	3.24	2.90	1.74	1.20	2.40
R25	2.46	3.26	3.17	2.67	2.38	2.70	3.17	0.51	2.13	2.67



The ranking of the alternatives according to the second 2-tuple TOPSIS are presented in Table 15. Out of 25 risks examined, 8 were evaluated in the scale of "High," the majority fluctuates around medium values, while only 3 received a "Low" score. Despite the moderate answers of the experts who avoided higher rates as discussed in Section 2.4.3, the percentage of high-importance risks indicate a broad concern of the stakeholders for the envisaged transition. Specifically, the risks with the higher importance with almost identical scores are the "Lack of investment framework" and the "Narrow consideration of competition." The performance of these risks indicative a request from the experts to the state to develop a coherent strategy that will address the high investments costs of the transition and deal with competitiveness issues especially from major exporting countries, like China, that can offer cheaper commodities due to lower energy efficiency investments (Mao and He, 2018) and the slower development of a universal carbon market (Weng and Xu, 2018). This is further established by the high performance of the risk "Imperfect picture of transition," leading to the conclusion that the design of a clear transitional pathway that addresses the aforementioned concerns is vital.

Table 15: Final ranking of risks based on the collective solution.

Ranking	Alternative	2-tuple TOPSIS Linguistic
1	R9	(High, 0.04)
2	R18	(High, 0.02)
3	R17	(High, -0.15)
4	R25	(High, -0.21)
5	R3	(High, -0.31)
6	R8	(High, -0.46)
7	R24	(High, -0.46)
8	R6	(High, -0.47)
9	R7	(Medium, 0.45)
10	R11	(Medium, 0.44)
11	R15	(Medium, 0.42)
12	R13	(Medium, 0.29)
13	R23	(Medium, 0.25)
14	R14	(Medium, 0.23)
15	R21s	(Medium, 0.09)
16	R16	(Medium, 0.02)
17	R19	(Medium, 0.02)
18	R20	(Medium, -0.05)
19	R4	(Medium, -0.06)
20	R22	(Medium, -0.27)
21	R2	(Medium, -0.34)



22	R12	(Medium, -0.40)
23	R10	(Low, 0.47)
24	R5	(Low, 0.37)
25	R1	(Low, -0.06)

In Figure 12, the results are presented following the allocation of the risks to the groups described in Table 11.

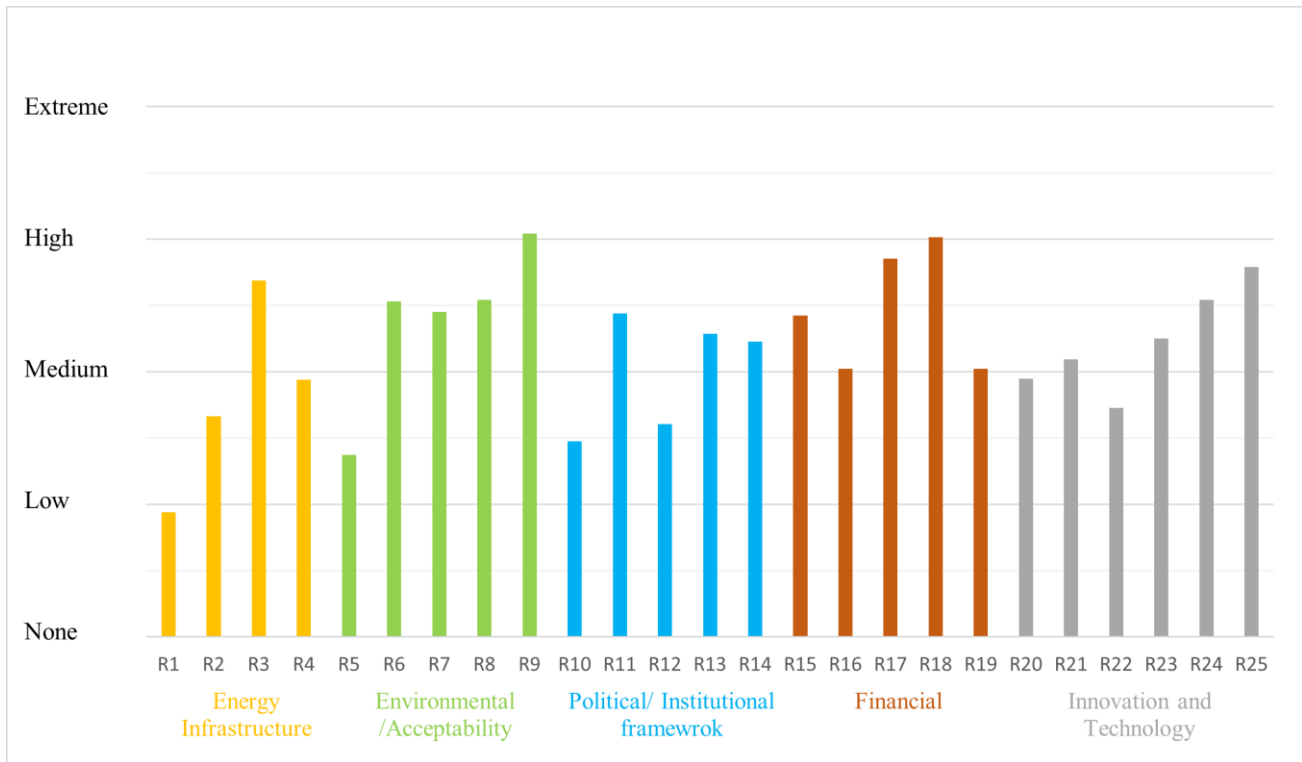


Figure 12: Clustered results of the collective solution.

From an infrastructural perspective, the “Lack of storage capacity” is considered the most important risk, since it is associated with the ability of the grid to maintain high shares of renewable energy productions. The procedures for investments in infrastructure and the stability of the grid perform slightly below medium, showcasing that, if the storage capacity is improved, the stakeholders are confident about the efficiency of the infrastructure economically and technologically. The transparency of the infrastructural procedures concerns stakeholders the least, not only in the same cluster, but over the complete set of alternatives, which indicates that, if the financial, technological, and social aspects of the transition are determined, it will be easier to adapt to procedural requirements.

In the environmental cluster, apart from the lack of an investment framework, consumption of resources received attention, since the activities of the iron and steel industry commence from the iron ores, as discussed in Section 2.4.1. Significant concern also exists over the behavior of the end-users both through “Insufficient consideration of lifestyles” and “Social resistance against investments.” Interestingly, however, the risk of “Social Injustices” that could arise in a transition and affect the local communities received low importance, ending in the second to last place. Despite being concerned over the resistance they may face over the transition of the sector, stakeholders

lack the understanding or the will to address the primal reasons that can cause resistance from the community. The importance of understanding the negative impacts, such as job losses, in the process of developing the plan requested by the stakeholders should be a key aspect of a “just transition” (Newell and Mulvaney, 2013), built on a social dialogue that includes all interested parties (Nikas et al., 2018a).

Regarding the political/institutional framework, the balanced results indicate that there are some concerns over “Fluctuation of CO₂ prices” and the “Lack of political leadership” that should not be neglected, but they do not raise immediate threats. On this cluster “Short-sighted energy/climate planning” seems to be the most important risk, with the stakeholders fearing that the current plans lack long-term vision. On the other hand, the stakeholders believe that “Market distortions” and the “Non-evidence-based regulatory framework” do not constitute significant risks, placing them in the lower positions of the ranking.

Having discussed the “Narrow consideration of competition” which has been identified by stakeholders as one of the top two risks, “Nonengaging/unstable markets” also received a comparably high score, establishing the financial cluster as an important factor of the risks associated with the transition. Industries like iron and steel that provide supplies for other major industries are bound to the stability of these markets and especially their reluctance of adopting cleaner solutions (Janipour et al., 2020). This is associated with the “Price risks due to new technologies,” since low-carbon products may cause higher prices, which may lead to “Uneven distribution of transition costs,” two risks that both received medium importance. Financial coordination among the EU countries is also an aspect identified as fairly important by the stakeholders to outbalance the competitive advantage of countries like China, as previously discussed.

In the innovation and technology group, we discussed the importance of developing a clear picture of the envisaged transition, with the clustered results also indicating this picture should incorporate effective information flow channels. In the innovation system of iron and steel, these networks will allow cooperation in the distribution of knowledge and implementation of innovative projects (Esparcia, 2014). “Technological lock-ins in iron and steel,” “Limited funding capacity,” “Bad timing of new industry technologies,” and “Little integration across multiple sectors” are risks of medium importance that should be taken into account, as part of this broader strategy.

2.4.4.3 Consensus level

To calculate the consensus level of the experts compared to the global solution we use the methodology proposed in Section 2.2.4 and then compare the results with the original method proposed by Herrera-Viedma et al. (2002). The results are shown in Table 16 and Figure 13, where for both models a value of $b=1$ was used, since only one round of stakeholder engagement took place so there was no need to add rigorosity on the assessments. Specifically, for the methodology of Herrera-Viedma et al. (2002) the OWA operator was set to $\beta=0.8$ in the middle of the proposed interval for the variable, the ties in the rankings were not broken, while it is presumed that the set of solutions consist of the alternative ranked first.

Table 16: Consensus measure and proximity levels of individual solutions compared to the collective.

		Herrera-Viedma <i>et al.</i> (2002)	Proposed Methodology
Proximity level	EXP1	94.4	84.4
	EXP2	58.3	83.1
	EXP3	66.3	85.6
	EXP4	55.9	82.8
	EXP5	91.5	84.3



	EXP6	94.9	86.3
	EXP7	60.1	89.1
	EXP8	92.9	79.4
	EXP9	90.8	84.6
	EXP10	64.7	86.9
Consensus measure		77.0	84.6

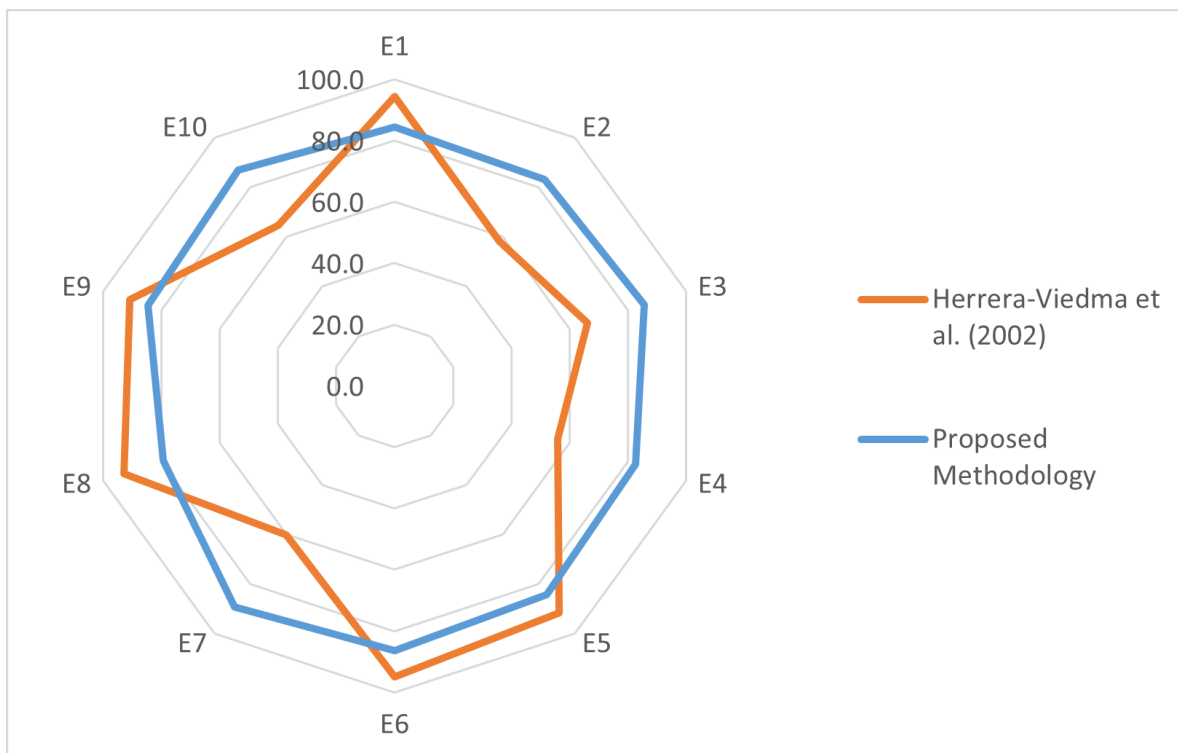


Figure 13: Proximity level of each expert.

From the results, it is showcased that the proposed consensus model is less rigorous than the initial methodology both in terms of the total consensus level and the variance of the proximity of each expert.

Our method results to a consensus level of 84.6% compared to the 77% level of the initial model. The main reason for this difference derives from the way Herrera-Viedma *et al.* calculate the dissimilarity, which is based on the position in the rankings of the collective and the experts' solutions, whereas in the proposed method the scores of TOPSIS are used. In this case study, many alternatives were concentrated around the "medium" scale. For that reason, calculating dissimilarity simply based on the position can exaggerate the existing differences. For example, as we can see on Table 15, the positions from 6 to 11 in the collective solution are separated by only a 0.12 difference in the five-term scale. Therefore, no strong preference can be deduced, rather than merely a tendency. However, the 5-place distance between the rankings of these risks in a total of 25 alternatives can strongly increase the dissimilarity level. This exaggeration is mitigated in the proposed methodology, since the 2-tuple TOPSIS results are used, taking into consideration the exact distance in the assessment of the individual expert and the collective solution, thus using all the available information to calculate the consensus level.

For the proximity levels of each expert to the collective solution, the results show less variance in the proposed

methodology compared to the initial partially due to the exaggeration explained above, but also because of the choice and use of the OWA operator, a bias already recognized by Herrera-Viedma *et al.* Specifically, by using the value of $\beta=0.8$ the alternatives that are considered part of the solution set are given a dominant weight compared to the rest. In this case, we considered the set of solutions to include only the first alternative in the collective solution. However, the argument about the bias can be valid even if more alternatives were included in the solution set, since the exaggeration would simply include a limited number of alternatives rather than the complete set. In MCDM methods based on ranking in the energy sector, valuable insights can be gained even by examining the patterns on the last places (Ribeiro *et al.*, 2013). To limit the dependence on the first alternatives, we used the scores of 2-tuple TOPSIS as the weights of the distances placing more importance on the risks ranked higher, while not undercalculating the outputs from the lower positions. For example, Expert 8 performed poorly on the majority of the alternatives both based on our methodology and the calculation of the differences excluding the top alternative for the methodology of Herrera-Viedma *et al.* However, because the expert ranked "R9" first similarly with the collective solution, he received a very high proximity level on the latter method, whereas in our case matching the first solution managed to keep them to adequate proximity levels around 80%, but they were also punished for their failure to assess the rest of the alternatives appropriately, receiving a smaller percentage than the rest of the experts. The opposite phenomenon was observed in the case of Expert 7 who performed very well in most alternatives, but miscalculated the first alternative by rating it with a medium score, leading to an exaggeration of their consensus level by the method of Herrera-Viedma *et al.*

As seen in Figure 10 the experts collectively showed a moderate behavior toward lower grades. For example, Expert 9's solutions show a low deviation with most of them slightly fluctuating around medium values, as seen in Figure 11. However, both consensus models gave the expert a high consensus percentage due to the fact that many alternatives in the collective solutions were also rated around medium. Both models need to consider this bias toward moderate behavior and not punish experts that are more willing to use the full extent of the linguistic scale to better express the existing differences among the alternatives.

2.5 Conclusions

In this research, APOLLO, a fuzzy decision support tool is presented to deal with MCDM problems in climate change and policy issues. Stakeholder engagement processes are enabled by using linguistic variables which are more similar to the way experts think. Therefore, it is easier for them to provide the initial feedback and understand the final results derived by the tool. On the first stage, APOLLO uses an adaptation of the 2-tuple TOPSIS (Sohaib *et al.*, 2019) to analyze the initial assessments and calculate the ranking and the evaluations of the alternatives for each expert independently. These evaluations are then used as input of the next 2-tuple TOPSIS calculation to find the collective solution of the group of experts (Martínez *et al.*, 2015).

However, the assessments of the experts may include significant dissimilarities, which threaten the acceptance of the final solution. To increase robustness of the solution, APOLLO incorporates a new consensus measuring model that builds on Herrera-Viedma *et al.* (2002). The contribution of the model lies on the fact that it uses the 2-tuple TOPSIS evaluations to weight the distances between the experts and the collective solution. From that perspective, each alternative is given the necessary importance for the calculation of consensus and proximity, limiting rigorous assessments.

The added value of APOLLO lies in it constituting a complete tool to perform risk assessments and solve broader problems of DM related to sustainability and decarbonization policies, as its features are tailored to the specificities of the domain (in terms of types of alternatives and criteria, need for large number of stakeholders, and requirements for socially just action driven by consensus). The tool provides robust solutions through measuring



consensus among experts, and results that are comprehensible to all audiences and thus all stakeholder groups, making it easier for them to trust the analysis and convert findings into concrete actions.

The tool and the proposed framework are used in an Austrian case study, where stakeholders evaluate the importance of potential risks threatening the low-carbon transition of the iron and steel industry.

We showcase that despite the generally moderate initial answers provided by the stakeholders, many risks received a final evaluation of “high” based on the 5-scale term used for in linguistic model. This indicates that there is a broad concern over the sustainable transition of the sector. Experts agreed with a consensus level of 85% that the most important risks threatening the transition refer to the “Lack of investment framework” and the “Narrow consideration of competition,” closely followed by the “Nonengaging/unstable markets” and the “Imperfect picture of the transition.” These results can be interpreted as a plea from the experts to policymakers to create a coherent and clear transformational strategy that provides financial resources toward low-carbon technologies that are associated with increased shares of RES production, while also dealing with competition from emerging powerhouses. Regarding the system’s ability to manage the high penetration of RES, storage capacity is another risk evaluated as important from the experts.

In our study, a key limitation was that the experts evaluated the alternatives only once, which eliminated the possibility to perform a complete CRP, by providing them with feedback to alter their initial assessments. Therefore, APOLLO can be enhanced to incorporate a CRP cycle (Palomares et al., 2014), which can be tested in a multiple-round stakeholder engagement case study to achieve a higher level of agreement in the group (Saint and Lawson, 1994). As part of consensus measuring, the moderate behavior should be formally examined, since current models may punish an expert that deviates from median values. However, such an expert can provide insights along the entire scale used, instead of fluctuating around median values. APOLLO can also be coupled with evolutionary approaches like the “multi-level perspective” (Geels, 2002) to create a holistic framework that captures both the qualitative aspects of innovation in a transition and quantitative multi-criteria risk assessment.



3 Towards sustainable development and climate co-governance: a multicriteria perspective

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3.1. Introduction

In 2000, the UN held the Millennium Summit to encourage world leaders to commit to fulfilling a set of eight targets known as the Millennium Development Goals (MDGs) until 2015 (UN, 2000). These targets placed significant weight on alleviating extreme poverty in multiple dimensions that include environmental sustainability (Sachs and McArthur, 2005) and were generally considered an important step to monitoring socio-economic growth especially for developing countries (Easterly, 2009), while also engaging NGOs and citizens (Brinkerhoff et al., 2007) in the process. The observed progress towards the targets (Sachs, 2012) led world leaders to extend the MDGs for the next 15-year period (Griggs et al., 2013) by enhancing the targets until 2030, paving the way for the adoption of the Sustainable Development Goals (SDGs) in 2015, in parallel with the Paris Agreement. As part of the Agenda for Sustainable Development, the SDGs constituted a set of seventeen interconnected goals (Nilsson et al., 2016) with a broad range of targets that represent multiple sustainability dimensions, including land and water life preservation, clean energy, and socio-political goals. Climate action (SDG 13) has been found to have strong interlinkages with other SDGs (Köberle et al., 2020), showcasing that SDGs and the Paris Agreement are inseparable, since the pathway towards a "well-below" 2°C affects, and is affected by, different SDG targets (Nerini et al., 2018b).

Despite the undoubted value of SDGs in studying pathways and roadmaps to sustainability (Fuss et al., 2016; Roe et al., 2019), policymakers at the country level are still hesitant on their efforts to pursue these goals due to lack of clear understanding on how to translate the global targets in their national and local contexts (Bryan et al., 2019). On the other hand, it has been found that SDGs can be adequately assessed with climate policy assessment tools (Grubler et al., 2018), including integrated assessment models (IAMs) or climate-economy and energy systems models (Nikas et al., 2019a). The representation of SDGs in IAMs was thoroughly examined by van Soest et al. (2019), who argued that most goals are only partially represented through some of their sub-goals/indicators. This is because these sub-goals are not always useful or meaningful in terms of mitigation analysis and fall outside modelling capabilities. For example, Fujimori et al., (2019) highlight the importance of combating climate change (SDG 13) in connection with SDG 2 due to trade-offs between climate change mitigation and food security, via the "people at risk of hunger" metric, i.e. a subset of the broader "food security" notion. Similarly, Iyer et al., (2018) limited the analysis on certain SDG subsets to study the impacts of nationally determined contributions (NDCs) on SDGs using the GCAM model, using air quality, energy access, energy security, food security, and ocean health as proxies for measuring SDGs 3, 7, 2 and 14 respectively. On the other hand, Luderer et al. (2019) represented air quality using a more diverse set of metrics, including particular matter formation and ionising radiation, which is relevant in scenarios with increased nuclear power. McCollum et al. (2018b) in a model intercomparison exercise studied SDGs 2, 3, 4, 6, 7 in line with the Paris Agreement goals. Table 17 presents recent modelling studies that discuss SDG implications from climate change mitigation policies.



Table 17: Recent modelling studies that discuss implications on SDGs from mitigation policies

Study	SDG1	SDG2	SDG3	SDG4	SDG5	SDG6	SDG7	SDG8	SDG9	SDG10	SDG11	SDG12	SDG13	SDG14	SDG15	SDG16	SDG17
Luderer et al., 2019			√			√						√		√	√		
von Stechow et al., 2016		√	√				√	√	√			√	√	√			
Fujimori et al., 2019		√											√				
Doelman et al., 2020		√											√				
Vandyck et al., 2018		√	√				√						√		√		
Gil and Bernardo, 2020							√	√					√				
van der Zwann et al., 2018	√						√	√					√				
van Soest et al., 2019	√	√	√	√	√	√	√	√	√	√	√	√	√	√	√	√	√
Rosenzweig et al., 2017		√	√														
Parkinson et al., 2019						√							√				
Ribas et al., 2017							√										
Ribas et al., 2019	√	√	√	√	√	√	√	√		√							



McCollum et al., 2018a	√	√	√	√	√	√	√	√	√	√	√	√	√	√	√	√	√
Roe et al., 2019		√				√						√		√	√		
Dooley et al., 2018		√											√		√		
Zhou et al., 2020		√	√			√	√										
Michaels and Wirths, 2020														√	√		
Dalla Longa and van der Zwaan, 2017							√				√		√				
McCollum et al., 2018b		√	√	√		√	√						√				
Taliotis et al., 2020							√						√				
Wachsmuth et al., 2019			√														
Fuhrman et al., 2019			√							√							
Lucas et al., 2019		√	√	√		√	√						√				
Byers et al., 2018	√	√				√	√						√		√		
Jakob et al., 2019		√	√	√													



Godinez-Zamora et al., 2020		√											√	√		
Liu et al., 2019		√	√				√						√		√	
Iyer et al., 2018		√	√				√						√			
van der Zwaan et al., 2019							√						√			
van de Ven et al., 2019			√				√						√			
Johnson et al., 2019						√										
Portugal-Pereira et al., 2018			√								√					
Humpenöder et al., 2018		√					√						√	√	√	
Doelman et al., 2019		√											√			
Garcia-Casals et al., 2019								√								
Fujimori et al., 2020		√	√			√	√	√	√			√			√	
Capellán-Pérez, 2020							√									
Rafaj et al., 2018			√				√				√		√			



Gil et al., 2019	√	√												√	√	√		
Fuss et al., 2016	√	√					√								√	√		
Haga et al., 2020							√							√		√		
Tatarewicz et al., 2019							√							√				
Kearney, 2019														√				
Dioha M. Et al., 2020											√							
O'neil et al., 2020				√														
Lanati et al., 2019							√											
Dagnachew et al., 2018							√											

Although these state-of-the-art studies provide valuable insights in terms of achieving SDGs, the fact that results are heavily influenced by parameter choices made by modelling teams or forced due to limitations in model capabilities may lead to reluctance or hesitation to make use of the resulting policy prescriptions. This adds to an existing criticism of IAMs that they are complex and often regarded as black boxes (Doukas et al., 2018), making it difficult for stakeholders to translate their outcomes into action or even engage in the scientific process in the first place. However, this strong interdependence of SDGs with energy and the various and complex interactions among them creates the necessity to establish new approaches in integrated assessment policy efforts (McCollum et al., 2018a). To bridge this gap, much like other complex problem domains (Zopounidis and Doumpos, 2002), multi-criteria decision analysis (MCDA) is often used to assist decision makers in the challenging task of climate policymaking (Doukas and Nikas, 2020). Combined with climate- and energy-economic models, MCDA is usually implemented to optimise the modelling outputs and create robust policy mixes (Shmelev and Van Den Bergh, 2016), evaluate alternatives (Baležentis and Streimikiene, 2017) or rank associated transitional risks (Jun et al., 2013; Nikas et al., 2018a). However, MCDA can also be used to provide input to models through the inclusion of stakeholders and their preferences. Such mixed methodologies are found to perform better in terms of dealing with complexities in decision making than solemnly relying on IAMs (Scholten et al., 2017). This shifts the discussion on the climate change and action framing in the broad sustainability spectrum from what IAMs alone can provide (Nikas et al., 2021), to what stakeholders believe is important to study and which assumptions are more impactful.



In the context of expanding modelling capabilities to incorporate stakeholder preferences, this study uses the 2-tuple TOPSIS model, an MCDA technique, to prioritise the SDGs. The selected framework draws from a systematic literature review on MCDA studies that examined SDGs, in different approaches, with special focus on climate policy. In a group decision making framework based on a regional stakeholder workshop for the PARIS REINFORCE research and innovation project, we reach a ranking of SDGs ranking expressing the preference of the participating 31 stakeholders in terms of the need to incorporate SDGs in modelling exercises and extract SDG-relevant indicators from climate-economy modelling simulations. An important point this study also attempts to capture is the fluctuations in preferences between the different stakeholder groups. Towards identifying these trends and increasing robustness of the outputs, the analysis is also coupled with consensus measuring techniques.

3.2. The use of MCDA in SDG analysis

MCDA is a dominant field of operational research, with a wide range of applications. In relation to climate change, MCDA techniques have been found to be successfully employed to support decision makers in sustainability and climate policy problems (Doukas and Nikas, 2020). In this section we examine the extent to which MCDA has recently been used in the literature to assess SDGs and map the different roles SDGs play in the analysis. To investigate this, a thorough literature review was conducted to identify relevant scientific publications since 2016 by using the following two queries in Google Scholar:

- "multiple-criteria decision" +SDGs +"sustainable development goals"
- "multi-criteria decision" +SDGs +"sustainable development goals"

This search resulted in a vast literature review comprising 164 peer-reviewed articles in scientific journals related to the implementation of MCDA models for the analysis of SDGs. A first filtering can be conducted according to the method of MCDA used (Figure 14). It is important to note that several studies used more than one MCDA methods, as well as that Figure 14 presents only the methods employed in more than one study. Some studies furthermore used a method that they developed, without naming it (e.g. Choi et al., 2020), or failed to name the method used (e.g. Wu et al., 2020a).



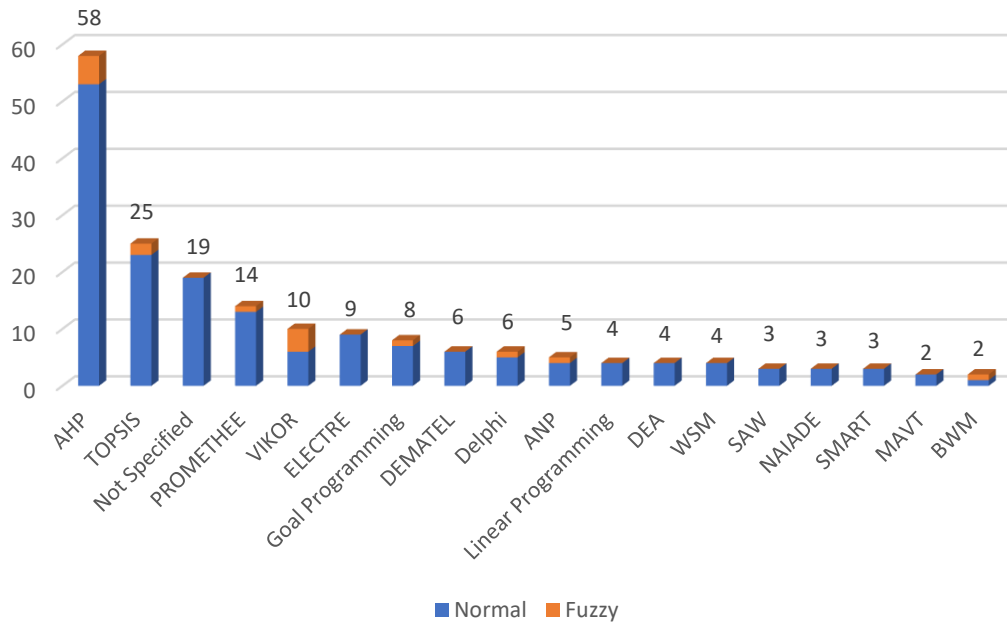


Figure 14: The number of papers using each MCDA method

Figure 14 indicates that AHP is the dominant method, due to its versatility to be used standalone or in combination with other frameworks, then followed by TOPSIS. For example, Phonphoton and Pharino (2019) examined alternative solutions for the waste management system of Bangkok, Thailand, focusing on criteria like food security (SDG 2), human health (SDG 3), water resources (SDG 6) and impact on biodiversity (SDG 15). Ullah et al. (2018) investigated the impact of three alternative gaseous fuel types on the transportation sector of Pakistan, using SDG-based criteria tracing to human well-being (SDG 3), economic growth (SDG 8) and climate action (SDG 13). Coupled with other methods, AHP is frequently applied to calculate the criteria weights in sustainability problems (Neofytou et al., 2020), before feeding the results to other frameworks performing the final evaluation of the alternatives. An interesting example is Guzmán-Sánchez et al. (2018), who used AHP with TOPSIS, to assess the impact of various roof types on the sustainability of the building sector through AHP-weighted indicators that are directly linked to sub-goals of various SDGs (1, 2, 3, 6, 7, 8, 11, 12, 13, 14, and 15).

Another important insight from Figure 14 is that several studies used fuzzy MCDA methods. For example, 40% of the VIKOR studies use the fuzzy version of the method, such as Hameed et al. (2020) that used fuzzy VIKOR to examine the impact of several risks related to e-waste and, linking risks to SDGs as criteria, concluded that pollution from e-waste recycling is one of the major risks, linked to SDG 13. Fuzzy methodologies are found to be relevant in handling uncertainty (Linkov et al., 2006), which is a key aspect of exercises that include stakeholders. However, MCDA methods can also be applied in stakeholder engagement processes without necessarily using fuzzy versions (Huang et al., 2011). Table 18 summarises the key studies that include stakeholder engagement as part of the MCDA framework for SDGs-related analysis. Although numerous studies include experts in the analysis, we highlight those mobilising the knowledge embedded in a noteworthy number of participants while presenting a diversity in means of engagement, regions, and focus areas.

