Université Paris Ouest, Nanterre – La Défense
École Doctorale Économie, Organisation, Société
Laboratoire EconomiX – UMR CNRS 7235
U.F.R. SEGMI

Année 2016

N° attribué par la bibliothèque
|_|_|_|_|_|_|_|_|_|_|

THÈSE

pour l'obtention du grade de Docteur en Économie

Présentée par

Claire Nicolas

Sous la direction d'Alain Ayong Le Kama, Professeur à l'Université Paris Ouest

Robust energy and climate modeling for policy assessment

Thèse soutenue publiquement à l'Université Paris Ouest, Nanterre – La Défense
le 1 juin 2016

Devant le jury composé de :

Valérie Mignon	Professeur, Université Paris Ouest	Présidente du jury
Patrick Criqui	Directeur de recherches, Université de Grenoble II	Rapporteur
Patrice Geoffron	Professeur, Université Paris Dauphine	Examinateur
Alain Haurie	Professeur émérite, Université de Genève	Rapporteur
Alain Ayong Le Kama	Professeur, Université Paris Ouest	Directeur
Stéphane Tchung-Ming	Chercheur, IFPEN	Examinateur

Remerciements

Cette thèse est le fruit d'un travail collaboratif.
Au sein de l'IFPEN, j'ai eu la chance de pouvoir travailler avec Val et Manu que je remercie vivement pour les articles réalisés ensemble mais aussi pour tous les conseils et les relectures que je leur ai imposés. Merci aussi à Fred, Benoît, Marion, Andrea et Anthony pour leurs relectures et leur soutien au long de ces trois ans passés dans le même bureau ou dans celui que j'envahissais le matin pour mon café quotidien (merci Fred Clooney).
Je tiens aussi à exprimer toute ma gratitude à Amit Kanudia. Avoir eu l'opportunité d'utiliser son modèle TIAM-World fut d'une grande aide et les conversations avec lui furent toujours très divertissantes, illustrant à merveille l'expression « passer du coq à l'âne », et illuminées par son humour si particulier.
Merci aussi à Jérôme, dit Jéjé. Grâce à sa bienveillance et sa disponibilité, j'ai eu la possibilité de me luxer l'épaule à Montréal et de découvrir le touch rugby à Cambridge sans avoir à batailler outre mesure contre l'administration.
Je ne peux évidemment pas clore ce volet de remerciements IFPEN sans remercier de tout mon cœur Steph, grâce à qui cette aventure a commencé il y a plus de 4 ans autour d'une bière à Nation : « -tu vas bientôt chercher un nouveau doctorant ?», « -ouais », « je crois que ça pourrait m'intéresser », « ok ». Son ombre flotte sur la plupart des lignes écrites dans ce manuscrit. Lorsque le lecteur trouvera limpide une notion, une phrase ou une explication, qu'il soit sûr que Stéphane n'est pas loin. Merci Steph pour ce cheminement, les roulées, les journées à Maison-Alfort, Montréal, les blagues pourries, tes fulgurances, tes explications qui rendent tout limpide et aident à débrouiller le sac de nœuds qu'est mon cerveau.
Merci enfin à tous ceux de la DEV avec qui j'ai ri, pesté, fumé, parlé rugby… Je ne sais si mon prochain job sera : psy, coach ou caviste mais ces années passées à l'IFP m'ont ouvert de nombreux horizons professionnels !

Mes remerciements vont ensuite au jury pour avoir accepté la longue tâche de lire ce manuscrit. Et je remercie tout particulièrement Alain, mon directeur de thèse, pour

sa supervision bienveillante et peu oppressante. J'ai apprécié sa vivacité d'esprit, en particulier au début de ma thèse quand je venais lui présenter des concepts étrangers à son champs de recherche, de manière confuse et brouillonne et que je repartais de nos rencontres, rassurée et avec de nouvelles idées.

Merci finalement à tous mes « potes » : les filles du rugby (Flo, Marie, Em, Momo, Chloé, Val, Ade...) pour les conversations rugby, carrière, féminisme, relation homme-femme et Tinder ; les mecs de la Chaire (Victor, Clément, Simon et Florian) pour les conversations sur les innombrables défauts des néo-classiques, le monde académique, les relations humaines et Tinder, mes vieux potes (Judith, Manu, Julie, Julie, Mélanie, Adri, Daniel...) pour les conversations sur l'ambition, mais pourquoi la thèse, les 30 ans et Tinder. Merci aussi à mes grands-parents et en particulier à ma grand-mère pour son attentive relecture du chapitre 1 et aussi pour les conversations sur le théâtre, l'art, la politique et ... Tinder (mais qu'est-ce que Tinder ?).

Et enfin merci à Benj (Benny B now) d'avoir supporté mes silences et mes ongles rongés pendant ces trois ans. Et surtout de m'avoir soutenue quand je suis rentrée un soir en annonçant que je songeais à faire une thèse.

Acknowledgments

I also would like to thank Gérard Moutet from Total and John Reilly and Sergey Paltsev the director and deputy director of the Joint Program on the science and policy of global change at MIT. The first one allowed me to visit the JP on the behalf of Total sponsorship while John and Sergey hosted me in their lab for 7 months. I won't forget Raina, Arun, Tox, Christian, Paul, Amanda and Michael, thanks to them my stay at the JP was not too lonely. And finally, thanks to Alice, Matthieu, Marie and Arnaud meeting you made my installation in Boston easier that what I expected!

Comment se résoudre à un devenir sans surprise, à une histoire où plus rien ne peut survenir à l'horizon, sinon la menace d'une continuation? Ce qui surviendra, nul ne le sait. Mais chacun comprend qu'il faudra, pour le percevoir, être calme, divers, et exagérément libres.

Patrick Boucheron

Robust energy and climate modeling for policy assessment

ABSTRACT

Energy-economy and energy-economy-environment models are widely used to assess energy and climate policies. Developed during the last forty years, these models allow the study of the interactions between the energy-transport system, the economy and the climate system. These interactions are very complex as they involve linkages, feedback loops and delays that are not perfectly known and that take place over a long time horizon.
This complexity along with the large uncertainties weighing on the model parameters and main assumptions explain why the use of models in the policy debate, (where the models address issues on climate change scenarios and on energy planning), is largely criticized.
Based on this observation, our work aimed primarily at increasing the robustness of these models, to reinforce the relevance of their use to evaluate economic policy impacts.
At first, we examine how these models should be used to contribute effectively to the climate and energy policy analysis debate. We review the evolution of the modeling practice and question it, discussing its relevance. We then focus on the uncertainty treatment and on the basis of this review, we implement an alternative way of considering parameter uncertainty when "modeling the future" using robust optimization.

Améliorer la robustesse de l'évaluation des politiques climatique et énergétique

RESUME

La plupart des exercices d'analyse de politiques climatiques ou énergétiques font appel à des modèles dits "d'évaluation intégrée" (MEIs). Ces modèles économie-énergie-climat sont des modèles numériques pluridisciplinaires destinés à étudier les questions liées au changement climatique et à sa gestion. Socles d'une accumulation de connaissance, ils ont une visée prospective et aident à traduire les débats qualitatifs des instances de décisions nationales et internationales en un ensemble de données quantitatives, scientifiquement vérifiables. Leur faible capacité à prendre en compte les incertitudes inhérentes à tout exercice de prospective mais aussi leur trop grande complexité expliquent pourquoi ces MEIs sont si souvent décriés et leur utilisation remise en question.
Ce constat a guidé nos travaux dont l'objectif était de contribuer à améliorer la robustesse des MEIs, afin de renforcer la pertinence de leur utilisation pour l'analyse de l'impact de politiques économiques sur le climat-énergie. Nous avons d'abord examiné comment ces modèles participent aux débats sur le changement climatique et comment améliorer leur utilisation. Nous avons retracé la genèse de ces modèles et leur évolution et analysé les principales critiques qui leur sont adressées. Dans un second temps, nous nous sommes focalisés sur l'un des principaux reproches faits aux MEIs : le traitement de l'incertitude. Sur la base de ces analyses, nous avons mis en œuvre une approche récente de traitement des problèmes d'incertitude paramétrique: l'optimisation robuste, méthode encore très peu utilisée dans le cadre d'études prospectives.

Contents

Authors List

Chapter 1 has been written by C. Nicolas.

A version of Chapter 2 has been submitted as Nicolas, C., Saint-Antonin, V. and Tchung-Ming, S. to Energy Policy (WP 2014-56 Economix).

Chapter 3 is a reproduction of Nicolas, Tchung-Ming & Hache (2016). Submitted to Energy Economics in June 2016.

Chapter 4 is a version of Nicolas, Tchung-Ming, Delage and Bahn (2016).

Chapter 5 is a version of Nicolas, Paltsev, Winchester, Chen and Morris (2016), MIT Joint Program working paper .

Introduction

Climate change is an issue that has been quite recently integrated to the economic and political fields. If we consider the creation of the IPCC in 1988 (Intergovernmental Panel on Climate Change) as a recognition of the need for actions 30 years ago it would seem that the actions undertaken so far have led to very few results. A reason sometimes cited for this is the inadequacy of economic theory, more particularly of neo-classical theory, to address climate change. This question forms part of the wider debate of strong sustainability (Daly, 1972, 1974, 1977) versus weak sustainability (Solow, 1974, 1986, Hartwick, 1977, 1978).

This discussion is summarized in Pottier (2014) where a focus is made on climate change issues. Economic theory has a “simple” answer to solve climate change or more broadly, negative externality issues: a Pigovian tax or an equivalent mechanism such as a cap-and-trade market (Pigou, 1932, Coase, 1960). This would take the externality into account and allow the “power of the market” to work its magic and restore the “harmony of interests”. To be efficient, the carbon tax must be applied to all economic sectors and must grow over time (Nordhaus, 1991, Pearce, 1991). Unfortunately, this "first best" way of solving climate change issues is not feasible in the real world for many reasons (such as among others interregional and intergenerational equity, wealth disparity, historic responsibility, culture) as the recent COP 21 (Conference of the Parties) demonstrated. Moreover, climate change could be considered as a byproduct of the previous two centuries of growth and technological progress; the increasing use of fossil fuels that came together with unprecedented wealth has led to an ever faster warming of the planet. Hence addressing the climate change issue would, in a way, be synonymous with slowing economic growth. The sole existence of climate change itself could be a refutation of neoclassical theory, particularly of its stand on the natural harmony of human interests made possible thanks to market mechanisms.

Other economists do not go as far and instead consider ways to correct the shortfalls of neoclassical tools to better address climate change issues. Heal and Millner (2014) explore alternative frameworks that may be more appropriate than the expected utility hypothesis to address climate change issues. Michl (2008) also discusses the drawbacks of the neoclassical theory using the example of the Stern/Nordhaus controversy and calls for a return to classical theory. More recently, working on the models used to evaluate climate change policies, Vogt-schilb (2015) investigates the effects of incorporating inertia and irreversibilities inherent to the accumulation of low carbon capital on how much real practice diverge from theoretical understanding of climate policies.

Recognizing that many climate and energy policy evaluations are conducted in a deterministic way, setting aside the numerous uncertainties weighing on the triplet Economy-Energy-Climate, we aim to find more robust ways to evaluate these policies and to inform the decision maker.

We suppose in this thesis that, while a carbon tax may be the most efficient way to tackle the climate change issue[1], it is not a realistic instrument for a worldwide application. Hence the need to develop second-best, regionalized and sectoral, instruments is real. To do so, Integrated Assessment Models (IAMs) and energy system models are important as they enable the representation of complex interactions that may be difficult to account for with a simple model and help assess these regional and sectoral tools. They also allow for making more complex the mental models of decision makers.

In this work we focus on IAMs and their use and explore ways of using them in a more robust way to better inform and support the decision making process[2]. We first work on the impacts of the modeling structure of IAMs on the accuracy of the policy analysis exercise then we question the uncertainty handling in climate or energy policy evaluations and propose to use robust optimization, a recently developed approach, to address parametric uncertainty in prospective models.

Climate & Energy Policy evaluation : the critical use of models

Energy-economy and energy-economy-environment models are widely used to assess energy and climate policies. Developed in the aftermath of the groundbreaking work conducted, inter alia by the Club of Rome in the early seventies, these models allow us to study the interactions between the energy (and transportation) system, the economy and the climate system. These very complex interactions involve linkages, feedback and delays that are not perfectly known and that take place over a long time horizon. Also called Integrated Assessment Models (IAMs), they are formulated using analytical and theoretical methods coming from several disciplines including but not limited to climate sciences, economics, engineering and operations research. They operate under various paradigms (e.g., bottom-up or top-down, optimization or simulation) and have the ability to answer a wide range of questions such as identifying promising technological pathways (Labriet et al., 2010), evaluating various climate policies (see Hu et al., 2012) or assessing the impact of policy measures on resource exhaustion (see McGlade and Ekins, 2015).

The level of complexity and the large uncertainties present in the models explain why

[1] Albeit in a "perfect" world, economically speaking

[2] We do not work on policy instruments but on the tools used to evaluate them.

models are used to generate insights, not foresights, and why they are good tools to explore internally consistent plausible futures and better understand the energy system. A large diversity of institutions work with these models: governments, industry, academic institutions, international institutions amongst others.

The origins of integrated assessment modeling date back to the middle of last century. The "Limits to Growth" enterprise played a major role in establishing a conceptual mathematical framework to address global issues. According to Vieille Blanchard (2011), the debates it raised led to a strong consensus on the merit of economic growth (unlike what was advocated by "The Limits") and to legitimize IAM ways of modeling world climate issues[3]. Yet IAMs are quite criticized, complaints ranging from the models' high complexity or the validation issues to criticisms widely acknowledged like the uncertainty handling (Matarasso, 2003, Weitzman, 2009, Hedenus et al., 2013). A particularly virulent critique, Pindyck (2013), states that considering the numerous uncertainties *surrounding* the climate system behavior or the impacts of climate change on economic aspects and the inability of IAMs to consider very low probability but catastrophic events, the IAM-based analysis of climate policy creates "a perception of knowledge and precision that is illusory and misleading".

Uncertainty: a core feature of long-term policy analysis

Uncertainty is the key element of prospective exercises and it is undeniable that its presence in the long-term energy-economy-climate outlook may deeply affect the relevance of the policy analysis and impact the decision making process.

First there are multiple causes of uncertainty in IAMs, particularly in bottom-up ones. Uncertainty can arise from: (i) prediction error, affecting parameters of the model such as demands or costs as their values in the future are usually forecasted; (ii) modeling error resulting from our imprecise knowledge on various physical and economic 'mechanisms' (e.g., physical processes governing the climate or consumer preferences impacting the adoption of new technologies) that forces modelers to use simplified (and possibly quite imprecise) representations of these processes; (iii) measurement errors affecting technical parameters or e.g., in the computation of price elasticities using econometric methods or (iv) implementation error, relying on computing and modeling choices (e.g., in the choice of convex functional forms for the sole purpose of ensuring computational tractability, see chapter 2).

Second, even small variations in data can impact the feasibility or optimality properties of a given solution (Ben-tal and Nemirovski, 2000). Indeed, optimal solutions elaborated with optimization models like the ones used in this thesis (TIMES paradigm) are based on complex, high cardinality sets of exogenous assumptions on the data populating the models.

Finally, energy system models are often of large size, and relevant techniques need to be identified to solve large-scale problems contaminated with "massive data uncertainty".

[3]Ways that we could call orthodox in contrast to other paradigms developed ie by Nicholas Georgescu-Roegen in The Entropy Law and the Economic Process (1971)

Before looking more deeply into Robust Optimization, it should be noted that uncertainty is not a forgotten child of IAMs modelers. A short presentation of the methods usually employed will allow us to then explain why robust optimization is a good complement to the existing tools.

Sensitivity analysis and multi-scenario analysis
Sensitivity analysis (SA) is a widely used approach which allows to investigate the impact of particular parameters on the model solution. Its drawbacks are that the model needs to be run numerous times if the set of uncertain parameters is large and moreover it does not provide unambiguous hedging strategies. When probability distributions are defined for the uncertain data, Monte-Carlo type of analysis can be done but this technique can rapidly become computationally intractable as the number of uncertain parameters increases.
Deterministic multi-scenario analysis is very useful in scoping the range of impacts of key parameters on the possible climate adaptation and mitigation responses (Kunreuther et al., 2014). It works more or less like sensitivity analysis as scenario/ensemble analyses can be performed without quantifying the uncertainty (via probabilities) of the underlying unknown parameters but like SA it implies an unavoidable ambiguity in interpreting ensemble results since they tend to be used in a deterministic fashion without recognizing that they are only one of many possible outcomes (Clarke et al., 2014, Kunreuther et al., 2014). Moreover, this method leaves the policy adviser in a quandary as to what policy to initiate now, given the often widely diverging courses of action solutions proposed by each of the alternative scenarios, even in the short term.

Stochastic programming
Stochastic optimization provides an appealing and rigorous framework for describing a few contrasted states of the world (Wets, 1989). One of the main advantages of this approach is to obtain an explicit single hedging strategy even in the context of high uncertainty, contrary to classical multi-scenarios analysis. One of its drawbacks is computational: it quickly leads to large-scale instances of the original model, hence to very long computing times and to intractability issues in numerical computations as the problem grows. Moreover, as with Monte-Carlo simulations, probability distribution have to be defined over the entire tree of decisions though these distributions are often unknown because of a lack of information, of knowledge, of measures or more.

Robust optimization: a new method
Robust optimization is a recent technique used in the field of operations research that we find appropriate to tackle some uncertainty issues in energy system models. It was developed at the end of the 1990s because of two joint observations: (i) in some optimization problems, data "can “drift” around their nominal values, varying in some given uncertainty set” (Ben-Tal et al., 2004) and (ii) even small variations in data can impact the feasibility or optimality properties of a given solution (Ben-tal and Nemirovski, 2000).

To date and to the best of our knowledge, robust optimization has almost never been used in energy modeling, with the exception of one team of modelers (Babonneau et al., 2011, 2010, Andrey et al., 2015).

Early developments of RO date back to Soyster (1973) who initiated an approach of obtaining relevant (i.e. feasible) linear programming solutions although matrix coefficients are inexact. RO has known many developments in the last 15 years by generalizing Soyster approach (Bertsimas and Sim, 2004) or using different formalisms (Ben-tal and Nemirovski, 2002, El Ghaoui et al., 1998). It is currently emerging as a promising technique for applications to energy and environment problems.
Unlike the two methods presented above, RO formulations offer parsimonious ways of dealing with problems of high dimensionality, requiring minimal information about the true probability distributions (Ben-tal and Nemirovski, 2002). While stochastic or Monte-Carlo frameworks require definitions of probability density functions, the principle of RO consists in set-based descriptions of uncertainties. As such, only the extent to which parameters are likely to vary needs to be known (although this information may be itself difficult to acquire) – this corresponds to the support of the density functions.
The general principle of RO consists in immunizing a solution against adverse realizations of uncertain parameters within given uncertainty sets. The basic requirement for a robust solution is that constraints of the problem are not violated whatever the realization of the parameters in the set. The major modeling issue then consists in identifying computable robust counterparts for the initial optimization program, depending on the model class and the nature of the uncertainty region. Ben-tal et al. (2012) and Bertsimas et al. (2010) review techniques for building such robust counterparts (RC) in general cases. One particular case of interest for our work is the case of a linear program combined with a polyhedral uncertainty set, for which the RC is itself a linear program. For a more detailed presentation of the RO methodology, see the appendix 5.8.

In this thesis, we try to improve the assessment of future climate and energy policies by using robust optimization. Our work highlights the fact that decision makers should be made more aware of the uncertainties surrounding prospective exercises and of the necessity of considering the global picture instead of asking for only one "holy" number. The computing power now available allows for the integration of more and more parameters in the models and for the evaluation of more and more scenarios. The focus should be directed on how to handle the scenarios and how to understand and interpret the results obtained with optimization under uncertainty methods.

In the first chapter of this thesis, we briefly outline the genesis of Integrated Assessment Models and how the modeling methodology has evolved since the end of World War II. After describing the main modeling paradigms, Chapter I focuses on the criticisms faced by IAMs: the models' high complexity (Kelly, D. L., & Kolstad, 1998, Henriet et al., 2014), their big size (Bhattacharyya and Timilsina, 2010), the validation issue (DeCarolis et al., 2012), the difficulty of working on disruptive scenarios (Ha-duong and Matarasso,

2006), the "hidden values" issue (Morgan and Henrion, 1990) and finally the principal reproach made to IAMs, uncertainty and its treatment by model users (Matarasso, 2003, Weitzman, 2009, Hedenus et al., 2013).
In chapter 2, we rekindle an old debate by questioning the impact of detailing a (sub)sector in a global energy-transportation model on the evaluation of mitigation policies. We choose to focus on the refining sector because (i) it is central for assessing decarbonization pathways in transport, since scenarios will always consist of reducing the *fossil fuel intensity* of transport, (ii) it is a relevant case of a sector for which representation widely differs across models and (iii) it offers a unique set of complex joint production in the energy sector. To investigate whether the level of detail in the refinery description impacts optimal mitigation options, we consider a long-term, national, linear-programming-based, energy transport system model (TIMES based). We find that the refinery description used in the energy system model does matter when trying to evaluate energy or climate policy applied to the transportation sector. It impacts the policy costs, but also the technology trajectories chosen at the optimum. Essentially, the balance between energy efficiency and carbon intensity of transport may be affected by the accuracy of the description of the *pivotal* refining sector. This proves that technology outlooks are critically dependent not only on the economic paradigms and input data, but also on the technical specifications of sectors. Hence, when scenarios are obtained with only partially adequate tools, the policy implications that follow are subject to a greater level of uncertainty. Consequently, increasing sectoral accuracy should be motivated by the wish to gain wider quantitative insights on potential evolution of the energy system and, above all, by the wish to improve the robustness of outcomes. When data is not available or when the modeling team does not possess the necessary competency to detail a sector, an extensive sensitivity analysis on the sectors' technical parameters becomes necessary.

Robust Optimization for climate and energy policy assessment
With chapter 2, the sensitivity of energy system models' outcomes to parameter values has been established. Moreover, it seems absolutely necessary to make uncertainty management a core feature of long-term, climate related policy analysis. Like Rozenberg (2014), we suppose that in the context of deep uncertainties, finding the optimal instrument is illusory but we try to bring to light methods that can inform robust decision-making frameworks for climate mitigation and energy policy.

Following chapter 2's conclusion, we chose to consider the aforementioned unknown parameters as uncertain and to transform the "lack of data/skills/time" initial problem into an uncertainty problem. It is this idea that led us to study and consider robust optimization (RO) to address the parameter uncertainty issue.
In Chapter 3 we use a model of the French energy system to identify relevant, cost-effective (/optimal) mitigation strategies in the transportation sector when the costs of future technologies and energy sources are uncertain. While cost assumptions are a cornerstone of technology-rich long-term models, the issue of uncertain cost projections is not frequently addressed in the literature. There are good reasons for that (large number

of costs, which would require high amounts of computations; lack of historical data to calibrate stochastic processes); nevertheless, there is a need to determine how optimal technological paths from a model are sensitive to these exogenous assumptions. By using robust optimization, we are able to introduce uncertainty simultaneously on a high number of cost parameters without notably impacting the computing time. Using MIRET, a French Times paradigm model, we introduce uncertainty on all the energy costs and on the investment costs of energy production and transportation which represent more than a hundred of parameters. To account for the very different nature of the uncertain parameters we model two different kinds of uncertainty, one that propagates itself overtime and a "spot uncertainty" close to volatility. We then apply this formal setting to a numerical experiment where we cross-test the impact of two fossil energy prices and two CO_2 emissions reduction targets. We show that the impact on the objective function ranges between 3 and 8%, depending on the level of uncertainty and the scenario we consider. This cost increase is due partly to technological substitutions that take place because the relative costs of technologies are modified by uncertainty introduction and partly to the fact that some technologies have no substitute, hence if their cost is modified, we have no other choice but to bear with it. As uncertainty increases, as does technology diversification to hedge against it. In the transportation sector, low-carbon alternatives (CNG, electricity) appear consistently as hedges against cost variations, along with biofuels. Yet, when "uncertainty" (what we call the uncertainty budget) is really high, the diversification strategy is not used anymore as all the cost parameters are likely to deviate (to increase). In that case, the relative costs of technologies are reestablished more or less like in the deterministic case.
Policy implications of diversification strategies are of importance; in that sense, the work undertaken here is a step towards the design of robust technology-oriented energy policies. To a certain extent, our results tend to illustrate the fact that under major uncertainty on technological progress, attention should be paid to a larger number of technologies and pathways.

In chapter 4, we study how uncertainties weighing on the climate system impact the optimal technological pathways the world energy system should take to comply with stringent mitigation objectives. As climate change is a recent and complicated field of research, the last decade has brought multiple answers regarding climate system evolution, but has also raised many new questions that still need to be addressed. The imperfect knowledge of global warming mechanisms and the large variety of IAMs lead the model users to reach conclusions that are sometimes very different. In the well-known Stern review (Stern, 2007), Stern advocates for immediate action to abate emissions basing his argumentation on the results of the PAGE model, yet Nordhaus reaches, with his DICE model, the conclusion that immediate and massive actions are not necessary and that a wait-and-see attitude makes sense from an economic point of view (Nordhaus, 2008).
In this study, we work with the TIAM-World model (Loulou, 2008) that relies on the TIMES modeling approach. Often used to analyze climate change policies or objectives,

this model contains a climate module inspired by the DICE model (Loulou et al., 2010). Using robust optimization techniques, we assess the impact of the climate system parameter uncertainty on energy transition pathways under 2 climate constraints (2°C and 3 °C). Unlike other studies (e.g., Syri et al., 2008, Labriet et al., 2015); we consider all the climate system parameters. This is of primary importance since (i) parameters and outcomes of climate models are all inherently uncertain (parametric uncertainty) and (ii) the simplified models at stake summarize phenomena that are by nature complex and non linear in a few, sometimes linear, equations so that structural uncertainty is also a major issue.
The use of robust optimization allows us to identify economic energy transition pathways under climate constraints for which the outcome scenarios remain relevant for any realization of the climate parameters. In this sense, scenarios/transition pathways are made robust. Moreover, with this methodology, we can identify which climate parameter or which combination of climate parameters are the most sensitive in our model, since they can be ranked based on their adverse effect on the climate dynamics and the emissions profiles, and we can also quantify the uncertainty cost. We find that the abatement strategies are quite different between the two temperature targets. For the 3 degrees one, both the carbon intensity and the primary energy intensity of the economy decrease with uncertainty while for the 2 degree target, the energy intensity increases and the carbon intensity decreases with uncertainty on climate parameters. This stringent goal is reached by investing massively in carbon removal technologies such as bioenergy with carbon capture and storage (BECCS) which have yields much lower than traditional fossil fueled technologies. Another interesting fact of the 2°C hedging trajectories is the drastic increase of the nuclear electricity production. The massive use of nuclear or carbon removal technology is highly uncertain, if not unrealistic, as BECCS is a very expensive technology that is not competitive in the absence of a high CO_2 price while the development of the nuclear industry could be hampered by social acceptance issues.

The last chapter of this thesis is quite different from the others. Having realized in chapter 4 that ambitious climate targets were met in TIAM by using technologies allowing negative carbon emissions (power plants powered with biomass followed by Carbon Capture and Storage), we look more deeply in the mitigation literature to find that these technologies are extensively used in most studies and particularly in the IPCC reports. Yet, the uncertainties surrounding the implementation and development of BECCS are huge and very diverse: technological, agricultural, societal. In this chapter we try to highlight the main obstacles that could hamper BECCS development and that could forbid humanity to reach ambitious mitigation objectives. Then using EPPA, the computable general equilibrium (CGE) model of MIT, we try to assess BECCS potential and its sensitivity to the uncertainties previously identified. We find that the most sensitive parameters for BECCS deployment in EPPA are the ones linked to biomass availability and CCS cost. We also find negative CO_2 emissions around 40 Gton/yr in 2100 which is in the high range of the other IAM estimates.

Bibliography

Andrey, C., Babonneau, F., Haurie, A., Labriet, M., 2015. Modélisation stochastique et robuste de l'atténuation et de l'adaptation dans un système énergétique régional. Application à la région Midi-Pyrénées. Natures Sciences Sociétés 23 (2), 133–149.

Babonneau, F., Kanudia, A., Labriet, M., Loulou, R., Vial, J.-P., jul 2011. Energy Security: A Robust Optimization Approach to Design a Robust European Energy Supply via TIAM-WORLD. Environmental Modeling & Assessment 17 (1-2), 19–37.

Babonneau, F., Vial, J.-P., Apparigliato, R., 2010. Robust Optimization for Environmental and Energy Planning. In: Filar, J., Haurie, A. (Eds.), Uncertainty and Environmental Decision Making, internatio Edition. Vol. 138. Springer, Ch. 3, p. 370.

Ben-Tal, a., Goryashko, A., Guslitzer, E., Nemirovski, A., mar 2004. Adjustable robust solutions of uncertain linear programs. Mathematical Programming 99 (2), 351–376.

Ben-tal, A., Hertog, D. D., Vial, J.-P., 2012. Deriving robust counterparts of nonlinear uncertain inequalities.

Ben-tal, A., Nemirovski, A., 2000. Robust solutions of Linear Programming problems contaminated with uncertain data. Mathematical Programming 88 (3), 411–424.

Ben-tal, A., Nemirovski, A., 2002. Robust Optimization — Methodology and Applications. Mathematical Programming 92 (3), 453–480.

Bertsimas, D., Brown, D. B., Caramanis, C., 2010. Theory and applications of Robust Optimization. SIAM Review 53 (3), 464–501.

Bertsimas, D., Sim, M., feb 2004. The Price of Robustness. Operations Research 52 (1), 35–53.

Bhattacharyya, S. C., Timilsina, G. R., 2010. A review of energy system models. International Journal of Energy Sector Management 4 (4), 494–518.

Clarke, L., Jiang, K., Akimoto, K., Babiker, M., Blanford, G., Fisher-Vanden, K. Hourcade, J.-C., Krey, V., Kriegler, E., Löschel, McCollum, D., Paltsev, S., Rose, S., Shukla, P. R., Tavoni, M., van der Zwaan, B. C. C., van Vuuren, D., 2014. Assessing Transformation Pathways. In: Climate Change 2014: Mitigation of Climate Change. Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change, cambridge Edition. Cambridge, United Kingdom and New York, NY, USA, Ch. 6, WP3.

Coase, R. H., 1960. The Problem of Social Cost. Journal of Law and Economics 3, 1–44.

Daly, H., 1972. In defense of a steady-state economy. American Journal of Agricultural Economics (54), 945–954.

Daly, H., 1974. The economics of the steady state. American Economic Review 2 (64), 15–21.

Daly, H., 1977. Steady-State Economics. Freeman, San Francisco.

DeCarolis, J. F., Hunter, K., Sreepathi, S., 2012. The case for repeatable analysis with energy economy optimization models. Energy Economics 34 (6), 1845–1853.

El Ghaoui, L., Oustry, F., Lebret, H., 1998. Robust solutions to uncertain semidefinite programs. Society for Industrial and Applied Mathematics 9 (1), 33–52.

Ha-duong, M., Matarasso, P., 2006. Comment intégrer l'économie , l'énergie et le climat ? 52, 92–97.

Hartwick, J. M., 1977. Intergenerational equity and the investing of rents from exhaustible resources. American Economic Review 5 (67), 972–974.

Hartwick, J. M., 1978. Substitution among exhaustible resources and intergenerational equity. Review of Economic Studies (45), 347–354.

Heal, G., Millner, A., 2014. Reflections: Uncertainty and decision making in climate change economics. Review of Environmental Economics and Policy 8 (1), 120–137.

Hedenus, F., Johansson, D., Lindgren, K., 2013. A Critical Assessment of Energy-economy-climate Models for Policy Analysis. Journal of Applied Economics and Business Research 3 (2), 118–132.

Henriet, F., Maggiar, N., Schubert, K., 2014. A stylized applied energy-economy model for france.

Hu, Z., Cao, J., Hong, L. J., 2012. Robust Simulation of Global Warming Policies Using the DICE Model. Management Science 58 (December 2012).

Kelly, D. L., & Kolstad, C. D., 1998. Integrated assessment models for climate change control. International yearbook of environmental and resource economics (November 1998), 171–197.

Kunreuther, H., Gupta, S., Bosetti, V., Cooke, R., Dutt, V., Duong, M. H., Held, H., Llanes-Regueiro, J., Patt, A., Shittu, E., Weber, E., 2014. Integrated Risk and Uncertainty Assessment of Climate Change Response Policies. Climate Change 2014: Mitigation of Climate Change, contribution of Working Group III to the IPCC Fifth Assessment Report, 151–206.

Labriet, M., Loulou, R., Kanudia, A., nov 2010. Uncertainty and Environmental Decision Making. Vol. 138 of International Series in Operations Research & Management Science. Springer US, Boston, MA.

Labriet, M., Nicolas, C., Tchung-Ming, S., Kanudia, A., Loulou, R., 2015. Energy decisions in an uncertain climate and technology outlook : how stochastic and robust analyses can assist policy-makers. In: Giannakidis, G., Labriet, M., Gallachóir, B. Ó., Tosato, G. (Eds.), Informing energy and climate policies using energy systems models, springer s Edition. Springer, Ch. 03.

Loulou, R., 2008. ETSAP-TIAM: the TIMES integrated assessment model. part II: mathematical formulation. Computational Management Science, 5 (1), 41–66.

Loulou, R., LEHTILA, A., Labriet, M., 2010. TIMES Climate Module (Nov. 2010). TIMES Version 2.0 User Note (November).

Matarasso, P., 2003. Les origines des méthodes de modélisation dans le champs du changement climatique. In: Workshop Centre Alexandre Koyré "Modèles et systèmes complexes, le changement climatique global ".

McGlade, C., Ekins, P., jan 2015. The geographical distribution of fossil fuels unused when limiting global warming to 2 C. Nature 517 (7533), 187–190.

Michl, T., 2008. Discounting Nordhaus.

Morgan, M., Henrion, M., 1990. Uncertainty: a guide to dealing with uncertainty in quantitative risk and policy analysis, cambridge Edition. Cambridge.

Nordhaus, W. D., 1991. To slow or not to slow: The economics of the greenhouse effect. ,. The Economic Journal 101 (407), 920–937.

Nordhaus, W. D., 2008. A Question of Balance: Weighing the Options on Global Warming Policies. Vol. 87.

Pearce, D., 1991. The Role of Carbon Taxes in Adjusting to Global Warming. The Economic Journal 101 (407), 938–948.

Pigou, A., 1932. The economics of welfare. Macmillan and Co., London.

Pindyck, R. S., 2013. Climate Change Policy : What Do the Models Tell Us ? Journal of Economic Literature 51, 860–872.

Pottier, A., 2014. L'économie dans l'impasse climatique. Ph.D. thesis.

Rozenberg, J., 2014. Eléments sur la robustesse des politiques climatiques. Ph.D. thesis, Ecole des Hautes Etudes en Sciences Sociales.

Solow, R., 1974. Intergenerational equity and exhaustible resources. Review of Economic Studies (14), 29–45.

Solow, R., 1986. On the intergenerational allocation of natural resources. Scandinavian Journal of Economics 1 (88), 141–149.

Soyster, L. A., 1973. Convex Programming with Set-Inclusive Constraints and Applications to Inexact Linear Programming. Operations Research 21 (5), 1154–1157.

Stern, N., 2007. The Economics of Climate Change: The Stern Review. Cambridge University Press.

Syri, S., Lehtila, A., Ekholm, T., Savolainen, I., Holttinen, H., Peltola, E., feb 2008. Global energy and emissions scenarios for effective climate change mitigation—Deterministic and stochastic scenarios with the TIAM model. International Journal of Greenhouse Gas Control 2 (2), 274–285.

Vieille Blanchard, É., 2011. Les limites à la croissance dans un monde global. Ph.D. thesis.

Vogt-schilb, A., 2015. Eléments sur la transition vers du capital bas carbone Essays on the transition to clean capital par. Ph.D. thesis, Paris Est.

Weitzman, M. L., 2009. On modeling and interpreting the economics of catastrophic climate change. The Review of Economics and Statistics 91 (February), 1–19.

Wets, J., 1989. Stochastic programming. Elsevier Science Publishers B.V., Nort Holland.

