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Integration of societal aspects in optimisation-based electricity system modelling

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''Integration of societal aspect in optimisation-based electricity system modelling''

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Preface

This thesis is written as concluding work for my master program for the Master of Science in the field of Sustainable energy technology at the Technical University of Delft. This thesis was conducted in collaboration with the University of Geneva which gave me the wonderful opportunity to work together in Switzerland with their Renewable Energy Systems research group.

This thesis would not have been possible with the help of this group. Especially the head of the group Evelina Trutnevyte for the incredible opportunity she gave me to be part of her team, Dr. Xin Wen for the daily supervision and great help and Xenneth Brunninx of the TU Delft for all the feedback and supervision over the nine months. It was a great experience working together with the research group and fully dive in to one topic and really try to understand everything!

Qin Crebas
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Abstract

Currently, restricting the utilisation of fossil fuels and thereby limiting global warming to remain below 2ºC stands as one of the most crucial challenges confronting us. The electricity sector is one of the main contributors of CO_2 emissions, but it is changing in a rapid pace with a decarbonizing rate which is faster compared to all other fossil sectors. To facilitate the decarbonizing of the electricity sector, optimisation models can provide a valuable framework to gather information about the futuristics of the electricity market. As optimisation models can handle all sort of characteristics like demand and supply which should always be the same, certain policies, energy security, economic development and costs they play an important role in the transition toward more renewables and less fossil fuels. However, these optimisation models do not always present the right solution as societal factors are mostly missing, which can lead to misleading results.

In this paper we will specifically look at the D-EXPANSE optimisation model from the University of Geneva and incorporate two societal aspects. This will be implemented as a hindcasting exercise to examine whether or not it will improve the model compared to the regular model where no societal factors are implemented. This is applied on 31 European countries from 1990 until 2019. The societal aspects that are included in the D-EXPANSE model are *public acceptance* and *heterogeneity of actors*. Public acceptance is incorporated in the optimisation model with specifically limiting the CO_2 emissions per country with the help of survey data provided from 2009 until 2023 in combination with the set global European emission targets. Heterogeneity of actors is implemented by specifically adjusting the weighted average cost of capital per technology per country per year.

The main results are that it is still unclear whether or not the implementation of societal factors improves the accuracy of the model as a whole. For the implementation of public acceptance 9 out of the 18 countries experience a positive change regarding the error compared to the model where no societal factors are implemented. For the implementation of heterogeneity of actors 13 out of the 26 countries experienced an improvement, and for the combination of both factors 12 out of the 22 countries showed improvements. With this in mind, it is not justifiable that the implementation of public acceptance and/or heterogeneity of actors in this way improves the model which is shown as a hindcasting exercise.

This thesis fails to provide evidence supporting the idea that the inclusion of societal factors enhances the capabilities of optimisation models. This contradicts existing literature, which emphasizes that the incorporation of societal factors is a primary reason why optimisation models struggle to accurately predict the future. One potential explanation for this discrepancy in our findings may lie in the specific methods used to implement actor heterogeneity and public acceptance in the model. For the public acceptance model, it is shown that there is still room for improvement with a different upper limit for the amount of CO_2 emissions per country. This can increase accuracy up to 5 percentage points. Therefore, future research should focus on refining the implementation of societal factors, especially considering the accelerating pace of decarbonisation in the electricity sector. Factors such as supply and demand, electricity costs, and energy security remain crucial features that cannot be underestimated. Moreover, with the increasing integration of renewables into the electricity generation, societal factors will continue to exert a growing influence on the progress and implementation.

Table of content

Preface 2
Abstract 3
List of Abbreviation 6
1 Introduction 7
1.1 Energy system models 9
1.1.1 Uncertainty in energy system optimisation models 9
1.2 Societal factors 10
1.3 Research gaps and research questions 11
2 Literature review of societal factors 13
2.1 Heterogeneity of actor 13
2.2 Public acceptance 16
3 Methods 18
3.1 The electricity optimisation system model D-EXPANSE 20
3.2 Integrating public acceptance through climate change beliefs with CO_2 constraints 21
3.2.1 CO_2 constraint implementation based on public opinion on climate change. 22
3.2.2 Two ways of incorporating the CO_2 constraint 24
3.2.3 Sensitivity analysis on CO_2 emission constraints 25
3.3 Incorporating actor heterogeneity through differentiated WACCs. 26
3.4 Modelling to generate alternatives (MGA) 29
3.5 Error calculation 30
4 Results 31
4.1 Reference model version compared to the real-world 32
4.2 The two public acceptance models, yearly budget public acceptance model and the cumulative budget public acceptance model 33
4.2.1 Disparities between two model versions, yearly budget public acceptance model and the cumulative budget public acceptance model. 36
4.2.2 Detailed results of the cumulative budget public acceptance model 37
4.2.3 Results of the sensitivity analysis on CO_2 emission targets with the cumulative budget public acceptance model. 42
4.3 Implementing differentiated WACCs in the model for actor heterogeneity 44
4.4 Cumulative budget public acceptance model and heterogeneity of actors' model version 46
4.5 Model version comparison 51
5 Discussion and future work 54
6 Conclusion 57
Own reflection 59

Appendix 60
References 67

List of Abbreviation

AUT	Austria
BEL	Belgium
BGR	Bulgaria
CYP	Cyprus
CZE	Czech Republic
DEU	Germany
DNK	Denmark
ESP	Spain
EST	Estonia
FIN	Finland
FRA	France
GBR	Great Britain
GRC	Greece
HUN	Hungary
IRL	Ireland
ITA	Italy
LUX	Luxembourg
LVA	Latvia
MLT	Malta
NLD	The Netherlands
POL	Poland
PRT	Portugal
SVK	Slovakia
SVN	Slovenia
SWE	Sweden
ROU	Romania
LTU	Lithuania
HRV	Croatia

1 Introduction

The utilization of fossil fuels for energy production is the primary driver of climate change. However, in light of the Paris Agreement and the establishment of European targets, there is the need to shift towards a more sustainable world (Raiser et al., 2020). The core objective of these agreements is to limit global warming below 2ºC, with an even more ambitious target of staying below 1.5ºC. Achieving these agreements requires a full elimination of green house gasses of all sectors within the economy. Among these sectors, the electricity sector emerges as a significant contributor to CO_2 emissions, accounting for 40% of total greenhouse gas output (IEA, 2023). Currently, the decarbonisation of electricity and heat generation is progressing at a faster pace than in other sectors, making it the most cost-effective way of reducing carbon emissions (Plazas-Niño et al., 2022; Russo et al., 2022). This accelerated decarbonisation is primarily driven by the adoption of renewable energy sources, such as wind farms and solar panels (Lamb et al., 2021).

Researches can offer policymakers a framework using energy models. These models provide specific electricity mixes solutions were multiple objectives, inputs and constraints can be added. These models serve as valuable tools for establishing a framework within the electricity sector (Pfenninger et al., 2014). However these models fall short of aligning with real-world data, are surrounded by uncertainty and provide limited flexibility (J. F. DeCarolis, 2011; Trutnevyte, 2016). To provide more flexibility to policymakers, multiple solution can be presented with the use of modelling to generate alternatives (MGA) (J. F. DeCarolis et al., 2016; Neumann & Brown, 2021; Yue et al., 2018). MGA is a way of systematically exploring the near optimal solution where many different outcomes are presented, with a chosen higher cost than that of the cost optimisation mode. There are many different energy models on the market, but we chose to use an energy system optimisation model (ESOMs), namely D-EXPANSE. This was facilitated by the University of Geneva, as the research group of renewable energy system have developed and worked on this model.

More information about different type of energy models can be found in Section 1.1. Section 1.2 highlights how the discrepancy between the modelled and actual electricity mixes are misaligned which is partly due to the failure to incorporate societal factors into energy system optimisation models (Geels et al., 2020; Krumm et al., 2022; Pfenninger et al., 2014). Among these societal factors, the two most important factors are public acceptance and heterogeneity of actors (Geels et al., 2020; Krumm et al., 2022; Trutnevyte, 2016; Vivien Fisch-romito et al., 2023). The literature review of societal factors in Section 2 provides a more in-depth analysis of these societal factors. As last, in Section 1.3, the research gaps and questions are explained. In the introduction we utilise the flow diagram in Figure 1, which shows the structure of the introduction.

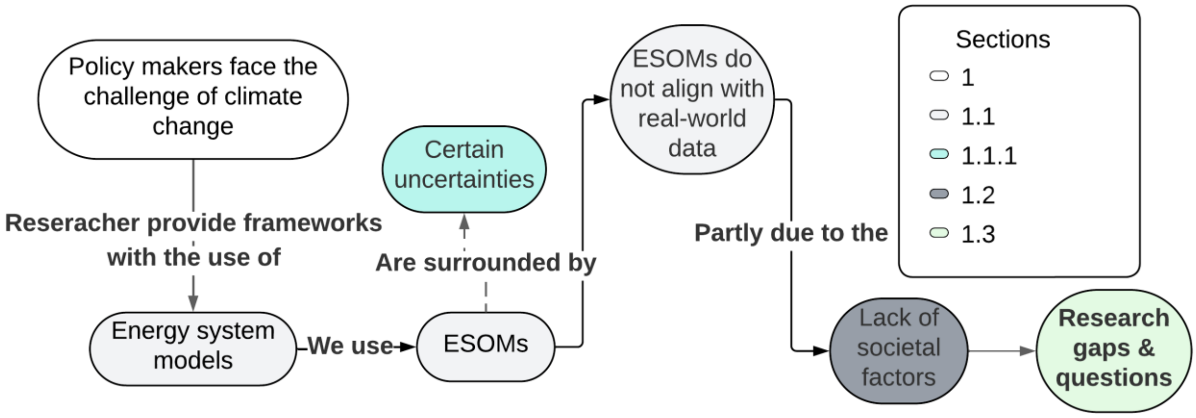

Figure 1 Flow diagram for the introduction with the colors representing the representative section. ESOMs stands for energy system optimisation models.

1.1 Energy system models

To facilitate the transition to a more sustainable world energy system models represent a useful tool to evaluate feasible future energy scenarios. Further, policymakers should address security and affordability of the energy system (Jing et al., 2021). There are numerous energy models to facilitate this framework, but energy system optimisation models (ESOMs) have found extensive application in providing valuable insights into climate and energy policies across various levels, including local, national, and global scales (Krumm et al., 2022; Yue et al., 2018). ESOMs possess several analytical advantages. They establish a consistent framework for evaluating techno-economic performance across all the processes they represent. Moreover, they have the versatility to encompass a wide range of energy scenarios, thereby enabling the incorporation of diverse energy and environmental policies. ESOMs are characterized by their comprehensive coverage of technology and can model an entire energy system, providing the means to assess various feasible energy scenarios (Plazas-Niño et al., 2022). These energy scenarios serve as a valuable tool for planning the future energy mix across a range of diverse assumptions, enabling a deeper understanding of the potential impact on the energy landscape (J. DeCarolis et al., 2017; Li, 2017; Wen et al., 2022). There is a variety of ESOMs available today including TIMES (MARKEL) (Tash et al., 2019; Yu et al., 2020), Calliope (Lombardi et al., 2019), TEMOA (Cotterman et al., 2021), ENGINE (Koecklin et al., 2021), GENeSYSMOD (Auer et al., 2020) and D-EXPANSE (Trutnevyte, 2013). For our research, we will use D-EXPANSE which builds on previous work from D-EXPANSE as described in Trutnevyte, (2013). D-EXPANSE is later developed by Li & Trutnevyte, (2017); Trutnevyte, (2016); Wen et al., (2022, 2023) and is an electricity system optimisation model for 31 European countries. We use D-EXPANSE as our research is conducted in corporation with the University of Geneva and they developed and are working on D-EXPANSE.

The primary focus of ESOMs is to optimize the operation and expansion of the energy system while considering a range of objectives and constraints, where the primary focus on objectives is cost minimization. Typically, a single solution is computed, driven by the objective function, and it often represents the most cost-efficient outcome within the defined constraints. This single solution can hold the specific generation and capacity which accommodates the most cost-efficient outcomes. The cost-optimal solution is sometimes confined to a narrow cost range, meaning that slight modifications in the objective function or input parameters can heavily influence the cost-optimal solution (Pfenninger et al., 2014). These cost-optimal solutions tend to underplay the inherent uncertainty and the wide range of potential outcomes within an electricity system (Berntsen & Trutnevyte, 2017; J. F. DeCarolis, 2011; Trutnevyte et al., 2016). Furthermore, the cost-optimal solution is surrounded by uncertainty for reasons like social economic factors, resource availability, technological innovation and big disruptions in the energy sector like COVID (J. DeCarolis et al., 2017; J. F. DeCarolis, 2011; Lombardi et al., 2020). Therefore, it is good to mention that these energy models provide insight into a hypothetical future that does not exist.

1.1.1 Uncertainty in energy system optimisation models

Regarding the uncertainty of ESOMs, there are two types of uncertainties, parametric and structural uncertainty (Yue et al., 2018). Structural uncertainties refer to model uncertainties regarding equations which define the model structure. Parametric uncertainties refer to uncertainties regarding the input parameters. From these two uncertainties addressing structural uncertainty is a more challenging task (J. F. DeCarolis, 2011). One potential approach to limit these uncertainties is to construct larger and more complex models, but this may offer limited additional insights into alternative ways to structure and analyse the system and may not necessarily eliminate structural uncertainty (J. DeCarolis et al., 2017; J. F. DeCarolis, 2011). In dealing with uncertainties in ESOMs, six approaches have been identified (J. DeCarolis et al., 2017; Neumann & Brown, 2021; Yue et al., 2018): Stochastic programming (SP), Monte Carlo analysis (MCA), modelling to generate alternatives (MGA), robust optimisation (RO), global sensitivity analysis (GSA) and scenario analysis.

All these methods described represent parametric uncertainty, except for MGA which addresses the issue of structural uncertainty. MGA operates by using the optimal solution as an anchor point to generate a set of alternative solutions within a certain region. The size of this region is determined by the amount of slack. Slack is defined as the amount of which the cost (or other output parameters) the MGA can overshoot (Berntsen & Trutnevyte, 2017; Neumann & Brown, 2021). Another approach by implementing MGA is to assess which technologies are necessary, which ones can be excluded from the electricity mix, and which ones are more preferred regarding political will (Lombardi et al., 2020). By using MGA and considering the slack, policymakers can evaluate how much additional investment is required to achieve the desired solution and make informed decisions (Lombardi et al., 2020; Neumann & Brown, 2021). Nowadays, the implementation of MGA in ESOMs has become a widespread practice, as shown by multiple papers (Berntsen & Trutnevyte, 2017; J. F. DeCarolis, 2011; Li & Trutnevyte, 2017; Trutnevyte, 2016). In these studies, MGA is typically used to show maximally different solutions, helping to identify possible solutions within a specified cost range (Neumann & Brown, 2021; Trutnevyte, 2016).

1.2 Societal factors

While the significance of ESOMs continues to grow with the ongoing climate challenges, the aspect of societal aspects inside ESOMs remain absent (Krumm et al., 2022). This is particularly remarkable because renewable energy projects are becoming increasingly reliant on societal elements, which serve as both driving and limiting forces in the transition (Wüstenhagen et al., 2007). People can actively contribute as prosumers and co-owners of energy projects. Conversely, public perception can act as a barrier to the integration of PV and wind farms (Krumm et al., 2022; Pfenninger et al., 2014). Neglecting these societal factors in the future will only lead to widening disparities and hinder the progress of the energy transition, potentially resulting in misguided policy decisions (Barazza & Strachan, 2020; Krumm et al., 2022; Trutnevyte et al., 2019). Regarding these societal factors, our literature review (Geels et al., 2020; Krumm et al., 2022; Trutnevyte et al., 2019; Vivien Fisch-romito et al., 2023), has identified three primary drivers of the most significant societal factors in ESOMs:

- Public acceptance
- Heterogeneity of actors
- Transformation dynamics

We will solely focus on two subjects: heterogeneity of actors and public acceptance. Transformation dynamics lies outside the scope of our research. Public acceptance pertains to the public’s sentiment regarding particular energy technologies or energy combinations and whether they express support or opposition towards them. Additional information can be found in Section 2.2. On the other hand, heterogeneity of actors refers to the presence of multiple actors in the electricity market, some of whom may not always make rational and cost-optimal solution decisions. However, ESOMs operate under the assumption of a single social planner who makes decisions that are both cost-optimal and rational. Further details on this topic can be found in Section 2.1. An overview of the research gaps and questions is presented in Section 1.3.

1.3 Research gaps and research questions

This study primarily aims to address two research gaps within the field of incorporating societal factors into ESOMs. Firstly, while existing literature has examined the integration of actor heterogeneity into agent-based modelling, there exists a gap when it comes to incorporating the heterogeneity of actors within ESOMs, this is normally not done as ESOMs use a single objective optimisation (Krumm et al., 2022). Secondly, despite several instances of implementing public acceptance into ESOMs (Baur et al., 2022; Cotterman et al., 2021; J. F. DeCarolis, 2011; Koecklin et al., 2021; Krumm et al., 2022; Segreto et al., 2020), a gap persists in understanding how to account nationally specific climate public acceptance across Europe and how these considerations relate to ESOM errors (Geels et al., 2020; Krumm et al., 2022; Trutnevyte, 2016).

To address the existing research gaps, we have incorporated several enhancements within the D-EXPANSE model (which is in more detail explained in Section 3.1). Upon analysis, it becomes evident that the model lacks specific resolution within individual countries, thus failing to account for the impact of local-level (community) public acceptance. Consequently, survey data at the country-specific level, tailored more toward general opinions, across the majority of European countries, would be more applicable to integrate in our model. Combining this with the insights from two papers (Bergquist et al., 2022; Furnham & Robinson, 2022), revealed a correlation between public opinion on climate change belief and political affiliation. This connection suggests that such beliefs find representation in politics, where politicians may enact laws in line with public sentiment. Further, to leverage the findings of these surveys on public opinions regarding the seriousness of climate change, we have integrated them within the framework of CO_2 constraints, in conjunction with the European targets. Although various integration methods are possible, the European targets functions as a reference for determining the allowable CO2 emissions per country. This reference can be adjusted based on public perceptions of the severity of climate change. For more detailed information regarding the integration of public acceptance can be found in Section 3.2.

Regarding the incorporation of actor heterogeneity, we encountered challenges due to the presence of a single social planner. This posed difficulties in distinguishing between multiple players with varying hurdle rates and preferences, as shown by the work of (Barazza & Strachan, 2020). Nonetheless, the variation in hurdle rates, presented an avenue for general-level modifications. Consequently, we turned to data from Polzin et al., (2021) to access specific Weighted Average Cost of Capital (WACC) values across countries and technologies. This information replaced the uniform discount rate, introducing diversity among different market players (the countries and technologies), rather than treating all countries and technologies as identical market players. These discount factors play an important role in distinguishing between technologies within a country, as shown by García-Gusano et al., (2016); Mier & Azarova, n.d.; Trutnevyte, (2016), which emphasize the significance of the discount factor in ESOMs for calculating the optimal energy mix. More information about the integration of heterogeneity in D-EXPANSE can be found in Section 3.3.

These two new model version, public acceptance and heterogeneity of actors, in the D-EXPANSE model undergo evaluation against the original D-EXPANSE model. These two model versions will be employed in a hindcasting exercise to determine their impact on the overall performance of the model. Through this assessment using actual data, we will analyse the model's performance by measuring discrepancies between capacity and generation of the actual data and model data. Error calculations will be conducted for each country, allowing us to scrutinize the effectiveness of the two D-EXPANSE versions and the original D-EXPANSE model. This process will help in selecting the optimal model based on the findings (Chaturvedi et al., 2013).

In light of these research gaps, our study seeks to answer the following research questions:

- What is the effect of country-specific CO_2 limits, based on the combination of European targets and the perceived severity of climate change, on an electricity system optimisation model?
- What is the impact of using differentiated weighted average cost of capital, based on technology and country, in comparison to a uniform discount factor in an electricity system optimisation model?
- How does the introduction of public acceptance and heterogeneity of actors in an electricity system optimisation model impact model accuracy when applied to 31 European countries?
- What is the range of near-optimal solution of the relative error, when implementing public acceptance and/or heterogeneity of actors in an electricity system optimisation mode, as opposed to the reference model version?

The paper is structured as follows: the detailed explanation of the D-EXPANSE model used is shown in Section 3.1, the construction of a new model version for public acceptance and heterogeneity of actors are shown in respectively Section 3.2 and 3.3. Section 3.4 discusses the MGA within the model, whereas Section 3.5. outlines the process of calculating the error for comparing the different model version to the real-world data. The key results and discussion for the new model version of public acceptance is shown in Section 4.2, while the results of the model version of the heterogeneity of actors is shown in Section 4.3, a combination of the two factors is presented in Section 4.4. The discussion and possible future work are discussed in Section 4, and as last the conclusion of the research can be found in Section 6.

2 Literature review of societal factors

This section will describe the two societal aspects that are implemented into the D-EXPANSE model. The first explanation is about heterogeneity of actors in Section 2.1. The second societal factor is public acceptance which is explained in Section 2.2. An overview of the topics for the literature review can also be found in Figure 2

Figure 2 Literature review of the two societal aspects.

2.1 Heterogeneity of actor

Heterogeneity of actors refers to the variation in characteristics, behaviours, and decision-making processes among different actors, which can influence their participation in the energy system. Although ESOMS assumes that all actors act rationally and strive for cost optimisation, real-world decision-making involves multiple parties and can be influenced by various factors excluding money. Each individual actors aims to maximize its utility, and in a scenario of perfect competition and perfect information, cost minimisation would naturally occur. However, this ideal scenario does not align with the complexities of the real world but is imposed by the model. In reality, some actors may prioritise branding or perceived reliability over cost optimisation, or they may be motivated by social or environmental factors, such as a desire to reduce their carbon footprint. Thus, actors are not solely influenced by costs, and these complex factors can slow down decision-making in reality compared to what models may suggest and therefore generate errors on the long term (Li, 2017; Li & Strachan, 2017; Trutnevyte, 2016). Moreover, individual consumer behaviour can affect energy demand and technology adoption, while policymakers' decisions can impact the regulatory environment and availability of funding for energy projects (De Cian et al., 2020; Li & Strachan, 2017; Stavrakas et al., 2019). Implementing the behaviour of actor and agency in these models is hard but crucial as it could significantly delay the climate mitigation efforts (Hirt et al., 2020).

Heterogeneity of actors is often implemented in agent based models (e.g. BRAIN (Barazza & Strachan, 2020), ATOM (Stavrakas et al., 2019), BSAM (Nikas et al., 2020)). These models excel at representing autonomous and diverse agents, including their initial beliefs, resistance and investment probabilities. However, agent-based models come with certain drawbacks, such as their inability to adequately represent the electricity system, which holds true for ESOMs as well (Barazza & Strachan, 2020; De Cian et al., 2020). Additionally, their solutions are not necessarily optimal but instead consist of scenarios with multiple assumptions, rendering them challenging to interpret (Ma & Nakamori, 2009), and issued related to parametrisation (Ringler et al., 2016). Furthermore, previous research has explored agent-based modelling with the integration of heterogeneous actors, either through narrative scenarios or by introducing different market players with varying preferences (Barazza & Strachan, 2020; Michas et al., 2020; Nikas et al., 2020; Stavrakas et al., 2019). This resulted in possible barriers to effective decarbonisation and lower the speed (Barazza & Strachan, 2020). Hence, delving into the integration of heterogeneous actors within ABMs may lack appeal, and we do not have any ABMs available to us.

The incorporation of actor heterogeneity within ESOMs is especially prevalent as prior research primarily focused on specific countries or regions (Mier & Azarova, n.d.; Tash et al., 2019). Therefore, there exists a gap in integrating actor diversity across different countries in ESOMs (Krumm et al., 2022; Stavrakas et al., 2019). This gap can be attributed to challenges in accommodating various market participants within ESOMs. One of the most critical limitations, emphasized by Mercure et al., (2016), is that optimisation models in the decision-making process utilize a single social planner which produces normative solutions. Normative solutions focus on identifying optimal strategies that align with established norms, regulations, and standards, while descriptive solutions aim to understand the operation and behaviour of energy systems. While both of these solutions are viable, the presence of a single social planner makes it more challenging to accommodate multiple market players.

Currently, many ESOMs utilize uniform discount rates that are consistent across all countries and technologies, however this approach fails to capture the real-world diversity of discount rates (García-Gusano et al., 2016; Li & Strachan, 2017; Trutnevyte, 2016). Especially, as significant differences in discount rates exist between countries, even within Europe (Ondraczek et al., 2015). Our objective is to address the challenge of actor heterogeneity by introducing differentiated weighted average cost of capital (WACC) into our ESOM. In this context, we evaluate the impact of differentiated discount rates across technologies and countries. WACC represents the expected rate of return that an investor anticipates from their investment (more information about the distinction of WACC and discount factors can be found in Section 3.3). It is used in discounting future cash flows and holds particular significance for renewable energy projects (Ondraczek et al., 2015). The value of the WACC is a critical parameter in ESOMs, as it can significantly alter the determination of which technology is considered the most economically viable among others (García-Gusano et al., 2016; Trutnevyte, 2016). Research conducted with model-based approaches has demonstrated that the cost-optimal solution within ESOMs are highly sensitive to the assumed cost of capital (García-Gusano et al., 2016; Hirth & Steckel, 2016; Iyer et al., 2015; Steffen, 2020).