Table 18: MCDA studies on or around SDGs including stakeholder engagement

Study	Method	Means of engagement	Region	Focus area
-------	--------	---------------------	--------	------------



(Ahmed et.al, 2020b)	Delphi, AHP, Fuzzy VIKOR	Electronic questionnaires to 12 industrialists, zone planners, environmentalists, and government officials	Pakistan	Selection of sustainable and Special Economic Zones
(Balali and Valipour, 2020)	AHP	Interviews and questionnaires with 144 experts in Shiraz (Iran) buildings	Iran	Identify and prioritise the most suitable building facade's smart materials according to SDGs
(D'agata et al., 2020)	TOPSIS	666 surveys with fisher households and 89 communities' key informants	Madagascar, Kenya	Social adaptive capacity of fishing households
(Deshpande et al., 2020)	MAVT	31 responses in a scientific workshop	Norway	Assessment of environmental, economic, and social impacts of landfilling, incinerating, and recycling of waste fishing gears
(Hameed et al., 2020)	Fuzzy VIKOR	150 surveys with engineers, industrial experts and academics on chemical and material engineering	Pakistan	Evaluation of environmental risks using Modified-SIRA
(Jamal et al., 2020)	AHP	Survey with 71 academics, industry experts and consultants	Australia	Microgrid planning and off-grid power supply system options for a remote rural area
(Zeug et al., 2020)	Mean averages	64 stakeholders (society, business and science stakeholder groups)	Germany	Relevance of SDGs to bioeconomy
(Lehner et al., 2018)	AHP	83 remote sensing experts' judgements from online questionnaires	Global	Indicators for sustainable city development through remote sensing data, in the context of the International Standard ISO 37120



Apart from reviewing the MCDA methods used for SDG analysis, it is important to investigate the roles SDGs played in each study. Three categories are identified based on how SDGs are assessed:

1. Criteria (SDGs are either directly used as criteria or indirectly through sub-goals)
2. Focus areas (SDGs provide the scope, context and/or research questions of the studies)
3. Alternatives (SDGs constitute, or are related with the selected alternative options)

Expectedly, the first of these categories is the most common as progress in sustainability dimensions, explicitly referred to via SDGs or implicitly tracing back to SDGs, provide a useful evaluation for alternative strategies, technologies, policies, etc. (Figure 15).

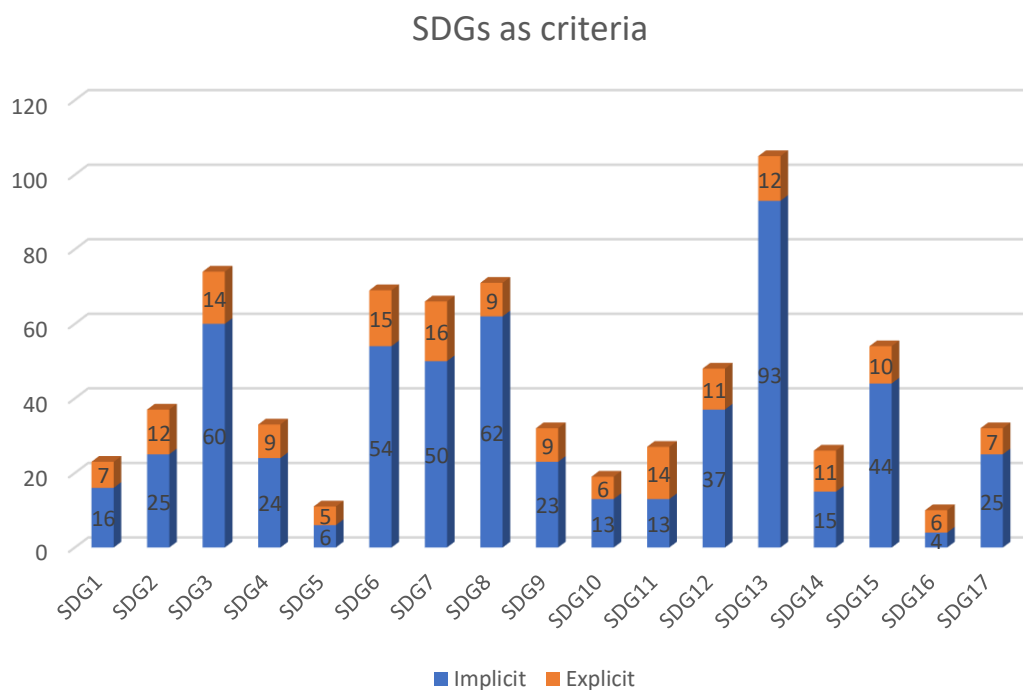


Figure 15: Number of papers that examine each SDG as an MCDA criterion

Figure 15 showcases that the SDGs most referred to as criteria on MCDA methods are climate action (SDG 13), good health and well-being (SDG 3), decent work and growth (SDG 8), clean water (SDG 6), and affordable and clean energy (SDG 7). In most of these studies, SDGs are implicitly used to define related criteria, highlighting a tendency of the sustainability literature to focus on indicators like emission reduction, health and economic impacts, and access to clean energy and water, to assess the different alternatives. For example, Diemuodeke et al. (2019) used TOPSIS to evaluate various alternatives for hybrid energy systems in Nigeria based on CO₂ emissions and renewable energy share, both constituting SDG sub-indicators (13.2.2 and 7.2.1, respectively).

In relation to climate change mitigation, over 100 of the examined studies used SDG 13 as an explicit or implicit criterion in their analysis or focus on its achievement. Table 19 presents some of these studies that find application in a broad range of sustainability areas and regions. On the other hand, since most MCDA studies focus on the selection of technological or policy alternatives, societal issues like inequalities and peace are rarely examined. In



particular, SDGs 5 (Gender Equality), 10 (Reduced Inequalities) and 16 (Peace, Injustice and Strong Institutions) are assessed the least.

Table 19: MCDA studies on SDGs with a focus on climate action (SDG 13)

Study	Method	Region	Focus area
(Ahmed et al., 2020a)	Fuzzy AHP, Fuzzy VIKOR	Pakistan	Re-examining the objectives of national climate policy
(Ahmed and Mishra, 2020)	AHP	Small Island Developing States	Water-related challenges
(Hassan et al., 2019)	MCDA	Pakistan	Energy and environmental security
(Shem et al., 2019)	Weighted Sum Method	Vietnam	Policy portfolio evaluation for low carbon transition
(Sanneh, 2018)	Fuzzy AHP	Sub-Saharan Africa (with focus on Ghana and Senegal)	Prioritisation of climate change adaptation measures
(Soni et al., 2017a)	Fuzzy PROMETHEE	India (as part of the India-EU strategic Dialogue)	Penetration of ICT and efficacy of e-governance across multiple sectors

Less MCDA studies focus on SDGs as their focus area, instead of criteria (Figure 16), explicitly focusing on specific SDGs. For instance, Budiman et al. (2017) assessed various poverty alleviation programs in Indonesia and identified eligible citizens to examine the impact of each scheme on fulfilling SDG 1 (poverty-related) targets, using a diverse combination of AHP, VIKOR, TOPSIS, PROMETHEE, ELECTREE, SMART, and SAW. Similarly, Diaz-Sarachaga et al. (2017) proposed a new assessment framework for infrastructure investments in developing countries, which is one of the main subjects of SDG 9 (Industry, Innovation, and Infrastructure), using AHP and MIVES. In contrast, very few MCDA studies examined SDGs as alternatives (Figure 17).



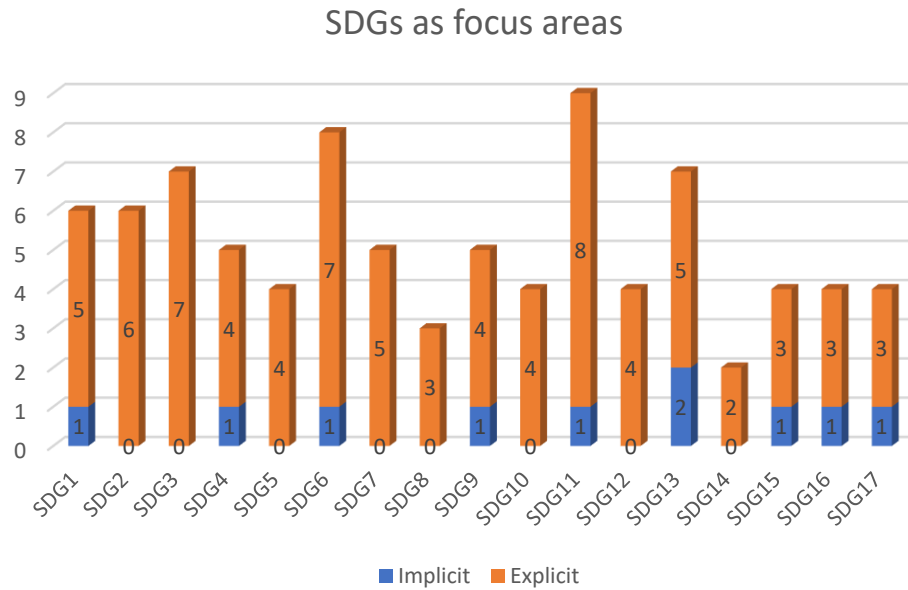


Figure 16: Number of MCDA studies examining one or multiple SDGs as a focus area

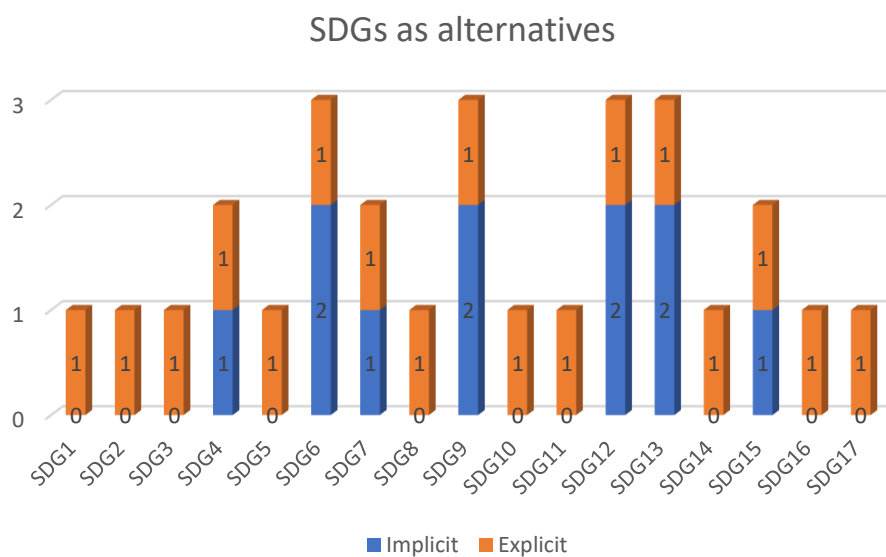


Figure 17: Number of MCDA studies assessing one or more SDGs as an alternative

One of the most direct attempts to treat SDGs as alternatives was performed by Zeug et al. (2020), who attempted to prioritise the SDGs based on the relevance of the corresponding sub-goals to bioeconomy; the ranking was produced from the aggregation of the evaluations of different stakeholders based on average values. Rampasso et al. (2019) examined Brazil’s education and the insertion of sustainability in engineering curricula, which can be linked to SDG target 4.7, aiming to provide every person with relevant education; using TOPSIS, they evaluated ten challenges to introducing sustainability in engineering classes. Gupta and Singh (2020) introduced the Graph Theory Matrix Approach (GTMA) as a framework for assessing the sustainability of logistics service providers in India. Finally, D’Alpaos and Andreolli (2020) conducted a literature review regarding urban quality assessment to search for the most investigated aspects regarding the improvement of urban environment, with SDG-relevant



aspects comprising their alternatives, which they evaluated with AHP across social, economic and environmental criteria.

3.3. Urgency of SDG assessment, in relation to climate policy, from the experts' point of view

3.3.1 Scope

In this section, we perform a multi-criteria analysis to evaluate stakeholders' assessments of climate action in relation to the sustainable development spectrum. In a regional workshop that was held in November 2019 in Brussels, Belgium, stakeholders were asked to contribute to responding to the research question: "How urgent is it to assess each SDG in line with climate change and the Paris Agreement goals?". To achieve the objective of the study, the 2-tuple TOPSIS method is employed, coupled with a consensus measuring technique to increase robustness of the outcome and understand the dynamics between the different categories of stakeholders involved. The aim is to use the results of the MCDA analysis to inform the climate-economy modelling community on the most important SDGs that should be integrated in modelling exercises, and against progress on which climate action should be evaluated.

3.3.2 Context: Event, alternatives & criteria

The stakeholder engagement event was held as part of the "1st PARIS REINFORCE Stakeholder Council Dialogue workshop", entitled "Enhancing climate policy through co-creation", which took place on November 21, 2019, at the premises of Bruegel, in Brussels, Belgium. During the MCDA/SDG session, 31 participants from different backgrounds and level of expertise (Figure 18) were asked to evaluate the SDGs against a set of predefined criteria, using an online polling platform.

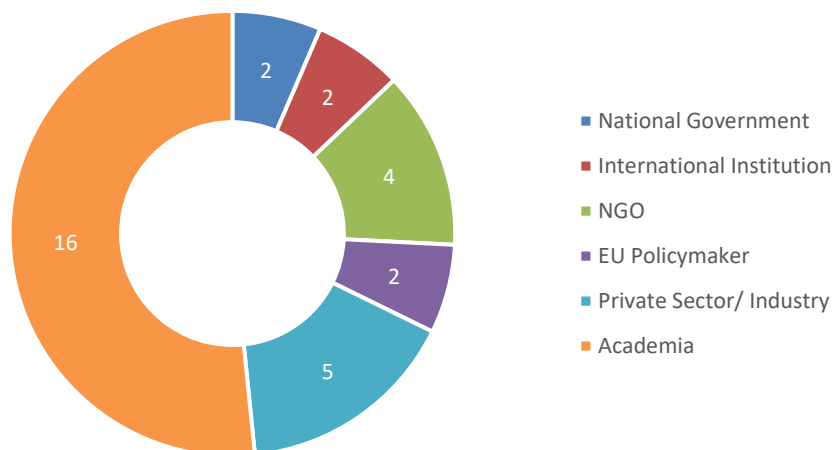


Figure 18: Distribution of Stakeholder Groups

To engage with the research question of the study, the SDGs are placed as the alternatives of the analysis. Since the main objective of IAMs is to evaluate scenarios that assess the technological and economic feasibility of climate policy and goals (Ackerman et al., 2009), we axiomatically exclude SDG 13 from the analysis, when searching for

additional SDGs to include in modelling activities. SDG 17, related to global partnerships and cooperation, is also excluded from the analysis as it falls outside the scope of integrated assessment modelling tools, which is to evaluate Paris Agreement pledges (Krey et al., 2019).

The stakeholders were asked to evaluate each SDG based on three criteria: importance, relevance to climate change, and trend of progress. These were selected on the basis of forming a consistent family of criteria that attempt to capture the broader viewpoint of the experts. Specifically, the “importance” criterion aims to capture a broad perception of the importance of fulfilling the targets of each SDG in society; relevance to climate change focuses more on the interlinkages between climate change and each of the other SDGs, reflecting whether an SDG should be examined coupled with climate goals. Finally, trend of progress aims to capture stakeholders’ knowledge and perception of the improvements made so far towards achieving each SDG. The details on the formulation of the problem are presented in Table 20.

Table 20: Alternatives and evaluation criteria used in the analysis

Alternatives	Evaluation Criteria
SDG 1: No Poverty	<u>C1. Importance</u>
SDG 2: Zero Hunger	<i>How important do you find this SDG is to address?</i>
SDG 3: Good Health and Well-Being	{very low, low, moderate, high, very high importance}
SDG 4: Quality Education	
SDG 5: Gender Equality	
SDG 6: Clean Water and Sanitation	<u>C2. Relevance</u>
SDG 7: Affordable and Clean Energy	<i>How relevant to climate action do you think this SDG</i>
SDG 8: Decent Work and Economic Growth	<i>is?</i>
SDG 9: Industry, Innovation and Infrastructure	{very low, low, moderate, high, very high relevance}
SDG 10: Reduced Inequalities	
SDG 11: Sustainable Cities and Communities	
SDG 12: Responsible Consumption and Production	<u>C3. Trend of Progress</u>
SDG 14: Life Below Water	<i>How do you perceive the trend of progress in meeting</i>
SDG 15: Life on Land	<i>the sub-goals of this SDG so far?</i>
SDG 16: Peace, Justice and Strong Institutions	{very low, low, moderate, high, very high progress}

Due to the supplementary nature of the criteria, the resulting ranking is expected to reflect, from a stakeholders' perspective, the urgency to further study the integration of each SDG in modelling activities based on three key questions: how important is an SDG, how relevant to climate change is it and what is the progress so far? In line with the research question and to better express the urgency we adapt the last criterion to express the lack of progress. In that case an SDG receives the highest ranking and therefore the most urgent to study in models, when it is evaluated as important, relevant but at the same time there is limited progress in meeting the determined goals.

3.3.3 Methodology

3.3.3.1 The 2-tuple model

The results are displayed in a universal 5-term scale {very low, low, medium, high, very high}. These terms are closer to the natural language of the stakeholder in line with the computing with word methodology in sustainability decision making problems (Doukas et al., 2010), which increases the comprehensibility of the analysis outcomes. To fully exploit the linguistic terms, the 2-tuple model is used (Herrera and Martinez, 2000; Martinez and Herrera, 2012), which consists of a 2-tuple linguistic representation (s, a) , where s is a linguistic term and a is a numeric value representing a symbolic translation to increase accuracy without overcomplicating the interpretation of the end result.

Let $S = \{s_0, \dots, s_g\}$ be a linguistic term set and $\beta \in [0, g]$ be the result of a symbolic aggregation operation, where $g + 1$ is the cardinality of S . Let $i = \text{round}(\beta)$ and $\alpha = \beta - i$ be two values, such that $i \in [-0.5, 0.5]$; then α is called a symbolic translation. The symbolic translation of a linguistic term s_i is a numerical value within $[-0.5, 0.5]$ indicating the difference of the information between the calculated value $\beta \in [0, g]$, and its closest element within $\{s_0, \dots, s_g\}$ indicating the content of the closest linguistic term S ($i = \text{round}(\beta)$).

In essence, the 2-tuple linguistic representation model extends the use of indexes modifying the fuzzy linguistic approach, by adding a symbolic translation that represents the linguistic information by means of a linguistic 2-tuple.

$$a = \begin{cases} [-0.5, 0.5), & \text{if } s_i \in \{s_1, s_2, \dots, s_{g-1}\} \\ [0, 0.5), & \text{if } s_i = s_0 \\ [-0.5, 0), & \text{if } s_i = s_g \end{cases}$$

Finally, for a linguistic term set $S = \{s_0, \dots, s_g\}$ and a value supporting the result of a symbolic aggregation operation $\beta \in [0, g]$, the 2-tuple expressing the equivalent information to β is calculated:

$$\Delta: [0, g] \rightarrow S \times (-0.5, 0.5)$$



$$\Delta(\beta) = (s_i, \alpha), \text{ with } \begin{cases} s_i & i = \text{round}(\beta) \\ \alpha & = \beta - i \quad \alpha \in [-0.5, 0.5) \end{cases}$$

Evidently, the conversion of a linguistic term into a linguistic 2-tuple consists of adding a value 0 as symbolic translation: $si \in S \Rightarrow (si, 0)$.

3.3.3.2 The 2-tuple TOPSIS model

As a ranking multicriteria methodology that calculates the distance of an alternative from a positive and a negative ideal solution, TOPSIS (Yoon and Hwang, 1981) has been found to perform significantly well in fuzzy systems with the extension of Fuzzy TOPSIS (Chen et al. 2006). It is also preferred and frequently employed in climate policy to handle uncertainty in relevant decision-making problems (Doukas and Nikas, 2020). In this study, the 2-tuple TOPSIS is used, combining the original TOPSIS method with the 2-tuple model. One of the first applications of a combination between 2-tuples and TOPSIS was performed by Doukas et al. (2010) to assess RES alternatives in the Greek electricity system, while the proposed framework was also later used to assess energy and environmental policies of Small-Medium Enterprises (Doukas et al., 2014), with 2-tuples allowing to present input and output data without affecting internal calculations of TOPSIS. The 2-tuple TOPSIS model was formally introduced by Wei (2010), where the proposed methodology was applied in an investment problem with multiple experts. To deal with the loss of linguistic interpretation, Sohaib et al. (2019) introduced a distance function in the calculation of the 2-tuple TOPSIS by setting different linguistic domains for the evaluation of the preferences, the weights, and the final distances. However, in decision making problems that include stakeholder engagement with feedback processes, using three different linguistic domains may be technically correct from a modelling perspective but create difficulties in stakeholders to quantify the final results, thus affecting their ability to translate them into action. Although the addition of the distance function is a useful tool to distinguish between the interpretation of initial preferences and final distances, defining strictly different domains to evaluate them is not necessary, as long as the distance function is properly handled. Labella et al. (2020) followed the methodology introduced by Sohaib et al. (2019), including the distance function, but the same general 5-scale term was used both for the preferences and the calculation of the distances. Understanding that the terms in the two scales may be the same but used to express different variables allowed the mapping of each value in a universal domain without disturbing linguistic interpretability. Here, we argue that the approach used in Labella et al. (2020) is better suited for climate policy problems with stakeholder engagement to allow them to compare the results in the values in which they provided the initial input. Therefore, in this study we use the methodology followed by Labella et al. (2020), described below:

- (i) Defining a weight vector $U_t = (u_j^t)_{1 \times n}^T$, where $u_j^t \in U$ is the linguistic preference by stakeholder e_t for criterion c_j and U is a linguistic term set, with $U = \{u_1, u_2, \dots, u_p\}$ transformed into a 2-tuple linguistic decision matrix $U_t = (u_j^t, 0)_{1 \times n}^T$.
- (ii) Calculating the normalised 2-tuple weight vector $U_t^N = (\bar{u}_j^t, \bar{\beta}_j^t)_{1 \times n}^T$ for each stakeholder e_t as $(\bar{u}_j^t, \bar{\beta}_j^t) = \Delta_u \left(\frac{\Delta_u^{-1}(u_j^t, 0)}{T_U - 1} \right)$, $j = 1, 2, \dots, n$ and T_U is the cardinal of set U .
- (iii) Defining the decision matrix $X_t = (r_{ij}^t)_{m \times n}$, where $(r_{ij}^t) \in S$ is the linguistic value preference provided by stakeholder e_t for alternative a_i over criterion c_j , and S is the linguistic term set, with $S = \{s_1, s_2, \dots, s_t\}$ transformed into a 2-tuple linguistic decision matrix $X_t = (r_{ij}^t, 0)_{m \times n}$.
- (iv) Calculating the weighted decision matrix $\bar{X}_t = (\bar{r}_{ij}^t, \bar{\alpha}_{ij}^t)_{m \times n}$ for each stakeholder e_t , with $(\bar{r}_{ij}^t, \bar{\alpha}_{ij}^t) = \Delta_S \left(\Delta_u^{-1}(\bar{u}_j^t, \bar{\beta}_j^t) \cdot \Delta_S^{-1}(r_{ij}^t, 0) \right)$, $i = 1, 2, \dots, m, j = 1, 2, \dots, n$.



- (v) Calculating the positive and negative ideal solutions for each stakeholder e_t as: $(r^{t,+}, \alpha^{t,+}) = \{(r_1^{t,+}, \alpha_1^{t,+}), (r_2^{t,+}, \alpha_2^{t,+}), \dots, (r_n^{t,+}, \alpha_n^{t,+})\}$ and $(r^{t,-}, \alpha^{t,-}) = \{(r_1^{t,-}, \alpha_1^{t,-}), (r_2^{t,-}, \alpha_2^{t,-}), \dots, (r_n^{t,-}, \alpha_n^{t,-})\}$, where $(r_j^{t,+}, \alpha_j^{t,+}) = \max_i\{\{\bar{r}_{ij}^t, \bar{\alpha}_{ij}^t\} | c_j \in B\}$ or $\min_i\{\{\bar{r}_{ij}^t, \bar{\alpha}_{ij}^t\} | c_j \in B'\}$ and $(r_j^{t,-}, \alpha_j^{t,-}) = \min_i\{\{\bar{r}_{ij}^t, \bar{\alpha}_{ij}^t\} | c_j \in B\}$ or $\max_i\{\{\bar{r}_{ij}^t, \bar{\alpha}_{ij}^t\} | c_j \in B'\}$, where $i = 1, 2, \dots, m, j = 1, 2, \dots, n$ and where B and B' are the benefit and cost criteria sets respectively.
- (vi) Determining the distance of each alternative from the positive and negative ideal solutions for each stakeholder e_t as: $(\xi_i^{t,+}, \eta_i^{t,+}) = \Delta_{S'} \left(\frac{1}{n} \sum_{j=1}^n \frac{(T_{S'}-1)}{(T_S-1)} \cdot (|\Delta_{S'}^{-1}(\bar{r}_{ij}^t, \bar{\alpha}_{ij}^t) - (r_j^{t,+}, \alpha_j^{t,+})|) \right)$ and $(\xi_i^{t,-}, \eta_i^{t,-}) = \Delta_{S'} \left(\frac{1}{n} \sum_{j=1}^n \frac{(T_{S'}-1)}{(T_S-1)} \cdot (|\Delta_{S'}^{-1}(\bar{r}_{ij}^t, \bar{\alpha}_{ij}^t) - (r_j^{t,-}, \alpha_j^{t,-})|) \right)$, where $S' = \{s'_1, s'_2, \dots, s'_{t'}\}$ is the linguistic term set for the distances, T_S and $T_{S'}$ the cardinals of sets S and S' respectively.
- (vii) Calculating the relative closeness degree of each alternative from the positive ideal solution for each stakeholder e_t as: $(\xi_i^t, \eta_i^t) = \Delta_{S'} \left(\left(\frac{\Delta_{S'}^{-1}(\xi_i^{t,-}, \eta_i^{t,-})}{\Delta_{S'}^{-1}(\xi_i^{t,+}, \eta_i^{t,+}) + \Delta_{S'}^{-1}(\xi_i^{t,-}, \eta_i^{t,-})} \right) \cdot (T_S - 1) \right)$, $i = 1, 2, \dots, m$ and T_S the cardinal of set S . In the current form the results are expressed in the linguistic scale S used by the stakeholders to increase interpretability. The results could have been displayed in the scale S' which was defined explicitly to express distances, however presenting the results in the new terms, despite been more appropriate, could confuse the stakeholders.
- (viii) Computing the collective 2 tuple linguistic decision matrix $X = (\tilde{r}_{it}, \tilde{\alpha}_{it})_{m \times k}$, where $(\tilde{r}_{it}, \tilde{\alpha}_{it}) = (\xi_i^t, \eta_i^t)$, $i = 1, 2, \dots, m, t = 1, 2, \dots, k$. In this step the stakeholders are considered equally weighted. By adjusting steps 1-4, the new matrix X could be calculated to also include weights for the expert.
- (ix) Calculating the positive and negative ideal collective as: $(r^+, \alpha^+) = \{(r_1^+, \alpha_1^+), (r_2^+, \alpha_2^+), \dots, (r_k^+, \alpha_k^+)\}$ and $(r^-, \alpha^-) = \{(r_1^-, \alpha_1^-), (r_2^-, \alpha_2^-), \dots, (r_k^-, \alpha_k^-)\}$, where $(r_t^+, \alpha_t^+) = \max_i\{\{\tilde{r}_{it}, \tilde{\alpha}_{it}\} | c_j \in B\}$ or $\min_i\{\{\tilde{r}_{it}, \tilde{\alpha}_{it}\} | c_j \in B'\}$ and $(r_t^-, \alpha_t^-) = \min_i\{\{\tilde{r}_{it}, \tilde{\alpha}_{it}\} | c_j \in B\}$ or $\max_i\{\{\tilde{r}_{it}, \tilde{\alpha}_{it}\} | c_j \in B'\}$, where $i = 1, 2, \dots, m, t = 1, 2, \dots, k$ and B and B' are the benefit and cost criteria sets respectively.
- (x) Determining the distance of each alternative from the positive and negative ideal solutions for each stakeholder t as: $(\xi_i^+, \eta_i^+) = \Delta_{S'} \left(\frac{1}{k} \sum_{t=1}^k \frac{(T_{S'}-1)}{(T_S-1)} \cdot (|\Delta_{S'}^{-1}(\tilde{r}_{it}, \tilde{\alpha}_{it}) - (r_t^+, \alpha_t^+)|) \right)$ and $(\xi_i^-, \eta_i^-) = \Delta_{S'} \left(\frac{1}{k} \sum_{t=1}^k \frac{(T_{S'}-1)}{(T_S-1)} \cdot (|\Delta_{S'}^{-1}(\tilde{r}_{it}, \tilde{\alpha}_{it}) - (r_t^-, \alpha_t^-)|) \right)$, where $S' = \{s'_1, s'_2, \dots, s'_{t'}\}$ is the linguistic term set for the distances, T_S and $T_{S'}$ the cardinals of sets S and S' respectively.
- (xi) Finally, calculating the relative closeness degree of each alternative from the positive ideal solution as: $(\xi_i, \eta_i) = \Delta_{S'} \left(\left(\frac{\Delta_{S'}^{-1}(\xi_i^-, \eta_i^-)}{\Delta_{S'}^{-1}(\xi_i^+, \eta_i^+) + \Delta_{S'}^{-1}(\xi_i^-, \eta_i^-)} \right) \cdot (T_S - 1) \right)$, $i = 1, 2, \dots, m$ and T_S the cardinal of set S . The results could have been displayed in the distance scale S' , but instead they are converted to the scale the stakeholders provided their answers in for clarity of results, needed in the next steps.

As evident from the description of the framework steps, two rounds of 2-tuple TOPSIS are used in line with the approach suggested by Krohling and Campanharo (2011) for fuzzy TOPSIS, and then extrapolated for behavioural and 2-tuple TOPSIS (Nikas et al., 2018a; Labella et al., 2020). The first round calculates an initial solution independently for each stakeholder and then, from the intermediate results, a new matrix is formed, where 2-tuple TOPSIS is again applied, with stakeholders being the "criteria" of the new TOPSIS model.

3.3.3.3 Consensus measuring

In group decision making problems, dissimilarities may exist between individual answers and the collective solution. Experts from different backgrounds, like in this study, tend to evaluate alternatives differently representing a variety of perspectives and interests. To measure these different assessments, Kacprzyk and Fedrizzi (1986) introduced the concept of “soft” consensus as a metric to capture and calculate the level of dissimilarity, since reaching total consensus is usually not possible. Consensus measuring techniques, either independently or as part of complete consensus reaching processes that include feedback mechanisms, have played an important role in group decision making, especially when including linguistic variables (Herrera et al., 1996). To calculate consensus, usually two approaches are followed (Dong et al., 2018); the preferences of stakeholders are compared either with one another in pairs (e.g. Palomares et al., 2013) or with a collective solution (e.g. Ben-Arieh and Chen, 2006). Herrera-Viedma et al. (2002) argued that, by comparing a collective solution with individual preferences, it is possible to capture differences in rankings rather than evaluations, avoiding overevaluating different assessments that lead to similar rankings. Labella et al. (2020) extended this approach by using the evaluation of the 2-tuple TOPSIS as a collective solution to weigh the distances from individual preferences, capturing both differences in rankings and exact numerical dissimilarities. Overall, a lot of different consensus measuring models exist, with Palomares et al. (2014) mapping them based on the processes followed, to state that it is imperative not only that models be created or compared, but also that the suitability of a model to solve specific types of group decision making problems be described. The model proposed in Labella et al. (2020), already used for risk assessment of a sustainability transition, is found appropriate to deal with climate policy group decision problems with multiple stakeholders. In such problems, due to the conflicting nature of interests among the different groups participating, usually it is not always the purpose of the process to force a consensus solution that would be very difficult to implement, but to understand the different dynamics among the participants. For that purpose, a framework that employs a ranking MCDA model to arrive to an initial solution and then calculates a consensus measure to increase robustness of such solution and allow further processing to identify where each group stands, can act as a first step in the efforts to increase climate science diplomacy (Nikas et al., 2020a) and co-ownership. The steps of the consensus measuring model are described below:

- (i) The dissimilarity of each expert for each alternative $p_i(x_j)$ is calculated by comparing the distance between the result of the 2-tuple TOPSIS of that alternative in the experts' individual solution and in the collective one as follows: $p_i(x_j) = p(R^i, R^c)(x_j) = \left(\frac{|R_j^c - R_j^i|}{T-1} \right)^b \in [0,1]$, $b \geq 0$, where i stands for each expert, j stands for each alternative, b can be in the range of $(0,1)$ to control the rigorousness of the model, R_j^c is the result of the 2-tuple TOPSIS of the alternative j in the group solution, R_j^i is the result of the 2-tuple TOPSIS of the alternative j in expert's i solution, and T the cardinal of the linguistic term set, used to normalise the dissimilarity values.