1 Modeling the future: from "*Limits to Growth*" to the actual Integrated Assessment Modeling

Depuis le fameux rapport du Club de Rome (1972) jusqu'à la période actuelle, il y a eu abondance de travaux sur les modèles d'aide à la décision en matière de politiques énergétique et climatique. L'utilisation de ces grands modèles énergie-économie ou de modèles d'évaluation intégrée (énergie-économie-climat) est en constante augmentation avec une tendance à leur complexification pour mieux répondre à la connaissance de la réalité géographique ou sectorielle sans cesse affinée.
Plusieurs facteurs concomitants ont favorisé l'utilisation de ce type de modèles, que nous décrirons plus longuement par la suite. En premier lieu, la naissance de la prospective après la seconde guerre mondiale, de manière presque simultanée aux Etats-Unis (Rand Corporation, Hudson Institute) et en France (Centre d'Etudes Prospectives de Gaston Berger) avec des divergences toutefois sur les finalités: aux Etats-Unis les premiers travaux, centrés sur les sciences et la technologie, ont comme principal financeur le complexe militaro-industriel, alors qu'en France ils s'inscrivent dans un but de planification. Plus globalement, la discipline va se professionnaliser, s'institutionnaliser et asseoir ses principes méthodologiques en s'organisant sur des bases scientifiques. Ce qui l'amène à s'éloigner des démarches antérieures: au lieu de postuler le prolongement des tendances passées, elle va travailler sur le long-terme et tenter d'étudier les transformations technologiques et sociétales profondes. La prospective va, en outre, bénéficier de l'apparition d'une science des systèmes complexes qui permet de mieux représenter les nombreuses interactions et rétroactions entre énergie, économie et climat.
Depuis leur émergence, ces modèles ont grandement évolué tant sur le plan méthodologique que sur les domaines d'application qu'ils englobent. Dans le cadre du Groupement Intergouvernemental d'Etudes sur le Climat (GIEC), l'utilisation de modèles a pour mérite d'assurer la cohérence des scénarios du futur en offrant un cadre global. Que les modèles soient utilisés comme outils de simulation, pour explorer les futurs possibles, ou comme outils d'optimisation, pour trouver la meilleure politique à adopter en vue d'atteindre un objectif climatique ou énergétique, leurs résultats permettent de fournir des « insights »

(connaissances, idées) sur le comportement des systèmes et de repérer des phénomènes peu intuitifs et difficilement envisageables lorsque l'on se repose uniquement sur des « modèles mentaux ».
Si la démarche sous-jacente à la création de modèles est très « scientifique », il est nécessaire de souligner qu'ils reposent sur des hypothèses fortes (des valeurs) que l'on ne peut ignorer lors de l'analyse des résultats. En effet, nombre de présupposés du modèle comme des choix de modélisation renvoient à la vision sociétale des utilisateurs. Le taux d'actualisation en est une parfaite illustration car il ne saurait avoir de valeur unique, admise par tous. Or cette valeur, impactant notablement le résultat des modèles, reflète un choix en matière d'équités intra et intergénérationnelle; et c'est là un des principaux sujets de discorde soulevés par le « problème climatique ».
Cette remarque en appelle une autre : si le nombre de modèles et de modélisateurs est en constante progression, les critiques n'épargnent pas la démarche elle-même. On lui reproche de ne pas suffisamment considérer les incertitudes qui entourent de nombreux paramètres et hypothèses du modèle. Et lorsque l'on tente de prendre en compte ces incertitudes, la méthode n'apparaît pas non plus exempte de défauts et soulève de nouvelles critiques. Cela fait dire à certains économistes et scientifiques que l'utilisation de ce type de modèles n'est pas appropriée pour traiter du changement climatique et qu'il serait plus raisonnable de revenir à des approches (ou des modèles) plus simples (Pindyck, 2013).

Nous tenterons ici de montrer que les modèles énergie-économie ou énergie-économie-climat permettent d'enrichir l'information des acteurs économiques et institutionnels en leur offrant un outil d'aide à la décision et ce malgré l'incertitude qui pèse sur les résultats fournis par les exercices de modélisation. Cela suppose sans doute un changement des pratiques avec une prise en compte bien plus systématique de l'incertitude lors de la présentation des résultats des modèles. Nous tenterons d'explorer les différentes manières d'envisager cette réalité, tout en soulignant sa nature protéiforme qui oblige à adapter les outils utilisés pour son traitement.

Dans un premier temps, nous reviendrons sur la genèse des modèles énergie-économie mais surtout des modèles énergie-économie-climat, communément appelés modèles d'évaluation intégrée (MEIs). Nous décrirons ensuite ces modèles avant d'expliciter les principales critiques qui leur sont attribuées en insistant sur la plus récurrente d'entre elle : le traitement de l'incertitude, quant aux autres objections, nous leur apporterons une réponse rapide. Et pour terminer ce chapitre introductif, nous interrogeons les pratiques qui permettraient de dépasser le débat sur l'utilité des modèles.

1.1 L'après-guerre : terreau fertile pour la prospective et la modélisation

[1]

Les modèles d'évaluation intégrée, largement utilisés pour traiter des questions de politique climatique ou énergétique, ont connu un développement intensif durant les quarante dernières années. De nombreux auteurs (Vieille Blanchard (2011), Hedenus et al. (2013), Bhattacharyya and Timilsina (2010),. . .) attribuent à la démarche de modélisation du Club de Rome la paternité de ces modèles globaux.
En effet, si le rapport du Club de Rome de 1972, entre catastrophisme écologique de l'époque et approche gestionnaire de la prévision technologique, fut largement critiqué ; il est cependant à l'origine de nombreuses démarches de modélisation tentant de répondre aux questions "Quel type de croissance peut-on souhaiter/réaliser?" et "Comment l'obtenir?".

1.1.1 Limits to growth : à l'origine de la démarche prospectiviste?

1945-1970 : une destinée prométhéenne pour l'humanité ?
A la suite de la seconde guerre mondiale, les transformations politiques et les avancées technologiques telles que la bombe atomique, le nucléaire civil ou encore l'usage intensif des pesticides entrainent l'émergence d'une vision catastrophiste du futur aussi bien parmi les scientifiques que dans la population occidentale et plus particulièrement américaine. C'est d'ailleurs la crainte du danger atomique qui serait à l'origine du développement de la pensée écologique (Le Bras, 1994). L'utilisation d'un arsenal nucléaire fut en effet critiquée à la fois par une partie des scientifiques du projet Manhattan[2] et par la population. L'institutionnalisation de cette critique avec la création du « Comittee for Nuclear Information » par Barry Commoner en 1958 et la pression de l'opinion publique forcent, en août 1963, les Etats-Unis à adopter le « Test Ban Treaty » interdisant les essais nucléaires dans l'atmosphère.
Pour Vieille Blanchard (2011), le deuxième point à l'origine du catastrophisme de la période 1945-70 est d'ordre démographique. Apparaît en effet au sortir de la guerre un courant de pensées pour lequel les ressources limitées que la planète est capable de fournir ne suffiront bientôt plus à nourrir la population en croissance exponentielle. Aux Etats-Unis Julian Huxley le premier Directeur Général de l'UNESCO, Fairfield Osborn, directeur de la Société Zoologique de New York et William Vogt, écologue de formation et auteur de *La Faim du monde* (*Road to Survival*, 1948) sont les chefs de file de ce courant (Vieille Blanchard, 2011 p58-60). Ils s'opposent à l'optimisme régnant alors dans les agences onusiennes qui ont foi dans le progrès technologique et annoncent une « révolution verte » capable d'accompagner la croissance démographique grâce à l'augmentation substantielle des rendements agricoles. C'est à cette période que naissent les politiques

[1] Cette section repose en partie sur le travail de thèse d'Elodie Vieille Blanchard (Élodie Vieille Blanchard, *Les Limites À La Croissance Dans Un Monde Global*, 2011).

[2] « Projet Manhattan » est le nom de code du projet de recherche à l'origine de la première bombe atomique durant la Seconde Guerre mondiale. Il fut mené par les États-Unis avec la participation du Royaume-Uni et du Canada.

visant à favoriser le contrôle des naissances et qu'apparaissent les plannings familiaux. Allant de pair avec la hantise d'une surpopulation planétaire, les craintes liées à la croissance exponentielle de la pollution font leur apparition. « Silent Spring » publié en 1962 par Rachel Carson dénonce la contamination de l'environnement par les produits chimiques (DDT, insecticides...) et lance l'alerte sur les dangers potentiels pour le devenir de l'humanité.
La fin des années 60 aux Etats-Unis est ainsi marquée par des discours catastrophistes quant à la survie de l'espèce humaine et sur la nécessaire intégration des questions liées aux ressources et à l'environnement pour son développement futur.

Dans le même temps, certains économistes développent un courant de pensée, dit hétérodoxe, militant pour une autre façon d'aborder leur discipline en s'inspirant de modèles thermodynamiques. Trois des grandes figures de ce mouvement, Georgescu-Roegen [3], Boulding [4] et Daly [5] réfutent le fait que la crise écologique puisse être réglée à l'aide d'instruments juridiques ou fiscaux dans la mesure où ces derniers ne permettent pas d'influer sur les raisons profondes de la crise : l'organisation sociale ou les processus de production (Vieille Blanchard, 2011 p194). Les modèles inspirés de la physique permettent d'intégrer, entre autres, les problèmes d'irréversibilité et les effets retards (décalage temporel) des phénomènes naturels et autorisent une meilleure représentation de la complexité des écosystèmes et de leur réaction à des sollicitations anthropogéniques.

Développement d'une "futurologie" (étude du futur)
Parallèlement à ces deux tendances, on observe alors l'essor d'une science du futur qui ne s'appelle alors pas encore prospective. Cette science, avant tout au service du développement technologique aux Etats-Unis[6], a une visée plus philosophique et normative en Europe. En France, l'approche est plus humaniste et sociétale et trouve ses racines dans l'anticipation littéraire chère à H. G. Wells.

Ainsi, Gaston Berger et Bertrand de Jouvenel proposent une approche visant à appréhender les futurs possibles et à déterminer quels choix nous conduiraient vers un futur porteur de sens (vision normative). Berger est souvent présenté comme le fondateur de la prospective qu'il envisage comme une science de l'anticipation d'un avenir qui serait « moins à découvrir qu'à inventer ». Constatant que la mutation du monde s'accélère et introduit de vraies ruptures avec les tendances passées, Berger plaide pour une modification de la façon d'appréhender l'avenir : il faudrait moins faire appel à des démarches telles que l'analogie et l'extrapolation et plus se servir de ce qu'il appelle l'imagination créatrice

[3] The Entropy Law and the Economic Problem, 1970 et Energy and Economic Myths, 1975
[4] The economics of the coming spaceship Earth, 1966
[5] Toward a stationary-state economy, 1971
[6] La RAND Corporation a été originellement créée en 1946 sous l'impulsion d'un général afin d'étudier et de comparer des options technologiques et stratégiques en matière de politique de défense (Vieille Blanchard, 2011 , p294)

quand on envisage l'action[7]. Cela implique d'avoir clairement identifié la finalité de nos actions et de réussir à penser l'avenir comme la résultante de nos agissements présents et en l'affranchissant du poids du passé (Berger et al., 1967). De la même manière Bertrand de Jouvenel, le fondateur de la revue « Futuribles », se réfère à la nécessité d'envisager l'avenir de manière très libre, en usant d'imagination pour considérer un grand nombre de futurs possibles.
Si les approches françaises sont moins technologiques et scientifiques que celles développées aux US, elles ne considèrent pas pour autant la technologie uniquement sous l'angle de la menace mais elles y voient aussi une source potentielle de progrès pour l'humanité. Aux États-Unis, la pratique de modélisation évolue pour intégrer peu à peu des questions sociales dans les modèles technologiques (à l'instar du Hudson Institute). Cependant cet outil se soucie encore assez peu de réalisme. Ainsi, un rapport du Hudson Institute dans le cadre de la "Commission de l'an 2000" décrira un futur post-industriel idéalisé où le travail a largement cédé la place aux loisirs et où problèmes énergétiques et problèmes de pollution ont été résolus.
C'est dans ce contexte scientifique et social que l'entreprise du Club de Rome est initiée par Aurelio Peccei à la fin des années 1960.

1.1.2 Le Club de Rome

Industriel italien, Peccei a participé après la guerre à la reconstruction de plusieurs entreprises nationales en travaillant en particulier pour Fiat et Allitalia. Non content de ses succès dans le domaine, il s'implique dans divers groupes de rencontre politiques et c'est grâce à l'un d'eux qu'il a l'occasion de connaître Alexander King en 1967. Les deux hommes s'accordent sur la nécessité de promouvoir la planification de long terme (*longer-range thinking*) auprès des gouvernements occidentaux. Rapidement ils sont rejoints par un petit groupe d'industriels et de politiques européens réunis autour de trois concepts : une perspective globale, le long terme et la « Problématique », un réseau de problèmes intrinsèquement liés et qui menacent l'avenir de l'humanité (« the cluster of interwined problems»). Le questionnement du Club de Rome ne porte pas dans un premier temps sur une cible unique: comment pallier le déséquilibre écologique du système planétaire et comment réduire le fossé technologique qui se creuse entre US et Europe sont deux des questions qui préoccupent majoritairement le Club. Afin de traiter ces problèmes, les participants du Club de Rome s'entendent sur la nécessité de mettre en place une approche systémique, globale et qui place l'industrialisation au cœur de la démarche (en tant qu'élément producteur d'externalités négatives).

C'est Hasan Ozbekhan, un scientifique turc travaillant sur la théorie des systèmes qui, en rejoignant le Club de Rome, allait préciser la démarche scientifique qui conduirait au

[7] Il s'écarte ainsi d'une tradition envisageant le monde comme donné et inchangeable, tradition dont fait partie Auguste Comte (« Savoir pour prévoir afin de pouvoir.»). En effet, si c'est le cas, à quoi bon agir puisque « tout » est prédéterminé tandis que si l'on peut agir, la prédiction perd de son intérêt puisqu'elle sera invalidée dès lors que l'action aura lieu. (http://philippesilberzahn.com/2011/11/07/gaston-berger-prospective-pourfendeur-prevision/)

rapport des « Limits ». Il recommande un traitement normatif de l'avenir en utilisant des outils de planification issus de la théorie des systèmes. Toutefois contrairement à ce qui se fait dans l'industrie, il préconise de ne pas mettre la technologie au centre des modèles mais d'y placer plutôt des concepts écologiques afin de considérer l'ensemble des faits humains « comme un écosystème unique » (Ozbekhan, 1969 p.146.). Son ambition est alors « d'examiner, aussi systématiquement que possible, la nature et la configuration des profonds déséquilibres qui définissent la problématique d'aujourd'hui [...], et de tenter de déterminer la dynamique des interactions qui semblent exacerber la situation » (Ozbekhan for The Club of Rome, 1970 p.9). En revanche, son ambition initiale est bien plus large que ce que le modèle finalement retenu, celui de Jay Forester, permettra de faire. Il aurait souhaité un modèle modulable et malléable dans lequel la structure soit tout autant modifiable que les paramètres, et souhaitait une refonte globale de l'exercice de modélisation.

La complexité de la chose ainsi que les contraintes temporelles conduisent le Club de Rome à préférer le modèle déjà existant « World » de Jay Forrester . Ce modèle, qui sera amélioré et détaillé par l'équipe de Dennis Meadows suite au retrait du projet de Forrester, est un modèle de dynamique des systèmes[8] qui permet de simuler les interactions entre population, capital industriel, pollution, ressources, production alimentaire et écosystèmes. Le monde est modélisé dans son ensemble. Chacune des variables est donc censée représenter la variable agrégée mondiale et l'horizon temporel des simulations est lointain (2100). Sobrement intitulé World3, car il fait suite au modèle World2 de Forrester, ses résultats serviront à l'élaboration du fameux rapport « *The limits to growth* » vendu à 3 millions d'exemplaires (Halte à la croissance! en français).

The limits to growth: le modèle

Le paradigme de modélisation choisi, les liens établis entre l'évolution de la pollution et le taux de mortalité ou encore entre la raréfaction des ressources et le niveau de vie ont pour conséquence que les simulations de World3 aboutissent aux mêmes résultats par des cheminements similaires : le système croit avant de s'effondrer à cause de la pollution ou de l'épuisement des ressources (« *overshoot and collapse* »). Les variantes effectuées sur les hypothèses technologiques ne permettent que de repousser l'effondrement du système. Cela amène l'équipe à envisager des scénarios en rupture totale avec les politiques de l'époque en ce qu'ils intègrent des hypothèses de croissance nulle de la population et de la production industrielle. A ce prix, l'effondrement du système est évité. C'est cette hypothèse qui sera largement médiatisée lors de la parution du rapport « *The limits to growth* » qui plaide pour une stabilisation de la richesse et de la population mondiale au prétexte que les ressources de la planète sont finies et que celle-ci n'est pas capable « d'absorber » sans dommage n'importe quel niveau de pollution. La revendication d'une croissance nulle va entrainer de la part d'économistes et de politologues de virulentes

[8] La dynamique des systèmes est une approche faisant partie de la théorie des systèmes qui vise à comprendre le comportement des systèmes complexes dans le temps. Le système est représenté par un ensemble d'éléments reliés par des boucles de rétroactions et dont l'évolution est décrite par des équations récursives en temps discret.

critiques, portant en particulier sur l'entreprise de modélisation, et un rejet du rapport et de la méthodologie.
La première critique porte sur l'absence de représentation de l'économie : contrairement aux modèles précédemment utilisés, les prix sont absents du modèle qui n'intègre pas de calage économétrique ni de prise en compte du marché et de ses « vertus » équilibrantes (qui permettraient d'encourager les substitutions aux matières premières via un enchérissement de celles-ci). La deuxième critique met en cause une vision pessimiste du progrès technique. Alors que la croissance de la population et de la production sont modélisées de manière exponentielle, le progrès technique reste lui linéaire. Par ailleurs, la découverte de nouvelles ressources n'est pas envisagée.
Enfin, le dernier point technique souvent évoqué porte sur le type de modélisation retenu. Contrairement à un modèle de contrôle optimal où des décisions peuvent venir modifier les trajectoires (et témoignent de la capacité à s'adapter de l'humanité), World3 ne permet pas de prendre en compte un éventuel infléchissement politique (Matarasso, 2003).
Sur le plan conceptuel la posture des modélisateurs, élite des pays industrialisés qui prétend dicter le bon fonctionnement du monde selon Simmons (1973), est vivement dénoncée. Le choix de modéliser le monde comme un tout est aussi lourd de conséquences car il omet le problème de la répartition des richesses et donc de la réduction (ou de l'accroissement) des inégalités (Galtung, 1973).
Pour finir, Kaysen (1972) dans son article sobrement intitulé « Le modèle qui criait au loup » de 1972 dénonce l'opacité entrainée par le recours à la modélisation, qui selon lui permet d'occulter son véritable dessein : traiter des problèmes des « riches » et rendre objectives des recommandations somme toute très politiques.

Limits to Growth : un impact politique varié
Aux Etats-Unis et au Royaume-Uni, le rapport est vite relégué au second rang et la nécessité de voir la croissance perdurer n'est pas mise en doute. En revanche, dans le reste de l'Europe, la lettre de Mansholt[9] a une portée retentissante (en particulier du côté des communistes). Le rapport et la lettre entrainent de vives discussions au sein des différentes formations politiques européennes, qui ne perdurent pas après 1972.

1.1.3 Une autre croissance?

A partir de là, le débat sur la croissance perd son caractère manichéen. Emerge alors l'idée de croissance durable, entretenue par les modèles qui voient le jour en réponse à World3. Les questions que ces derniers sont tenus de résoudre ne sont plus: la croissance est-elle viable? mais plutôt: quel type de croissance souhaitons-nous? ou Comment intégrer les écosystèmes dans le système productif? Différents modèles construits afin de répondre aux critiques soulevées par celui du Club de Rome sont alors développés au

[9]Le Néerlandais Sicco Mansholt membre de la Commission Européenne écrit en février 1972, en s'inspirant des travaux du Club de Rome, au président de la Commission une lettre où il propose d'élaborer une politique planifiée de décroissance matérielle. Cette lettre connaîtra la célébrité grâce au Parti Communiste Français, Mansholt sera d'ailleurs élu président de la Commission mais ne parviendra pas à mettre ses idées en application.

milieu des années 70.
Ainsi, le Club de Rome lui-même commande une étude alternative à Mihajlo Mesarovic et Eduard Pestel visant à prendre en compte les disparités régionales en utilisant un modèle désagrégé. Parmi la dizaine de modèles qui voit le jour dans le sillage de World3, on peut mentionner celui de la fondation Bariloche, dont l'ambition est de prendre en compte les disparités Nord-Sud et de faire entendre la voix des pays non-industrialisés ou encore le modèle input-output créé par Wassily Leontief (1977) pour le compte de l'ONU pour évaluer le réalisme des objectifs de développement[10]. Tous ces modèles ont des structures très différentes mais la même vocation : influencer les décisions politiques (Vieille Blanchard, 2011 p524).
A mesure que les années passent et que se profilent les années 80, les modèles deviennent de plus en plus désagrégés régionalement et sectoriellement, ils intègrent de plus en plus de méthodes issues de la théorie économique classique et pour certains, l'horizon temporel se réduit. Parallèlement, les questions qu'ils sont censés traiter évoluent aussi : de questions très larges ayant trait à la survie de l'humanité (en caricaturant à peine), on passe à des demandes beaucoup plus précises (ibid, p526). Au début des années 1990, il ne reste plus grand-chose des modèles développés en réponse à la publication de « The limits to growth ». Sur une vingtaine recensés en 1981 par l'IIASA (International Institute for Applied Systems Analysis), plus de la moitié ont disparu cinq ans plus tard.

L'émergence des modèles d'évaluation intégrée
En parallèle, de nouveaux paradigmes de modélisation globale émergent au sein de la Cowles fondation ou de l'IIASA. C'est après un passage dans la fondation Cowles à la fin des années 1960 qu'Alan Manne va mettre en place ce qui deviendra le modèle MARKAL en s'appuyant sur le cadre de l'analyse d'activités[11] développé à la fondation par Koopmans entre autres. Le secteur énergétique de MERGE est lui aussi créé sur la base de l'analyse d'activités tandis que le second cadre théorique développé à la fondation, celui de la croissance optimale, est la clé de voûte du fonctionnement global de MERGE (ainsi que de DICE, le modèle de Nordhaus, et de MARKAL-MACRO). On détaillera le fonctionnement de ces modèles dans la partie suivante.
DICE, créé en réaction à World3 dont Nordhaus était un virulent détracteur, voit le jour en 1992 à l'issu d'un long processus de développement. Après avoir écrit divers articles pour déconstruire les conclusions du rapport des Limites (Nordhaus and Tobin, 1972, Nordhaus, 1973), Nordhaus entreprit de construire un modèle alternatif qui échapperait aux travers de celui de Forrester. C'est après un séjour à Vienne à l'IIASA qu'il

[10] Leontief, Wassily, Carter A. et Petri P., The Future of the World Economy, Oxford University Press, New York (1977).

[11] En 1937 Von Neumann introduit une représentation de la production dans laquelle un nombre fini de processus de production distincts, caractérisés chacun par des proportions constantes d'input et d'output, peuvent se conjuguer pour produire un ensemble de demandes de biens ou services. Cette représentation est fondée sur deux nomenclatures, une nomenclature de « biens » et une nomenclature « d'activités ». Elle possède trois aspects absolument fondamentaux : (i) alternatives de production (plusieurs processus pouvant produire les mêmes biens, (ii) productions jointes, (iii) comptabilisation des productions en unités physiques (Matarasso, 2001).

développe son premier modèle destiné à traiter du réchauffement climatique (Nordhaus, 1977). Dans ce modèle, il amende un module originellement créé pour optimiser la production énergétique en y ajoutant des sources d'émissions de CO_2. Le modèle fournit la manière optimale de répondre à une demande en énergie tout en respectant une contrainte sur les émissions de CO_2 (modèle coût efficacité). Poursuivant ses recherches, Nordhaus améliore encore son outil en y intégrant cette fois l'impact de la hausse des émissions de CO_2 sur l'économie (modèle coût-bénéfice, Nordhaus, 1980) pour finalement aboutir en 1992 à la première version de DICE (*Dynamic Integrated Climate Economy model*) qui contient en sus un module climatique (Nordhaus, 1992).
La prise en compte progressive du changement climatique dans les modèles de Nordhaus reflète plus largement la lente sensibilisation collective à ce problème. Ainsi à l'instar de DICE, les modèles d'évaluation intégrée des années 90 englobent l'ensemble de la chaîne causale responsable du réchauffement planétaire (allant de l'activité humaine à la hausse de la température à l'impact de cette dernière sur l'économie).

En 1995, le GIEC (Groupe d'experts Intergouvernemental sur l'Evolution du Climat) recense 22 modèles d'évaluation intégrée (MEIs) dans la lignée de celui de Nordhaus. Ces modèles n'ont pas pour la plupart vocation à répondre à des questions aussi larges et ambitieuses que celles auxquelles s'attaquait le Club de Rome. La nécessité de la croissance est une hypothèse préalable à la grande majorité des MEIs, sa soutenabilité et les conditions de sa réalisation étant des sujets d'étude. Ainsi il n'est plus besoin ni question d'envisager de rupture sociétale très forte pour éviter un effondrement de la civilisation ou une auto-asphyxie de l'humanité puisqu'on suppose ex-ante qu'un arrêt de la croissance entrainerait de facto des pertes de bien-être nettement plus importantes que ne pourrait le faire la pollution. Seul un petit nombre de chercheurs, les économistes de l'écologie, continue à se pencher sur ces questions et à appeler à une refonte des interactions entre l'Homme et son environnement.

Pour conclure cette brève rétrospective, on peut souligner le fait que les modèles utilisés aujourd'hui pour la prospective climatique ou énergétique ont certes de nombreux points communs avec l'approche du Club de Rome : la pollution est traitée comme un problème mondial, le système planétaire est considéré comme interdépendant, la nécessité de traiter les grands problèmes humains avec des outils d'analyse et de planification et la nécessité de l'interdisciplinarité pour traiter ces problèmes sont posées comme préalables. Mais ils ont aussi des différences notables en particulier au niveau du paradigme de modélisation. Les modèles récents sont tous basés sur la théorie économique classique avec le présupposé que l'économie est en mesure de régler les problèmes énergétiques et climatiques qui se posent à l'humanité. Ces modèles développés dans les années 1990 ont une longue postérité puisque les plus connus sont encore très largement utilisés (Dice, Markal, Merge). Pour autant, ils n'échappent pas aux critiques et aux controverses ce qui témoigne, une fois de plus, du caractère profondément politique du travail de modélisation.

Avant de nous intéresser aux reproches formulés à l'encontre des MEIs, nous allons décrire cet objet composite, à la croisée de diverses disciplines.

1.2 Les modèles d'évaluation intégrée (MEIs)

La définition de l'évaluation intégrée est relativement large. D'après le GIEC : « Assessment is integrated when it draws on a broader set of knowledge domains that are represented in the research product of a single discipline. Assessment is distinguished from disciplinary research by its purpose: to inform policy and decision making, rather than advance knowledge for its intrinsic value" (Weyant et al., 1996). Les MEIs, formulés en mêlant les approches théoriques et analytiques de différentes disciplines scientifiques (climatologie, océanographie, économie, sociologie, sciences de l'ingénieur, mathématiques appliquées, écologie...), ont, entre autres, pour vocation de comprendre les mécanismes du changement climatique anthropogénique. Pour ce faire, ils tentent de représenter au mieux la chaîne causale qui part de l'activité humaine (système énergétique et transport) et qui va jusqu'au changement climatique en passant par les émissions de gaz à effet de serre (GES, voir figure 1.1). Certains modèles vont plus loin et visent à modéliser l'impact physique, économique et sociologique du changement climatique (Ambrosi and Courtois, 2004).

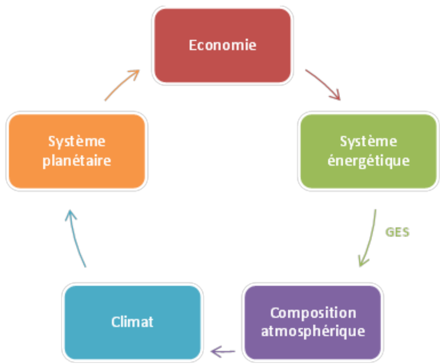


Figure 1.1: Les différentes composantes possibles des MEIs

La diversité des modèles d'évaluation intégrée permet de répondre aux multiples ambitions de celle-ci. Weyant et al. (1996) et Parson and Fisher-Vanden (1997) décrivent plusieurs contributions des MEIs : (i) l'évaluation des politiques de lutte contre le changement climatique, (ii) la structuration des connaissances autour du changement climatique et leur mise en cohérence, (iii) la quantification de l'importance relative du changement climatique face aux autres problèmes auxquels l'humanité est confrontée (pauvreté, inégalité...). L'article de Parson et Fisher-Vanden insiste en outre sur le fait que les MEIs peuvent contribuer à l'avancée du savoir sur le système complexe formé par l'humain et ses activités, la biosphère et l'atmosphère. Matarasso (2003) souligne, lui, le rôle de catalyseur des discussions, à la fois dans les milieux politiques et scientifiques, que les modèles apportent, en permettant de structurer les arguments et d'ordonner les débats.

Faire le lien entre les nombreuses disciplines scientifiques impliquées dans le changement climatique n'est pas sans difficulté, ce qui explique les nombreuses simplifications introduites dans les MEIs. A titre d'exemple, les climatologues travaillent avec des modèles très complexes du changement climatique. La taille de ces modèles, le temps de calcul nécessaire à leur fonctionnement et leur niveau de désagrégation régionale font qu'il n'est pas réaliste de les coupler directement avec des modèles du système énergétique ou de l'économie. Les temps de calcul s'en trouveraient largement rallongés, les relations de causalité seraient très difficiles à explorer et le niveau d'expertise nécessaire à l'analyse des résultats (et à la manipulation du modèle) serait quasiment introuvable. Ainsi, les différents MEIs existants divergent beaucoup, que ce soit du point de vue de leur représentation du système climatique, de leur découpage régional, de la façon dont l'économie est prise en compte ou au niveau de la désagrégation du système énergétique. Cette grande diversité des modèles s'explique par le fait que, contrairement à ce qui a cours dans les sciences naturelles et physiques, l'exercice de modélisation ne vise pas uniquement à comprendre le fonctionnement d'un système afin d'être ensuite en mesure de prévoir son comportement lorsque les conditions initiales ou les variables de contrôles sont modifiées. Les trajectoires des variables climatiques dépendent en partie de choix humains qui ne peuvent être modélisés avec précision (ou certitude). Pour implémenter les comportements décisionnels des acteurs, différents types de stratégies sont envisagés. Les variables de contrôle peuvent être fixées de manière exogène, l'idée étant alors de tester différents scénarios (d'investissement par exemple) et de voir à quel changement climatique il est possible d'aboutir. Une deuxième façon de faire est de doter les agents d'une rationalité limitée. Le comportement des acteurs a été étudié pour des périodes antérieures et des relations entre les variables passées, les prix actuels et éventuellement d'autres variables d'état actuelles permettent de calculer la valeur de la variable étudiée au pas de temps suivant.

Il existe ainsi de nombreux modèles d'évaluation intégrée utilisés par la communauté de chercheurs travaillant sur le sujet du changement climatique. Certains modèles ont une audience et une utilisation très larges (DICE, TIAM) quand d'autres ne sont développés et exploités qu'au sein d'un seul et même laboratoire (IMACLIM-R).
Les principales différences généralement relevées entre les modèles ont trait au paradigme de modélisation :

- Modèle top-down ou bottom-up
- Modèle de simulation ou d'optimisation
- Equilibre général ou équilibre partiel.

La taxonomie des modèles est loin d'être unique d'autant que de nombreux modèles entrent dans diverses catégories à la fois. Afin de catégoriser les modèles, de nombreuses approches ont été explorées : Hoffman and Wood (1975) trient les modèles par la méthode de résolution/simulation utilisée (programmation linéaire, simulation basée sur des

travaux économétriques, dynamique des systèmes, théorie des jeux). Pandey (2002) ou encore Nakata (2004) utilisent des tableaux double-entrée pour ranger les modèles en les classant de manière plus fine : entrent en jeu le paradigme de modélisation, la régionalisation, l'horizon temporel, les secteurs de l'économie représentés... Dans leur revue de littérature sur les MEIs, Bhattacharyya and Timilsina (2010) détaillent plus encore la typologie en faisant intervenir des notions telles que le besoin en données, les compétences nécessaires à l'équipe de modélisateurs, le temps de calcul...
Les revues de littérature sur les MEIs étant très nombreuses, l'objet de cette partie n'est pas de rajouter une classification supplémentaire. Nous présenterons ainsi ci-dessous les principales classes de modèles ainsi que les principes théoriques qui les régissent.

Les modèles bottom-up
Les modèles bottom-up, aussi appelés modèles d'ingénieur, reposent sur une représentation technologique détaillée du système énergétique; leur ambition étant de traiter des problèmes énergétiques et climatiques sous l'angle technologique. Ils intègrent généralement aussi bien une représentation fine des réserves en ressources naturelles, des procédés de production électrique que des moyens de transport ou de chauffage domestique et industriel. Ce détail autorise une comptabilité relativement précise des émissions de gaz à effet de serre.
La plupart de ces modèles sont des modèles d'optimisation (par exemple tous les modèles utilisant Markal ou Times) dans lesquels le coût total du système est minimisé ou le profit est maximisé. L'optimisation intertemporelle effectuée sous-tend une anticipation parfaite des agents.
Il existe aussi des modèles bottom-up fonctionnant sur le principe de la simulation (POLES, les modèles construits avec LEAP). Pour ces derniers, les processus de décision et de fonctionnement des marchés sont décrits à l'aide de relations estimées entre autres de manière économétrique ou calibrées sur des données statistiques.
La représentation détaillée des technologies existantes et futures (quand c'est possible) et leur mise en relation permet de prendre en compte des spécificités sectorielles et de voir émerger des effets de système, par exemple lors de l'évaluation d'une politique climatique (ce qui est impossible avec des modèles plus agrégés), ou encore de fournir des résultats sur le coût technologique d'une politique climatique ou énergétique.
En revanche ce sont généralement des modèles d'équilibre partiel, dans lesquels la demande en énergie ou en services énergétiques est exogène (ou très simplifiée lors de l'utilisation d'un module macro-économique agrégé). Ils ne permettent donc pas d'analyser les rétroactions de l'adaptation du système énergétique sur l'économie.

Les modèles top-down
A l'inverse des modèles bottom-up, les modèles top-down dérivent plus d'une vision d'économistes et tentent de représenter finement l'économie (marchés, équations de budget des agents représentatifs).
Partant d'un équilibre macro-économique ou macro-sectoriel, ils le désagrègent progressivement pour arriver au secteur énergétique. Leur avantage principal réside dans la

prise en compte des rétroactions des modifications du secteur énergétique sur l'économie. Par ailleurs, la modélisation fine de l'économie autorise la prise en compte des contraintes de financement, des structures fiscales des différentes régions du monde étudiées, de l'évolution des balances des paiements et des échanges internationaux. Autant de contraintes ou de flux difficiles ou impossibles à intégrer dans la plupart des modèles bottom-up.
Comme le mentionne Zagamé (2008), 'les modèles top down décrivent a priori le système énergétique à partir de fonctions de production, où l'énergie figure de façon plus ou moins détaillée, comme un facteur de production substituable ou complémentaire avec d'autres facteurs comme le travail et les autres produits intermédiaires'. L'évident inconvénient de ce type de modèle est l'utilisation de ces fonctions de production et de consommation agrégées qui ne permettent pas de tenir compte de bon nombre de contraintes du système énergétique ou des spécificités de certains de ses secteurs. Ce point a été largement critiqué, en particulier par Solow (1988, p314) qui rappelle la nécessité d'être prudent lors de l'interprétation des résultats issus de fonctions de production agrégées[12]. Ou encore par Frondel and Schmidt (2002, p72) qui montrent dans leur article à quel point l'utilisation d'une forme fonctionnelle donnée impacte les résultats et leur interprétation tout en ayant peu de lien avec la réalité technologique [13].
En ce qui concerne le mode de résolution, deux grandes classes de modèles top-down sont utilisées pour la prospective énergétique et climatique de long terme : les modèles d'équilibre général à anticipation adaptative (EPPA, IMAGE) et les modèles d'équilibre général à anticipations parfaites ou rationnelles (DICE). Dans les premiers, les agents sont myopes et ne prennent pas le futur en compte dans leurs décisions (qui sont donc basées sur les prix présents et le comportement passé) tandis que dans les seconds, les agents optimisent leur bien-être sur tout l'horizon temporel. Un des problèmes récurrents posé par ce dernier type de modèles a trait aux « arrangements » nécessaires pour assurer la convergence du modèle : Stanton et al. (2008) et Ackerman (2002) pointent le fait que les rendements des fonctions de production doivent être décroissants ou constants pour que le modèle fournisse un unique optimum ce qui va à l'encontre d'une modélisation réaliste du progrès technique.

Les modèles hybrides
Une alternative à ces deux types de modèles est le modèle hybride qui combine une approche de type équilibre général avec une description relativement fine des technologies du secteur énergétique. Fonctionnant avec anticipations parfaites (Merge) ou avec anticipations adaptatives (IMACLIM-R), ces modèles nécessitent pour leur fonctionnement d'adapter les mécanismes modélisés afin d'assurer la convergence. Comme le souligne Zagamé, « les données de l'ingénieur sont rarement cohérentes avec les données économiques qui assurent les équilibres ressources emplois des S.A.M (Social Accounting

[12] *"For instance, these total-factor-productivity calculations require not only that market prices can serve as a rough and ready approximation of marginal products, but that aggregation does not hopelessly distort these relationships."*

[13] *"inferences obtained from previous empirical analyses appear to be largely an artifact of cost shares and have little to do with statistical inference about technology relationships."*

Matrix) pour les modèles d'équilibre général ». Dans le cas des modèles bottom-up sur lesquels on vient greffer un module macro-économique, il est à noter que ce module est généralement très agrégé (un unique secteur de production dans TIAM-Macro par exemple).
Une autre façon d'hybrider un modèle consiste à faire ce que l'on appelle du *soft-linking* : en couplant itérativement un modèle top-down et un modèle bottom-up. Cette technique exige un travail de synthèse très fastidieux sur les résultats du modèle à introduire dans le modèle suivant et est très consommatrice de temps. Par ailleurs, la convergence du modèle global ainsi formé est loin d'être assurée.