This differentiating becomes even more significant when considering the financing disparities between conventional fossil fuel power plants and renewable power plants. The primary distinction between these two types of technologies lies in the fact that renewable energy technologies are highly capital -intensive (CAPEX) at the start, with no ongoing fuel costs, whereas fossil fuel technologies have higher operation and maintenance costs (including fuel costs) (O&M) and are therefore less capital-intensive. An important parameter for distinguishing between power plants in terms of their cost-effectiveness in generating electricity is the levelized cost of electricity (€/kWh) (LCOE). The formula for calculating the LCOE is shown in Equation 1 (Aldersey-Williams & Rubert, 2019):

$$LCOE = \frac{\sum_{t=1}^{n} \frac{I_t + M_t + F_t}{(1+r)^t}}{\sum_{t=1}^{n} \frac{E_t}{(1+r)^t}} \tag{1}$$

Here *I* represent the initial costs, *M* is the maintenance and operations expenditures, *F* the fuel costs, *E* the electrical energy generated, *r* the discount rate/WACC over the project all over each year *t* for the expected lifetime *n*. In projects that involve substantial investments, which is often the case, the capital expenditure is significantly influenced by the cost of capital (Mazzucato & Semieniuk, 2018). A higher

WACC will therefore result in an increase in the LCOE, greatly impacting project financing and the overall competitiveness of the power plant (García-Gusano et al., 2016; Keppo & Strubegger, 2010; Ondraczek et al., 2015). Given that renewables are capital-intensive at the start; the cost of capital constitutes a substantial portion of the LCOE for renewable energy projects. Consequently, a higher WACC tends to favor fossil fuels to a greater extent, while a lower WACC tend to favor renewable power plants. This dynamic is particularly pronounced in developing countries, where the WACC tend to be higher compared to more developed economies (Polzin et al., 2021). Considering that mostly renewable energy projections are inaccurate in ESOMs (Gilbert & Sovacool, 2016; Trutnevyte, 2016), there is a case to be made for exploring the impact of varying WACC values on the outcomes of these models. Differentiated (WACCs) are employed to represent various market players for each technology and in each country, illustrating the diversity among technologies across different nations.

2.2 Public acceptance

With the continued growth of renewable energy, numerous studies have highlighted the importance of incorporating public acceptance into energy models (Devine-Wright, 2008; Schubert et al., 2015; Süsser et al., 2022a). Public acceptance refers to the degree to which a community or society is willing to accept and support a specific energy technology or policy. It encompasses various factors, including public perception, attitudes, beliefs, values, trust, and participation in decision-making processes. Neglecting to consider this aspect can introduce inaccuracies into energy models, affecting their performance in depicting the energy transition, including its speed, impacts, technological options for the energy transition, potential for renewables and producing overly optimistic and potentially deceptive outcomes (Süsser et al., 2022b). Ultimately, these inaccuracies can impact the decisions made by policymakers who get information from these energy models to shape a more sustainable future (Cotterman et al., 2021; Wolsink, 2012).

The relevance of public acceptance is particularly pronounced in the context of renewable energy sources. For one, renewable energy projects tend to be smaller in scale, resulting in an increased number of project sites. Additionally, since most renewable energy projects have relatively low energy densities, their visual impact is more noticeable compared to fossil fuels projects equivalent capacity. Furthermore, the fuel required for fossil fuels generation is extracted from underground sources, remaining largely unseen, while renewable energy harness energy directly at the source, making it more visible (Wüstenhagen et al., 2007). A comprehensive understanding of public acceptance can be derived from the extensively referenced paper by (Wüstenhagen et al., 2007), which categorizes public acceptance into three main categories: Socio-political, community and market acceptance.

Socio-political acceptance represents the broadest level of social acceptance and involves the acceptance of technologies and policies across key stakeholders, policymakers, and public opinion. While there is a strong consensus about climate change (as shown in 3.2.1), research papers indicate a distinction between general and local acceptance. Particularly, local acceptance tend to be lower than general public opinion as observed by (Baur et al., 2022), although other papers suggest the opposite (Carley et al., 2020; Wolsink, 2006, 2012). The acceptance of local projects does not always align with socio-political acceptance, even when surveys indicate general approval of the technology. Hence, a clear distinction exists between socio-political and community (local) acceptance (Baur et al., 2022; Devine-Wright, 2008; Segreto et al., 2020). Community acceptance focuses on the specific approval of siting decisions and projects. In this context, knowledge, trust in the stakeholders and positive perceptions about the benefits of renewable projects are positively correlated with the support for these projects, with variation in outcomes across different renewables technologies (Carley et al., 2020). Thirdly, market acceptance pertains to the process by which new energy technologies or innovations are adopted and integrated into the market, and the extent to which consumers and companies accept them. In the context of this research, market acceptance holds a less prominent role, as the market acceptance of renewable energy sources is currently widespread (Schumacher et al., 2019).

Given the nationwide resolution of our model (more described in Section 3.1), community acceptance, so projects on a local/regional scale, are impossible to implement. Hence, we will primarily focus on socio-political acceptance concerning the seriousness of climate change. We chose to focus on the severity of climate change because key parameters related to socio-political acceptance include policy-specific beliefs, such as fairness, *evaluations regarding climate change's impacts*, trust established through information exchange and public involvement, distributional justice and siting issues, where evaluations regarding climate change's impacts is the highest most correlating parameter after fairness

(Bergquist et al., 2022; Segreto et al., 2020). While there has been some research on the integration of public acceptance into ESOMs (Krumm et al., 2022), existing approaches often use scenario analysis (Cotterman et al., 2021; Fitiwi et al., 2020; Schlachtberger et al., 2018) or consider various pathways to achieve net-zero emissions by 2050 (Tröndle et al., 2020). Another approach, as shown by Koecklin et al., (2021), involves adjustments to maximum capacity per region based on surveys. Notably, these studies have predominantly focused on regional and country-specific contexts. In this paper, our aim is to bridge the gap in country-specific public acceptance across Europe. Instead of relying on highly defined scenarios, we use country-specific maximum CO_2 emissions based on overall public opinion regarding the seriousness of climate change throughout the years. As climate change's impact is highly correlated with policies, it is reasonable to assume that if people are more concerned about climate change, more policies are implemented, leading to reduced CO_2 emissions. First, we assess whether our model's performance improves using this approach compared to the basic model. Furthermore, we test this hypothesis by examining the correlation between the actual reduction in CO_2 emissions in the real-world and public opinion regarding climate change.

3 Methods

To explore the impact of incorporating societal factors into the optimisation model D-EXPANSE, we examine five different model versions covering the period from 1990 to 2019 across 31 European countries. We will incorporate two societal factors; one is public acceptance and secondly is heterogeneity of actors. First, the original D-EXPANSE model which is called the *reference model version* is explained. Subsequently, two model versions which are related to public acceptance, the *yearly budget public acceptance model* and the *cumulative budget public acceptance model* are introduced. Additionally, a model version focused on heterogeneity of actors, the *heterogeneity of actors' model version* is constructed. As last, heterogeneity of actors and public acceptance is combined in a model called *cumulative budget public acceptance & heterogeneity of actors' model*. This integration of both models is created with the combination of the cumulative budget public acceptance model and the heterogeneity of actors' model version. The details of these models are summarized in Figure 3.

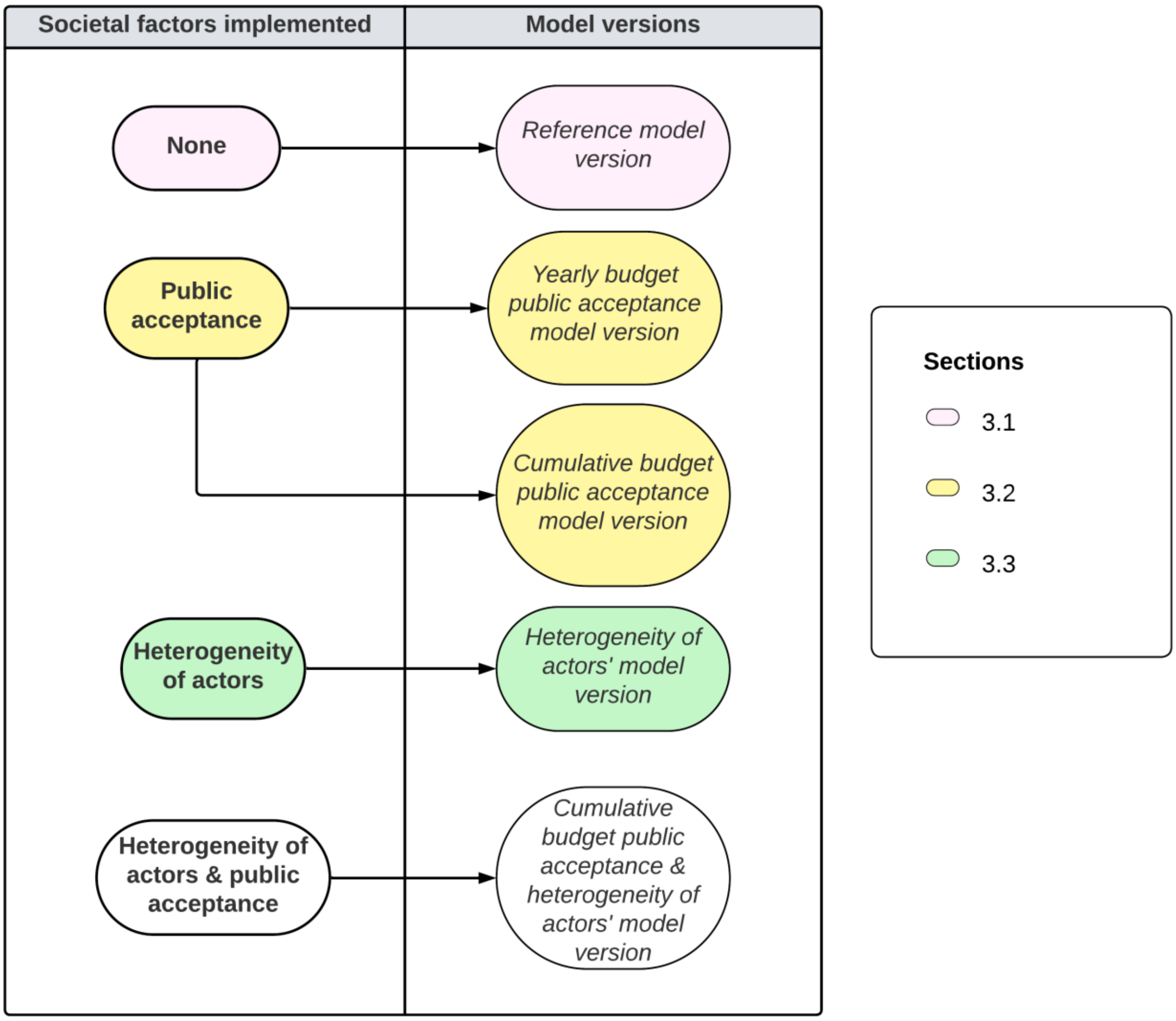

Figure 3 Structure of the methods with the five different model versions. The heterogeneity of actors & public acceptance model version is not separately explained as it is just the combination of the cumulative budget public acceptance model and the heterogeneity of actors' model. The original model can be found in Section 3.1, the two public acceptance model versions in Section 3.2 and the heterogeneity of actors' model version in Section 3.3

These four new model versions, so the model versions with the incorporation of a societal factor, are compared to the *reference model version*, which serves as the existing baseline. The public acceptance models are modified with a limitation of the amount of CO_2 emissions which is specific per country regarding the opinion on climate change in combination with the European targets. The heterogeneity of actors' model versions is adjusted regarding the differentiated discount factor across countries and technologies. An overview of the study can be found in Table 1. All these models provide one optimal solution which is surrounded by space for near-optimal solutions. These near optimal solutions are addressed with the help of MGA which is described in Section 3.4. Lastly the error in comparison to the real-world is computed which is explained in Section 3.5.

Societal factors	Data	Additional implementation to D-EXPANSE	Model version name	Method Section	Result Section
None	-	-	*Reference model version*	3.1	4.1
Public acceptance	Survey data European commission regarding climate change	Limit on CO_2 emissions	*Yearly budget public acceptance model*	3.2	4.2.1
			Cumulative budget public acceptance model version	3.2	4.2.1 & 4.2.2
Heterogeneity of actors	Data from (Polzin et al., 2021) about the WACCs	Differentiated discount factor	*Heterogeneity of actors' model version*	3.3	4.3
Public acceptance and Heterogeneity of actors	Survey data European commission regarding climate change and data from (Polzin et al., 2021) about the WACCs	Limit on CO_2 emissions and differentiated discount factors	*Cumulative budget public acceptance & heterogeneity of actors' model version*	-	4.3

Table 1 Structure of the methods and results for the different model versions.

We construct these four different models to assess the utility of integrating societal factors into energy optimisation models and to identify which societal aspects exerts the most influence in creating an energy system optimisation which is more accurate. Comparisons will be made among the various model features, and a hindcasting exercise will be conducted using actual country-specific data. This exercise consists in calculating the relative error between the actual data and the modelled data for capacity and generation. By analysing the relative error for each country and model, we can compare countries and evaluate the different models. This relative error is then traced back to the societal factors underlying each model version. These model versions are all originated from the original D-EXPANSE model developed by University of Genève's research group (Wen et al., 2023).

3.1 The electricity optimisation system model D-EXPANSE

The D-EXPANSE (Dynamic version of EXploration of PAtterns in Near- optimal energy ScEnarios) model is a cost optimisation-based model for the national electricity sector (Trutnevyte, 2016; Wen et al., 2022, 2023). D-EXPANSE is technology rich, meaning it encompasses a large variety of available technologies, which are country-specific. These technologies include brown coal, hard coal, gas, oil, biomass, biogas, nuclear, solar PV, onshore wind, offshore wind, nuclear, pumped hydro storage, run of river hydropower, hydro dam, geothermal and waste incineration. For hydro dams and pumped hydro storage, a significant altitude difference is required, for offshore wind power there has to be a sea. If a country does not have a nuclear power plant, it is not possible to build one from scratch. D-EXPANSE follows a bottom-up structure, which means it initially optimizes individual processes before integrating them to form the complete energy system. D-EXPANSE has perfect foresight, implying that the model knows all the parameters across the modelling time horizon. The model is a linear optimisation model with a yearly resolution. It optimizes for individual countries, providing a global country-level resolution. We include 31 European countries, encompassing the entire European Union (EU27), Iceland, Norway, Switzerland, and the United Kingdom, spanning the period from 1990 to 2019. For the electricity demand, the D-EXPANSE model generates two most representative days with 48 hours' time resolution (time slices). These two representative days are constructed for each year via K-means clustering based on the historical hourly electricity demand per country (Wen et al., 2022). In the basic version of D-EXPANSE there are no societal factors included and serves as a comparison tool. This basic version of D-EXPANSE is called the *reference model version*.

There is the possibility for import and export for each country (excluding Iceland). These connections represent a single node that can either be positive or negative, with specific capacity and generation values. The model does not specify the origin of these imports and exports. The interconnection with neighbouring countries is simplified to one transmission line for each country. The D-EXPANSE model has input data from two main categories: country-specific data (such as population, GDP per capita, annual supplied electricity, etc.) and technology-related data (like fuel costs, technology efficiency, carbon intensity of technologies, build rates, etc.). Details about this input data and its origins are available in (Jaxa-Rozen et al., 2022). The model's outputs, include data on annual generation and installed capacity of each technology, total and annual CO_2 emissions, total costs, investment costs etc. Additionally, we conducted a comparative analysis of the historical trajectory of the electricity system using real-world data as a reference to evaluate the output of the reference model version. The comparison of this model version with real-world data is presented in Section 4.1.

Using the D-EXPANSE model, we can create retrospective cost-optimal scenarios with the potential for Modelling to Generate Alternatives (MGA) and compare them to national real-world transitions. MGA are model outputs which provide near optimal solutions. The MGA incorporates a slack value, which indicates the extent to which the MGA run can increase its costs compared to the cost-optimal solution. Initially, the cost-optimal run is executed, and its solution is integrated into the MGA alongside a specified slack value and a predetermined number of runs. This process aims to generate a range of alternative solutions to facilitate the range of near optimal solutions. During the MGA the goal is to explore a range of solutions that go beyond the optimal reference run in terms of cost (more information in Section 3.4).

3.2 Integrating public acceptance through climate change beliefs with CO_2 constraints

We constructed two model versions aimed at integrating public acceptance from the original D-EXPANSE model. Additionally, we performed a sensitivity analysis to assess the accuracy of these newly developed model versions. Both model versions utilize an upper limit on CO_2 emissions, which is determined by existing climate change opinions combined with the European target. Within these two model versions, there are two different strategies. The first strategy imposes an annual budget constraint preventing the model from exceeding this limit each year, generating the *yearly budget public acceptance model*. The second approach establishes a cumulative constraint ensuring that the total sum of CO_2 emissions generated by the model over the timeframe of 1990 until 2019 remains below the predefined limit (the predefined limit is the cumulative CO_2 emissions from the constraint). This model version is called the *cumulative budget public acceptance model.* An overview of this approach is presented in the workflow of Figure 4. The detailed explanation about the construction of the constraint can be found in Section 3.2.1, the details of the two different model versions are explained in Section 3.2.2.

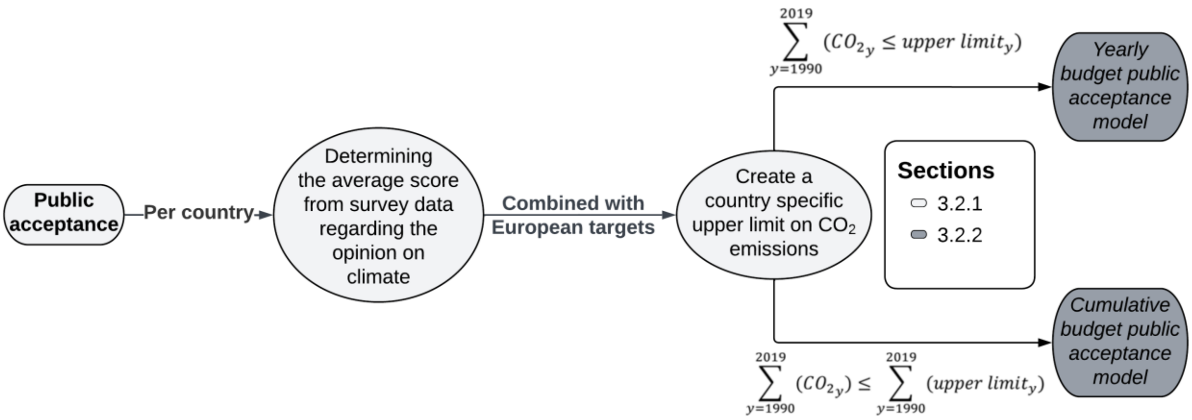

Figure 4 Workflow diagram of the implementation of public acceptance in D-EXPANSE. The methods in light grey colours are explained in Section 3.2.1, the methods in dark grey colours are explained in Section 3.2.2. There are two public acceptance model constructed, one where the cumulative CO_2 emissions can not go over the cumulative upper limit, the cumulative budget public acceptance model. The other model is where the CO_2 emissions can not surpass the upper limit on a yearly basis, the yearly budget public acceptance model.

In the sensitivity analysis we construct 25 distinct CO_2 emissions upper limits. These limits are determined based on the CO_2 emission of all countries in 2019 relative to their 1990 emissions, based on the lowest and the highest actual relative CO_2 emissions countries. Notably, these 25 upper limits allow the model to emit varying amounts of CO_2 emissions cumulatively. This means that we apply the *cumulative budget public acceptance model* across all 25 set upper limits, producing outcomes like electricity generation and capacity per technology. Subsequently, we analyse these results by comparing them to real-world data. This analysis involves calculating the error, which is explained in Section 3.5, between the model-generated capacity and generation and real-world capacity and generation to identify which upper limit (corresponding to CO_2 emissions levels) generates the lowest error. Following from this calculation, we explore the potential of generating lower errors compared to the constraint which is constructed in Section 3.2.1. Further we aim to analyse if there is a correlation between the upper limit which generates the lowest error and the public opinion regarding climate change. Our primary objective in this methodological approach is to investigate the existence of a correlation between climate change beliefs and actual emissions reductions. The detailed explanation about this approach is shown in Section 2.2.3, with the workflow diagram for the sensitivity analysis shown in.

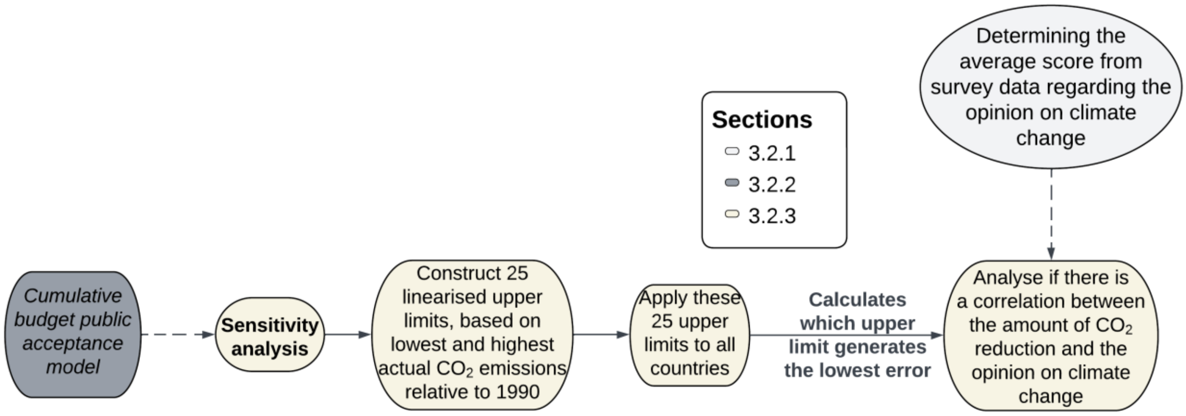

Figure 5 workflow diagram for the sensitivity analysis in Section 3.2.3. The sensitivity analysis is only conducted on the cumulative budget public acceptance model. The constraint with the lowest error is compared to the average score from the survey data regarding climate change. The cumulative budget public acceptance model can be found in Section 3.2.2 and the average score can be found in Section 3.2.1.

3.2.1 CO_2 constraint implementation based on public opinion on climate change.

Survey data in combination with European targets will serve as the baseline for our incorporation of public acceptance. We selected survey data from the European Commission (*Climate Action EU Survey*, n.d.), primarily because it provides extensive coverage across most countries across multiple years, thus enabling us to access country-specific climate change opinion data. Additionally, Europe member countries have collectively set a series of multi-year targets, which for all countries combined should be achieved. This allows for compensation across member states. These European targets are shown in Table 2 and are conducted from (Delreux & Ohler, 2019).

Year	European targets
1990	In 2000 back to 1990 levels
1997	8% decrease by 2012
2007	20% decrease by 2020
2014	30% decrease by 2030

Table 2 European targets with a percentage decrease in comparison to the 1990 values

The integration of this target into the model involves the addition of a specific country constraint, aligning with the European targets. The first target is to revert to emissions levels equal to those of 1990. We chose to have a constraint before 2000 as investments need to be fulfilled until 2019. Therefore, the first ten years are important as they invest in energy technologies which still contribute to the electricity in 2019. We chose to have a constraint which has a sinusoidal increase of 20% in CO_2 emissions. This approach provides some flexibility in modelling the electricity mix without excessively impacting the cumulative budget public acceptance model. For all the subsequent European targets, a linearization approach is applied. This means that the same percentage decrease of CO_2 emissions is applied for each year. Implying that if you have an 8% decrease over 15 years (the second target), the model decreases CO_2 emissions every year (relative to the 1990 levels) with 0.533%. The next CO_2 target starts from 100% emissions relative to 1990 levels and has a linearly decrease. In cases where multiple CO_2 targets overlap, the model prioritizes the most stringent one. A visual representation of this constructed constraint can be found in Figure 6.

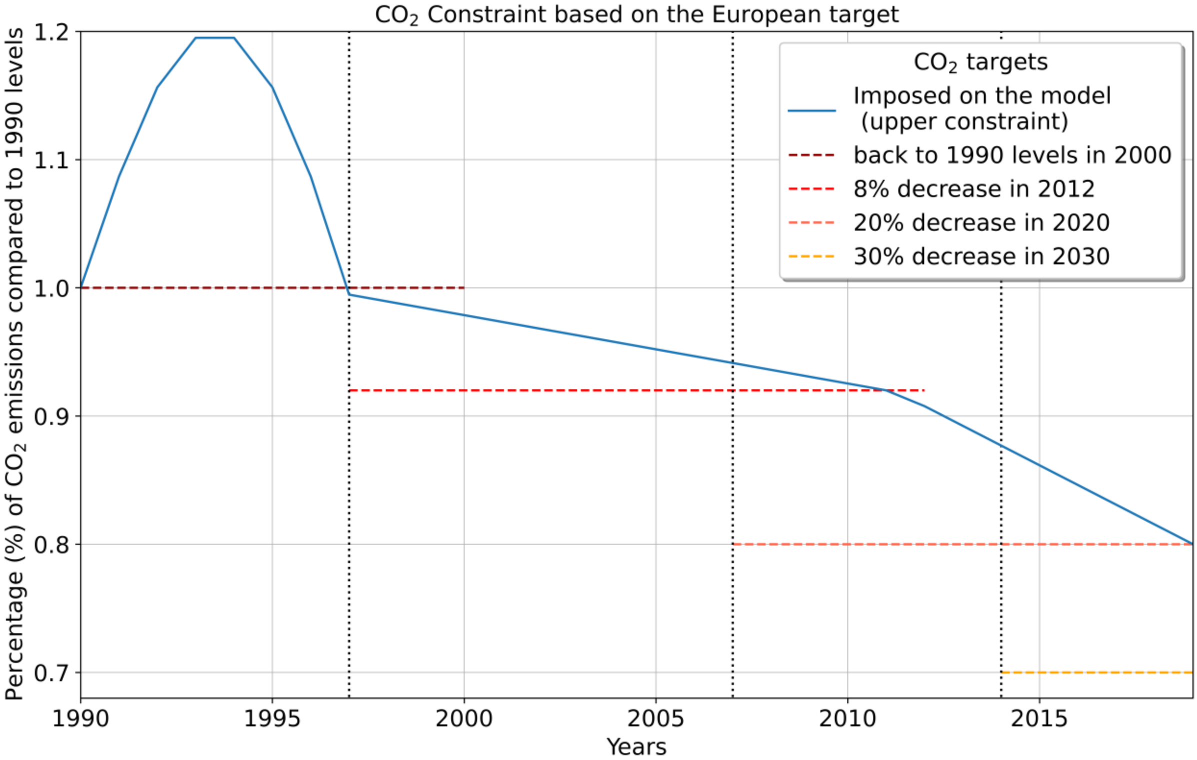

Figure 6 Visualization of the construction of the constraint with the CO_2 targets set by the European Union. The black dotted vertical line represents the year a new target is set.