(ii) Next, we calculate the consensus degree of all experts on each alternative x_j using the following expression

$$C(x_j) = 1 - \frac{\sum_{i=1}^m p_i(x_j)}{m}, \text{ where } m \text{ stands for the total number of experts.}$$

- (iii) Finally, we calculate the consensus measure over the set of alternatives, called C_X : $C_X = \frac{\sum_{j=1}^k C(x_j) * R_j^c}{\sum_{j=1}^k R_j^c}$, where k is the total number of alternatives. In this approach the aggregation is performed through a weighted average formula, where the evaluation of the 2-tuple TOPSIS of the global solution for each alternative is used as the weight of the consensus degree over this alternative.



(iv) Applying a similar approach with the consensus measure, the proximity of i -th expert to the global

$$P_X^i = \frac{\sum_{j=1}^k (1-p_i(x_j)) * R_j^C}{\sum_{j=1}^k R_j^C}$$

3.3.4 Results

During the workshop, the 31 participants provided their assessments of the 15 SDGs included in this study, based on the three criteria and the corresponding questions described in Table 20. As already explained, the answers are converted in a common five-term linguistic scale {very low, low, medium, high, very high}, while the answers on the third criterion of progress are inverted to express the lack of progress. By combining all the criteria, we can calculate the urgency to study each SDG in climate policy modelling exercises. Figure 19 illustrates the distribution of the answers in the linguistic scale.

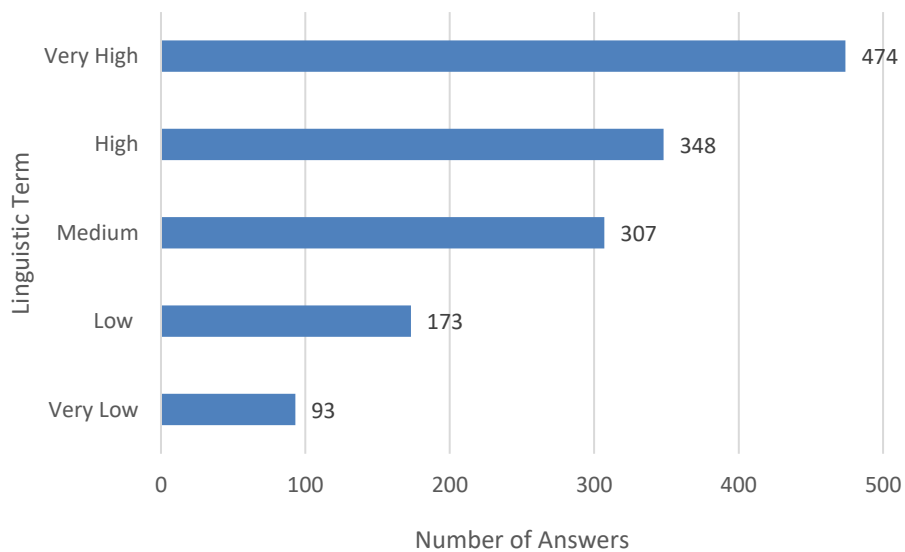
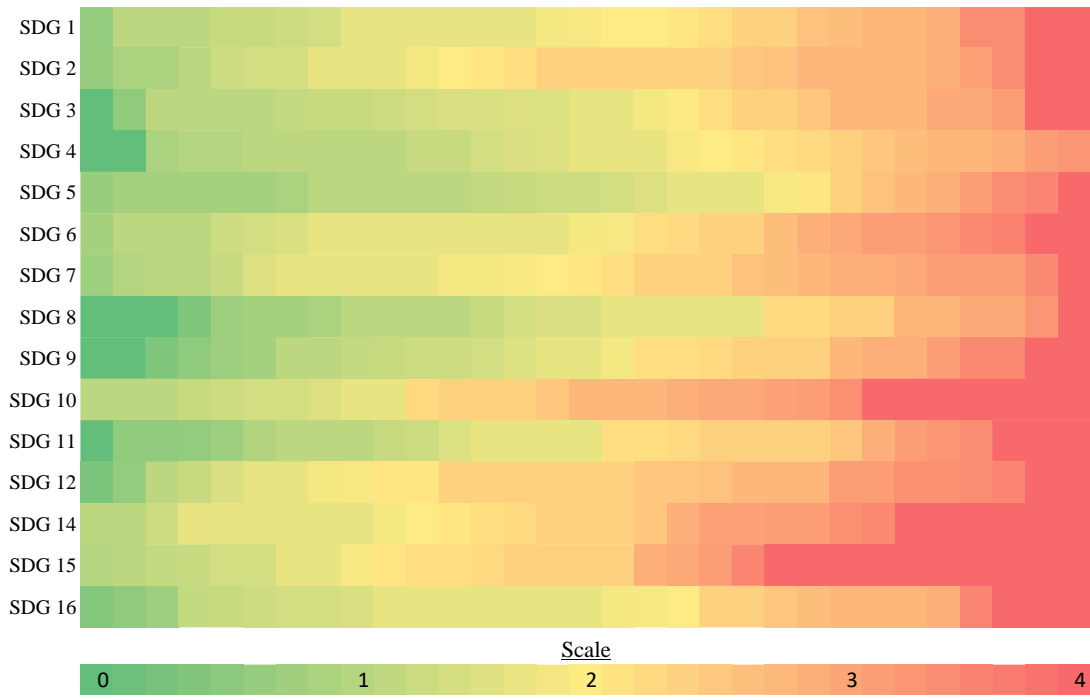


Figure 19: Distribution of assessments in the linguistic scale

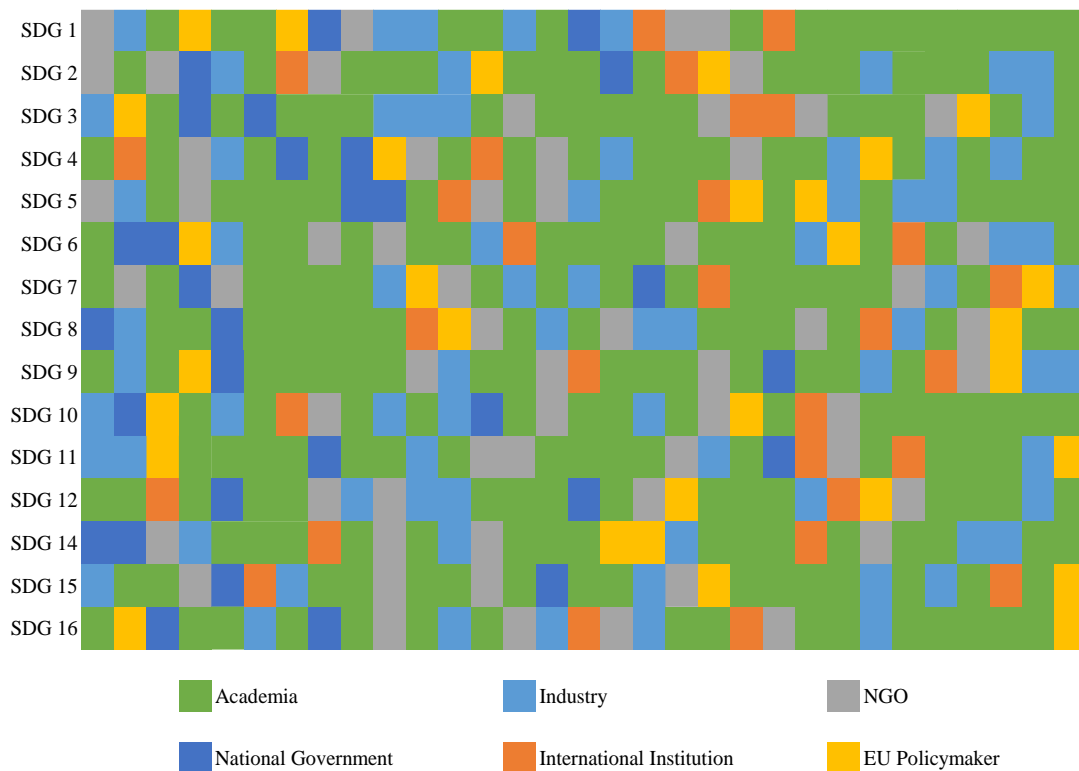
The importance of the SDGs and the necessity to continue progressing towards meeting the goals is already evident. The stakeholders' answers tend to be in the higher end of the scale with "high" and "very high" assessments dominating almost 58% of the total answers and the average value being (High, -0.33), despite decision makers in general following a more moderate behaviour (Mascarenhas et al., 2014) and/or preferring moderate alternatives (Chen et al., 2020). Even though this is an initial step of the analysis, these answers could be interpreted as a general interest of the stakeholders in the integration of SDGs in models and the insights such exercises can provide.

The input is then inserted in the 2-tuple TOPSIS model described in Section 3.3.2. After the first round of analysis, a final assessment of the SDGs is carried out for each stakeholder individually. To visualise this intermediate output, we rank the assessments of the stakeholders per SDG to produce the heatmap presented in Figure 20a. The heatmap provides us with a first impression on the urgency of each SDG in the assessment of the stakeholders, while the corresponding breakdown of the results highlights some tendencies of each group (Figure 20b).





(a)



(b)

Figure 20: (a) SDG urgency heatmap and (b) group breakdown of assessments after the first round of 2-tuple TOPSIS

In particular, SDGs 14 and 15 seem to concentrate the highest values, indicating a first preference of the stakeholders for issues related to life below water and on land, being concerned about the effect of climate change on the life cycles of plants and animals. Reduced Inequalities (SDG 10) also seem to be an important priority of

the stakeholders with almost two-thirds of the evaluations being in the higher end of the scale. However, although general inequalities were assessed as important, with stakeholders understanding that the effects of climate change can be harsher on certain societal groups, gender inequalities (SDG 5) received lower evaluations, possibly reflecting knowledge of limited capabilities of modelling frameworks to look into gender issues and therefore lower expectations.

Most stakeholder groups showed variance in the evaluations among the members of each group, with the answers of the stakeholders being spread in the entire range of the scale of the map (Figure 20b). This deviation is expected, especially in the groups represented by more participants (e.g. academia). Notably, however, two groups showed patterns in their assessments. Members from international institutions provided evaluations that are placed slightly higher on the map, while on the contrary most evaluations from national policymakers were placed in the lower terms, with very few exceptions breaking through the other end; Figure 21 enhances the evaluations of national policymakers. This is also evident from the fact that after averaging the answers of the stakeholders, coming from national governments, no SDG received an assessment of more than (medium, 0.23), possibly reflecting either a sense of comfort with the progress made in each SDG and with the need for further analysis and/or a dedicated focus on climate change and action per se.

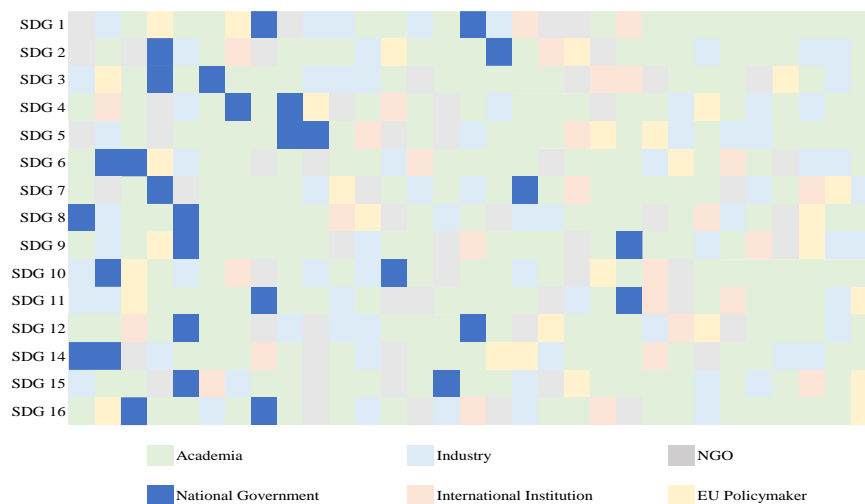


Figure 21: SDG assessments by national government representatives

After the intermediate outputs, the SDG ranking and evaluation of each stakeholder is used in a new round of 2-tuple TOPSIS, as described in Section 3.3.2, to produce the collective solution of the group. The final ranking is presented in Table 21 and Figure 22.

Table 21: Final prioritisation of the SDGs from the engaged group of stakeholders

Ranking	Evaluation
SDG 15: Life on Land	(High, 0.05)
SDG 14: Life Below Water	(High, -0.02)
SDG 10: Reduced Inequalities	(High, -0.08)
SDG 12: Responsible Consumption and Production	(High, -0.32)

SDG 2: Zero Hunger	(Medium, 0.44)
SDG 7: Affordable and Clean Energy	(Medium, 0.42)
SDG 6: Clean Water and Sanitation	(Medium, 0.4)
SDG 1: No Poverty	(Medium, 0.26)
SDG 16: Peace, Justice and Strong Institutions	(Medium, 0.21)
SDG 11: Sustainable Cities and Communities	(Medium, 0.08)
SDG 3: Good Health and Well-Being	(Medium, -0.01)
SDG 9: Industry, Innovation and Infrastructure	(Medium, -0.12)
SDG 4: Quality Education	(Medium, -0.29)
SDG 5: Gender Equality	(Medium, -0.33)
SDG 8: Decent Work and Economic Growth	(Low, 0.45)

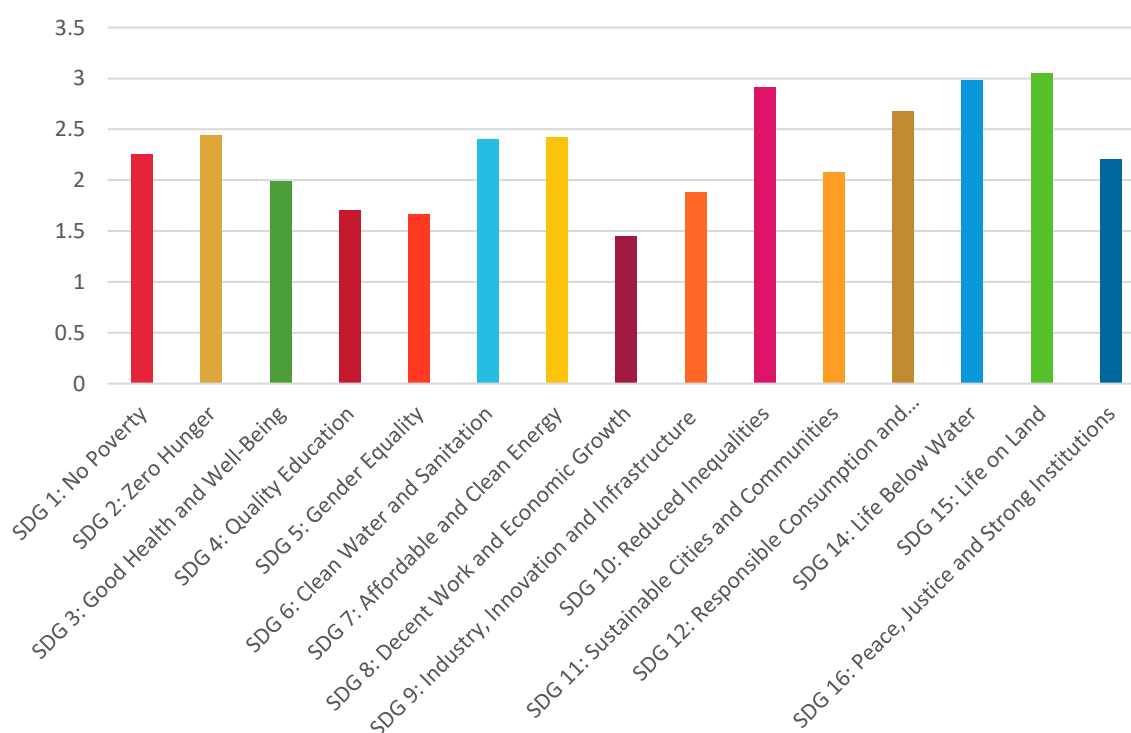


Figure 22: Final Ranking and evaluations of the SDGs

Results of the second step of the analysis validate previous insights, with 4 out of the 15 SDGs being assessed with a “high” evaluation, ten receiving evaluations around “medium”, and only one receiving a “low” evaluation. As previously discussed, life on land, life below water and reduced inequalities were prioritised, with responsible consumption and production—frequently associated with climate change—also performing well. On the other hand, decent work and economic growth failed to gather attention, with stakeholders either considering it as less

important than others or reflecting that there is already good progress towards this goal. It is also evident from the results that stakeholders prioritised SDGs covering aspects on which the impact from climate change is more evident, while SDGs with less profound links with climate change, like gender equality or quality education, fell behind in the ranking.

We already observed that certain groups display different evaluation patterns. From that perspective, it is interesting to calculate the collective solution of each group independently. For that reason, using APOLLO (Labella et al., 2020), the second round of 2-tuple TOPSIS is repeated for each group, this time including only the members of the group itself. Since the idea behind TOPSIS is to compare alternatives to a positive and negative ideal solution, which are defined internally in the framework, and given that the runs were independent for each group, the results should not be interpreted as a direct quantitative comparison of the assessments, but only to compare the order they produce for each group. In Figure 23 the results of this process are presented without a linguistic scale to avoid misinterpretation.



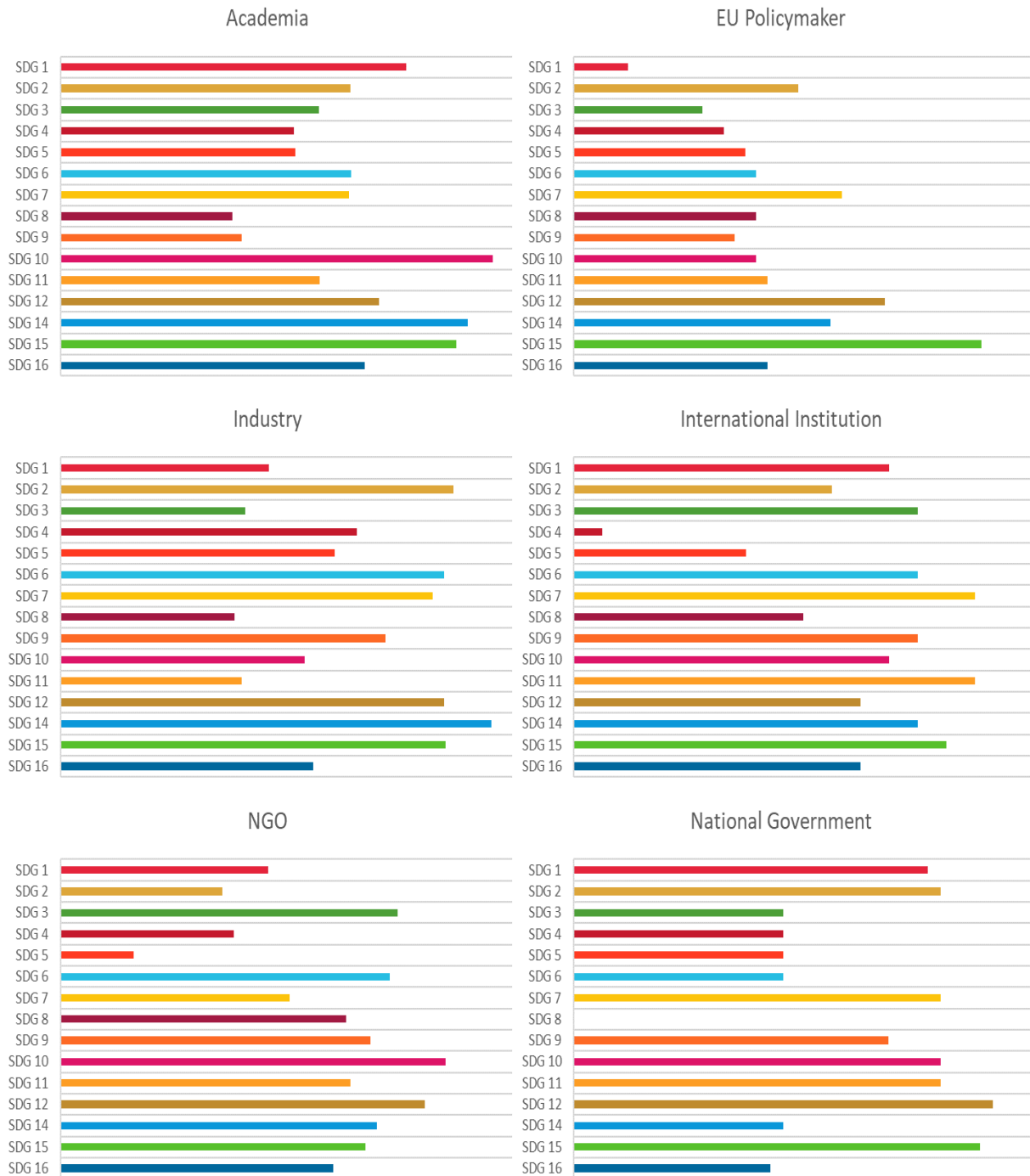


Figure 23: Independent prioritisation of the different stakeholder groups

Despite significant differences between the groups, in five of the six groups the first SDG in the ranking is one of the four that received a “high” evaluation in the collective solution (SDGs 10, 12, 14, 15). This provides a first indication of the consensus among the group about which SDGs are considered a priority in studying through modelling activities, since they received high evaluations in most groups despite their final order. Alterations in the ranking of SDGs with medium initial priority were expected since each group evaluates based on different viewpoints. Similarly, a consensus also seems to exist regarding the lowest priorities, with SDGs 4 and 8 underperforming in most groups.

Having acquired a qualitative assessment of the consensus of the group and especially the highest and lowest



priorities, we calculate the consensus measure based on the framework described in Section 3.3.3. Comparing the prioritisation of each expert from the first round of TOPSIS with the collective prioritisation from the second round, the level of consensus is estimated at 81.4%. Based on this, the proximity level between each individual stakeholder and the collective solution is presented in Figure 24.

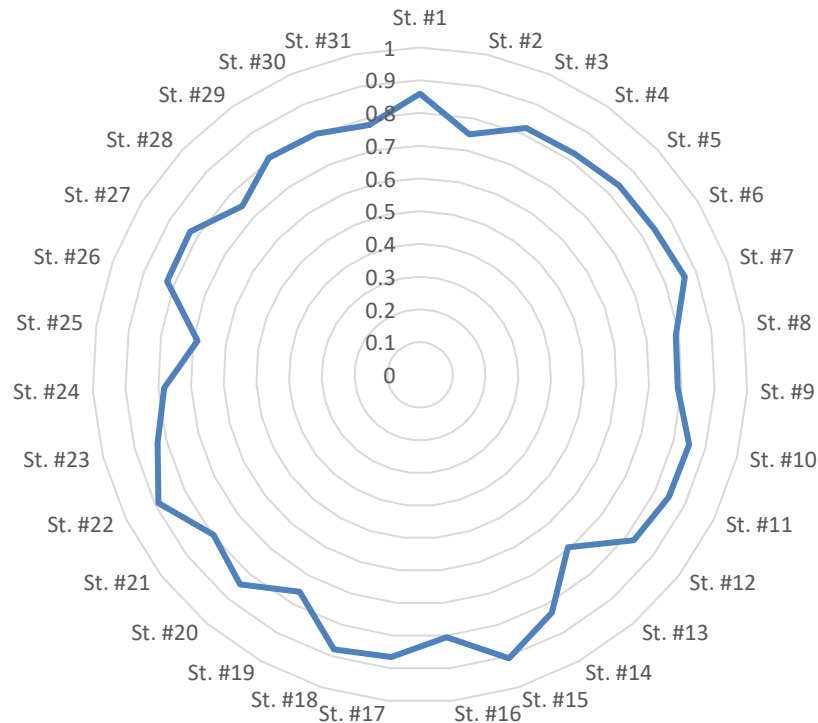


Figure 24: Proximity level of each stakeholder with the collective solution

From Figure 24, we can observe that the range of proximity levels is among 69% (Stakeholder #25) and 90% (Stakeholder #15), indicating significant differences among the stakeholders. To capture these differences in the preferences of the groups of stakeholders, we independently compare the stakeholders in each group with the collective solution. For example, to calculate the group consensus level of academia, we include only the stakeholders of this group and compare them with the global solution. This process is repeated for each group. Additionally, from the independent group solutions presented in Figure 24, we calculate an internal consensus level comparing this group solution with the solutions of the stakeholders of the group. The first measure is an indication of how close the stakeholders of each group are with the collective solution, while the second indicates how close the members of each group are with one another. The results are presented in Figure 25.

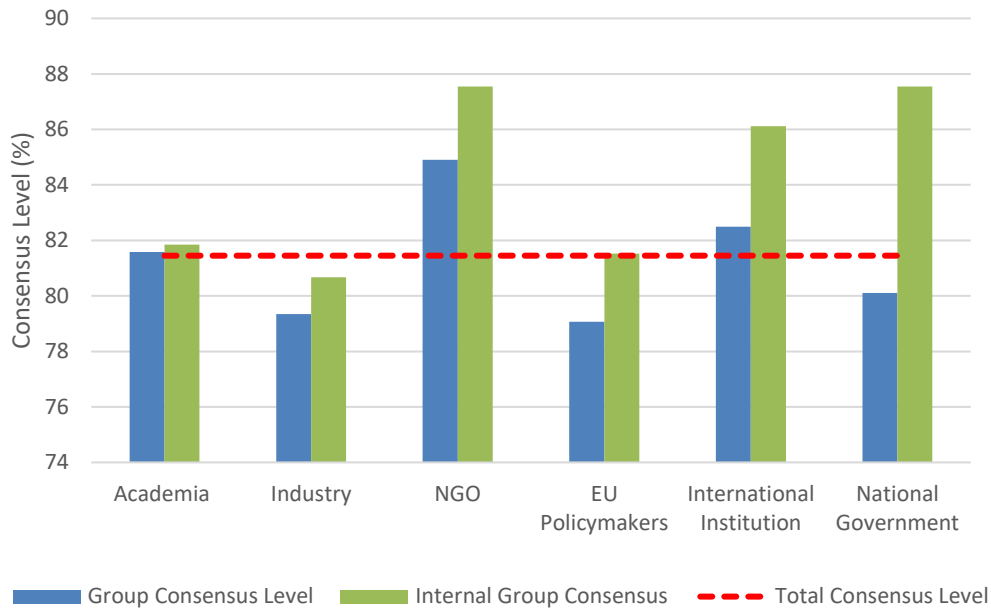


Figure 25: Group consensus level with collective solution and internally

Expectedly, internal consensus is higher than the group consensus level with the collective solution in all groups. Industry representatives as well as EU and national policymakers had lower consensus than the total, while NGOs had the highest level, with members from academia and international institutions being around the average value. Members from NGOs, international institutions and national governments had very high levels of internal consensus, which for the latter led to the highest difference between the consensus on the collective solution and the internal consensus.

3.3.5 Discussion

This study attempted to answer a key research question of how urgent climate stakeholders believe it is to incorporate SDGs in climate- and energy-economy modelling exercises by prioritising them based on their perceived importance, relevance to climate change, and progress achieved so far. Early in the analysis, it became evident that the engaged stakeholders considered that further studying SDGs in relation to climate change is critical. Most of their initial answers were concentrated towards the higher end of the linguistic scale, with the “very high” term receiving the most answers. This indicates that stakeholders not only believe that SDGs are important and relevant to climate change and action, but also that until now limited progress has been made in achieving meeting them. Given a general tendency of stakeholders to follow a moderate behaviour and avoid extreme values of the scale, these high ratings provide a first indication that climate stakeholders are highly interested in integrating SDGs more in modelling exercises.

Both from the intermediate multicriteria analysis and the final ranking, a preference can be deduced regarding SDGs 10, 12, 14, and 15, which received high evaluations from the majority of the stakeholders, as evident in the heatmap and an evaluation around “high” in the final ranking. In fact, life on land and below water (SDGs 15 and 14) were prioritised the most, indicating that stakeholders are mostly concerned about the effects of climate change on ecosystems and biodiversity, as well as how human behaviour affect the broader environment and life on it, especially correlated with how humans treat resources (SDG 12). This output is interesting as few modelling studies are found to have analysed impacts on biodiversity, while SDGs related to inequalities are not well covered in modelling studies, apart from a limited number of indicators (van Soest et al., 2019). On the latter front, the

connection between broader and gender inequalities as well as poverty and the increase of vulnerabilities caused from climate change creates an interlinkage between SDGs 1, 5 and 10 (UNESCO, 2017). However, in this study stakeholders' evaluations showed a large spread in the scale for these SDGs, with reduced inequalities ranking high, poverty eradication in the middle, and gender inequalities in the bottom. This difference is prone to two interpretations. First, it could express a genuine preference of SDG 10 as more important than the others, implying that by focusing on achieving broader social equality targets will promote progress in the others; but it could also reflect misconceptions and lack of knowledge about broader effects of climate change in societal issues. Considering that reduced inequalities indeed ranked high in the prioritisation leads to the conclusion that stakeholders do not ignore inequality issues altogether but provided a preference of what they consider most important to integrate in the formalised modelling frameworks. The overall analysis may reflect that stakeholders chose to emphasise what is hitherto overlooked in modelling studies (e.g. SDGs 14 and 15), instead of aspects that are by default included in these studies (e.g. SDG 8). Despite the latter's widely acknowledged importance in promoting sustainable work and growth, this result adds to the debate on whether SDG 8 adequately focuses on decent work without conflict with the entire agenda (Rai et al., 2019). More co-creation studies with stakeholders could shed light on the reasons behind the experts' preferences, especially when related with different evaluations for SDGs with evident synergies, as our study hints that modelling activities do not seem to adequately consider stakeholders preferences.

To increase robustness of the final calculated ranking, the consensus level was also measured, at 81.4%, indicating a significant level of agreement despite the divergence of the stakeholders' backgrounds, enhancing the output that the four SDGs identified with a high evaluation are the majority's preferences. Despite this agreement, fluctuations of both the ranking and the evaluations are present among the different groups. The most notable example lies in the results of the national policymaking group, with assessments concentrated in the lower end of the scale. While the consensus of the group with the global solution was below average, internal consensus was very high at around 87%. With concerns rising over the progress on achieving the targets of the goals (Sachs et al., 2019b), this result opens the question on whether national governments are fully committed to achieving sustainability or even understanding the importance of following up on the 2030 Agenda.

3.4. Conclusions

This study attempted to prioritise SDGs based on the evaluations of 31 stakeholders from different backgrounds in order to shed light on which SDGs they consider most urgent to study in modelling activities. This necessity derives from a systematic literature review, which identified that modelling exercises have difficulties representing SDGs and only achieve so through sub-goals and approximate metrics. Similarly, a lack of studying SDG directly as MCDA alternatives is reflected in the small number of such studies, in which in fact SDGs are mostly referred to implicitly. Therefore, to achieve the purpose of the analysis, a group decision making framework was employed based on the 2-tuple TOPSIS model that uses linguistic variables, which are closer to the language that experts are more comfortable using, and further enhanced using consensus measuring calculations to improve robustness of the outputs. The SDGs are inserted in the analysis as alternatives with the aim to prioritise them based on their importance, relevance to climate change and achieved progress so far. Due to the high evaluations that the stakeholders provided, we concluded that they collectively consider SDGs to be a very critical part of future modelling exercises. A key output of the analysis was that a select few SDGs (15, 14, 10, 12) on life below water and on land, equality and responsible production and consumption were the most vital from the stakeholders' point of view. Despite fluctuations among the rankings of the different groups, these SDGs performed consistently high, with a consensus of 81.4%. Another interesting output was the fact that national governments representatives participating in the workshop tended to evaluate the importance of integrating SDGs in climate



policy modelling analysis significantly lower than the rest of the groups, possibly reflecting the determination or ability of EU national governments to align national Paris Agreement-compliant pathways with the sustainability agenda.