Il y a donc une très large diversité au sein des modèles destinés à traiter des politiques climatiques et énergétiques (voir figure 1.2 pour une synthèse). Large diversité

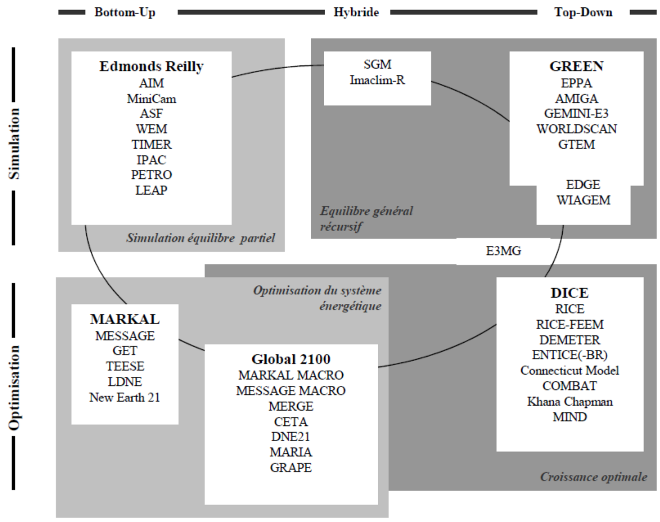


Figure 1.2: Topologie des MEIs (Source: CIRED)

qui s'explique aussi par le fait que tous ces modèles n'ont pas vocation à répondre aux mêmes questions.

La polysémie du mot modèle et les différentes approches de la prospective
Nous avons vu dans l'introduction que la pratique naissante de la prospective après la seconde guerre mondiale avait pris des directions très différentes en Europe et aux Etats-Unis. Si l'approche américaine était avant tout exploratoire, l'approche française se voulait très normative. Divergence de vues qui se traduit déjà dans la façon d'entendre les signifiés du mot "modèle" voire plus largement du concept « la science » ainsi que l'exprime Walras dans une de ses Notes d'humeur : « M. Pareto croit que le but de la science est de se rapprocher de plus en plus de la réalité par des approximations successives. Et moi, je crois que le but final de la science est de rapprocher la réalité d'un certain

idéal ; et c'est pourquoi je formule cet idéal »[14]. On retrouve cette dichotomie dans les modèles d'évaluation des politiques climatiques ou énergétiques. Si les modèles initiaux tels que celui de Forrester étaient bien des modèles d'évaluation d'une politique, une partie des modèles développés ensuite furent des modèles de « recherche d'une politique optimale » (Matarasso, 2003).

Les modèles qu'on pourrait qualifier « de simulation » (résolus de manière séquentielle ou récursive jusqu'à la dernière période) ont une approche exploratoire. Basées sur une extrapolation tendancielle du passé, ces modèles sont utilisés pour explorer un ensemble des futurs possibles du système. Pour ce faire un certain nombre de visions qualitatives du futur sont traduites quantitativement dans des modèles numériques dont les sorties fournissent des scénarios alternatifs du développement du système énergie-économie-environnement. Ils permettent de répondre à des questions du type :
- Que se passerait-il si... on ne fait rien ? ... on impose une taxe sur le CO_2 ?

Pour certains modélisateurs, utiliser ce type de modèle ne fait pas sens car « le comportement réel du système économie/énergie/climat n'est pas causal mais bien téléonomique, c'est à dire que les décisions sont prises en fonction des buts à atteindre » (Ha-duong and Matarasso, 2006) . Les modèles d'optimisation intertemporelle, à visée normative, permettent en imposant un état final au système, d'explorer les sentiers possibles pour atteindre cet état ou au contraire de révéler l'infaisabilité de celui-ci. Une autre vocation de ces modèles est d'explorer les alternatives souhaitables afin d'être à même de déterminer la vision la plus désirable de la société future et de pouvoir légiférer et agir afin de tendre vers cette vision. Les principales questions auxquelles répondent ces modèles sont par exemple :

- Comment agir au mieux pour atteindre un objectif donné d'émissions de GES ?
- Quelle stratégie adopter si un accord international sur le climat est incertain ?
- Quel pourcentage optimal de véhicules électriques dans le parc européen pour rejoindre les objectifs de la Commission européenne ?
- Des questions de faisabilité comme est-il réaliste de ?

Les modèles utilisés pour l'aide à la décision dans les domaines énergétiques et climatiques sont très divers tant sur le plan théorique que quant à leur domaine d'application. Cela explique en partie le grand nombre de critiques qui leur est adressé et que nous allons tenter de synthétiser dans la section suivante.

1.3 Des incertitudes radicales et autres reproches faits aux MEIs

Si la plupart des modèles énergétiques et des MEIs utilisés aujourd'hui a été créée bien après celui du Club de Rome et souvent de façon à répondre aux attaques dont ce

[14] Léon Walras, Notes d'humeur publiée dans Volume XIII : œuvres diverses de Léon Walras, Paris, Economica, 2000, P. Dockès, C. Mouchot, J. P. Potier (éd.).

dernier avait fait l'objet, la critique ne les épargne pas pour autant. Les reproches sont de plusieurs ordres: reproches d'ordre technique visant la façon dont sont implémentés les modèles, reproches d'ordre éthiques visant les valeurs sous-jacentes aux modèles, valeurs loin de faire l'unanimité parmi les économistes et enfin reproches d'ordre méthodologique, le plus prégnant dans la littérature, il touche aux nombreuses incertitudes présentes dans les modèles et à leur prise en compte.
Cette revue des défauts des modèles d'évaluation intégrée et des modèles énergétiques n'a pas pour vocation à être exhaustive mais à souligner les imperfections qui nous semblent être le plus fréquemment pointées du doigt.

Des modèles mal adaptés à la représentation d'un monde en mouvement?
La création de modèles énergétiques détaillés ou de MEIs nécessite un nombre important de données et de compétences de modélisation. Construire un de ces modèles en « partant de zéro » est un travail titanesque ce qui explique que la plupart de ces modèles ait été créée en agrégeant des modèles préexistants. Ces outils n'ayant pas été conçus dans l'objectif d'être ensuite couplés à d'autres entités, l'agrégation peut s'avérer difficile et exiger des simplifications des deux parties. Par ailleurs, les modélisateurs sont rarement des spécialistes de l'ensemble des domaines qu'ils tentent d'intégrer. Si ces différents points ne soulèvent pas a priori de problèmes insurmontables, certains économistes (Parson and Fisher-Vanden, 1997) suggèrent tout de même que dans certains cas les évaluations résulteraient davantage d'un bricolage entre les outils à disposition du modélisateur que d'une approche cartésienne et globalement pensée pour produire un modèle intégré.

Dans la ligne directe de la critique précédente, d'autres reprochent aux modèles intégrés leur trop grande complexité. Pour Henriet et al. (2014) ou encore Kelly, D. L., & Kolstad (1998) cette dernière obère la capacité à comprendre l'origine des résultats et les chaînes causales qui y conduisent. D'autre part, afin d'améliorer les modèles, leurs créateurs ont eu tendance à pousser leur développement et par exemple à régionaliser des modèles autrefois globaux (DICE devenant RICE par exemple), à détailler des secteurs auparavant agrégés, à coupler des modèles entre eux... La taille des modèles est ainsi en constante croissance et la cohérence des données qui s'y trouvent ainsi que leur actualité est de plus en plus difficile à maintenir. Par ailleurs, la désagrégation régionale réalisée oblige à trouver des données dans des zones géographiques où leur collecte est particulièrement difficile voire inexistante (Bhattacharyya and Timilsina, 2010).

Autre attaque fréquemment dirigée contre les modèles énergie-économie et les MEIs: la difficulté qu'il y a à confronter leurs résultats avec la réalité. La reproduction des données passées n'étant pas forcément un gage de validité pour un modèle de prospective (Guivarch, 2014), l'accord sur la façon de valider ces modèles n'est pas immédiat. Une des conditions de validation d'un modèle relevée par Hodges and Dewar (1992) est la possibilité d'observer et de mesurer les situations modélisées. Cela est faisable dans le cadre d'un modèle énergie-économie mais a posteriori seulement ce qui est un inconvénient sérieux quand on travaille sur des horizons temporels lointains.

En revanche, si les modèles ne peuvent être formellement validés, leurs performances peuvent être évaluées. La communauté scientifique doit donc être en capacité de juger les différents modèles ce qui implique une documentation claire et une transparence de la part des équipes développeuses. Pratique malheureusement peu courante encore (DeCarolis et al., 2012). Mener une comparaison inter-modèles est une autre façon d'évaluer les résultats d'un modèle donné (i.e. Kriegler et al., 2015) sachant qu'une divergence de ses résultats n'est pas le gage d'une absence de validité. Les efforts pour établir des cadres d'évalutaion des modèles (i.e. Schwanitz, 2013) n'ont pas encore débouché sur un véritable consensus au sein de la communauté.

Enfin, Ha-duong and Matarasso (2006) formulent une dernière objection à l'encontre des modèles énergie-économie qui nous paraît valide. La plupart des modèles économiques de long-terme est formulée et calibrée autour d'un équilibre afin d'étudier les problématiques liées à la croissance économique. L'exploration d'alternatives susceptibles d'entraîner l'économie loin de cet équilibre risque donc de faire sortir le modèle de sa « zone de validité ». Cela soulève d'importantes questions quant à l'utilisation des modèles pour étudier des scénarios dits de rupture, que celle-ci soit climatique, technologique ou comportementale.

Des modèles pétris de valeurs... masquées ?

L'épistémologie classique des sciences économiques tend à distinguer l'économie positive de l'économie normative. La première a pour ambition de décrire objectivement ce qui est, quand la seconde se penche sur la recherche de ce qui doit être. On considère traditionnellement que l'économie positive est dénuée de jugement alors que l'économie normative est guidée par des valeurs. Cependant cette vision est contestée dans la mesure où « la possibilité d'une science positive repose sur l'établissement de tests non ambigus, dénués de jugement de valeur » (Pottier, 2014 p5). Ces tests sont bien souvent controversés étant donné la difficulté de les réaliser sans introduire de jugement de valeur, ne serait-ce que dans la méthodologie[15].

La même distinction s'opère dans le « monde » des modèles entre modèles de simulation, à visée plutôt positive, et modèles d'optimisation complètement normatifs. Cependant si l'observation d'un système humain peut se réclamer de la positivité, la mise en œuvre du modèle implique une démarche qui s'en écarte car les choix de modélisation, qu'ils soient théoriques ou qu'ils aient traits à la valeur des paramètres, sont nécessairement guidés par les jugements de valeur des concepteurs.

Elodie Vieille Blanchard (2011, chapitre 9) montre comment les cosmologies et les méthodologies de modélisation des développeurs entraînent la création de modèles dont les résultats viennent conforter les visions et les idéologies préexistantes.

Ces différents points expliquent et légitiment en partie les critiques à l'encontre des utilisateurs des modèles climatiques et énergétiques qui n'exposeraient pas de manière claire et nette les valeurs sous-jacentes à leur entreprise.

[15] Dans un autre ordre d'idées, Gunnar Myrdal contestait en 1930 la posture des économistes qui se prétendent objectifs alors qu'ils utilisent des concepts élaborés à partir de la philosophie du droit naturel.

Dans cet ordre d'idée, Pindyck (2013) adresse de nombreuses attaques aux MEIs. Il s'en prend notamment à la toute-puissance du modélisateur dans le choix des paramètres et des formes fonctionnelles du modèle[16]. Il est en effet indéniable (et légitime) que le modélisateur représente le monde qu'il modélise comme il le conçoit. Pindyck dans cet article fait entre autres référence au débat qui a opposé Nordhaus et Stern quant au choix du taux d'actualisation à utiliser dans les MEIs (Nordhaus optant pour un taux proche de ceux du marché tandis que Stern adopte pour sa part un taux très bas pour des raisons d'équité inter-générationnelle). Ces deux choix découlant d'une vision très différente à la fois en termes d'éthique et de responsabilité, ils sont tous les deux valables et ne devraient pas être problématiques dès lors qu'ils sont clairement exposés contrairement à ce que Pindyck affirme. Le reproche qu'on pourrait donc éventuellement adresser aux utilisateurs des modèles, c'est l'absence de transparence dont ils font parfois preuve et l'absence de précautions prises lors de la présentation de leurs résultats. De même que Pindyck, Morgan and Henrion (1990) listent les « difficultés soulevées par les idéologies de l'analyste » (« difficulties arising from the ideological perspectives of the analyst ») parmi les cinq imperfections qu'ils attribuent à l'utilisation de modèles pour éclairer la décision politique.

Un autre type de « croyance » prévaut chez les modélisateurs, perceptible via deux hypothèses implicites à la construction et à l'utilisation des modèles énergie-économie et des modèles intégrés (Parson and Fisher-Vanden, 1997):

- Il est possible de modéliser de manière adéquate tous les phénomènes pertinents
- Les résultats des modèles sont pertinents pour éclairer les décideurs politiques

Ces hypothèses ne sont que rarement posées explicitement et méritent qu'on s'y attarde un peu. Il paraît effectivement nécessaire de rappeler que bon nombre de procédés ou d'interactions sont approximés lors du processus de modélisation (pour différentes raisons qui vont du simple manque de données à des raisons plus profondes comme une absence de compréhension globale du phénomène). Ainsi les résultats du modèle se doivent d'être interprétés à l'aune de ses intrants et de sa structure (ce qui sous-entend aussi qu'une personne extérieure au modèle aura beaucoup de difficultés à tirer des enseignements valides de ses résultats). Par ailleurs, le modèle est adapté à chaque fois qu'il est utilisé pour répondre à un nouvel exercice. Il ne saurait donc être question d'utiliser les résultats d'un modèle optimisé pour traiter un point, dans le cadre d'une autre demande: nombre d'hypothèses, agrégations et choix effectués perdraient alors leur sens (voir le chapitre 3 pour un exemple) et risqueraient d'entrainer un biais dans les résultats.

Cette dernière remarque nous permet de rebondir sur une autre imperfection de l'exercice de modélisation, relevée par Morgan and Henrion (1990). Ils reprochent aux équipes de

[16] *«You might think that some input choices are more reasonable or defensible than others, but no, "reasonable" is very much in the eye of the modeler. Thus these models can be used to obtain almost any result one desires. »*

développeurs de ne pas être suffisamment précis quant aux objectifs du projet de modélisation. Comme nous l'avons soulevé précédemment, un modèle n'est en aucun cas apte à traiter tous les problèmes posés par le changement climatique par exemple. Sa structure mathématique (simulation, optimisation), son niveau de détail, sa désagrégation sectorielle ou régionale contraignent son champ d'action et limitent le périmètre des questions auxquelles il a vocation à répondre. Si ce point peut sembler évident à un utilisateur habituel des modèles, il est loin de l'être pour des observateurs extérieurs tels que les décideurs politiques par exemple. Dans un souci d'honnêteté intellectuelle, il est donc nécessaire d'exposer clairement le but de l'exercice, les modifications apportées au modèle ainsi que les hypothèses retenues.

L'incertitude ou les incertitudes : la bête noire des modèles d'aide à la décision

La décision politique s'effectue toujours en présence d'un nombre conséquent d'incertitudes qu'il serait illusoire de prétendre éliminer tant elles touchent des domaines différents. La croissance économique, la réaction des citoyens à un changement de politique ou à une évolution sociétale, les décisions des autres gouvernements, l'évolution des prix, le progrès technique... sont autant de variables profondément incertaines. Les modèles d'aide à la décision, peuplés par ces variables, fournissent donc des résultats sujets à caution. Aussi le traitement de l'incertitude, ou parfois son non-traitement, fait l'objet d'une critique récurrente. Plus que récurrente, on pourrait la dire permanente puisqu'on la retrouve dans quasi tous les articles sur notre sujet (Matarasso, 2003, Ambrosi and Courtois, 2004, Ha-duong and Matarasso, 2006, Guivarch, 2014, Bhattacharyya and Timilsina, 2010, Hedenus et al., 2013, Stanton et al., 2008, Vecchione, 2013).

Des modèles trop grands et trop complexes

Une des raisons de l'absence de traitement de l'incertitude dans bon nombre d'exercices de prospective est évoquée par Hunter et al. (2013) et a trait à la structure même des modèles.

Leur taille et leur complexité croissantes mobilisent de plus en plus de capacités et de temps de calcul ce qui décourage de faire des études de sensibilité poussées. Etudes qui représenteraient pourtant dans certains cas la seule alternative possible pour tenir compte de l'incertitude qui pèse sur les hypothèses du modèle et au-delà sur les inconnues d'origine variée dont ils sont peuplés. Si bien qu'on pourrait s'aventurer sans trop de risque à dire que l'ensemble des données des modèles sont incertaines, à des degrés différents et avec une typologie de l'incertitude qui varie d'un élément à l'autre.

Une incertitude polymorphe

Par exemple, l'incertitude qui plane sur les variables exogènes aux modèles, telles que la croissance économique ou celle du progrès technique, dont la projection a été faite à l'aide d'autres modèles sur la base des trajectoires passées, est à distinguer de celle qui affecte les paramètres techniques utilisés dans les modèles bottom-up. Ces derniers sont incertains dans le sens où des erreurs physiques de mesure peuvent s'y glisser lors de leur estimation ce qui est conceptuellement différent d'une « erreur » de prévision. Par ailleurs, l'utilisation de valeurs moyennes pour ces paramètres risque d'introduire des biais. Cette incertitude pourrait au premier abord paraître négligeable mais comme nous le verrons dans la suite de la thèse, une faible variation du rendement d'une technologie peut entraîner un bouleversement des ratios de coûts marginaux et donc conduire à des trajectoires d'investissement optimales très différentes. Si l'impact de ce type d'incertitude peut être notable au niveau micro-économique, il est en revanche peu important sur les variables macro-économiques. Cette remarque n'implique pas qu'il faille s'abstenir de traiter le problème de la variabilité des paramètres technologiques: c'est une décision à prendre au regard de la problématique traitée à l'aide du modèle.

Les incertitudes de type « binaire » sont très différentes : il n'est plus question là d'un paramètre susceptible de prendre une valeur dans un intervalle connu autour d'un nominal mais d'un phénomène qui survient ou non. Par exemple, l'existence d'un accord international sur un prix du CO_2 ou encore l'apparition d'une technologie de rupture. Ce sont deux évènements très difficiles à prévoir car le premier cas implique par exemple une coopération internationale inédite en tant de paix (Schelling, 2010) et la mise en place d'engagements contraignants compliqués à faire respecter. Le second cas supposerait préalablement d'importants efforts de recherche et développement dans le domaine de l'énergie, efforts en baisse en Occident depuis le milieu des années 70 (ibid, p79). Outre qu'ils sont ardus à probabiliser et à dater, ces évènements ont potentiellement une énorme influence sur les décisions des acteurs économiques et politiques. Il semble donc peu raisonnable de discuter de l'avenir du système énergétique ou climatique sans tenir compte du caractère incertain de ces deux points (exemples pris parmi de nombreux autres).

Le climat et ses rétroactions : incertitudes immenses et radicales
Une gamme d'incertitudes spécifiques concerne les MEIs ou plus largement tous les modèles qui contiennent un module climatique.
Les lois et paramètres qui régissent le climat font l'objet d'innombrables recherches et sont en voie d'identification mais la variabilité dans les estimations reste très importante. Il en va ainsi de la sensibilité du climat : les estimations du GIEC la situent entre 1.5°C et 4.5°C, soit une variation du simple au triple en fonction de l'étude.
On pourrait patienter en misant sur le succès de la recherche scientifique. Un comportement attentiste présente cependant deux risques : l'inertie du système fait qu'il y a un vrai danger à différer les mesures, nous ne serons certainement plus capables de les prendre le jour où nous le souhaiterons. Par ailleurs, les avancées de la connaissance des sciences du climat pourraient entraîner plus d'incertitudes que nous n'en avons actuellement. En éclairant des relations qui nous paraissaient établies, un progrès de la science pourrait au contraire faire apparaitre à quel point des liens de causalité qui nous semblaient évidents sont en fait bien plus complexes que nous ne le pensions, accroissant ainsi l'incertitude qui pèse sur le système. Dans ce domaine, il subsiste d'autres inconnues, nous ne sommes pas plus assurés quant à l'impact de l'évolution du climat sur l'activité humaine, point

plus obscur encore s'il se peut.

Les modèles qui intègrent une rétroaction du climat sur l'économie le font à l'aide de ce que l'on appelle les fonctions de dommage. Contrairement à de nombreuses fonctions utilisées en économie, souvent discutables, les fonctions de dommage ne peuvent être calibrées, et ce par manque de données historiques. La hausse de la concentration du CO_2 est un évènement récent, les délais entre une modification du CO_2 atmosphérique et une élévation de la température sont tels que les émissions anthropiques du siècle dernier commencent à peine à impacter la température terrestre, nous interdisant de tirer des conclusions sur les effets globaux de la température sur l'économie.
D'autant plus qu'une hausse de la température atmosphérique n'implique pas que cette hausse soit uniformément répartie mais devrait plutôt entraîner des changements de climat localement. Certaines zones deviendraient plus humides tandis que d'autres s'assécheraient, les rendements des terres agricoles évoluant de concert.
Ainsi, les fonctions de dommage sont souvent arbitrairement choisies (Pindyck, 2013), si bien que l'estimation de l'impact du changement climatique sur l'économie demeure une véritable gageure. Elles lient la température et/ou sa croissance à des dommages infligés à l'économie et sont généralement calibrées autour d'un delta de température allant de deux à trois degrés. Ce qui se passerait si la température augmentait davantage est donc hors du domaine de validité du modèle et nous rencontrons la critique formulée par Weitzman (2009) à l'encontre des MEIs.

De la prise en compte des évènements rares à portée dévastatrice
Très peu de MEIs incluent formellement l'incertitude, la plupart d'entre eux se contentant de traiter les prévisions concernant le CO_2 ou les dommages climatiques comme des faits sûrs pour ensuite réaliser une analyse de sensibilité sur quelques paramètres. Cette inclusion formelle de l'incertitude passe, selon Weitzman, par l'utilisation de fonction de densité de probabilité (FDP) de l'élévation de la température ou encore des impacts par exemple. Les fonctions utilisées dans les MEIs sont à queue mince et par ailleurs arbitrairement tronquées (dans la mesure où la densité porte sur des ensembles finis) ce qui implique une probabilité extrêmement faible des évènements catastrophiques, thèse que réfute Weitzman. Pour lui les FDP sont à queue épaisse, ce qui interdit leur troncation et donc prive de valeur les approximations réalisées dans la plupart des MEIs.
En effet, Weitzman met en avant l'absence de précédent des phénomènes qui se produisent à l'heure actuelle. Les études montreraient que la concentration atmosphérique de CO_2 n'avait jamais augmenté de plus de 30 ppm sur des périodes de 1000 ans. Or cette augmentation a été atteinte en dix-sept ans seulement (entre 1993 et 2010). Ces changements inédits introduisent une incertitude importante sur l'évolution du comportement du système planétaire[17] que ne reflètent malheureusement pas les formes fonctionnelles adoptées dans les exercices de modélisation.

[17] Par exemple, les écosystèmes ont réussi à absorber une bonne partie de la pollution émise ces 50 dernières années. Rien n'indique cependant que l'on ne soit pas en train de s'approcher du seuil de rupture de ces écosystèmes.

Les catastrophes « à queue épaisse » invalident en partie les analyses coûts/bénéfices classiques réalisées en économie. Weitzman propose aux économistes du climat de contourner ou du moins de minorer le problème en présentant leurs analyses comme « arbitrairement imprécises » et dépendantes d'hypothèses subjectives. La reconnaissance claire de la radicalité de l'incertitude qui pèse sur les analyses du changement climatique permettrait de traiter du changement climatique dans une logique assurancielle, à l'aide de FDP à queue épaisse, en n'occultant pas la possible irruption d'évènements certes rares mais porteurs d'impacts dramatiques pour l'être humain.
Une autre façon de pallier cette difficulté peut être d'adopter une attitude « extrémiste » à l'instar de (Dupuy, 2010) qui plaide pour la prise en compte du scénario de le plus pessimiste quand deux conditions sont réunies : l'incertitude est radicale, invalidant selon lui l'analyse coûts bénéfices, et l'enjeu est immense (avenir de l'humanité). Position confortée chez Dupuy par l'idée bergsonienne que les humains sont incapables de croire que le pire pourrait arriver, il leur faut être confrontés à l'avènement de la catastrophe pour admettre sa possibilité. Ils envisagent en fait la catastrophe comme probable (avec l'aide de la raison) mais la perçoivent comme fondamentalement impossible. Cette idée conduit Dupuy à rejeter l'idée du principe de précaution puisqu'en appliquant les outils classiques de prévention des risques au changement climatique, l'humain ne sera pas capable de considérer les cas pour lesquels il n'a pas de solution. L'approche de Dupuy, très conservatrice, a peu (voire pas) de succès.

Les critiques adressées aux modèles d'aide à la décision en matière énergétique ou climatique portent tant sur la structure des modèles que sur les manières de les utiliser. Davantage de transparence, à la fois sur les valeurs qui sous-tendent la recherche que sur la façon dont le problème prégnant de l'incertitude est pris en compte, semble pourtant être la solution capable de satisfaire une partie des détracteurs.

1.4 Vers une utilisation plus transparente des modèles?

Il semble tout d'abord nécessaire de rappeler que les grands modèles utilisés pour évaluer les politiques climatiques et énergétiques n'ont pas pour objectif de réaliser des prévisions. La mise en évidence de rétroactions, de chaînes causales ou d'évènements inattendus ou encore l'obtention d'ordre de grandeur sur l'abattement en CO_2 réalisable ou sur le coût d'une politique, voilà autant de connaissances auxquelles ils donnent accès.
Cette approche est validée par Ha-duong and Matarasso (2006) qui considèrent qu'il n'est pas « nécessaire de prétendre prédire l'avenir dans sa globalité pour apporter des éléments de réponse scientifiques à un problème, fût-il global ». Cette vision de l'utilisation des modèles permet donc de s'affranchir au moins partiellement des problèmes de vérification et de validité des modèles qui existent dans les sciences dites dures.
Puisque les scénarios issus de nos modèles sont toujours faux, c'est ailleurs qu'il faut focaliser notre attention. Il nous semble que la robustesse des résultats et l'identification des incertitudes qui « comptent » sont deux conditions qui permettraient de valider et de justifier l'utilisation des modèles en vue d'aider à la décision.

Comme vu précédemment, la trop grande complexité des modèles est un reproche souvent formulé à leur encontre. Pourtant, Rozenberg (2014) et Hedenus et al. (2013) estiment cette complexité inévitable, étant donnée la diversité des acteurs impactés par le changement climatique ou les politiques énergétiques ; acteurs tous désireux de comprendre par quel biais ils seront touchés par les décisions politiques (ou l'absence de décisions).
S'il est donc impossible de simplifier les outils en les ré-agrégeant, une approche pédagogique et transparente lors de la présentation de leurs résultats semble indispensable.
Par ailleurs, on ne rappellera jamais assez l'importance de l'adéquation du modèle avec la question à laquelle il est censé contribuer. Un MEI n'est en aucun cas ce que l'on appelle vulgairement un « presse-bouton » et le traitement d'une nouvelle problématique nécessite toujours un temps de développement et d'adaptation du modèle. La finalité de l'étude se doit donc d'être clairement établie et exposée de même que les principales caractéristiques du modèle porteuses de valeurs sujettes à la controverse (anticipation parfaite des agents, taux d'actualisation…).

Les derniers points évoqués permettent de rebondir sur un autre aspect, abordé par Hedenus et al. (2013) : l'importance de l'équipe de modélisation. C'est un sujet qui revient peu dans les articles portant sur les modèles énergétiques et qui est pourtant primordial pour garantir la cohérence et l'intégrité de l'outil [18]. Tous les secteurs 'réels' représentés doivent être connus et compris par l'équipe avant d'être modélisés ce qui suppose souvent que l'équipe soit pluridisciplinaire. De plus, la démarche d'utilisation comporte plusieurs phases qui ne font pas intervenir les mêmes compétences : implémentation initiale, problématisation, scénarisation, implémentation des scénarios et « runs » du modèle, analyse des résultats… La problématisation et la scénarisation peuvent se faire avec des chercheurs étrangers au modèle mais leur bonne réalisation nécessite tout de même l'assistance de pratiquants informés. Toutefois, l'analyse des sorties d'un modèle paraît difficilement réalisable de manière pertinente si son contenu n'est pas bien connu. Le risque s'ajoute de passer à côté d'inadéquation de la modélisation avec le sujet traité ou encore à côté d'effets de système. Enfin , un haut niveau de compétence/d'information est nécessaire pour éviter l'utilisation du modèle en-dehors de son domaine de validité.

La réponse à une partie des critiques évoquées dans la partie précédente peut donc passer par un effort accru de pédagogie et de transparence. Cela permettrait en effet de régler en partie le problème lié aux valeurs sous-jacentes aux modèles, de clarifier les objectifs de la modélisation qu'on ne pourrait plus accuser de cacher d'obscurs desseins. Les compétences de l'équipe assurent, elles, la cohérence du modèle et son utilisation dans de bonnes conditions ainsi qu'une compréhension de ses résultats. En revanche en ce qui concerne les incertitudes, une approche transparente est nécessaire mais non suffisante. Il faut certes reconnaître et affirmer l'ambition exploratoire et non prédictive des modèles, mais il faut aussi faire l'effort d'intégrer dans les pratiques de modélisation

[18] Il est aussi évoqué par Bhattacharyya and Timilsina (2010) dans leur revue des MEIs quand ils classent les modèles aussi en fonction de leur facilité d'utilisation et d'appréhension.

la présence d'outils destinés à prendre en compte l'incertitude. Une étude de sensibilité peu poussée en marge de l'étude a l'avantage d'être simple à réaliser mais risque de ne fournir que peu « d'insights » sur le fonctionnement du modèle (Morgan and Henrion, 1990). Morgan and Keith (2008) soutiennent, eux, que se focaliser sur un petit nombre de scénarios très détaillés risque de produire des scénarios mentaux si convaincants qu'ils entraineraient une confiance excessive dans les résultats.

Alors que faire pour assurer la robustesse des modèles ou au moins des analyses des politiques qu'ils inspirent? Si les grandes incertitudes qui pèsent sur l'avenir des systèmes climatiques et énergétiques rendent illusoires l'obtention d'un instrument optimal (Rozenberg, 2014), la recherche d'approches robustes pour éclairer les décideurs politiques dans ce domaine doit, en revanche, être poursuivie. C'est ce que nous entreprenons de faire dans la suite de cette thèse.

Le traitement de l'incertitude
La prise en compte de l'incertitude dans les modèles énergétiques et climatiques est un champ de recherche déjà exploré. La réalisation d'études de sensibilité, l'utilisation de méthode de Monte-Carlo, le recours à l'optimisation stochastique, voilà autant de méthodes déjà éprouvées dans les modèles d'aide à la décision. Ces techniques n'ont pas vocation à traiter les mêmes cas d'incertitudes et sont par ailleurs conceptuellement assez différentes. On distinguera les méthodes qui permettent d'endogénéiser l'incertitude et fournissent des stratégies robustes de celles, plus exploratoires, telles que l'analyse de sensibilité ou la scénarisation, qui utilisent les modèles de manière déterministe.

Les méthodes déterministes
L'analyse de sensibilité
L'analyse de sensibilité a pour objectif d'analyser la robustesse du modèle en étudiant l'impact de la variabilité des facteurs d'entrée du modèle sur les variables de sortie. En déterminant les entrées responsables du maximum de la variabilité, le modélisateur est ensuite capable d'amender son outil ou de tirer des conclusions quant au fonctionnement du système qu'il cherche à comprendre.
Les valeurs des paramètres qui varient lors des analyses de sensibilité peuvent être déterminées arbitrairement par le modélisateur ou en utilisant la méthode de Monte-Carlo (i.e. Hope (2006), Ackerman et al. (2010), Dietz (2011)).
Le problème de cette méthode réside dans le temps de calcul nécessaire à son application. En effet, quand bien même on ne testerait que 2 valeurs pour chacun des n paramètres en entrée du modèle, tester toutes les combinaisons paramétriques possibles suppose de faire 2^n simulations. Sachant que les grands modèles énergétiques ou climatiques contiennent des millions de données et exigent parfois des temps de résolution proche de la demi-heure, cette approche n'est pas toujours réaliste.

La scénarisation
L'utilisation d'un très grand nombre de scénarios en entrée du modèle, suivie d'une anal-

yse statistique des sorties est une procédure relativement récente. Elle permet à la fois de mieux comprendre le fonctionnement du système, d'intégrer l'incertitude, de mettre en évidence la robustesse de certaines trajectoires, de sélectionner des petits groupes de scenarii (Trutnevyte, 2014)... Mais la méthode se heurte aux mêmes problèmes que ceux de l'analyse de sensibilité : le très grand nombre de simulations à réaliser et la sélection en amont des paramètres/hypothèses à faire varier. En effet, il aura fallu au préalable choisir les valeurs que l'on souhaite tester et construire un ensemble de scénarios cohérents (Rozenberg, 2014 chapitre 5), travail fastidieux au regard de la taille des modèles.

La méthode de Monte Carlo
Dans ce cadre, il est nécessaire de connaître la distribution de probabilité des paramètres incertains. Une fois cette distribution affectée à chacun des paramètres clés (ou du moins estimés clés) du modèle, la méthode consiste à effectuer des tirages aléatoires de ces paramètres et de faire tourner le modèle avec des combinaisons des résultats des tirages. Ce qui permet d'obtenir une probabilité d'occurrence des résultats du modèle.
Par ailleurs si la méthode de Monte Carlo autorise une meilleure compréhension des effets croisés de l'incertitude sur plusieurs paramètres simultanément, elle a comme défaut de rester dans un cadre déterministe (Dietz et al., 2007). La connaissance nécessaire des fonctions de densité de probabilité de l'incertitude est un autre obstacle inhérent à la méthode ainsi que l'explique Nordhaus (2008, p.127-128) « *We assume normal distributions primarily because we fully understand their properties. We recognize that there are substantial reasons to prefer other distributions for some variables, particularly ones that are skewed or have "fat tails," but introducing other distributions is highly speculative at this stage and is a more ambitious topic than the limited analyses that are undertaken here*». Ces différents obstacles amènent certains auteurs à considérer la méthode de Monte Carlo ou encore l'analyse de sensibilité comme une première étape, non suffisante, de l'aide à la décision en situation d'incertitude (Kunreuther et al., 2014).

Les méthodes qui endogénéisent l'incertitude
L'optimisation stochastique
Utilisée dans les modèles d'optimisation, cette méthode permet de prendre en compte l'incertitude qui pèse sur un élément du modèle dès lors que l'on connaît sa fonction de densité de probabilité. L'identification de stratégies de couverture (hedging) est alors possible. Le cadre non déterministe fournit par l'optimisation stochastique permet de décrire en les probabilisant un petit nombre d'états contrastés du monde et d'identifier un scenario optimal intégrant l'incertitude. Cette méthode est par exemple appliquée aux cas de l'apparition possible d'une technologie de rupture (backstop technology) (Labriet et al., 2012) ou d'un éventuel accord climatique mondial (Labriet et al., 2015) ou encore quand il s'agit d'étudier l'impact éventuel de notre méconnaissance du système climatique (Syri et al., 2008). Elle a en revanche le défaut d'être très gourmande en temps de calcul et de ne s'appliquer qu'à un petit nombre d'incertitudes.

L'optimisation robuste : une nouvelle approche
Méthode récente issue de la recherche opérationnelle et encore très peu appliquée dans le champ économique ou dans celui de l'évaluation des politiques climatiques ou énergétiques, l'optimisation robuste permet de traiter de manière parcimonieuse l'incertitude dans les modèles de grande taille (Ben-tal and Nemirovski, 2002). Outre qu'elle fournit un cadre peu gourmand en calcul, elle n'implique pas la connaissance des distributions de probabilité des paramètres incertains.
Le principe général de l'optimisation robuste consiste à immuniser une solution contre la réalisation adverse d'un certains nombres de paramètres (c'est-à-dire que les contraintes du problème doivent être respectées quelle que soit la valeur des paramètres prise dans leur ensemble d'incertitude). Le choix du degré de conservatisme est laissé à l'utilisateur du modèle et fait souvent l'objet d'une étude paramétrique.
On verra dans cette thèse quels peuvent être les apports de cette méthodologie pour l'aide à la décision en situation d'incertitude et aussi comment elle vient compléter, sans redondance, la liste des moyens d'assurer la robustesse des modèles.

In the following chapter, I focus on the impact of the subsectoral level of detail in an energy system model on climate policy evaluation. The optimal level of detail is one of the tricky question faced by the modeler when she implements its model given the time and data consuming nature of detailing a sector.
Using the example of the oil refining sector, I show how its level of detail modifies petroleum product marginal cost ratios. Then the optimal strategies identified with the model to fulfill a climate constraint are notably different from the ones obtained with a model where the refining sector is aggregated. Essentially, the balance between energy efficiency and carbon intensity of transport may be affected by the accuracy of the description of the pivotal refining sector. Consequently, increasing this sector accuracy level should not only be motivated by the wish to gain wider quantitative insights on potential evolution of the energy system but also by the wish to improve the robustness of the model outcomes.

Bibliography

Ackerman, F., 2002. Still dead after all these years: interpreting the failure of general equilibrium theory. Journal of Economic Methodology 9, 119–139.

Ackerman, F., Stanton, E. a., Bueno, R., 2010. Fat tails, exponents, extreme uncertainty: Simulating catastrophe in DICE. Ecological Economics 69, 1657–1665.

Ambrosi, P., Courtois, P., 2004. Impacts du changement climatique et modélisation intégrée , la part de l'arbitraire. Natures Sciences Sociétés 12, 375–386.

Ben-tal, A., Nemirovski, A., 2002. Robust Optimization — Methodology and Applications. Mathematical Programming 92 (3), 453–480.

Berger, G., Massé, P., de Bourbon-Busset, J., Darcet, J., 1967. Étapes De La Prospective. Bibliothèque de prospective.

Bhattacharyya, S. C., Timilsina, G. R., 2010. A review of energy system models. International Journal of Energy Sector Management 4 (4), 494–518.

DeCarolis, J. F., Hunter, K., Sreepathi, S., 2012. The case for repeatable analysis with energy economy optimization models. Energy Economics 34 (6), 1845–1853.