All the European targets are periodically adjusted based on the European Commission's survey data, which provides insights on a two-year notice. This survey has been conducted from 2009 until 2023, featuring a series of questions on diverse topics related to climate change. The question we focus on is: "how serious a problem do you think climate change is at this moment?" They could answer from 1 (not a serious problem) – 10 (very serious problem). To assess the sensitivity of the model towards survey data input, we utilize four different scenarios to determine the mean values, which are explained in the Appendix. The scores which are given by the survey are subdivided into three groups (which were present on the data): in the range of 1-4: not a serious problem; 5-6: a fairly serious problem; 7-10 a very serious problem, the scores of 'No Specific Preference (NSP)' is left out. To transform the survey data to the constraint, it is converted as follow: the European target is the upper limit, where the baseline scenario without any requirement for reduction is the lower limit. The mean value for each country is computed for every two-year survey, and the constraint is subsequently adjusted based on this mean value. To clarify, when the mean value is 5, the constraint will represent a 50% reduction from the European targets (meaning that if the target implies an 8% decrease there will only be a 4% decrease). If the mean value reaches 10, it indicates 100% target implementation. Conversely, if the mean value is 0, it sets the boundary at 0% of the target, having no constraint, and so on. These particular thresholds were selected because they serve as predefined points of reference, aligning with the upper limit of the European target and the baseline scenario (0% reduction).

The relative decrease from survey data in CO_2 emissions compared to the European target across all countries, is shown in Figure 7. For all the countries during the years the mean response is relative positive regarding climate change seriousness as all the mean values are above the 6 or higher (scale was 1-10). Additionally, the disparity among the nations is relatively small, with the minimum value 6.3

(LVA), while the maximum mean value is 8.4 (PRT). Moreover, the two times the standard error ($\frac{standard\ deviation}{\sqrt{sample\ size}}$) are minimal, indicating that most data points are relatively tightly clustered around the mean value. The mean value over the two-year period adjusts the constraint, which is shown in Figure 6, based on the percentage of that mean value. For instance, if the mean value for those specific two years is seven, the European target is set to be only 70% stringent, resulting in an increase of CO_2 emissions of the upper limit by 30% relative to the European target.

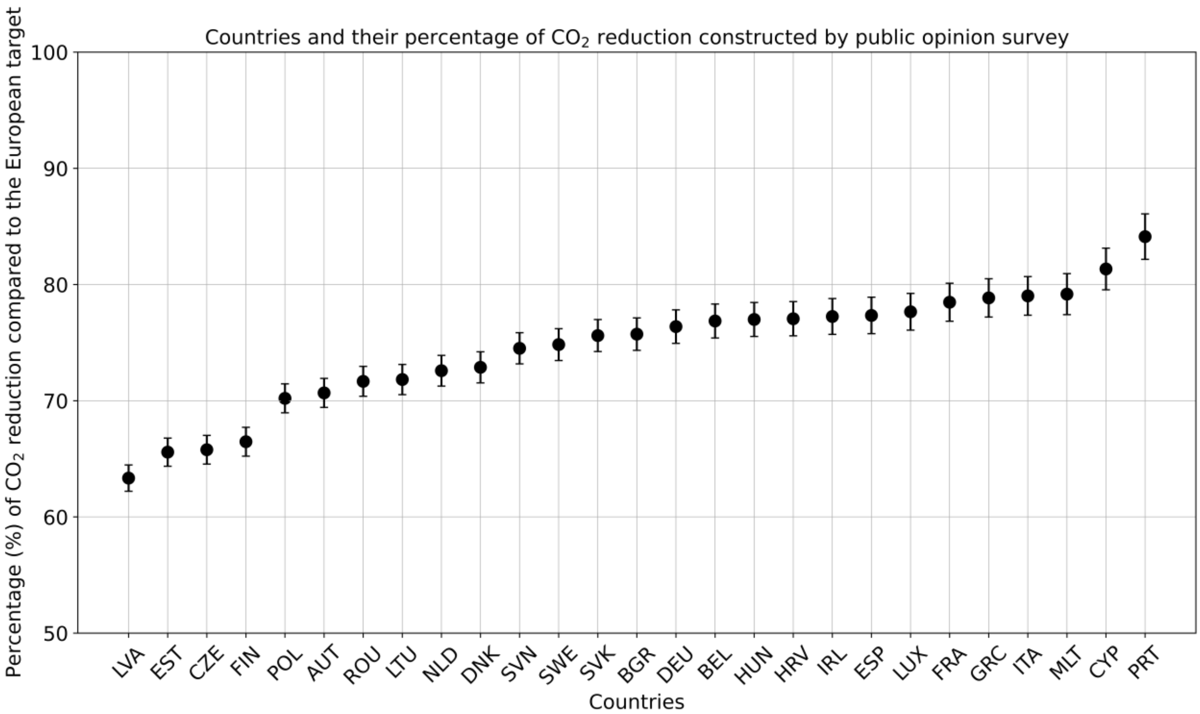

Figure 7. Countries and the opinion on climate change, mean value across 2009 until 2021. With error margins which represent 2 times the standard error. Note that the scale is form 50 until 100, while there is the possibility to score from 0 to 100.

3.2.2 Two ways of incorporating the CO_2 constraint

As discussed in Section 3.2 the CO_2 constraint is implemented in two ways. Firstly, the constraint is structured to set a yearly limit on the model's CO2 emissions. This ensures that this model version cannot exceed the constraint's CO2 emissions limit for each year. This model version is referred to as the *yearly budget public acceptance model*. For the second model version, the constraint is constructed such that the cumulative CO_2 emissions of the constraint (CO_2 emissions over 30 years 1990 –2019) cannot be exceeded by the cumulative CO_2 emissions of the model version. This approach allows the model to adjust its emissions, emitting more CO_2 at the beginning if it generates lower emissions in the future, or vice versa, in such a way that the two cumulative CO_2 emissions are at least equal. This flexibility accommodates the European Union's targets, which are not strictly annual but binding for the end of the periods. This version is set to be the *Cumulative budget public acceptance model*. The results of the yearly budget public acceptance model and the cumulative budget public acceptance model are compared in Section 4.2.1.

3.2.3 Sensitivity analysis on CO_2 emission constraints

Supplementary, our objective was to explore the possibility of adjusting the constraint to achieve the lowest error possible, as discussed in Section 3.2. This to assess how the variation compares to the constraint introduced in Section 3.2.1, while also examining any potential correlations between the amount of CO_2 emissions which generates the lowest error and the survey data on the severeness of climate change. This correlation would yield that the more people are aware of climate change the more a country is associated with emitting lower amounts of CO_2 emissions. To formulate the 25 linear constraints, we utilise the country with the actual highest and the country with the actual lowest CO_2 emissions ratios in 2019 relative to 1990 levels as upper and lower bounds. Cyprus exhibits the highest CO_2 emissions compared to 1990 levels with 193%, while Spain has the lowest CO_2 emissions compared to the 1990 levels with 30%. Within this range, 25 linearised constraints, so representing 25 CO_2 emission values, are constructed and visualized in Figure 8. These 25 constraints span the spectrum from the upper limit to the lower limit, all originating from 100% CO_2 emissions in 1990. These constraints are applied to all countries, resulting in the generation of 25 distinct scenarios. The cumulative budget public acceptance model is used to generate the needed results. This implies that the CO_2 emissions can surpass the constraint at certain levels as long as the total CO_2 emissions of the constraint is not higher than the total CO_2 emissions provided by the model.

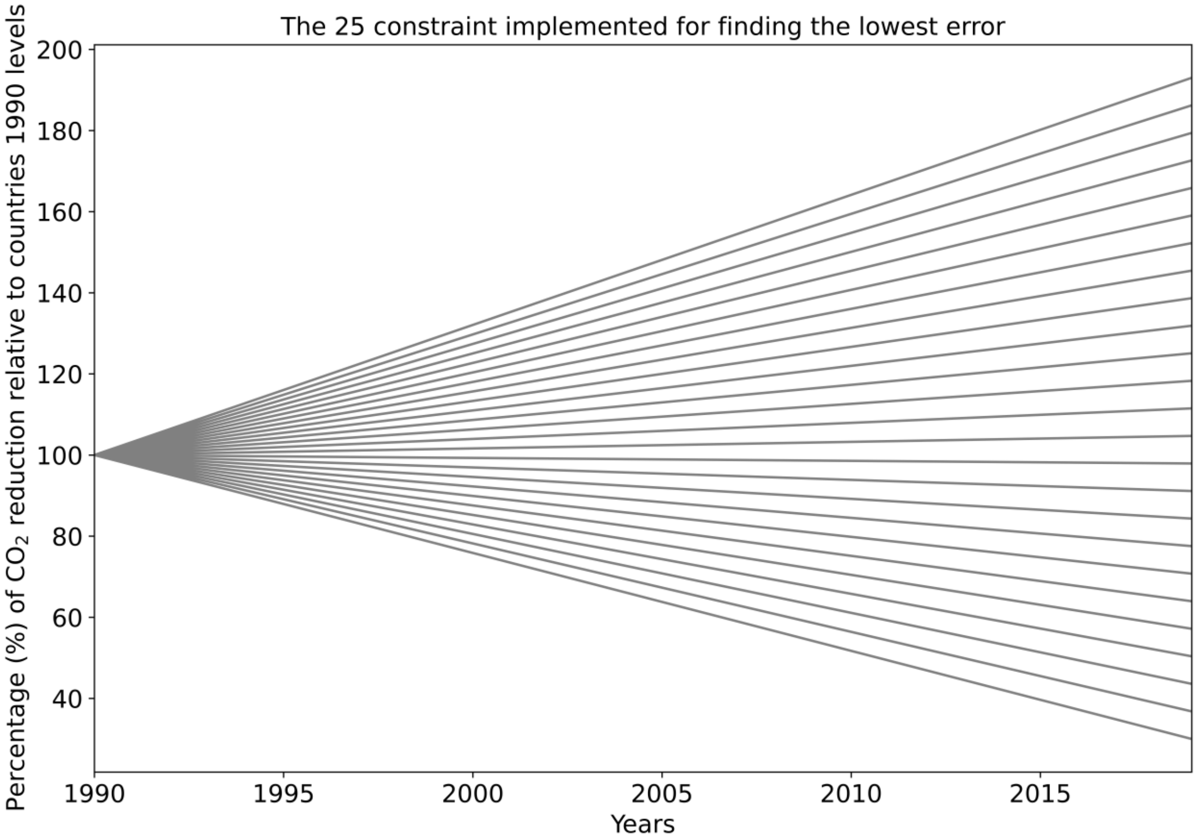

Figure 8 25 Constraints implemented to find the lowest error ranging from 193% until 30 % relative to 1990 CO_2 emissions. All the constraints start from 100% in 1990 and are linearized.

3.3 Incorporating actor heterogeneity through differentiated WACCs.

In heterogeneity of actors' model version, there is no uniform discount factor anymore but a yearly differentiating WACC (weighted average cost of capital) is implemented. In the reference model version of D-EXPANSE a modelling assumption for the uniform discount rate is used with a value of 3.5% (Jaxa-Rozen et al., 2022; Wen et al., 2022). In the new version the values for the differentiated WACCs spanning the spectrum of 2009 until 2019 are provided by the authors of Polzin et al., (2021). The countries present in the dataset are: AUT, BEL, BGR, CYP, CRO, CZE, DEU, DNK, ESP, EST, FIN, FRA, GBR, GRC, HUN, IRL, ITA, LTU, LUX, LVA, MLT, NLD, POL, PRT, SVK, SVN, SWE and ROU, countries not present in the dataset but present in D-EXPANSE, like NOR, ISL and CHE are left out. Every country is provided with yearly differentiated specific risk-free rate. The WACC values are provided for each country and each technology. The technologies included are brown coal/hard coal (are the same values), gas, nuclear, hydro dam, hydro run off river, solar PV, onshore wind, offshore wind and biomass. Given that not all technologies in the optimisation model are given, we have to make certain assumptions. The WACC values of brown coal are the same for oil, biomass is the same as waste incineration, geothermal energy similar to gas, and biogas is transformed to biomass with the ratio 4.9/4.7 (*Sweet Edge, Swiss Energy Research for the Energy Transition*, n.d.). Additionally, we set the value for import/export/storage at 0.05 (*Projected Costs of Generating Electricity*, 2020). As the values before 2009 are not available we assume that the value from 1990 to 2008 is the value in 2009.

For renewable power plants (solar PV, onshore/offshore wind and biomass), a single WACC value in 2015 is provided. This country and technology specific WACC is composed out of several factors, which are shown in Equation 2:

$$WACC_{ct} = r_{ft} + p_t + p_c + \epsilon_{ct} \tag{2}$$

r_f stands for the risk-free rate, this rate is the hypothetical rate of return on an investment which would have zero risk. It is a baseline for evaluating the potential returns of other investment which includes risks. Typically, goverments bonds have a very low default risk and are used as proxies for the risk-free rate which is here the case aswell. t Stands for the technology, p_c Is the policy specific rate of a country. This premium reflects the investor's perception on the risks of the specific country including the additional uncertainties, whereas p_t is the risk including the market and the specific technology. With a randomized ϵ which is the residual of a company-specific risks. The single WACC value for the renewable power plants in 2015 is adjusted in the range from 2009 untill 2019 with the changing risk-free rate from that country in the certain year. Incorporating the WACC values into D-EXPANSE requires the utilization of the discount factor. Normally, the discount rate is converted into a discount factor through the following Equation 3:

$$df = \frac{1}{(1+dr)^{years}} \tag{3}$$

We utilize the discount rate (*dr*), in the reference model set at 3.5%, and the discounted factor (*df*) to calculate the present value of future cash flows. While the WACC is not precisely the same as the discount rate, both are employed for discounting future cash flows. WACC is a more specific approach that considers the cost of capital for companies, whereas the discount rate is more broadly applicable and can encompass various rates of return in different financial scenarios (Ondraczek et al., 2015). As our focus is only on the discounting of future cash flows it is reasonable to assume that both are similar. With this case the discount factor can be calculated using the WACCs, instead of a general discount rate.

The differentiated WACCs per technology are shown for Ireland in Figure 9. Figure 10 shows the differences in WACC value across the countries for the technology gas.

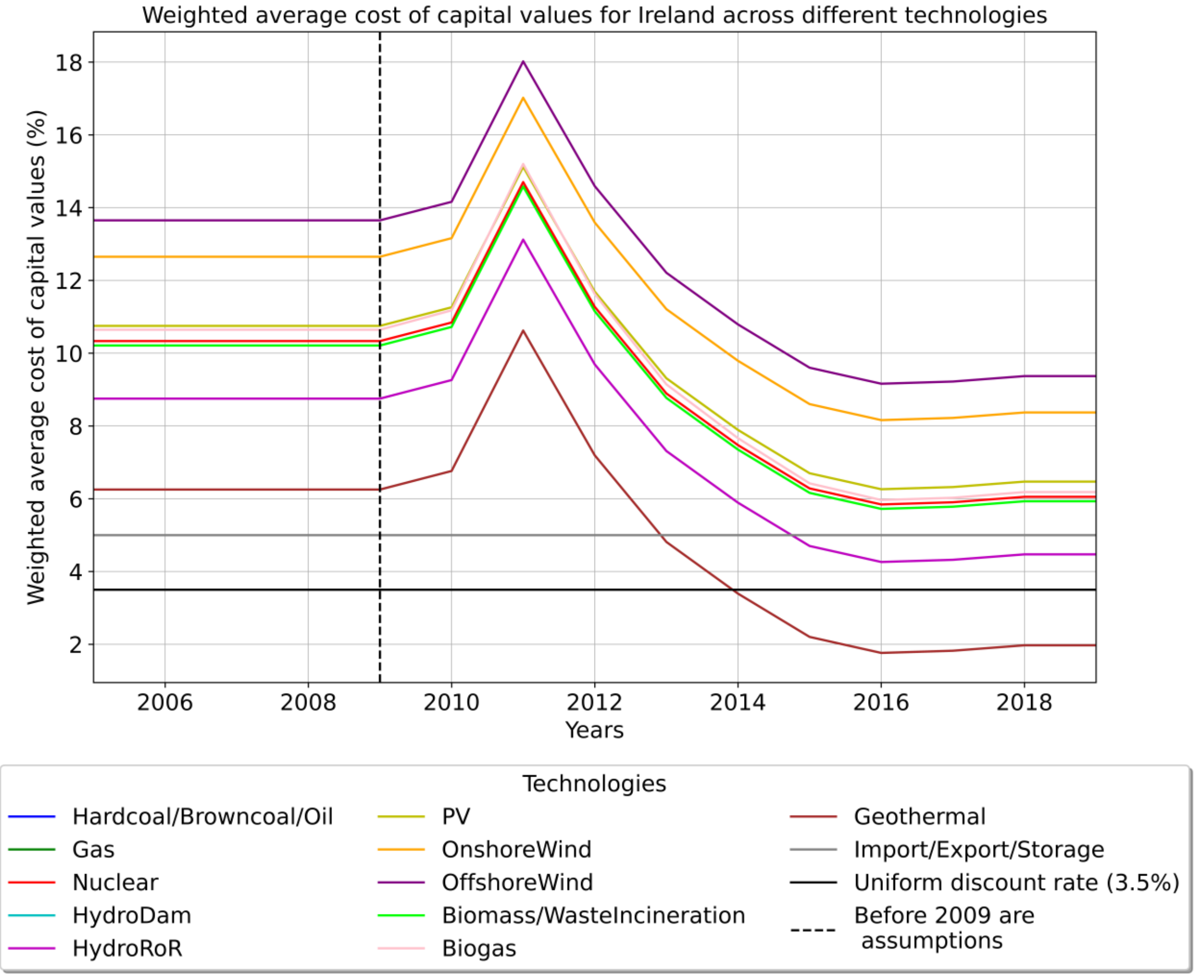

Figure 9 WACC values for different technologies across different years for Ireland. The values before the year 2009 are assumption and are the same values as in 2009.

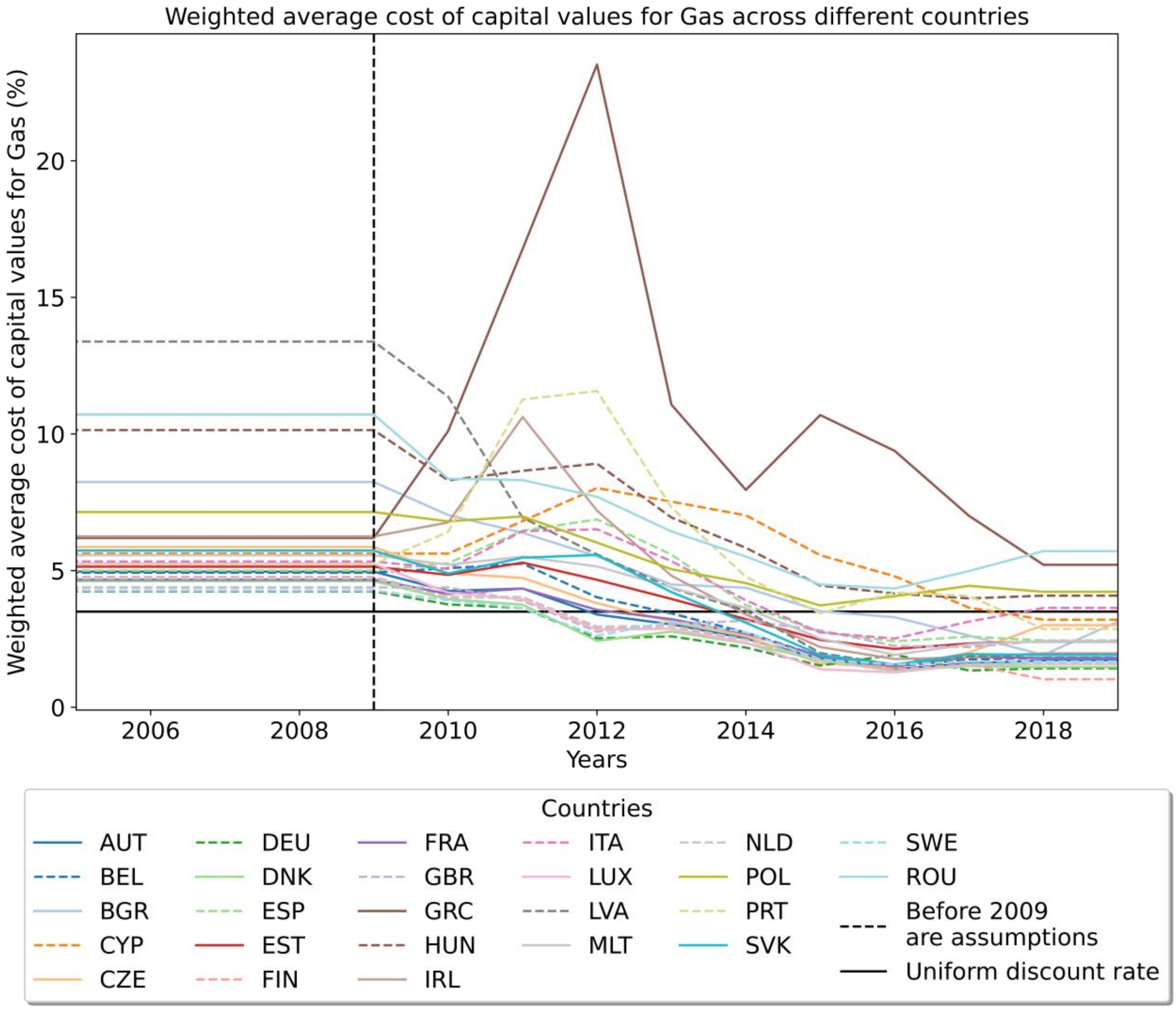

Figure 10 Differentiated WACC values across countries for the technology gas. The values before the year 2009 are assumption and are the same values as in 2009.

It clearly stands out that the uniform discount rate which is used in the reference model is lower side than the differentiated WACCs. The jump of WACC value for Ireland around 2010 is due to the economic crisis happening at that moment. Comparing these findings with the ECB (*Key ECB Interest Rates*, 2023) and the IEA (*Projected Costs of Generating Electricity*, 2020) the WACC values appear reasonable. Nevertheless, considering that the values from 1990 to 2009 are the same, there is still a big potential for being inaccurate due to the long timeframe.

3.4 Modelling to generate alternatives (MGA)

The D-EXPANSE model has the possibility to explore near-optimal solutions. First a cost optimal scenario of the D-EXPANSE model is conducted, afterwards this cost optimal scenario is put into the MGA model where certain parameters are adjusted. The MGA model gives, with a uniform distribution, every technology on every year a number from the set {1,0,-1}. This set means that the technology generation is maximized {1}, minimised {-1}, or neutral {0} on that year within the given constraints. The MGA model can be run multiple times to create a diverse set of possible solutions. By optimising each different scenario, broad solutions are presented with each time a different outcome. For the implementation of heterogeneity of actors, the amount of MGA runs was set to 200 as well as for the reference model run. This means that there are 200 solutions presented with different maximum generation from different technologies with a small, under 15%, cost increase. For the public acceptance implementation 75 runs are emitted for each of the four scenarios (explained in the Appendix) generating 300 MGA runs for each country.

The cost objective function is adjusted to the corresponding slack, this means that the model does not provide the cost-optimal anymore but can have a slight increase of the costs compared to the cost-optimal solution. In this MGA performance a slack of 15% in coherence with (J. F. DeCarolis, 2011; Mercure et al., 2016; Trutnevyte, 2016) is chosen. This slack enables the MGA to explore solutions where the cost is allowed to increase up to 15% (but not necessarily has to). In the context of the two public acceptance model versions (Section 3.2), we introduce a 15% slack not only for cost but also for the CO_2 emissions. This slack on the CO_2 emissions means that the upper limit of the cumulative budget public acceptance model can increase by a maximum of 15%. This approach aims to showcase a more diverse set of electricity mixes, as the CO_2 upper limit may serve as the limiting factor in exploring alternative energy solutions. For the other model versions, so the reference model version and the heterogeneity of actors' model version only the cost slack is used. By calculating the error via Section 3.5, a comparison can be made with errors from the MGA with the possibility of increased costs and the error calculated for the cost optimal solution. The MGA results can be useful for policy makers as it can show a more political desirable solution with only a small increase of the cost (Lombardi et al., 2020).