The study can provide valuable insights for future research. Modelling activities can be informed by the results and place more importance in including and representing the SDGs that the stakeholders considered as more important: significant efforts are placed in improving modelling capacity (Nikas et al., 2021); adding complexity to integrate everything in one-size-fits-all approaches may prove infeasible, but focusing on aspects that stakeholders and policymakers themselves deem critical paves a technically more realistic way. Additionally, this study can be further improved by including more regions especially from developing countries to capture different needs and approaches. This could also increase the number of participants, further increasing the robustness of the results and validating the tendencies observed in groups with a small number of participants.



4 Climate and sustainability co-governance in Kenya: a multi-criteria analysis of stakeholders' perceptions and consensus

This study is currently under review in: Koasidis, K., Nikas, A., Karamaneas, A., Saulo, M., Tsiouridis, I., & Doukas, H. (2021). Climate and sustainability co-governance in Kenya: a multi-criteria analysis of stakeholders' perceptions and consensus. *Environmental Science & Policy*, under review.

4.1. Introduction

Climate change is undeniably one of the most severe threats faced by humanity in the efforts towards sustainability. This is especially the case for the developing African countries, with climate change being a major challenge to the region due to distinctive socio-economic (Ochieng et al., 2016; Sanneh, 2018) and geographic (Sanneh, 2018) factors. The Paris Agreement and the 2030 Agenda for Sustainable Development, both established in 2015, embody highly intertwined targets and guidelines to act for the climate crisis in conjunction with sustainable development (Nikas et al., 2021), but for the developing world these targets have contexts and meanings that transcend the mitigation-oriented focus of high-income, major emitters. Many countries in the African region have already set the proper coordination and governance mechanisms for the implementation of Sustainable Development Goals (SDGs) by setting respective roadmaps and action plans in response to climate change (Allen et al., 2018). However, progress toward sustainable development is still very limited for a multitude of reasons.

For Kenya, in particular, these inter alia include lack of a detailed regulatory framework, poor infrastructure and innovation, insufficient human capital, as well as limited public awareness and acceptance (Neofytou et al., 2020). Another major bottleneck hindering progress can be found in limited access to energy (Moner-Giona et al., 2018), both at a regional and national level, with only 23% of East Africa and 18% of Kenya having access to electricity (Dagnachew et al., 2017; Schwerhoff and Sy, 2018), with the Sub-Saharan African (SSA) region ranking lower than any other in the world in terms of access to modern energy sources (Van de Ven et al., 2019). This severe problem is further observed in rural Eastern African areas, where the share of electricity access is even lower, only at 12% of the population (Dagnachew et al., 2017). With the 2010 electricity generation capacity being lower than 2 GW in Kenya and showing only a small increase by 2017 (Kazimierczuk, 2019), energy needs are covered by alternative fuels like biomass for cooking purposes and oil in the transportation sector (Dalla Longa and van der Zwaan, 2017). Despite biomass use in SSA being higher than the rest of the world (Liembach et al., 2018), non-renewable fuelwood remains the dominant fuel used (Van de Ven et al., 2019) prolonging the existence of poor cooking methods, with more than half of Kenyan households relying on traditional biomass stoves to accommodate their cooking needs—even more in rural areas.

Additionally, the availability and quality of food supply in the country is subject to limitations since most open-access sites feature poor ecological conditions, regarding coral reefs and fishing grounds, affecting many coastal communities relying on fisheries (D'Agata et al., 2020). In another dimension showcasing the interplay of climate change and other sustainability priorities, global warming threatens the productivity of crop yields and the efficiency of the agricultural sector (Mason-D'Croz et al., 2019), one of the key pillars of the Kenyan economy (Kogo et al., 2021), and hence the ability of agricultural enterprises to secure their productivity and the capacity to preserve the local environment (Norese et al., 2020), considering that the agriculture, forestry and land use (AFOLU) sector produces the highest amount of greenhouse gas (GHG) emissions (UNFCCC, 2010). Combined



with extreme poverty and a very low GDP per capita in the SSA region (Leimbach et al., 2018), these conditions contribute to nutrition being of poor and low calorific quality. As a result, not longer than a decade ago a third of Eastern African population was facing hunger risk, compared to a global average of 15%, highlighting food availability concerns even among other African regions; it is also projected to remain around 2,500 kcal per person in 2030, well below the 3,000 kcal global average (Mason-D'Croz et al., 2019).

Lack of energy access, extreme poverty, low food consumption alongside unsafe water supplies, insufficient sanitation, and indoor air pollution have consequently caused significant health-related issues in the region, leading to high mortality shares. For example, household air pollution is killing 60 per 100,000 residents mainly due to poor cooking techniques (Dagnachew et al., 2020). Kenya, finally, ranks poorly in child and maternal health (Luque et al., 2017), despite high vaccination preparedness (León et al., 2019), leading to increased child mortality. More than 100 million children lack access to modern energy sources, with similar shares for access to clean water and sanitation (Lucas et al., 2019). Until recently, SSA noted 125 deaths per 1,000 births before the age of 5 due to malaria, which is almost twice the global share. In fact, malaria cases and other communicable diseases are expected to double in the region due to service cancellations (UN's Department of Economic and Social Affairs, 2020).

So far, mitigation analysis in the region has been based on climate-economy (integrated assessments) models, which however focus on supply-side transformations to achieve climate targets (Creutzig et al., 2018). For SSA countries these models tend to predict significant increases in investments in renewable energy sources (RES) (Longa and van der Zwaan, 2017). Mid-term solutions aiming to inform the country's Nationally Determined Contributions (NDC) propose a variety of solutions to drive a sustainable pathway addressing the threats faced, like biogas (Forouli et al., 2020), geothermal energy (Schwerhoff and Sy, 2018) and PV micro-grids (Dagnachew et al., 2017; 2018). With all these solutions focusing on power generation, concerns have been raised over the ability of African, and especially SSA, countries to achieve such high penetration of RES, with projections indicating this may prove much more difficult than initially anticipated (Alova et al., 2021).

Considering the inconsistencies between model preferences and feasibility, policy scenarios produced by these models can provide useful insights but can also be difficult to implement in the context of SSA/Kenya. Complexity of such models (Sachs et al., 2019a) and especially modelling parameterisation, which significantly influences final results, can cause reluctance when the scientific process is detached from stakeholders, who tend to treat IAMs as black boxes and are hesitant in translating the outputs into action (Doukas et al., 2018). To bridge this gap and establish new approaches in integrated assessment for climate action and sustainable development while addressing potential policy spillovers across sectors and sustainability domains (McCollum et al., 2018a), multi-criteria decision aid (MCDA) can be used to engage stakeholders in the process and support decisions in climate policymaking (Doukas and Nikas, 2020). So far, MCDA has been used to supplement modelling analysis to handle uncertainty, optimising outputs to establish robust policy mixes (Shmelev and Van Den Bergh, 2016) and prioritising scenarios and transitional risks (Baležentis and Streimikiene, 2017; Jun et al., 2013). With mixed methodologies having been found to perform better in terms of mitigation analysis (Scholten et al., 2017) and the ability of MCDA to elicit stakeholder preferences to inform scenario planning (Zheng et al., 2016), MCDA can be used not only for output analysis, but to provide input for better informed, context-relevant, stakeholder-driven modelling, resulting in insights that are beneficial from multiple perspectives (Nikas et al., 2021).

In line with previous research in support of climate change mitigation and acknowledging the role of theoretical modelling in it, this study attempts to engage with Kenyan stakeholders in order to capture their perceptions of prioritising action for SDGs and sectoral decarbonisation. Drawing from Koasidis et al. (2021), it builds on an MCDA framework based on the 2-tuple group TOPSIS model (Labella et al., 2020), designed to facilitate eliciting



stakeholders' unbiased assessments, aiming to inform future modelling activities on topics, research questions and scenarios of interest.

4.2. Methods and tools

4.2.1. Stakeholder engagement and elicitation of preferences

In the context of the PARIS REINFORCE research and innovation project orienting on stakeholder-driven modelling in support of climate action, a regional stakeholder workshop was held with experts from Kenya, in 28 October 2020. In the workshop, held virtually due to COVID-19 implications for travel and organisation of events, 23 stakeholders participated in a dedicated session and live polling, in order to evaluate and help (a) assess the sectoral decarbonisation priorities in terms of contributing to sustainable development; and (b) prioritise the urgency of each SDG in the context of the country's climate action.

In the workshop session, stakeholders were asked to express their preferences in two questionnaires filled in via an online polling platform, sli.do, with regard to prioritising decarbonisation action in Kenya by sectors, in terms of sustainable development; and sustainable development, as broken down into SDGs in the UN's 2030 Agenda, in terms of climate action in the country. The questionnaires allowed stakeholders to use familiar linguistic terms, to then be used in the analysis, thereby increasing human perception of both the inputs and the outputs in the same format (Doukas et al., 2010).

In the first questionnaire, stakeholders were invited to assess the importance of the decarbonisation of six sectors, namely power generation (POWER), agriculture, forestry and land use (AFOLU), heavy and light industry (INDUSTRY), the tertiary and services sector (SERVICES), residential buildings and energy use (RESIDENTIAL), and public and private transportation (TRANSPORT), based on four criteria: human development, resource use, earth system conservation, and equality. Similarly, in the second questionnaire, the engaged stakeholders were asked to evaluate fourteen out of the seventeen SDGs, based on their relevance to climate change and action, the trend of progress in Kenya, the national policy ambition, and their importance in the Kenyan context. SDG 13 (climate action) is not included as an alternative in the questionnaire, as it is with respect to climate action that SDGs are evaluated. Similarly, SDGs 16 (peace, justice, and strong institutions) and 17 (partnership for the goals) are excluded from the analysis because, first, they have been found underrepresented in models individually and/or in conjunction with other SDGs and, second, they are similarly underrepresented in the PARIS REINFORCE modelling ensemble (Sognaes et al., 2020; Giarola et al., 2020). Tables 22 and 23 summarise key information of each questionnaire.

Table 22: Alternatives, criteria, and linguistic scale of questionnaire on sectoral decarbonisation priorities in terms of contributing to Kenya's sustainable development

Alternatives	Evaluation Criteria	Linguistic Scale
RESIDENTIAL	<u>C1. Human Development</u>	<u>Evaluation Scale</u>
POWER	<i>How important would decarbonising this sector be for human development (economy growth, employment education, health)?</i>	{none, very low, low, medium, high, very high, excellent}
INDUSTRY		
SERVICES		

TRANSPORT	<u>C2. Resource Use</u>	
AFOLU	<i>How important would decarbonising this sector be for resource use (clean/affordable energy, food, water)?</i>	<u>Weight Scale</u>
		{very low, low, medium, high, very high}
	<u>C3. Earth System Conservation</u>	
	<i>How important would decarbonising this sector be for earth system conservation (biodiversity, climate)?</i>	
	<u>C4. Equality</u>	
	<i>How important would decarbonising the power sector be for equality (social, gender)?</i>	

Table 23: Alternatives, criteria, and linguistic scale of questionnaire on urgency of each SDG the context of Kenya's climate action

Alternatives	Evaluation Criteria	Linguistic Scale
SDG 1: No Poverty	<u>C1. Significance</u>	<u>Universal Scale</u>
SDG 2: Zero Hunger	<i>How significant do you find this SDG is to address in the Kenyan Context?</i>	{very low, low, medium, high, very high}
SDG 3: Good Health and Well-Being		
SDG 4: Quality Education	<u>C2. Relevance</u>	
SDG 5: Gender Equality	<i>How relevant to climate action do you think this SDG is?</i>	
SDG 6: Clean Water and Sanitation		
SDG 7: Affordable and Clean Energy	<u>C3. Trend of Progress</u>	
SDG 8: Decent Work and Economic Growth	<i>How do you perceive the trend of progress in meeting the goals of this SDG so far?</i>	
SDG 9: Industry, Innovation & Infrastructure		
SDG 10: Reduced Inequalities	<u>C4. Ambition</u>	



SDG 11: Sustainable Cities and Communities	<i>How do you perceive the ambition of the Kenyan policy towards meeting the goals of this SDG so far?</i>	
SDG 12: Responsible Consumption & Production		
SDG 14: Life Below Water		
SDG 15: Life on Land		

4.2.2. Multiple-criteria group decision analysis

To analyse stakeholder input and carry out the multiple-criteria analysis, we employ APOLLO (Labella et al., 2020), a multi-criteria group decision support model that uses the 2-tuple TOPSIS method.

The 2-tuple group TOPSIS MCDA framework essentially comprises (a) the TOPSIS multi-criteria framework (Yoon and Hwang, 1981) that is among the most popular MCDA methods in climate change decision making (Doukas and Nikas, 2020) and sustainable development (Koasidis et al., 2021), (b) the 2-tuple linguistic representation model (Martinez and Herrera, 2012), and the group TOPSIS variant (Krohling and Campanharo, 2011) as enhanced in a two-stage TOPSIS approach by Nikas et al. (2018a). The framework entails the following steps:

- (i) Defining a weight vector $U_t = (u_j^t)_{1 \times n}^T$, where $u_j^t \in U$ is the linguistic preference by stakeholder e_t for criterion c_j and U is a linguistic term set, with $U = \{u_1, u_2, \dots, u_p\}$ transformed into a 2-tuple linguistic decision matrix $U_t = (u_j^t, 0)_{1 \times n}^T$.
- (ii) Calculating the normalised 2-tuple weight vector $U_t^N = (\bar{u}_j^t, \bar{\beta}_j^t)_{1 \times n}^T$ for each stakeholder e_t as $(\bar{u}_j^t, \bar{\beta}_j^t) = \Delta_u \left(\frac{\Delta_u^{-1}(u_j^t, 0)}{T_U - 1} \right)$, $j = 1, 2, \dots, n$ and T_U is the cardinal of set U .
- (iii) Defining the decision matrix $X_t = (r_{ij}^t)_{m \times n}$, where $(r_{ij}^t) \in S$ is the linguistic value preference provided by stakeholder e_t for alternative a_i over criterion c_j , and S is the linguistic term set, with $S = \{s_1, s_2, \dots, s_t\}$ transformed into a 2-tuple linguistic decision matrix $X_t = (r_{ij}^t, 0)_{m \times n}$.
- (iv) Calculating the weighted decision matrix $\bar{X}_t = (\bar{r}_{ij}^t, \bar{a}_{ij}^t)_{m \times n}$ for each stakeholder e_t , with $(\bar{r}_{ij}^t, \bar{a}_{ij}^t) = \Delta_S \left(\Delta_u^{-1}(\bar{u}_j^t, \bar{\beta}_j^t) \cdot \Delta_S^{-1}(r_{ij}^t, 0) \right)$, $i = 1, 2, \dots, m, j = 1, 2, \dots, n$.
- (v) Calculating the positive and negative ideal solutions for each stakeholder e_t as: $(r^{t,+}, \alpha^{t,+}) = \{(r_1^{t,+}, \alpha_1^{t,+}), (r_2^{t,+}, \alpha_2^{t,+}), \dots, (r_n^{t,+}, \alpha_n^{t,+})\}$ and $(r^{t,-}, \alpha^{t,-}) = \{(r_1^{t,-}, \alpha_1^{t,-}), (r_2^{t,-}, \alpha_2^{t,-}), \dots, (r_n^{t,-}, \alpha_n^{t,-})\}$, where $(r_j^{t,+}, \alpha_j^{t,+}) = \max_i \{(\bar{r}_{ij}^t, \bar{a}_{ij}^t) \mid c_j \in B\}$ or $\min \{(\bar{r}_{ij}^t, \bar{a}_{ij}^t) \mid c_j \in B'\}$ and $(r_j^{t,-}, \alpha_j^{t,-}) = \min_i \{(\bar{r}_{ij}^t, \bar{a}_{ij}^t) \mid c_j \in B\}$ or $\max_i \{(\bar{r}_{ij}^t, \bar{a}_{ij}^t) \mid c_j \in B'\}$, where $i = 1, 2, \dots, m, j = 1, 2, \dots, n$ and where B and B' are the benefit and cost criteria sets respectively.
- (vi) Determining the distance of each alternative from the positive and negative ideal solutions for each stakeholder e_t as: $(\xi_i^{t,+}, \eta_i^{t,+}) = \Delta_{S'} \left(\frac{1}{n} \sum_{j=1}^n \frac{(T_{S'} - 1)}{(T_S - 1)} \cdot (|\Delta_S^{-1}(\bar{r}_{ij}^t, \bar{a}_{ij}^t) - (r_j^{t,+}, \alpha_j^{t,+})|) \right)$ and $(\xi_i^{t,-}, \eta_i^{t,-}) = \Delta_{S'} \left(\frac{1}{n} \sum_{j=1}^n \frac{(T_{S'} - 1)}{(T_S - 1)} \cdot (|\Delta_S^{-1}(\bar{r}_{ij}^t, \bar{a}_{ij}^t) - (r_j^{t,-}, \alpha_j^{t,-})|) \right)$, where $S' = \{s'_1, s'_2, \dots, s'_t\}$ is the linguistic term set

for the distances, T_S and $T_{S'}$ the cardinals of sets S and S' respectively.

- (vii) Calculating the relative closeness degree of each alternative from the positive ideal solution for each stakeholder e_t as: $(\xi_i^t, \eta_i^t) = \Delta_{S'} \left(\left(\frac{\Delta_{S'}^{-1}(\xi_i^{t-}, \eta_i^{t-})}{\Delta_{S'}^{-1}(\xi_i^{t+}, \eta_i^{t+}) + \Delta_{S'}^{-1}(\xi_i^{t-}, \eta_i^{t-})} \right) \cdot (T_S - 1) \right)$, $i = 1, 2, \dots, m$ and T_S the cardinal of set S . In the current form the results are expressed in the linguistic scale S used by the stakeholders to increase interpretability.
- (viii) Computing the collective 2 tuple linguistic decision matrix $X = (\tilde{r}_{it}, \tilde{\alpha}_{it})_{m \times k}$, where $(\tilde{r}_{it}, \tilde{\alpha}_{it}) = (\xi_i^t, \eta_i^t)$, $i = 1, 2, \dots, m, t = 1, 2, \dots, k$. In this step the stakeholders are considered equally weighted. By adjusting steps 1-4, the new matrix X could be calculated to also include weights for the expert.
- (ix) Calculating the positive and negative ideal collective as: $(r^+, \alpha^+) = \{(r_1^+, \alpha_1^+), (r_2^+, \alpha_2^+), \dots, (r_k^+, \alpha_k^+)\}$ and $(r^-, \alpha^-) = \{(r_1^-, \alpha_1^-), (r_2^-, \alpha_2^-), \dots, (r_k^-, \alpha_k^-)\}$, where $(r_t^+, \alpha_t^+) = \max_i \{(\tilde{r}_{it}, \tilde{\alpha}_{it}) \mid c_j \in B\}$ or $\min_i \{(\tilde{r}_{it}, \tilde{\alpha}_{it}) \mid c_j \in B'\}$ and $(r_t^-, \alpha_t^-) = \min_i \{(\tilde{r}_{it}, \tilde{\alpha}_{it}) \mid c_j \in B\}$ or $\max_i \{(\tilde{r}_{it}, \tilde{\alpha}_{it}) \mid c_j \in B'\}$, where $i = 1, 2, \dots, m, t = 1, 2, \dots, k$ and B and B' are the benefit and cost criteria sets respectively.
- (x) Determining the distance of each alternative from the positive and negative ideal solutions for each stakeholder t as: $(\xi_i^+, \eta_i^+) = \Delta_{S'} \left(\frac{1}{k} \sum_{t=1}^k \frac{(T_{S'} - 1)}{(T_{S'} - 1)} \cdot (|\Delta_{S'}^{-1}(\tilde{r}_{it}, \tilde{\alpha}_{it}) - (r_t^+, \alpha_t^+)|) \right)$ and $(\xi_i^-, \eta_i^-) = \Delta_{S'} \left(\frac{1}{k} \sum_{t=1}^k \frac{(T_{S'} - 1)}{(T_{S'} - 1)} \cdot (|\Delta_{S'}^{-1}(\tilde{r}_{it}, \tilde{\alpha}_{it}) - (r_t^-, \alpha_t^-)|) \right)$, where $S' = \{s'_1, s'_2, \dots, s'_T\}$ is the linguistic term set for the distances, T_S and $T_{S'}$ the cardinals of sets S and S' respectively.
- (xi) Finally, calculating the relative closeness degree of each alternative from the positive ideal solution as:
- $$(\xi_i, \eta_i) = \Delta_{S'} \left(\left(\frac{\Delta_{S'}^{-1}(\xi_i^-, \eta_i^-)}{\Delta_{S'}^{-1}(\xi_i^+, \eta_i^+) + \Delta_{S'}^{-1}(\xi_i^-, \eta_i^-)} \right) \cdot (T_S - 1) \right), i = 1, 2, \dots, m \text{ and } T_S \text{ the cardinal of set } S.$$

4.2.3. Consensus measuring

Two of the main criticisms TOPSIS and other ranking MCDA methods receive focus on the lack of internal procedure to calculate the weights of criteria, and the subjectivity of information provided by the stakeholders, when used in decision-making problems (Huang and Li, 2012; Shafabakhsh et al., 2014). Furthermore, such participatory settings feature conflicting natures associated with stakeholders coming from different backgrounds; in such group decision making problems forcing a middle solution may yield a result of low acceptance (Ben-Arieh and Chen, 2006; Fu and Yang, 2010). It is, therefore, interesting to explore the gaps between different stakeholder groups as well as couple each alternative with a consensus level.

Using the 2-tuple variant of TOPSIS, like other fuzzy solutions to the these issues (Mangla et al., 2015; Bayram and Şahin, 2016), and further coupling it with a coherent methodology for measuring the levels of agreement, the proposed framework attempts to address these challenges. The employed consensus measuring framework (Labella et al., 2020), entails the following steps:

- (i) The dissimilarity of each expert for each alternative $p_i(x_j)$ is calculated by comparing the distance between the result of the 2-tuple TOPSIS of that alternative in the experts' individual solution and in the collective one as follows: $p_i(x_j) = p(R^i, R^c)(x_j) = \left(\frac{|R_j^c - R_j^i|}{T-1} \right)^b \in [0, 1]$, $b \geq 0$, where i stands for each expert, j stands for each alternative, b can be in the range of $(0, 1)$ to control the rigorousness of the model, R_j^c is the result of the 2-tuple TOPSIS of the alternative j in the group solution, R_j^i is the result of the 2-tuple TOPSIS of the alternative j in expert's i solution, and T the cardinal of the linguistic term set, used to normalise the



dissimilarity values.

- (ii) Next, we calculate the consensus degree of all experts on each alternative x_j using the following expression

$$C(x_j) = 1 - \frac{\sum_{i=1}^m p_i(x_j)}{m}, \text{ where } m \text{ stands for the total number of experts.}$$

- (iii) Finally, we calculate the consensus measure over the set of alternatives, called C_X : $C_X = \frac{\sum_{j=1}^k C(x_j) * R_j^C}{\sum_{j=1}^k R_j^C}$, where k is the total number of alternatives.

- (iv) Applying a similar approach with the consensus measure, the proximity of i -th expert to the global solution can be calculated: $P_X^i = \frac{\sum_{j=1}^k (1 - p_i(x_j)) * R_j^C}{\sum_{j=1}^k R_j^C}$.

4.2.4. Increasing robustness: integrating the two individual exercises into one

The two seemingly separate individual MCDA exercises, where climate action and sustainability dimensions are decision alternatives and evaluation criteria respectively in the first, and vice versa in the second, are then coupled by using the second exercise as a feedback to the first one, allowing to modify the criteria weights and increase robustness of the results. In particular, the four criteria used in the sectoral analysis are used as clusters of the SDGs: we draw from the SDG classification made by Van Soest et al. (2019) and adapt to the Kenyan context as well as the scope of our study and the SDG representation, by focusing on equality instead of infrastructure as the fourth cluster of our analysis.

Considering this interplay between the two questionnaires, the analysis is performed in two phases. First, the assessments of the stakeholders are analysed independently, serving to directly elicit their tacit preferences. Second, considering the connection between the SDGs and their clusters used as criteria in the sectoral analysis, the assessments of the stakeholders from the two questionnaires are integrated as illustrated in Figure 26. Assuming that providing assessments for the SDG analysis requires a broader and more holistic understanding of sustainable development in Kenya, this second questionnaire is used as a criteria weight filtering for the first exercise: the SDG analysis results are used as a correction for the criteria weights provided by the stakeholders, grouped and producing an average value depending on their affiliation with the respective criterion. By doing so, we can improve the consensus levels of the engaged group and increase the robustness of the analysis outcomes.



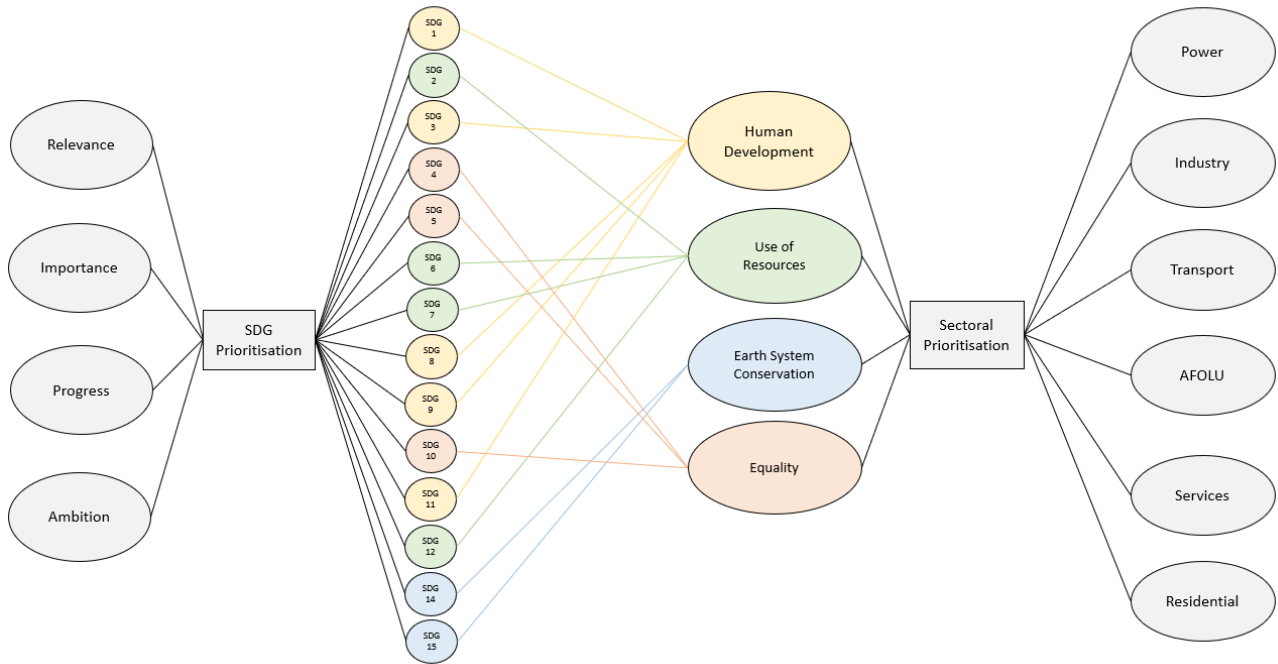


Figure 26: Integration of the two MCDA exercises

4.3. Results and Discussion

4.3.1 Initial sectoral analysis

During the first session, 21 stakeholders featuring different backgrounds and levels of expertise evaluated the importance of decarbonising each economic sector in different sustainability pillars, as clusters of SDGs. The distribution of their background is presented in Figure 27 (note: one of the stakeholders did not disclose how they would describe their current working capacity).

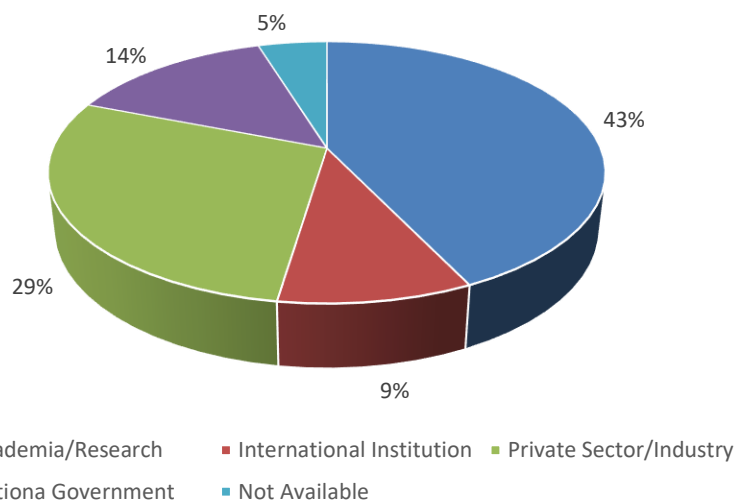


Figure 27: Distribution of stakeholders across groups in the first exercise

Based on the assessments of the stakeholders in a seven-term scale of importance, {None, Very Low, Low, Medium,



High, Very High, Excellent}), and the methodology described in Section 2, the global solution (i.e. sectoral ranking) of the MCDA problem is calculated. The ranking of each alternative is presented in Figure 28. From this initial prioritisation, no clear group preference can be derived for the sectors, as decarbonisation is deemed as similarly important across them. A distinction can be made about services, which was the only sector with a very low evaluation, indicating that stakeholders perceive the decarbonisation of the other sectors as more urgent and relevant to sustainable development overall. Compared to the other alternatives, services received varying evaluations across the stakeholder pool, even in the criteria that the importance of the sector performed highly; it was also deemed less critical in terms of human development and equality. Considering the challenges identified in the Kenyan and SSA context, this opens the question as to what extent stakeholders correlate carbon dominance and issues like access to clean water and sanitation services in the region (Hyvärinen et al., 2020).

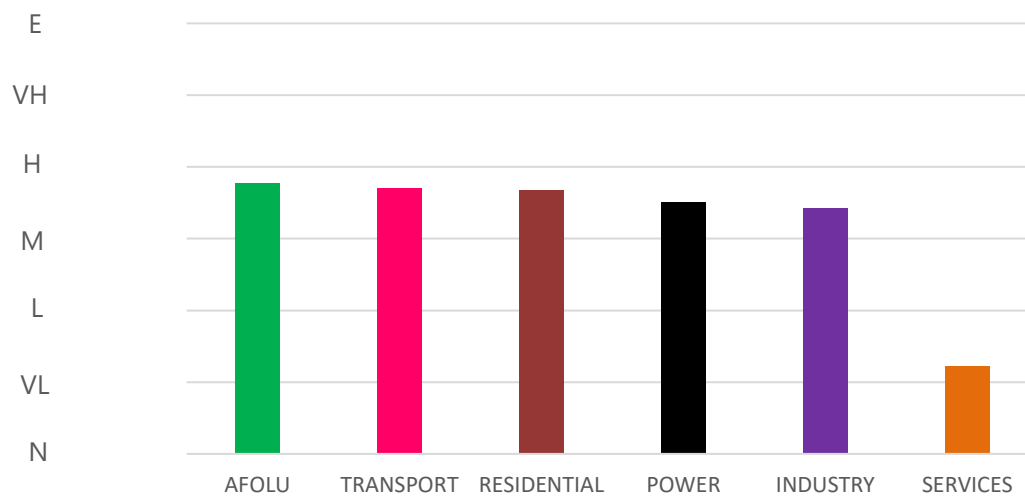


Figure 28: Initial prioritisation of sectoral decarbonisation

Although the AFOLU sector, being critical in terms of both contribution to the national economy and emissions produced, seems to receive the highest prioritisation, it is not deemed as markedly more important than the remaining sectors. In fact, due to the negligible differences among their evaluations and with the exception of services, all sectors ended on the medium-to-high scale. Since TOPSIS calculates the distance between the positive and negative ideal solution, this intermediate evaluation should not be interpreted as a medium importance of all sectors, rather than a lack of strong preference over each alternative. This initial global solution received a low consensus level of 78.1%, with stakeholders individually showcasing a large range of personal consensus fluctuating from 65% to 92%, thereby highlighting the limited capacity to produce robust insights without taking the consensus into account. Figure 29 expands the decision-making process to include not only the evaluation, but also the consensus level of each alternative in this collective solution. Despite the indifference in preferences, consensus allows a better distinction among the alternatives. The agricultural sector presents the highest consensus among the examined alternatives, being the only sector that tilts in the higher consensus area, i.e. outperforming the global consensus levels. On the other hand, the residential and transport sectors seem to be more of a “middle-of-the-road” solution, while industry and power generation display low consensus. To better understand how these differences are produced, the internal solution of each stakeholder group is also presented in Figure 30.