Dietz, S., 2011. The treatment of risk and uncertainty in the US Social Cost of Carbon for Regulatory Impact Analysis Centre for Climate Change Economics and Policy. Social Research (64), 1–13.

Dietz, S., Hope, C., Patmore, N., Aug. 2007. Some economics of 'dangerous' climate change: Reflections on the Stern Review. Global Environmental Change 17 (3-4), 311–325.

Dupuy, J.-P., 2010. Pour un catastrophisme éclairé. In: Touffut, J.-P. (Ed.), Changement de climat, changement d'économie ? Albin Michel, Paris, pp. 85–99.

Frondel, M., Schmidt, C., 2002. The Capital-Energy Controversy: An artifact of Cost shares? The Energy Journal 23 (3).

Galtung, J., 1973. ' The Limits to Growth ' and Class Politics *. Journal of peace research 10, 101–114.

Guivarch, C., 2014. Exploration des liens entre croissance, énergie et émissions de gaz à effets de serre. In: Séminaire Thématique LIED.

Ha-duong, M., Matarasso, P., 2006. Comment intégrer l'économie , l'énergie et le climat ? 52, 92–97.

Hedenus, F., Johansson, D., Lindgren, K., 2013. A Critical Assessment of Energy-economy-climate Models for Policy Analysis. Journal of Applied Economics and Business Research 3 (2), 118–132.

Henriet, F., Maggiar, N., Schubert, K., 2014. A stylized applied energy-economy model for france.

Hodges, J., Dewar, J., 1992. Is it you or your model talking?: A framework for model validation. Tech. rep., RAND, Santa Monica.

Hoffman, K. C., Wood, D. O., 1975. Energy System Modeling and Forecasting.

Hope, C., 2006. The Marginal Impact of CO2 from PAGE2002: An Integrated Assessment Model Incorporating the IPCC's Five Reasons for Concern. The Integrated Assessment Journal 6, 16–56.

Hunter, K., Sreepathi, S., DeCarolis, J. F., 2013. Modeling for insight using Tools for Energy Model Optimization and Analysis (Temoa). Energy Economics 40, 339–349.

Kaysen, C., 1972. The Computer that Printed Out W*O*L*F*. foreign affairs 50 (4), 660–668.

Kelly, D. L., & Kolstad, C. D., 1998. Integrated assessment models for climate change control. International yearbook of environmental and resource economics (November 1998), 171–197.

Kriegler, E., Riahi, K., Bosetti, V., Capros, P., Petermann, N., van Vuuren, D. P., Weyant, J. P., Edenhofer, O., Jan. 2015. Introduction to the AMPERE model intercomparison studies on the economics of climate stabilization. Technological Forecasting and Social Change 90, 1–7.

Kunreuther, H., Gupta, S., Bosetti, V., Cooke, R., Dutt, V., Duong, M. H., Held, H., Llanes-Regueiro, J., Patt, A., Shittu, E., Weber, E., 2014. Integrated Risk and Uncertainty Assessment of Climate Change Response Policies. Climate Change 2014: Mitigation of Climate Change, contribution of Working Group III to the IPCC Fifth Assessment Report, 151–206.

Labriet, M., Kanudia, A., Loulou, R., Dec. 2012. Climate mitigation under an uncertain technology future: A TIAM-World analysis. Energy Economics 34, S366–S377.

Labriet, M., Nicolas, C., Tchung-Ming, S., Kanudia, A., Loulou, R., 2015. Energy decisions in an uncertain climate and technology outlook : how stochastic and robust analyses can assist policy-makers. In: Giannakidis, G., Labriet, M., Gallachóir, B. O., Tosato, G. (Eds.), Informing energy and climate policies using energy systems models, springer s Edition. Springer, Ch. 03.

Le Bras, H., 1994. Les limites de la planète. Mythes de la nature et de la population. Flammarion.

Matarasso, P., 2001. Integrated Assessment Models of Global Change. In: Encyclopedia of Global Environmental Change.

Matarasso, P., 2003. Les origines des méthodes de modélisation dans le champs du changement climatique. In: Workshop Centre Alexandre Koyré "Modèles et systèmes complexes, le changement climatique global ".

Morgan, M., Henrion, M., 1990. Uncertainty: a guide to dealing with uncertainty in quantitative risk and policy analysis., cambridge Edition. Cambridge.

Morgan, M. G., Keith, D. W., 2008. Improving the way we think about projecting future energy use and emissions of carbon dioxide. Climatic Change 90, 189–215.

Nakata, T., 2004. Energy-economic models and the environment. Progress in Energy and Combustion Science 30, 417–475.

Nordhaus, W., 1992. The 'DICE' Model: Background and Structure of a Dynamic Integrated Climate-Economy Model of the Economics of Global Warming. Cowles Foundation Discussion Paper.

Nordhaus, W. D., 1973. World Dynamics: Measurement Without Data. Economic Journal 83 (332), 1156–1183.

Nordhaus, W. D., 1977. Strategies for the control of carbon dioxide. Cowles Foundation Discussion Paper 443, 78.

Nordhaus, W. D., 1980. Thinking about Carbon Dioxide: Theoretical and Empirical aspects of optimal control strategies.

Nordhaus, W. D., Tobin, J., 1972. Is Growth Obsolete? In: Economic Research: Retrospect and Prospect Vol 5: Economic Growth. Vol. 5. NBER, Yale, pp. 1–80.

Ozbekhan, H., 1969. Toward a General Theory of Planning. In: Jantsch, E. (Ed.), Perspectives of planning. No. 1. OECD, Paris, pp. 47–155.

Pandey, R., 2002. Energy policy modelling: Agenda for developing countries. Energy Policy 30 (March 2001), 97–106.

Parson, E., Fisher-Vanden, K., 1997. Integrated assessment models of global climate change. Annual Review of Energy and the Environment 22, 589–628.

Pindyck, R. S., 2013. Climate Change Policy : What Do the Models Tell Us ? Journal of Economic Literature 51, 860–872.

Pottier, A., 2014. L'économie dans l'impasse climatique. Ph.D. thesis, Ecole des Hautes Etudes en Sciences Sociales.

Rozenberg, J., 2014. Eléments sur la robustesse des politiques climatiques. Ph.D. thesis, Ecole des Hautes Etudes en Sciences Sociales.

Schelling, T., 2010. Un faisceau d'incertitudes. In: Touffut, J.-P. (Ed.), Changement de climat, changement d'économie ? Albin Michel, Paris, pp. 67–84.

Schwanitz, V. J., Dec. 2013. Evaluating integrated assessment models of global climate change. Environmental Modelling & Software 50, 120–131.

Simmons, H., Apr. 1973. 13. System dynamics and technocracy. Futures 5 (2), 212–228.

Solow, R., 1988. Growth theory and after. The American Economic Review 78 (3), 307–317.

Stanton, E. a., Ackerman, F., Kartha, S., 2008. Inside the integrated assessment models: Four issues in climate economics. Climate and Development 1, 166.

Syri, S., Lehtila, A., Ekholm, T., Savolainen, I., Holttinen, H., Peltola, E., Feb. 2008. Global energy and emissions scenarios for effective climate change mitigation—Deterministic and stochastic scenarios with the TIAM model. International Journal of Greenhouse Gas Control 2 (2), 274–285.

The Club of Rome, 1970. The predicament of mankind. Tech. rep.

Trutnevyte, E., 2014. Innovative Techniques for Quantitative Scenarios in Energy and Environmental Research : a Review.

Vecchione, E., 2013. Peut-on délibérer du futur ? Nouvelles perspectives des modèles d'évaluation intégrée. Congrès AFSP Paris 2013, 1–31.

Vieille Blanchard, E., 2011. Les limites à la croissance dans un monde global. Ph.D. thesis, Ecole des Hautes Etudes en Sciences Sociales.

Weitzman, M. L., 2009. On modeling and interpreting the economics of catastrophic climate change. The Review of Economics and Statistics 91 (February), 1–19.

Weyant, J., Davidson, O., Dowlatabadi, H., 1996. Integrated Assessment of Climate Change: An Overview and Comparison of Approaches and Results. In: Bruce, J. (Ed.), Climate Change 1995: Economic and Social Dimensions of Climate Change, cambridge Edition. Cambridge.

Zagamé, P., 2008. Modèles de l'énergie et nouvelles théories du progrès technique. Tech. rep., Le Conseil Français de l'Energie, Paris.

2

(How) does sectoral detail affect the robustness of policy insights from energy system models? The refining sector's example

2.1 Introduction

Energy system models (ESMs) have been developed since the 1970s to address questions in two main areas, namely energy security and sustainability/climate change. In the latter case, they are often used to formulate and evaluate public objectives and policies intending to limit Greenhouse Gas (GHG) emissions. Objectives are usually presented in terms of abatement targets, for the whole energy sector (Zhang et al., 2015, Labriet et al., 2015, Ning et al., 2013). Energy and environmental policies can be global or sectoral – e.g. applied to the power or the electricity sector – and deal with both quantity or price instruments aiming at internalizing the climate change externality (like standards, taxes as in Borjesson and Ahlgren (2012), subsidies see Waide and Brunner (2011) and market(s)). Policy implications can also be derived from technology assessments, highlighting potential improvement and bottlenecks of existing policies to sustain particular technologies or pathways (Spearrin and Triolo, 2014, van der Zwaan et al., 2013, Seixas et al., 2015, Indati Mustapa and Ali Bekhet, 2016). All these exercises have a major common point: they allow to gain qualitative insights from (often) large quantitative models, so that policy makers and stakeholders can enhance their mental models of the world and take better-informed decisions. Although the interest of such models is widely recognized for the previous benefit, one of their main drawbacks lies in their complexity. The intricacy of many sectors and radically uncertain socio-economic phenomena contributes to produce long-term scenarios that could suffer from a clear lack of robustness (Pindyck, 2013). This means that policy conclusions may not be robust to changes in exogenous assumptions as energy resources or prices, techno-economical detail of key technologies, or demands [1]. Another potential flaw of ESMs is more rarely assessed: it deals with the robustness of outcomes with respect to the modeling detail of the various sub-sectors constituting the system. Among the rare available examples, Dodds (2014) shows how dis-aggregating the residential sector can help improve heat decarbonization assessments. Cayla and Maizi (2015) prove that detailing the transport demand induces more

[1] To circumvent these issues, modelers use advanced techniques: extensive scenarios analysis (Babaee et al., 2014), Monte-Carlo simulations (MIT, 2012), or explicit uncertainty modeling (see G. Giannakidis et al. (2015) for a review, and see Cai et al. (2009))

realistic vehicle fleet trajectories, especially by smoothing the penny-switching nature of optimization models. However, no such effort has been made to evaluate the impact of describing the fuel supply technologies more or less accurately on the policy insights and recommendations deduced from the model results.

In this study, we investigate whether the level of detail in the description of refining technologies impacts optimal mitigation options in the transport sector within an ESM, and hence the nature of the insights gained. In the transportation sector, CO_2 emissions can globally be computed as:

$$CO_2 = \underbrace{CarbonIntensity}_{\frac{gCO_2}{MJenergy}} \times \underbrace{EnergyEfficiency}_{\frac{MJenergy}{km_{travelled}}} \times \underbrace{DistanceTravelled}_{km_{travelled}} \tag{2.1}$$

$$\tag{2.2}$$

Mitigation policies thus include three main options: reducing the fuel carbon intensity (by using more natural gas, biofuels, electricity...), increasing the energy efficiency of mobility devices (more hybrid cars and buses, electric vehicles...) and managing demand (reducing the distance traveled). The relative weight of these options to reach a given abatement target depends on their relative costs. Our main assumption relates to the fact that changing the technical and economical description of a sub-sector within the transportation chain could affect the relative abatement costs of the decarbonization options. Hence, the technological pathways could change, leading to different policy implications.

The level of detail of each sector description within a specific model is often linked to the available public technical data or with the competencies of the modelers' team, but it is also clearly linked to the "real" complexity of these sectors[2]. We then select the oil refining sector as a case study. First, the refining sector is complex to depict (Al-Muslim and Dincer, 2005, Tehrani Nejad Moghaddam and Saint-Antonin, 2008): there are lots of possible refinery's inputs (different kinds of crude oil, natural gas, hydrogen, naphtha, ethanol, FAME...) and even more outputs with varying yields and qualities (LPG, naphtha, several gasoline and diesel, jet fuel, kerosene, heating oil, marine bunker fuel, fuel oil with several sulfur contents, coke...). Furthermore, a refining plant contains from 10 up to 40 process units and refining schemes can vary a lot. Within the overall energy system, it shows a unique chain of complex, interdependent and largely integrated process units. Second, it seems that only a few global energy models incorporate detailed refining descriptions (NEMS for example Morris et al. (2002)). If there have been a few attempts to incorporate condensed descriptions of the refining sector in larger models (Babusiaux and Champlon, 1982), the discrepancies between these representations and the "real" sector complexity likely leads to misspecifications.
First, oil refining is typically a case where adaptation to changing relative demands can take several forms. To modify their final oil product yields, refiners can treat more or less heavy crudes, change the refinery's input or, alternatively, they could treat the same crude through different chains of processes. The key underlying idea is that none of this can occur without costs. Hence, a meaningful refinery model should adequately depict the costs of changing the structure of final products.
Second, from the economic viewpoint, oil refining represents a textbook case for several reasons. Climate change and security of supply somehow aim at reducing the use of oil, which is used in the form of refined products. So, the relevance of substitution options will depend on their

[2]We refer here to the Collins English dictionary's definition of complex: "Made up of various interconnected parts; composite".

relative prices compared to fossil fuels, which in turn depend on the extent of the description of this sector.
Third, refining offers a unique set of complex joint production (Baumol, 1972) in the energy sector: its products are then sold in the global energy system, and specifications of final products related to the qualities of crude oil imply that intermediate products are numerous, and only partially substitutable.

In this paper, we build an experimental numerical setting to test our assumption that inadequate model specifications may lead to less robust technology outlooks, hence less robust policy insights. Our aim is to contribute to the literature by testing an identical set of policy objectives with an energy-transport model by changing only the aggregation level of the oil refining sector. Therefore, we can isolate the single effect of technological detail on the optimal solutions and assess the robustness of the subsequent policy insights. In section 2, we present a stylized model to understand how the description of technologies impacts optimal choices. In section 3, we describe the full-scale TIMES model used for the study and the different oil refining models implemented and in section 4 we detail the scenarios employed and the main results obtained.

2.2 Pricing in linear programming-based energy systems models

The experimental design we set up in this section relies on linear programming (LP), a common paradigm for energy system modeling Bhattacharyya and Timilsina (2010). Therefore, it is worth starting with a more formal investigation on the impact of technology specifications on pricing and optimal choices in such partial equilibrium models. The stylized model presented below aims at fulfilling this goal.

2.2.1 Principles

A LP model computes at the optimum both energy flows and associated prices for each good endogenously traded. The production-consumption balance of each intermediate product within the model must be positive: producers (sellers) are mandated to produce at least the amount that consumers (buyers) are willing to buy. Shadow prices are computed as the dual values of these balance constraints - or, the decision variables of the dual linear program. It is said that shadow prices equal marginal values of the traded commodities. Supply-demand equilibria in linear programming take the well-known graphical form of stepwise constant supply and demand curves, which are implicitly built by the model (Figure 2.1). There, each step in the supply and demand curves represents the offer and demand of the good by a given technology. Marginal values are used as internal cession prices between the various sectors. Their interpretation (differing from that of marginal costs) is the following: the marginal value may reflect adaptation on the supply or the demand side of the market for the considered good. In the case of joint production processes (such as oil refining), marginal values of the joint goods are dependent from each other. Then, several phenomena are likely to modify the structure of the supply and demand curves for a given good:

- the techno-economic description of the various technologies (including joint production technologies such as oil refining as a special case);
- the introduction of public policies or objectives.

In this research, we retain on the normative perspective taken by a public policymaker who wants to reduce the GHG externality created by transport. Therefore, he defines a desirable emission

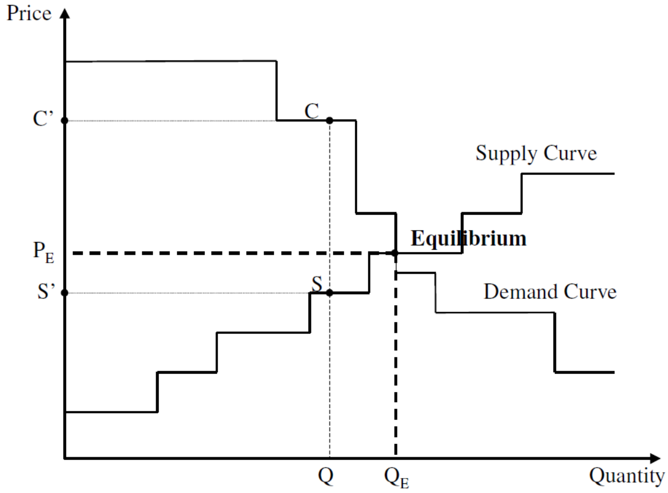


Figure 2.1: Supply and demand equilibrium of an endogenously traded good within a LP energy system model

cap corresponding to a certain abatement level compared to historical values or a business-as-usual scenario. This objective is implemented as an exogenous constraint in the model, so that the total emissions from the transport sector cannot exceed the cap. To fulfill this constraint, it is possible to reduce the carbon intensity of transport fuels, or increase the sector's energy efficiency, or a mix of both. This would happen because in vertically-related markets such as fuel and transport markets, the prices of the upstream commodities (fossil or bio-fuels) will affect the cost of supply of the downstream industries (the transportation markets in this case). On top of that, all of these technologies will contribute to carbon emissions or carbon savings. From the partial equilibrium assumption, we get the optimal technological decisions and the shadow price of carbon simultaneously. Both will then depend on the costs and environmental effectiveness of the technologies used.
Therefore, different technology descriptions within the same modeling framework, could alter the structure of marginal values, and thus the competitiveness of e.g. abatement options in a carbon-constrained world. Changing the description of the refinery should change the shadow price of carbon for a given cap, and hence the recourse (or not) to abatement options. We now illustrate this phenomenon with a stylized model.

A stylized model

To understand the impact of technology description on shadow prices and optimal choices, we build a stylized energy-transportation model.
In this model, primary energy is transformed into fuels in order to meet two exogenous demands: one of mobility and one of gasoline (see figure 2.2). To comply with the mobility constraint, the drivers have the choice of using a regular diesel car (DSLCar) or a low energy diesel car (LEDCAR) with a better efficiency but whose cost per kilometer is higher ($c_{ml} > c_{mc}$). The vehicles are fueled with diesel and biofuel, and there is a norm on biofuel incorporation (it can not represent more than N% of the global fuel). The biofuel (x_b) is produced by the processing of biomass (in quantity x_2), c_2 is the cost of production of one unit of biofuel (it includes the costs

of biomass and its processing). Diesel (x_d) comes from the processing of crude oil in the refinery (in quantity x_1), gasoline (x_g) is jointly produced with diesel (c_1 is the sum of the purchase and the refining of one unit of crude oil). Two different descriptions of the oil refining sector

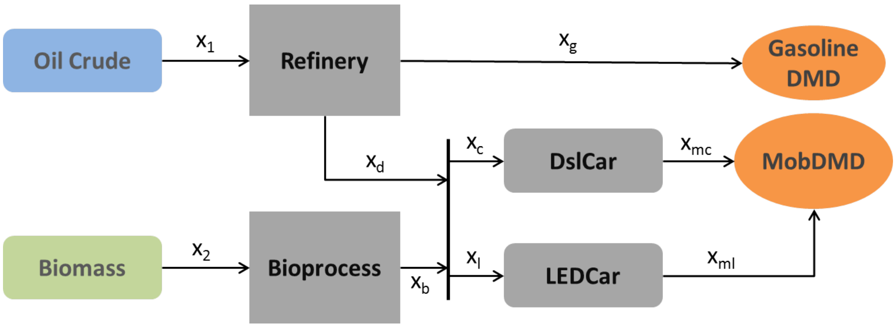


Figure 2.2: Stylized Model

are implemented in this common framework, one with a fixed yields refinery, the other with a completely flexible refinery. In the latter case, the yields of each product out of the refinery can vary freely between 0 and 1. In each of these cases, the shadow prices of the outputs will depend on the relative demands for the two products in a different way.
Our problem is to minimize the cost of the global system given the exogenous levels of demand of mobility and gasoline (eq 2.4 and 2.5), the production constraints (eq 2.6 to 2.11), the biofuel specification (eq 2.12) and the CO_2 emissions ceiling (eq 2.13).
It can be written as follows for the fixed yields Refinery:

$$\begin{cases} \min c_1 x_1 + c_2 x_2 + c_{ml} x_{ml} + c_{mc} x_{mc} & & (2.3) \\ s.t. & & \\ x_{mc} + x_{ml} \geq MobDMD & (y) & (2.4) \\ x_g \geq GDMD & (y_g) & (2.5) \\ x_d + x_b \leq x_c + x_l & (y_i) & (2.6) \\ x_g - \Gamma_g x_1 = 0 & (\theta_g) & (2.7) \\ x_d - \Gamma_d x_1 = 0 & (\theta_d) & (2.8) \\ x_b - \Gamma_b x_2 = 0 & (\theta_b) & (2.9) \\ x_{mc} - \gamma_c x_c = 0 & (\theta_{mc}) & (2.10) \\ x_{ml} - \gamma_l x_l = 0 & (\theta_{ml}) & (2.11) \\ -N x_d + (1-N) x_b \leq 0 & (\beta) & (2.12) \\ \varepsilon_g x_g + \varepsilon_d x_d \leq \bar{E} & (\sigma) & (2.13) \end{cases}$$

Where x_g and x_d are the quantity of gasoline and diesel produced by the refinery. x_{mc} and x_{ml} are respectively the number of kilometers traveled with diesel cars and low emissions diesel cars. ε_g, ε_d the emission factor of gasoline and diesel. $\bar{E}$ is the ceiling on CO_2 emissions. Γ_g, Γ_d, Γ_b, Γ_{mc} and Γ_{ml} are respectively the yields of the refinery in gasoline and diesel, of the bioprocess in biofuel, and of the regular and the high efficiency diesel cars.
In the case of the flexible refinery, the equations are the same except the (2.7) and (2.8) which have to be replaced by:

$$x_d + x_g = x_1 \qquad (\lambda) \qquad (2.14)$$

Albeit simple, this model already contains enough complexity to require specific assumptions to be solved analytically in particular cases. The two scenarios described below deal with the relative costs of the alternative fuel and mobility technologies, for the two refineries[3].
In the **Scenario Bio**, we suppose that :

- the Ledcar technology is not used because too expensive: $cml \rightarrow \infty, x_{ml} = x_l = 0$
- The biofuel constraint is not saturated: $\beta = 0$

In the **Scenario Ledcar**, we suppose that biofuels are not used because too expensive: $c_2 \rightarrow \infty, x_2 = x_b = 0, \beta = 0$
We solve this minimization problem and compare the CO_2 marginal values obtained for the two different refineries (see appendix A and A for the first order conditions, the resolution and the other Lagrange multiplier values). Results are presented in table 2.1

	Fixed yields refinery	Flexible refinery
Scenario Bio	$\sigma^{bio}_{fix} = (c_2 \frac{\Gamma_d}{\Gamma_b} - c_1)\frac{1}{\varepsilon_d \Gamma_d + \varepsilon_g \Gamma_g}$	$\sigma^{bio}_{flex} = (\frac{c_2}{\Gamma_b} - c_1)\frac{1}{\varepsilon_d}$
Scenario Ledcar	$\sigma^{ledcars}_{fix} = \frac{1}{\varepsilon_d \Gamma_d + \varepsilon_g \Gamma_g}(-c_1 + \Gamma_d \frac{c_{ml} - c_{mc}}{\Gamma_{ml} - \Gamma_{mc}} \Gamma_{mc} \Gamma_{ml})$	$\sigma^{ledcars}_{flex} = (\frac{c_{ml} - c_{mc}}{\Gamma_{ml} - \Gamma_{mc}} \Gamma_{mc} \Gamma_{ml} - c_1)\frac{1}{\varepsilon_d}$

Table 2.1: Shadow price of the carbon constraint in each scenario

The first thing we can notice is that the marginal value associated to the CO_2 constraint (σ) differs between refinery descriptions for a given scenario. It means that for the same level of the carbon ceiling, the technological options chosen to mitigate emissions could differ.
We plot the evolution of the objective function value as the carbon cap grows more and more stringent for the two refineries with a given set of parameters (figure 2.3 and see appendix A for the parameters values). The carbon ceiling is not binding at the same level for the two refineries.

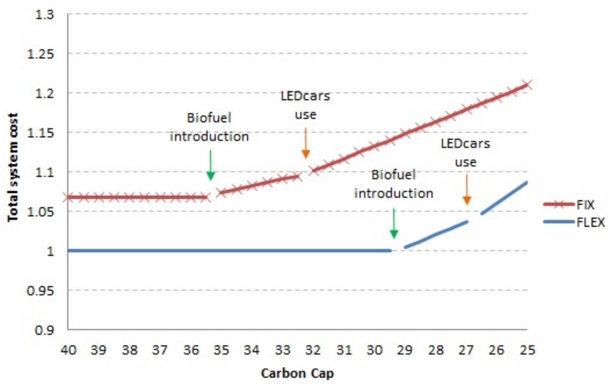


Figure 2.3: Objective function evolution with the carbon ceiling

[3]In the case of the fixed yields refinery, we assume that gasoline is produced in excess

In the fix refinery case, gasoline is in excess (the mobility constraint is saturated but the gasoline one is not) hence the total emissions of this model are higher than in the flexible refinery case. Because of the parameters values we have: $\sigma^{bio}_{fix} < \sigma^{ledcar}_{fix}$ and $\sigma^{bio}_{flex} < \sigma^{ledcar}_{flex}$, which explains why the first option chosen to mitigate emissions is biofuel.
Another interesting point is the fact that biofuel use allows to mitigate more emissions in the fix refinery case than in the flex one (3 units vs 2.5 units). Indeed, using more biofuels reduces the need of diesel so the refinery processes less crude oil and subsequently reduces its gasoline production. As a result, the gasoline excess is less important so indirectly, incorporating biofuel in the vehicle fuel helps also to reduce emissions due to gasoline. This situation does not happen for the flexible refinery since gasoline excess is nonexistent in this model.

We then use parameter values that would allow a different result, we raise c_2 in order to have $\sigma^{bio}_{flex} > \sigma^{ledcar}_{flex}$ (see figure 2.4). Moreover, we modify the fix refinery yields, lowering the diesel yield and raising the gasoline one.

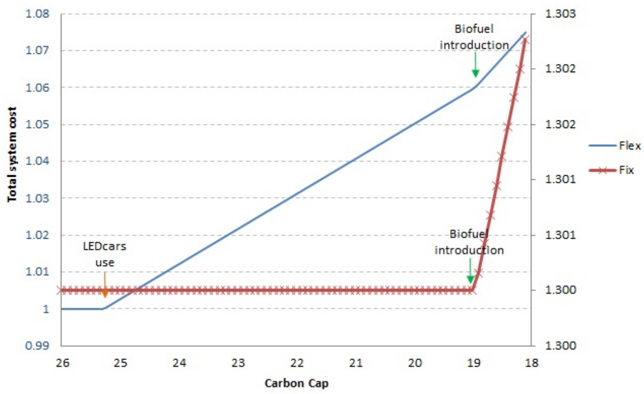


Figure 2.4: Objective function evolution, low diesel yield

As a result of the low diesel yield, it is optimal for the fix refinery model to use ledcars even with no carbon constraint. The comparison of the two models' runs with a carbon ceiling is distorted since the flexible refinery does not have this problem. The marginal values of the carbon constraint are really different (see the slope of the two curves) hence if the choice of mitigation technologies were larger we can not be assured that the same technologies would be chosen to abate emissions.
Moreover, with this set of parameters these two models have different abatement capacities: the fix one can abate up to 1.5 units of carbon when the flex one can abate 7.8 units of carbon.

To understand how a complex refinery would behave, we added two processes to the fix refinery (HC1 and HC2): these processes convert gasoline into diesel with different costs and yields. It is not mandatory to use the new processes. The new refining scheme and parameter values can be found in appendix A. We did the same exercise than earlier and for the initial values of the parameters, we obtain the following results (see figure 2.5):
The cheapest process HC1 is used even when there is no carbon constraint as it allows to reduce the gasoline waste. After that, the cost ratios of the other options lead biofuels to be introduced first, then HC2 and finally the low-energy vehicle technology. The little flexibility introduced with the two new processes is not sufficient for the objective function trajectory to

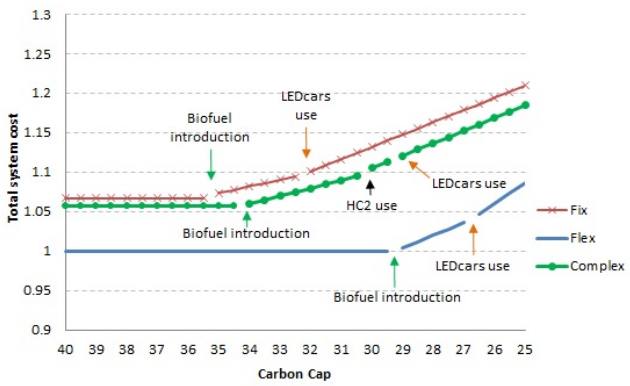


Figure 2.5: Objective function evolution, with 3 refineries

change drastically. Yet, we can observe that the "complex" refinery trajectory is nested between the two others and that the flexibility delays the adoption of new technologies.

This simple stylized example illustrates that refinery models characterized by different levels of flexibility exhibit different shadow price structures. Submitted to a series of increasingly stringent carbon caps, we show that the responses of the three models differ: abatement options are utilized differently in quantity (production level) and are triggered for different cap levels. For example, as we can see in figure 2.5, and for a 30% cap:

- fix refinery model: both biofuels and efficient cars in the optimal solution;
- complex refinery model: only biofuels in the optimal solution;
- flexible refinery: no alternative technology in the optimal solution.

At this point, a decision maker facing such scenarios may be tempted to formulate policy recommendations that may differ. For example, he could weigh the amount of public funds dedicated to sustain the alternative technologies differently. Such potential traps are an issue, at least theoretically. Whether this would affect results in a more complex, real-size model is the question addressed in the next subsection.

2.3 An energy-transport system model

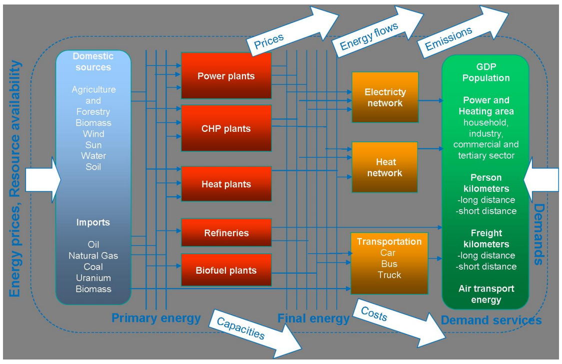
In this section, we present the IFPEN-developed MIRET model: a long-term, multi-period, techno-economic planning model that covers the energy-transport system in detail. Its scope is continental France, and the time horizon is 2050, with 2007 as base-year.
MIRET is generated using TIMES, a bottom-up technology rich optimization modeling framework allowing a detailed representation of energy systems, ranging from sectoral representations to global energy systems. TIMES enables the extensive description of the equipment stocks and physical flows across technologies from the extraction of primary energy resources to the final consumption of energy and energy services. Under this well established paradigm (Labriet et al., 2010, Lorne and Tchung-Ming, 2012), a Reference Energy System is built to cover the stock of equipment and flows for the reference year, the characteristics of future technologies, the potential and costs for primary energy. This being given, the model aims at providing final

energy services / energy while maximizing -via linear programming- the total surplus (sum of the surpluses of the consumers and suppliers), which acts as a proxy for welfare in each region or country of the model.

2.3.1 General presentation

The model schematics is presented in Figure 2.6. It presents a block diagram that links elements described in the model according to four main dimensions: energy supply, technologies, demand and policies Loulou and Goldstein (2005).

Figure 2.6: Model schematics



The reference energy system is thus composed (from left to right) of:

- *a primary energy supply* block: includes imported fossil energy (crude oil, coal, natural gas), biomass (starch crops – wheat, corn; sugar crops – sugar beet; oil crops – rapeseed, sunflower; lignocellulosic biomass – forest wood, crop residues, dedicated energy crops);
- *an energy technology* block, whose technologies transform primary energy into energy vectors and energy services: it includes oil refining (see next section), biofuel units (first generation – ethanol, FAME , HVO ; second generation – ethanol and synthetic FT-Diesel), electricity generation (power plants – all technologies; combined heat and power), preparation of fuels for transport at blending (diesel, biodiesel B30, gasoline grades E5 and E10 and E85, jet fuel – including fossil and bio bases), and end-use technologies for road mobility (personal vehicles and Light – thermal, hybrid, plug-in hybrid / gasoline, diesel, natural gas, flexfuel, electric cars; buses and trucks – thermal, hybrid / gasoline, diesel, biodiesel);
- *a final energy / energy services demand* block: Electricity demand by time period (four days representing each season, the power load being hourly described for each of these days), mobility demands (short and long distance for passenger vehicles and buses, traffic for LUV, demand for freight mobility), demands for exported products (oil products, electricity);
- *a policy* block: includes measures and constraints of several types affecting all sectors. Some are of microscopic nature, such as quality norms for refinery products, number of functioning hours of fuel turbines power plants, etc. Some are macroscopic in nature, e.g. sectoral carbon tax.

2.3.2 Basic formalism

The objective function of the underlying linear program takes the form:

$$OBJ = \sum_{t \in periods} (1 + disct_t)^{2007-t} TotCosts_t$$

where $disct_t$ is the discount rate. It is simply the discounted sum of the total annual costs ($TotCosts$), the main ones being: annualized capital costs due to investments in new processes, decommissioning costs, fix costs, variable costs and tax and subsidies. The linear program P is as follows:

$$(P) = \begin{cases} \min \mathrm{c}^T x & \\ s.c. & \\ Ax \geq b & (y) \\ Tx = 0 & (\tau) \\ Kx \leq k & (\lambda) \\ Qx \leq q & (\omega) \\ Sx \leq s & (\sigma) \\ x \geq 0 & \end{cases}$$

c is the column vector of all discounted unit costs. The constraints $Ax \geq b$ correspond to the final demands of energy and energy services to be satisfied. The equation set $Tx = 0$ describes the fundamental input-output relationships of each technology, namely the mass or energy balance of each technology. The set $Kx \leq k$ includes all capacity constraints, either technology or resource based. For example, (i) the electricity produced by a given technology is limited by the combination of the stock installed and seasonal or hourly availability factors, (ii) the use of scarce resources, e.g. woody biomass, are limited for use for power, heat, combined heat and power and biofuels production. $Qx \leq q$ accounts for the quality equations of some of the products. This is especially the case of refinery products, whose quality must respect certain specifications to be marketed. Finally, the set $Sx \leq s$ includes all sorts of institutional constraints (e.g., the French legislation limits the number of functioning hours of certain power plants – notably fuel turbines), calibration constraints and share constraints.

2.3.3 The refinery sector – from aggregated to detailed

In this section we detail the four refinery models used in the study.

Three concise models of the French refining sector

In the first MIRET model, the refinery is modeled with a single process. The process inputs are crude oil, natural gas and oxygen and the outputs are LPG, Naphtha, gasoline (GSL), jet fuel, heating oil (HOL), diesel (DSL), fuel oil (RFO) and coke (see Figure 2.7).

The throughput yields can each vary between two values and are optimized by the model (with the obvious constraint that the yields sum equals 1). These two minimum and maximum values for each petroleum product have been determined with regard to the 2007 French refining tool and they evolve with time in order to take into account a possible adaptation of the refining industry to the local market changes (see Figure 2.8). There is no cost associated with the yield structure evolution. For the purpose of our study, we developed and modified this initial semi-flexible refinery model: we built what we call a Fix refinery model where the yield vector is fix (it evolves with times only, see Figure 2.9) and a totally flexible one, called Flexible Refinery, for which the throughput yields can take any value between 0 and 1, allowing the model to get rid of

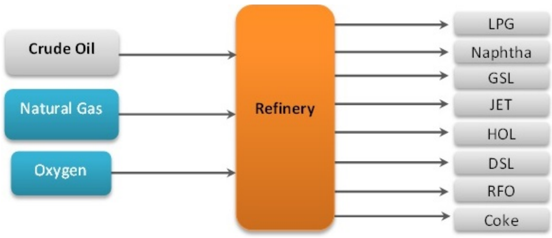


Figure 2.7: MIRET's semi-flexible Refinery

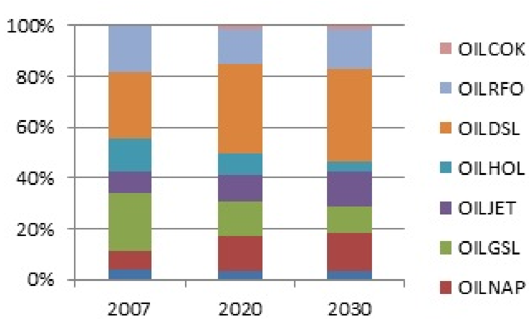


Figure 2.8: Product yields variations - French semi-flexible Refinery

the co-product issue. These two models are extreme: the fix one forbids any adaptation so that the amount of fatal products of the refinery cannot be reduced but by lowering the refinery's utilization rate. On the contrary, with the flexible refinery, the fatal products are not a problem since they are not produced at all. The mathematical representation of these 3 refinery models

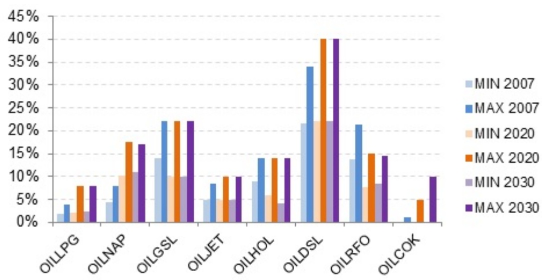


Figure 2.9: Yields vectors - Fix Refinery

is the following:

Semi-flexible Refinery | Flexible Refinery | Fix Refinery

$$\begin{cases} \forall i \in [1,8] \\ \lambda_i CR \leq y_i \leq \upsilon_i CR \\ 0 \leq \lambda_i \leq \upsilon_i \leq 1-\delta \\ s.t. \\ \sum_i y_i = CR(1-\delta) \end{cases} \qquad \begin{cases} \forall i \in [1,8] \\ 0 \leq y_i \leq CR(1-\delta) \\ s.t. \\ \sum_i y_i = CR(1-\delta) \end{cases} \qquad \begin{cases} \forall i \in [1,8] \\ y_i = \alpha_i CR \\ With \\ \sum_i y_i = CR(1-\delta) \end{cases}$$

With y_i the quantity of each of the eight refinery outputs, CR the crude oil quantity entering the refinery and δ the autoconsumption and losses of the refinery. These models differ only by the yields' vector. The cost per unit of input, the refinery CO_2 emissions, the nature of the outputs... are the same for the three models.