3.5 Error calculation

To facilitate a meaningful comparison between different models, it's essential to compute a universal parameter. The error metric allows for a comprehensive assessment of how models perform relative to one another. By applying the error metric to the actual transition data, it becomes possible to determine whether a model exhibit improved or poorer behaviour in comparison to the reference model. To calculate the error for optimisation models many different formulas exists. Following the paper from (Wen et al., 2022) the Symmetric mean absolute percentage error (sMAPE) is used as this describes the percentage error, shown in Equation 4. With a percentage error it is possible to compare the quantities of different countries, regardless of their magnitudes.

$$error = \frac{|\hat{y}_i - y_i|}{\frac{(|\hat{y}_i| + |y_i|)}{2} + \epsilon} \tag{4}$$

Here, y_i is the value for the actual world and $\hat{y}_i$ is the value for the model output. ϵ Stands for a small value (in this case ϵ = 1e^{-6}), to prevent a division by zero. This error is attributed to the generation and capacity. Specifically, it involves calculating the discrepancy between the actual generation and capacity, and the model's generation and capacity, for each year and technology, using the error formula. These differences are aggregated across all years and technologies, resulting in a cumulative error with both generation and capacity. This cumulative error is subsequently normalized against the maximum error, which is 2 per year per technology. Now, the errors are comparable for the different countries and different models. However, the sMAPE error has its limitations. For instance, consider a scenario where a relatively small technology generates either 2 GWh or 100 GWh in two different scenarios, however, in the real world it generates 0 GWh. When calculating the sMAPE for both cases, it yields a maximum error of 2. Nevertheless, it's important to note that the second case significantly further deviates from reality compared to the first case.

4 Results

Continuing from Section 3, we present the outcomes and findings derived from the five model versions. These model versions include the original D-EXPANSE with no societal factors, two models which incorporate public acceptance, one version incorporating heterogeneity of actors and one which incorporates public acceptance and heterogeneity of actors. The results are explained in more detail as follows: First, showing the results of the original reference model version compared to the actual data in Section 4.1. Secondly, analysing the disparities between the cumulative budget public acceptance model and the yearly budget public acceptance model shown in Section 4.2.1. This is followed by a more in-depth analysis of the results of the cumulative budget public acceptance model in Section 4.2.2. Subsequently, the implementation of the differentiating WACCs which is implemented in the heterogeneity of actors' model version is shown in Section 4.3. Lastly, we merge the influences of the heterogeneity of actors' model version and the cumulative budget public acceptance model by applying both, as shown in Section 4.4. An overview of the different models and results is shown in Figure 11.

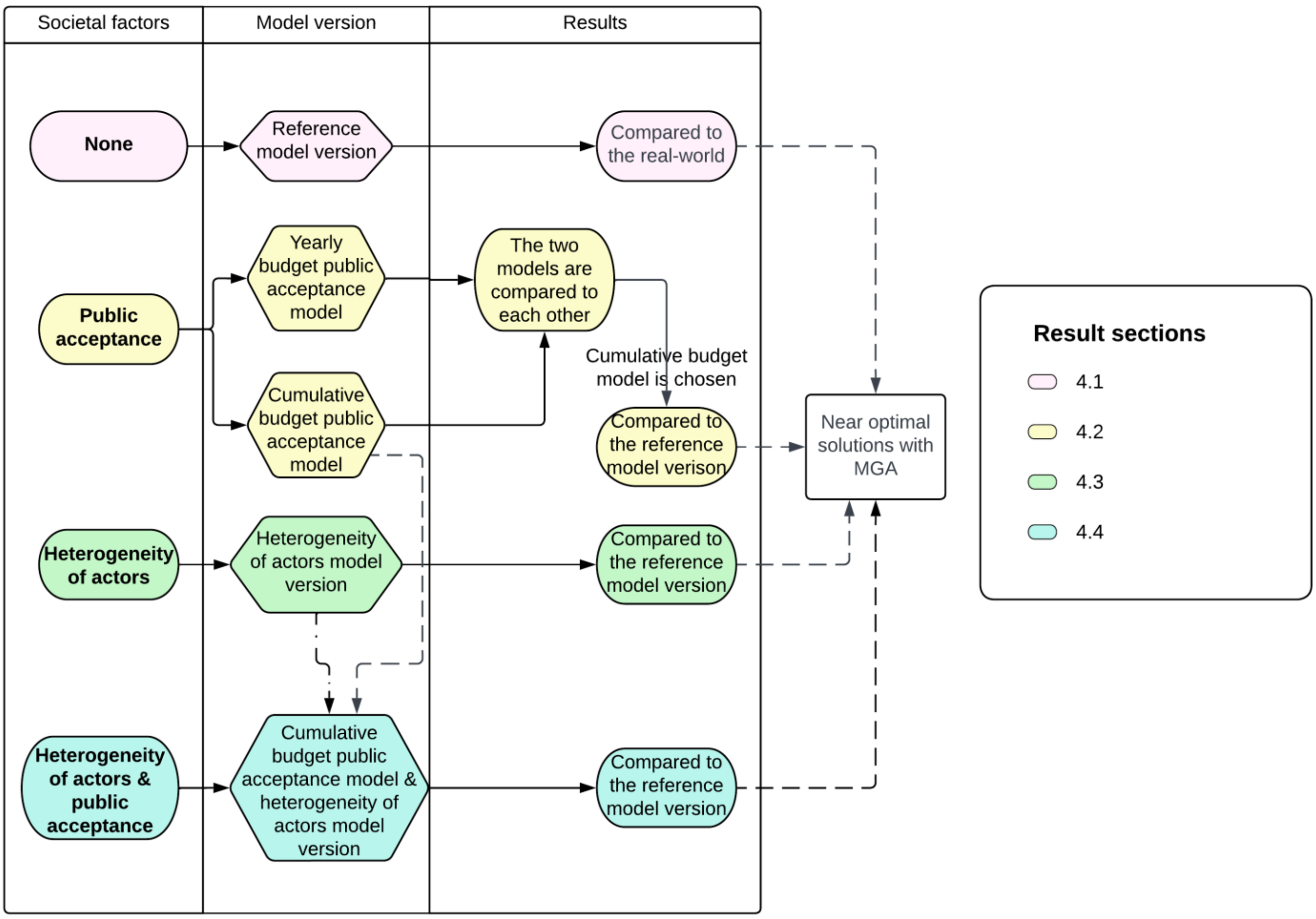

Figure 11 Results workflow diagram. The results from a colour can be found in the corresponding result section. All the results undergo modelling to generate alternatives (MGA) analysis to construct the near optimal solution space around the cost-optimal point.

4.1 Reference model version compared to the real-world

When executing the reference model, the first step involves examining the amount of CO_2 emissions emitted and comparing it to real-world CO_2 emissions. Table 3 shows that the countries are grouped in different categorises dependent on the actual CO_2 emissions over the years and the CO_2 emissions of the reference model version. There are four groups constructed, the first group has in the real-world an increase of emissions around 1995, but after 1995 dropped emission's to around 90%, for the reference model version the emissions increase around 1995 and later drops to 120%. For the second group, the emissions of the real-world stay around the 100% and can drop to 60% in 2019, whereas the reference model version the CO_2 emissions keep increasing. For the third group (which only consist out of Cyprus), the reference model version and the real-world emission keep increasing to 200%. The last group consist out of the countries which saw a decrease of the CO_2 emissions for both the reference model version and the real-world.

Real-world CO_2 emissions	CO_2 emissions of reference model version	Countries	Under projection of the reference model version	Over projection of the reference model version
Increases heavily around 1995 up to 140%~180%, decreases around 2008 to be in 2019 around 90%.	Increase around 1995 up to 130%~140% decreases around 2008 to be around 120% in 2019.	ESP, GRC, IRL, NLD	Oil, Onshore wind, PV	Nuclear, hard coal
60%~100% in 2019	120%~250% in 2019	AUT, CZE, ITA, LUX, MLT, PRT	Waste incineration, gas, PV and onshore wind, storage	Hard/brown coal
Increases up to 225% around 2010	Increases up to 200% around 2010	CYP	Oil, PV, onshore wind	Gas, biogas and hard coal
Dropped to 40%~70% emissions in 2019	Dropped to 60%~80% emissions in 2019	HUN, GBR, EST, DNK, DEU, BGR, BEL, LVA, POL, SVN, HRV, LTU	Biomass, PV and onshore wind	Nuclear

Table 3 Categorization of different countries and their actual CO_2 emissions. Because the category underneath the constraint is so big, there are no specific technologies which stand out for all the countries. Further, the category is the least interesting as with the new version of the model nothing will change in the generation.

For the case of the group of Portugal, the disparity between the real-world and the reference model version primarily arises from the increased deployment of hard/brown coal in the reference model, while the real-world data has a higher level of waste incineration, gas and renewables (mostly PV and onshore wind) generation. For the group of Spain, especially, the deployment of nuclear and hard coal is prevalent in the reference model version whereas in the real world more PV and onshore wind is generated. For the group of Hungary, the real-world data generates more Biomass, PV and onshore wind, whereas the reference model version sees a greater increase in nuclear power. For Cyprus the difference is very prevalent for generation of gas for the reference model version, for the real-world it mostly generates biomass. In summary, the primary distinctions between the reference model version and the real world are that the reference model version underestimates PV and onshore wind, while over estimating waste incineration, biogas and hard coal generation.

This difference between the real-world and the model outcomes is not due to differences in demand or costs, as these are incorporated into the model based on historical data. The demand peaks for most countries between 2005 and 2010 with a slight decrease of demand towards 2020. For the group of Portugal, the primary distinction arises from the greater utilisation of renewable energy sources in the real-world compared to the model's representation. A key factor contributing to this difference is the hydro storage component. In practice, the utilization of hydro storage enables electricity providers to pump water to a higher altitude when electricity prices are low and release it to a lower altitude to generate electricity when prices are high. This method of pumping and generating electricity enables the power plant company to generate more revenue than simply producing electricity as required. However, in the model, there is no possibility to generate this kind of revenue. Consequently, in the model's electricity mix there will be less hydro storage than in the case of the real-world. Especially for Luxembourg the hydro storage component is the biggest factor in the difference between the CO_2 emissions for the model and the real-world. In the case of Portugal itself, the government has introduced several advantageous incentives, such as feed-in tariffs for renewable energy production. Additionally, local municipalities benefit from a share of the income generated by wind energy projects, which has led to increased public acceptance of these renewable initiatives ('30 Years of Policies for Wind Energy', 2013). Our model does not incorporate these governmental incentives since they are temporary in nature and are subject to rapid changes, like changing political landscape, whereas the model is designed for a more enduring perspective. This significant government support has propelled wind energy in the real world, contrasting with the model where such policies are absent, resulting in wind energy being less cost-effective in the model compared to reality.

4.2 The two public acceptance models, yearly budget public acceptance model and the cumulative budget public acceptance model

The model was initially designed to run for 31 countries, however when applied the CO_2 constraint, several countries had to be excluded due to the model's inability to find a viable solution. These excluded countries include CHE (due to the lack of survey data), FIN, FRA, NOR, SWE and ROU. The reason for the model's failure to find a solution in these cases is that the reference model version generates a substantial increase in CO_2 emissions for these countries compared to the 1990 levels. An example of this scenario is illustrated in Figure 12, where the reference model generates a significant increase in CO_2 emissions. When attempting to restrict these CO_2 emissions by imposing the constraint outlined in Section 3.2.1, the CO_2 emissions are limited to such an extent that other constraints could no longer be fulfilled, thereby imposing an error on the model. The constraints that lead to these infeasible solutions across all countries are primarily related to the ramp rate of renewable technologies and capacity transfer over the years. Achieving a significant increase in renewables to generate the same amount of electricity within the given timeframe is not feasible, as the technologies cannot be deployed so rapidly in the D-EXPANSE model. The limiting factor here is the ramp rate and the build rate which is too low to generate so much renewable electricity, to impose the CO_2 constraint. The build rate for the renewables in Finland is 0.25 GW/year for PV and for onshore wind 0.75 GW/year, but the specific values are country specific. Additionally, the generation of the power plants should be between the minimum load factor and the maximum load factor. The minimum load factor for hard coal is at least 50%, this in combination with the imposed CO_2 constraint will still generate too much CO_2. The combination of these constraints contributes to the errors. A potential solution to address this issue is to examine the parameters within the D-EXPANSE model and compare them to real data, checking for significant discrepancies. This can be crucial, as the observed actual CO2 emissions do not exhibit such a substantial increase. Furthermore, can it be that certain policies are implemented to stop the emitting of coal plants with money from the government. Then the minimum load factor is not required anymore, but is still required for the model.

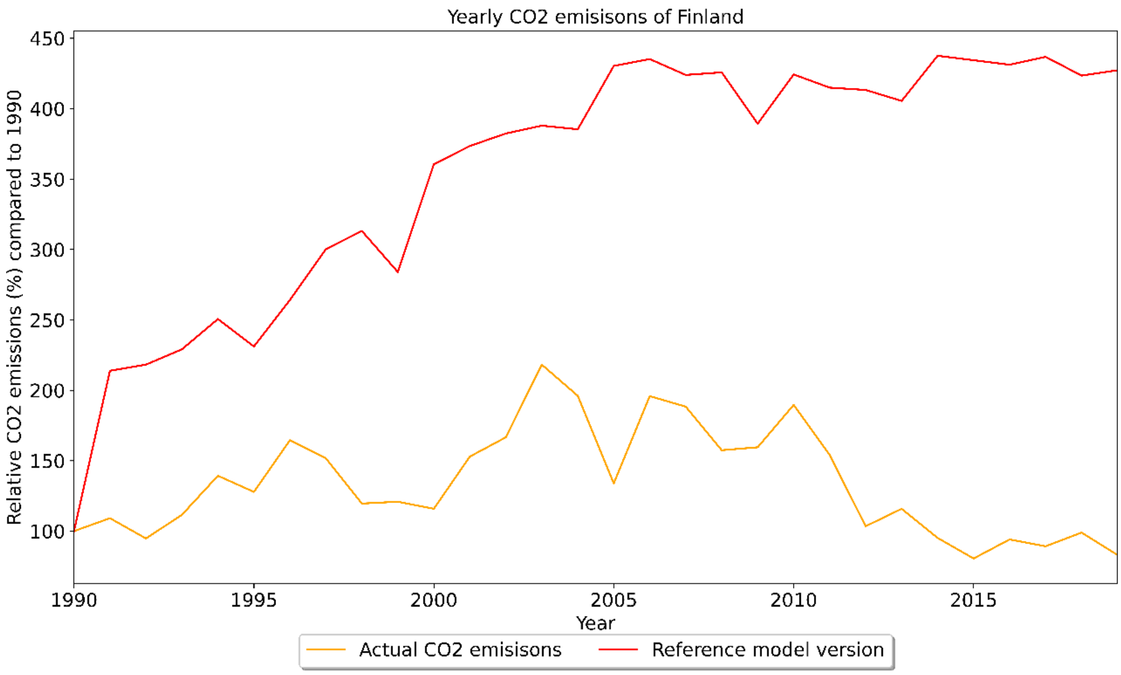

Figure 12 Yearly CO_2 emissions for Finland. The values on the y-axis are percentage values compared to the initial CO_2 emissions in 1990.

The patterns observed in Figure 12 for Finland holds true for all other countries (France, Norway, Sweden and Romania) that could not conform to the imposed CO_2 upper limit. The model generates a substantial increase in CO_2 emissions compared to the 1990 levels, with Norway being an extreme case, exhibiting both a significant real-world emissions increase (a 60-fold increase) and model calculations emissions (up to 100-fold increase), which is shown in the Appendix. When comparing the real-world and the reference model version of Finland, we observe notable differences. Specifically, hard coal is more prevalent in the model, resulting in the observed surge in CO_2 emissions in Figure 12. Furthermore, there is more export, import and biogas generation in the real world, contributing to lower CO_2 emissions. The CO_2 emissions of import is the average CO_2 emissions of the neighbouring countries.

When comparing costs between the two scenarios, we find a 1.4-fold increase in costs for the real-world compared to the model run. This discrepancy in generation is shown for Finland in Figure 13. Furthermore, this difference in generation is partly due to there being a solid policy framework to impose carbon neutrality in 2035. This framework includes feed-in premiums and feed-in tariffs for renewables, such as biogas and wood-based fuels. Additionally, there is a CO_2 tax on fossil fuels that steers the electricity production towards cleaner electricity production. Notably, biomass and biogas are excluded from that CO_2 tax (Luc Pelkams et al., 2021). Consequently, our model cannot accurately replicate real-world outcomes, as these taxes and subsidies are not considered. Thus, due to these policies, the most cost-optimal solution according to the model will generate more CO_2 emissions in comparison to the real-world.

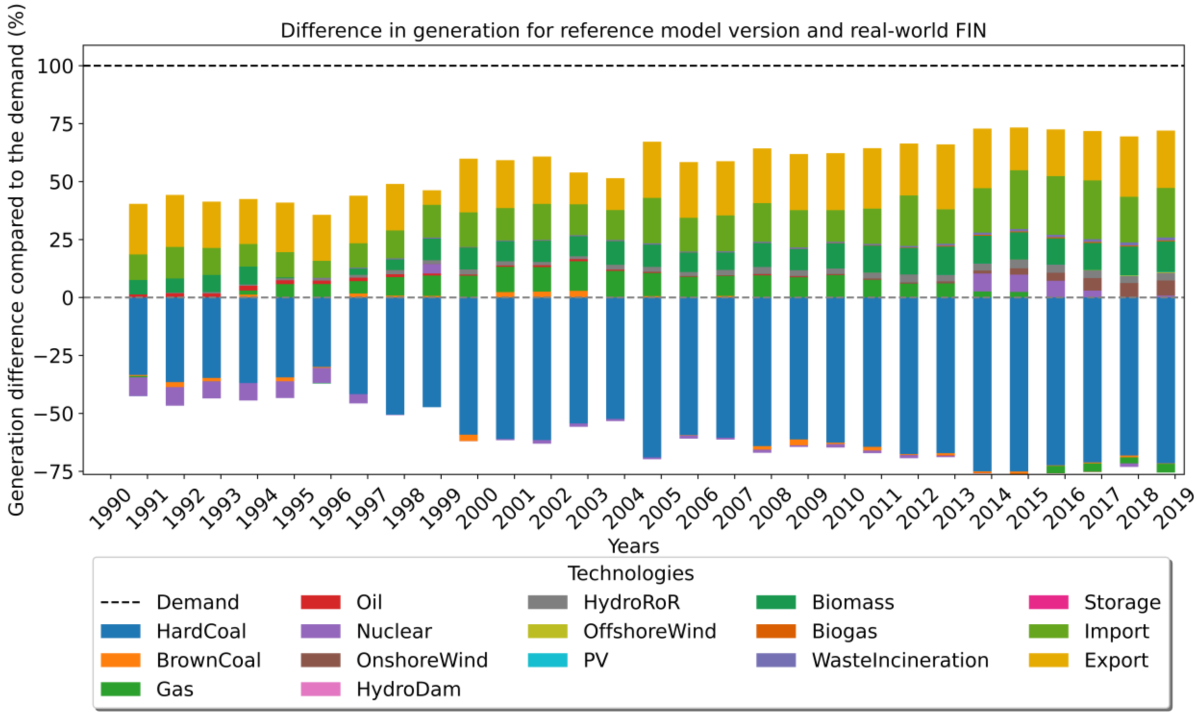

Figure 13 Difference between the actual world and the model outputs relative to the demand. This means that -50% indicates a 50% relative to the demand increase of a certain technology from the model compared to the reference model. The demand for Finland goes from 70 TWH around 1995 to 90 TWH around 2010 and stays there. Negative values indicate more generation from the model as generation=real world- reference model.

4.2.1 Disparities between two model versions, yearly budget public acceptance model and the cumulative budget public acceptance model.

As described in Section 3.2.2 two model versions incorporating public acceptance, the yearly budget public acceptance model and the cumulative budget public acceptance model are tested. One where the CO_2 emissions cannot exceed the constraint value on a yearly basis (the yearly budget public acceptance model), and one where the total CO_2 emissions cannot exceed the cumulative constraint values over 30 years (the cumulative budget public acceptance model). To observe the two model's behaviour, we examine the case of Portugal. Portugal serves as a perfect example because it demonstrates the most improvement when implementing public acceptance in reference to the reference model version. A first indication of how these two models behave is shown in Figure 14.

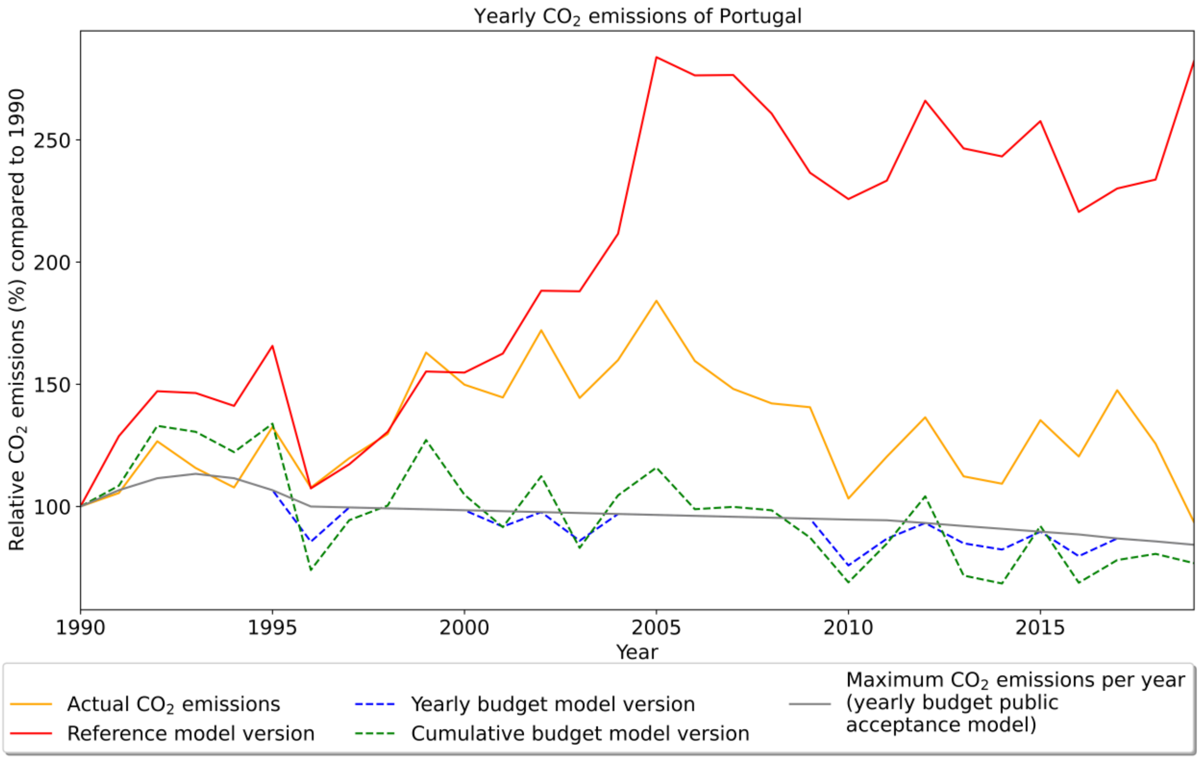

Figure 14 Yearly CO_2 emissions relative to the values of 1990. Both the yearly budget public acceptance model and the cumulative budget public acceptance model are shown as well as the upper limit of the CO_2 emissions for the yearly budget public acceptance model. This is the upper limit which the yearly budget model can not pass on a yearly basis, the cumulative budget model version can not pass the sum, so from 1990 to 2019, of these CO_2 emissions.

Figure 14 clearly indicates the impact of the two models. As one can see the blue line representing the yearly budget public acceptance model, consistently remains below the maximum upper limit of CO_2 emissions (as intended). In contrast, the cumulative budget public acceptance model exhibits some flexibility and occasionally surpasses this upper limit, as for this model the constraint is only active for the whole period and not binding every year. This flexibility is due to it being cheaper to in one year emit more CO_2 and in the other year safe more CO_2. This can have multiple origins like demand, weather and investments. This behaviour of both models is consistent throughout all countries. The cumulative budget public acceptance model is intended to better keep the shape of the reference model version curve intact and make investment decisions at a more cost-effective time step. This is a better real-world approximation as the upper limit set by the politicians is not binding for every year but it is good if the end goal (the target) is met. ***This is why we have selected this cumulative budget public acceptance***

model to analyse the results. Both model versions do not differ that much and the errors regarding the real world are similar (both shown in the Appendix). The normalized mean error compared to the real world for all the countries for the *yearly budget public acceptance model* is 37.64%, with the standard deviation being $2\sigma = 10.50\%$, whereas the same mean error for the *cumulative budget public acceptance model* is 37.44%, with $2\sigma = 11.03\%$. Meaning that there quite large differences across the countries inside the models, but that the models in total do not differ that much from each other. Overall, the differences in generating electricity for the two models are substantial. In the case of Portugal, the relative difference between the two models over the whole time period in generation for all technologies is 13.2%. While the mean difference between the two models for all countries combined is 12.3% in terms of generation. For the installed capacity the relative change is only 6.68%. The costs of the yearly budget constraint are consistently higher than those of the cumulative budget constraint, exhibiting a mean increase of 2.1%. This discrepancy arises because the yearly budget constraint is more stringent in comparison to the cumulative budget constraint, leading to the higher costs.