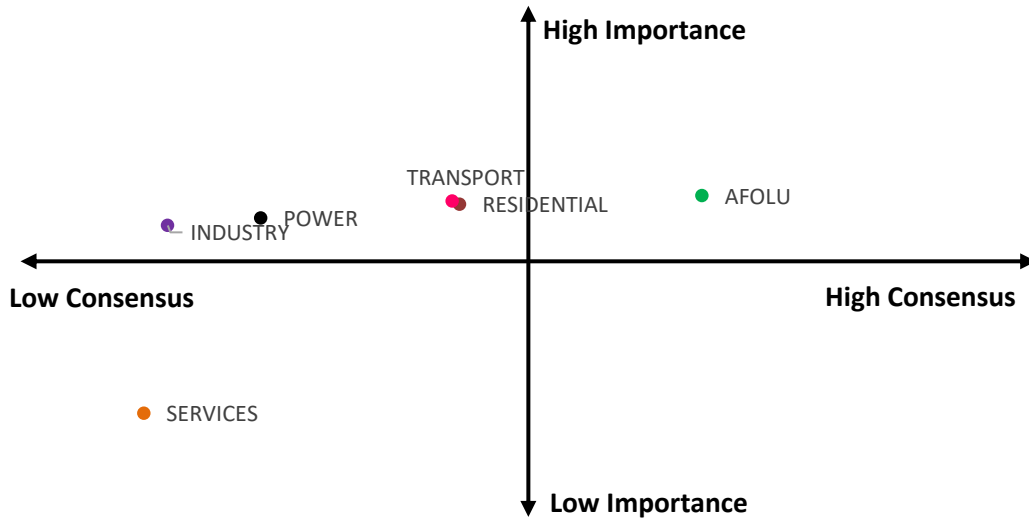


Figure 29: Importance-Consensus levels of each sector in the initial analysis

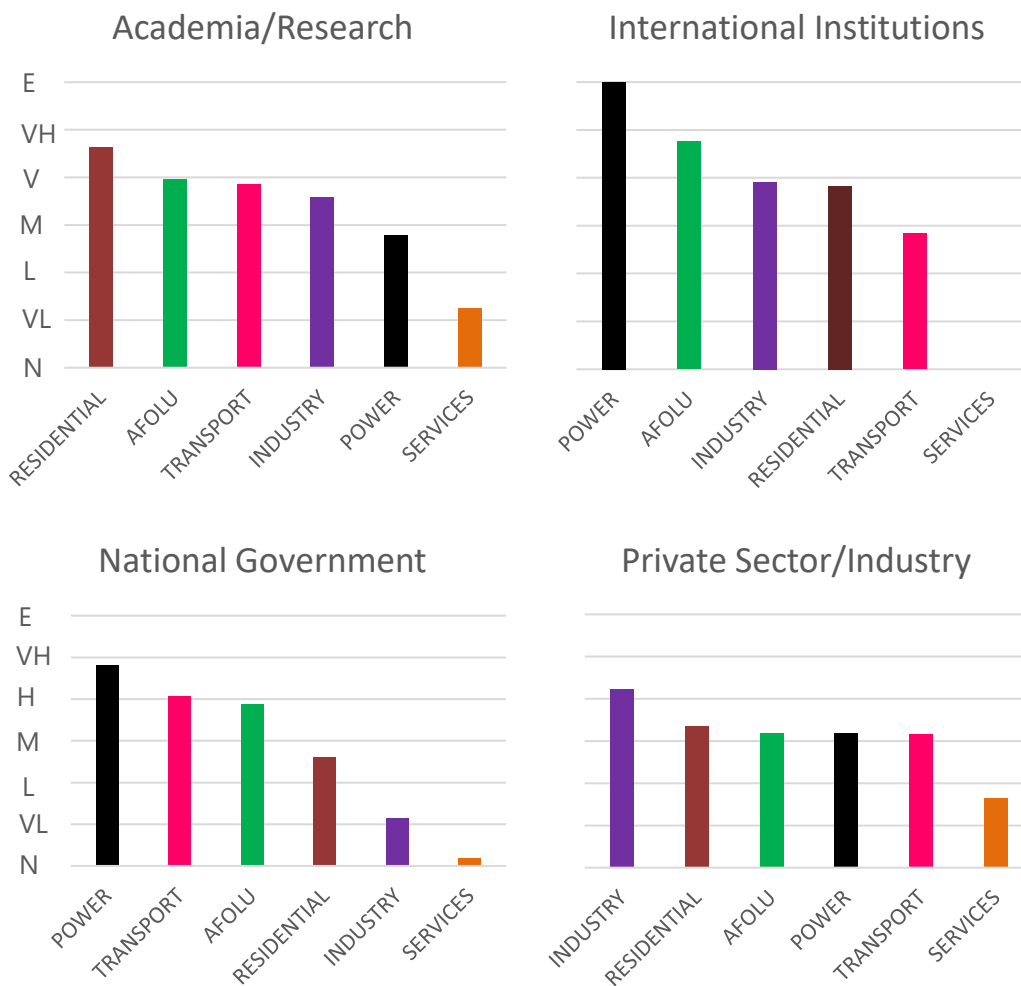


Figure 30: Prioritisation of each sector per stakeholder group



Figure 30 provides many interesting insights, since each group of stakeholders considers a different sector as the most critical to decarbonise, in respect to sustainable development. Academia and research stakeholders favour the residential sector, with AFOLU being the second most important sector, according to their responses. As already presented in the Kenyan context above, the residential sector is an important factor regarding air pollution since households rely on traditional biomass for their energy needs due to lack of access to electricity and modern energy sources. On the other hand, international institutions and national government stakeholders consider the power sector as the most important, indicating that lack of access to electricity should be sought in transformations in power generation. It is also important to mention that both groups consider the agricultural sector highly important. Finally, private and industrial sector representatives appear to consider that industry is the most important one to decarbonise in Kenya. High prioritisation of their professional domain may seem biased; however, the remainder of their ranking follows similar patterns to the broader stakeholder pool, placing the residential and agricultural sectors at the second and third position, respectively.

The fluctuation highlighted in Figure 30 confirms the outputs of our consensus analysis, with the AFOLU sector, despite not being evaluated as the most important sector by any group, appearing consistently in the higher places of the ranking. The rest of the alternatives display significant fluctuations, especially power and industry, justifying the lower ranks in the consensus axis (Figure 29). In fact, the power sector, despite ranking first among two groups, was evaluated poorly by the others. Similarly, the bias of private and industrial sector stakeholders in upvoting their sector is also observed in Figure 31, where the internal consensus of the group is lower than the global consensus, while all other groups expectedly had higher internal consensus.

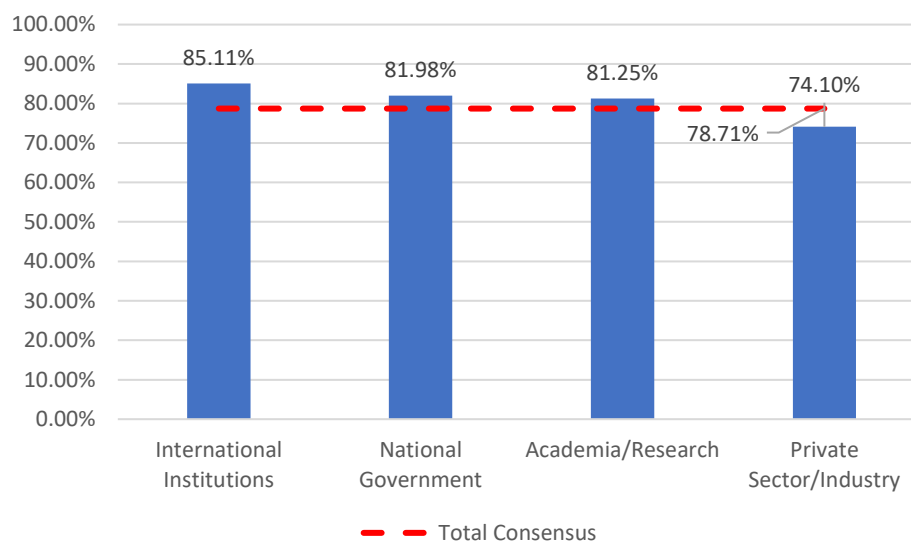


Figure 31: Internal consensus for the first exercise per stakeholder group

4.3.2 SDG Analysis

The first exercise showed unclear prioritisation of sectors for decarbonisation with regard to sustainability gains, also backed by low consensus levels among stakeholders. A second exercise was carried out, with two objectives: first, to prioritise SDGs as key research topics in model-based mitigation analysis; and, second, to reinforce in a feedback mechanism the sectoral analysis, by introducing weights to the evaluation criteria used of that exercise. This time, following a kind invitation motivating those with a broader understanding of the SDG framework, its progress and relevance to the country's context and its relationship with climate change and action, sixteen



stakeholders participating in the workshop chose to engage in this exercise. Figure 32 presents the distribution of their working capacity.

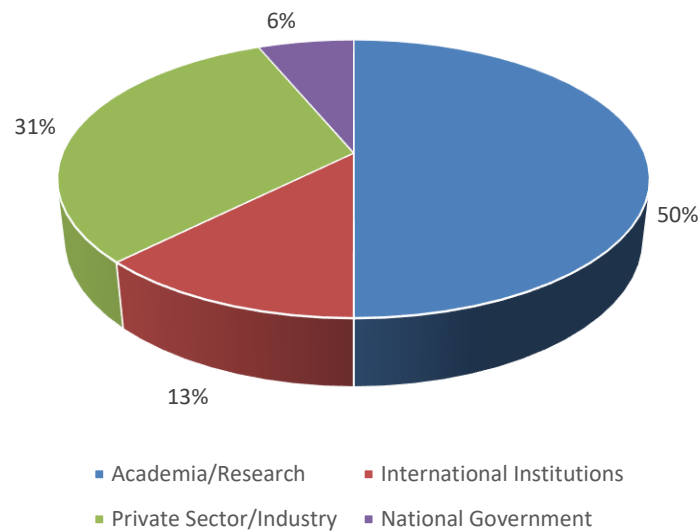


Figure 32: Distribution of stakeholders across groups in the second exercise

Applying the methodological framework described in Section 2, Figure 33 illustrates the global results of the exercise, ranking the 14 SDGs according to stakeholders' responses. Evidently, SDG15 (Life on Land) received the highest prioritisation with an evaluation of (High, -0.11). Both the connection between climate change and SDG15 and of its impact towards achieving the sub-goals of this SDG are well-established (Hamidov et al., 2018): Kenya heavily depends on traditional and non-sustainable biomass, leading to significant implications for land use change, agriculture, and deforestation. Considering the trade-offs between these aspects and SDG15 (Campbell et al., 2018) as well as the corresponding food implications identified in the local context, without overlooking the numerous endangered species of the country (Earth's Endangered Creatures, 2020), this provides an initial validation of the importance of the changes in the AFOLU sector, as established in the first questionnaire. Also it indicates that stakeholders prioritised AFOLU based both on the sector's importance for the economy and emissions, and on broader land use and biodiversity concerns.

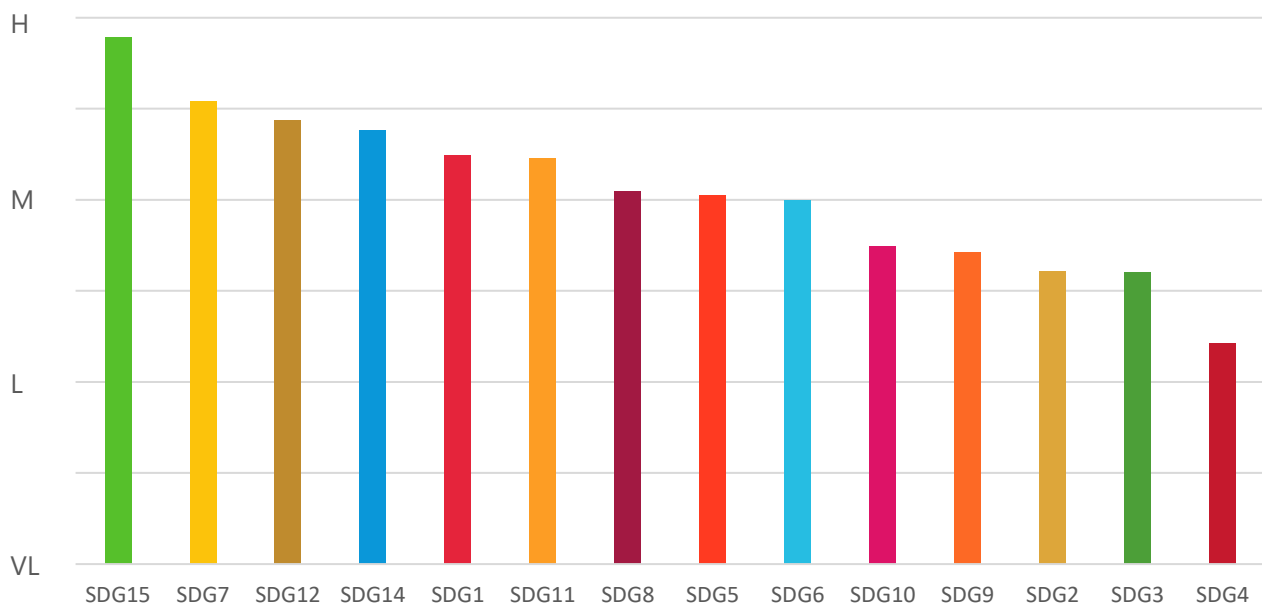


Figure 33: Prioritisation of SDGs in relation to climate action in Kenya

Specifically, fear of biodiversity loss can be another driver for the prioritisation of SDG15 as the most important sustainability goal, due to the perceived relationship between habitat destruction and the current global health emergency (IPBES, 2020). Aside from COVID-19, although health issues in general, like high mortality especially in children, are already identified as a major threat in the broader SSA region, the corresponding goal (SDG3) was not found among the top priorities, ranking in fact second to last. However, this should not be interpreted as indifference toward such issues, as the evaluation considers the importance of each SDG in relation to climate change. Nevertheless, it is an important finding, as most modelling studies in the literature exploring interactions between climate action and other SDGs in the region focus inter alia on SDG3 (e.g. Van de Ven et al., 2019; Forouli et al., 2020; Rafaj et al., 2021; Vandyck et al., 2018), mostly targeting sub-goals and indicators like air quality (Iyer, et al., 2018), which remains an important and fairly studied aspect, but missing the link to broader systemic drivers, which apparently stakeholders consider of further importance.

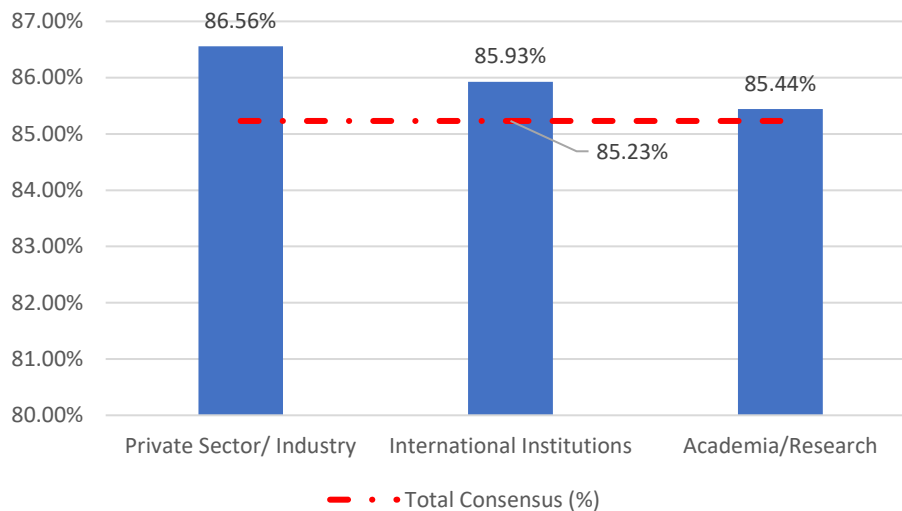


Figure 34: Internal consensus for the second exercise per each stakeholder group (excluding the small group of national government stakeholders taking part in this exercise)

SDG7 (affordable and clean energy), another SDG directly related with threats identified in the country, was the only other SDG with an evaluation in the high range of the linguistic scale. Severe lack of energy access appears to be the root of major issues the country faces, with stakeholders expressing the need to address this threat in conjunction with climate change. Achieving the targets of this SDG requires more than securing universal energy access, especially for developing countries. Emphasis needs to be placed on providing clean and affordable energy access (SDG7.1), as well as on drawing significant investments toward clean energy research and infrastructure (SDGs 7.a.1 and 7.b.1). Recent energy-innovation initiatives in the country need to be expanded to maximise impact on the local community (Chan et al., 2017). At the same time, improvements in energy efficiency (SDG7.3) should not be disregarded, especially considering that SDG12 (responsible consumption and production) also ranked high. With African countries, including Kenya, facing an uphill battle to achieve widespread penetration of renewables until 2030 (Alova et al., 2021), energy efficiency can have a significant impact on improving energy access in the near-term (du Can et al., 2018). Therefore, according to the participating stakeholders, establishing a comprehensive investment plan toward clean energy infrastructure and research that also considers distinct local elements, such as reliance on non-sustainable biomass and energy efficiency, should be among the top priorities of a national strategy for a sustainable transition.

SDG4 (quality education) is ranked last according to the stakeholders, in fact with a large gap separating it from the other SDGs, performing in the low importance term of the scale (Low, 0.21). Most educational issues Kenya faces are related to higher education (McCowan, 2018) and, although improvements in access to education rates have been noted in the last decades, stagnation of quality indicators like completion rates still pose major challenges (Sifuna, 2007). However, it should be noted that previous studies showed stakeholders also prioritise improvements in the quality of education in primary and secondary schools, when assessing the impact of demand-side electricity sector transformations (Dal Maso et al., 2020). In our case, it could be that this impact was disregarded by the pool of stakeholders, that it was considered indirect in SDG13 interacting with SDG7 interacting in turn with SDG4, or that implementing demand-side solutions with clear implications for climate change is perceived to have an impact on education but not vice versa.

The heatmap of Figure 35 illustrates the distribution of stakeholders' multi-criteria assessments of each SDG, which



can be extracted within APOLLO as an intermediate step of the MCDA framework: TOPSIS is first applied on the alternatives against the criteria for each stakeholder, and then once more on the alternatives against the stakeholder assessments (Nikas et al., 2018a). In addition to validating previous insights, we can see that SDG9 (industry, innovation and infrastructure) was rather favourably assessed by some stakeholders, yet this did not manage to place it among the least critical SDGs. Apart from displaying significant variance in responses and therefore low consensus levels, this consistently confirms the low sectoral prioritisation of industry in the first exercise, further hinting that stakeholders of the corresponding group slightly boosted the sector and respective SDG in the rankings. It is also an indication of this bias with respect to SDG9, as highlighted in Figure 36. Apart from SDG9 and SDG14 (life below water), most SDGs orbit around the center of the axes, with fluctuations that generally follow the patterns identified in the absolute ranking. Although SDG14 did not stand out in the ranking, it showed the highest consensus among the stakeholders meaning that almost all groups agreed on its importance, in line with literature emphasising the necessity for mitigating marine pollution and addressing known issues like overfishing (Alati et al., 2020).

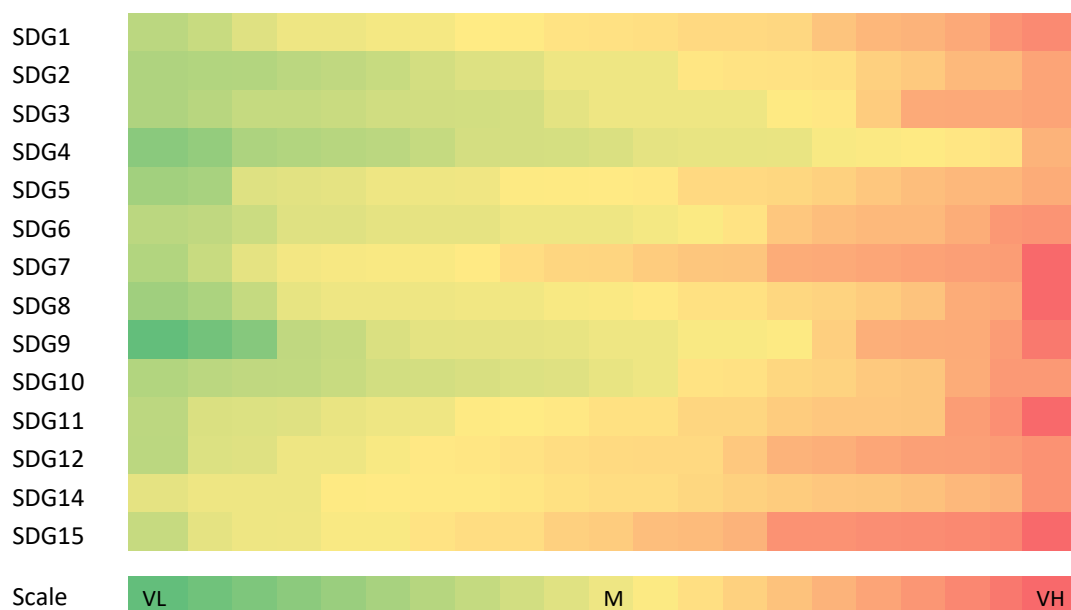


Figure 35: SDG intensity heatmap

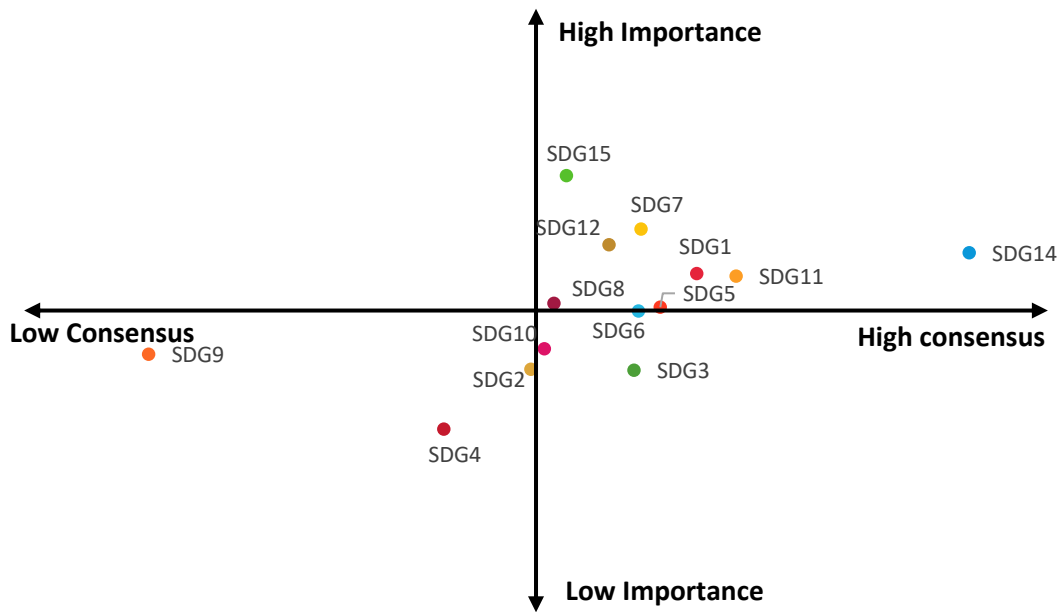


Figure 36: Importance-Consensus of each SDG

Figure 37 presents the fluctuations of rankings by different groups, which mostly followed the patterns of the global ranking. Interesting outliers are also present, with stakeholders from international institutions prioritising SDG11 (sustainable cities and communities), and government representatives highlighting the importance to SDGs 10 (reduced inequalities), 3 (good health and well-being) and 6 (clean water and sanitation). While most of these issues are well established threats to Kenya’s sustainability, these preferences hint that the government is prioritising efforts on the social dimension. Interestingly, however, this group drove evaluations higher compared to the other stakeholders: private sector stakeholders showed overall indifference to SDGs, including those ranked the most important.



Figure 37: SDG ranking per stakeholder group

4.3.3 Revisiting the sectoral analysis

As explained in Section 2, the weights of the criteria of the first exercise are revisited to reflect the prioritisation of the SDGs from the second exercise. In particular, the evaluation criteria weights are modified based on the average evaluations of the SDGs included in each cluster, and therefore calibrated to minimise errors induced by human subjectivity. Figure 38 displays the rankings of the initial analysis, i.e. the analysis with the unmodified weights as provided by the stakeholders, and the rankings after calibration of the weights based on the results of the second exercise. In the initial solution, the five sectors, excluding services that in both cases ranked poorly, were placed around the medium scale, making it difficult to establish clear prioritisation. After the weight calibration process, the final ranking shows a clearer distribution, with the residential sector emerging as the most important sector and an evaluation around Very High. In fact, the sector presented the highest difference compared to the initial prioritisation. The key difference that led to this change is the improved consensus: the residential sector seems to be evaluated as highly important by most stakeholder groups despite not necessarily ranking first for all groups. The process drove consensus to reach a level of 82.6%, rising from 78.8% in the initial exercise.

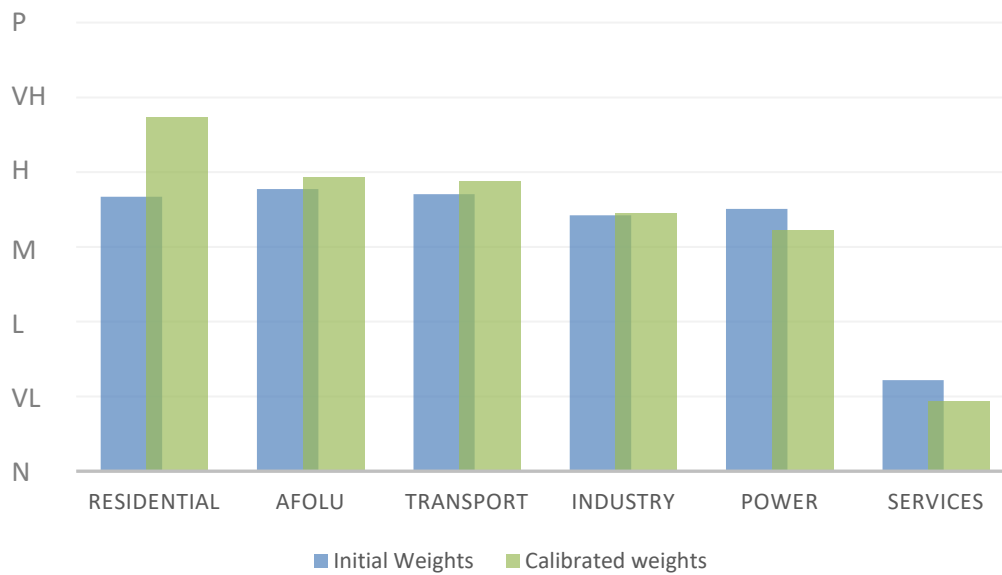


Figure 38: Prioritisation of the sectors based on the three approaches

A common criticism of MCDA methods having no internal weight (re-)calculation method seems to apply, as the calibration process have had an impact on the final ranking, albeit limited, but most importantly it has had an impact on the achieved consensus. Figure 39 shows the differences in the internal (stakeholder group) consensus in the two analyses, with and without weight calibrations. Although the small increase in total consensus is overall evident, consensus among the much smaller international institution group was actually reduced after applying the calibrated weights. Delving into the weight inputs of the members of the group and comparing them to their SDG prioritisations, significant discrepancies appear, especially in the order of importance of each criterion, giving in the initial exercise an inconsistent sense of internal consensus among the group. Contrary, the weight calibration process increased the internal consensus of the private sector/industry group by reducing the bias induced by members of the group towards evaluating their own sector. Overall, these discrepancies were not enough to impact the global solution; however, as part of climate diplomacy the goal is not only to reach or improve global consensus, but also to understand the different dynamics and conflicts among different groups. Climate policy has much to gain by attempting to implicitly elicit stakeholder assessments to reduce human subjectivity and understand the driving motives of each participant.

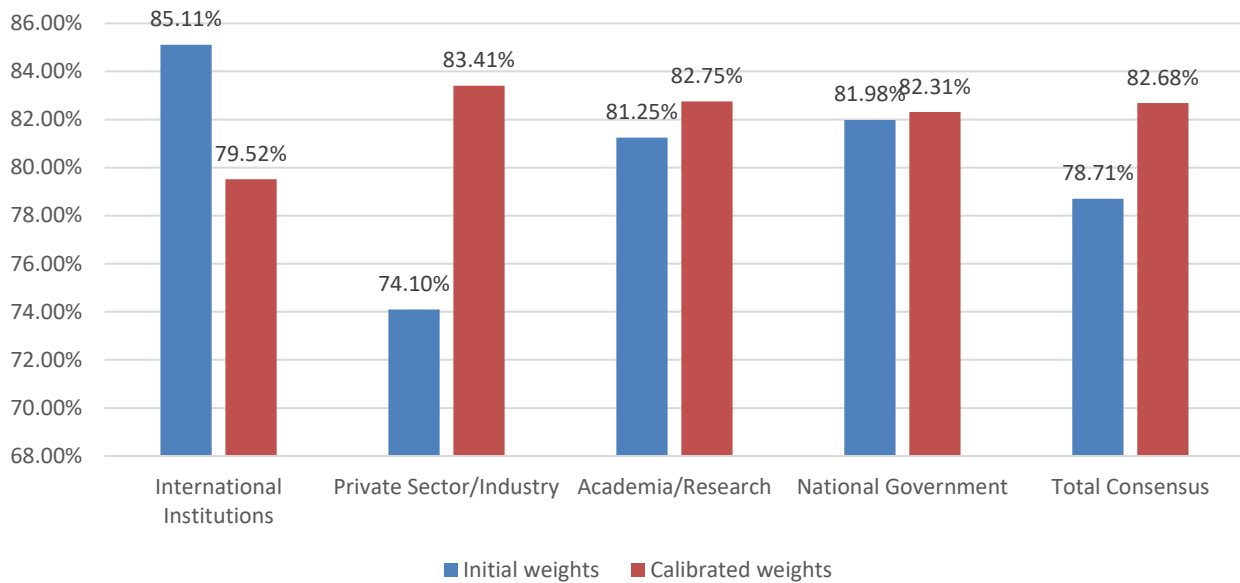


Figure 39: Comparison of internal consensus levels per group with and without weight calibration

Improvements in consensus are also evident in Figure 40, with the majority of alternatives being placed in the high priority-high consensus quadrant, while preserving the distinctions among the sectors. In fact, although most sectors improved their position consensus-wise, the AFOLU sector maintained its position in the scatter, indicating that the strong preference of the participating stakeholders from the initial steps holds after criteria weight calibration, without being affected by the modified weights nor the shift toward the residential sector, indicating robust preference, as hinted and discussed earlier.