A detailed model of the French refining sector

The initial Miret's refinery model and its two variants have several issues that we tried to tackle by building a more complex French refining model. The first issue is that the yields' flexibility allowed by the simple refinery model is free which is far from being realistic. To change the throughputs of his refinery, the refiner can first switch to a crude oil more appropriate to meet his production targets. But, this solution does not enable him to deeply change the plant production profile. To do so he has to adapt the process units' utilization rate which can be costly or he has to invest in new units. For example, to produce more diesel and less fuel oil, the conversion units have to run more and since they have high operational expenditures, the refining cost will increase.
The second issue of the simple refinery model regards the fuel specifications. Usually, simple models do not take into account the oil and product quality and the difficulty (and cost) to meet the fuel specifications. However, this aspect is really important and constraining particularly for the blending of biofuel in the transportation fuels (ethanol in gasoline).
The third problem of the simple model is the representation of the petroleum product marginal values and more particularly of their ratio which are distorted, among other things by the costless flexibility of the yield vector.
And finally, a more complex model of the refining sector allows to improve the CO_2 emissions representation. Indeed in the three simple refinery models, CO_2 emissions are linearly correlated with the amount of crude oil treated whereas in the "reality", the CO_2 emissions are related to the amount and type of fuel used in the refinery plant fuel (natural gas, internal fuel gas, fuel oil, FCC coke, hydrogen...) and are also linked to the processes used (high pressure processes are more fuel intensive than others).
For the reasons presented above, we built a Complex refinery model. The retained refining structure consisted in the most common processing units, among which an atmospheric distillation unit, a vacuum distillation unit, a catalytic reforming unit, a gasoil hydrodesulphurization unit, an ETBE unit, a catalytic cracker, an hydrocracker, combined with alkylation and isomerization units to improve the quality of the gasoline pool, and a visbreaking unit to process residues from these units (the refining scheme is presented in Figure 2.10). This conversion refinery is very close to the current structure of the French refining industry but it may change to be adapted in line with future developments or in some scenarios considered over the next thirty years. To face the possible evolutions of demand and measures that could be adopted about the tightening of petroleum product specifications such as reduction in the sulphur content in diesel oil and heavy fuel oil, a coking unit has been added in the modeled refining structure in order to permit a lesser production of fuel oil. More expensive deep conversion units as partial oxydation unit and a deep hydrodesulphurization unit are not in the model since the French refining has

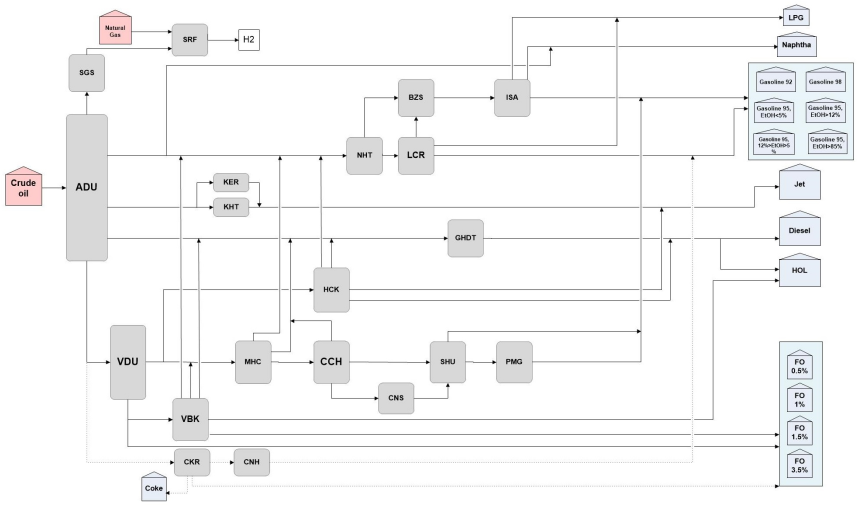


Figure 2.10: French refining scheme

been in a bad shape for a decade and large investments in this industry seem pretty unrealistic. Regarding the main input of the refinery, there is at the moment only one crude oil entering the refinery whose characteristics are representative of the mix of crude oil used in France in 2007.

To summarize, the three simple refinery models are very close except for the yields' vector. For the same crude oil treatment, the refining cost and emissions will be similar but we will obtain different amounts of petroleum products (see table 2.2).
More importantly, the marginal value ratios of the petroleum products will vary a lot between the three models: with the flexible one, all ratios are equal to 1 since at the optimum, all the produced products have the same marginal values, for the fix refinery the ratios risk taking extreme values whereas the simple model should give moderate but not necessarily accurate ratios. The description of the process flexibility will thus impact its cost of adaptation to changing demand structures.
Conversely, with the complex refinery model, we should obtain rather accurate (realistic) petroleum product marginal value ratios. The CO_2 emissions and the total refining cost of this refinery depend on the quantity and type of petroleum products produced. Indeed, the fuel production determines how and which refining processes are used and since the various process units have very different fuel consumption and operational expenditure, this knowledge greatly impacts the total cost and emissions.

	Complex	Semi-flexible	Flexible	Fix
Yields	Flexible, with costs	Flexible within allowed ranges. The flexibility is free.	Totally flexible. The flexibility is free.	Totally fixed
Product specifications	Yes	No		
CO_2 emissions	Depend on the processes used	Proportional to the quantity of crude oil treated		
Costs	Depend on the processes used	Proportional to the quantity of crude oil treated		
Adaptation	Costly	Cost-free		None

Table 2.2: Refineries, Summary

2.4 Model detail, global mitigation strategies and sectoral policies

2.4.1 Scenarios

Economic, demographic and technological assumptions
GDP (2007€) scenario is built based on existing projections for France. At the 2030 horizon, DGTPE scenarios is selected; 2050 extension is based on OECD long-term growth projections. This scenario traduces a slow-down of growth in the next decades. Assumptions regarding the

	2010-2020	2020-2030	2030-2050
GDP growth	1.4%	2%	1.4%

Table 2.3: French GDP growth

French population evolution are presented in appendix 3.2.3. Appendix B provides the main sources for numerical assumptions and parameters and in particular for technological costs.

Carbon constraints
Two types of carbon constraints have been tested. In the first case, a cap is applied on the cumulative global CO_2 emissions. In the second case, the cap is applied on cumulative fossil CO_2 emissions from transportation only.
Even though an annual cap is more likely to be instituted, we chose to use a cap on cumulative emissions mainly for a modeling reason: with this constraint we obtain a unique CO_2 price for each refinery model. With an annual ceiling, there is one CO_2 marginal value per year and since the refinery models do not necessarily adapt at the same time, the interpretation of the CO_2 marginal value variations between the models is not easy. The other reason is that it gives more flexibility to the model: an annual decreasing ceiling largely drives (and constrains) the model while a global one allows the model to adapt at any time.
For both constraints (global and sectoral), the cap is set relatively to a reference level. This reference level is the CO_2 emission value obtained in the base case, i.e. a case with no constraint on CO_2 emissions (see Figure 2.11). We can notice on this figure that the various refinery models have very few impacts on the global or sectoral emissions when no constraint is applied on CO_2.
Six levels of carbon constraints have been applied on the cumulative emissions of CO_2 between 2011 and 2050, ranging between a 10% and a 60% reduction compared with the total emissions

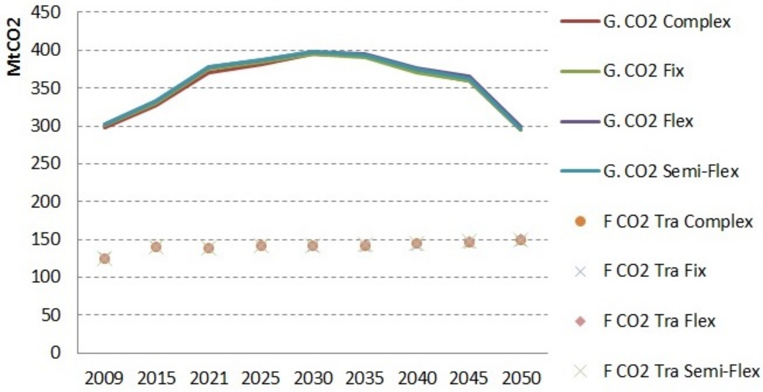


Figure 2.11: Global & Fossil Transportation CO_2 emissions for the base case (No emission ceiling)

obtained in the base case.

2.5 Results and Discussion

2.5.1 Global carbon constraint

For the first set of carbon constraint, the global CO_2 cap, the differences between the runs with the complex refinery model and those with the three other types of refinery are not very important. The reduction effort is first supported by the other industrial sectors (see Figure 2.12 for an illustration). In the semi-flex refinery case, the emission reduction first comes from the heating

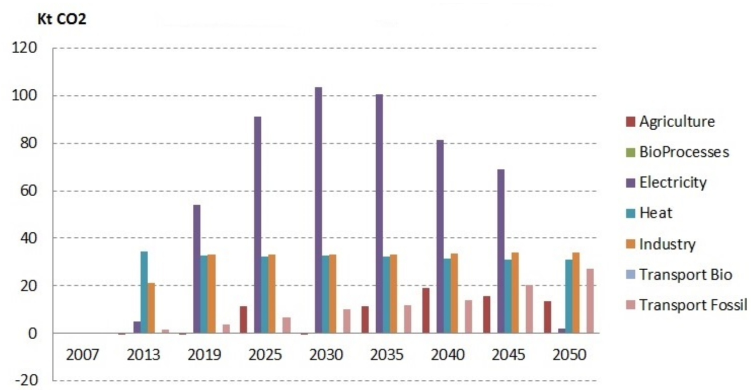


Figure 2.12: CO_2 emission abatement by sector for the semi-flex refinery model (ceiling: 40% reduction)

sector because it is relatively cheap to switch from gas produced heat to bio produced heat. Then the power sector contributes to the emission reduction with an increased use of renewables and a decreased use of coal and gas processes. The transportation sector's emission reductions are very low until 2030, at this date the sector stands for 65% of global CO_2 emissions (versus 45% in 2007).

The paths followed by the objective function or the CO_2 marginal values are slightly similar for the four different models (see Figure 2.13) when the constraint is not too stringent. When the CO_2 ceiling reaches very low values, the four models began to behave diversely.

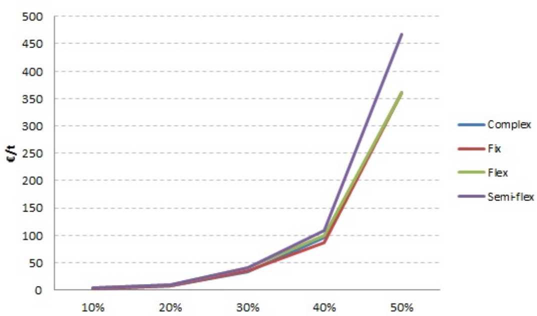


Figure 2.13: CO_2 marginal value for different levels of the ceiling

When trying to evaluate the impact of a global CO_2 ceiling on the energy-transport system,

adding details to the refinery model is not necessarily compulsory. It begins to be important when the ceiling evaluated is very ambitious (for example, the 50% ceiling leads to a CO_2 marginal value of 360€/t which is a very high value regarding the actual European CO_2 market). When the ceiling values are more classic, the refinery model does not impact the optimal solution. Indeed, there is a general consensus that reducing GHG emissions is very expensive in transport compared to other sectors (Waisman et al., 2013). So when a global cap is applied on CO_2 emissions, GHG cuts in transportation would appear only when the constraint becomes very stringent, irrespective of the description of the oil refining process.
This observation may however depend on the level of penetration of oil products in other energy sectors. To this respect, the French case is an exception: most of the electricity production is nuclear and the residential sector shows a high level of electrification. Therefore, the oil sector is largely dedicated to the production of fuels for transport and feedstock for petrochemicals. Other countries or regions may have more integrated energy profiles.

Sectoral carbon constraint

The following results present scenarios with a sectoral cap for which tailpipe fossil CO_2 emissions are constrained.
The first notable thing is the diversity in the adaptation adopted by the different models. The possible arbitrage is the following: the model can wait to adapt but will have to abate much more future emissions or it can reduce its emissions immediately which will allow him to emit more in the future. By looking at the CO_2 emission trajectories of the models, we can notice that the complex refinery model usually reacts first, and lowers its emissions in two steps when the other refineries adapt in a more abrupt way (see figure 2.14). The flexible refinery does not react very early but its reaction is radical when it happens. Another way to notice the differences induced by the various refinery models in the energy system model is to look at the four objective values trajectories which are slightly different (see appendix C).
The diversity of the CO_2 trajectories is the result of the different ways and timing of adaptation of the four models. To comply with the emission ceilings, the model has 3 possibilities:

- decarbonizing the fuels burnt in the vehicles by using biofuels for example
- using vehicles with a better energy efficiency
- switching to new energy sources for transportation, as electric vehicles for example

In this case, decreasing the mobility demand is not an option as we consider an inelastic demand[4] (the demand is an exogenous input of the model).
These 3 ways of reducing transportation sector emissions are all used when the constraint is high enough but not necessarily in the same proportions.
When the constraint is really stringent, the four models have the same way of adapting and very similar carbon marginal values. Indeed, with a very low carbon ceiling the choices to mitigate emissions are not numerous. It explains why the four models end up using the same technologies and biofuels. For this reason, it is not very interesting to look at the low ceiling results and we are going to study the models behavior for the intermediary ceiling values.

The figure 2.15 shows the evolution of transportation energy intensity and carbon intensity under 2 levels of reduction: 20% and 40%. The trajectories of energy intensity are pretty similar for the four models even though the vehicle fleets are different. It is relatively cheap and fast to

[4] We did the exercise with an elastic demand and the results do not change. For the sake of simplicity, we chose to present the results with an inelastic demand.

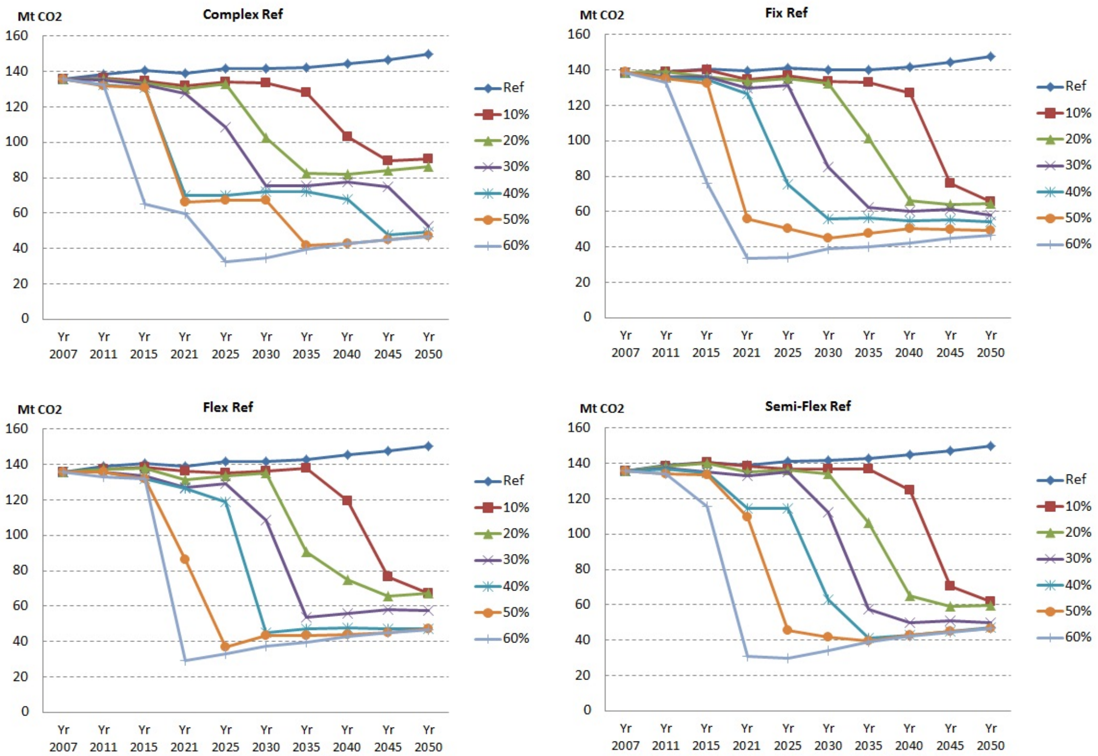


Figure 2.14: Fossil CO_2 emissions of transport for the various models

modify the car fleet composition since the car lifetime is rather short (15 years). Besides, the efficiency of the various new car technologies does not vary a lot so the impact on the global energy intensity is minor. It is different for the carbon intensity: the decarbonization of vehicle fuel seems to happen at different periods for the four models.

Taking a close look at the car fleet composition helps to understand some of the differences in the evolution of the energy and carbon intensities. The car fleet trajectories (figure 2.17) diverge notably for the small and the large cars. It is less the case for the medium size cars: in this category, the new diesel motorization is always and largely preponderant (see appendix C).

For the small cars, the type of refinery used has a huge impact on the investment trajectory. With the 80% ceiling (20% reduction), the fix and the semi-flex refineries favor the natural gas cars when the flexible and the complex one use it only as a transition technology. An obvious other way to decarbonize the transportation sector is to use biofuels (see appendix C for figures). The complex refinery generally makes earlier use of biofuels and ends up using less of it than the other ones. When the CO_2 constraint is really stringent (60% reduction), all models use the same amount and proportion of biofuels. Yet, when the constraint is less strict the amounts are still similar but the complex model uses a largest variety of biofuels: with the 20% reduction of emissions, the complex model consumes seven times more ethanol than the other ones.

The large differences between models regarding the car fleet and the biofuel consumption can partly be explained by the refinery utilization. The cheapest way to reduce emissions in the fixed and semi-flexible refinery cases seems to be to stop using the refinery at the end of the period (figure 2.18). The more stringent the constraint, the earlier the refinery utilization rate

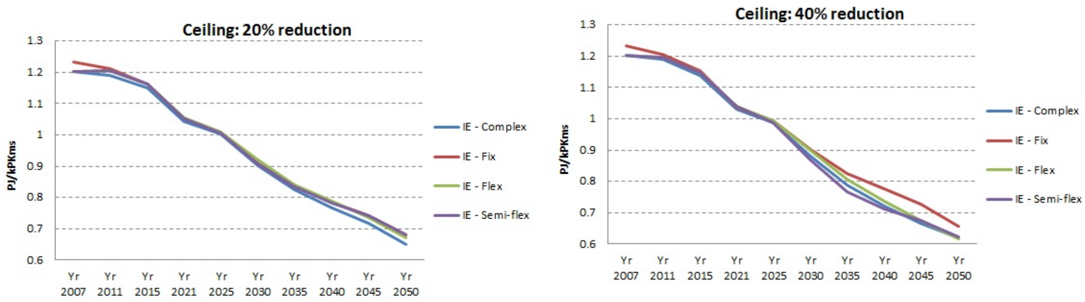


Figure 2.15: Transportation energy intensity with 2 ceilings: 20% and 40% reduction

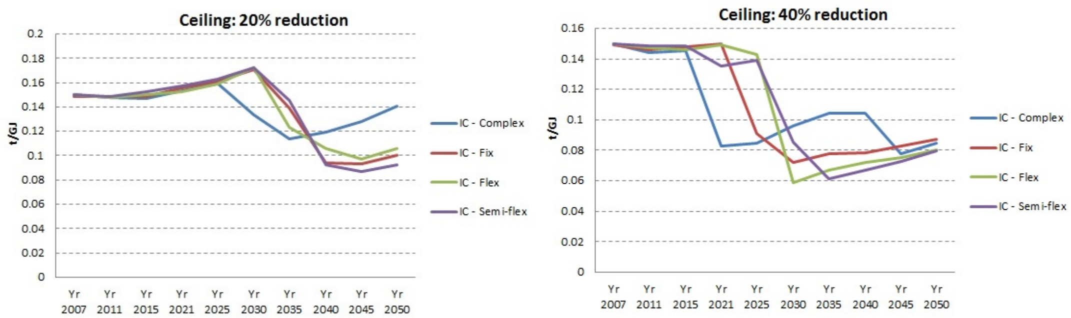


Figure 2.16: Transportation carbon intensity with 2 ceilings: 20% and 40% reduction

collapses[5]. This leads the model to invest in car technologies independent of oil products and explains why these two models largely invest in CNG cars when the other two stick with small gasoline cars. The refinery closure scenario is neither realistic nor politically acceptable since it would raise energy security issues. Consequently, model users should be really careful when they draw conclusions using the results obtained with refinery models such as the semi-flexible or the fix ones. And obviously, these latter models can not answer all types of questions, in particular not the one regarding the future of the French refining sector.

To conclude this exercise on the comparison of four refining models, the question of depicting conventional fuel production within global energy system models deals mainly with the *adaptability* of the sector. This includes two major items, namely (i) the evolution of the global utilization rate of the equipment and (ii) the representativeness of the product shadow prices for changing demand structures. Overall, only the detailed refinery offers an adequate confidence level on both items. We can state that the fix refinery model is to be avoided when it is possible as it is by construction really constrained; especially, it underestimates future utilization rates. The semi-flexible refinery model should better represent the petroleum product marginal value ratios than the flexible one but as we observe on the figure 2.18, its global adaptation ability is not always sufficient. Lastly, the flexible refinery model is obviously too flexible and using it leads to underestimating the costs of the energy transition and to considering unrealistic tech-

[5]The scenarios leading to the refining sector shutdown are not politically acceptable (in terms of energy security and employment). But adding constraints on the refinery utilization rate would drive model outcomes too much.

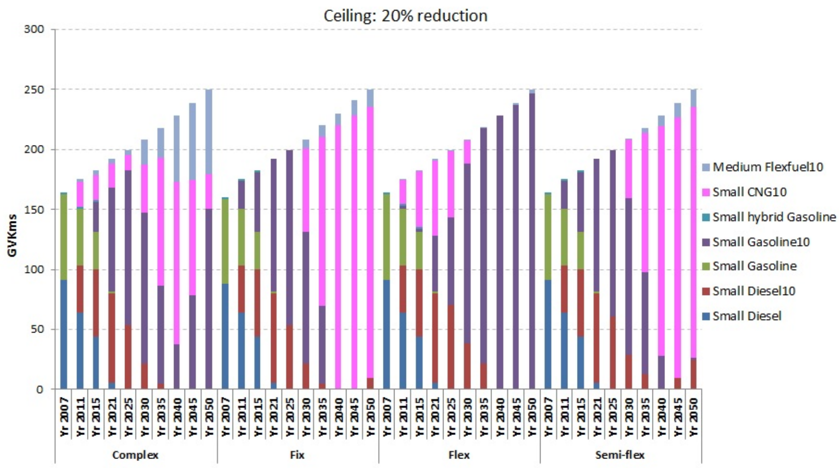


Figure 2.17: Small Cars activity: 20% reduction

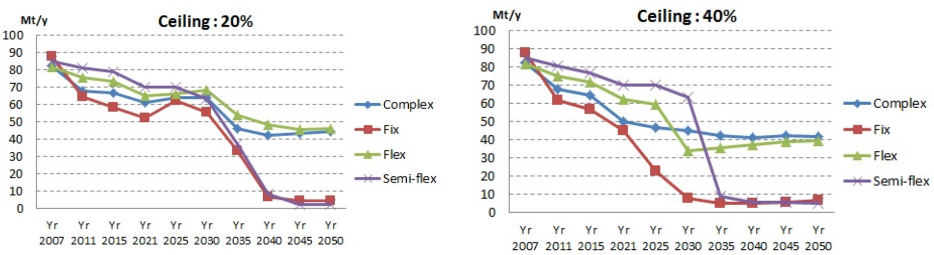


Figure 2.18: Refinery treatment: 20% and 40% emission reduction

nological paths. The results seem to suggest that when the question deals with mitigation in the transportation sector it is necessary to use a detailed refining model.

2.6 Conclusions and Policy Implications

In this work, we illustrate a rarely debated issue: modeling more or less details can induce bias which can lead to different policy insights. We take the oil refining sector as a representative case of modelers' difficulties because of its particularities: the diverse possible origins of fuel components, multiple flexibilities and joint production. These bottlenecks boil down to the stylized representation of the cost of adaptation of oil refining to changes in relative demands. We show that the refinery description used in the energy system model matters when trying to evaluate energy or climate policy applied to the transportation sector. It impacts the policy costs but also the technology trajectories chosen at the optimum. In the results presented, this is notably true for biofuels and alternative car technologies. Essentially, the balance between energy efficiency and carbon intensity of transport may be affected by the accuracy of the description of the refining sector.

This proves that technology outlooks are critically dependent not only on the economic paradigms

and input data, but also on the technical specification of sectors. Hence, when scenarios are obtained with only partially adequate tools, the policy implications that follow are subject to a greater level of uncertainty. Consequently, increasing this sector accuracy level should be motivated by the wish to gain wider quantitative insights on potential evolution of the energy system and above all by the wish to improve the robustness of outcomes. When data is not available or when the modeling team does not possess the necessary competency to detail a sector, an extensive sensitivity analysis on the sector technical parameters becomes necessary. As stated by Hedenus et al. (2013), “this kind of analysis is often absent from policy reports or academic literature. Yet, it allows the decision maker to gain wider insights on the energy system mechanisms and it could avoid misinterpretations due to modeling bias".
This result calls for questions for both modelers and policy makers, which go beyond the technicalities and want to improve the robustness of their analyses. Past experience shows that policy makers are probably aware of such issues. Current practices seem to indicate that long-term questions are often asked to different research groups, using various models. The fact that they get different outcomes should not necessarily be an issue - in principle, there are not necessarily specific reasons why different groups of people, using different models, explore an inherently uncertain future with the same perspective. Still, a distinction should be made between these shortcomings and bias induced by model misspecifications.
This first conclusion should be mitigated if we consider the more general question of the optimal way of abating CO_2 emissions of the whole energy system. In our study, the refining sector's level of complexity has little impact on the results. However, outcomes may be different in more global models, where the refining sector has stronger relationships with other sectors such as electricity, industry or petrochemicals. In such cases, prices of heavy fuel oil (versus natural gas, energy efficiency...) or naphtha (as a feedstock, versus natural gas or biofeedstocks) may drive optimal substitution options. Finally, the main result of this study is rather intuitive for model users: the level of complexity of the model sectors should depend on the question addressed by the modeling team. There is not an optimum level of details compatible with any problem. A very detailed model of all sectors would certainly be able to answer a large range of questions but it would be tedious to implement, long to run and difficult to interpret.
Finally, detailing a sector should be done when the data is available and its mechanisms well understood. Without these two points a simpler approach should be promoted to avoid a false sense of accuracy. So, if robust analyses rely on accurate economical and technological descriptions, lack or excess of details are enemies of modelers. As mentioned by van Delden et al. (2011), "Model complexity increases with the number of variables and processes incorporated and by linking various model components. More complex models may generate unnecessary detail, while simple models may omit essential processes. It is not enough to apply Occam's razor to just one model component, as the requirements also apply to the integrating linkages between components". This theme gains in importance in other communities as well, e.g. in ecosystemic modeling: Fulton et al. (2003) (Hannah et al., 2010). Challenges thus drive research teams in seemingly orthogonal directions: robust modeling of increasingly integrated, uncertain phenomena.

Bibliography

Al-Muslim, H., Dincer, I., 2005. Thermodynamic analysis of crude oil distillation systems. International Journal of Energy Research 29 (7), 637–655.

Babaee, S., Nagpure, A. S., DeCarolis, J. F., 2014. How much do Electric drive vehicles matter for future US Emissions. Environmental Science and Technology 3 (48), 1382–1390.

Babusiaux, D. I., Champlon, D. I., 1982. La Modélisation du secteur raffinage dans mini-dms-énergie. Revue de l'institut français du pétrole, 443–453.

Baumol, W., 1972. On taxation and the control of externalities. The American Economic Review 62 (3), 307–322.

Bhattacharyya, S. C., Timilsina, G. R., 2010. A review of energy system models. International Journal of Energy Sector Management 4 (4), 494–518.

Borjesson, M., Ahlgren, E., 2012. Assessment of transport fuel taxation strategies through integration of road transport in an energy system model—the case of Sweden. International Journal of Energy Research 36, 648–669.

Cai, Y., Huang, G., Tan, Q., 2009. An inexact optimization model for regional energy systems planning in the mixed stochastic and fuzzy environment. International Journal of Energy Research 33, 268–282.

Cayla, J., Maizi, N., 2015. Integrating household behavior and heterogeneity into the TIMES-Households model. Applied Energy (139), 56–67.

Dodds, P. E., Nov. 2014. Integrating housing stock and energy system models as a strategy to improve heat decarbonisation assessments. Applied Energy 132, 358–369.

G. Giannakidis, Labriet, M., Gallachóir, B. O., Tosato, G. (Eds.), 2015. Informing Energy and Climate Policies Using Energy Systems Models: nsights from Scenario Analysis Increasing the Evidence Base Series:. Vol. 30. Springer International Publishing.

Hannah, C., Vezina, A., John, M. S., Jan. 2010. The case for marine ecosystem models of intermediate complexity. Progress in Oceanography 84 (1-2), 121–128.

Hedenus, F., Johansson, D., Lindgren, K., 2013. A Critical Assessment of Energy-economy-climate Models for Policy Analysis. Journal of Applied Economics and Business Research 3 (2), 118–132.

Indati Mustapa, S., Ali Bekhet, H., 2016. Analysis of CO2 emissions reduction in the Malaysian transportation sector: An optimisation approach. Energy Policy (89), 171–183.

Labriet, M., Cabal, H., Lechón, Y., Giannakidis, G., Kanudia, A., May 2010. The implementation of the EU renewable directive in Spain. Strategies and challenges. Energy Policy 38 (5), 2272–2281.

Labriet, M., Nicolas, C., Tchung-Ming, S., Kanudia, A., Loulou, R., 2015. Energy decisions in an uncertain climate and technology outlook : how stochastic and robust analyses can assist policy-makers. In: Giannakidis, G., Labriet, M., Gallachóir, B. O., Tosato, G. (Eds.), Informing energy and climate policies using energy systems models, springer s Edition. Springer, Ch. 03.

Lorne, D., Tchung-Ming, S., 2012. The French biofuels mandates under cost uncertainty – an assessment based on robust optimization. Les cahiers de l'énergie 87.

Loulou, R., Goldstein, G., 2005. Documentation for the TIMES Model PART II.

MIT, 2012. The Future of Natural Gas – An Interdisciplinary MIT Study. Tech. rep.

Morris, S. C., Goldstein, G. A., Fthenakis, V. M., 2002. NEMS and MARKAL-MACRO models for energy-environmental-economic analysis : A comparison of the electricity and carbon reduction projections. Environmental Modeling and Assessment, 207–216.

Ning, S., Yeh, S., Chen, J., Hung, M., Lin, Q., Cai, Y., Yeh, Y., 2013. Identification of optimal strategies for sustainable energy management in Taiwan. International Journal of Energy Research 37, 268–282.

Pindyck, R. S., 2013. Climate Change Policy : What Do the Models Tell Us ? Journal of Economic Literature 51, 860–872.

Seixas, J., Simões, S., Dias, L., Kanudia, A., Fortes, P., Gargiulo, M., 2015. Assessing the cost-effectiveness of electric vehicles in European countries using integrated modeling. Energy Policy (80), 165–176.

Spearrin, R., Triolo, R., 2014. Natural gas-based transportation in the USA: economic evaluation and policy implications based on MARKAL modeling. International Journal of Energy Research 38, 1879–1888.

Tehrani Nejad Moghaddam, A., Saint-Antonin, V., 2008. Impact of tightening the sulfur specifications on the automotive fuels' CO2 contribution: A French refinery case study. Energy Policy 07 (36), 2449–2459.

van Delden, H., van Vliet, J., Rutledge, D., Kirkby, M., Jul. 2011. Comparison of scale and scaling issues in integrated land-use models for policy support. Agriculture, Ecosystems & Environment 142 (1-2), 18–28.

van der Zwaan, B., Keppo, I., Johnsson, P., 2013. How to decarbonize the transport sector? Energy Policy (61), 562–573.

Waide, P., Brunner, C., 2011. Energy-Efficiency Policy Opportunities for Electric Motor-Driven Systems.

Waisman, H., Guivarch, C., Lecocq, F., 2013. The transportation sector and low carbon growth pathways: modelling urban, infrastructure, and spatial determinants of mobility. Climate Policy 01 (13), 106–129.

Zhang, Q., McIellan, M., Li, H., 2015. An integrated scenario analysis for future zero-carbon energy systems. International Journal of Energy Research 39, 993–1010.