4.2.2 Detailed results of the cumulative budget public acceptance model

Now that the cumulative budget public acceptance model is chosen, more detailed results can be produced. To generate the near optimal solution space around the cost optimal solution, MGA runs are performed. For the reference model version 200 MGA runs and for the cumulative budget public acceptance model 75 MGA runs. During this MGA there is a cost relaxation of 15 % and during the second MGA run there is an increase of the CO_2 emission constraint of 15% as well (for more information see method 3.4). The results for the cumulative CO_2 emissions for Portugal are shown in Figure 15.

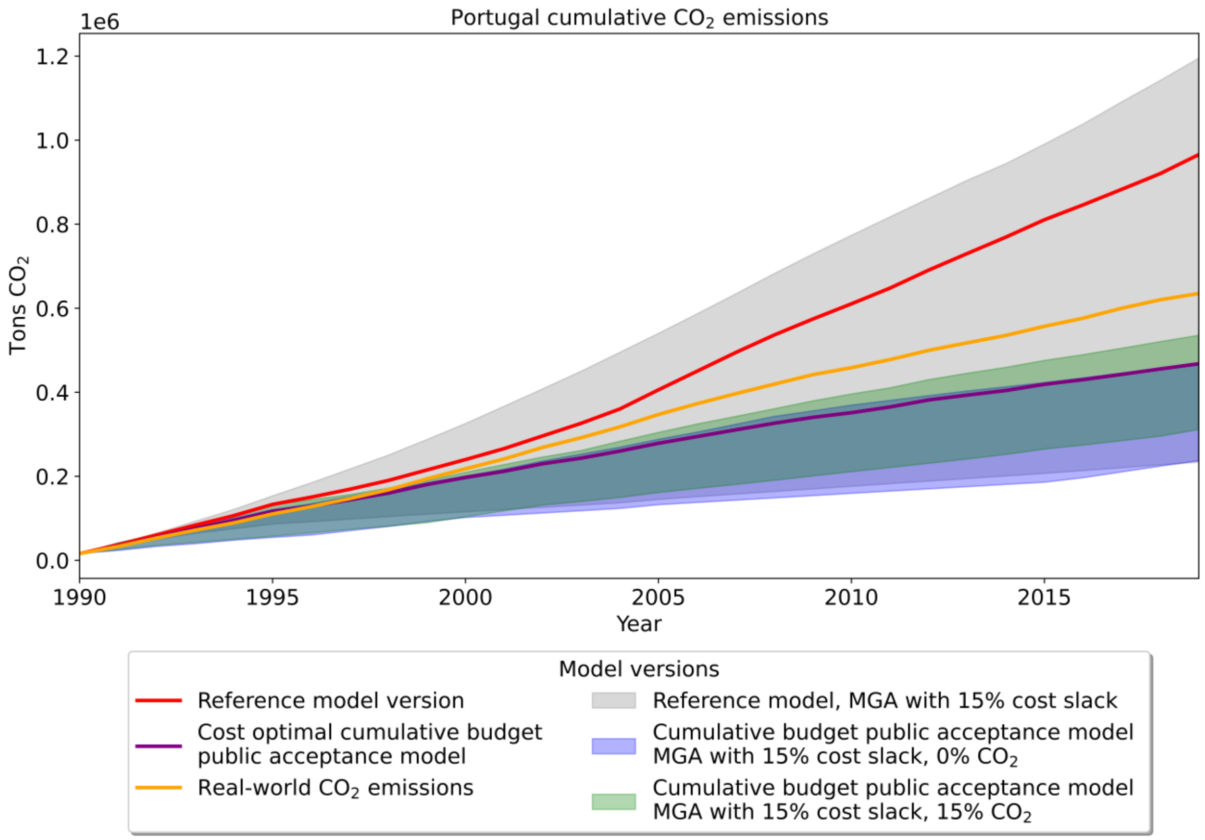

Figure 15 Cumulative CO_2 emissions for Portugal. There are three different models presented, the actual CO_2 emissions, the reference model output, and the cumulative budget public acceptance model output. The reference

model undergoes an MGA with only 15% cost slack, whereas the cumulative budget public acceptance model has two MGAs one with only 15% cost slack and one with 15% cost slack and 15% CO_2 slack.

When considering all countries, with Portugal as an illustrative case, we observe distinct outcomes in the three MGA performances. The MGA performance on the reference model with a cost increase of 15%, depicted by the grey area, displays the widest range of cumulative CO_2 emissions. This is due to the absence of an upper limit on CO_2 emissions, allowing for higher emissions compared to the cumulative budget public acceptance model. The sole restricting factor for this MGA is the 15% cost relaxation, rather than a CO_2 emissions limit. In the green area, representing the MGA performance on the cumulative budget public acceptance model with a relaxation in the costs and CO_2 emissions, there is a notable increase in cumulative CO_2 emissions around 15% up to the cost-optimal solution. This aligns with the 15% CO_2 slack integrated into this MGA performance and remains consistent across all countries. The blue area, the MGA performance on the cumulative budget public acceptance model with only the cost relaxation, the cost-optimal solution serves as the upper limit, with variations in outcomes occurring below this threshold for the cumulative CO_2 emissions.

All these differences across the three MGA performances are particularly noticeable for the countries *not* included in the group of Hungary in Table 3. This is because the group of Hungary does not experience significant changes when implementing the cumulative budget public acceptance model compared to the reference model version as the CO_2 constraint is not active for this group. The CO_2 restriction is currently inactive, as both the real-world data and the modelled data show that opting for less CO_2-intensive technologies is more cost-effective, leading to a reduction in CO_2 emissions. Consequently, the cumulative CO_2 emissions for all the MGA performances, for this group, overlap more than in the case of Portugal, due to the absence of a limiting CO_2 factor, an example is shown in the Appendix. Given these observations, when choosing between the two MGA performances under the cumulative public acceptance model, the MGA performance with a 15% CO_2 slack offers a more accurate representation of the uncertainty. This approach accounts for the possibility of exceeding the CO_2 emissions limits set by constraints. When imposing the other MGA performance, the constraint might create the impression of minimal uncertainty beyond the cost-optimal run. However, in real-world scenarios, this constraint may not always be as strictly binding as the model assumes. To get an idea which MGA performance generates the lowest error Figure 16 shows the relative error compared to the real world for the cost-optimal solution and the two different MGA scenarios.

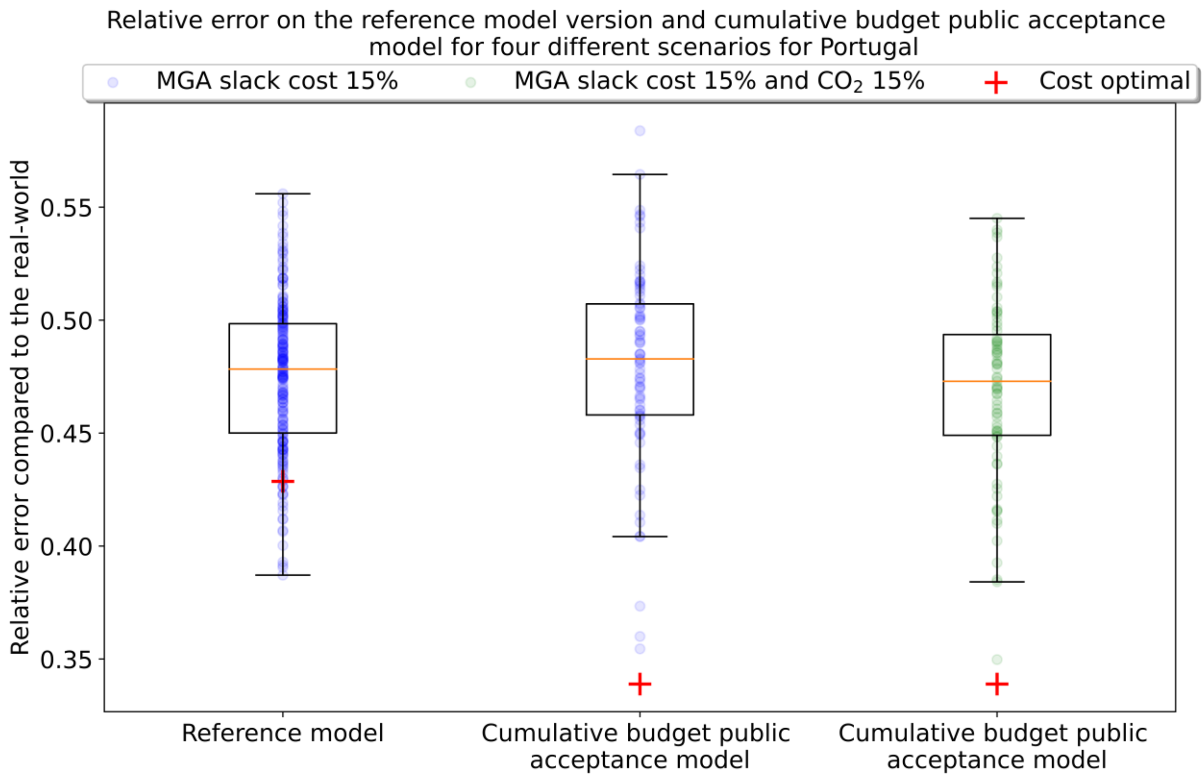

Figure 16 The relative error in comparison to the real-world, with the cost optimal cases a cross (in red). There are 75 MGA runs for the cumulative budget public acceptance model and 200 for the reference model, with two different amounts of CO_2 slack 0% and 15%, with both 15% cost slack. A figure about all the four different scenarios can be found in the Appendix.

Figure 16 shows the near optimal solutions around the cost optimal solution and the two MGA versions (one with only cost relaxation of 15% and one with cost and CO_2 relaxation both 15%). The cost optimal solution, so the solution which is provided by the model, is shown as a red cross in Figure 16. Comparing the two MGA performances, there is not a wider spread of near optimal solutions for the MGA performance of only one relaxation in comparison to the MGA performance with both relaxations across all countries. This is curious as the MGA scenario with 15% extra increase in CO_2 emissions has more possibilities to explore more diverse electricity mixes. One explanation of this phenomenon could be that the MGA performance with the increase of CO_2 emissions only creates a small extra diverse electricity mix compared to the MGA performance with only the cost increase. This means that the relative error will not change that much, which is the case. Furthermore, in this case of Portugal the cost optimal error is lower than the divergence indicated by the MGA. This means that even with the possibility to increase the costs it not possible to generate lower error in comparison to the real-world. This indicates that there are other limiting factors limiting the cumulative budget public acceptance model to be more accurate. Such as other input parameters or constraints like load factor, learning rate and costs. For other countries the cost-optimal solution lies more in the middle of the width of the near-optimal solutions. In the case of Portugal, the cumulative budget public acceptance model is an improvement compared to the reference model as the cost-optimal solution has a lower relative cost-optimal solution.

For all countries, the width of the relative error for the near-optimal solutions from all three MGAs is similar. Only the cost-optimal solution can notably differ between the reference model version and the cumulative budget public acceptance model. Two times the standard deviation (2σ) of the relative error for a specific country is roughly the same across all three MGA performances, indicating that the range around the mean value for the MGA is the same in all cases, which is shown in Figure 17. The average two times standard deviation of the error across all countries for the MGA on the cumulative budget public acceptance model with only the cost relaxation is 0.0833, whereas the MGA on the same model but with both relaxations (costs and CO_2) has a mean value of 0.07666. This demonstrates that the width around the cost-optimal solution of the relative error is a bit smaller for the MGA with both relaxations than for the MGA with only one relaxation. However, as there is only a relatively small sample size of the MGA (75 runs), the difference is not too large. The most important aspect is that the three MGA runs, so the one on the reference model and the two on the cumulative budget public acceptance model all have similar widths regarding the relative error to the real-world.

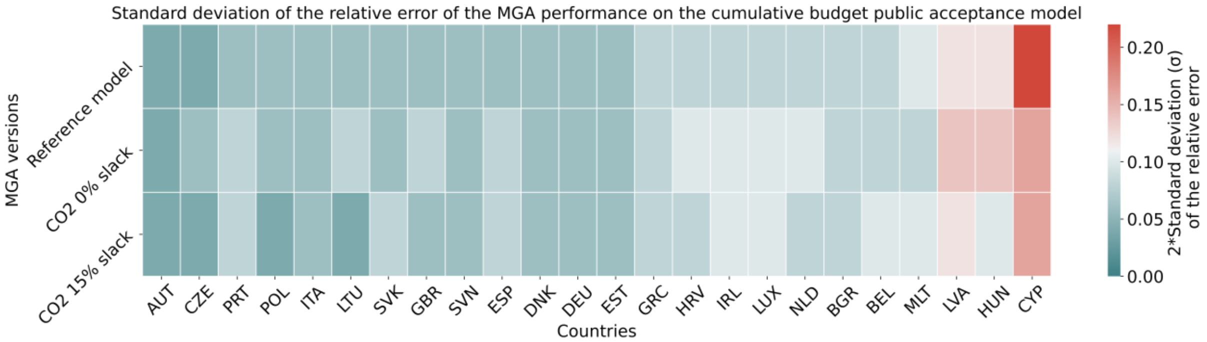

Figure 17 Heatmap for two times the standard deviation of the near-optimal solutions of the MGA's performance regarding the relative error in comparison to the real-world. All MGA run with 15% cost slack, for the cumulative budget public acceptance model one MGA has 0% CO_2 slack whereas the other has 15% CO_2 slack. The standard deviation is calculated for 75 MGA runs (middle scenario) and 200 MGA runs for the reference model.

For all countries, a summary of the relative error from the cumulative budget public acceptance model in comparison to the reference model version is shown in Figure 18. There are three distinct groups prevalent, one where the implementation of public acceptance led to an enhancement of the accuracy, one group where there is no difference between the two models, and one group where the cumulative budget public acceptance model increased the error relative to the reference model version. The group which experienced a decrease of the error consist out of nine out of the 24 countries. These countries include AUT, CZE, HUN, ITA, LUX, NLD, POL, PRT, and SVK. Notably, Portugal (PRT) stands out as the country with the most significant improvement, achieving a 9.0 percentage points enhancement in performance, compared to the reference model version. The group in contrast, where the error increased, consists out of nine of the 24 countries. Among these countries are BGR, CYP, ESP, EST, GRC, IRL, LVA, MLT, SVN, where Cyprus experienced a substantial decline in model accuracy, with a 9.7 percentage points decrease. The last group where nothing changed consist out of BEL, DEU, GBR, HRV, LTU and DNK. This is due to the constraint being inactive, signifying that the cumulative sum of the cost-optimal solution in the reference model version is already below the constraint's total emission. Consequently, this constraint will not influence the model's outcomes compared to that of the reference model version.

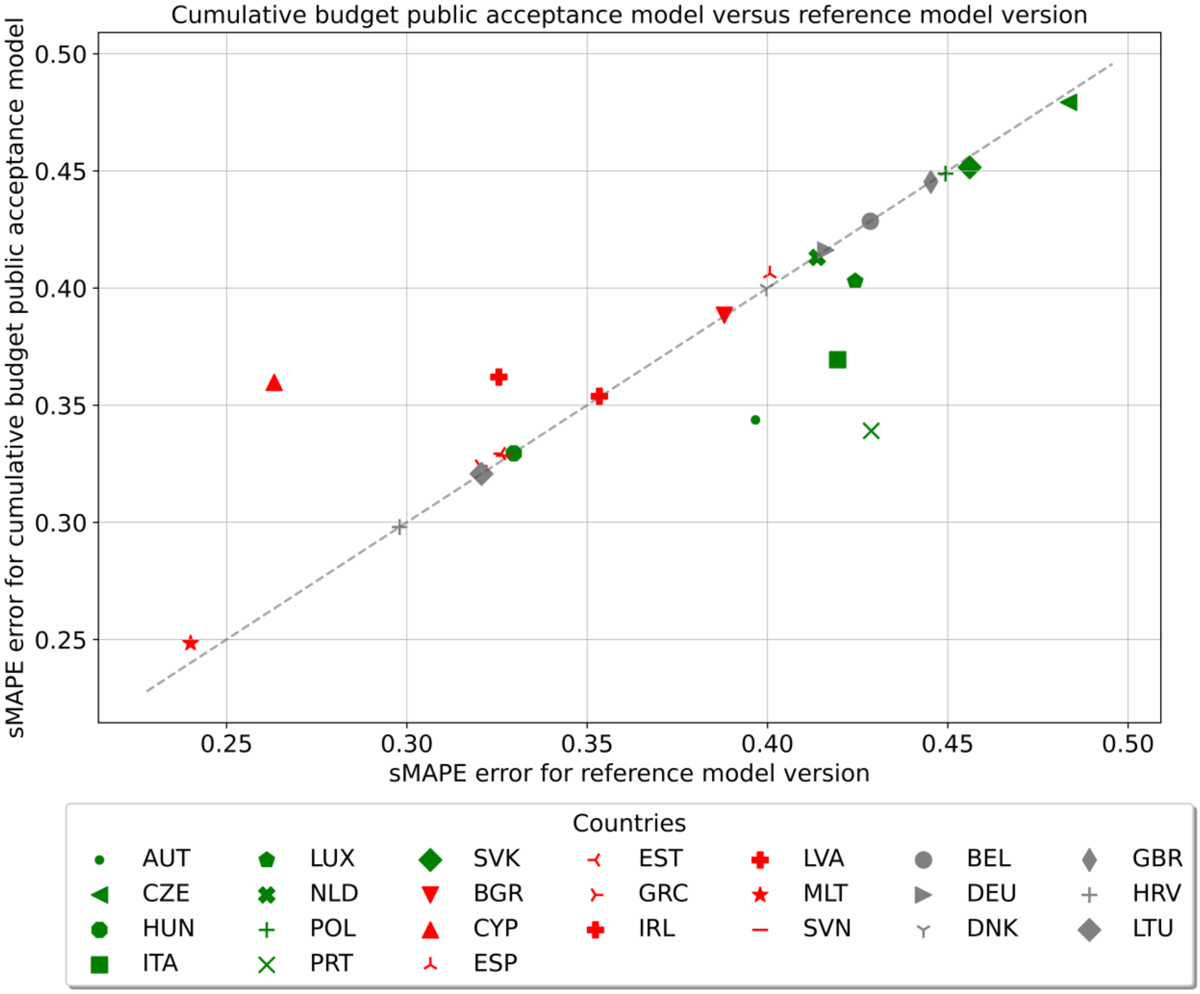

Figure 18 Relative error for the public acceptance model version in comparison to the reference model version. The grey line represents the middle of these values, under the grey line the error for the public acceptance model version is lower (green), above the line the points are red. The grey countries are where the constraint does not have an influence. The error is calculated in comparison to the real-world and normalized for the maximum error.

For the cumulative budget public acceptance model the countries which display an improvement of the error tend to do so by, in comparison to the reference model version, decreasing the generation of hard coal, brown coal and oil, but increasing the generation of nuclear, hydro dam and gas, onshore wind. These countries align with the countries of the group of Portugal shown in Table 3, with the exception of Malta. This group experienced a big increase in CO_2 emissions in the reference model versions, but the actual CO_2 emissions did not undergo the same increase. The CO_2 upper limit helps to limit this CO_2 increase and steer the cumulative budget public acceptance model version towards more accurate results. Conversely, for the group which experienced an increase of the relative error, was mostly due to the cumulative budget public acceptance model generating more onshore wind power generation. On the other hand, this model decreased generation in gas, brown/hard coal and oil. It is logical to expect that with the implementation of the upper limit fewer fossil fuels are employed, but it is intriguing to see that in the countries where errors increased, the cumulative budget public acceptance model appears to heavily invest in onshore wind plants. The group of countries where errors increased seems to be consistent with the group in Table 3 of Spain and the group of Cyprus, excluding the Netherlands. These countries experienced a substantial increase in CO_2 emissions around 1995 in the real-world, with the reference model version more closely mirroring this path than the cumulative budget public acceptance model. Consequently, the cumulative budget public acceptance model's error increases in comparison to the reference model version. Lastly, for the group represented by Hungary in Table 3, there is minimal variation in electricity generation between the two models, with sometimes only a slight change for the import and export in certain years. In general, it is evident that this approach to implement societal factors into the D-EXPANSE model has no clear evidence of improving the model as a whole. While some countries benefit from this approach, others experience a decline in performance.

4.2.3 Results of the sensitivity analysis on CO_2 emission targets with the cumulative budget public acceptance model.

In Figure 19, the outcomes of applying the 25 constraints to the cumulative budget public acceptance model and calculating the least error are shown. The percentage of CO_2 emissions in 2019 regarding those of 1990 levels, is compared to the mean survey value across all years. Interestingly, the apparent correlation for R^2 is -2, between the mean survey data and the extent of CO_2 reduction. This implies that the less people care about climate change the more reduction of CO_2 emissions is implied. This will be highly unlikely as Bergquist et al., (2022); Segreto et al., (2020) demonstrates that the severity of climate change is one of the influential factors affecting political party voting patterns. This pattern can be attributed to the limited sample size of the countries, and the survey data just not correlating with major voting patterns. Further, the findings suggest that our current approach with the constraint appears to be a bit too high as 11 out of the 18 countries analysed, show greater improvements in the model's performance when subjected to a stricter constraint. These countries are POL, ITA, LUX, DEU, SVK, SVN, DNK, BGR, CZE, LVA and AUT. The other 7 countries have a decrease in the error if the constraint would have been less stringent. These countries are ESP, CYP, IRL, PRT, MLT, GRC, and NLD. Most countries only see a slight improvement of 5 percentage points in comparison to the cumulative budget public acceptance model, with the expectation being Luxemburg and Cyprus, where a change in the constraint can lead to a decrease in the relative error of up to 12 percentage points. Further, there is no clear correlation between the percentage of improvements in comparison to the cumulative budget public acceptance model and the extent of CO_2 reduction and/or public opinion on climate change. With this sensitivity analysis, it is clear that our constraint is too conservative meaning that the constraint is still too high. A stricter constraint, so a constraint which limit the amount of CO_2 emissions more will increase the accuracy of the model.

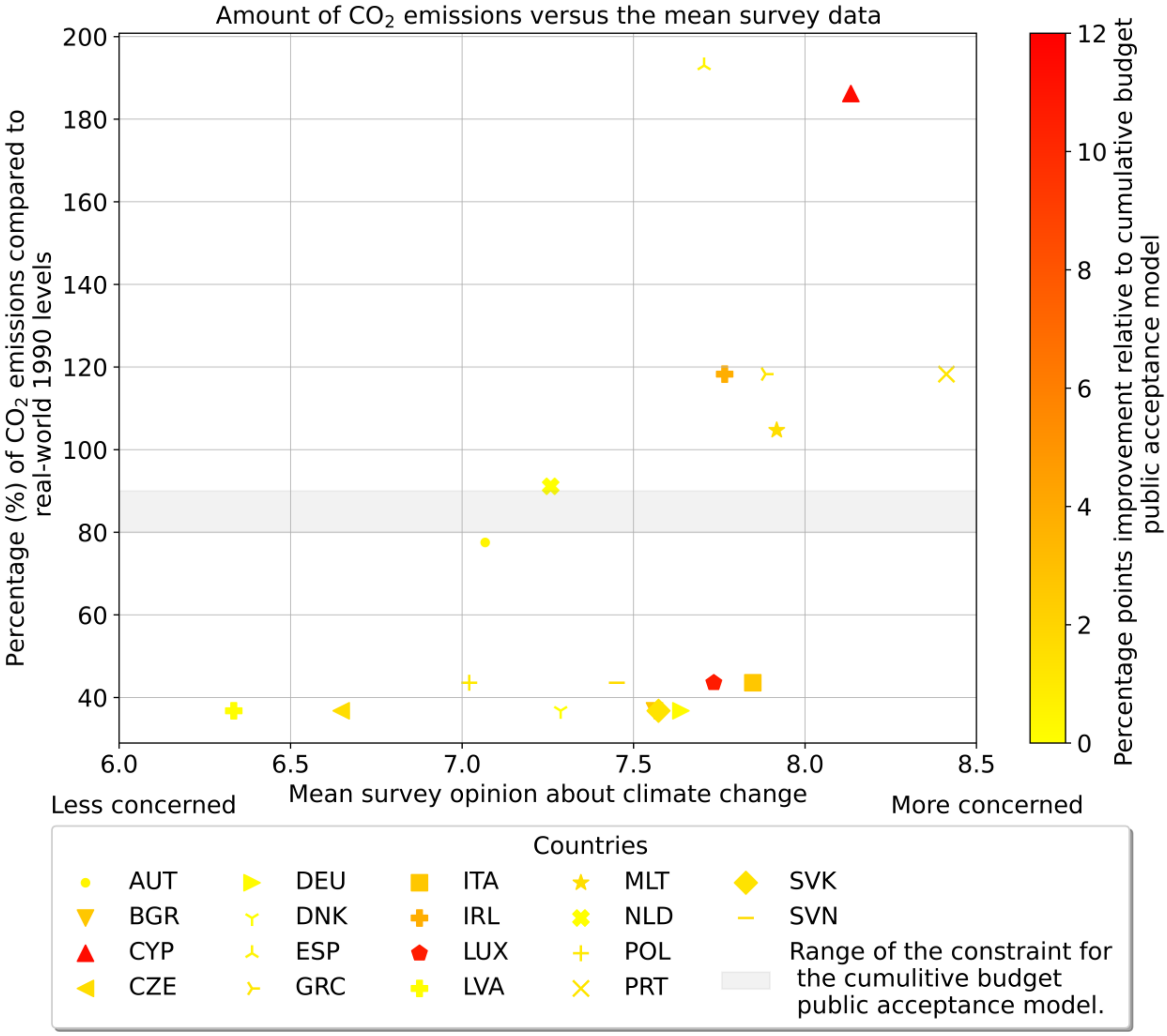

Figure 19 Constraint with percentage of CO_2 emissions compared to 1990 levels with the lowest error in comparison to the mean survey data excluding countries which had no improvement. The colorbar represents the amount of improvement in comparison to the cumulative budget public acceptance model. The grey area represents the constraint imposed by the mean survey data and which is currently active in the cumulative budget public acceptance model. The mean survey data ranged from 0 to 10 with the question: 'how serious a problem do you think climate change is at this moment?'