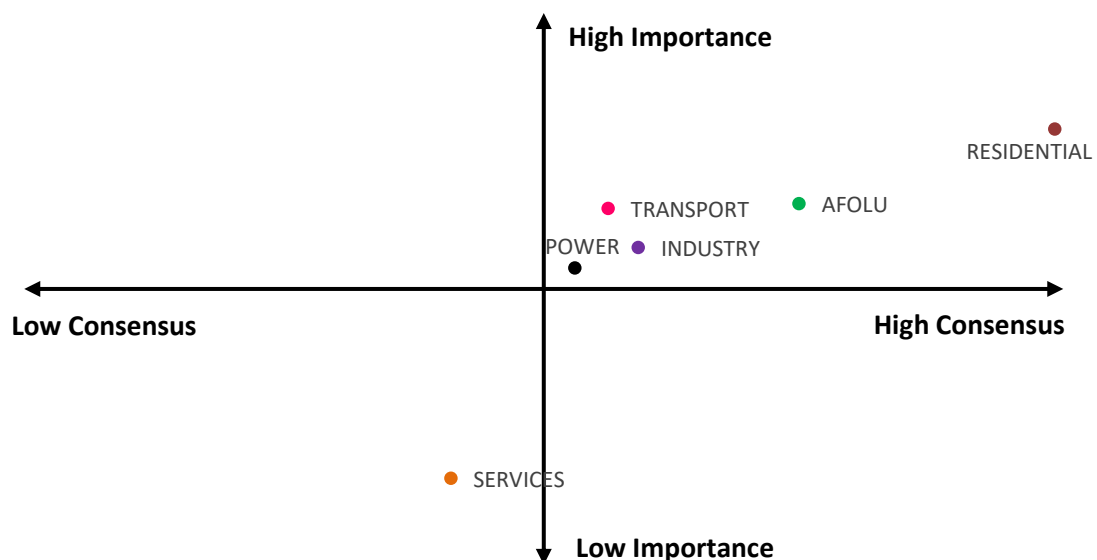


Figure 40: Importance-Consensus of each sector in the final analysis

This prioritisation of the residential and AFOLU sectors fit and enhance the narrative from both a sectoral and an SDG perspective. Stakeholders are concerned over the lack of access to electricity and related issues, such as reliance on non-sustainable biomass and implications over AFOLU and SDG15. The group of experts, in a better informed MCDA framework of the Kenyan sustainability context, also provide additional insights into the preferred prioritisation of these issues. Pointing towards SDG7 and the residential sector while stepping back from power



generation, the engaged stakeholders acknowledge that deep penetration of renewables is likely to be harder than anticipated and therefore prefer to prioritise near-term demand-side transformations, with the transport sector following closely. Considering the discrepancies between national strategies and sectoral policies, which in the case of the AFOLU sector have so far led focus to orient on economic growth (Faling, 2020), our results indicate the necessity to build cross-sectoral policies between AFOLU and the residential sector accounting for the impact on SDGs 15 and 7, and especially the key threats identified in the context of Kenya, like limited electricity access, extensive use of non-sustainable biomass and respective health implications.

4.4. Conclusions

This study aims to provide insights for policymakers and modellers alike, into stakeholder preferences over the interplay between climate action at the sectoral level and sustainable development for Kenya and the broader Sub-Saharan African region, in which five intertwined threats loom large, posing significant challenges for the design of an effective and sustainable transition pathway: climate change, lack of access to electricity, extreme poverty, poor cooking means/nutrition, and health issues. To better address these threats in line with Paris Agreement targets and the 2030 Agenda for Sustainable Development, a multi-criteria decision aid framework is designed, based on the 2-tuple group TOPSIS and a consensus measuring approach, and applied to a stakeholder workshop with Kenyan stakeholders, via two seemingly separate yet highly intertwined questionnaires. The first aimed at assessing the importance of the decarbonisation of economic sectors for four sustainable development axes, and the second at prioritising SDGs in relation to progress, ambition, as well as relation to climate action and the national context.

Initially, a traditional MCDA approach was employed, in which stakeholders provided their assessments of each alternative against the four criteria, while offering criteria weights themselves. In this exercise, they appeared divided over the importance of the different sectors considering almost all of them as equally important, with only the services sector straying as least important. Considering consensus for each sector, AFOLU more clearly stood out from the rest of the alternatives. This preference was confirmed in the SDG prioritisation exercise employing a similar setting, with SDG15 (life on land) ranking first as the most critical to SDG to both integrate with climate action and pay attention to in mitigation analysis for Kenya. These outputs trace back to the national and regional context, where limited electricity production has driven reliance on non-renewable biomass, and especially fuelwood, consequently leading to indoor air pollution and employment of poor cooking methods. With their evaluations, stakeholders highlighted the importance of considering AFOLU, biodiversity and ecosystem implications of the region's sustainable transition, especially regarding use of biomass and the switch to more efficient fuels. From a modelling perspective, this indicates that indirect links between social issues and climate change should also be considered outside the energy access and mitigation spectrum commonly explored (e.g. van der Zwaan et al., 2018; Van de Ven et al., 2019; Dagnachew et al., 2020; Forouli et al., 2020), instead of traditional metric-based evaluations that left stakeholders less interested. After modifying weights based on the results of the second exercise, another iteration of the sectoral decarbonisation exercise showed decisively singled out the residential sector, both as a top priority and agreed upon by stakeholders the most; the AFOLU sector, although now outranked, still remained fairly important as a result of the steadily strong consensus. This new prioritisation can also be linked with efforts for affordable and clean energy (SDG7), which apart from SDG15 was the only other SDG receiving a high evaluation, thereby further highlighting stakeholders' concern over the challenge of limited access to modern energy. At the same time, stakeholders hinted that a solution in the shorter run should not rely exclusively on renewable energy diffusion, which can be much more difficult than anticipated, but consider demand-side transformations in the residential sector. The latter, as with some SDGs prioritised the most, is another aspect underrepresented in the modelling capabilities (Nikas et al., 2020a), which is another core



finding on its own. Increasing energy efficiency with targeted research and improving fuel quality can be an effective way to promote renewables and address AFOLU challenges and concerns. Overall, future cross-sectoral policies in the AFOLU and residential sectors should consider implications on these issues and the progress towards the respective SDGs.

Drawing from the outputs of this study, future modelling advancements and exercises could prioritise analysis of the sectors and SDGs identified as most pertinent by the Kenyan stakeholders to shed light on Paris-compliant pathways that at the same time address local threats and ensure the region's sustainable development. The proposed framework can be enhanced in cross-country comparison setups, enabling to gain insights into how different stakeholders from different national and regional contexts perceive the SDG framework, in relation to their country's climate action, and vice versa, for better informed modelling that transcends one-size-fits-all comfort zones.



Bibliography

- Abu-Taha, R. (2011, July). Multi-criteria applications in renewable energy analysis: A literature review. In *2011 Proceedings of PICMET'11: Technology Management in the Energy Smart World (PICMET)* (pp. 1-8). IEEE.
- Ackerman, F., DeCanio, S. J., Howarth, R. B., & Sheeran, K. (2009). Limitations of integrated assessment models of climate change. *Climatic change*, 95(3-4), 297-315.
- AfDB/OECD/UNDP (2016). African Economic Outlook 2016. OECD, Paris. Available at: https://www.afdb.org/fileadmin/uploads/afdb/Documents/Publications/AEO_2016_Report_Full_English.pdf
- Ahmed, F., & Mishra, V. (2020). Estimating relative immediacy of water-related challenges in Small Island Developing States (SIDS) of the Pacific Ocean using AHP modeling. *Modeling Earth Systems and Environment*, 6(1), 201-214.
- Ahmed, W., Tan, Q., Shaikh, G. M., Waqas, H., Kanasro, N. A., Ali, S., & Solangi, Y. A. (2020a). Assessing and Prioritizing the Climate Change Policy Objectives for Sustainable Development in Pakistan. *Symmetry*, 12(8), 1203.
- Ahmed, W., Tan, Q., Solangi, Y. A., & Ali, S. (2020b). Sustainable and Special Economic Zone Selection under Fuzzy Environment: A Case of Pakistan. *Symmetry*, 12(2), 242.
- Akermi, R., & Triki, A. (2017). The green energy transition and civil society in Tunisia: Actions, motivations and barriers. *Energy Procedia*, 136, 79-84.
- Alati, V. M., Olunga, J., Olendo, M., Daudi, L. N., Osuka, K., Odoli, C., ... & Nordlund, L. M. (2020). Mollusc shell fisheries in coastal Kenya: Local ecological knowledge reveals overfishing. *Ocean & Coastal Management*, 195, 105285.
- Albadvi, A., Chaharsooghi, S. K., & Esfahanipour, A. (2007). Decision making in stock trading: An application of PROMETHEE. *European journal of operational research*, 177(2), 673-683.
- Ali, E. (2006). Criteria for assessing sustainable energy technology for rural bangladesh. *International Journal of Development Issues*.
- Allen, C., Metternicht, G., & Wiedmann, T. (2018). Initial progress in implementing the Sustainable Development Goals (SDGs): a review of evidence from countries. *Sustainability Science*, 13(5), 1453-1467.
- Alova, G., Trotter, P.A., Money, A. (2021). A machine-learning approach to predicting Africa's electricity mix based on planned power plants and their chances of success. *Nature Energy*. <https://doi.org/10.1038/s41560-020-00755-9>
- Antanasijević, D., Pocajt, V., Ristić, M., & Perić-Grujić, A. (2017). A differential multi-criteria analysis for the assessment of sustainability performance of European countries: Beyond country ranking. *Journal of cleaner production*, 165, 213-220.
- Antosiewicz, M., Nikas, A., Szpor, A., Witajewski-Baltvilks, J., & Doukas, H. (2020). Pathways for the transition of the Polish power sector and associated risks. *Environmental Innovation and Societal Transitions*, 35, 271-291.
- Apostoli, A. J. (2016). India's energy-climate dilemma: The pursuit for renewable energy guided by existing climate change policies. *J. Earth Sci. Clim. Change*, 7, 362.
- Araújo, K. (2014). The emerging field of energy transitions: progress, challenges, and opportunities. *Energy*



Research & Social Science, 1, 112-121.

- Arens, M., Worrell, E., & Schleich, J. (2012). Energy intensity development of the German iron and steel industry between 1991 and 2007. *Energy, 45*(1), 786-797.
- Arens, M., Worrell, E., Eichhammer, W., Hasanbeigi, A., & Zhang, Q. (2017). Pathways to a low-carbon iron and steel industry in the medium-term—the case of Germany. *Journal of Cleaner Production, 163*, 84-98.
- Ari, I., & Sari, R. (2017). Differentiation of developed and developing countries for the Paris Agreement. *Energy Strategy Reviews, 18*, 175-182.
- Azam, M., Khan, A. Q., Zafeiriou, E., & Arabatzis, G. (2016). Socio-economic determinants of energy consumption: An empirical survey for Greece. *Renewable and Sustainable Energy Reviews, 57*, 1556-1567.
- Bachner, G., Mayer, J., Steininger, K. W., Anger-Kraavi, A., Smith, A., & Barker, T. S. (2020). Uncertainties in macroeconomic assessments of low-carbon transition pathways—The case of the European iron and steel industry. *Ecological Economics, 172*, 106631.
- Balali, A., & Valipour, A. (2020). Identification and selection of building façade's smart materials according to sustainable development goals. *Sustainable Materials and Technologies, 26*, e00213.
- Balali, V., Zahraie, B., & Roozbahani, A. (2014). Integration of ELECTRE III and PROMETHEE II decision-making methods with an interval approach: Application in selection of appropriate structural systems. *Journal of Computing in Civil Engineering, 28*(2), 297-314.
- Baležentis, T., & Streimikiene, D. (2017). Multi-criteria ranking of energy generation scenarios with Monte Carlo simulation. *Applied energy, 185*, 862-871.
- Bandura, R. (2005). Measuring country performance and state behavior: A survey of composite indices. *New York: Office of Development Studies, United Nations Development Programme (UNDP)*.
- Batinge, B., Musango, J. K., & Brent, A. C. (2019). Sustainable energy transition framework for unmet electricity markets. *Energy Policy, 129*, 1090-1099.
- Bayram, H., & Şahin, R. (2016). A simulation based multi-attribute group decision making technique with decision constraints. *Applied Soft Computing, 49*, 629-640.
- Beale, E., Beugin, D., Dahlby, B., Drummond, D., Olewiler, N., & Ragan, C. (2015). *Provincial Carbon Pricing and Competitiveness Pressures*. Canada's Ecofiscal Commission.
- Behzadian, M., Kazemzadeh, R. B., Albadvi, A., & Aghdasi, M. (2010). PROMETHEE: A comprehensive literature review on methodologies and applications. *European journal of Operational research, 200*(1), 198-215.
- Bekaert, G., & Harvey, C. R. (2017). Emerging equity markets in a globalizing world. *Available at SSRN 2344817*.
- Ben-Arieh, D., & Chen, Z. (2006). Linguistic-labels aggregation and consensus measure for autocratic decision making using group recommendations. *IEEE Transactions on Systems, Man, and Cybernetics-Part A: Systems and Humans, 36*(3), 558-568.
- Bender, M. J., & Simonovic, S. P. (1997). Consensus as the measure of sustainability. *Hydrological sciences journal, 42*(4), 493-500.
- Bergek, A., & Mignon, I. (2017). Motives to adopt renewable electricity technologies: Evidence from Sweden. *Energy Policy, 106*, 547-559.
- Bhattacharyya, S. C. (2006). Energy access problem of the poor in India: Is rural electrification a remedy?. *Energy*



policy, 34(18), 3387-3397.

- Bloch, H., Rafiq, S., & Salim, R. (2012). Coal consumption, CO2 emission and economic growth in China: Empirical evidence and policy responses. *Energy Economics*, 34(2), 518-528.
- BMWF (2016). Economic Report 2016. Federal Ministry of Science, Research & Economy. Available at: http://www.bmwf.gv.at/Wirtschaftspolitik/Wirtschaftspolitik/Documents/Wirtschaftsbericht_2016_Englisch_WEBversion.ok%20HW9.pdf, Accessed on 21.09.2019
- Bonfadelli, H. (2016). Climate change communication in Switzerland. In *Oxford Research Encyclopedia of Climate Science*.
- Borouhaki, S., & Malczewski, J. (2010). Measuring consensus for collaborative decision-making: A GIS-based approach. *Computers, environment and urban systems*, 34(4), 322-332.
- Bouyssou, D. (1990). Building criteria: a prerequisite for MCDA. In *Readings in multiple criteria decision aid* (pp. 58-80). Springer, Berlin, Heidelberg.
- Bouzarovski, S. (2018). Energy Poverty Policies at the EU Level. In *Energy poverty* (pp. 41-73). Palgrave Macmillan, Cham.
- Brans, J. P., Vincke, P., & Mareschal, B. (1986). How to select and how to rank projects: The PROMETHEE method. *European journal of operational research*, 24(2), 228-238.
- Brinkerhoff, J., Smith, S., & Teegen, H. (2007). NGOs and the Millennium Development Goals: citizen action to reduce poverty. New York: Palgrave Macmillan.
- Bryan, B. A., Hadjikakou, M., & Moallemi, E. A. (2019). Rapid SDG progress possible. *Nature Sustainability*, 2(11), 999-1000.
- Bryson, N. (1996). Group decision-making and the analytic hierarchy process: Exploring the consensus-relevant information content. *Computers & Operations Research*, 23(1), 27-35.
- Budiman, E., Dengen, N., & Indrawan, W. (2017, October). Integrated multi criteria decision making for a destitute problem. In 2017 3rd International Conference on Science in Information Technology (ICSITech) (pp. 342-347). IEEE.
- Burck, J., Hagen, U., Höhne, N., Nascimento, L., & Bals, C. (2019). Climate Change Performance Index 2020: results. Business, D. (2020). Comparing Business Regulation in 190 Economies. *International Bank for Reconstruction and Development. The World Bank. Washington*, 135.
- Byers, E., Gidden, M., Leclère, D., Balkovic, J., Burek, P., Ebi, K., ... & Johnson, N. (2018). Global exposure and vulnerability to multi-sector development and climate change hotspots. *Environmental Research Letters*, 13(5), 055012.
- Campbell, B. M., Hansen, J., Rioux, J., Stirling, C. M., & Twomlow, S. (2018). Urgent action to combat climate change and its impacts (SDG 13): transforming agriculture and food systems. *Current opinion in environmental sustainability*, 34, 13-20.
- CANADA N R (2016). Energy Fact Book. Available at: https://www.nrcan.gc.ca/sites/www.nrcan.gc.ca/files/energy/pdf/EnergyFactBook_2016_17_En.pdf
- Capellán-Pérez, I., de Blas, I., Nieto, J., de Castro, C., Miguel, L. J., Carpintero, Ó., ... & Frechoso, F. (2020). MEDEAS: a new modeling framework integrating global biophysical and socioeconomic constraints. *Energy &*



Environmental Science, 13(3), 986-1017.

- Carrasco, L. E. G., & Cerda, R. (2019). Promoting renewable energy and the risk of energy poverty in Chile. *Narratives of Low-Carbon Transitions*, 91.
- Caymaz S (2013). Dutch coal tax could change but not increase – ministry. Available at: <https://www.icis.com/explore/resources/news/2013/07/03/9684560/dutch-coal-tax-could-change-butnot-increase-ministry/>
- Chan, G., Goldstein, A. P., Bin-Nun, A., & Narayanamurti, V. (2017). Six principles for energy innovation. *Nature*, 552(7683), 25-27.
- Chappin, E. J., & Ligtoet, A. (2014). Transition and transformation: A bibliometric analysis of two scientific networks researching socio-technical change. *Renewable and sustainable energy reviews*, 30, 715-723.
- Chen, C. T., Lin, C. T., & Huang, S. F. (2006). A fuzzy approach for supplier evaluation and selection in supply chain management. *International journal of production economics*, 102(2), 289-301.
- Chen, X., Qu, K., Calautit, J., Ekambaram, A., Lu, W., Fox, C., ... & Riffat, S. (2020). Multi-criteria assessment approach for a residential building retrofit in Norway. *Energy and Buildings*, 215, 109668.
- Cherp, A., Vinichenko, V., Jewell, J., Brutschin, E., & Sovacool, B. (2018). Integrating techno-economic, socio-technical and political perspectives on national energy transitions: A meta-theoretical framework. *Energy Research & Social Science*, 37, 175-190.
- Choi, D., Ahn, Y. H., & Choi, D. G. (2020). Multi-criteria decision analysis of electricity sector transition policy in Korea. *Energy Strategy Reviews*, 29, 100485.
- Climate Action Tracker (2016). Indonesia - Climate Action Tracker. Available at: <http://climateactiontracker.org/countries/indonesia.html>
- Climate Action Tracker (2019). <https://climateactiontracker.org/>
- Cohen, G., Jalles, J. T., Loungani, P., & Marto, R. (2018). The long-run decoupling of emissions and output: Evidence from the largest emitters. *Energy Policy*, 118, 58-68.
- Creutzig, F., Roy, J., Lamb, W. F., Azevedo, I. M., De Bruin, W. B., Dalkmann, H., ... & Weber, E. U. (2018). Towards demand-side solutions for mitigating climate change. *Nature Climate Change*, 8(4), 260-263.
- D'agata, S., Darling, E. S., Gurney, G. G., McClanahan, T. R., Muthiga, N. A., Rabearisoa, A., & Maina, J. M. (2020). Multiscale determinants of social adaptive capacity in small-scale fishing communities. *Environmental Science & Policy*, 108, 56-66.
- Dagnachew, A. G., Hof, A. F., Lucas, P. L., & van Vuuren, D. P. (2020). Scenario analysis for promoting clean cooking in Sub-Saharan Africa: Costs and benefits. *Energy*, 192, 116641.
- Dagnachew, A. G., Lucas, P. L., Hof, A. F., & van Vuuren, D. P. (2018). Trade-offs and synergies between universal electricity access and climate change mitigation in Sub-Saharan Africa. *Energy Policy*, 114, 355-366.
- Dagnachew, A. G., Lucas, P. L., Hof, A. F., Gernaat, D. E., de Boer, H. S., & van Vuuren, D. P. (2017). The role of decentralized systems in providing universal electricity access in Sub-Saharan Africa—A model-based approach. *Energy*, 139, 184-195.
- Dal Maso, M., Olsen, K. H., Dong, Y., Pedersen, M. B., & Hauschild, M. Z. (2020). Sustainable development impacts of nationally determined contributions: assessing the case of mini-grids in Kenya. *Climate Policy*, 20(7),



815-831.

- Dalla Longa, F., & van der Zwaan, B. (2017). Do Kenya's climate change mitigation ambitions necessitate large-scale renewable energy deployment and dedicated low-carbon energy policy?. *Renewable Energy*, 113, 1559-1568.
- D'Alpaos, C., & Andreolli, F. (2020). Urban quality in the city of the future: A bibliometric multicriteria assessment model. *Ecological Indicators*, 117, 106575.
- das Neves Almeida, T. A., & García-Sánchez, I. M. (2016). A comparative analysis between composite indexes of environmental performance: An analysis on the CIEP and EPI. *Environmental science & policy*, 64, 59-74.
- Davis, M., Ahiduzzaman, M., & Kumar, A. (2018). How will Canada's greenhouse gas emissions change by 2050? A disaggregated analysis of past and future greenhouse gas emissions using bottom-up energy modelling and Sankey diagrams. *Applied energy*, 220, 754-786.
- de Bruyn-Szendrei, K., van der Gaast, W., & Spijker, E. (2019). Expanding solar PV—risks and uncertainties associated with small-and large-scale options. *Narratives of Low-Carbon Transitions*, 105.
- Demski, C., Butler, C., Parkhill, K. A., Spence, A., & Pidgeon, N. F. (2015). Public values for energy system change. *Global Environmental Change*, 34, 59-69.
- Department of energy and climate change. (2016). Energy Trends June 2016
- Deshpande, P. C., Skaar, C., Brattebø, H., & Fet, A. M. (2020). Multi-criteria decision analysis (MCDA) method for assessing the sustainability of end-of-life alternatives for waste plastics: A case study of Norway. *Science of the Total Environment*, 137353.
- Diakoulaki, D., Georgiou, P., Tourkoulis, C., Georgopoulou, E., Lalas, D., Mirasgedis, S., & Sarafidis, Y. (2007). A multicriteria approach to identify investment opportunities for the exploitation of the clean development mechanism. *Energy Policy*, 35(2), 1088-1099.
- Diaz-Sarachaga, J. M., Jato-Espino, D., & Castro-Fresno, D. (2017). Methodology for the development of a new Sustainable Infrastructure Rating System for Developing Countries (SIRSDEC). *Environmental Science & Policy*, 69, 65-72.
- Diemuodeke, E. O., Addo, A., Oko, C. O. C., Mulugetta, Y., & Ojapah, M. M. (2019). Optimal mapping of hybrid renewable energy systems for locations using multi-criteria decision-making algorithm. *Renewable Energy*, 134, 461-477.
- Dioha, M. O., & Kumar, A. (2020). Sustainable energy pathways for land transport in Nigeria. *Utilities Policy*, 64, 101034.
- Michaelis, P., & Wirths, H. (2020). DICE-RD: an implementation of rate-related damages in the DICE model. *Environmental Economics and Policy Studies*, 1-30.
- Dissou, Y. (2010). Oil price shocks: Sectoral and dynamic adjustments in a small-open developed and oil-exporting economy. *Energy Policy*, 38(1), 562-572.
- Doelman, J. C., Stehfest, E., Tabeau, A., & van Meijl, H. (2019). Making the Paris agreement climate targets consistent with food security objectives. *Global Food Security*, 23, 93-103.
- Doelman, J. C., Stehfest, E., van Vuuren, D. P., Tabeau, A., Hof, A. F., Braakhekke, M. C., ... & van Meijl, H. (2020). Afforestation for climate change mitigation: Potentials, risks and trade-offs. *Global Change Biology*, 26(3), 1576-1591. doi: 10.1016/j.jup.2020.101034"
- Dong, Y., Zhao, S., Zhang, H., Chiclana, F., & Herrera-Viedma, E. (2018). A self-management mechanism for



- noncooperative behaviors in large-scale group consensus reaching processes. *IEEE Transactions on Fuzzy Systems*, 26(6), 3276-3288.
- Dooley, K., Christoff, P., & Nicholas, K. A. (2018). Co-producing climate policy and negative emissions: trade-offs for sustainable land-use. *Global Sustainability*, 1.
- Doukas, H., & Nikas, A. (2020). Decision support models in climate policy. *European Journal of Operational Research*, 280(1), 1-24.
- Doukas, H., Karakosta, C., & Psarras, J. (2010). Computing with words to assess the sustainability of renewable energy options. *Expert Systems with Applications*, 37(7), 5491-5497.
- Doukas, H., Nikas, A., González-Eguino, M., Arto, I., & Anger-Kraavi, A. (2018). From integrated to integrative: Delivering on the Paris Agreement. *Sustainability*, 10(7), 2299.
- Doukas, H., Tsiouisi, A., Marinakis, V., & Psarras, J. (2014). Linguistic multi-criteria decision making for energy and environmental corporate policy. *Information Sciences*, 258, 328-338.
- du Can, S. D. L. R., Pudleiner, D., & Pielli, K. (2018). Energy efficiency as a means to expand energy access: A Uganda roadmap. *Energy Policy*, 120, 354-364.
- Duran, E., Aravena, C., & Aguilar, R. (2015). Analysis and decomposition of energy consumption in the Chilean industry. *Energy Policy*, 86, 552-561.
- Dutu, R. (2016). Challenges and policies in Indonesia's energy sector. *Energy Policy*, 98, 513-519.
- Dvoroková, K. (2014). Sigma Versus Beta-convergence in EU28: do they lead to different results. *Mathematical methods in finance and business administration*, 88-94.
- Earth's Endangered Creatures. Earthsendangered.com. (2020). Retrieved from <http://earthsendangered.com/search-regions3.asp>.
- Easterly, W. (2009). How the millennium development goals are unfair to Africa. *World development*, 37(1), 26-35.
- Ecologic Institute, Climact (2019). Planning for net zero: assessing the draft National Energy and Climate Plans. Available at: <https://europeanclimate.org/wp-content/uploads/2019/05/Planning-for-Net-Zero.-Assessing-the-draft-NECPs.pdf>
- Elias, R. S., Yuan, M., Wahab, M. I. M., & Patel, N. (2019). Quantifying saving and carbon emissions reduction by upgrading residential furnaces in Canada. *Journal of Cleaner Production*, 211, 1453-1462.
- Ernst & Young (2017), Renewable Energy Country Attractiveness Index Methodology. Available at: <http://www.ey.com/gl/en/industries/power---utilities/ey-renewable-energy-country-attractiveness-index-library>. Accessed on 15.01.2020
- Esparcia, J. (2014). Innovation and networks in rural areas. An analysis from European innovative projects. *Journal of rural studies*, 34, 1-14.
- Europe, C. A. N. (2018). Off Target—Ranking of EU Countries' Ambition and Progress in Fighting Climate Change. *Climate Action Network Europe: Brussels, Belgium*.
- European Commission (2016). European Innovation Scoreboard. Available at: http://ec.europa.eu/growth/industry/innovation/facts-figures/scoreboards_en
- European Commission (2017). Climate change, Special Eurobarometer 459/ Wave EB87.1. Brussels, Belgium. Available at: https://ec.europa.eu/clima/sites/clima/files/support/docs/report_2017_en.pdf



- European Environment Agency (2014). Progress towards 2008-2012 Kyoto targets in Europe. EEA Technical report, No. 18/2014. Publications Office of the European Union. Luxembourg.
- Eurostat (2015). Eurostat statistics by theme. Available at: <http://ec.europa.eu/eurostat/data/browse-statistics-by-theme>.
- Lanati, F., Gelmini, A., & Viganò, G. (2019, September). The evolution of the Italian power system in 2030 to support more than 55% of renewables on electricity consumption. In 2019 AEIT International Annual Conference (AEIT) (pp. 1-6). IEEE. doi: 10.23919/AEIT.2019.8893430
- Faling, M. (2020). Framing agriculture and climate in Kenyan policies: A longitudinal perspective. *Environmental Science & Policy*, 106, 228-239.
- Fischedick, M., Marzinkowski, J., Winzer, P., & Weigel, M. (2014). Techno-economic evaluation of innovative steel production technologies. *Journal of Cleaner Production*, 84, 563-580.
- Forouli, A., Doukas, H., Nikas, A., Sampedro, J., & Van de Ven, D. J. (2019). Identifying optimal technological portfolios for European power generation towards climate change mitigation: a robust portfolio analysis approach. *Utilities Policy*, 57, 33-42.
- Forouli, A., Nikas, A., Van de Ven, D. J., Sampedro, J., & Doukas, H. (2020). A multiple-uncertainty analysis framework for integrated assessment modelling of several sustainable development goals. *Environmental Modelling & Software*, 131, 104795.
- Freimane, R., & Bāliņa, S. (2016). Research and development expenditures and economic growth in the EU: A panel data analysis. *Economics and Business*, 29(1), 5-11.
- Fu, C., & Yang, S. L. (2010). The group consensus based evidential reasoning approach for multiple attributive group decision analysis. *European Journal of Operational Research*, 206(3), 601-608.
- Fuhrman, J., McJeon, H., Doney, S., Shobe, W., & Clarens, A. F. (2019). From Zero to Hero?: Why Integrated Assessment Modeling of Negative Emissions Technologies Is Hard and How We Can Do Better. *Frontiers in Climate*, 1, 11.
- Fujimori, S., Hasegawa, T., Krey, V., Riahi, K., Bertram, C., Bodirsky, B. L., ... & van Vuuren, D. (2019). A multi-model assessment of food security implications of climate change mitigation. *Nature Sustainability*, 2(5), 386-396.
- Fujimori, S., Hasegawa, T., Takahashi, K., Dai, H., Liu, J. Y., Ohashi, H., ... & Hijioka, Y. (2020). Measuring the sustainable development implications of climate change mitigation. *Environmental Research Letters*.
- Fuss, S., Jones, C. D., Kraxner, F., Peters, G. P., Smith, P., Tavoni, M., ... & Moreira, J. R. (2016). Research priorities for negative emissions. *Environmental Research Letters*, 11(11), 115007.
- Gaete-Morales, C., Gallego-Schmid, A., Stamford, L., & Azapagic, A. (2018). Assessing the environmental sustainability of electricity generation in Chile. *Science of The Total Environment*, 636, 1155-1170.
- Garcia-Casals, X., Ferroukhi, R., & Parajuli, B. (2019). Measuring the socio-economic footprint of the energy transition. *Energy Transitions*, 3(1-2), 105-118.
- Geels, F. W. (2002). Technological transitions as evolutionary reconfiguration processes: a multi-level perspective and a case-study. *Research policy*, 31(8-9), 1257-1274.
- Geels, F. W., Kern, F., Fuchs, G., Hinderer, N., Kungl, G., Mylan, J., ... & Wassermann, S. (2016). The enactment of socio-technical transition pathways: a reformulated typology and a comparative multi-level analysis of the