Appendix

A Stylized Model

First order conditions

The variables in parentheses are the Lagrangian multipliers associated to each variable. First order conditions give for the fixed yields refinery:

$$\begin{cases} 0 \leq c_1 - \theta_g\Gamma_g - \theta_d\Gamma_d & \perp x_1 \geq 0 & (15) \\ 0 \leq c_2 - \theta_b\Gamma_b & \perp x_2 \geq 0 & (16) \\ 0 \leq -y_g + \theta_g + \sigma\varepsilon_g & \perp x_g \geq 0 & (17) \\ 0 \leq \theta_d - y_i - N\beta + \sigma\varepsilon_d & \perp x_d \geq 0 & (18) \\ 0 \leq \theta_b - y_i + (1-N)\beta & \perp x_b \geq 0 & (19) \\ 0 \leq c_{mc} - y + \theta_{mc} & \perp x_{mc} \geq 0 & (20) \\ 0 \leq c_{ml} - y + \theta_{ml} & \perp x_{ml} \geq 0 & (21) \\ 0 \leq -\theta_{ml}\Gamma_{ml} + y_i & \perp x_l \geq 0 & (22) \\ 0 \leq -\theta_{mc}\Gamma_{mc} + y_i & \perp x_c \geq 0 & (23) \end{cases}$$

And for the flexible one:

$$\begin{cases} 0 \leq c_1 - \lambda & \perp x_1 \geq 0 & (24) \\ 0 \leq c_2 - \theta_b\Gamma_b & \perp x_2 \geq 0 & (25) \\ 0 \leq -y_g + \sigma\varepsilon_g + \lambda & \perp x_g \geq 0 & (26) \\ 0 \leq -y_i - N\beta + \sigma\varepsilon_d + \lambda & \perp x_d \geq 0 & (27) \\ 0 \leq \theta_b - y_i + (1-N)\beta & \perp x_b \geq 0 & (28) \\ 0 \leq c_{mc} - y + \theta_{mc} & \perp x_{mc} \geq 0 & (29) \\ 0 \leq c_{ml} - y + \theta_{ml} & \perp x_{ml} \geq 0 & (30) \\ 0 \leq -\theta_{ml}\Gamma_{ml} + y_i & \perp x_l \geq 0 & (31) \\ 0 \leq -\theta_{mc}\Gamma_{mc} + y_i & \perp x_c \geq 0 & (32) \end{cases}$$

Resolution

Scenario Bio:
We suppose that :

- the Ledcar technology is not used because too expensive
- The biofuel constraint is not saturated

$cml \to \infty, x_{ml} = x_l = 0, \beta = 0$
Flexible Refinery

$$\begin{cases} \text{With equation (24): } \lambda = c_1 \\ \text{With equations (25) \& (28): } \theta_b = y_i = \dfrac{c_2}{\Gamma_b} \\ \text{With equation (32): } \theta_{mc} = \dfrac{c_2}{\Gamma_b \Gamma_{mc}} \\ \text{With equation (27): } \sigma = (\dfrac{c_2}{\Gamma_b} - c_1)\dfrac{1}{\varepsilon_d} \\ \text{With equation (29): } y = \dfrac{c_2}{\Gamma_b \Gamma_{mc}} + c_{mc} \\ \text{With equation (26): } y_g = \dfrac{\varepsilon_g}{\varepsilon_d}(\dfrac{c_2}{\Gamma_b} - c_1) + c_1 \end{cases}$$

Fixed yields Refinery.
We consider that gasoline is in excess, $y_g = 0$

$$\begin{cases} \text{With equations (16)\& (19): } \theta_b = y_i = \dfrac{c_2}{\Gamma_b} \\ \text{With equation (23): } \theta_{mc} = \dfrac{c_2}{\Gamma_b \Gamma_{mc}} \\ \text{With equation (20): } y = \dfrac{c_2}{\Gamma_b \Gamma_{mc}} + c_{mc} \\ \text{With equations (15),(17) \& (18):} \\ \theta_g = \dfrac{\varepsilon_g}{\varepsilon_d \Gamma_d + \varepsilon_g \Gamma_g}(c_1 - c_2 \dfrac{\Gamma_d}{\Gamma_b}) \\ \theta_d = \dfrac{\varepsilon_d}{\varepsilon_d \Gamma_d + \varepsilon_g \Gamma_g}(c_1 - c_2 \dfrac{\Gamma_d}{\Gamma_b}) + \dfrac{c_2}{\Gamma_b} \\ \sigma = (c_2 \dfrac{\Gamma_d}{\Gamma_b} - c_1)\dfrac{1}{\varepsilon_d \Gamma_d + \varepsilon_g \Gamma_g} \end{cases}$$

Scenario Ledcar:
Biofuels are not used because too expensive.
$c_2 \to \infty, x_2 = x_b = 0, \beta = 0$
Flexible Refinery

$$\begin{cases} \text{With equation (24): } \lambda = c_1 \\ \text{With equations (29) to (32):} \\ \theta_{mc} = \dfrac{c_{ml} - c_{mc}}{\Gamma_{ml} - \Gamma_{mc}} \Gamma_{ml} \\ \theta_{ml} = \dfrac{c_{ml} - c_{mc}}{\Gamma_{ml} - \Gamma_{mc}} \Gamma_{mc} \\ y = \dfrac{c_{ml}\Gamma_{ml} - c_{mc}\Gamma_{mc}}{\Gamma_{ml} - \Gamma_{mc}} \\ y_i = \dfrac{c_{ml} - c_{mc}}{\Gamma_{ml} - \Gamma_{mc}} \Gamma_{mc}\Gamma_{ml} \\ \text{With equation (27): } \sigma = (\dfrac{c_{ml} - c_{mc}}{\Gamma_{ml} - \Gamma_{mc}} \Gamma_{mc}\Gamma_{ml} - c_1)\dfrac{1}{\varepsilon_d} \\ \text{With equation (16): } y_g = (\dfrac{c_{ml} - c_{mc}}{\Gamma_{ml} - \Gamma_{mc}} \Gamma_{mc}\Gamma_{ml} - c_1)\dfrac{\varepsilon_g}{\varepsilon_d} + c_1 \end{cases}$$

Fixed yields Refinery. We consider that gasoline is in excess, $y_g = 0$

$$\begin{cases} \text{With equations (20) to (23):} \\ \theta_{mc} = \dfrac{c_{ml} - c_{mc}}{\Gamma_{ml} - \Gamma_{mc}} \Gamma_{ml} \\ \theta_{ml} = \dfrac{c_{ml} - c_{mc}}{\Gamma_{ml} - \Gamma_{mc}} \Gamma_{mc} \\ y = \dfrac{c_{ml}\Gamma_{ml} - c_{mc}\Gamma_{mc}}{\Gamma_{ml} - \Gamma_{mc}} \\ y_i = \dfrac{c_{ml} - c_{mc}}{\Gamma_{ml} - \Gamma_{mc}} \Gamma_{mc}\Gamma_{ml} \\ \text{With equations (15),(17) \& (18):} \\ \theta_g = \dfrac{\varepsilon_g}{\varepsilon_d\Gamma_d + \varepsilon_g\Gamma_g} c_1 - \dfrac{\Gamma_d\varepsilon_g}{\varepsilon_d\Gamma_d + \varepsilon_g\Gamma_g} \dfrac{c_{ml} - c_{mc}}{\Gamma_{ml} - \Gamma_{mc}} \Gamma_{mc}\Gamma_{ml} \\ \theta_d = \dfrac{\varepsilon_d}{\varepsilon_d\Gamma_d + \varepsilon_g\Gamma_g} (c_1 + \Gamma_g \dfrac{\varepsilon_g}{\varepsilon_d} \dfrac{c_{ml} - c_{mc}}{\Gamma_{ml} - \Gamma_{mc}} \Gamma_{mc}\Gamma_{ml}) \\ \sigma = -\dfrac{c_1}{\varepsilon_d\Gamma_d + \varepsilon_g\Gamma_g} + \dfrac{\Gamma_d}{\varepsilon_d\Gamma_d + \varepsilon_g\Gamma_g} \dfrac{c_{ml} - c_{mc}}{\Gamma_{ml} - \Gamma_{mc}} \Gamma_{mc}\Gamma_{ml} \end{cases}$$

Stylized complex model

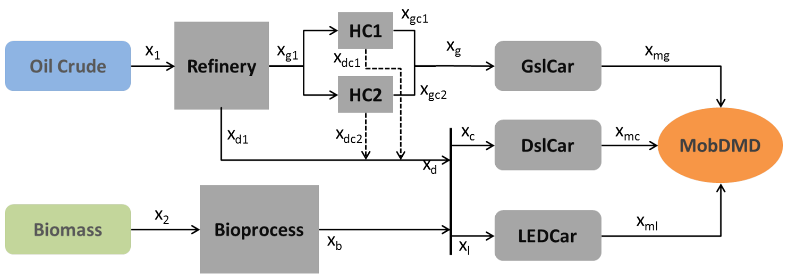


Figure 19: Complexified refinery

Parameters values

	Case 1	Case 2
Γ_g	0.4	0.7
Γ_d	0.6	0.3
Γ_b	0.4	0.4
γ_c	0.5	0.5
γ_l	1	1
c_1	0.02	0.02
c_2	0.028	0.03
c_{mc}	0.2	0.2
c_{ml}	0.3	0.25
N	0.1	0.1
Mobdmd	4	4
Gdmd	2	2
ε_d	3.16	3.16
ε_g	2	0
cHC1*	0.02	-
cHC2*	0.08	-
Γ_{dHC1}*	0.1	-
Γ_{dHC2}*	0.2	-

Figure 20: Parameters values used for the stylized model (*:Complex case only.)

B Hypothesis

Population growth

Population scenario is based on the central scenario of INSEE regional projections for 2040. 2050 extension is based on 2030-2040 average annual growth rate (see figure 21).

Parameters

The table below (fig 22) provides the main sources for numerical assumptions and parameters and in particular for technological costs:

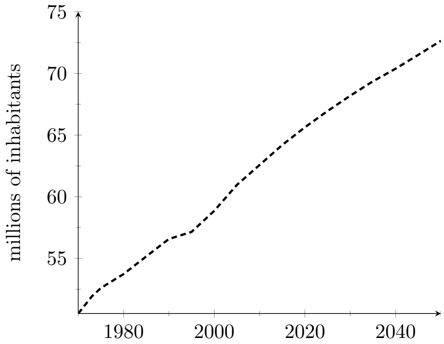


Figure 21: French population evolution

Scenario components	Sector	Data sources
Primary energy	Fossil energy	IEA (2011)
	Agricultural biomass	INRA
	Woody biomass	FCBA
Energy technologies	Refining	Internal IFPEN
	Biofuels	Internal IFPEN
	Road mobility (Passengers and Freight)	Internal IFPEN
	Power plants	EDF, IEA (2010), MINEFI (2008)
Demand scenarios	Other oil products	IFPEN/LEPII
	Pass. And Freight mobility	CAS (2009)
	Electricity	RTE (2011)
Policies	Carbon price	IEA (2011)
	Biofuels	EC (2009), EC (2010)

Figure 22: Main sources for numerical assumptions

C Results

The flexible refinery model adapts logically at the lesser cost since the yields flexibility is free in this case.

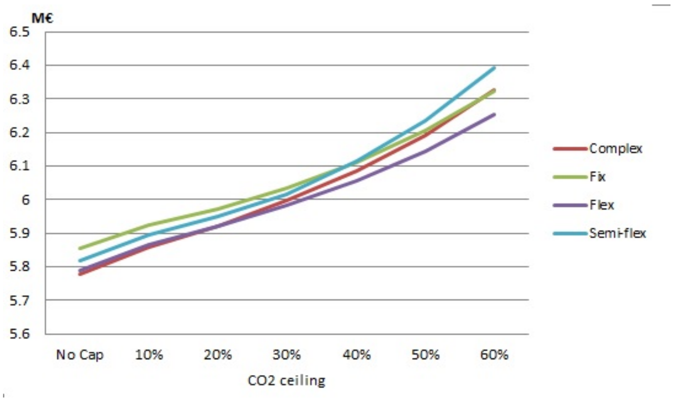


Figure 23: Objective value evolution with different levels of CO_2 emission ceilings

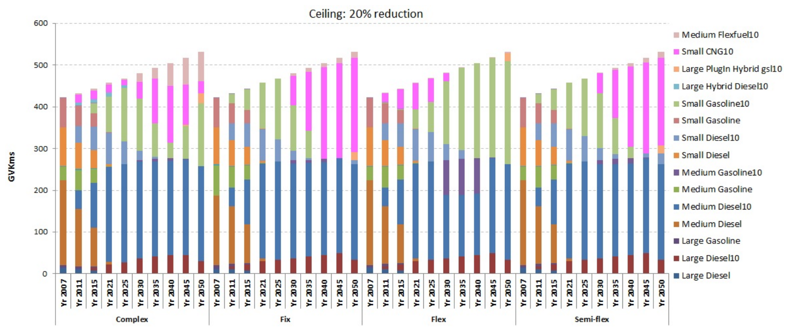


Figure 24: Cars activity : 80% Ceiling

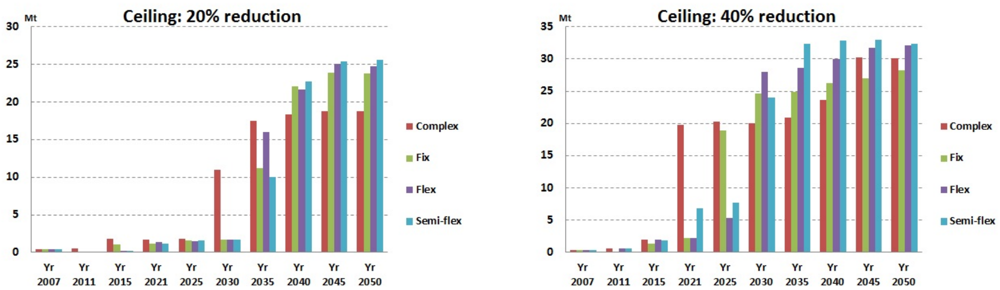


Figure 25: Biofuels in Transportation: 20% and 40% reduction

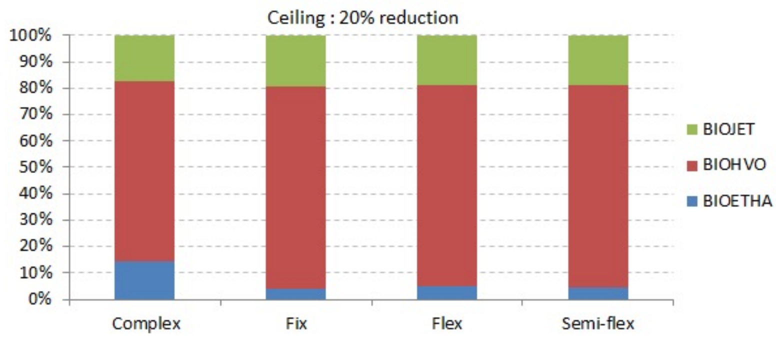


Figure 26: Biofuel use in proportion during the whole period : 20% reduction

Transition

As seen in the previous chapter, energy system modeling is very sensitive to parameter uncertainty. It is obviously also the case for most optimization problems which can rapidly become unfeasible with a slight variation of some of their parameters.
In Ben-tal and Nemirovski (2000), the authors show using NETLIB, a library of 90 linear programming problems from different applications of operations research, that a variation of only 0.01% of some coefficients was enough to result in constraint violations in more than 15% of the cases and, when the variation reached 1%, almost a third of the cases were unfeasible. It leads the authors to conclude that "In real-world applications of Linear Programming one cannot ignore the possibility that a small uncertainty in the data (intrinsic for most real-world LP programs) can make the usual optimal solution of the problem completely meaningless from a practical viewpoint." The need to identify solutions that are immune to the actual realization of uncertain parameters explained the emergence of robust optimization.

Real world optimization models are contaminated with data uncertainty and it is particularly the case for energy system models. Indeed, solutions elaborated with optimization models like TIMES are based on complex, high cardinality sets of exogenous assumptions on the data populating the models. In short, LP will "sort" technologies by decreasing economic merit order to meet various policy objectives with maximum efficiency. Consequently, different sets of assumptions could yield to different relative costs, and in turn to a different optimal technological portfolio. It could deeply affect the relevance of policy insights obtained with the models and leave the decision maker disoriented.

Robust optimization is a way to solve this dilemma as its application on decision models helps identifying solutions that are immune with respect to the actual realization of the uncertain parameters (within a given uncertainty region). Let's for example consider the following (nominal) optimization problem:

$$\min_{x} \{f(x,y) : g_j(x,y) \leq 0, \forall j = 1, ..., J\} \tag{2.33}$$

where x is a vector of decision variables, y is a vector of parameters that affect the decision and that could be uncertain, $f(.,.)$ is a cost function and $g_j(.,.)$ is a constraint that can be e.g. technical or social.
We now assume that the parameters y are not perfectly known and that they can take value

in the uncertainty set Y. Following Ben-tal et al. (2009) formulation, we can write the robust counterpart of the previous problem:

$$\min_{x} \left\{ \max_{y \in Y} f(x,y) : g_j(x,y) \leq 0, \forall y \in Y, \forall j = 1, ..., J \right\} \tag{2.34}$$

The "minimax" formulation ensures that the solutions obtained will be feasible independently of the realization of y. We can equivalently reformulate the previous equation:

$$\min_{x,\alpha} \left\{ \alpha : \begin{matrix} f(x,y) - \alpha \leq 0 \\ g_j(x,y) \leq 0 \end{matrix} \right\} \forall y \in Y, \forall j = 1, ..., J \Bigg\} . \tag{2.35}$$

This simple formulation will allow us to compare the Robust Optimization paradigm with more traditional ways of dealing with uncertainty in optimization problems, in this case with Sensitivity Analyis, multi-scenarios analysis and stochastic optimization.

Stochastic programming

Stochastic optimization provides an appealing and rigorous framework for describing a few contrasted states of the world (Wets, 1989). Here the uncertain data are supposed to be random. In simple cases, the probability distribution of the random data is known allowing us to write the stochastic problem as a chance constrained one. Yet, sometimes it is only partially known and we have to have recourse to ambiguous chance constrained formulation:

$$\min_{x,\alpha} \{ \alpha : Prob_{y\tilde{}P} \{ f(x,y) - \alpha \leq 0 \ \& \ g_j(x,y) \leq 0 \ \forall j = 1, ..., J \} \geq 1 - \epsilon \} . \tag{2.36}$$

where $\epsilon << 1$ is a tolerance level and P the distribution of the parameters y. In the case of ambiguous chance constrained problems, P is partially known and belongs to a family of probability distributions $\mathcal{P}$, then the uncertain problem is the following:

$$\min_{x,\alpha} \{ \alpha : Prob_{y\tilde{}P} \{ f(x,y) - \alpha \leq 0 \ \& \ g_j(x,y) \leq 0 \ \forall j = 1, ..., J \} \geq 1 - \epsilon, \forall P \in \mathcal{P} \} . \tag{2.37}$$

We can immediately see that the SO problems are less conservative than the RO ones. However, probability distributions have to be defined over the entire tree of decisions even though these distributions are often unknown because of a lack of information, of knowledge, of measures or simply because the uncertain data is not of stochastic nature. The second possible drawback of SO is that we have to be willing to accept probabilistic guarantees as in this framework the constraints are not totally "hard". The third drawback of SO is computational: the approach quickly leads to large-scale instances of the original model, hence to very long computing times and to intractability issues in numerical computations as the problem grows. And moreover, chance constraints often results in non-convex feasible sets leading to computationally intractable problems (Ben-tal et al., 2009).

Sensitivity and multi-scenario analyses

Sensitivity analysis is a widely used tool to evaluate the continuity properties of the optimization model solution as a function of the uncertain parameters. This evaluation requires the model to be run multiple times with alternative values of the parameters which can rapidly become a computational burden. When probability distributions are defined for the uncertain data, Monte-Carlo type of analysis can be done but again this technique can rapidly become computationally intractable as the number of uncertain parameters increases.

Deterministic multi-scenario analysis is very useful in scoping the range of impacts of key parameters on the possible climate adaptation and mitigation responses (Kunreuther et al., 2014). It constitutes an usual approach where alternative scenarios of plausible future developments are formulated. In such an approach, unknown parameters can be given extreme values, one at a time, with the intention of circumscribing the space of possibilities. The scenarios thus defined form ensembles of scenarios. Systematic ways of choosing parameter values to cover the space of possibilities efficiently are based on design of experiments. Among the different possible scenarios, "representative sets" may be identified and play a crucial role as guides for scenario analysis by the research community. In the climate change arena, multi-scenario analysis is frequent, as proposed by the scenarios of the IPCC or the modelling exercises of the Energy Modelling Forum (Kriegler et al., 2014), amongst others. Scenario/ensemble analyses can be performed without quantifying the uncertainty (via probabilities) of the underlying unknown parameters. However, this also implies an unavoidable ambiguity in interpreting ensemble results since they tend to be used in a deterministic fashion without recognizing that they are only one of many possible outcomes (Clarke and Jiang 2014; Kunreuther et al. (2014)). Moreover, such scenarios leave the policy adviser in a quandary as to what policy to initiate now, given the often widely diverging courses of solutions proposed by each of the alternative scenarios, even in the short term.
Another way of using this approach is described by Rozenberg et al. (2014) who propose a methodology to develop Shared Socioeconomic Pathways (SSPs) or long-term socioeconomic scenarios that describe possible world evolutions in demographic, social, economic, and technological terms up to 2100, with a “backwards” approach. The idea is to identify a priori the uncertain parameters of the model that could impact the mitigation challenge, to vary these parameters’ values to create a very large number of scenarios and finally to select a few relevant SSPs from these thanks to statistical cluster-finding algorithms.

Stochastic optimization and RO have the advantage of offering an explicit single hedging strategy even in the context of high uncertainty, contrary to classical multi-scenario analysis or sensitivity analysis. SO and RO both focus on the question of building an uncertainty-immunized solution to an optimization problem with uncertain data, RO being easier to implement and to use as the underlying probability distributions of the parameters do not need to be known or guessed. Moreover, robust counterpart of linear programming problems stay linear provided a few hypotheses on the uncertainty sets (see appendix 3.2.1 for more details), allowing us to introduce uncertainty on a very large number of parameters.
Given the really high number of parameters populating IAMs and energy system models, and given the imperfect knowledge we have on the type of uncertainty weighing on this data, we think RO could be a really useful approach to improve the decision making process.
In the next two chapters we assess technology trajectories under climate constraints using robust optimization. Working with TIMES paradigm models, we try to understand what are the advantages of this new approach and how we can interpret the models’ results.

Bibliography

Ben-tal, A., El Ghaoui, L., Nemirovski, A., 2009. Robust Optimization.

Ben-tal, A., Nemirovski, A., 2000. Robust solutions of Linear Programming problems contaminated with uncertain data. Mathematical Programming 88 (3), 411–424.

Kriegler, E., Weyant, J. P., Blanford, G. J., Krey, V., Clarke, L., Edmonds, J., Fawcett, A., Luderer, G., Riahi, K., Richels, R., Rose, S. K., Tavoni, M., van Vuuren, D. P., jan 2014. The role of technology for achieving climate policy objectives: overview of the EMF 27 study on global technology and climate policy strategies. Climatic Change 123 (3-4), 353–367.

Kunreuther, H., Gupta, S., Bosetti, V., Cooke, R., Dutt, V., Duong, M. H., Held, H., Llanes-Regueiro, J., Patt, A., Shittu, E., Weber, E., 2014. Integrated Risk and Uncertainty Assessment of Climate Change Response Policies. Climate Change 2014: Mitigation of Climate Change, contribution of Working Group III to the IPCC Fifth Assessment Report, 151–206.

Rozenberg, J., Guivarch, C., Lempert, R., Hallegatte, S., 2014. Building SSPs for climate policy analysis: A scenario elicitation methodology to map the space of possible future challenges to mitigation and adaptation. Climatic Change 122, 509–522.

3

Energy transition in transportation under cost uncertainty- an assessment based on robust optimization

3.1 Introduction

The global context of European energy policies is generally presented as grounded on three main pillars: competitiveness of the industrial sector and competitive markets, energy security and sustainability. In order to achieve these goals in a cost-efficient way, the European Union (EU) has put in place a set of binding legislation in order to (i): reduce its Greenhouse gas (GHG) emissions by 20% below 1990 levels for the year 2020, (ii): to get a 20% improvement in energy efficiency and (iii): to raise the share of renewables in the energy sector to 20%(10% in the transportation sector) compared to 9.8% in 2010. This 2020 climate and energy package is known as the "20-20-20" targets. But the European Commission (EC) also considered long term objectives and set CO_2 emission target reductions for 2030 and 2050 (respectively 40% and 80% compared to 1990 levels). In its report "A Roadmap for moving to a competitive low carbon economy in 2050", the European Commission set out a cost-effective pathway for achieving deep emission cuts by the middle of the century. As transport is one of the sectors where GHG emission abatement is the most costly (Waisman et al., 2013), its expected reductions are less ambitious as they range between 54 and 67% in 2050 (depending on the scenario considered).

The transportation sector represents 31.6% of final energy consumption in the EU (EU-28) and, as it uses mainly imported fossil resources, is key in the European energy policy context. The high dependency level of the EU member states (86% of the oil consumption is imported (Enerdata, 2016)) and the oil imports concentration (54% of imports came from Norway, Russia and Saudi Arabia in 2013 (Eurostat, 2016)) led to significant energy security debate within the EU. The share of fossil fuels in the transportation energy mix (98%) questioned the climate change policy. Hence the vehicle energy efficiency improvement, the decarbonization of the fuels and a better management of the mobility demand are the three levers countries can use to abate CO_2 emissions (Ancre, 2015, 2014) and to conjointly reach other objectives as the reduction to oil dependency or health benefits (by reducing local pollution). This explains why the EU is willing to step up its efforts to accelerate the development and early deployment of electrification, and in general, of alternative fuels and propulsion methods (SCelecTRA, 2015).
However, the costs and benefits of imposing norms on vehicle efficiency or propulsion and biofuel mandates should be assessed in the light of the large uncertainties surrounding these pathways,

in terms of availability and cost of these new technologies; see e.g. Schade and Wiesenthal (2011) for biomass and biofuel technologies. By extension, the potential costs and benefits of various norms or mandates should be assessed with respect to uncertain relative costs of biofuels compared to conventional fuels and to uncertain costs of alternative propulsion technologies relative to conventional ones. Some of the rare examples of such approaches include Rozakis and Sourie (2005) and Schade and Wiesenthal (2011), who use Monte-Carlo simulation to highlight the large variations in biofuel subsidies depending on key macroeconomic variables.

Energy systems involve (i) long-lasting, irreversible investments, some of which are nowadays in R&D phase (ii) the use of very volatile primary energy sources (crude oil, natural gas, coal, biomass, etc.), so that decisions concerning transportation policies must be taken now for the next decades in the presence of large uncertainties. Practically, long-term assessments of these policies should account not only for their costs, but also for their potential multiple benefits, and in a context of pervasive uncertainty that embrace both microeconomic (technology costs) and macroeconomic (energy prices) variables.
This work is grounded on this last observation; its contributions are twofold. From a methodological perspective, we argue that robust optimization techniques are appropriate for introducing cost uncertainty from many sources in long-term energy models (primary energy sources, technology investment). Similar methods were recently introduced in large-scale prospective models (Babonneau et al., 2011) for different purposes. We explain that in the process of addressing different levels of uncertainty à la Bertsimas and Sim (2004), we "endogenously" generate various relative cost sets that determine the competitiveness of the pathways included in the model. Those cost scenarios are generated according to a worst-case logic, which is consistent with a specific definition of risk preferences.
This method captures the effect of numerous uncertainty sources on optimal solutions, what stochastic optimization more hardly does (given the computing issues induced by a large number of stochastic variables). On the other hand, RO endogenously accounts for uncertainty, while Monte-Carlo "only" performs advanced sensitivity analysis. Moreover, because it relies on set-based uncertainty models, it avoids the recourse to (often ad hoc) definition of probability densities of uncertain parameters. In short, we propose to test how a robust optimization technique can be used to evaluate a public policy in a system model, accounting for such systemic uncertainty.
We apply this methodology to an appraisal of the French energy transition pathways in the transportation sector. Under various uncertainty levels for economic parameters included in the model and various CO_2 abatement objectives, we evaluate the technical and hedging extra-costs of the various pathways with respect to a no-policy case and we assess the robustness of the different technological options. At the technology level, different strategies appear when we vary the uncertainty level: for low levels, optimal choices show a taste for diversity. Technological diversification is used as a hedge against uncertainty. Yet, as uncertainty increases technological diversification is close to the one of the deterministic case. In the transport sector, low-carbon alternatives (CNG, electricity) appear consistently as hedges against cost variations, along with biofuels.

The paper is structured as follows. In section 2, we present the robust optimization technique and insist on some theoretical implications. Section 3 presents the long-term MIRET model for the French energy-transport system and how we implemented the Robust optimization methodology. In section 4, we describe the scenarios constructed for this study and the results we obtained. Section 5 concludes on some methodological and policy insights.

3.2 Robust optimization: dealing with "non-probabilized" uncertainty

Real world optimization models are structurally affected by data uncertainty and it is particularly the case for energy system models. Indeed, optimal solutions elaborated with optimization models like e.g. Times paradigm models (Loulou and Goldstein, 2005) are based on complex, high cardinality set of exogenous assumptions on the data populating the models. In short, optimization (linear programming in Times case) will “sort” technologies by decreasing economic merit order to meet various policy objectives with maximum efficiency (minimum cost). Consequently, different sets of assumptions could yield to different relative costs, and in turn to a different optimal technological portfolio. It could deeply affect the relevance of policy insights obtained with the models and leave the decision maker disoriented.
This statement is still valid when the uncertainty set in which the parameters take value is narrow: Ben-tal and Nemirovski (2000) show in their paper that even very small variations in data can impact feasibility or optimality properties of a given solution.
To tackle this parameter uncertainty problem, different methods exist and are employed: sensitivity analysis (via e.g. deterministic scenario analysis or Monte-Carlo) and stochastic programming.
Deterministic multi-scenario analysis is very useful in scoping the range of impacts of key parameters on the model output (Kunreuther et al., 2014). In this approach, alternative scenarios of plausible future developments are formulated and unknown parameters can be given extreme values, one at a time, with the intention of circumscribing the space of possibilities. In the climate change arena, multiscenario analysis is frequent, as proposed by the scenarios of the IPCC (Intergovernmental Panel on Climate Change) or the modelling exercises of the Energy Modelling Forum (Kriegler et al., 2014), among others. Scenario/ensemble analyses can be performed without quantifying the uncertainty (via probabilities) of the underlying unknown parameters. However, this also implies an unavoidable ambiguity in interpreting ensemble results since they tend to be used in a deterministic fashion without recognizing that they may have a low probability of occurrence and are only one of many possible outcomes (Clarke et al., 2009, Kunreuther et al., 2014). Moreover, such scenarios leave the policy maker in a quandary as to what policy to initiate, given the often widely diverging courses of action solutions proposed by each of the alternative scenarios, even in the short term.
On the contrary, one of the main advantages of the stochastic programming approach is to obtain an explicit single hedging strategy while uncertainty prevails. Yet, stochastic programming has one major computational drawback: it quickly leads to large-scale instances of the original model, hence to very long computing times and to intractability issues in numerical computations as the problem grows. Moreover, probability distributions of the uncertain data have to be defined over the entire tree of decision when it often happens that these distributions are unknown (because of a lack of information, of knowledge, of measures...).
This is where robust optimization steps in as it offers parsimonious ways of dealing with problems of high dimension while requiring minimal information about the true 'probability' distributions (Ben-tal and Nemirovski, 2002).

3.2.1 General presentation of robust optimization

Early developments of robust optimization (RO) date back to Soyster, 1973 who initiated an approach of obtaining relevant (i.e. feasible) Linear Programming solutions although matrix coefficients are inexact. RO has known many developments in the last 15 years by generalizing Soyster approach (Bertsimas and Sim, 2004) or using different formalisms (Ben-tal and Nemirovski, 2002, El Ghaoui et al., 1998). Its applications to energy and environment problems are currently emerging as a promising technique for practitioners.

The general principle of RO consists in immunizing a solution against adverse realizations of uncertain parameters within given uncertainty sets. The basic requirement for a robust solution is that constraints of the problem are not violated whatever the realization of the parameters in the set. The major modelling issue then consists in identifying, depending on the model class and the nature of the uncertainty region, computable robust counterparts for the initial optimization program. Ben-Tal et al. (2014) and Bertsimas et al. (2010) review techniques for building such robust counterparts (RC) in general cases.
A particular case of interest for us is the case of a linear program combined with a polyhedral uncertainty set, for which the RC is itself a linear program. The application presented below is based on this principle.
Mathematical formulation of robust linear programming
As mentioned above, while stochastic or Monte-Carlo frameworks require the definition of probability density functions, the principle of RO consists in set-based descriptions of uncertainty. As such, only the extent to which parameters are likely to vary needs to be known (although this information may be itself difficult to acquire). This corresponds to the support of the density functions.
To introduce the mathematical representation of RO, we follow Bertsimas and Sim (2004) and consider the following linear problem:

$$\textbf{(P)} : \begin{cases} \min c^T x \\ s.t.\ Ax \leq b \\ x \in \mathbb{R}_+^n, A \in \mathbb{R}^{m*n} \end{cases} \tag{3.1}$$

We assume that the uncertainty only affects the coefficients $a_{i,j}(i \in I, j \in J)$ of the matrix A and that all the coefficients are independent (for the sake of the exposition). The coefficients can vary in a symmetric range: $a_{i,j} \in [\overline{a_{i,j}} - \widehat{a_{i,j}}, \overline{a_{i,j}} + \widehat{a_{i,j}}]$ known by the decision maker, where $\overline{a_{i,j}}$ is the nominal value of the parameter and $\widehat{a_{i,j}}$ the uncertainty set half-length (and corresponds to the precision of the estimates). As stated above, no specific probability distribution is needed. We can now introduce the parameter $\Gamma \in [0, |J|]$ named the budget of uncertainty whose role is to adjust the robustness of the methodology against the level of conservatism of the solution.

By writing $a_{i,j} = \overline{a_{i,j}} + z_{i,j}\widehat{a_{i,j}}$, hence $z_{i,j} = \dfrac{a_{i,j} - \overline{a_{i,j}}}{\widehat{a_{i,j}}}$, $z_{i,j} \in [-1, 1]$ we can reformulate the problem (P) and write its robust counterpart (Prob):

$$\textbf{(Prob)} : \begin{cases} \min c^T x \\ s.t. \\ \sum\limits_j \overline{a_{i,j}} x_j + \max\limits_{z_{i,j}} \sum\limits_j z_{i,j} \widehat{a_{i,j}} x_j \leq b_i, \forall i \in I \\ |z_{i,j}| \leq 1, \forall i, j \\ \sum\limits_j |z_{i,j}| \leq \Gamma_i, \forall i \in I \\ x \in \mathbb{R}_+^n \end{cases} \tag{3.2}$$

More generally, by limiting the number of parameters allowed to deviate, Γ represents the degree of pessimism on the problem parameters. When $\Gamma_i = 0$, the robust problem is identical to the nominal one and when $\Gamma_i = |J|$, it is equal to the "worst case" problem (and we are back to the

Soyster solution).

For the sake of the illustration, we will suppose in this case that: $\widehat{a_{i,j}} \geq 0 \ \forall i, j$; for the general case resolution see Ben-tal et al. (2009).
Using strong duality arguments, the maximization problem in the constraint becomes a minimization problem (Delage, 2015). We have $\forall i \in I$, the primal of the subproblem (P2) and its dual (D2) :

$$\textbf{(P2)} : \begin{cases} \max_z \sum_j z_{i,j} \widehat{a_{i,j}} x_j^* \\ \text{s.t.} \\ 0 \leq z_{i,j} \leq 1, \forall j & (\mu) \\ \sum_j z_{i,j} \leq \Gamma_i, & (\lambda) \end{cases} \qquad \textbf{(D2)} : \begin{cases} \min_{\lambda,\mu} \lambda_i \Gamma_i + \sum_j \mu_{i,j} \\ \text{s.t.} \\ \lambda_i + \mu_{i,j} \geq \widehat{a_{i,j}} x_j^*, \forall j \\ \lambda_i \in \mathbb{R}_+, \mu_{i,j} \in \mathbb{R}_+ \end{cases} \tag{3.3}$$

The dual problem can be reinjected into the original problem allowing us to reformulate the robust problem (Prob) as a usual linear programming problem:

$$\textbf{(Prob)} : \begin{cases} \min c^T x \\ s.t. \\ \sum_j \overline{a_{i,j}} x_j + \lambda_i \Gamma_i + \sum_j \mu_{i,j} \leq b_i, \forall i \in I \\ \lambda_i + \mu_{i,j} \geq \widehat{a_{i,j}} x_j, \forall j \in J, \forall i \in I \\ \lambda \in \mathbb{R}_+, \mu \in \mathbb{R}_+ \\ x \in \mathbb{R}_+^n \end{cases} \tag{3.4}$$

Hence, the robust counterpart of the problem is still a linear programming problem (a little bit bigger) and conserves the good properties of this class of model in terms of tractability and computational time (Bertsimas and Thiele, 2006).
The formulation above also allows to consider uncertain parameters in the objective function as we can always rewrite the problem with an auxiliary variable (e.g α) and minimize α subject to an additional constraint that we could make robust:

$$\min_{\alpha,x} \left\{ \alpha : c^T x \leq \alpha, Ax \leq b, x \in \mathbb{R}_+^n \right\} \tag{3.5}$$

3.2.2 Introducing uncertainty on costs: motivations

One general motivation for introducing robust optimization in linear program lies in the fact that "real-world" problems are contaminated with uncertainties (measurement...). In the context of long-term prospective modeling, forecasting errors on input data are a major issue. For long-term assessments, energy system models built on a bottom-up paradigm require as input data the definition of primary energy prices and technology costs over the whole horizon. While there are many ways to define such prices and costs (expert elicitation, data analysis, literature reviews...), it remains unavoidable that such projections are spoilt by mistakes.
Long term energy prices dynamics result from a complex combination of macroeconomic (growth, cycles, productivity, employment rate, exchange rate, interest rate), technological (marginal cost of production, costs of substitutes, access to reserves, depletion rate...), geopolitical (resources nationalism, bilateral or multilateral relations between countries, world oil transit chokepoints such as Hormuz and Malacca straits), market (supply, demand, stocks) and strategic forces. In its

World Energy Outlook (WEO), the International energy agency (IEA) focus on a set of factors in order to explain a low price scenario (OPEC strategy, geopolitical developments, non-OPEC supply, world economic growth, energy subsidies that are highly uncertain globally but also elements by elements (IEA, 2015). Hence the structure of the energy markets and the different players (International Oil Company, National Oil Company, independent oil & gas producers...) offer a wide range of strategies (rate of extraction for example) that will heavily impact the medium term energy prices in the medium and long run.
Costs of new technologies are likewise subject to great uncertainty. In a recent retrospective study, the International Council on Clean Transportation compares costs projections of mobility technologies – passenger cars and LDVs – with actual observations; they conclude that (i) there is a large spread in costs projection and (ii) ex-post comparisons fall quite far from actual observations. This issue also arises for energy supply technologies (see e.g. Levi and Pollitt (2015) in the case of electricity), as argued by Weiss et al. (2010). The long-run of technology investment costs depends on the intensity and effectiveness of R&D, learning effects, costs of raw materials, or organizational issues Ancre (2015). In bottom-up models, these assumptions are exogenous and most of the time implicitly defined within the quantitative projections on investment and/or operation costs. Therefore, they can be considered as externalities in the energy sectors. Adverse events can occur if the rate of technological improvement is not as expected (e.g., R&D is slower than anticipated, or faces unexpected challenges), or the accumulated experience is slower (because of lower learning rates and/or lower increase rates of installed capacities – Yeh and Rubin (2012), Bhattacharjya et al. (2006), Papineau (2006), Salvatore (2013), Rubin et al. (2015)).
For all these reasons, it seems relevant to evaluate the robustness of a given model's outcomes to prices and costs assumptions. Some existing studies attempt to assess such questions through sensitivity analysis (cite), Monte-Carlo simulations (Gritsevskyi and Nakićenovi, 2000) or stochastic programming (Cao et al., 2013). Here, we choose to rely on robust programming, so that a large number of uncertain input data can be dealt with. Moreover, as compared to multiplying exogenous scenarios, we can derive technological paths which are immune to drifts of costs assumptions within their domains of validity. From a quantitative perspective, we elaborate two uncertainty models to capture the existence of:

- *unexpected, transitory primary energy prices spikes and economic cycles*: these price variations can occur in a given model period and be resorbed in the next period – the price goes back to its nominal path. In this case, there is no intertemporal perspective on uncertainty propagation (figure 3.1, left-hand side);
- *persistent, intertemporal drifts in the evolution of technology investment costs*: adverse realizations of positive externalities on the evolution of costs (spillovers...) will delay the fall of costs of new technologies. In this case, an upward drift in a given period will affect the costs of the technology in each later model period (figure 3.1, right-hand side).

Clearly, any price or cost assumption may be affected by a combination of these two phenomena; in this first step, we maintain separate descriptions essentially for tractability reasons. However, this approach could easily be generalized to a more general case (see below).

3.2.3 Economic interpretation

The uncertainty introduction leads to a "degradation" of the objective function (as new constraints are added to the program). The extra system cost due to robustness can be measured (for a given value of Γ and a maximum deviation of the parameters $\widehat{a}$) as the difference between the two optimal objective functions (the deterministic and the robust ones).