4.3 Implementing differentiated WACCs in the model for actor heterogeneity

Figure 20 shows the error for the heterogeneity of actors' model version in comparison to the reference model. Not all countries included in the Polzin et al., (2021) database are part of this study; the countries that are missing are CHE, LTU, and NOR, and they have been excluded from the research. 13 of the 26 countries experienced an improvement in comparison to the reference model case. These countries include BGR, CYP, CZE, DNK, ESP, EST, FRA, GBR, ITA, LVA, MLT, POL and ROU. On the other hand, in 13 out of the 26 countries there was an increase in the error relative to the reference model version. These countries are: AUT, BEL, DEU, FIN, GRC, HUN, IRL, LUX, NLD, PRT, SVK, SVN and SWE. Observing the results, there are almost no outliers and most of the countries show a correlation between the error of the heterogeneity of actors' model version and the reference model version. The exceptions are Greece, which experiences a 7.9 percentage points increase in the error. On the other hand, the main beneficiaries are Malta, where the errors have decreased by 6.5 percentage points, Cyprus by 4.3 percentage points, and Bulgaria by 6.4 percentage points. Notably, both islands (Cypress and Malta) see such a decrease in the error, these islands are small where a single investment can have large influence on the electricity mix. Overall, it is difficult to see a correlation between the countries and apparent error.

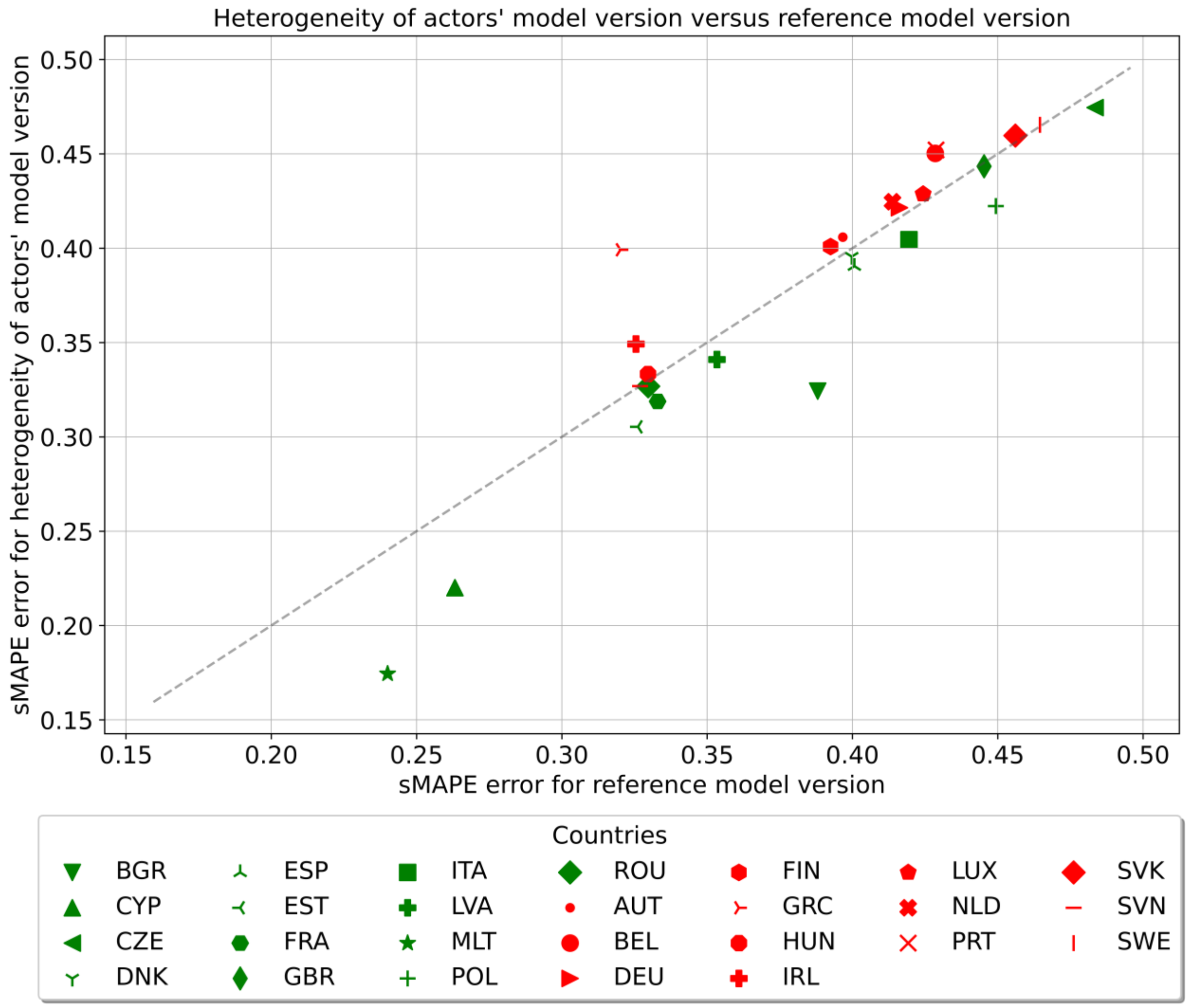

Figure 20 Heterogeneity of actors' model version relative to the reference model version. The grey line indicates the middle; under the grey line it is an improvement relative to the reference model version (indicated by green). The sMAPE error is relative to the real-world and normalized for the maximum error.

When analysing the electricity mixes for the heterogeneity of actor's model in comparison to the reference model version different technologies stand out. We observe that for the group which experienced a decrease in the error with the heterogeneity of actors' model version the technologies oil, brown/hard coal, onshore wind and nuclear generate more electricity in comparison to the reference model version. On the other hand, solar PV, hydro reservoir and gas are more present in the reference model version. For the countries which experience an increase in error, the technologies are difficult to estimate as most technologies are not consistent throughout the years. To assess the near-optimal errors, an MGA performance is conducted. To illustrate the range of near-optimal solutions from the MGA, an example is provided for Malta, which stands out as the best-performing country with the implementation of heterogeneity of actors.

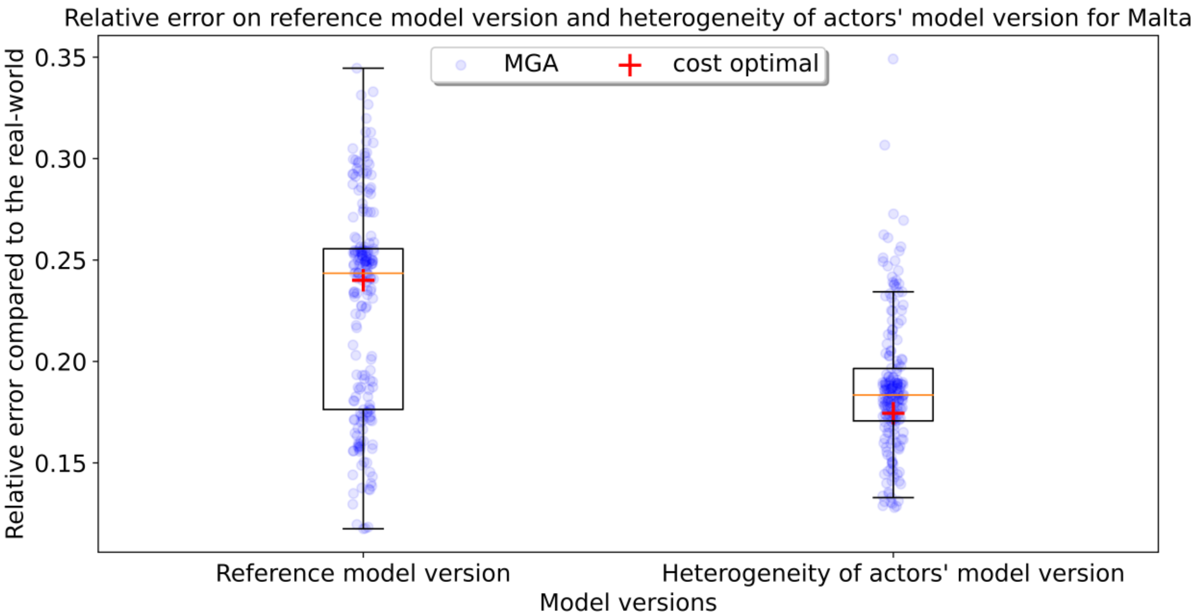

Figure 21 Relative error for the reference model version and the heterogeneity of actors' model version with both 200 MGA runs for Malta. The red cross indicates the cost optimal solution.

Figure 21 shows that in this case, the heterogeneity of actors' model outperforms the reference model version. Not only has the cost-optimal solution a lower error, but the range of near-optimal solution defined by the MGA has a relatively smaller width as well. This would imply that the heterogeneity of actors' model increases the accuracy and limits the range of near-optimal solutions. Nevertheless, this is not the case as this only holds true for Malta which is a small island where a single investment can have large impact. For all the other countries the range of near optimal solutions looks like Figure 22. For these countries, the range of the near-optimal solution between the heterogeneity of actors' model and the reference model version is the same and around 20%. For most countries, the only result that shows a meaningful change is the cost-optimal output results which are summarized in Figure 20. Overall, the performance of implementing the WACC to show differentiating actors does not show any total improvement in the model. Only half of the countries improved the model, whereas for the other half, it worsened the error.

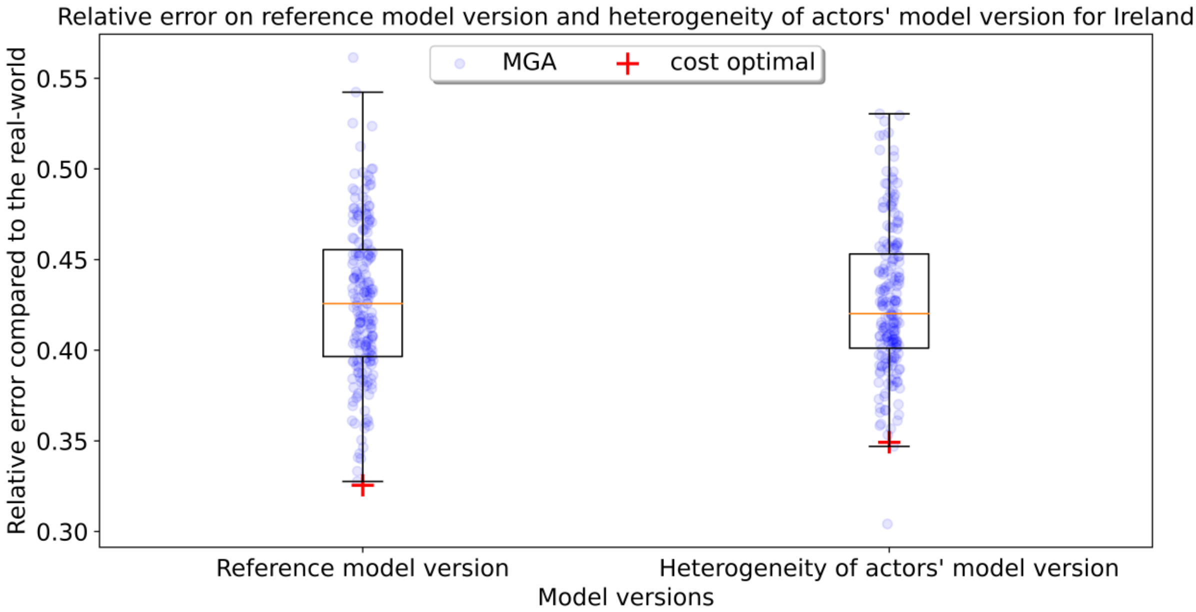

Figure 22 Relative error for the reference model version and the heterogeneity of actors' model version with both 200 MGA runs for Ireland. The red cross indicates the cost optimal solution.

4.4 Cumulative budget public acceptance model and heterogeneity of actors' model version

Figure 23 gives an impression on the error for the combination of the cumulative budget public acceptance model & heterogeneity of actors' model version in comparison to the reference model version 11 of the 21 countries experienced a decreased error when implementing both parameters. These countries being: AUT, BGR, CZE, ESP, EST, GBR, ITA, LUX, LVA, POL, PRT and SVK. In contrast, the ten other countries experienced an increase in the error compared to the reference model version. These countries include BEL, CYP, DEU, DNK, GRC, HUN, IRL, MLT, NLD and SVN. The technologies which generate more electricity, in the countries with a decrease in the error, in the combination of the two models compared to the reference model are: onshore wind, oil and biomass. On the contrary, mostly gas-based electricity is generated to a greater extent in the reference model compared to the combination. For the countries which experienced an increase in the error compared to the reference model version, the technologies show a similar trend with the generation of on- and offshore wind, oil and nuclear generating more electricity in the cumulative budget public acceptance model & heterogeneity of actors' model version and mostly gas generation more present in the reference model version. This result is fascinating, as gas generates less CO_2 emissions compared to oil, but the cumulative budget public acceptance model & heterogeneity of actors' model version which has a limit on CO_2 emissions imposed by the constraint use more oil than gas, compared to the reference model version. This can happen due to the higher uncertainty surrounding the WACC value for oil, as it is assumed to be identical to that of hard coal.

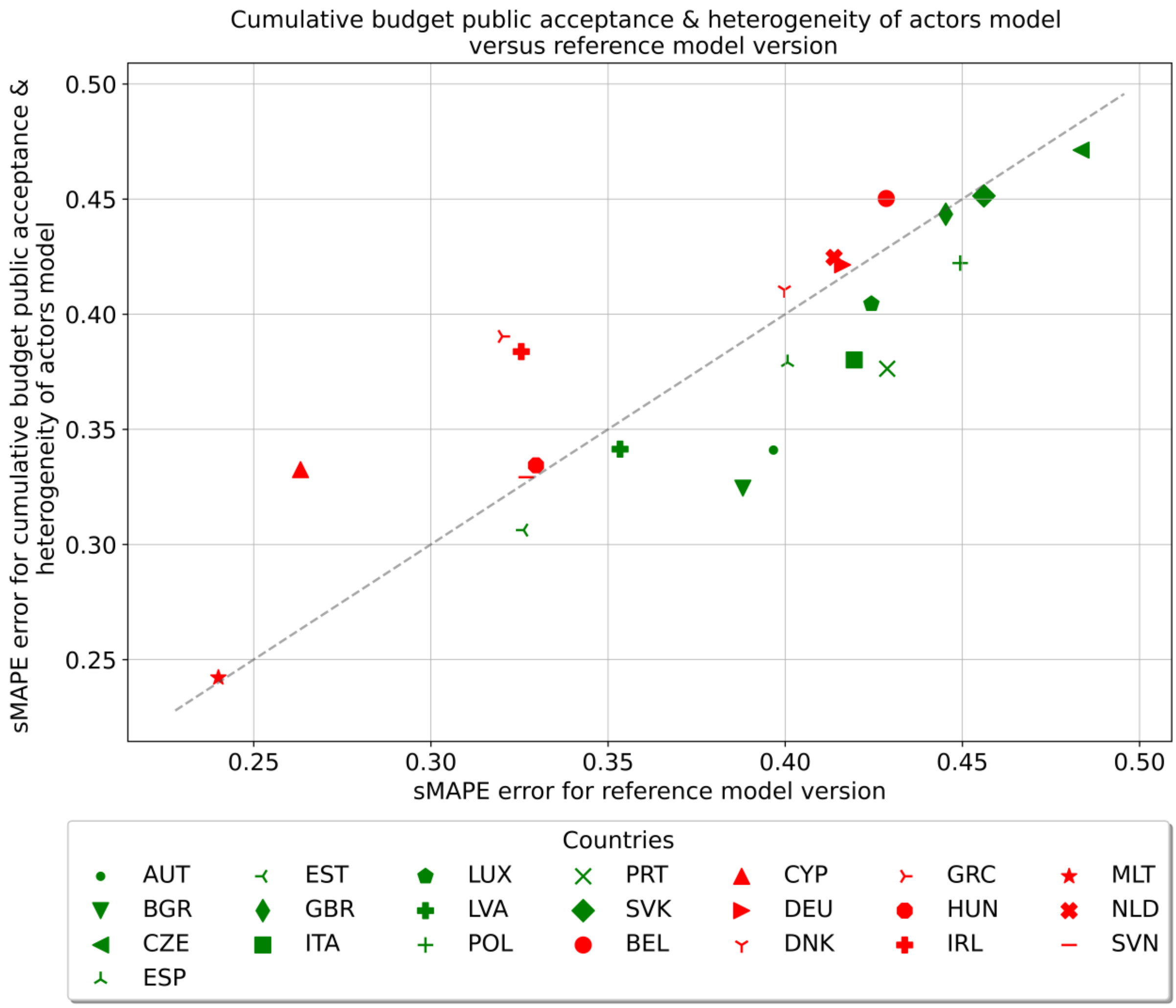

Figure 23 Relative error of the cumulative budget public acceptance & heterogeneity of actors' model version in comparison to the reference model version. The grey line represents the middle, under the grey line (in green) shows the countries which perform better in comparison to the reference model. The sMAPE error is calculated and normalized to the real-world.

There is more variation between the error for the cumulative budget public acceptance model & heterogeneity of actors' model version and the reference model version, the results are not as correlated as for Figure 20. The countries that stand out are Cyprus (6.9 percentage points) and Greece (7.0 percentage points) which have a heavily increased error, in contrast, Bulgaria (6.4 percentage points) and Portugal (5.2 percentage points) experienced a substantial decrease in the error all compared to the reference model version. As this model versions exists with just the combination of the two models, the heterogeneity of actors' and the cumulative budget public acceptance model version one would expect that the errors would add up. However, it is interesting to note that if you combine the errors equally for the heterogeneity of actors' model version and the cumulative budget public acceptance model version it will not add up to the error indicated by the cumulative budget public acceptance model & heterogeneity of actors' model version. For example, Austria has an increase in error of 0.9 percentage points for the heterogeneity of actors' model version and for the cumulative budget public acceptance model version it has a decrease in the error of 5.3 percentage points, while the combination of the two models has a decrease of the error of 5.6 percentage points. Even with an increase of the error for the heterogeneity of actors' model the combination still outperforms the cumulative budget public acceptance model. Further, for Cyprus it has a decrease in the error for heterogeneity of actors' model version by 4.3 percentage points and for the cumulative budget public acceptance model version an increase in the error of 9.7 percentage points but the combination results in an increase of the error of 6.9 percentage points. For both Bulgaria and Greece, the MGA performance is shown. This as these are the best and worst performing countries when combining both models, they are shown in respectively Figure 24 and Figure 25.

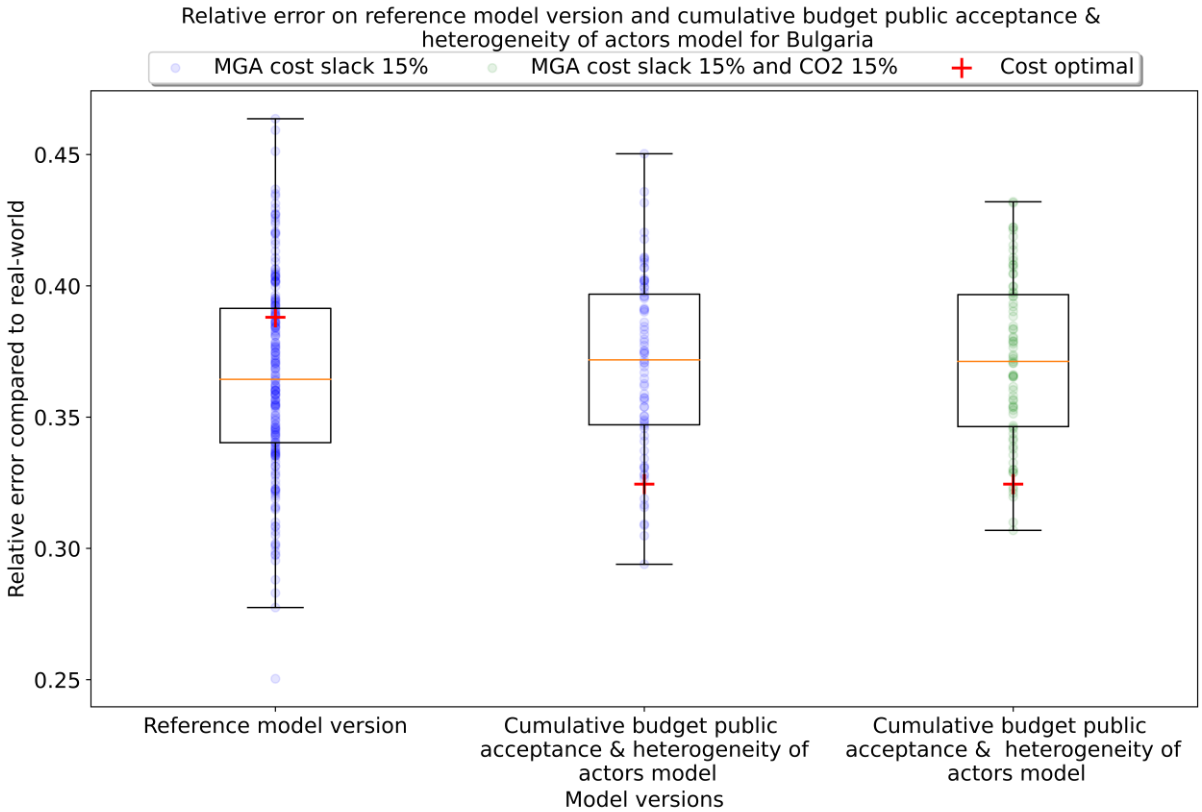

Figure 24 Relative error in reference to the real-world for Bulgaria. Both MGA have a cost slack of 15% one a CO_2 slack of 0% (blue) and the other of 15% (green). The reference model version, the cumulative budget public acceptance & heterogeneity of actors' model version are both presented. The cost optimal solution of the model is presented with the red cross.

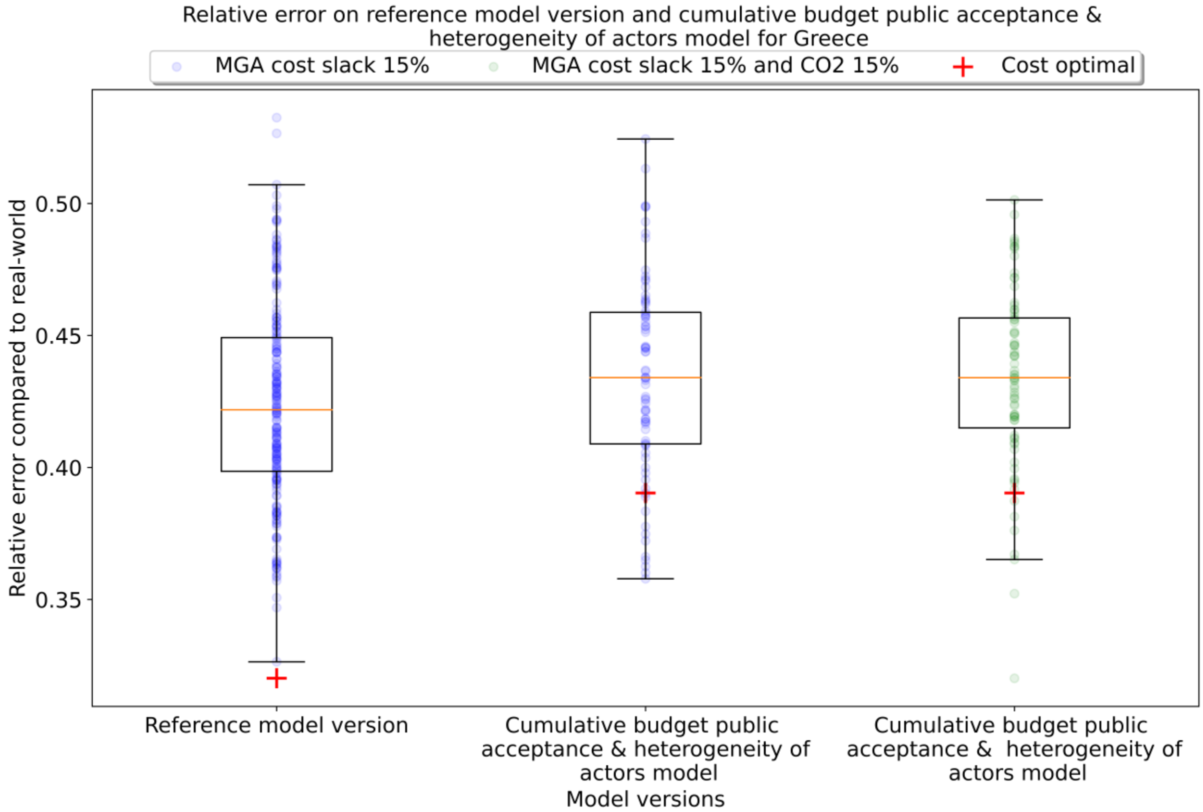

Figure 25 Relative error in reference to the real-world for Greece. Both MGA have a cost slack of 15% one a CO_2 slack of 0% (blue) and the other of 15% (green). The reference model version, the cumulative budget public acceptance & heterogeneity of actors' model version are both presented. The cost optimal solution of the model is presented with the red cross.