- German and UK low-carbon electricity transitions (1990–2014). *Research Policy*, 45(4), 896-913.
- Gerres, T., Ávila, J. P. C., Llamas, P. L., & San Román, T. G. (2019). A review of cross-sector decarbonisation potentials in the European energy intensive industry. *Journal of Cleaner Production*, 210, 585-601.
- Ghazinoory, S., Daneshmand-Mehr, M., & Azadegan, A. (2013). Technology selection: application of the PROMETHEE in determining preferences—a real case of nanotechnology in Iran. *Journal of the Operational Research Society*, 64(6), 884-897.
- Ghosh, D., & Ghosh, A. (2016). RAPID DESK BASED STUDY.
- Giarola, S., Mittal, S., Vielle, M., Perdana, S., Campagnolo, L., Delpiazzi, E., Bui, H., Anger-Kraavi, A., Kolpakov, A., Sognaes, I., Peters, G.P., Hawkes, A., Koberle, A., Grant, N., Gambhir, A., Nikas, A., Doukas, H., Moreno, J., & Van de Ven, D.J. (2020). Challenges in the harmonisation of global integrated assessment models: a comprehensive methodology to reduce model response heterogeneity. *Science of the Total Environment*. Under Review.
- Gielen, D., Boshell, F., Saygin, D., Bazilian, M. D., Wagner, N., & Gorini, R. (2019). The role of renewable energy in the global energy transformation. *Energy Strategy Reviews*, 24, 38-50.
- Gil, J. D., Daioglou, V., van Ittersum, M., Reidsma, P., Doelman, J. C., van Middelaar, C. E., & van Vuuren, D. P. (2019). Reconciling global sustainability targets and local action for food production and climate change mitigation. *Global Environmental Change*, 59, 101983.
- Gil, L., Bernardo, J., (2020). An approach to energy and climate issues aiming at carbon neutrality, *Renewable Energy Focus*, Volume 33, Pages 37-42, ISSN 1755-0084, <https://doi.org/10.1016/j.ref.2020.03.003>.
- Global Energy Observatory (2019). Available at: <http://globalenergyobservatory.org/countrysummary.php>, Accessed on 03.09.2019.
- Global Innovation Index (2016). The Global Innovation Index. Available at: <https://www.globalinnovationindex.org/analysis-indicator>, Accessed on 13.9.2019
- Godinez, G., Victor-Gallardo, L., Angulo-Paniagua, J., Ramos, E., Howells, M., Usher, W., ... & Quirós-Tortós, J. (2020). How Modelling Tools Can Support Climate Change Policy: The Case of Costa Rica in the Energy Sector. Available at SSRN 3560584.
- Griggs, D., Stafford-Smith, M., Gaffney, O., Rockström, J., Öhman, M. C., Shyamsundar, P., . . . Noble, I. (2013). Policy: Sustainable development goals for people and planet. *Nature*, 495(7441), 305.
- Grubler, A., Wilson, C., Bento, N., Boza-Kiss, B., Krey, V., McCollum, D. L., ... & Cullen, J. (2018). A low energy demand scenario for meeting the 1.5 C target and sustainable development goals without negative emission technologies. *Nature energy*, 3(6), 515-527.
- Guler, B., Çelebi, E., & Nathwani, J. (2018). A 'Regional Energy Hub' for achieving a low-carbon energy transition. *Energy Policy*, 113, 376-385.
- Gupta, A., & Singh, R. K. (2020). Developing a framework for evaluating sustainability index for logistics service providers: graph theory matrix approach. *International Journal of Productivity and Performance Management*.
- Gupta, M. (2016). Willingness to pay for carbon tax: A study of Indian road passenger transport. *Transport Policy*, 45, 46-54.
- Guzman-Sanchez, S., Jato-Espino, D., Lombillo, I., & Diaz-Sarachaga, J. M. (2018). Assessment of the contributions



- of different flat roof types to achieving sustainable development. *Building and Environment*, 141, 182-192.
- Haga, C., Maeda, M., Hotta, W., Inoue, T., Matsui, T., Machimura, T., ... & Saito, O. (2020). Scenario Analysis of Renewable Energy–Biodiversity Nexuses Using a Forest Landscape Model. *Frontiers in Ecology and Evolution*, 8, 155.
- Hameed, H. B., Ali, Y., & Petrillo, A. (2020). Environmental risk assessment of E-waste in developing countries by using the modified-SIRA method. *Science of The Total Environment*, 138525.
- Hamidov, A., Helming, K., Bellocchi, G., Bojar, W., Dalgaard, T., Ghaley, B. B., ... & Schönhart, M. (2018). Impacts of climate change adaptation options on soil functions: A review of European case-studies. *Land degradation & development*, 29(8), 2378-2389.
- Hanger-Kopp, S., Lieu, J., & Nikas, A. (2019). *Narratives of Low-Carbon Transitions*. Taylor & Francis.
- Harrison, K. (2012). A tale of two taxes: The fate of environmental tax reform in Canada. *Review of Policy Research*, 29(3), 383-407.
- Harvey, H., Orvis, R., & Rissman, J. (2018). Putting Us on Track to a Low-Carbon Future. In *Designing Climate Solutions* (pp. 25-33). Island Press, Washington, DC.
- Hassan, M., Khan Afridi, M., & Irfan Khan, M. (2019). Energy policies and environmental security: A multi-criteria analysis of energy policies of Pakistan. *International Journal of Green Energy*, 16(7), 510-519.
- He, Y., Xu, Y., Pang, Y., Tian, H., & Wu, R. (2016). A regulatory policy to promote renewable energy consumption in China: Review and future evolutionary path. *Renewable Energy*, 89, 695-705.
- Hepburn, C., & Teytelboym, A. (2017). Climate change policy after Brexit. *Oxford Review of Economic Policy*, 33(suppl_1), S144-S154.
- Herrera, F., & Herrera-Viedma, E. (1996). A model of consensus in group decision making under linguistic assessments. *Fuzzy sets and Systems*, 78(1), 73-87.
- Herrera, F., & Martínez, L. (2000). A 2-tuple fuzzy linguistic representation model for computing with words. *IEEE Transactions on fuzzy systems*, 8(6), 746-752.
- Herrera, F., Herrera-Viedma, E., & Verdegay, J.L. (1996). A model of consensus in group decision making under linguistic assessments. *Fuzzy sets and Systems*, 78(1), 73-87.
- Herrera-Viedma, E., Herrera, F., & Chiclana, F. (2002). A consensus model for multiperson decision making with different preference structures. *IEEE Transactions on Systems, Man, and Cybernetics-Part A: Systems and Humans*, 32(3), 394-402.
- Hölgens, R. (2019). Resource dependence and energy risks in the Netherlands since the mid-nineteenth century. *Energy Policy*, 125, 45-54.
- Huang, I. B., Keisler, J., & Linkov, I. (2011). Multi-criteria decision analysis in environmental sciences: Ten years of applications and trends. *Science of the total environment*, 409(19), 3578-3594.
- Huang, Y. S., & Li, W. H. (2012). A study on aggregation of TOPSIS ideal solutions for group decision-making. *Group Decision and Negotiation*, 21(4), 461-473.
- Humpenöder, F., Popp, A., Bodirsky, B. L., Weindl, I., Biewald, A., Lotze-Campen, H., ... & Rolinski, S. (2018). Large-scale bioenergy production: how to resolve sustainability trade-offs?. *Environmental Research Letters*, 13(2), 024011.



- Hwang, C. L., & Yoon, K. (1981). Methods for multiple attribute decision making. In *Multiple attribute decision making* (pp. 58-191). Springer, Berlin, Heidelberg.
- Hyde, K., Maier, H. R., & Colby, C. (2003). Incorporating uncertainty in the PROMETHEE MCDA method. *Journal of Multi-Criteria Decision Analysis*, 12(4-5), 245-259.
- Hyvärinen, A. M., Keskinen, M., & Levänen, J. (2020). Innovation process and uncertainties in resource-constrained environments: A case from the water service sector in East Africa. *Environmental Science & Policy*, 114, 242-252.
- Iddrisu, I., & Bhattacharyya, S. C. (2015). Sustainable Energy Development Index: A multi-dimensional indicator for measuring sustainable energy development. *Renewable and Sustainable Energy Reviews*, 50, 513-530.
- IEA (2017). Real-world policy packages for sustainable energy transitions- Shaping energy transition policies to fit national objectives and constraints, Insight Series.
- IMF. (2016). World economic outlook: Subdued demand: Symptoms and remedies.
- International Atomic Energy Agency. (2005). *Energy Indicators for Sustainable Development*. International Atomic Energy Agency.
- International Bank for Reconstruction and Development / The World Bank (2018). *Policy Matters: Regulatory Indicators for Sustainable Energy* (No. 132782, pp. 1-140). The World Bank.
- International Energy Agency (2012). World Energy Outlook 2012.
- IPBES. (2020). IPBES Workshop on Biodiversity and Pandemics. Retrieved from: <https://ipbes.net/pandemics>
- IRENA (2017). Methodology background document: Development of a decarbonisation pathway for the global energy system to 2050. Available at: https://www.irena.org/-/media/Files/IRENA/REmap/Methodology/IRENA_REmap_Decarbonisation_Pathway_Methodology_2017.pdf?la=en&hash=ADC8F7D359F5C23A3F50744E66D8E3E163ED97C4
- Ishizaka, A., & Nemery, P. (2013). *Multi-criteria decision analysis: methods and software*. John Wiley & Sons.
- Iyer, G., Calvin, K., Clarke, L., Edmonds, J., Hultman, N., Hartin, C., ... & Pizer, W. (2018). Implications of sustainable development considerations for comparability across nationally determined contributions. *Nature Climate Change*, 8(2), 124-129.
- Jakob, M., Edenhofer, O., Kornek, U., Lenzi, D., & Minx, J. (2019). Governing the Commons to Promote Global Justice-Climate Change Mitigation and Rent Taxation.
- Jamal, T., Urmee, T., & Shafiullah, G. M. (2020). Planning of off-grid power supply systems in remote areas using multi-criteria decision analysis. *Energy*, 117580.
- Janipour, Z., de Nooij, R., Scholten, P., Huijbregts, M. A., & de Coninck, H. (2020). What are sources of carbon lock-in in energy-intensive industry? A case study into Dutch chemicals production. *Energy Research & Social Science*, 60, 101320.
- Jeong, J. S. (2018). Design of spatial PGIS-MCDA-based land assessment planning for identifying sustainable land-use adaptation priorities for climate change impacts. *Agricultural Systems*, 167, 61-71.
- Johnson, N., Burek, P., Byers, E., Falchetta, G., Flörke, M., Fujimori, S., ... & Langan, S. (2019). Integrated solutions for the water-energy-land nexus: Are global models rising to the challenge?. *Water*, 11(11), 2223.
- Jun, K. S., Chung, E. S., Kim, Y. G., & Kim, Y. (2013). A fuzzy multi-criteria approach to flood risk vulnerability in



- South Korea by considering climate change impacts. *Expert Systems with Applications*, 40(4), 1003-1013.
- Kacprzyk, J. (1986). Group decision making with a fuzzy linguistic majority. *Fuzzy sets and systems*, 18(2), 105-118.
- Kacprzyk, J. (1987). Towards «human-consistent» decision support systems through commonsense knowledge-based decision making and control models: a fuzzy logic approach. *Computers and Artificial Intelligence*, 6(2), 97-122.
- Kacprzyk, J., & Fedrizzi, M. (1986). Soft'consensus measures for monitoring real consensus reaching processes under fuzzy preferences. *Control and Cybernetics*, 15(3-4), 309-323.
- Kacprzyk, J., & Fedrizzi, M. (1988). A 'soft'measure of consensus in the setting of partial (fuzzy) preferences. *European Journal of Operational Research*, 34(3), 316-325.
- Kaly, U., Briguglio, L., McLeod, H., Schmall, S., Pratt, C., & Pal, R. (1999). *Environmental Vulnerability Index (EVI) to summarise national environmental vulnerability profiles*. SOPAC.
- Kazmierczuk, A. H. (2019). Wind energy in Kenya: A status and policy framework review. *Renewable and Sustainable Energy Reviews*, 107, 434-445.
- Kearney, P. (2019). Re: Submission on Ireland's Draft National Energy and Climate Plan 2021-2030.
- Kiula, O. (2018). Decarbonisation perspectives for the Polish economy. *Energy Policy*, 118, 69-76.
- Klauer, B., Drechsler, M., & Messner, F. (2006). Multicriteria analysis under uncertainty with IANUS—method and empirical results. *Environment and Planning C: Government and Policy*, 24(2), 235-256.
- Koasidis, K., Karamaneas, A., Kanellou, E., Neofytou, H., Nikas, A., & Doukas, H. (2021). Towards sustainable development and climate co-governance: a multicriteria stakeholders' perspective. In *Multiple Criteria Decision Making for Sustainable Development: Pursuing Economic Growth, Environmental Protection And Social Cohesion*, in press. Springer, Cham.
- Köberle, A. C., Rochedo, P. R., Lucena, A. F., Szklo, A., & Schaeffer, R. (2020). Brazil's emission trajectories in a well-below 2° C world: the role of disruptive technologies versus land-based mitigation in an already low-emission energy system. *Climatic Change*, 162(4), 1823-1842.
- Kogo, B. K., Kumar, L., & Koech, R. (2021). Climate change and variability in Kenya: a review of impacts on agriculture and food security. *Environment, Development and Sustainability*, 23, 23-43.
- Kompas, T., & Che, T. N. (2016). A structural and stochastic optimal model for projections of LNG imports and exports in Asia-Pacific. *Heliyon*, 2(6), e00108.
- Kooij, H. J., Oteman, M., Veenman, S., Sperling, K., Magnusson, D., Palm, J., & Hvelplund, F. (2018). Between grassroots and treetops: Community power and institutional dependence in the renewable energy sector in Denmark, Sweden and the Netherlands. *Energy Research & Social Science*, 37, 52-64.
- Krey, V., Guo, F., Kolp, P., Zhou, W., Schaeffer, R., Awasthy, A., ... & He, C. (2019). Looking under the hood: A comparison of techno-economic assumptions across national and global integrated assessment models. *Energy*, 172, 1254-1267.
- Krohling, R. A., & Campanharo, V. C. (2011). Fuzzy TOPSIS for group decision making: A case study for accidents with oil spill in the sea. *Expert Systems with applications*, 38(4), 4190-4197.
- Kuncheva, L. I. (1994). Pattern recognition with a model of fuzzy neuron using degree of consensus. *Fuzzy Sets and Systems*, 66(2), 241-250.



- Kurniawan, R., & Managi, S. (2018). Coal consumption, urbanization, and trade openness linkage in Indonesia. *Energy Policy*, 121, 576-583.
- Labella, Á., Koasidis, K., Nikas, A., Arsenopoulos, A., & Doukas, H. (2020). APOLLO: A Fuzzy Multi-criteria Group Decision-Making Tool in Support of Climate Policy. *International Journal of Computational Intelligence Systems*, 13(1), 1539-1553.
- Labella, Á., Liu, Y., Rodríguez, R. M., & Martínez, L. (2018). Analyzing the performance of classical consensus models in large scale group decision making: A comparative study. *Applied Soft Computing*, 67, 677-690.
- Larsson, M., Mohseni, F., Wallmark, C., Grönkvist, S., & Alvfors, P. (2015). Energy system analysis of the implications of hydrogen fuel cell vehicles in the Swedish road transport system. *International journal of hydrogen energy*, 40(35), 11722-11729.
- Leach, A., Adams, A., Cairns, S., Coady, L., & Lambert, G. Climate leadership report to Minister. 2015.
- Lechtenböhrer, S., Nilsson, L. J., Åhman, M., & Schneider, C. (2016). Decarbonising the energy intensive basic materials industry through electrification—Implications for future EU electricity demand. *Energy*, 115, 1623-1631.
- Lee, K. S., & Werner, R. A. (2018). Reconsidering monetary policy: An empirical examination of the relationship between interest rates and nominal GDP growth in the US, UK, Germany and Japan. *Ecological Economics*, 146, 26-34.
- Lehner, A., Erlacher, C., Schlögl, M., Wegerer, J., Blaschke, T., & Steinnocher, K. (2018). Can iso-defined urban sustainability indicators be derived from remote sensing: An expert weighting approach. *Sustainability*, 10(4), 1268.
- Leimbach, M., Roming, N., Schultes, A., & Schwerhoff, G. (2018). Long-term development perspectives of Sub-Saharan Africa under climate policies. *Ecological Economics*, 144, 148-159.
- León, T., Liern, V., & Pérez-Gladish, B. (2019). A multicriteria assessment model for countries' degree of preparedness for successful impact investing. *Management Decision*.
- Li, F. G., & Strachan, N. (2019). Take me to your leader: Using socio-technical energy transitions (STET) modelling to explore the role of actors in decarbonisation pathways. *Energy Research & Social Science*, 51, 67-81.
- Ligtvoet, A., Cuppen, E., Di Ruggero, O., Hemmes, K., Pesch, U., Quist, J., & Mehos, D. (2016). New future perspectives through constructive conflict: Exploring the future of gas in the Netherlands. *Futures*, 78, 19-33.
- Lilliestam, J., & Hanger, S. (2016). Shades of green: Centralisation, decentralisation and controversy among European renewable electricity visions. *Energy Research & Social Science*, 17, 20-29.
- Linkov, I., Satterstrom, F. K., Kiker, G., Seager, T. P., Bridges, T., Gardner, K. H., ... & Meyer, A. (2006). Multicriteria decision analysis: a comprehensive decision approach for management of contaminated sediments. *Risk Analysis: An International Journal*, 26(1), 61-78.
- Liu, J. Y., Fujimori, S., Takahashi, K., Hasegawa, T., Wu, W., Takakura, J. Y., & Masui, T. (2019). Identifying trade-offs and co-benefits of climate policies in China to align policies with SDGs and achieve the 2° C goal. *Environmental Research Letters*, 14(12), 124070.
- Liu, P., & Chu, P. (2019). Renewables finance and investment: how to improve industry with private capital in China. *Journal of Modern Power Systems and Clean Energy*, 7(6), 1385-1398.



- Loh, J., & Wackernagel, M. (2004). Living planet report 2004.
- Lucas, P. L., Hilderink, H. B., Janssen, P. H., Samir, K. C., van Vuuren, D. P., & Niessen, L. (2019). Future impacts of environmental factors on achieving the SDG target on child mortality—A synergistic assessment. *Global Environmental Change*, 57, 101925.
- Luderer, G., Pehl, M., Arvesen, A., Gibon, T., Bodirsky, B. L., de Boer, H. S., ... & [Hertwich](#), E. G. (2019). Environmental co-benefits and adverse side-effects of alternative power sector decarbonization strategies. *Nature communications*, 10(1), 1-13.
- Luque, M., Pérez-Moreno, S., Robles, J. A., & Rodriguez, B. (2017). Measuring Child and Maternal Health in Developing Countries: A Proposal of New Hybrid MDG Composite Indices. *Applied Research in Quality of Life*, 12(3), 737-758.
- Maier, D. (2018). The Romanian national innovation performance in the EU context. *International Journal of Advanced Engineering and Management Research*, 3(6).
- Mangla, S. K., Kumar, P., & Barua, M. K. (2015). Prioritizing the responses to manage risks in green supply chain: An Indian plastic manufacturer perspective. *Sustainable Production and Consumption*, 1, 67-86.
- Manowska, A., Osadnik, K. T., & Wyganowska, M. (2017). Economic and social aspects of restructuring Polish coal mining: Focusing on Poland and the EU. *Resources policy*, 52, 192-200.
- Mao, X., & He, C. (2018). A trade-related pollution trap for economies in transition? Evidence from China. *Journal of Cleaner Production*, 200, 781-790.
- Mardones, C., & Flores, B. (2018). Effectiveness of a CO₂ tax on industrial emissions. *Energy Economics*, 71, 370-382.
- Marinakis, V., Doukas, H., Xidonas, P., & Zopounidis, C. (2017a). Multicriteria decision support in local energy planning: An evaluation of alternative scenarios for the Sustainable Energy Action Plan. *Omega*, 69, 1-16.
- Marinakis, V., Papadopoulou, A. G., & Psarras, J. (2017b). Local communities towards a sustainable energy future: Needs and priorities. *International Journal of Sustainable Energy*, 36(3), 296-312.
- Markard, J., Raven, R., & Truffer, B. (2012). Sustainability transitions: An emerging field of research and its prospects. *Research policy*, 41(6), 955-967.
- Martinez, L., & Herrera, F. (2012). An overview on the 2-tuple linguistic model for computing with words in decision making: Extensions, applications and challenges. *Information Sciences*, 207, 1-18.
- Martínez, L., & Herrera, F. (2014). Preface: Challenges of computing with words in decision making. *Information Sciences—Informatics and Computer Science, Intelligent Systems, Applications: An International Journal*, 258, 218-219.
- Martínez, L., Rodriguez, R. M., & Herrera, F. (2015). 2-tuple linguistic model. In *The 2-tuple Linguistic Model* (pp. 23-42). Springer, Cham.
- Martinez, L., Ruan, D., & Herrera, F. (2010). Computing with words in decision support systems: an overview on models and applications. *International Journal of Computational Intelligence Systems*, 3(4), 382-395.
- Martínez, L., Ruan, D., Herrera, F., Herrera-Viedma, E., & Wang, P. P. (2009). Linguistic decision making: Tools and applications.
- Martins, F., Felgueiras, C., & Smitková, M. (2018). Fossil fuel energy consumption in European countries. *Energy*



Procedia, 153, 107-111.

- Mascarenhas, A., Nunes, L. M., & Ramos, T. B. (2014). Exploring the self-assessment of sustainability indicators by different stakeholders. *Ecological indicators*, 39, 75-83.
- Mason-D'Croz, D., Sulser, T. B., Wiebe, K., Rosegrant, M. W., Lowder, S. K., Nin-Pratt, A., ... & Dunston, S. (2019). Agricultural investments and hunger in Africa modeling potential contributions to SDG2–Zero Hunger. *World development*, 116, 38-53.
- McCollum, D. L., Echeverri, L. G., Busch, S., Pachauri, S., Parkinson, S., Rogelj, J., ... & Riahi, K. (2018a). Connecting the sustainable development goals by their energy inter-linkages. *Environmental Research Letters*, 13(3), 033006.
- McCollum, D. L., Zhou, W., Bertram, C., De Boer, H. S., Bosetti, V., Busch, S., ... & Fricko, O. (2018b). Energy investment needs for fulfilling the Paris Agreement and achieving the Sustainable Development Goals. *Nature Energy*, 3(7), 589-599.
- McCowan, T. (2018). Quality of higher education in Kenya: Addressing the conundrum. *International Journal of Educational Development*, 60, 128-137.
- Meijering, J. V., Kern, K., & Tobi, H. (2014). Identifying the methodological characteristics of European green city rankings. *Ecological Indicators*, 43, 132-142.
- Michalos, A. C. (Ed.). (2014). *Encyclopedia of quality of life and well-being research*. Dordrecht: Springer Netherlands.
- MINETUR, Ministry of Industry, Energy and Tourism (2014). "Boletín Trimestral de Coyuntura Energética Cuarto Trimestre". Available at <http://www.minetur.gob.es/energia/balances/Balances/Paginas/CoyunturaTrimestral.aspx>
- Ministerio de Medio Ambiente de Chile (2015). Plan de Acción Nacional de Cambio Climático 2017-2022. Available at <http://portal.mma.gob.cl/wp-content/uploads/2016/04/Anteproyecto-PANCC-2017-2022-FINAL-2016-04-18.pdf>, Accessed on 10.10.2019
- Ministry of Environment and Energy (2018). Greek National Plan for Climate and Energy.
- Mohamadabadi, H. S., Tichkowsky, G., & Kumar, A. (2009). Development of a multi-criteria assessment model for ranking of renewable and non-renewable transportation fuel vehicles. *Energy*, 34(1), 112-125.
- Moner-Girona, M., Puig, D., Mulugetta, Y., Kougias, I., AbdulRahman, J., & Szabó, S. (2018). Next generation interactive tool as a backbone for universal access to electricity. *Wiley Interdisciplinary Reviews: Energy and Environment*, 7(6), e305.
- Mousa, E., Wang, C., Riesbeck, J., & Larsson, M. (2016). Biomass applications in iron and steel industry: an overview of challenges and opportunities. *Renewable and sustainable energy reviews*, 65, 1247-1266.
- Mu, E., & Pereyra-Rojas, M. (2017). Understanding the analytic hierarchy process. In *Practical decision making* (pp. 7-22). Springer, Cham.
- Nejat, P., Jomehzadeh, F., Taheri, M. M., Gohari, M., & Majid, M. Z. A. (2015). A global review of energy consumption, CO2 emissions and policy in the residential sector (with an overview of the top ten CO2 emitting countries). *Renewable and sustainable energy reviews*, 43, 843-862.
- Neofytou, H., Nikas, A., & Doukas, H. (2020). Sustainable energy transition readiness: A multicriteria assessment index. *Renewable and Sustainable Energy Reviews*, 131, 109988.



- Nerini, F. F., Tomei, J., To, L. S., Bisaga, I., Parikh, P., Black, M., ... & Milligan, B. (2018). Mapping synergies and trade-offs between energy and the Sustainable Development Goals. *Nature Energy*, 3(1), 10-15.
- Nerini, F., Hughes, N., Cozzi, L., Cosgrave, E., Howells, M., Sovacool, B., ... & Milligan, B. (2018). Shore up support for climate action using SDGs. *Nature*, 557(7703), 31-31.
- Newell, P., & Mulvaney, D. (2013). The political economy of the 'just transition'. *The Geographical Journal*, 179(2), 132-140.
- Nikas, A., Doukas, H., & López, L. M. (2018a). A group decision making tool for assessing climate policy risks against multiple criteria. *Heliyon*, 4(3), e00588.
- Nikas, A., Doukas, H., & Papandreou, A. (2019a). A detailed overview and consistent classification of climate-economy models. In *Understanding Risks and Uncertainties in Energy and Climate Policy* (pp. 1-54). Springer, Cham.
- Nikas, A., Doukas, H., Lieu, J., Tinoco, R. A., Charisopoulos, V., & van der Gaast, W. (2017). Managing stakeholder knowledge for the evaluation of innovation systems in the face of climate change. *Journal of Knowledge Management*.
- Nikas, A., Doukas, H., van der Gaast, W., & Szendrei, K. (2018b). Expert views on low-carbon transition strategies for the Dutch solar sector: A delay-based fuzzy cognitive mapping approach. *IFAC-PapersOnLine*, 51(30), 715-720.
- Nikas A., Gambhir A., Trutnevyte E., Koasidis K., Lund H., Thellufsen J.Z., Mayer D., Zachmann G., Miguel L.J., Ferreras-Alonso N., Sognnaes I., Peters G.P., Colombo E., Howells M., Hawkes A., van den Broek M., Van de Ven D.J., Gonzalez-Eguino M., Flamos A., & Doukas H. (2021). Perspective of comprehensive and comprehensible multi-model energy and climate science in Europe. *Energy*, 215, 119153.
- Nikas, A., Gkonis, N., Forouli, A., Siskos, E., Arsenopoulos, A., Papapostolou, A., ... & Doukas, H. (2019a). From near-term actions to long-term pathways—risks and uncertainties associated with the national energy efficiency framework. *Narratives of Low-Carbon Transitions*, 180.
- Nikas, A., Lieu, J., Sorman, A., Gambhir, A., Turhan, E., Baptista, B. V., & Doukas, H. (2020a). The desirability of transitions in demand: Incorporating behavioural and societal transformations into energy modelling. *Energy Research & Social Science*, 70, 101780.
- Nikas, A., Neofytou, H., Karamaneas, A., Koasidis, K., & Psarras, J. (2020b). Sustainable and socially just transition to a post-lignite era in Greece: a multi-level perspective. *Energy Sources, Part B: Economics, Planning, and Policy*, 15(10-12), 513-544.
- Nikas, A., Ntanos, E., & Doukas, H. (2019c). A semi-quantitative modelling application for assessing energy efficiency strategies. *Applied Soft Computing*, 76, 140-155.
- Nikas, A., Stavrakas, V., Arsenopoulos, A., Doukas, H., Antosiewicz, M., Witajewski-Baltvilks, J., & Flamos, A. (2020c). Barriers to and consequences of a solar-based energy transition in Greece. *Environmental Innovation and Societal Transitions*.
- Nilsson, M., Griggs, D., & Visbeck, M. (2016). Policy: map the interactions between Sustainable Development Goals. *Nature*, 534(7607), 320-322.
- Niță, A., Buttler, A., Rozyłowicz, L., & Pătru-Stupariu, I. (2015). Perception and use of landscape concepts in the procedure of Environmental Impact Assessment: Case study—Switzerland and Romania. *Land use policy*,



44, 145-152.

- Njuguna, J., & Muruka, C. (2017). Open defecation in newly created Kenyan counties: a situational analysis. *Journal of Health Care for the Poor and Underserved*, 28(1), 71-78.
- Norese, M. F., Corazza, L., Bruschi, F., & Cisi, M. (2020). A multiple criteria approach to map ecological-inclusive business models for sustainable development. *International Journal of Sustainable Development & World Ecology*, 1-17.
- O'Neill, B. C., Jiang, L., Samir, K. C., Fuchs, R., Pachauri, S., Laidlaw, E. K., ... & Ren, X. (2020). The effect of education on determinants of climate change risks. *Nature Sustainability*, 1-9.
- Ochieng, J., Kirimi, L., & Mathenge, M. (2016). Effects of climate variability and change on agricultural production: The case of small scale farmers in Kenya. *NJAS-Wageningen Journal of Life Sciences*, 77, 71-78.
- Odell, P. R. (2013). *An Economic Geography of Oil (Routledge Revivals)*. Routledge.
- OECD. Publishing, & Nuclear Energy Agency. (2010). *Projected costs of generating electricity*. International Energy Agency, Nuclear Energy Agency, Organisation for Economic Co-operation and Development.
- Oliveira, T. D., Gurgel, A. C., & Tonry, S. (2019). International market mechanisms under the Paris Agreement: A cooperation between Brazil and Europe. *Energy policy*, 129, 397-409.
- Orfanos, N., Mitzelos, D., Sagani, A., & Dedoussis, V. (2019). Life-cycle environmental performance assessment of electricity generation and transmission systems in Greece. *Renewable energy*, 139, 1447-1462.
- Ototo, G., & Vlosky, R. P. (2018). Overview of the Forest Sector in Kenya. *Forest Products Journal*, 68(1), 6-14.
- Ouyang, X., & Lin, B. (2015). An analysis of the driving forces of energy-related carbon dioxide emissions in China's industrial sector. *Renewable and sustainable energy reviews*, 45, 838-849.
- Palomares, I., Estrella, F. J., Martínez, L., & Herrera, F. (2014). Consensus under a fuzzy context: Taxonomy, analysis framework AFRYCA and experimental case of study. *Information Fusion*, 20, 252-271.
- Palomares, I., Martínez, L., & Herrera, F. (2013). A consensus model to detect and manage noncooperative behaviors in large-scale group decision making. *IEEE Transactions on Fuzzy Systems*, 22(3), 516-530.
- Papapostolou, A., Karakosta, C., & Doukas, H. (2017a). Analysis of policy scenarios for achieving renewable energy sources targets: A fuzzy TOPSIS approach. *Energy & Environment*, 28(1-2), 88-109.
- Papapostolou, A., Karakosta, C., Nikas, A., & Psarras, J. (2017b). Exploring opportunities and risks for RES-E deployment under Cooperation Mechanisms between EU and Western Balkans: A multi-criteria assessment. *Renewable and Sustainable Energy Reviews*, 80, 519-530.
- Pardo, N., & Moya, J. A. (2013). Prospective scenarios on energy efficiency and CO2 emissions in the European Iron & Steel industry. *Energy*, 54, 113-128.
- Parkhill, K., Demski, C. C., Butler, C., Spence, A., & Pidgeon, N. F. (2013). Transforming the UK energy system: public values, attitudes and acceptability-synthesis report.
- Parkinson, S., Krey, V., Huppmann, D., Kahil, T., McCollum, D., Fricko, O., ... & Raptis, C. (2019). Balancing clean water-climate change mitigation trade-offs. *Environmental Research Letters*, 14(1), 014009.
- Pattupara, R., & Kannan, R. (2016). Alternative low-carbon electricity pathways in Switzerland and its neighbouring countries under a nuclear phase-out scenario. *Applied energy*, 172, 152-168.
- Phonphoton, N., & Pharino, C. (2019). Multi-criteria decision analysis to mitigate the impact of municipal solid



waste management services during floods. *Resources, Conservation and Recycling*, 146, 106-113.