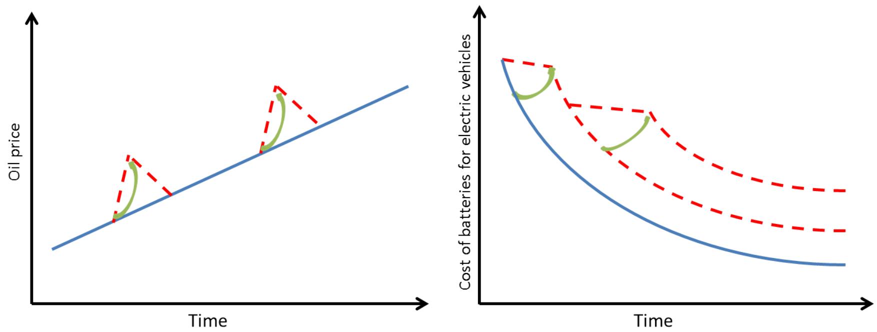


Figure 3.1: Uncertainty models: transitory (left-hand side) and permanent (right-hand side)

In short the robust objective function integrates the cost linked to a change in the technological variables and a cost linked to the diversification to hedge against the uncertainty.
In our case, when the objective function parameters are uncertain, we have:

$$(P_{rob}) : \begin{cases} \min \alpha \\ s.t.\ c^T x + \lambda \Gamma + e^T \mu \leq \alpha \\ Ax \leq b\ (y) \\ \lambda + \mu_j \geq \widehat{c_j} x_j, \forall j \in J\ (z_j) \\ x \in \mathbb{R}^n_+, \lambda \in \mathbb{R}_+, \mu \in \mathbb{R}_+ \end{cases} \tag{3.6}$$

and the difference between the optimal robust and deterministic objective functions is the following:

$$\Delta_{rob} = \underbrace{[\overline{c}^T (x^*_{rob} - x^*_{det})]}_{\text{Technical substitutions}} + \underbrace{[\lambda^* \Gamma + \sum_j \mu^*_j]}_{\text{Captive costs}} \tag{3.7}$$

The whole Δ_{rob} can be interpreted as a risk premium against the level of robustness determined by the couple (Γ, U) where U is the uncertainty set in which cost deviations take values.
More precisely, the first bracketed term of Δ_{rob} accounts for the technical substitution cost due to uncertainty. It is linked to the technical substitutions operated in the energy system as a hedging strategy against a potential increase of some technology costs (the most sensitive ones). The second bracketed term consists in a pure financial cost, in the sense that it comes straightforwardly from the use of technologies that will be used although their cost may increase (in other words, the less substitutable technologies). It is the unavoidable cost the system will have to "support" if the most sensitive costs deviate. These unavoidable costs can be explained by previous investments in technology sensitive to cost uncertainty or by the fact that no alternative to these technologies/ energy sources are present in the model.

Second, we shall observe that varying the uncertainty budget actually corresponds to endogenously varying the cost coefficients of the objective function. At optimum, using the primal form of the deviation sub-problem, we get the following expression for the objective function:
$f^*_{rob} = (\overline{c}_J + z^* \widehat{c}_J)^T x^*_J + \overline{c}^T_{\overline{J}} x^*_{\overline{J}}$,
where J and $\overline{J}$ are the sets of respectively the deviated costs and the ones that stay nominal at the optimum. This means that at optimum, the relative costs come as a solution of the problem. The term $(\overline{c_J} + z^* \widehat{c_J})$ corresponds to risk-adjusted costs according to a worst-case logic. The dual

version of this observation is equally meaningful; the shadow prices of the technical constraints are now related by $\overline{c_J} + z^* \widehat{c_J} - A^T y \geq 0$ which means that the shadow prices of the commodities are likewise risk-adjusted for the pair (Γ, U).
This has an important implication: in the process of varying the uncertainty budget, we somehow endogenously generate different relative cost systems on the basis of a risk assessment (defined by the deviation subproblem). This interpretation gives a sense, as proposed in the sequel of the paper, to performing a systematic sensitivity analysis on the uncertainty budget Γ, because it allows to test the model response to various cost regimes[1].

Finally, when it comes to uncertainty, one naturally expects to find some connections with *risk preferences*. A relationship between robust linear programs and risk-averse optimization exists; the link relies on the analysis of the uncertainty sets of the robust programs with respect to specific families of risk measures (for more details see e.g. Bertsimas and Brown (2009), Natarajan et al. (2009)). In particular, Bertsimas and Brown (2009) show that the space of polyhedral uncertainty sets can be generated by the class of CVaR risk measures. Consequently, the robust version of the energy model used in this work will show a *taste for diversity*.

3.2.4 Robust optimization: Integration in an intertemporal framework

In multistage optimization, when the uncertainty reveals itself at some point, the robust optimization method can be adapted to "wait and see" decisions: it is called Adjustable Robust Optimization (Ben-Tal et al., 2004, Ben-tal et al., 2009). In our case (intertemporal optimization under perfect foresight), the decision has to be made before the realization of the parameters is known (here and now decisions) yet since the whole model is inter-temporal and we have to discuss how the uncertainty propagates.
We will see in what follows different ways of allowing uncertainty to propagate over time.
As a general introduction, we shall formulate the original LP model in its intertemporal shape as follows:

$$\mathbf{(P)}: \begin{cases} \min \sum_{t\in\tau} \sum_{j\in J} c_{j,t} x_{j,t} \\ s.t.\ Ax \leq b \\ x \in \mathbb{R}^n_+, A \in \mathbb{R}^{m*n} \end{cases} \tag{3.8}$$

where $\tau = \{T_0, ...T\}$ is the set of model periods and $J = [1, N]$, where N is the number of cost parameters. We assume now that in each period, some of the cost coefficients will be affected by uncertainty. As discussed in section 3.2.2, we wish to introduce two types of uncertainty, one being related to "volatility" – in the sense that it should not propagate over time – and the second more structural.
With the non-propagative uncertainty, the cost parameters are allowed to deviate at each period around their exogenously determined nominal value: $c_{j,t} = \overline{c_{j,t}} + z_{j,t}\widehat{c_{j,t}}$, with $|z_{j,t}| \leq 1$. The question is then how to limit the number of deviations over the model time period. Once again, different solutions arise: we can limit the number of costs that are subject to uncertainty at each time period or for one given cost we can limit the number of periods where it can deviate. In the first case, the uncertainty budget will be time dependent ($\sum\limits_j |z_{j,t}| \leq \Gamma_t$), in the second case the uncertainty budget will be cost dependent ($\sum\limits_t |z_{j,t}| \leq \Gamma_j$).
With propagative uncertainty, we expect that cost deviations obtained in a given period will diffuse in later ones, since they reflect e.g. delays in technological progress, economies of scale

[1]Other approaches, e.g. Bertsimas and Sim (2004), Poss (2014), address the determination of an optimal uncertainty budget

etc... In that situation, we consider the following form for the cost equation: $c_{j,t} = c_{j,t-1} + z_{j,t}\widehat{c_{j,t}}$, with $|z_{j,t}| \leq 1$.
In practice, primary energy prices or the costs of technologies may be subject to the two types of uncertainty; for the sake of simplicity, the present study distinguishes the two. Therefore, we introduce two sets of uncertain coefficients, $J_t^{\{Un\}}$with $Un = \{NP, P\}$, $t \in \tau$, where $\{NP, P\}$ refers to the subsets of non propagative or propagative uncertainty. These sets are indexed over time and it seems natural to consider that the set of potential uncertain parameters will grow over time; at least, it should not be reduced (this would imply that some coefficients are more certain in the longer run that in the short-term). In our case, uncertainty sets are symmetrical polyhedra, $J_t^{\{NP\}} := \{c_t \in \mathbb{R}^n | \exists z_t \in [-1,1]^n, \sum |z_{j,t}| \leq \Gamma_t, c_{j,t} = \overline{c_t} + z_{j,t}\widehat{c_{j,t}}\}$ where uncertainty budgets are time-dependent so that the "nature control" reflects the evolution of the uncertainty sets. Based on the previous argument, we shall reasonably assume that the uncertainty budget grows over time, so that $\Gamma_t \leq \Gamma_{t'}$, $\forall t' \geq t$. Finally, we introduce the option of using – by symmetry with respect to Γ_t – a process-dependent, intertemporal uncertainty budget: it consists in controlling the amount of adverse events that may affect a particular technology cost or primary energy price (Γ^j) over the whole time horizon.

- Case 1: non-propagative uncertainty
  In this case, the deviation problem is written as

$$\textbf{(P)} : \begin{cases} \max_z \sum_{t \in \tau} \sum_{j \in J_t} z_{j,t}\hat{c}_{j,t}x_{j,t} \\ s.t.\ z_{j,t} \leq 1,\ \forall (t,j) \in \tau \times J_t^{NP},\ (\mu_{j,t}) \\ \sum_{j \in J_t} z_{j,t} \leq \Gamma_t,\ \forall t \in \tau,\ (\lambda_t) \\ \sum_{t \in \tau} z_{j,t} \leq \Gamma^j,\ \forall j \in J_t^{NP},\ (\lambda^j) \\ x_{j,t} \in \mathbb{R}^+, \forall (j,t) \end{cases} \tag{3.9}$$

  The dual version of this problem is then

$$\textbf{(P)} : \begin{cases} \min_{\mu,\lambda} \sum_{t \in \tau} \Gamma_t \lambda_t + \sum_{j \in J_t} \Gamma^j \lambda^j + \sum_{t \in \tau} \sum_{j \in J_t} \mu_{j,t} \\ s.t.\ \mu_{j,t} + \lambda_t + \lambda^j \geq \hat{c}_{j,t}x_{j,t},\ \forall (t,j) \in \tau \times J_t^{NP},\ (z_{j,t}) \end{cases} \tag{3.10}$$

  Here we use the two kinds of uncertainty budgets, one intertemporal and cost related and one periodic.

- Case 2: propagative uncertainty In this case, a process whose cost coefficient deviates in a given period will leave a "trace" in every subsequent period. We write the primal version of the deviation problem as

$$\textbf{(P)} : \begin{cases} \max_z \sum_{t \in \tau} \sum_{j \in J_t} \sum_{t' \leq t} z_{j,t'}\hat{c}_{j,t'}x_{j,t} \\ s.t.\ z_{j,t} \leq 1,\ \forall (t,j) \in \tau \times J_t^{P},\ (\mu_{j,t}) \\ \sum_{j \in J_t} z_{j,t} \leq \Gamma_t,\ \forall t \in \tau,\ (\lambda_t) \\ \sum_{t \in \tau} z_{j,t} \leq \Gamma^j,\ \forall j \in J_t^{P}\ (\lambda^j) \\ x_{j,t} \in \mathbb{R}^+, \forall (j,t) \end{cases} \tag{3.11}$$

  This yields the following dual formulation:

$$\textbf{(P)} : \begin{cases} \min_{\mu,\lambda} \sum_{t \in \tau} \Gamma_t \lambda_t + \sum_{j \in J_t} \Gamma^j \lambda^j + \sum_{t \in \tau} \sum_{j \in J_t} \mu_{j,t} \\ s.t.\ \mu_{j,t} + \lambda_t + \lambda^j \geq \hat{c}_{j,t} \sum_{t' \geq t} x_{j,t'},\ \forall (t,j) \in \tau \times J_t^{NP},\ (z_{j,t}) \end{cases} \tag{3.12}$$

The final cost-robust problem takes the form :

$$(P_{rob}) : \begin{cases} \min\limits_{x,\lambda,\mu} \sum_{t\in\tau} \sum_{j\in J} c_{j,t}x_{j,t} + \sum_{t\in\tau} \Gamma_t\lambda_t + \sum_{j\in J_t} \Gamma^j\lambda^j + \sum_{t\in\tau}\sum_{j\in J_t} \mu_{j,t} \\ s.t.\ Ax \le b \\ \mu_{j,t} + \lambda_t + \lambda^j \ge \hat{c}_{j,t}x_{j,t}, \forall(t,j) \in \tau \times J_t^{NP} \\ \mu_{j,t} + \lambda_t + \lambda^j \ge \hat{c}_{j,t}\sum_{t'\ge t} x_{j,t'}, \forall(t,j) \in \tau \times J_t^{P} \\ x \in \mathbb{R}_+^n, A \in \mathbb{R}^{m*n} \end{cases} \tag{3.13}$$

3.3 Implementation in an energy-transport system model

3.3.1 MIRET

In this section, we present MIRET, a TIMES model developed by IFPEN.
TIMES (The Integrated MARKAL-EFOM System) is a technology rich, bottom-up model generator, which uses linear-programming to produce a least-cost energy system, optimized according to a number of user constraints, over medium to long-term time horizons (Loulou and Goldstein, 2005). In the standard version, TIMES models minimize the total discounted energy system cost while in the elastic demand version, they maximize societal welfare (consumer + producer surpluses). Hence, TIMES models are partial equilibrium models of the energy system and the dynamic intertemporal optimization paradigm can be interpreted from the economic point of view as perfect foresight.
TIMES has been developed by the IEA-Energy Technology System Analysis Program (ETSAP) as the successor of MARKAL, another modeling framework[2], it allows researchers and practitioners to develop a wide variety of energy models all sharing common structural features.

MIRET: General presentation

As a TIMES incarnation, MIRET is built as a long-term, dynamic, techno-economic model that covers the French energy and transportation system in detail. Its time horizon is 2050, with 2007 as base year. MIRET was developed by IFPEN[3], and has been used in national case studies (Ancre, 2015, Nicolas et al., 2014, Menten et al., 2015, **?**). The structure and assumptions of MIRET are described in detail in (documentation is being written now, add citation in a few weeks!).
A high-level schematic of the Reference Energy System of MIRET is depicted in figure 3.2. The RES is built to cover the stock of equipment and flows for the reference year, the future technology characteristics, the costs and potential of primary energy... The four main dimensions of Times are depicted in each block of figure 3.2 diagram: primary energy supply, technology, final energy/energy services demand and policy.

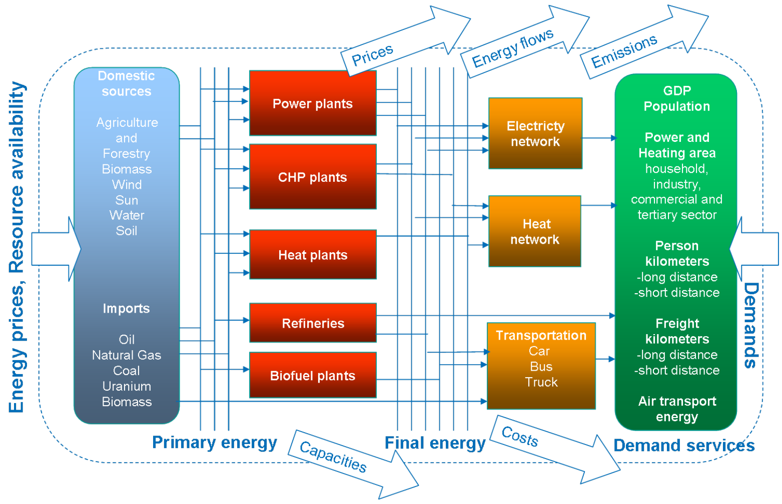
The reference energy system is thus composed (from left to right) of:

- *a primary energy supply* block: includes imported fossil energy (crude oil, coal, natural gas), biomass (starch crops – wheat, corn; sugar crops – sugar beet; oil crops – rapeseed, sunflower; lignocellulosic biomass – forest wood, crop residues, dedicated energy crops);
- *an energy technology* block, whose technologies transform primary energy into energy vectors and energy services: it includes oil refining (see next section), biofuel units (first generation – ethanol, FAME , HVO ; second generation – ethanol and synthetic FT-Diesel), electricity generation (power plants – all technologies; combined heat and power),

[2] See http://www.iea-etsap.org/web/index.asp for more information

[3] IFP Energies nouvelles (IFPEN) is a public-sector research and training center. It has an international scope, covering the fields of energy, transport and the environment.

Figure 3.2: Model schematics



preparation of fuels for transport at blending (diesel, biodiesel B30, gasoline grades E5 and E10 and E85, jet fuel – including fossil and bio bases), and end-use technologies for road mobility (personal vehicles and Light – thermal, hybrid, plug-in hybrid / gasoline, diesel, natural gas, flexfuel, electric cars; buses and trucks – thermal, hybrid / gasoline, diesel, biodiesel);

- *a final energy / energy services demand* block: Electricity demand by time period (four days representing each season, the power load being hourly described for each of these days), mobility demands (short and long distance for passenger vehicles and buses, traffic for LUV, demand for freight mobility), demands for exported products (oil products, electricity);
- *a policy* block: includes measures and constraints of several types affecting all sectors. Some are of microscopic nature, such as quality norms for refinery products, number of functioning hours of fuel turbines power plants, etc. Some are macroscopic in nature, e.g. sectoral carbon tax.

Basic formalism

The objective function of the underlying linear program takes the form:

$$OBJ = \sum_{t \in periods} (1 + disct_t)^{2007-t} TotCosts_t$$

where $disct_t$ is the discount rate. It is simply the discounted sum of the total annual costs ($TotCosts$), the main ones being: annualized capital costs due to investments in new processes, decommissioning costs, fix costs, variable costs and tax and subsidies. The linear program P is as follows:

$$(P) = \begin{cases} \min\ c^T x \\ s.c. \\ Ax \geq b \quad (y) \\ Tx = 0 \quad (\tau) \\ Kx \leq k \quad (\lambda) \\ Qx \leq q \quad (\omega) \\ Sx \leq s \quad (\sigma) \\ x \geq 0 \end{cases}$$

c is the column vector of all discounted unit costs. x is the vector of decision variables, including the investments and energy flows, and emissions into the environment at each period. The constraints $Ax \geq b$ correspond to the final demands of energy and energy services to be satisfied. The equation set $Tx = 0$ describes the fundamental input-output relationships of each technology, namely the mass or energy balance of each technology. The set $Kx \leq k$ includes all capacity constraints, either technology or resource based. For example, (i) the electricity produced by a given technology is limited by the combination of the stock installed and seasonal or hourly availability factors, (ii) the use of scarce resources, e.g. woody biomass, are limited for use for power, heat, combined heat and power and biofuels production. $Qx \leq q$ accounts for the quality equations of some of the products. This is especially the case of refinery products, whose quality must respect certain specifications to be marketed . Finally, the set $Sx \leq s$ includes all sorts of institutional constraints (e.g., the French legislation limits the number of functioning hours of certain power plants – notably fuel turbines), calibration constraints and share constraints.

3.3.2 Scenarios

Two scenario dimensions are explored with MIRET in this research.
The first dimension considers two contrasted sets of assumptions on the future price of fossil energy. Taking into account the recent fall of energy prices, we built what we could consider as a business as usual scenario and a low prices scenario. In the low prices scenario we assume that it will take quite some time for the fossil prices to recover from the current crisis while in the BAU scenario the assumption is that actual oil prices are not meant to last and should go up again soon (see figure, 3.3).
Fossil fuel price scenarios
The low oil prices scenario relates on various elements affecting the long run balance of the market. On the supply side, it assumes, for OPEC countries, a continuation of the strategy observed since November 2014, namely an increase of their own market share by refusing to reduce production in order to drive out higher-cost producers. From a geopolitical view, this scenario takes into account the return of Iran in the world oil market. In this context, OPEC countries will follow a dual logic by carefully monitoring the market: minimizing the substitution of oil for the consuming countries and thus ensuring the place of oil in the world energy mix; allowing each member state of the Organization to maintain its market share (and for particular cases to increase their production) compared to non-members states. This low oil prices scenario also assumes a strong resilience of production of non-conventional oil in the United States but also for traditional or new producers such as Brazil, Norway and Russia at the low price environment in the long term. This scenario should be sustained by an improvement of oil wells productivity contributing to lower the production costs. In addition to these elements, this scenario considers a less risky political environment by 2050, led by a continuous decrease of tensions in the Middle East. This scenario anticipate a conflict resolution in the medium-term in Libya, in Syria and in Iraq and a strong ability for producing countries, that are facing financial turmoil since

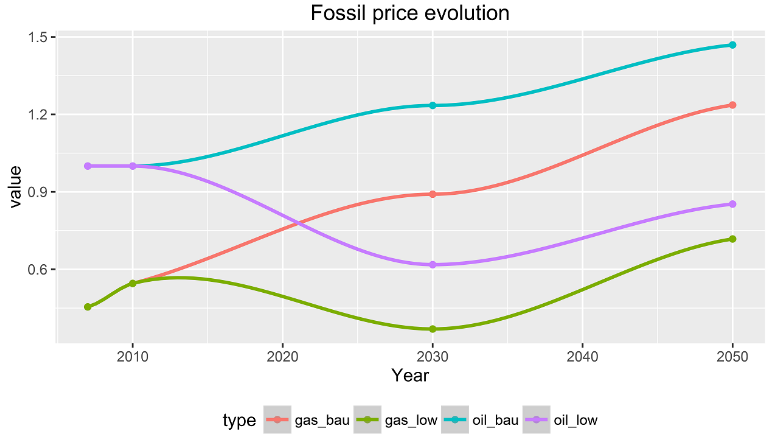


Figure 3.3: Oil and gas prices evolution

2015 (OPEC countries, Brazil, Russia ...), to maintain political stability and favorable economic investment and diversification process despite the strong collapse of the oil revenues. On the demand side, two key assumptions will shape this scenario: international growth pathways and subsidy reforms implementation. The low oil price scenario is based on a progressive lowering of world economic growth around 2.5%, driven by Asia, Africa and Latin America. In this context, global oil demand will not record any major rebound and stays around 100-105 million bpd in 2050. OECD demand should pursue the path observed since the 2000s, with a marked decrease in consumption, reflecting a more and more stagnant growth and a more constraint environmental framework. Furthermore, this scenario includes a major acceleration of the fossil fuels subsidies reforms in both producing countries and consuming countries which should limit oil demand in the long run.

The business as usual scenario incorporates various factors which lead to (i): rebalance the oil market in the medium run and (ii): conduct in the long run to an increase of the oil prices till 2050. On the supply side, the oil market experienced a sharp collapse of the prices between June 2014 and early 2016 which induce a sharp drop in oil investments from international oil companies (IOC) and national oil companies (NOC). After a decline of nearly 20% in 2015, investment in upstream oil fell by over 15% in 2016. This investment drop helps the market to rebalance in the medium run. Every year the market required around 3 million barrels per day (bpd) in order to satisfy oil demand growth and to offset oil fields depletion. By 2020, nearly 10 million bpd will be needed to help balance the market. However, the sharp decline in investment since 2014 will lag the arrival of the oil production in the market and contribute to price increase in the medium run. Oil markets often experimented this price cyclicality in the past. Thus, after the 1997 Asian crisis, exploration budgets of IOC and NOC had been reduced drastically before the rise in 2004, two years after the rebound in global demand.

In parallel OPEC members realize that the open valve strategy put in place in 2014 does not ensure a sustainable economic development and decide to end this market share gains policy with the implementation of a new agreement on the level of production thorough the organization. These factors - cyclic shift investment and production agreement in the OPEP- restrict the possibilities of a sharp rebound in oil supply.

In the demand side, world economic growth recovers to a high level (around 4%) with a strong acceleration in India and in the new emerging countries in Africa and Latin America. China continues to slow and operates its transition to a low carbon economy, but its economic and demographic weight still continue to influence the world oil demand.

The second dimension considers 2 alternate middle term mitigation targets for the French transportation sector. The 2 targets aim at reflecting in a simplified way the huge societal and political uncertainties weighing on the choice of an ambitious mitigation objective. The most ambitious target (CC3) aims at dividing by 3 the transportation sector emissions between 2010 and 2050 and by 4 at the global level (but as abatement in transportation is much more expensive than in other sectors, we chose a slightly less ambitious target), the "less" ambitious one (CC2) aims at cutting emissions by 50% by 2050 (and by 3 for the whole energy sector).

For each of these 4 scenarios, we did 15 runs with different values of the uncertainty budget ranging from 0 to 20% in 2% increments then from 20 to 100% in 20% increments. The 4 runs where the uncertainty budget is equal to 0 correspond to deterministic - perfect foresight runs when the 4 runs with a 100% uncertainty budget correspond to the worst-case - perfect foresight runs.

3.3.3 Uncertainty ranges

In this work, we want to assess how cost uncertainty impacts energy transition pathways in the transportation sector by using robust optimization. We hence need to define uncertainty sets for the various costs involved in transport but also to define how uncertainty propagate over time and across costs.
We assume that investment costs of new technologies available from 2015 and beyond are not known with certainty. For each of these technologies, the uncertainty model follows that described in section 3.2.1 as propagative uncertainty. On top of that, it is assumed that the unit costs of primary energy are also subject to uncertainty (non-propagative). This concerns fossil primary energy (crude oil, natural gas and coal), biomass (agricultural crops, imported vegetable oils, dedicated energy crops and agricultural and forest residues), and final energy imported (electricity, ethanol). And at last, the price of CO_2 is also considered in the uncertainty set, as a part of the WEO NPS price scenario13. These assumptions are summarized in Table 3.1. Overall

Scenario Component	Sector/commodity	Uncertainty Source	Uncertainty type
Primary Energy	Fossil Energy	Price	Volatility
	Agricultural Biomass	Price	Volatility
	Woody Biomass	Price	Volatility
Energy technologies	Refining	None	
	Biofuels	Investment Cost	Propagation
	Road Mobility (Passengers-Freight)	Investment Cost	Propagation
	Power plants	Investment Cost	Propagation

Table 3.1: Uncertainty sources

the uncertainty set comprises 35 primary energy costs and 133 investment costs, under the two dynamic uncertainty propagation models chosen this makes a total of around 1200 constraints and 1400 variables to be added to the original MIRET model (which contains roughly 210000 variables and 140000 equations).
In the final problem, uncertainty budgets for the two uncertainty models are pooled, so that we

do not control the degree of pessimism independently. We hence have only one parameter, Γ, that controls the "level of uncertainty" in the model.

3.4 Assessing energy transition scenarios in transportation under uncertainty: numerical results

Our main objective is to identify optimal technology trajectories to achieve mitigation targets and to establish their sensitivity to cost uncertainty.
We first analyze how uncertainty introduction impacts the global system cost and technological diversification at the global and sectoral level. Then, focusing on the transportation sector, we try to find robust technological pathways and investment strategies.

3.4.1 Robustness cost

Uncertainty introduction leads to a higher total system cost. On figure 3.4, we draw the evolution of the objective function with uncertainty as well as the cost of technical substitutions taking place because of uncertainty [4]. The total cost increase is quite fast when the uncertainty

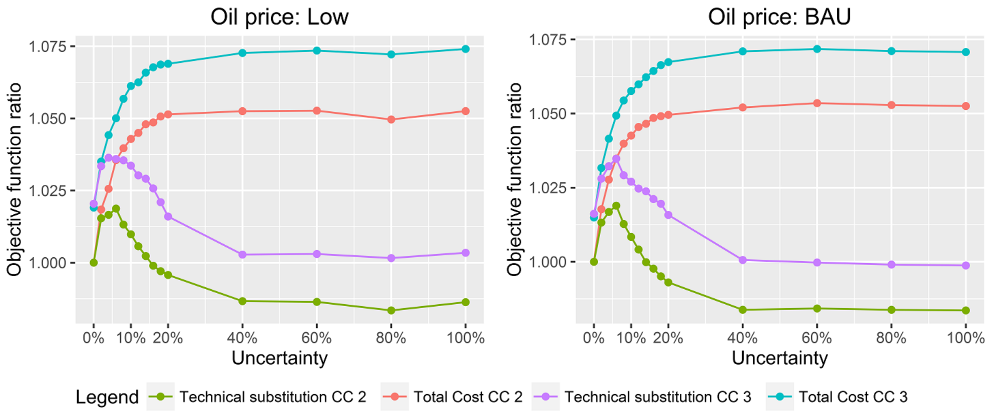


Figure 3.4: Total system cost evolution with uncertainty

budget is low and reaches an asymptote for a budget around 25%. The increases are very similar between the two fossil price scenarios: between no hedge ($\Gamma = 0$) and full hedge ($\Gamma = 100\%$), the cost raises by 5% with the low ceiling (CC2) and by 7.5% with the stringent ceiling (CC3) .
For low values of the uncertainty budget, most of the cost increase is due to technical substitutions. Uncertainty introduction leads to an endogenous variation of the relative costs which explains why when Γ is low technology choices at optimum are modified. As Γ grows, more and more costs deviate and relative costs are progressively re-established which explains why above $\Gamma = 8\%$, the increase of the objective function is mostly due to what we called the "captive cost" in 3.2.3. Beyond the 8-10% threshold arbitrage opportunities are less and less numerous and they almost disappear when Γ reaches 20%. Then, the model has to use technologies even

[4] as described in 3.2.3, Total Cost Ratio: $TCR_{\Gamma,oilprice,Cap} = \dfrac{TC_{\Gamma,oilprice,Cap}}{TC_{0\%,oilprice,2}}$, Technical Substitutions ratio: $TSR_{\Gamma,oilprice,Cap} = \dfrac{\sum_t \overline{c_t}(x_t^*(\Gamma) - x_t^*(0\%))}{TC_{0\%,oilprice,2}} + 1$

though their cost deviates and the "captive cost" share of the total cost increases with Γ.
The captive cost is quite low but not nil when Γ is low meaning that the system has to support part of the extra cost associated with adverse cost deviations. Two reasons at least are responsible for that: (i) if substitution options exist for most technologies, they can be limited or non-existent for others and (ii) it is usually more efficient to use existing capital stocks even though input prices increase rather than scrapping it to invest in other technologies (for example an increase of oil price will not lead to an early-scrapping of all diesel and gasoline cars nor to huge investment in biofuel production facilities, at least not in the short term).
Not surprisingly, the shape of the objective function is concave but more remarkably the shape of the cost decomposition also is rather concave. One of the standards results of linear programming is that it provides for each of the good consumed in the model a merit-order based supply curve which is upward-curving. In the case of uncertainty introduction, risk adjustments on costs modify this merit order. Then, some of the unused option become economical when costs are adjusted but these substitution options are limited. Consequently, the stock of substitution options become scarcer as the uncertainty budget grows (and that more costs are risk-adjusted) – and progressively the initial relative costs system is reestablished (as all the costs increase by 10%).

3.4.2 Cost parameters

With the RO approach, we are able to rank the cost parameters by sensitivity. To observe which are the most sensitive parameters, we look at the value of μ, the marginal value of the first constraint in the primal of 3.3. The highest the value of μ, the highest the model sensitivity to this parameter. The sum of μ is also part of the robust objective function, it is expressed in euros and represent part of the additional cost of robustness.
The first deviating costs are the fossil ones followed by biomass costs. As the uncertainty budget grows the importance of fossil fuel costs in the global cost increase is less and less important, regardless the scenario studied (see figure 3.5).

On this figure we plotted for the scenario BAU CC2: $\mu(i) = \sum_{j \in I} \mu(j)$, where I are the 5 groups identified : fossil fuel costs, biofuel costs and biotechnology investment costs, car investment costs, electricity production investment costs and other vehicle investment costs. And where $\mu(j)$ is the added variable in the objective function that controls the deviation of the cost of j or seen otherwise, it is the marginal value associated with the variable z_j (constraint line 3 of the system 3.2). The three other graphs represent the delta between the weight of the cost parameters for BAU CC2 and the other scenarios.
By comparing the graphs in pairs, we find that the model is very sensitive to fossil cost parameters for the BAU scenarios. When the price of oil and gas is low, these parameters weigh less on the objective function comparatively with other cost parameters.
What drives the impact of biofuel cost parameters for the model is the CO_2 constraint. With the higher constraint (CC3), the model is much more sensitive to these costs which seems quite logical as biofuels are one of the main mitigation options.
Up until $\Gamma = 20\%$, the model is more sensitive to transportation investment costs (cars and other vehicles) when the carbon ceiling is low (CC2) but above this value, the trend is reversed.

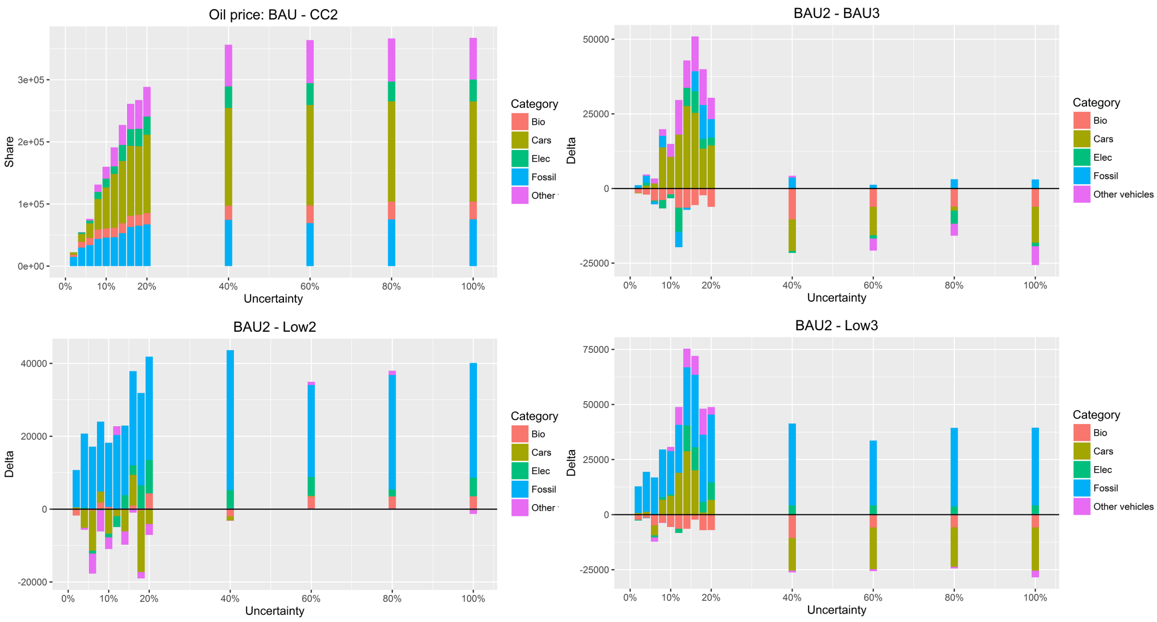


Figure 3.5: Weight of the cost parameters for different values of the uncertainty budget for the BAU CC2 case (top left) - Weight difference with BAU CC2 for the other scenarios

3.4.3 Technological diversification

In this section we analyze how the model reacts to uncertainty introduction, first at the global level before focusing on technological diversification in the transportation sector.

Figure 3.6 plots the French primary carbon intensity of GDP as a function of the energy intensity of GDP (both 2010 normalized) for each value of the uncertainty budget. For each

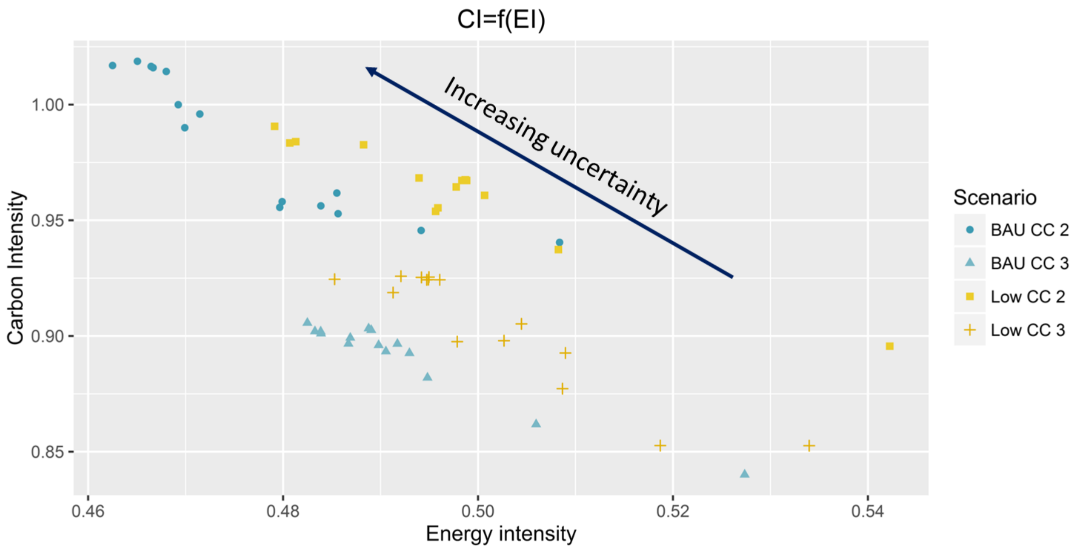


Figure 3.6: Carbon intensity (2010 normalized) as a function of French energy intensity of GDP (2010 normalized) for various values of the uncertainty budget in 2050

scenario, the scatter plot represents the trade-off between reducing the energy intensity of GDP and reducing the carbon intensity of energy to comply with mitigation objectives. In 2050, the emissions are the same irrespective of the uncertainty (for respectively the 2 CC2 and the 2 CC3 scenarios) and the only ways of decreasing emissions are to reduce: the carbon intensity of energy, the energy intensity of economy or the demand of energy services. Because of the flexibility on the demand (demand is elastic), the dot clouds do not exactly form straight lines. This trade-off is interesting to study: when uncertainty increases, the decarbonization of energy often comes with an increase of the total energy consumed (energy intensity). Indeed, renewable energies usually have lower yields than fossil ones particularly in transportation where the whole biofuel value chain is way less efficient than the ones of fossil fuels. The four scatter plots are consistently positioned on the graph: the two scenarios with mild carbon ceiling (CC2) are at the top left (high carbon intensity, low energy efficiency), carbon emission reductions being realized mostly through technological adaptation (more efficiency); while the two stringent carbon constraint scenarios (CC3) present higher energy intensity but lower carbon intensity, biofuels and renewable energies are introduced in the mix. And comparing the scenarios by pairs for the fossil fuel values, we find that scenarios with low prices for fossil have a higher carbon intensity for similar levelS of the energy intensity than the ones with the BAU price.
For the 4 scenarios, the energy intensity decreases sharply when Γ is low, at this point CO_2 emission reductions are realized through investments in cleaner technologies while the carbon intensity increases until it reaches an asymptote.