As provided, the width of the near optimal solutions around the cost optimal point for the cumulative budget public acceptance & heterogeneity of actors' model version for both countries show similar width in the error as the width of the reference model version. This is true for all countries, generating a standard deviation of the relative error compared to the real-world which is similar across all three model versions. This aspect is shown in Figure 26. The cost optimal solution for both countries regarding the cumulative budget public acceptance & heterogeneity of actors' model both are beneath the mean value for the near-optimal solutions, this indicates that the cost-optimal solution generates good results compared to the near-optimal solutions. There is almost no difference between the two MGAs on the cumulative budget public acceptance & heterogeneity of actors' model, while one MGA has more flexibility as it is an extra slack on the CO_2 emissions. This minimal difference between the three MGA's is shown in Figure 26.

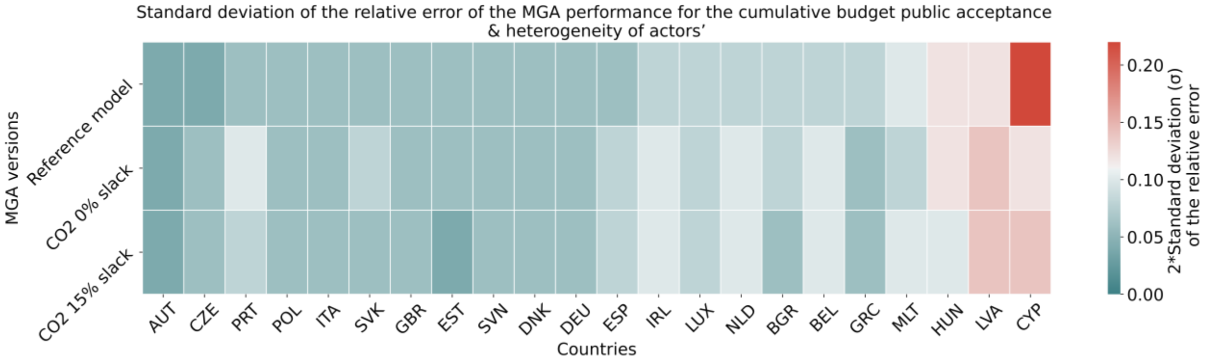

Figure 26 Heatmap for the 2σ for the relative error of the 75 MGA runs for the cumulative budget public acceptance & heterogeneity of actors' model version) and 200 MGA runs for the reference model version. All MGA are presented with 15% cost slack. For the MGA of the cumulative budget public acceptance & heterogeneity of actors' model version one is with 0% CO_2 slack and the other with 15% CO_2 slack.

4.5 Model version comparison

The primary outcome illustrating the model version's improvement compared to the reference model version can be observed in Figure 27.

Figure 27 Heatmap for the three different model versions implementation, the error (calculated via Section 3.5) is compared to each other. The values are relative values in comparison to the reference model version. Negative values (in blue) mean an improvement of the model and positive values (in red) means a decline of accuracy. If the model could not run on a certain country the result is white. The results in light grey are where the new model does not have an in/decrease in accuracy and nothing changed in comparison to the reference model version.

For the majority of countries, the incorporation of different model versions that consider societal factors only led to a percentage point change of less than five. As observed, not all countries have implemented every societal factor, resulting in cases where certain model versions cannot run, these cases are represented in white. The light grey values indicate that a certain model version could run, however, there was no meaningful difference between the appropriate model version and the reference model version (generating zero relative difference).

It is challenging to identify any consistent factors correlating with the variations in error rates across countries when comparing all the model versions to the reference model. When analysing the southern European region, the following countries experience an increase in error rates for the cumulative budget public acceptance & heterogeneity of actors' model: Greece, Malta and Cyprus. While Spain, Portugal and Italy experience an improvement of the accuracy. In another European region like the western region, with the countries, France, Belgium, Luxemburg, Austria, Germany, Denmark, United Kingdom, Ireland and Denmark, four countries experience an increase in error, and three show a decrease. Furthermore, metrics like GDP, population, or size do not exhibit correlation with error variation relative to the reference model version.

No correlation is observed between the two model versions concerning public acceptance and heterogeneity of actors. An increase in the relative error in one model does not necessarily corresponds to an increase in the other model. Only when considering the combined models, the cumulative budget public acceptance & heterogeneity of actors' model version, is a correlation seen between the individual model versions. This means that if both single model versions experience an error increase, the combined model will also experience an increase, and vice versa. However, when one model shows an increase and the other model (so the public acceptance model or the heterogeneity of actors' model) a decrease, it remains uncertain whether the cumulative budget public acceptance & heterogeneity of actors' model version will exhibit an increase or decrease in error. This uncertainty is exemplified by the diverse results observed in Portugal, Malta, Luxemburg, Estland, Spain, Cyprus, Austria.

For the different societal factors model versions, the characteristics of the relative error are shown in Figure 28. Figure 28 illustrates the relative error in comparison to the reference model version of the three societal models. Negative values indicate that it improves the model (therefore lowering the error).

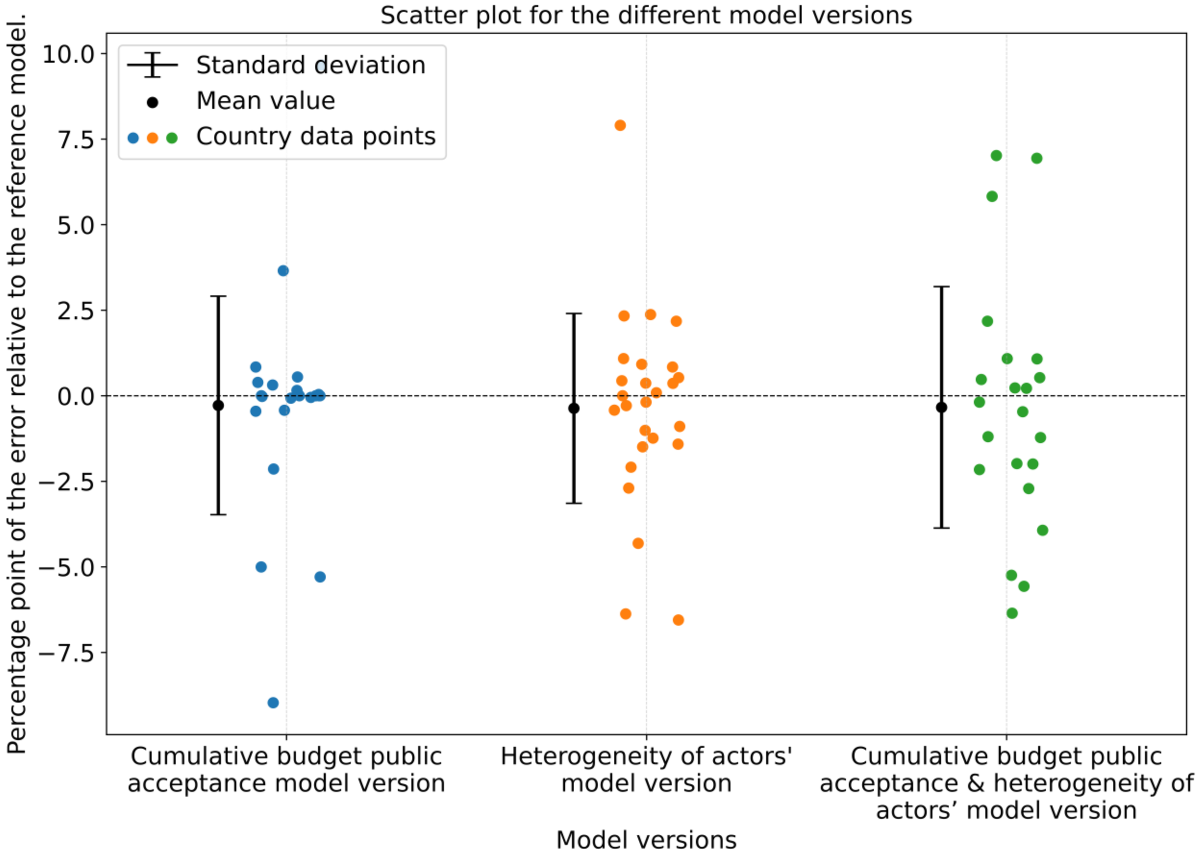

Figure 28 scatter plot of the relative error in comparison to the reference model version of the three societal models. Negative values indicate that it improves the model (therefore lowering the error).

For the heterogeneity of actors' model version, Bulgaria, Cyprus and Malta have a big decrease in the error relative to the reference model version, whereas Greece and Ireland have an increase in the error relative to the reference model version. The heterogeneity of actors' model generated results for 26 countries and 25 out of 26 countries gave a percentage point difference which is non-zero. The mean value percentage point relative to the reference model version is -0.368 percentage points. The standard deviation across all countries calculated via the MGA is quite high as the average standard deviation was 2.77 percentage points. As one can see this standard deviation is high in comparison to the mean value lies around zero, implying that the error can increase or decrease. Therefore, it is hard to conclude if this model implementation really improved the overall accuracy regarding the model outcomes.

For the public acceptance model version, only 13 countries out of the 24 gave a relative error change which was non-zero. The countries which experienced the biggest improvement in the error are Portugal and Austria, whereas Cyprus and Ireland have a big increase in the error. The mean value for the 13 countries is 0.377 percentage points. However, as the sample size is small the error width of the near-optimal solution is high with a standard deviation of 3.68 percentage points. Regarding this mean error and standard deviation, it is unclear if the implementation of the public acceptance in this way enhanced the model as a whole.

For the combination of the public acceptance & heterogeneity of actors' model version 22 out of the 22 countries provided non-zero relative error change. The countries which have the biggest improvements are Austria (-5.5 percentage points), Bulgaria (-6.4 percentage points) and Portugal (-5.25 percentage points), whereas Cyprus (7.0 percentage points), Greece (7.0 percentage points) and Ireland (5.8 percentage points) have the biggest increase in the error. The mean relative error value for the 22 countries is -0.3388 percentage points. The width of the near-optimal solutions is characterized by a relatively high standard deviation of 3.5 percentage points. As the mean value is again around zero, the standard deviation indicates that it is hard to tell if the relative error will in or decrease.

5 Discussion and future work

With the incorporating of societal aspects into our electricity system optimisation model, we conducted a performance accuracy comparison across five model versions: the reference model version, the yearly budget public acceptance model, the cumulative budget public acceptance model, the heterogeneity of actors' model and the cumulative budget public acceptance & heterogeneity of actors' model. These models are compared against the real-world or the reference model version across 31 countries over the period of 1990-2019. Our primary objective is to implement these model versions and compare it to gather information about the improvements that could be made for all countries. Here we try to answer the research questions phrased in Section 1.3 and discuss future work.

The integration of public acceptance is constructed by implementing a country specific CO_2 constraint on a cumulative and on a yearly basis. This constraint is altered with the public opinion on climate change. The differences in climate change opinion between countries is minimal and the value is quite high (around 7 on a scale from 1-10), therefore the differences in CO_2 constraint remains small. The CO_2 constraint led countries to limit their carbon emissions and transition towards more generation of gas, onshore wind and nuclear power plants. In terms of model accuracy compared to the reference model version, countries where the CO_2 emissions stay low and the reference model version increasing the CO_2 emissions the error is greatly reduced. These countries follow the European target quite well and therefore the constraint effectively matches these countries' CO_2 emissions. However, for other countries where the actual CO_2 constraint did not follow the European target, the constraint increased the error. As last there were six countries where the constraint was not active at all. Consequently, the overall performance of the cumulative budget public acceptance model version did not exhibit a consistent enhancement across all countries.

The implementation of heterogeneity of actors involved the incorporation of differentiated WACC values based on technology and countries from 2009 until 2019. The implementation of these differentiated WACCs aims to introduce a variable discount factor, as opposed to the uniform discount factor utilized in the reference model version. This adjustment leads to greater diversity across various technologies and results in distinct electricity mixes. However, the overall impact appears relatively modest, as shown in Figure 20, where most countries do not show any major outliers. Overall, there is more generation of onshore wind, nuclear and oil whereas PV and gas generation is less prevalent. This implies that the overall competitiveness of onshore, nuclear and oil is higher with the implementation of differentiated WACCs. Nonetheless, the overall model performance does not surpass that of the reference model version as only half of the countries observed a reduction in error, while the other half experienced an increase in error.

Across the three model versions there remains uncertainty about the improved accuracy of the models in comparison to the reference model version. For the implementation of heterogeneity of actors and the implementation of public acceptance the improvement was for only 50% of the countries where the other 50% of the countries experienced an increase of the relative errors. It is hard to pinpoint one 'superior' model which greatly outperforms the other ones. However, the heterogeneity of actors' model version has a slight edge, as this model had the least number of big outliers and showed a correlation between the reference model and the heterogeneity of actors' model version regarding the error and the mean value plus the standard deviation provided the best results. It still shows there is room for improvement when implementing societal factors into electricity optimisation models, as countries like Poland see a substantial decrease of the error when implementing heterogeneity of actors, implying that differentiating WACCs has a positive influence on the models outcome, which is consistent with (Mier & Azarova, n.d.; Trutnevyte, 2016).

The range of near-optimal solutions across the four model versions remained similar to the range of near-optimal solutions which is constructed on the reference model version. Only the case for Malta for the heterogeneity of actors' model experienced a substantial decrease in the variance of near-optimal solutions. The reduction in variance can be attributed to Malta's small size, where a single investment can significantly impact the model. The two MGAs constructed both with 15% cost slack and one with 15% CO_2 slack showed similar results across all models. The MGA with the highest flexibility (the one with the CO_2 slack) is preferable. This is evident in its representation of greater flexibility in line with the cumulative CO_2 emissions and its ability to better capture the underlying uncertainty. As the error margin did not significantly reduce when imposing the CO_2 slack, there are other factors which limit a better representation of the model. Using the cumulative budget public acceptance model countries such as Portugal and Greece demonstrate that the cost-optimal solution yields the minimal error compared to the MGA results. This observation suggests that there are additional limiting factors that hinder the model from achieving greater accuracy.

For future work, it will be intriguing to explore the impact of stricter CO_2 emissions targets for all countries as Figure 19 illustrates that there is still potential for improvement when imposing more stringent CO_2 constraints. Notably, the incorporation of the mean survey data in the CO_2 constraint did not yield improvements, as the variations between countries were minor, and there seems to be no correlation between public opinion and the reduction in CO_2 emissions. Consequently, this aspect can be omitted, and the focus can be solely directed towards the European Union's targets, which will serve as a baseline constraint for countries. Furthermore, it would be worthwhile to investigate the potential implementation of a carbon tax or a European trading system (ETS) in a new model version instead of an upper emissions constraint. At first, it's essential to estimate the carbon tax required to meet the CO_2 emissions targets. Subsequently, a carbon tax can become an effective tool for reducing emissions by imposing costs on emitters. This can generate revenue, which can be invested in green technologies such as PV and onshore wind, providing additional funding for greener solutions providing positive feedback. This approach aligns more closely with the European trading system (ETS), which is not precisely a carbon tax but rather a pricing mechanism for CO_2 emissions between companies, providing the incentive for companies to reduce emissions. Additionally, with the help of MGA more political desirable solution can be presented, even if they entail a higher cost for the overall electricity system.

There are more ways of incorporation public acceptance into electricity optimisation models. While our focus has been on climate change considerations in public acceptance, it's essential to recognize that public acceptance encompasses a broader spectrum of issues, including not in my backyard (NIMBY) (Carley et al., 2020; Wolsink, 2006) and market acceptance. To address the NIMBY aspect more effectively, enhancing regional spatial resolution is key. A better regional spatial resolution will help to investigate how overall opinions and local opinions deviate and can be implemented in the model. Local acceptance can be incorporated through surveys, where the capacity of renewable power plants is determined by survey outcomes. Additionally, analysing general demographics such as gender, age, income and education level can help to estimate overall public opinion regarding renewable energy projects (Bergquist et al., 2022). These expanded approaches to public acceptance can significantly enrich the modelling process.

Further research could focus on generating more historical data about the WACC values before 2009 and explore alternative methods of implementing WACC in an ESOMS that account for the distinction between WACC values and the discount rate. Since, the lack of significant improvements from the heterogeneity of actors may be attributed to the limited data available, spanning only from 2009 to 2018 and the values from 2009 are implemented for 1990 until 2009. This means that this value for 2009 has a large impact on the model's electricity mix. Further, historical WACC values are difficult to prolong to the future as large events like wars or oil crises could happen. This implies potential inaccuracies in WACC values before that period. Furthermore, it is essential to recognize that WACC values themselves are subject to uncertainties, and certain assumptions regarding these values could introduce errors into the model. Supplementary, both differences in WACCs between technologies and countries is explored at the same time, but it would be interesting to only implement one of these factors at the time.

There are multiple approaches for integrating heterogeneity of actors into ESOMs as demonstrated in the study by Tash et al., (2019). From this research more sophisticated methods for incorporating heterogeneity of actors, specifically different market players within countries can be explored. Through the analysis and differentiation of these various market participants, researchers can extract valuable insights regarding which actors exert the most significant influence on the energy system. This approach would provide a deeper understanding of the dynamics at play within each country's energy landscape and help identify strategies for optimizing the energy system based on the behaviour and decisions of these diverse market participants.

The uncertainty surrounded by the cost optimal solution could be improved in the future. Now, only structural uncertainty analysis has been conducted, but parametric uncertainty also has an influence in the model’s output. D-EXPANSE provides the possibility to do MCA (Monte Carlo analysis) to get a quantitative measure of risk in the model’s outputs, a combination of MCA and MGA can be conducted in the same way as Li & Trutnevyte, (2017). For the uncertainty margin there appears to be no difference between the MGAs with CO_2 slack 0 % and one with CO_2 slack 15%, this is intriguing as the latter would have more room to generate more near-optimal solutions and thereby have the possibility for a larger error margin. Right now, this is not the case implying that the CO_2 emissions constraint is not the limiting factor in exploring near optimal solutions. In addition, more MGA runs can be exploited to obtain a greater accuracy regarding the uncertainty range around the cost optimal solution as for now it is with 20% quite large. In certain countries such as Portugal, the cost optimal solution (so the solution which the model presents) generates the lowest error, even when there is greater potential for cost increase within the MGA. This suggests the presence of other limiting factors (like parametric uncertainty) impacting the model’s accuracy in modelling the real-world scenario. Nevertheless, this has its limitations as the model assumes that every parameter is known for the next 30 years. In real world scenarios, numerous variables can undergo significant changes, such as shift in demand and fluctuations in technology prices (Trutnevyte, 2016; Wen et al., 2022).

6 Conclusion

In this study, we have examined the impact of incorporating the two societal factors, public acceptance and heterogeneity of actors, within the D-EXPANSE model for 31 European countries over the period of 1990-2019. We developed four model versions from the original D-EXPANSE model, with the integration of public acceptance, heterogeneity of actors and a combination of both these factors. The public acceptance model version is constructed from the D-EXPANSE model by country specific limiting the CO_2 emissions with regard to public sentiment about climate change using a survey from 2009 until 2021 in combination with European targets. Our findings regarding the integration of public acceptance reveal a decrease in the error for 9 out of the 18 countries compared to the reference model version. To assess the stringency of our CO_2 limits, we conducted a sensitivity analysis with 25 alternative constraints. Our findings indicate that for 11 out of the 18 countries analysed a more stringent constraint than the one implemented would have led to a decrease in error, and would thereby enhance the accuracy of our model version. In that regard our constraint on the CO_2 emissions was too high and for future work a stricter CO_2 constraint would enhance the results.

Heterogeneity of actors is implemented in the original D-EXPANSE model with differentiated weighted average cost of capital (WACCS) across different technologies and countries with the data ranging from 2009 until 2018. In the original D-EXPANSE model a uniform discount factor of 3.5% was used. The uniform discount value is replaced with varied WACCs per technology and country to reflect the heterogeneity of actors. The results show that 13 out of the 26 countries experienced an improvement of the error compared to the reference model version, with a strong correlation between the error of the reference model and the error of the heterogeneity of actors' model. For the implementation of both societal factors, so public acceptance model version and the heterogeneity of actors' model version 12 out of the 22 countries have a decrease of the error compared to the reference model version.

Overall, drawing definitive conclusions from the comparison of the three models with the reference model version proves challenging. None of the models, through this hindcasting exercise, provide convincing proof for the superiority of one model over the others. All models show a performance increase for only around half of the countries or slightly above half, compared to the reference model, while the other countries it increased the error. With the public acceptance model having more possibilities to decrease the error as is seen by the sensitivity analysis which was conducted.

The literature review conducted in Section 2 emphasizes that both incorporating actor heterogeneity and accounting for public acceptance can significantly enhance model performance. Omitting these factors in future energy system optimisation models may lead to increased discrepancies in future analysis. Although the results demonstrate that the implementation of one or both societal aspects could lead to a decrease in error for a specific country by more than 7.5 percentage points, it is also noted that the error for a specific country could increase by more than 9 percentage points, compared to the reference model. Despite the inconclusive results, the literature suggests the importance of incorporating societal factors into energy system optimisation models. Because of the literature study societal aspects research needs to persist, and alternative approaches for the incorporation of societal factors should be explored, although the current thesis does not convincingly demonstrate an improvement in model accuracy through these specific implementations.

Furthermore, it remains essential to present not just a single solution but a spectrum of multiple potential electricity mixes, with a slight increase in costs. Providing multiple solutions demonstrates the diverse outcomes that could be achieved with a modest budget increase. Providing this range of possibilities enables policymakers to make better-informed decisions that can be more publicly accepted, even with a 10 percent higher price, instead of having only one electricity mix, with the lowest costs. The other solutions can have higher societal acceptance factors and therefore increase the transition to a more sustainable word. In the ongoing effort to combat climate change, societal factors become increasingly critical as we integrate more renewable energy sources into our electricity sector. These sources are particularly influenced by societal considerations. Therefore, it is valuable for modelers to explore ways to incorporate various societal factors on a country-specific and subnational scale. Policymakers use the framework provided by the optimisation model to make decisions about energy-related policies. With the right model, they can significantly enhance and smoothen the transition to a more sustainable world.

To conclude, this research project integrated two key societal factors, namely public acceptance and actor heterogeneity, into the D-EXPANSE model. The objective was to examine the influence of societal factors on energy system optimization models and assess how their inclusion can enhance model accuracy. Existing literature underscores the importance of integrating societal factors into Energy System Optimization Models (ESOMs), especially in the context of the ongoing shift towards a more greener electricity mix. However, our research did not conclusively demonstrate a significant improvement in the accuracy of the model with the inclusion of societal factors. Despite this, the thesis makes a noteworthy contribution by demonstrating two distinct approaches to incorporating societal factors into an ESOM. Additionally, it highlights that the integration of modeling to generate alternatives (MGA) can lead to improved model accuracy and present more politically desirable solutions, with only a marginal increase in costs. These findings suggest potential directions for other modelers to explore alternative forms of incorporating societal factors to enhance model accuracy.

Own reflection

In reflecting on my thesis journey, it becomes evident that it has been a very educational experience. This process has underscored the importance of structure in my work, the efficiency of my code, and the prompt resolution of any issues that may arise. I have come to realise that it is better to address problems at their root rather than opting for temporary workarounds. I have observed a notable improvement in my proficiency with Python, particularly in handling pandas' data frames, and a deepening of my understanding of different models. Hands on experience with an optimisation model and reading about all the other models gave me valuable insights. The optimisation models are particularly interesting now, as I have read most papers about these models, and it is curious to see what other modellers assumptions are made in comparison to our own model. Further, I now approach research results with greater scepticism, delving more profoundly to understand the underlying factors rather than accepting them at face value.

Contemplating what I would do differently, I recognize the significance of structured reading during the literature review. The initial lack of organisation in my reading approach resulted in the accumulation of less relevant papers. In the future, I intend to begin with comprehensive literature reviews to establish a solid foundation and structure. This strategy will assist in the early filtration and categorization of important materials, reducing unnecessary data accumulation and saving time. Furthermore, my exploration of various CO_2 scenarios revealed that they often yielded minor differences. In hindsight, focusing on only one CO_2 would have saved me a lot of computational time which could be attributed to something else.

Challenges were an integral aspect of this journey. The initial implementation of the CO_2 constraint, for instance, required a good understanding of the optimisation model and the Pyomo language. It was a trial-and-error process, and it took time to fully knew how it worked. However, as I started to better understand the optimisation model, the task of modifying the model became easier. Furthermore, after the initial implementation of the yearly budget public acceptance model, adjusting the other models proved to be significantly more straightforward. Another significant challenge lay in incorporating the heterogeneity of actors and accounting for public acceptance. While valuable insights were gained from discussions with colleagues, it became evident that certain aspects were either infeasible or too time-consuming to be practical.

Appendix

In Figure 29, Norway's CO_2 emissions from 1990 until 2019 are presented, with the actual data and the reference modelled data.