- Pistonesi, H., Padilla, V. R., & Chavez, C. (2000). *Energy and Sustainable Development in Latin America and the Caribbean: Guide for Energy Policymaking*. Latin American Energy Organization.
- Pohekar, S. D., & Ramachandran, M. (2004). Application of multi-criteria decision making to sustainable energy planning—A review. *Renewable and sustainable energy reviews*, 8(4), 365-381.
- Polat, G., Damci, A., Gurgun, A. P., & Demirli, I. (2016). Urban renewal project selection using the integration of AHP and PROMETHEE approaches. *Procedia engineering*, 164, 339-346.
- Portugal-Pereira, J., Koberle, A., Lucena, A. F., Rochedo, P. R., Império, M., Carsalade, A. M., ... & Rafaj, P. (2018). Interactions between global climate change strategies and local air pollution: lessons learnt from the expansion of the power sector in Brazil. *Climatic Change*, 148(1-2), 293-309.
- Pugliese, A., & Ray, J. (2009). Top-emitting countries differ on climate change threat. *Gallup*. Retrieved, 22.
- Purwanto, W. W., Muharam, Y., Pratama, Y. W., Hartono, D., Soedirman, H., & Anindhito, R. (2016). Status and outlook of natural gas industry development in Indonesia. *Journal of Natural Gas Science and Engineering*, 29, 55-65.
- Qvist, S. A., & Brook, B. W. (2015). Environmental and health impacts of a policy to phase out nuclear power in Sweden. *Energy Policy*, 84, 1-10.
- Radziejowska, A., & Zima, K. (2016). Multicriteria analysis in selecting the optimal variant of solar system. In *E3S Web of Conferences* (Vol. 10, p. 00078). EDP Sciences.
- Rafaj, P., Kiesewetter, G., Gül, T., Schöpp, W., Cofala, J., Klimont, Z., ... & Cozzi, L. (2018). Outlook for clean air in the context of sustainable development goals. *Global Environmental Change*, 53, 1-11.
- Rafaj, P., Kiesewetter, G., Krey, V., Schöpp, W., Bertram, C., Drouet, L., ... & van Vuuren, D. P. (2021). Air quality and health implications of 1.5–2° C climate pathways under considerations of ageing population: A multi-model scenario analysis. *Environmental Research Letters*.
- Rai, S. M., Brown, B. D., & Ruwanpura, K. N. (2019). SDG 8: Decent work and economic growth—A gendered analysis. *World Development*, 113, 368-380.
- Ramírez, F. J., Honrubia-Escribano, A., Gómez-Lázaro, E., & Pham, D. T. (2017). Combining feed-in tariffs and net-metering schemes to balance development in adoption of photovoltaic energy: Comparative economic assessment and policy implications for European countries. *Energy Policy*, 102, 440-452.
- Rampasso, I. S., Siqueira, R. G., Anholon, R., Silva, D., Quelhas, O. L. G., Leal Filho, W., & Brandli, L. L. (2019). Some of the challenges in implementing Education for Sustainable Development: Perspectives from Brazilian engineering students. *International Journal of Sustainable Development & World Ecology*, 26(4), 367-376.
- Reiter, G., & Lindorfer, J. (2015). Evaluating CO₂ sources for power-to-gas applications—A case study for Austria. *Journal of CO₂ Utilization*, 10, 40-49.
- Ren, H., Gao, W., Zhou, W., & Nakagami, K. I. (2009). Multi-criteria evaluation for the optimal adoption of distributed residential energy systems in Japan. *Energy Policy*, 37(12), 5484-5493.
- Ribas, A., Lucena, A. F., & Schaeffer, R. (2017). Bridging the energy divide and securing higher collective well-being in a climate-constrained world. *Energy Policy*, 108, 435-450.
- Ribas, A., Lucena, A. F., & Schaeffer, R. (2019). Closing the energy divide in a climate-constrained world: A focus



- on the buildings sector. *Energy and Buildings*, 199, 264-274.
- Ribeiro, F., Ferreira, P., & Araújo, M. (2013). Evaluating future scenarios for the power generation sector using a Multi-Criteria Decision Analysis (MCDA) tool: The Portuguese case. *Energy*, 52, 126-136.
- Rodríguez, R. M., & Martínez, L. (2013). An analysis of symbolic linguistic computing models in decision making. *International Journal of General Systems*, 42(1), 121-136.
- Rodríguez, R. M., Labella, Á., De Tré, G., & Martínez, L. (2018). A large scale consensus reaching process managing group hesitation. *Knowledge-Based Systems*, 159, 86-97.
- Rodríguez, R. M., & Martínez, L. (2010). A comparison among symbolic computational models in linguistic decision making. In *Computational Intelligence: Foundations and Applications* (pp. 499-504).
- Roe, S., Streck, C., Obersteiner, M., Frank, S., Griscom, B., Drouet, L., ... & Lawrence, D. (2019). Contribution of the land sector to a 1.5 C world. *Nature Climate Change*, 1-12.
- Rogers, S. H., Seager, T. P., & Gardner, K. H. (2004). Combining Expert Judgement and Stakeholder Values with Promethee: A case Study in Contaminated Sediments. In *Comparative risk assessment and environmental decision making* (pp. 305-322). Springer, Dordrecht.
- Rosenzweig, C., Arnell, N. W., Ebi, K. L., Lotze-Campen, H., Raes, F., Rapley, C., ... & Schewe, J. (2017). Assessing inter-sectoral climate change risks: the role of ISIMIP. *Environmental Research Letters*, 12(1), 010301.
- Roubens, M. (1997). Fuzzy sets and decision analysis. *Fuzzy sets and systems*, 90(2), 199-206.
- Saaty, R. W. (1987). The analytic hierarchy process—what it is and how it is used. *Mathematical modelling*, 9(3-5), 161-176.
- Saaty, T. L. (1980). The analytic hierarchy process (AHP). *The Journal of the Operational Research Society*, 41(11), 1073-1076.
- Sachs, J. D. (2012). From millennium development goals to sustainable development goals. *The Lancet*, 379(9832), 2206-2211.
- Sachs, J. D., & McArthur, J. W. (2005). The millennium project: a plan for meeting the millennium development goals. *The Lancet*, 365(9456), 347-353.
- Sachs, J., Meng, Y., Giarola, S., & Hawkes, A. (2019a). An agent-based model for energy investment decisions in the residential sector. *Energy*, 172, 752-768.
- Sachs, J., Schmidt-Traub, G., Kroll, C., Lafortune, G., & Fuller, G. (2019b). Sustainable development report 2019. *Bertelsmann Stiftung and Sustainable Development Solutions Network (SDSN): New York, NY, USA*, 2.
- Saint, S., & Lawson, J. R. (1994). *Rules for reaching consensus: A modern approach to decision making*. Pfeiffer.
- Sanneh, E. S. (2018). Climate Change Adaption. In *Systems Thinking for Sustainable Development* (pp. 41-53). Springer, Cham.
- Sareen, S., & Haarstad, H. (2018). Bridging socio-technical and justice aspects of sustainable energy transitions. *Applied energy*, 228, 624-632.
- Sarkodie, S. A., & Adom, P. K. (2018). Determinants of energy consumption in Kenya: a NIPALS approach. *Energy*, 159, 696-705.
- Scholten, L., Maurer, M., & Lienert, J. (2017). Comparing multi-criteria decision analysis and integrated assessment to support long-term water supply planning. *PLoS one*, 12(5), e0176663.



- Schwerhoff, G., & Sy, M. (2019). Developing Africa's energy mix. *Climate policy*, 19(1), 108-124.
- Sennaroglu, B., & Celebi, G. V. (2018). A military airport location selection by AHP integrated PROMETHEE and VIKOR methods. *Transportation Research Part D: Transport and Environment*, 59, 160-173.
- Sferra, F., Krapp, M., Roming, N., Schaeffer, M., Malik, A., Hare, B., & Brecha, R. (2019). Towards optimal 1.5° and 2° C emission pathways for individual countries: A Finland case study. *Energy Policy*, 133, 110705.
- Shafabakhsh, G., Hadjihoseinlou, M., & Taghizadeh, S. A. (2014). Selecting the appropriate public transportation system to access the Sari International Airport by fuzzy decision making. *European transport research review*, 6(3), 277-285.
- Shahbaz, M., Van Hoang, T. H., Mahalik, M. K., & Roubaud, D. (2017). Energy consumption, financial development and economic growth in India: New evidence from a nonlinear and asymmetric analysis. *Energy Economics*, 63, 199-212.
- Shakey, B. K. (2006). Supplier selection using AHP and promethee-2. *Int J Sci Res*, 6, 156-160.
- Shearer, C., Fofrich, R., & Davis, S. J. (2017). Future CO2 emissions and electricity generation from proposed coal-fired power plants in India. *Earth's Future*, 5(4), 408-416.
- Shem, C., Simsek, Y., Hutfilter, U. F., & Urmee, T. (2019). Potentials and opportunities for low carbon energy transition in Vietnam: A policy analysis. *Energy Policy*, 134, 110818.
- Shmelev, S. E., & Van Den Bergh, J. C. (2016). Optimal diversity of renewable energy alternatives under multiple criteria: An application to the UK. *Renewable and Sustainable Energy Reviews*, 60, 679-691.
- Sifuna, D. N. (2007). The challenge of increasing access and improving quality: An analysis of universal primary education interventions in Kenya and Tanzania since the 1970s. *International Review of Education*, 53(5-6), 687-699.
- Sijmons, D., & Van Dorst, M. (2012). Strong feelings: emotional landscape of wind turbines. *Sustainable energy landscapes: Designing, planning, and development*, 7, 45.
- Siksnylyte, I., Zavadskas, E. K., Bausys, R., & Streimikiene, D. (2019). Implementation of EU energy policy priorities in the Baltic Sea Region countries: Sustainability assessment based on neutrosophic MULTIMOORA method. *Energy Policy*, 125, 90-102.
- Simoës, S. G., Dias, L., Gouveia, J. P., Seixas, J., De Miglio, R., Chiodi, A., ... & Giannakidis, G. (2019). InSmart-A methodology for combining modelling with stakeholder input towards EU cities decarbonisation. *Journal of cleaner production*, 231, 428-445.
- Singh, H. V., Bocca, R., Gomez, P., Dahlke, S., & Bazilian, M. (2019). The energy transitions index: An analytic framework for understanding the evolving global energy system. *Energy Strategy Reviews*, 26, 100382.
- Sociological Research Center (2016). "Barómetro de Junio 2016". Estudio nº 3142. Available in http://www.cis.es/cis/export/sites/default/-Archivos/Marginales/3140_3159/3142/Es3142mar.pdf (Spanish).
- Sognaes, I., Gambhir, A., Van de Ven, D.-J., Nikas, A., Anger-Kraavi, A., Bui, H., Campagnolo, L., Delpiazzi, E., Doukas, H., Giarola, S., Grant, N., Hawkes, A., Koberle, A., Kolpakov, A., Mittal, S., Moreno, J., Perdana, S., Rogelj, J., Vielle, M., & Peters, G.P. (2020). A multi-model analysis of long-term emissions and warming implications of current mitigation efforts. *Nature Climate Change*. Under Review.
- Sohaib, O., Naderpour, M., Hussain, W., & Martinez, L. (2019). Cloud computing model selection for e-commerce



- enterprises using a new 2-tuple fuzzy linguistic decision-making method. *Computers & Industrial Engineering*, 132, 47-58.
- Sola, A. V. H., de Miranda Mota, C. M., & Kovaleski, J. L. (2011). A model for improving energy efficiency in industrial motor system using multicriteria analysis. *Energy Policy*, 39(6), 3645-3654.
- Song, L., Lieu, J., & Chen, Y. (2019). Risks and uncertainties in low-carbon pathways for the urban building sector. *Narratives of Low-Carbon Transitions*, 159.
- Soni, V., Anand, R., Dey, P. K., Dash, A. P., & Banwet, D. K. (2017a). Quantifying e-governance efficacy towards Indian–EU strategic dialogue. *Transforming Government: People, Process and Policy*.
- Sorman, A. H., García-Muros, X., Pizarro-Irizar, C., & González-Eguino, M. (2020). Lost (and found) in transition: Expert stakeholder insights on low-carbon energy transitions in Spain. *Energy Research & Social Science*, 64, 101414.
- Sorman, A. H., Pizarro-Irizar, C., García-Muros, X., González-Eguino, M., & Arto, I. (2019). On a rollercoaster of regulatory change—risks and uncertainties associated with renewable energy transitions. *Narratives of Low-Carbon Transitions*, 121.
- Sovacool, B. K., Kester, J., de Rubens, G. Z., & Noel, L. (2018). Expert perceptions of low-carbon transitions: Investigating the challenges of electricity decarbonisation in the Nordic region. *Energy*, 148, 1162-1172.
- Spanish Renewable Energy Association (2014). Study of the Macroeconomic Impact of Renewable Energies in Spain. Available at http://www.appa.es/descargas/ESTUDIO_APPA_14_ENG_WEB.pdf.
- Stoppok, M., Jess, A., Freitag, R., & Alber, E. (2018). Of culture, consumption and cost: a comparative analysis of household energy consumption in Kenya, Germany and Spain. *Energy research & social science*, 40, 127-139.
- Sultana, A., & Kumar, A. (2012). Ranking of biomass pellets by integration of economic, environmental and technical factors. *Biomass and bioenergy*, 39, 344-355.
- Surminski, S., & Williamson, A. (2012). Policy indexes—what do they tell us and what are their applications?: the case of climate policy and business planning in emerging markets.
- Szczerbowski, R., & Ceran, B. (2017). Development perspectives of the Polish power generation sector according to the climate preservation conference COP21 policies. In *E3S Web of Conferences* (Vol. 14, p. 01003). EDP Sciences.
- Tagliapietra, S., Zachmann, G., Edenhofer, O., Glachant, J. M., Linares, P., & Loeschel, A. (2019). The European union energy transition: Key priorities for the next five years. *Energy Policy*, 132, 950-954.
- Taliotis, C., Giannakis, E., Karmellos, M., Fylaktos, N., & Zachariadis, T. (2020). Estimating the economy-wide impacts of energy policies in Cyprus. *Energy Strategy Reviews*, 29, 100495.
- Tatarewicz, I., Lewarski, M., & Skwierz, S. (2019). SCENARIOS OF LOW-EMISSION ENERGY SECTOR FOR POLAND AND THE EU UNTIL 2050.
- The World Bank (2018). RISE country profiles. Available at: https://rise.worldbank.org/data/files/sections/rise_country_profiles.pdf
- Tirado, S., & Jiménez Meneses, L. (2016). Energy poverty, crisis and austerity in Spain. *People, Place and Policy*, 10(1), 42-56.



- Trading Economics (2015). Austria - Fossil fuel energy consumption (% of total). Available at: <https://tradingeconomics.com/austria/fossil-fuel-energy-consumption-percent-of-total-wb-data.html>, Accessed on 9.5.2019
- Tsoutsos, T., Drandaki, M., Frantzeskaki, N., Iosifidis, E., & Kiosses, I. (2009). Sustainable energy planning by using multi-criteria analysis application in the island of Crete. *Energy policy*, 37(5), 1587-1600.
- Tyrowicz, J., & van der Velde, L. (2014). Can we really explain worker flows in transition economies. *Faculty of Economic Sciences, University of Warsaw: Warszawa, Poland*.
- Ullah, K., Hamid, S., Mirza, F. M., & Shakoor, U. (2018). Prioritizing the gaseous alternatives for the road transport sector of Pakistan: A multi criteria decision making analysis. *Energy*, 165, 1072-1084.
- UN's Department of Economic and Social Affairs. Sdgs.un.org. (2020). Retrieved from <https://sdgs.un.org/goals/goal3>.
- UNESCO. (2017). Climate Change and Gender Equality. Retrieved from: <http://www.unesco.org/new/en/natural-sciences/priority-areas/gender-and-science/cross-cutting-issues/climate-change-and-gender-equality/>
- UNFCCC (2017). Greenhouse gas inventory data - detailed data by party. https://di.unfccc.int/detailed_data_by_party
- UNFCCC (2017). Paris Agreement - Status of Ratification. (n.d.). Available at: http://unfccc.int/paris_agreement/items/9444.php
- UNFCCC. (2010). Greenhouse Gas Inventory Data - Detailed data by Party. Retrieved from: https://di.unfccc.int/detailed_data_by_party
- Union, A. (2014). African strategy on climate change. *Addis Ababa: African Union*.
- United Nations. (2000). Millennium Summit (6-8 September 2000). Retrieved from https://www.un.org/en/events/pastevents/millennium_summit.shtml
- Van de Ven, D. J., Sampedro, J., Johnson, F. X., Bailis, R., Forouli, A., Nikas, A., ... & Doukas, H. (2019). Integrated policy assessment and optimisation over multiple sustainable development goals in Eastern Africa. *Environmental Research Letters*, 14(9), 094001.
- van der Zwaan, B., & Dalla Longa, F. (2019). Integrated assessment projections for global geothermal energy use. *Geothermics*, 82, 203-211.
- van der Zwaan, B., Kober, T., Dalla Longa, F., van der Laan, A., & Kramer, G. J. (2018). An integrated assessment of pathways for low-carbon development in Africa. *Energy Policy*, 117, 387-395.
- van Soest, H. L., van Vuuren, D. P., Hilaire, J., Minx, J. C., Harmsen, M. J., Krey, V., ... & Luderer, G. (2019). Analysing interactions among sustainable development goals with integrated assessment models. *Global Transitions*, 1, 210-225.
- van Vliet, O. (2019). Switzerland: Risks associated with implementing a national energy strategy. In *Narratives of Low-Carbon Transitions. Understanding Risks and Uncertainties* (pp. 139-156). Routledge.
- Vandyck, T., Keramidas, K., Kitous, A., Spadaro, J. V., Van Dingenen, R., Holland, M., & Saveyn, B. (2018). Air quality co-benefits for human health and agriculture counterbalance costs to meet Paris Agreement pledges. *Nature communications*, 9(1), 1-11.
- Venegas-Troncoso, T., Ugarte-Larraguibel, G., Vasco, D. A., Rouault, F., & Pérez, R. (2019). Feasibility study of the



- application of a cooling energy storage system in a chiller plant of an office building located in Santiago, Chile. *International Journal of Refrigeration*, 102, 142-150.
- Virla, L. D., Lieu, J., & Fitzpatrick, C. (2019). Finding common ground—the need for plural voices in lower-carbon futures of the Alberta oil sands. *Narratives of Low-Carbon Transitions*, 45.
- Vogl, V., Åhman, M., & Nilsson, L. J. (2018). Assessment of hydrogen direct reduction for fossil-free steelmaking. *Journal of Cleaner Production*, 203, 736-745.
- von Stechow, C., Minx, J. C., Riahi, K., Jewell, J., McCollum, D. L., Callaghan, M. W., ... & Baiocchi, G. (2016). 2° C and SDGs: united they stand, divided they fall?. *Environmental Research Letters*, 11(3), 034022.
- Wachsmuth, J., Denishchenkova, A., Fekete, H., Parra, P., Schaeffer, M., Ancygier, A., & Sferra, F. (2019). Fairness- and cost-effectiveness-based approaches to effort-sharing under the Paris agreement (No. S04/2019). Working Paper Sustainability and Innovation.
- Wagner, B., Hauer, C., Schoder, A., & Habersack, H. (2015). A review of hydropower in Austria: Past, present and future development. *Renewable and Sustainable Energy Reviews*, 50, 304-314.
- Wang, X., & Blaabjerg, F. (2018). Harmonic stability in power electronic-based power systems: Concept, modeling, and analysis. *IEEE Transactions on Smart Grid*, 10(3), 2858-2870.
- Warren, B., Christoff, P., & Green, D. (2016). Australia's sustainable energy transition: The disjointed politics of decarbonisation. *Environmental Innovation and Societal Transitions*, 21, 1-12.
- Wątróbski, J., Ziemba, P., Jankowski, J., & Ziolo, M. (2016). Green energy for a green city—A multi-perspective model approach. *Sustainability*, 8(8), 702.
- WEC (2016). World Energy Trilemma Index: Benchmarking the Sustainability of National Energy Systems. Available at: <https://www.worldenergy.org/publications/entry/2016-energy-trilemma-index-benchmarking-the-sustainability-of-national-energy-systems>
- Weitzel, M., Vandyck, T., Keramidis, K., Amann, M., Capros, P., den Elzen, M., ... & Saveyn, B. (2019). Model-based assessments for long-term climate strategies. *Nature Climate Change*, 9(5), 345-347.
- Weng, Q., & Xu, H. (2018). A review of China's carbon trading market. *Renewable and Sustainable Energy Reviews*, 91, 613-619.
- Wesseling, J. H., Lechtenböhmer, S., Åhman, M., Nilsson, L. J., Worrell, E., & Coenen, L. (2017). The transition of energy intensive processing industries towards deep decarbonization: Characteristics and implications for future research. *Renewable and Sustainable Energy Reviews*, 79, 1303-1313.
- Wibisono, G., & Badruzzaman, N. (2018). Strategy of smart meter infrastructure implementation using LPWAN technology, pilot project PLN Bali Case Study. In *MATEC Web of Conferences* (Vol. 218, p. 03013). EDP Sciences.
- Wierzbowski, M., Filipiak, I., & Lyzwa, W. (2017). Polish energy policy 2050—An instrument to develop a diversified and sustainable electricity generation mix in coal-based energy system. *Renewable and Sustainable Energy Reviews*, 74, 51-70.
- Wolking, B., Mayer, J., Tuerk, A., Bachner, G., & Steininger, K. (2019). Co-designing a low-carbon transition pathway focusing on energy supply for the iron and steel sector. *Narratives of Low-Carbon Transitions*, 25.
- World Economic Forum (2016). The Global Competitiveness Report 2016–2017.



- World Value Survey (2015). World Value Survey wave 6 (2010-2014), s.l.: World Values Survey Association.
- Wu, T., Song, H., Wang, J., & Friedler, E. (2020). Framework, Procedure, and Tools for Comprehensive Evaluation of Sustainable Stormwater Management: A Review. *Water*, 12(5), 1231.
- Yager, R. R., & Filev, D. P. (1994). Parameterized and-like and or-like owa operators. *International Journal of General System*, 22(3), 297-316.
- Yoon, K., & Hwang, C. L. (1981). TOPSIS (technique for order preference by similarity to ideal solution)—a multiple attribute decision making, w: Multiple attribute decision making—methods and applications, a state-of-the-at survey. Berlin: Springer Verlag.
- You, W., Geng, Y., Dong, H., Wilson, J., Pan, H., Wu, R., ... & Liu, Z. (2018). Technical and economic assessment of RES penetration by modelling China's existing energy system. *Energy*, 165, 900-910.
- Zadeh, L. A. (1975). The concept of a linguistic variable and its application to approximate reasoning—I. *Information sciences*, 8(3), 199-249.
- Zeug, W., Bezama, A., Moesenfechtel, U., Jähkel, A., & Thrän, D. (2019). Stakeholders' interests and perceptions of bioeconomy monitoring using a sustainable development goal framework. *Sustainability*, 11(6), 1511.
- Zhang, M., Bai, C., & Zhou, M. (2018). Decomposition analysis for assessing the progress in decoupling relationship between coal consumption and economic growth in China. *Resources, Conservation and Recycling*, 129, 454-462.
- Zheng, J., Egger, C., & Lienert, J. (2016). A scenario-based MCDA framework for wastewater infrastructure planning under uncertainty. *Journal of environmental management*, 183, 895-908.
- Zheng, J., Mi, Z., Coffman, D. M., Milcheva, S., Shan, Y., Guan, D., & Wang, S. (2019). Regional development and carbon emissions in China. *Energy Economics*, 81, 25-36.
- Zhou, W., McCollum, D. L., Fricko, O., Fujimori, S., Gidden, M., Guo, F., ... & Liu, C. (2020). Decarbonization pathways and energy investment needs for developing Asia in line with 'well below'2° C. *Climate Policy*, 20(2), 234-245.
- Ziv, G., Watson, E., Young, D., Howard, D. C., Larcom, S. T., & Tanentzap, A. J. (2018). The potential impact of Brexit on the energy, water and food nexus in the UK: A fuzzy cognitive mapping approach. *Applied Energy*, 210, 487-498.
- Zopounidis, C., & Doumpos, M. (2002). Multi-criteria decision aid in financial decision making: methodologies and literature review. *Journal of Multi-Criteria Decision Analysis*, 11(4-5), 167-186.



Appendix A

The application of the PROMETHEE method includes five steps:

Determination of the criteria weights, w_j , using the preferable method. The DM is asked to define the weights so as to counterbalance the importance of each alternative. The sum of these weights has to equal the unit: $\sum w_j = 1$. The methodology used for the calculation of the weights is presented in Section 1.4.2.

Determination of a preference function in order to translate deviation between the evaluations of two alternatives (a and b) on a specific criterion (g_j) into a preference degree. Each criterion has a preference function:

$$P_j(a, b) = F_j[d_j(a, b)] \quad (\text{A.1})$$

where F_j is a non-decreasing function of the observed deviations d_j and $d_j(a, b) = g_j(a) - g_j(b)$.

The larger the deviation, the stronger the preference (0 for no preference, 1 for strict preference). If $d_j \leq 0$ then $P_j(a, b) = 0$ in other case the analyst should choose between multiple types: Usual, U-Shape, V-Shape, Level, Linear and Gaussian. Some extra parameters may be used such as indifference threshold or preference threshold in case of using any type of the function except the Usual.

Calculation of a global preference index $\pi(a, b)$ which represents the intensity of preference of alternative a over b taking the weights into account.

$$\pi(a, b) = \sum_{j=1}^n P_j(a, b)w_j \quad (\text{A.2})$$

where, $P_j(a, b)$ is the preference function and w_j represents the weight of criterion j .

Calculation of outranking flows. Positive outranking flow $\varphi^+(a)$ and negative outranking flow $\varphi^-(a)$ measure how much the alternative a is outranking or outranked by the other alternatives.

$$\varphi^+(a) = \frac{1}{n-1} \sum_b \pi(a, b) \quad (\text{A.3})$$

$$\varphi^-(a) = \frac{1}{n-1} \sum_b \pi(b, a) \quad (\text{A.4})$$

Calculation of the net outranking flow. Finally, in order to completely rank all alternative actions, the net outranking flow $\varphi(\alpha)$ is determining using the equation below:

$$\varphi(\alpha) = \varphi^+(a) - \varphi^-(a) \quad (\text{A.5})$$

The indifference threshold (q) represents the largest value below which there is no preference for one alternative over another, and then the preference function equals 0. The preference threshold (p) represents the smallest value above which there is a strict preference for one alternative over another and in that case the preference function equals 1. The zone between (q) and (p) indicates weak preference and the preference function should be calculated according to the type of the chosen generalised criterion.



Appendix B

The Analytical Hierarchy Process (AHP) was developed by Saaty in 1980 and is based on the relative priority of each criterion over another, deriving from a comparison per pair, using a specific numerical scale. The first step in the process of calculating weights through the AHP method is to develop a table for pairwise comparisons, which reflects the preferences of the DMs upon the data under consideration. The table entry comes from a fundamental scale used for comparisons (Saaty scale or relative scale), as presented below:

Table 24: The fundamental scale of Saaty

Intensity of importance on an absolute scale	Definition
1	Equal importance
2	
3	Moderate importance of one over another
4	
5	Essential or strong importance
6	
7	Very strong importance
8	
9	Extreme importance
The intermediate values (2, 4, 6, 8) are used when compromise is needed.	
Reciprocal numbers of the above values	If activity a has one of the above numbers assigned to it when compared to activity b, then b has the reciprocal value when compared to a.

The DM then assigns the relevant importance between the criteria (in pairs) and insert them to the square comparison matrix:

Table 25: AHP comparison matrix

	g1	g2	...	gj	...	gn
g1	1	P12		P1j		P1n
g2	P21	1		P2j		P2n
...			(1)			
gi	Pi1	Pi2		Pij		
...					(1)	
gn	Pn1	Pn2		Pnj		1

In order to maintain the consistency of the matrix, $P_{ij} * P_{ji} = 1$.

Calculation of the weights included four basic steps in the approximate method (Mu and Pereyra-Rojas, 2017; Sennaroglu and Celebi, 2018), used in this research:

Calculation of the sum of each column:

$$S_{j_column} = \sum_{i=1}^n P_{ij}, \text{ for } j = 1 \dots n \quad (\text{B.1})$$

Division of each element of the matrix by the corresponding column sum to obtain the normalised matrix:



$$P_{norm,ij} = \frac{P_{ij}}{S_{j_column}} \quad (B.2)$$

Table 26: AHP normalised matrix

	g1	g2	...	gj	...	gn
g1	1/S1_column	P12/S2_column		P1j/Sj_column		P1n/Sn_column
g2	P21/S1_column	1/S2_column		P2j/Sj_column		P2n/Sn_column
...			(1)			
gi	Pi1/S1_column	Pi2/S2_column		Pij/Sj_column		
...					(1)	
gn	Pn1/S1_column	Pn2/S2_column		Pnj/Sj_column		1/Sn_column

Calculation of the sum of each line:

$$S_{i_line} = \sum_{j=1}^n P_{norm,ij}, \text{ for } i = 1 \dots n \quad (B.3)$$

Division of each line sum with the total number of the criteria (n), to calculate the weight of each criterion:

$$w_i = \frac{S_{i_line}}{n}, \text{ for } i = 1 \dots n \quad (B.4)$$

Once the criteria weights are calculated, consistency of the comparison matrix, which is filled with the DMs' subjective preferences, should be measured in order to ensure it is well below the tolerance limits of inconsistency. This procedure includes nine steps.

Presentation of the initial comparisons' matrix, adding in the first line the calculated weights:

Table 27: AHP comparison matrix and weights

	g1	g2	...	gj	...	gn
	w1	w2		wj		wn
g1	1	P12		P1j		P1n
g2	P21	1		P2j		P2n
...			(1)			
gi	Pi1	Pi2		Pij		
...					(1)	
gn	Pn1	Pn2		Pnj		1

Multiplication of each element with the corresponding weight:

$$P_{new,ij} = P_{ij} * w_j, \text{ for } i, j = 1 \dots n \quad (B.5)$$

Table 28: AHP weighted matrix calculations

	g1	g2	...	gj	...	gn
	w1	w2		wj		wn
g1	1*w1	P12*w2		P1j*wj		P1n*wn
g2	P21*w1	1*w2		P2j*wj		P2n*wn
...						
gi	Pi1*w1	Pi2*w2		Pij*wj		
...						
gn	Pn1*w1	Pn2*w2		Pnj*wj		1*wn



Calculation of the sum of each line (also known as weighted sum):

$$S_{new_i_line} = \sum_{j=1}^n P_{new_{ij}}, \text{ for } i, = 1 \dots n \quad (B.6)$$

Division of each sum with the corresponding diagonal element of the matrix

$$D_i = \frac{S_{new_i_line}}{P_{new_{ii}}}, \text{ for } i = j = 1 \dots n \quad (B.7)$$

Table 29: AHP normalised matrix calculations

	g1	g2	...	gj	...	gn	
g1	Pnew11	Pnew12		Pnew1j		Pnew1n	D1=Snew1_line/Pnew11
g2	Pnew21	Pnew22		Pnew2j		Pnew2n	D2=Snew2_line/Pnew22
...							
gi	Pnewi1	Pnewi2		Pnewij			Di=Snewi_line/Pnewii
...							
gn	Pnewn1	Pnewn2		Pnewnj		Pnewnn	Dn=Snewn_line/Pnewnn

Calculation of the average of D_i , also known as λ_{max} :

$$\lambda_{max} = \frac{\sum_{i=1}^n D_i}{n} \quad (B.8)$$

Calculation of the Consistency Index (CI):

$$CI = \frac{\lambda_{max} - n}{n - 1} \quad (B.9)$$

Calculation of the Consistency Ration (CR):

$$CR = \frac{CI}{RCI} \quad (B.10)$$

Where RCI is the Random Consistency Index. Saaty has calculated the CI of a number of randomly generated comparison matrices of different sizes as shown below:

Table 30: Saaty’s Random Consistency Index

n	1	2	3	4	5	6	7	8	9	10
RCI	0	0	0.58	0.9	1.12	1.24	1.32	1.41	1.45	1.49

If $CR \leq 10\%$, the level of inconsistency in the comparison matrix (Table 25) is acceptable and thus the process of decision-making may continue. Otherwise, the entries of the matrix should be revised to achieve better consistency.