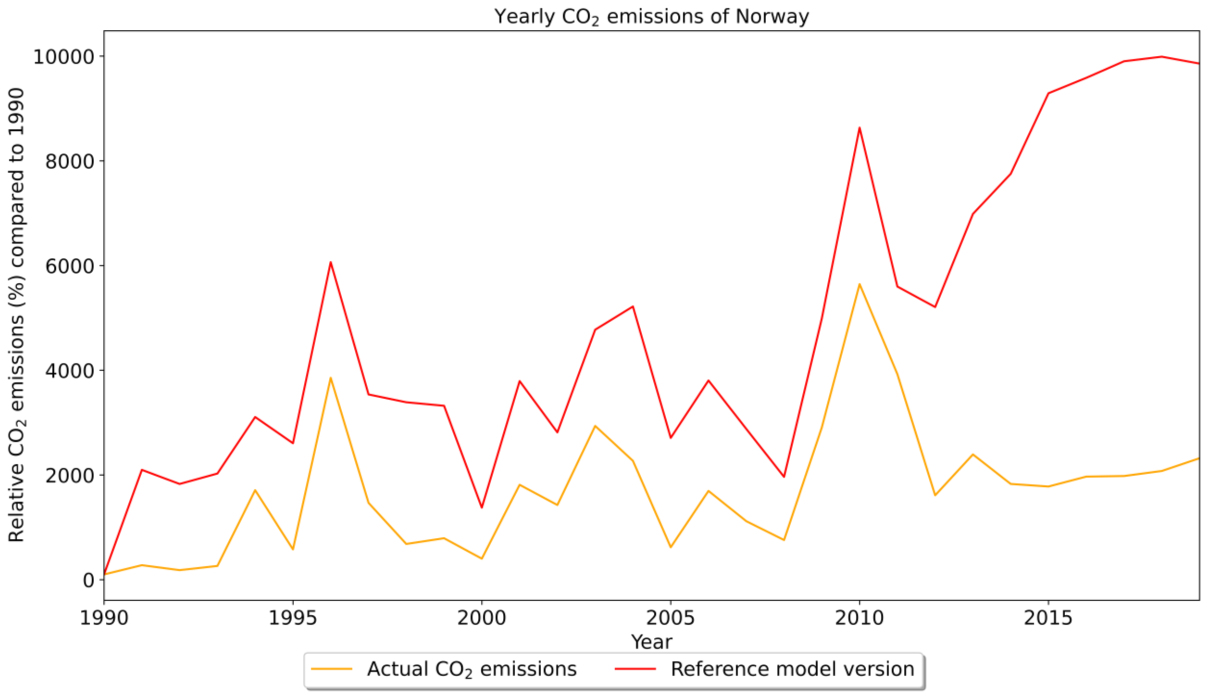

Figure 29 yearly CO_2 emissions of Norway, relative to the CO_2 emissions in 1990. With in red the reference model version and in yellow the actual CO_2 emissions.

One can see that compared to the levels of 1990 the CO_2 emissions have heavily increased. This increase in CO_2 emissions is largely due to the amount of oil which is found in Norway's territory from 1990 onwards (IEA, 2022).

The error of the yearly budget public acceptance model version against the reference model version is shown in Figure 30.

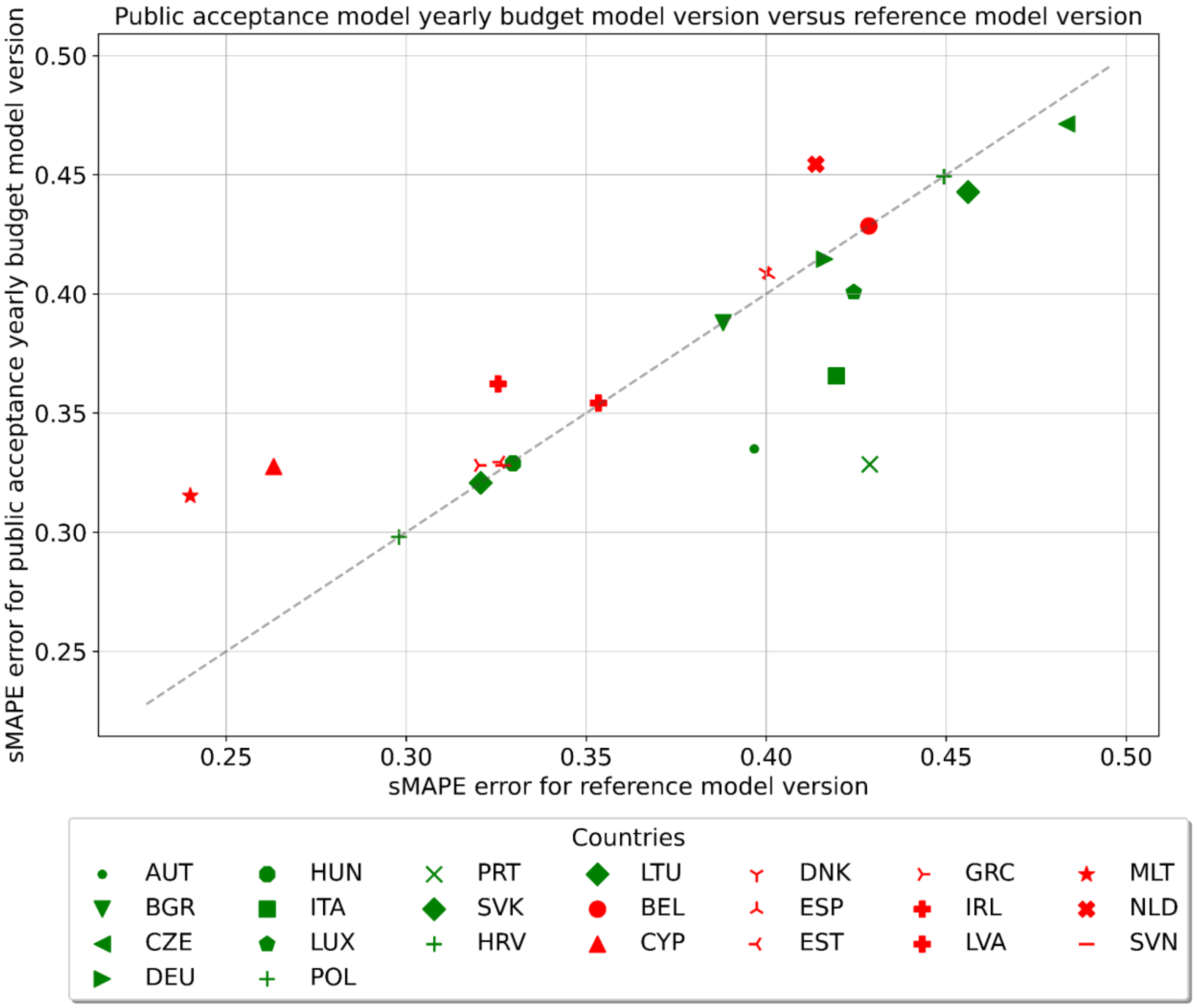

Figure 30 public acceptance model version with a yearly budget constraint models the reference model. Countries that improved the model outcomes are in green and under the diagonal line. Countries which are red experienced an increase in the error compared to the reference model version.

As one can see is the yearly budget public acceptance model, shows an improvement of 12 countries (AUT, BGR, CZE, DEU, HUN, ITA, LUX, POL, PRT, SVK, HRV and LTU) where for 11 countries (BEL, CYP, DNK, ESP, EST, GRC, IRL, LVA, MLT, NLD, SVN) it worsened the error. This is consistent with the cumulative budget public acceptance model version.

The error for the cumulative budget public acceptance model version against the yearly budget public acceptance model version is shown in Figure 31.

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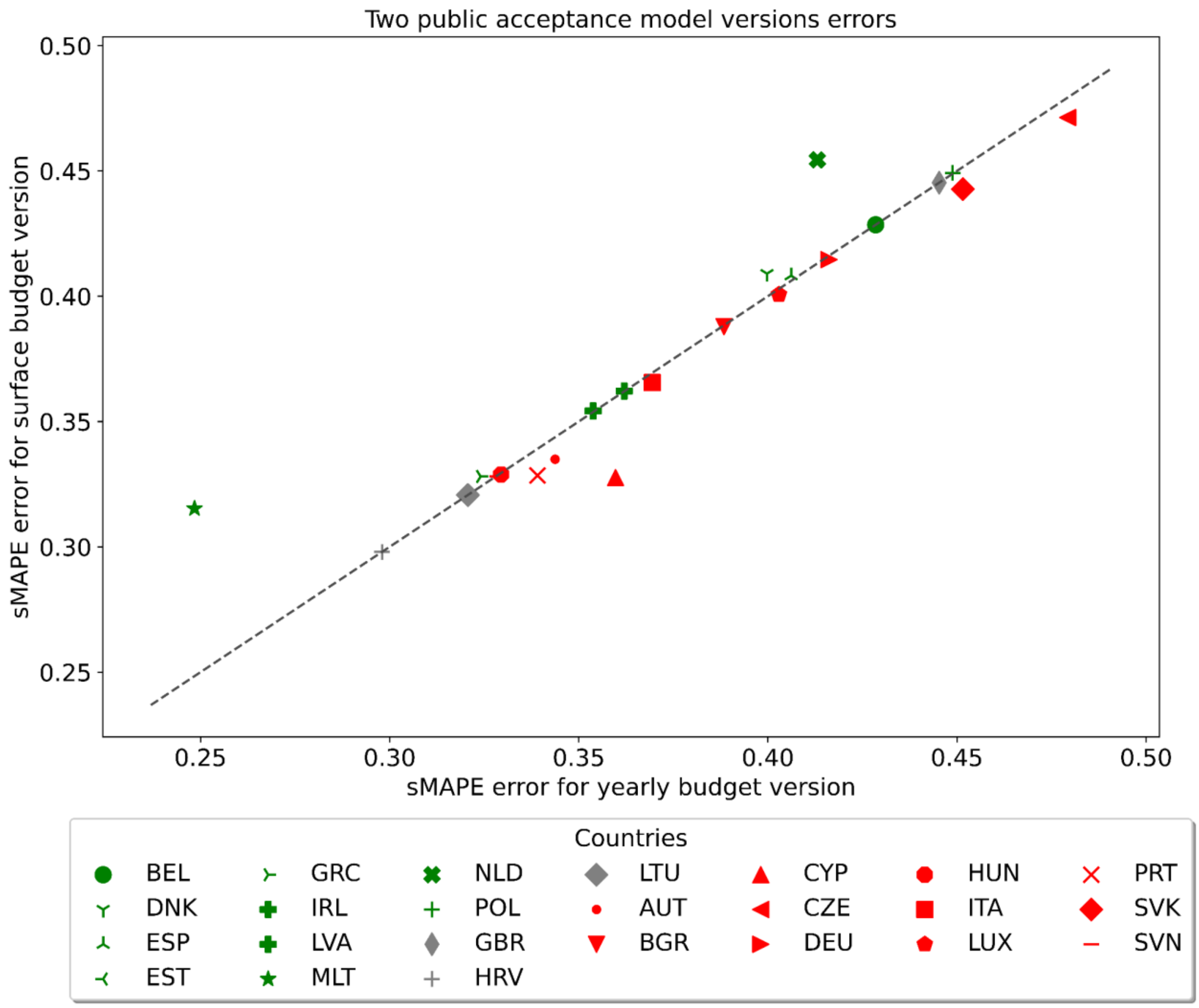

Figure 31 public acceptance model with two versions. The yearly budget constraint version on the x-axis, and the surface budget constraint on the y-axis. If the country is green the surface budget constraint generates a lower error, whereas if the country is red the yearly budget constraint generates a lower error. The grey countries are where the difference is zero.

There are almost no outliers between the two-model version, implying that it does not matter so much which model you chose. There are ten countries which show a decrease in the error for the cumulative budget public acceptance model, and 11 countries which show a (slight) decrease in the error for the yearly budget public acceptance model. Furthermore, there are 3 countries which have no difference regarding the reference model version or these two model versions.

Four scenarios

When looking at the survey data, an approach was constructed with four scenarios where each of the four scenarios calculated the mean value in a separate way. In this way we tried to access the sensitivity of the survey. The four scenarios constructed are: linear, middle, low and high. Each of these scenarios adopts a slightly different scaling factor for translating survey data scores into constraints, as illustrated in Table 4. The score the person in the survey has given is translated to the adjusted score per scenario.

Scenarios	**Lower limit**	Not a serious problem			A fairly serious problem		a very serious problem			**Upper limit**
Score from survey	1	2	3	4	5	6	7	8	9	10
Linear	0	2	3	4	5	6	7	8	9	10
Middle	0	2.5	2.5	2.5	5	5	7.5	7.5	7.5	10
Low	0	1	1	1	4	4	7	7	7	10
High	0	3	3	3	6	6	8	8	8	10

Table 4 Scores of the survey and the representative scores given by each of the four scenarios.

When making the constraint for the public acceptance model there was already a tiny difference between the 4 scenarios but looking across the 4 scenarios outputs from the model, they are almost identical in the deployment of capacity and generation. To illustrate the differences between the four scenarios the relative error in relation to the reference model version across countries is calculated as follows:

$$RE = \frac{y - RM}{RM}$$

Here, *RM* represents the reference model, *y* is the public acceptance model version output and *RE* stands for the relative error. This approach simplifies the assessment of whether the CO_2 constraint led to model enhancement (indicated by a negative value, decreasing the error). The result is shown in Figure 32, as illustrated across the four models there is no significant difference.

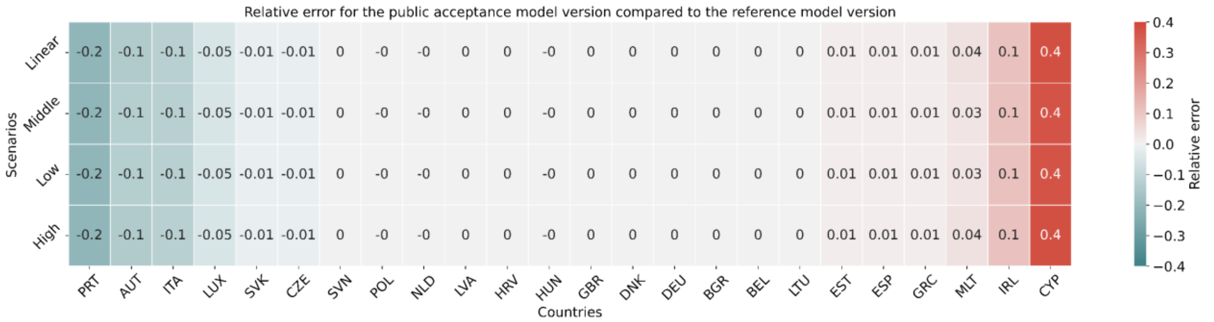

Figure 32 Heatmap for the relative error to the reference model across four different CO_2 scenarios.

In the end, the difference between the four scenarios was so small that this is left out of further research and the middle scenario is chosen.

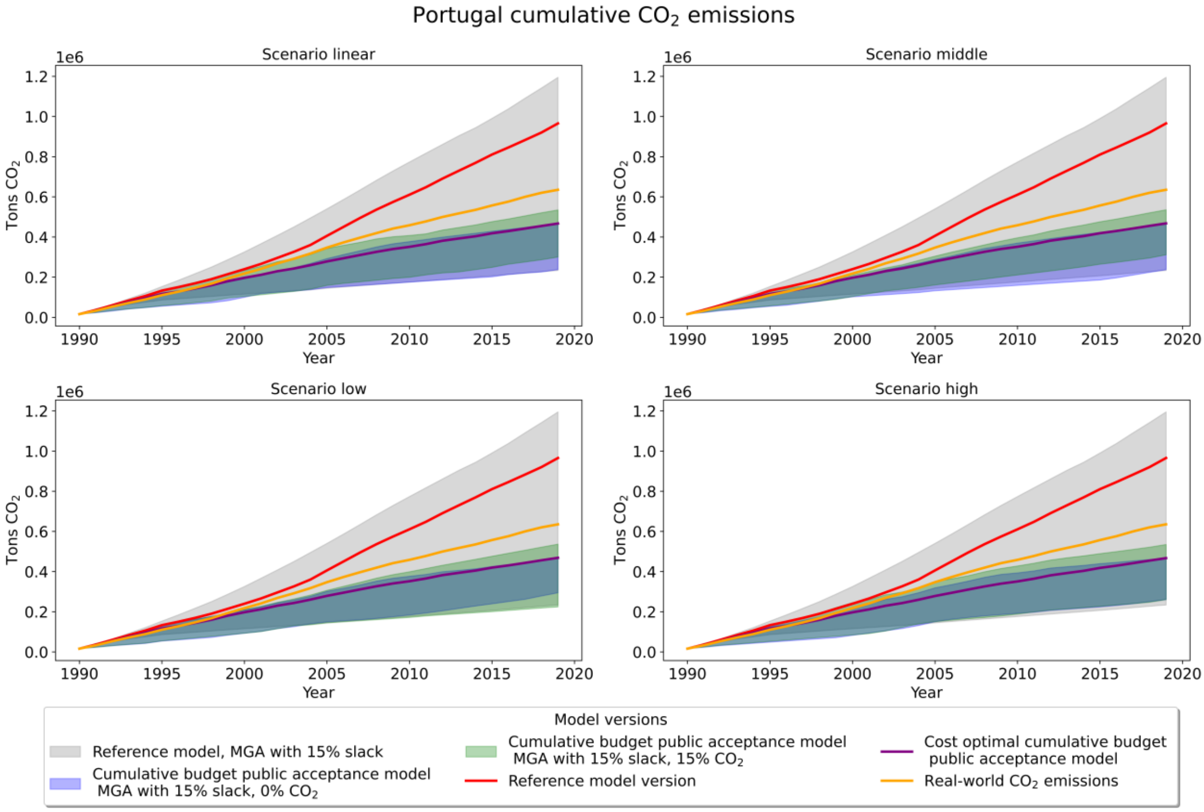

Figure 33 Cumulative CO2 emissions for Portugal. The four different CO2 scenarios are shown as well as the range of the two different MGA's. Further, the actual CO2 emissions, the reference model output, and the cumulative budget public acceptance model output are shown.

For the group of Hungary in Table 3 an example of the cumulative CO_2 emissions across four different scenarios is shown in Figure 34 for the case of Germany.

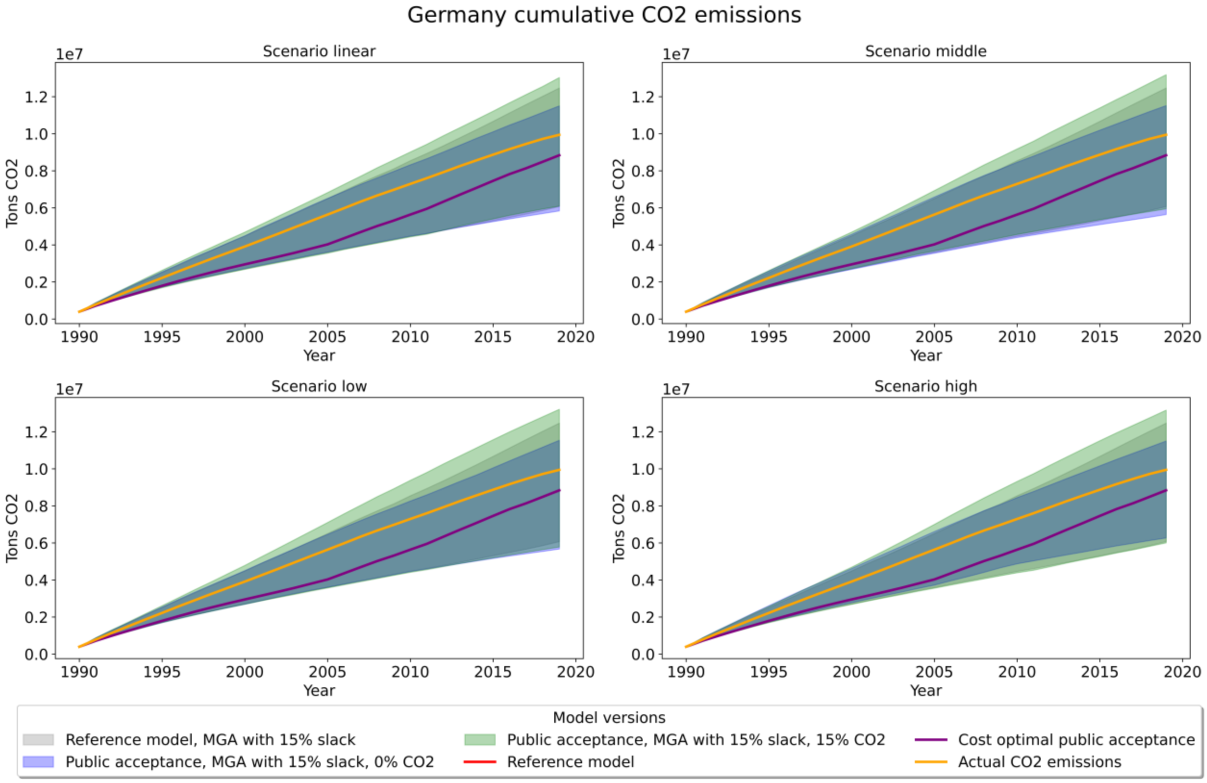

Figure 34 Cumulative CO_2 emissions for Germany. The four different CO_2 scenarios are shown as well as the range of the two different MGA's. Further, the actual CO_2 emissions, the reference model output, and the cumulative budget public acceptance model output are shown.

Here one can clearly see that all the three MGA performances overlap. This is due to that there is no limiting factor of the CO_2 constraint. This means that the three models are the same meaning that the three MGAs will overlap.

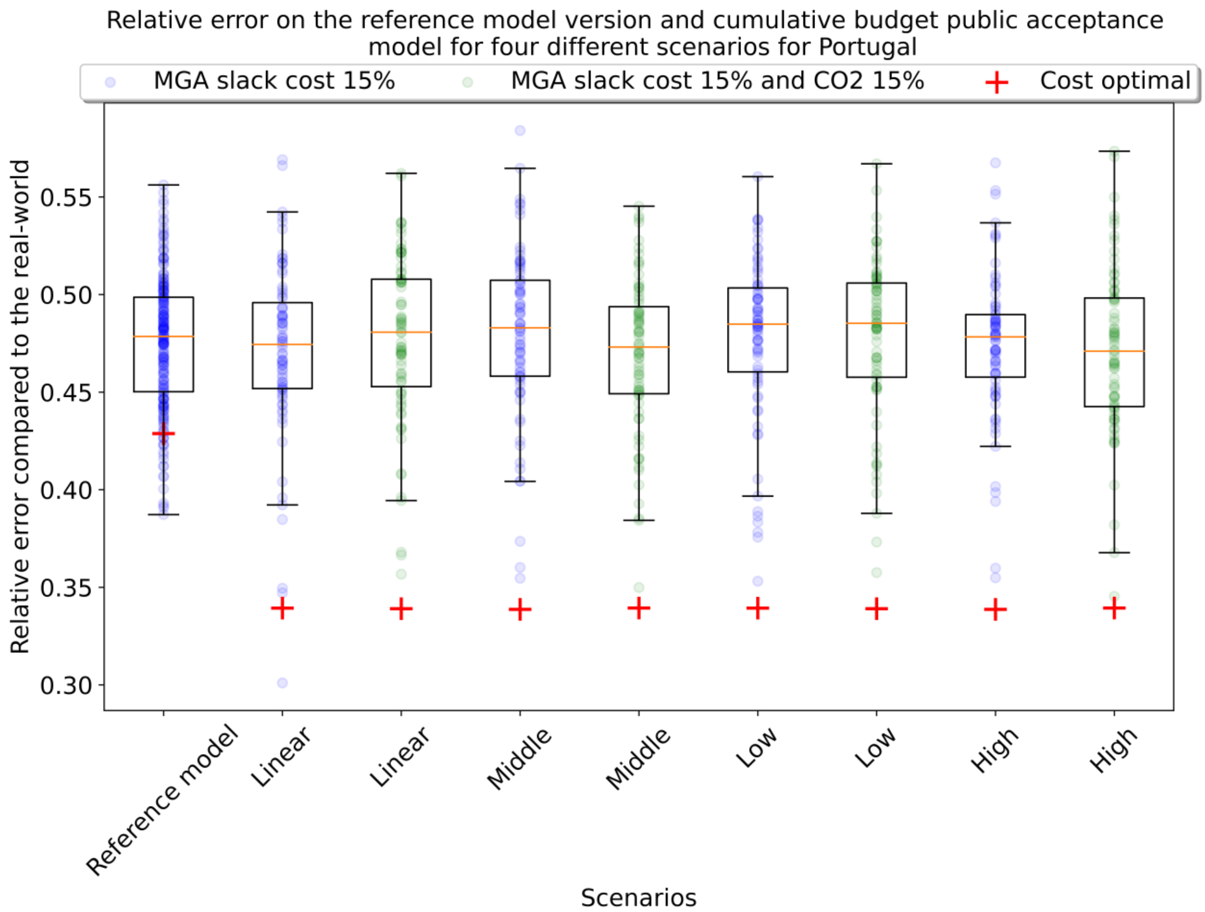

Figure 35 The relative error in comparison to the real-world, with the cost optimal cases across (in red) four different scenarios. As well as different MGA runs (75 per scenario, 200 for the reference model), two different amounts of CO_2 slack 0% and 15%, with both 15% cost slack.

Further, looking at the differences between the four scenarios, the cost optimal runs and the MGA performances a couple of things stand out. First, there is almost no difference in the deployment of CO_2 emissions for the cost optimal run for the cumulative budget public acceptance model across all four scenarios. Secondly, the MGA range around the cumulative budget public acceptance model remains similar across all four scenarios. Thirdly, analysing the results when calculating the relative error to the real world, there is again no notably difference in the cost optimal runs. The relative differences in the error are so minor they appear to be the same.

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