Technological changes allowing to lower the energy intensity of GDP are particularly important when the uncertainty budget is low.

To represent technological diversification, we use a metrics inspired from the Herfindahl-Hirschman Index (HHI). At the global level, we calculate and plot on figure 3.7 what we call HHI_{inv}:
$HHI_{inv} = \sum_i \frac{InvCost(i)^2}{(TotalInvCost^2)}$, where i are the various technologies present in the model (across sectors). When HHI_{inv} is high (close to one), it means that the investment in new technologies is not diversified. Conversely when this value is close to 0, the investment is quite diversified.
While at the transportation level we plot on figure 3.8 what we can call HHI_{act}:

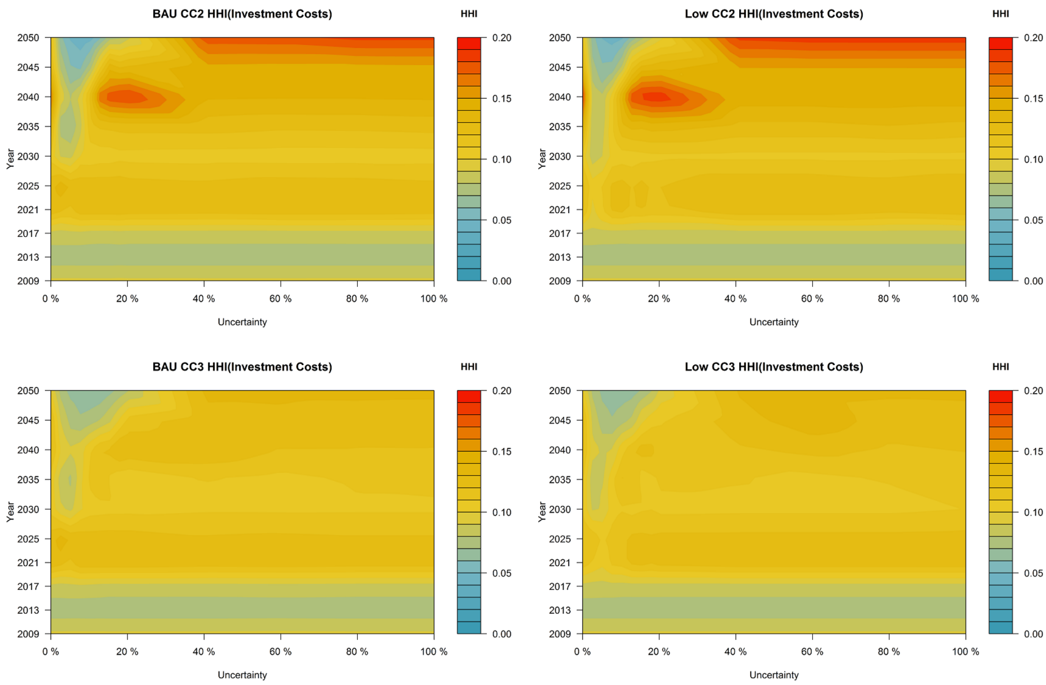


Figure 3.7: Diversification of investments with uncertainty and time

$HHI_{act} = \sum_i \frac{Activity(i)^2}{(TotalTranportACtivity)^2}$, where i are the various transportation technologies. HHI_{act} represents the diversity of the passenger car fleet in activity.
As stated previously, we can see on these figures that the introduction of uncertainty leads to much more diversity in investment and to an earlier occurrence of the diversification. Yet, as the uncertainty budget grows the HHI factors also increase because the cost ratios between the sensitive technologies do not change anymore (the substitution options that were economical when Γ was low are no longer economical as their costs have also deviated).
Before 2021, very few changes occur because the uncertainty introduction takes place at this date.
For the transportation sector, technological hedging strategies begin as early as 2025 when the uncertainty budget in inferior to 15%. For the low carbon constraint (CC2), the diversification exists but is not really high while for the stringent carbon constraint (CC3), diversification is

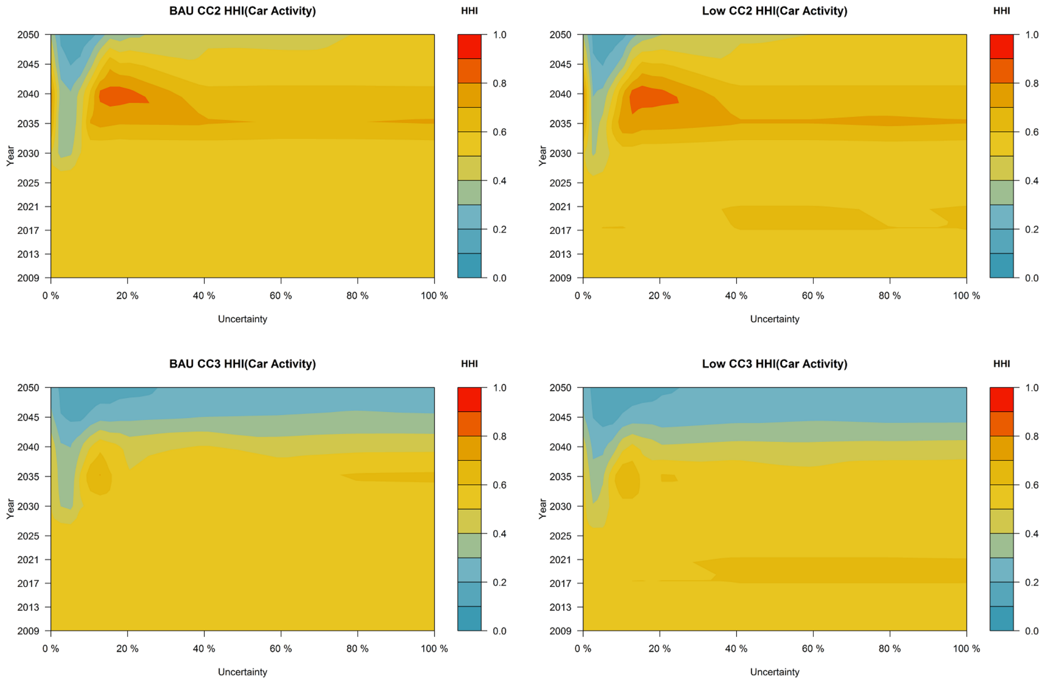


Figure 3.8: Transportation technology diversification with uncertainty and time

really present at the end of the period, and this is true irrespective of the uncertainty value.

3.4.4 Transportation sector: transition pathways

The implementation at the sectoral level of the technological diversification is a useful fact to observe as it is of interest for both policy makers, who often have recourse to specific policies (mandates, taxes, subsidies) to influence technological pathways, and technology experts or industry leaders who question the relevance and risk of investing in the development of some technologies.

Figure 3.9 plots the car activity by technology in millions of passengers/km. In 2035, irrespective of the scenario and the level of uncertainty considered, the vehicle fleet is quite stable and mainly divided between gasoline and diesel vehicles with a small presence of hybrid vehicles. On the contrary, in 2050 the uncertainty budget level greatly impacts the fleet. As stated previously, the highest diversification is found when Γ is between 0 and 20%. For high values of the uncertainty, the CC2 ceiling leads to a vehicle fleet with only gasoline and hybrid cars while, in the case of the CC3 ceiling, alternative vehicles (gas, ethanol and electricity fueled) are always present. The cohabitation of the CNG and the electric technology is not necessarily a good news nor it is realistic because the development of both fuel distribution infrastructure is quite expensive. Hence, considering building both infrastructure, for gas and electricity does not seem straightforward. In our model we do not account for the construction period which is one of the reason why these two technologies penetrate the market simultaneously and quite fast. On the

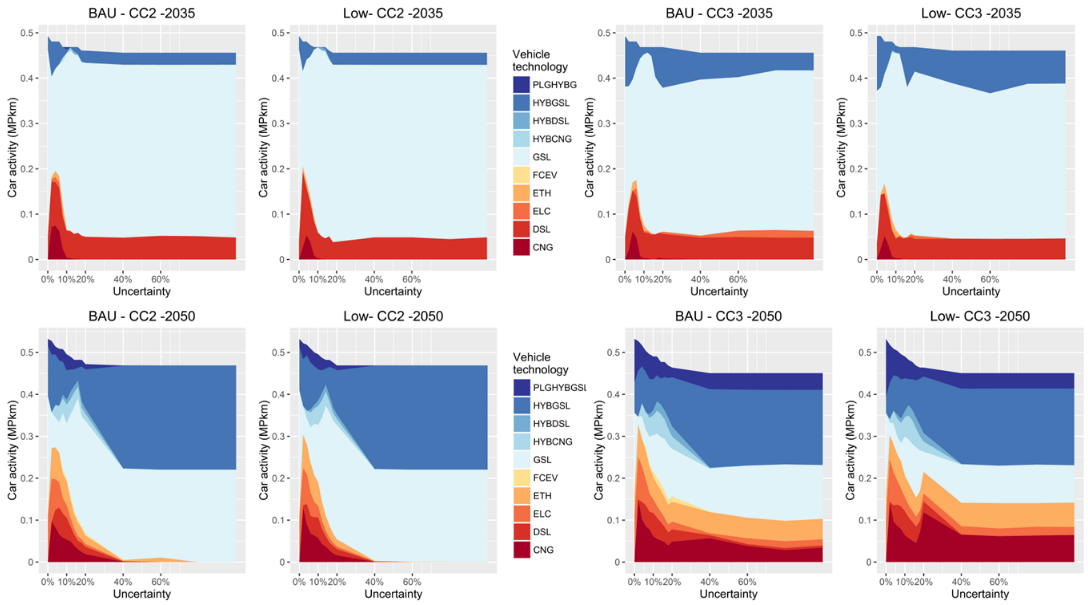


Figure 3.9: Car activity by technology in 2035 and 2050

figure 3.10, the composition of the liquid fuels used in the transportation sector is depicted. In that case we consider the fuel for all the terrestrial fleet, commercial vehicles included. Once again, what drives the fuel diversification is mostly the value of the carbon constraint: with the more stringent constraint, diversification is more important. Most of the diesel still used in transportation in 2050 is for the truck fleet as this sector has less substitution options than the passenger car fleet (we do model electric trucks in MIRET but the cost ratio with regular technologies is much higher than for passenger cars).

For the CC2 constraint, the difference between the BAU scenario and the Low one is tenuous.

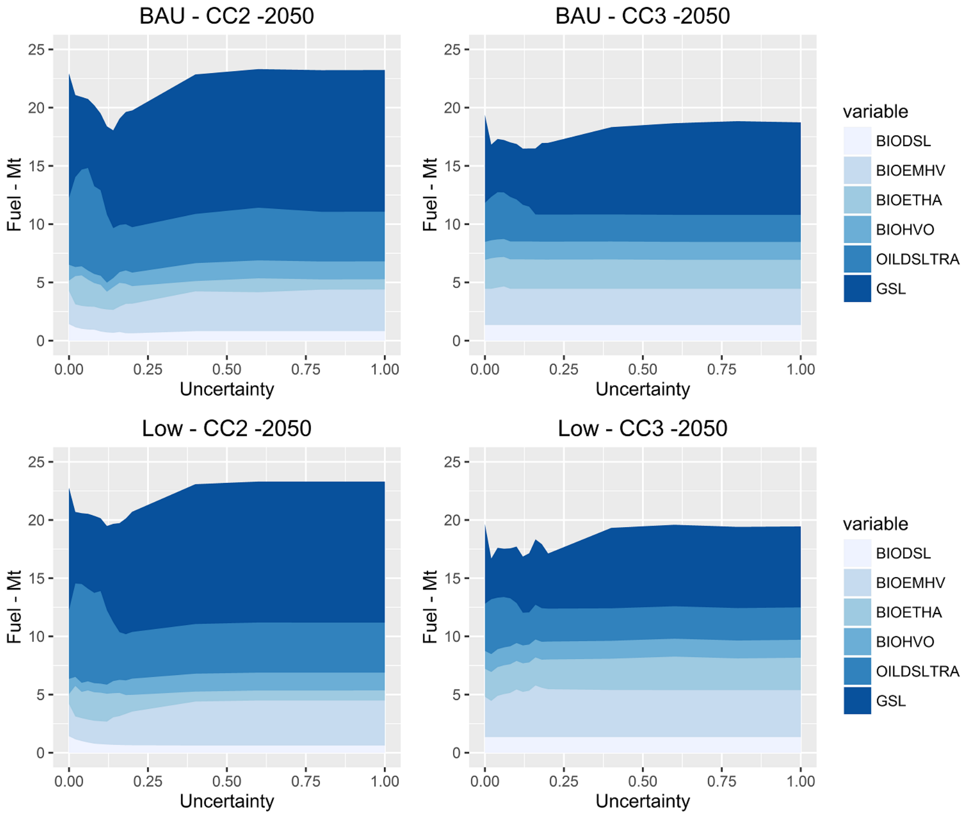


Figure 3.10: Liquid fuels used in transportation

Yet, with the CC3 ceiling, liquid fuel consumption is more important when the fossil price is low and in particular the consumption of diesel.
For all scenarios, the introduction of biofuels occurs mostly in the commercial fleet where substitution options are very expensive.

3.5 Conclusion

In this paper, we assess the impact of cost uncertainty on energy transition pathways in the French transportation sector by 2050. While cost assumptions are a cornerstone of technology-rich long-term models, the issue of uncertain cost projections is not frequently addressed in the literature. There are good reasons for that (large number of costs, which would require high amounts of computations; lack of historical data to calibrate stochastic processes); nevertheless, there is a need to determine how optimal technological paths from a model are sensitive to these exogenous assumptions. This analysis has been realized by augmenting a simple French energy system model (Times paradigm) with recent robust optimization techniques. In short, these techniques consist in identifying technology scenarios for which the total cost will not exceed the upper bound determined at a given uncertainty level, irrespective of the realization of uncertain phenomena. We account for uncertainty for both primary energy costs and technology costs, using two different models of uncertainty propagation. We then apply this formal setting to a numerical experiment where we cross-test the impact of two fossil energy prices and two CO_2 emissions reduction targets.

Our conclusions can be drawn at several levels. Accounting for cost uncertainty increases the total system cost between 3 and 8%, depending on the level of uncertainty and the scenario we consider. Two effects coexist. The cost increase is first due to technological substitutions for low values of the uncertainty budget: when costs derive, optimal choices partly consist in selecting other technologies/fuels to balance the effect of higher costs. However, as uncertainty increases, the "captive cost" gets higher: substitution options become scarcer and no other choice exists but to keep using cost-drifted energy sources and technologies.
Second, results can be analyzed at the technology level. In particular, one shall expect that under uncertainty, optimal choices show a taste for diversity. We find a robust behavior across the 4 scenarios we considered: when the uncertainty budget is quite low (between 2 and 15% of the uncertain parameters), technological diversification is used as a hedge against uncertainty. Yet, as the uncertainty budget increases it is less the case. It is as if in a situation where uncertainty prevails (and is radical), diversification is not a better choice than any other choice since whatever our final decision, we will be wrong. In the transport sector, low-carbon alternatives (CNG, electricity) appear consistently as hedges against cost variations, along with biofuels. To a lesser extent, hydrogen mobility appears in the transportation mix (only in the context of high energy prices and more stringent abatement targets).
Policy implications of diversification strategies are of importance; in that sense, the work undertaken here is a step towards the design of robust technology-oriented energy policies. To a certain extent, our results tend to illustrate the fact that under major uncertainty on technological progress, attention should be paid to a larger number of technologies and pathways. However, this assumes that technological progress and hence uncertainty are exogenous processes. Another way of alleviating this issue would consist in intensifying R&D in promising technologies. Moreover, technology diversification implies potential economic inefficiency, especially when large infrastructure deployments are needed. In such cases, diversification may imply a lower use of economies of scale. Therefore, the fundamental system responses to cost uncertainty should be adequately balanced with broader economic effects in order to design robust policies.

From the methodological perspective, we find that robust optimization is quite easily implemented in the linear programming context, it allows to account for uncertainty on a large number of parameters with parsimony and to explore the effect of cost variations in a systematic way. Macroeconomic uncertainties (energy prices) and microeconomic uncertainties (technology cost evolutions) can be accounted for in the same framework with different representations. Finally, this method allows the modeler or the decision maker to get a bigger picture and to better understand which are the most sensitive parameters of the model. For a prospective exercise, point forecasts are in a way meaningless as they are burdened by structural uncertainty. Hence, robust optimization should certainly be part of the modeler 's tool box as a complement to sensitivity analysis, Monte-Carlo analysis or stochastic programming.

Bibliography

Ancre, 2014. Les scénarios de l'ANCRE pour la transition énergétique. Tech. rep., Paris.

Ancre, 2015. Decarbonization Wedges. Tech. Rep. November, Paris.

Babonneau, F., Kanudia, A., Labriet, M., Loulou, R., Vial, J.-P., jul 2011. Energy Security: A Robust Optimization Approach to Design a Robust European Energy Supply via TIAM-WORLD. Environmental Modeling & Assessment 17 (1-2), 19–37.

Bachmann, T., Bouvart, F., Cheze, B., Gastineau, P., Kanudia, A., Preiss, P., Stoffregen, A., Tchung-Ming, S., Vinot, S., 2015. Scenarios for the electrification of transport. Tech. rep.

Ben-Tal, A., den Hertog, D., Vial, J.-P., feb 2014. Deriving robust counterparts of nonlinear uncertain inequalities. Mathematical Programming Series A.

Ben-tal, A., El Ghaoui, L., Nemirovski, A., 2009. Robust Optimization.

Ben-Tal, a., Goryashko, A., Guslitzer, E., Nemirovski, A., mar 2004. Adjustable robust solutions of uncertain linear programs. Mathematical Programming 99 (2), 351–376.

Ben-tal, A., Nemirovski, A., 2000. Robust solutions of Linear Programming problems contaminated with uncertain data. Mathematical Programming 88 (3), 411–424.

Ben-tal, A., Nemirovski, A., 2002. Robust Optimization — Methodology and Applications. Mathematical Programming 92 (3), 453–480.

Bertsimas, D., Brown, D. B., dec 2009. Constructing Uncertainty Sets for Robust Linear Optimization. Operations Research 57 (6), 1483–1495.

Bertsimas, D., Brown, D. B., Caramanis, C., 2010. Theory and applications of Robust Optimization. SIAM Review 53 (3), 464–501.

Bertsimas, D., Sim, M., feb 2004. The Price of Robustness. Operations Research 52 (1), 35–53.

Bertsimas, D., Thiele, A., feb 2006. A Robust Optimization Approach to Inventory Theory. Operations Research 54 (1), 150–168.

Bhattacharjya, D., Blanford, G., Calvin, K., Eom, J., Gillingham, K., 2006. Final Report : Integrated Assessment of Energy Technologies. Tech. rep., NTNU, Trondheim, Norway.

Cao, J. X., Wang, Y., Wei, Z. M., Wu, J., 2013. Solve the discrete network design problem under construction cost uncertainties with the stochastic programming approach. Procedia - Social and Behavioral Sciences 96, 1039 – 1049, intelligent and Integrated Sustainable Multimodal Transportation Systems Proceedings from the 13th {COTA} International Conference of Transportation Professionals (CICTP2013).

Clarke, L., Wise, M., Edmonds, J., Placet, M., Kyle, P., Calvin, K., Kim, S., Smith, S., 2009. CO2 Emissions Mitigation and Technological Advance : An Updated Analysis of Advanced Technology Scenarios (Scenarios Updated January 2009). Technology, 1–82.

Delage, E., 2015. Quantitative Risk Management Using Robust Optimization.

El Ghaoui, L., Oustry, F., Lebret, H., 1998. Robust solutions to uncertain semidefinite programs. Society for Industrial and Applied Mathematics 9 (1), 33–52.

Gritsevskyi, A., Nakićenovi, N., 2000. Modeling uncertainty of induced technological change. Energy Policy 28 (13), 907 – 921.

Kriegler, E., Weyant, J. P., Blanford, G. J., Krey, V., Clarke, L., Edmonds, J., Fawcett, A., Luderer, G., Riahi, K., Richels, R., Rose, S. K., Tavoni, M., van Vuuren, D. P., jan 2014. The role of technology for achieving climate policy objectives: overview of the EMF 27 study on global technology and climate policy strategies. Climatic Change 123 (3-4), 353–367.

Kunreuther, H., Gupta, S., Bosetti, V., Cooke, R., Dutt, V., Duong, M. H., Held, H., Llanes-Regueiro, J., Patt, A., Shittu, E., Weber, E., 2014. Integrated Risk and Uncertainty Assessment of Climate Change Response Policies. Climate Change 2014: Mitigation of Climate Change, contribution of Working Group III to the IPCC Fifth Assessment Report, 151–206.

Levi, P. G., Pollitt, M. G., 2015. Cost trajectories of low carbon electricity generation technologies in the UK : A study of cost uncertainty. Energy Policy 87, 48–59.

Loulou, R., Goldstein, G., 2005. Documentation for the TIMES Model PART II.

Menten, F., Tchung-Ming, S., Lorne, D., Bouvart, F., 2015. Lessons from the use of a long-term energy model for consequential life cycle assessment: The {BTL} case. Renewable and Sustainable Energy Reviews 43, 942 – 960.

Natarajan, K., Pachamanova, D., Sim, M., 2009. Constructing Risk Measures from Uncertainty Sets. Operations Research 57 (5), 1129–1141.

Nicolas, C., Saint-Antonin, V., Tchung-Ming, S., 2014. (How) does sectoral detail affect the robustness of policy insights from energy system models? The refining sector's example.

Papineau, M., 2006. An economic perspective on experience curves and dynamic economies in renewable energy technologies. Energy Policy 34, 422–432.

Poss, M., sep 2014. Robust combinatorial optimization with variable cost uncertainty. European Journal of Operational Research 237 (3), 836–845.

Rozakis, S., Sourie, J.-C., jan 2005. Micro-economic modelling of biofuel system in France to determine tax exemption policy under uncertainty. Energy Policy 33 (2), 171–182.

Rubin, E. S., Azevedo, I. M. L., Jaramillo, P., Yeh, S., 2015. Review article A review of learning rates for electricity supply technologies. Energy Policy 86, 198–218.

Salvatore, J., 2013. World Energy Perspective - Cost of Energy Technologies. Tech. rep., World Energy Council.

Schade, B., Wiesenthal, T., jan 2011. Biofuels: A model based assessment under uncertainty applying the Monte Carlo method. Journal of Policy Modeling 33 (1), 92–126.

Soyster, L. A., 1973. Convex Programming with Set-Inclusive Constraints and Applications to Inexact Linear Programming. Operations Research 21 (5), 1154–1157.

Waisman, H., Guivarch, C., Lecocq, F., 2013. The transportation sector and low carbon pathways: modelling urban, infrastructure and spatial determinants of mobility. Climate Policy 13 (01), 106–129.

Weiss, M., Junginger, M., Patel, M. K., Blok, K., 2010. Technological Forecasting & Social Change A review of experience curve analyses for energy demand technologies. Technological Forecasting & Social Change 77 (3), 411–428.

Yeh, S., Rubin, E. S., 2012. A review of uncertainties in technology experience curves. Energy Economics 34 (3), 762–771.

4

Robust Energy Transition Pathways for Global Warming Targets

4.1 Introduction

Anthropogenic greenhouse gas (GHG) emissions, such as carbon dioxide (CO_2) emissions from the combustion of fossil fuels, play an important role in the warming of the climate system according to the Intergovernmental Panel on Climate Change (Stocker et al., 2013). This global warming and the associated climate changes pause important threats to ecosystems and human societies (IPCC, 2014). To cope with these threats, a possible strategy is to reduce GHG emissions, the so-called mitigation approach[1]. The latter has been put forward by the Paris Agreement (United Nations, 2015) to the United Nations Framework Convention on Climate Change (UNFCCC), which calls for a strong reduction in GHG emissions to limit global temperature rise to "*well below*" 2 °C with an aim to limit the increase to 1.5 °C.

To design climate mitigation policies, and to analyze in particular energy transition pathways ensuring a strong abatement of GHG emissions, one may follow an integrated assessment (IA) approach. The latter typically combines the socio-economic elements that drive GHG emissions with the geophysical and environmental elements that determine climate changes and their impacts. Integrated assessment models (IAMs) are computational tools to perform IA. Examples of such models include: BaHaMa (Bahn et al., 2008), DICE (Nordhaus, 1994, 2014), FUND (Anthoff and Tol, 2013), MERGE (Manne et al., 1995), PAGE (Hope et al., 1993), POLES (Criqui et al., 1999) and TIAM-World (Loulou, 2008, Loulou and Labriet, 2008).

These IAMs operate under different paradigms (e.g., bottom-up or top-down, optimization or simulation, . . .). Besides, they vary in particular with respect to the level of modelling details for the mitigation options. At the two ends of the spectrum, DICE aggregates (following a top-down philosophy) all mitigation options into a single cost function, whereas TIAM-World offers a very detailed bottom-up representation of the energy sector with thousands of energy technologies, following the TIMES paradigm of the International Energy Agency. This large variety of IAMs used, together with our current imperfect knowledge of all the climate change mechanisms, yield sometimes very different climate policy recommendations. For instance, Stern (2007) has advo-

[1]Alternative strategies are adaptation to climate change impacts and the use of geoenginering measures.

cated using PAGE for immediate actions to abate GHG emissions. While, conversely, Nordhaus (2008) has reached with his DICE model the conclusion that immediate and massive actions are not necessary.

This lack of robustness across models leads some economists to disregard the use of current IAMs (Pindyck, 2013, Stern, 2013). It is indeed undeniable that the long-term energy-economy-climate outlook provided by current IAMs is clouded with a great degree of uncertainty that may deeply affect the relevance of the policy analyses performed and the validity of the policy recommendations formulated. The source of this uncertainty is multiple (see for instance van Asselt and Rotmans, 2002). Besides, even small variations in data can impact feasibility or optimality properties of a given solution (Ben-tal and Nemirovski, 2000). It is thus important to make uncertainty a core feature of long-term climate policy analyses using IAMs.

Several approaches have been followed to address uncertainties in IAMs, in particular: deterministic multi-scenario analysis, sensitivity analysis and Monte-Carlo simulations, stochastic programming and stochastic control. These approaches are quite useful but all have drawbacks. Sensitivity analysis and Monte-Carlo simulations allow to investigate the impact of particular parameters, but do not provide unambiguous hedging strategies. Deterministic multi-scenario analysis results are also difficult to interpret as models are run in a deterministic way with little possibility to probabilize the scenario occurrence. Stochastic programming drawback is that probability distributions (eventually parameterized) have to be defined over the whole tree and that conclusions might be sensitive to the choice of scenario and branching scheme. Moreover, stochastic programming may increase considerably the size of the problem to be solved, leading quickly to excessive computational times. Computational burden typically limits also the use of stochastic control approaches in IAMs.

In this paper, we use robust optimization (RO). Early developments date back to Soyster (1973), who initiated an approach to obtain relevant (feasible) LP solutions although matrix coefficients are inexact. This idea has been then largely explored with different formalisms (Ben-tal and Nemirovski, 2002, El Ghaoui et al., 1998) or by generalizing the Soyster approach (Bertsimas and Sim, 2004). RO allows to solve decision-making problems under uncertainty even when the underlying probabilities are not known. It consists in immunizing a solution against adverse realizations of uncertain parameters within given uncertainty sets. The basic requirement for a robust solution is that constraints of the problem are not violated whatever the realization of the parameters in the set. The issue consists then in identifying computable robust counterparts for the initial optimization program. Ben-tal et al. (2012) or Bertsimas et al. (2010) review techniques for building such robust counterparts in general cases.

Up to now, RO has not been used in IAMs, with the exceptions of Babonneau et al. (2011) and Andrey et al. (2015). A first contribution of our paper is to propose a general robust approach to consider uncertainty in simple climate models (SCMs) typically used by IAMs to represent climate evolution. Our approach relies on Bertsimas and Sim (2004). It consists in defining an uncertainty budget to control the degree of pessimism; in short, to limit the number of climate parameters allowed to deviate from their nominal values. We then rewrite the deterministic IAM to obtain its robust counterpart.

As an illustration, our approach is implemented in the TIAM-World integrated assessment model that relies also on a SCM. We first define plausible uncertainty ranges for the climate parameters of the TIAM-World model and then calibrate these ranges using existing literature (van Vuuren et al., 2009) against climate simulations from the MAGICC model (Meinshausen et al., 2011). Then, using a robust counterpart of TIAM-World, a second contribution of this paper is to enrich the climate debate by defining robust energy transition pathways for different global warming targets. In other words, we identify economic transition pathways under climate constraints for which the outcome scenarios remain relevant for any realization of the climate parameters. Moreover, we can assess which climate parameter or which combination of climate parameters are the most sensitive in our model and we can quantify the uncertainty cost. The originality of our numerical results is that, unlike other studies (e.g., Syri et al., 2008, Labriet et al., 2015), we consider uncertainty on all the climate system parameters of our IAM.

The rest of this chapter is organized as follows: we first present the approach in the general case (for all IAMs). We then describe how we implement the method in the TIAM-World model and finally we present the results of the selected scenarios and we review the different insights brought by the RO approach and how it can inform policy makers.

4.2 General approach

4.2.1 IAMs and SCMs

IAMs are used and built in order to assess strategies to address climate change. By describing the complex relationships between economic, environmental and social factors, IAMs aim to help the decision makers derive climate policy relevant insights.

The structure of the various IAMs is generally the same: the idea is to maximize the well-being or the social surplus under constraints which can be technical, economical, social or climatic. A general formulation of the problem could be:

$$\begin{cases} \max_x f(x), \ \text{(social surplus)} \\ s.t. \\ g(x) \leq 0, \ \text{(social, technological, economical constraints)} \\ Cl(x) \leq 0 \ \text{(climate constraints)} \\ x \in \mathbb{R}^n, \end{cases}$$

With IAMs, we try to depict the causal chain leading to climate change (see figure 4.1): the economic system consumes energy and in particular fossil energy, this fossil energy is burnt, emitting GHGs which in turn have an impact on the climate system. The modification of the latter affects the Earth with consequences on the economics (agriculture yields, water access...).

The complexity of the various fields considered in IAMs leads the modeler to use simplified representations of the relevant sectors and phenomena which introduces inaccuracies in the models. This simplification step is unavoidable to make the construction and use of IAMs tractable (van Vuuren et al., 2009), yet it can significantly impact the simulation results . It is particularly the case for the climate module (the carbon cycle and the climate system), sometimes referred to as simple climate model (SCM). SCMs are a simplified version of much more complex climate models called Atmosphere-Ocean Global Circulation Models (AOGCMs). The AOGCMs are mathematical climate models that represent both atmospheric and ocean processes and their interactions. Given the complexity of these models, their computing requirements are very high (their simulations can take weeks) and they are usually run on supercomputers. As most IAMs require less than a day to run (some run on a personal computer in a few minutes), a huge

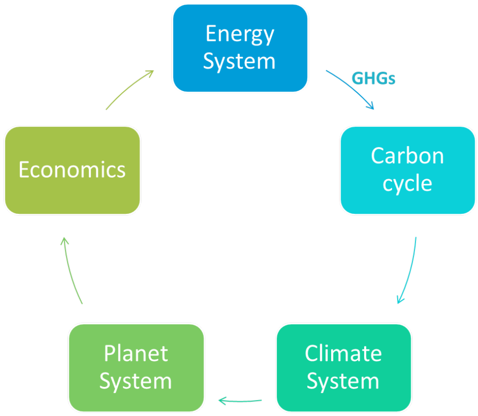


Figure 4.1: Integrated Assessment Models building blocks

research effort has been made to adapt the global circulation models in something more suitable. The first step was to build Earth System Models of Intermediate Complexity (EMICs), which still need minutes to days for one simulation. The SMCs used in IAMs are usually calibrated thanks to EMICs.

Small Climate Models

Even among SCMs, the degree of simplification of the model varies a lot. The most commonly used IAMs (MERGE, DICE, FUND) have really simple SCMs which are built as follows:

- a carbon cycle to determine the CO_2 concentration in the atmosphere
- the CO_2 atmospheric concentration and the other GHGs concentration (often exogenous) are used to calculate the resulting radiative forcing
- This radiative forcing allows to derive the equilibrium temperature

The carbon cycle
The carbon cycle is modeled in two ways in IAMs: it can be represented by different carbon "boxes" (e.g. the atmosphere, the upper ocean, the lower ocean...) with exchange rates as it is done in DICE or MAGICC-6 or it is represented by an impulse-response function (e.g. MERGE, FUND). Most SCMs do not have retroactions of the CO_2 concentration on the carbon cycle parameters which can be a problem as the CO_2 removal rate from the atmosphere is not constant because of the finite capacity of the ocean to take up CO_2.

Radiative forcing
The modeling of radiative forcing is pretty similar across SCMs. It is mostly defined by a logarithmic function of the actual atmospheric CO_2 concentration (ΔRF represent the variation of the radiative forcing since the pre-industrial period):
$\Delta RF_{CO_2}(t) = \gamma ln(\frac{[CO_{2,atm}]_t}{[CO_{2,atm}]_0})$, this logarithmic function being linearized in some IAMs (e.g. TIAM).
The only differences between models are the parameter values γ and $CO_{2,0}$ and the way the other GHGs are treated as:
$\Delta RF(t) = \Delta RF_{CO_2}(t) + \sum_{GHGs} \Delta RF_{GHGs}(t)$.

Temperature change
The atmospheric temperature change resulting from an increase of the radiative forcing is driven by the climate sensitivity and by the initial temperature of various "temperature reservoirs" (the atmosphere and the ocean can be considered as a whole or divided in different layers wich exchange heat). The main SCMs (those of DICE, MERGE, TIAM, FUND...) contain two linear equations:

$$\begin{cases} \Delta T_{atm}(t) = f(\Delta RF(t), \Delta T_{atm}(t-1), \Delta T_{oc}(t-1)) \\ \Delta T_{oc}(t) = g(\Delta T_{atm}(t-1), \Delta T_{oc}(t-1)) \end{cases}$$

$\Delta T_{reservoir}$ being the temperature variation of the reservoir since the pre-industrial period. The parameters of the two linear functions f and g varying for the various SCMs.

Given the diversity of SCMs and the large approximations introduced when they are "built", we aim to assess how robust these SCMs are and to understand which parameters or combinations of parameters are the most sensitive.

4.2.2 Uncertainty ranges

Differences among SCMs come in particular from their choices of key parameters. It is thus important to define 'appropriate' uncertainty ranges for these parameters. This will help assess how robust SCMs are and understand which parameters or combinations of parameters are the most sensitive. Evaluating such ranges reveals several difficulties (see, e.g., Hof et al., 2012, Hu et al., 2012, Butler et al., 2014). First, as already mentioned, SCMs are designed to evaluate climate responses with limited computational burdens. They rely thus on some structural simplifications. For instance, most SCMs ignore carbon and climate feedbacks in their description of the carbon dynamics. Such simplifications induce bias. As an illustration, refer to van Vuuren et al. (2009) that shows how differently carbon cycle can behave within a standard impulse-response experiment, depending on whether it includes or not feedbacks. Second, there is a parametric uncertainty due to the intrinsic volatility of the natural phenomena at stake, as well as the imperfection of measures and statistical estimations. As an illustration, Knutti and Hegerl (2008) exhibits different distributions and ranges for the climate sensitivity based on different lines of evidence. And third, there is a form of 'selection bias' due to heterogeneous degrees of information on parameters estimation and calibration. Overall, IAM-SCMs modellers may have a tendency to pay more attention to some parameters, based on available information.

4.2.3 Robust optimization approach

Let us consider again our basic IAM formulation:

$$\textbf{(P)} : \begin{cases} \max_x f(x) \\ s.t.\ g(x) \leq 0 \\ h(x,a) \leq 0 \end{cases} \tag{4.1}$$

where $x \in \mathbb{R}^n$ is a vector of decision variables, and $a \in \mathbb{R}^m$ is a vector of uncertain parameters in $h(x,a)$. In what follows, h will be a temperature constraint. We assume that any realization a_i might take on of three values $\{a_i^-, \bar{a}_i, a_i^+\}$, each representing the lowest value, nominal value, and highest value, respectively. This uncertainty typically gives rise to the following space of possible candidates for a:

$$\mathbb{U} = \left\{ a \in \Re^m \,|\, \exists\, z^+ \in \{0,1\}^m, z^- \in \{0,1\}^m, z^+ + z^- \leq 1,\, a_i = \bar{a}_i + (a_i^+ - \bar{a}_i)z^+ + (a_i^- - \bar{a}_i)z^- \right\}$$

Following Bertsimas and Sim (2004), it is possible to control the degree of pessimism of the solution by allowing only a subset of parameters to deviate from their nominal values. The concept of the uncertainty budget is based on the fact that it is highly unlikely that all the parameters take one of their two extreme values at the same time. This motivates the use of the following robust counterpart of the initial problem:

$$\textbf{(RC)} : \begin{cases} \max f(x) \\ s.t.\ g(x) \leq 0 \\ h(x,a) \leq 0, \forall a \in \mathbb{U}(\Gamma) \end{cases} \tag{4.2}$$

with

$$\mathbb{U}(\Gamma) = \left\{ a \in \Re^m \,\middle|\, \exists\, z^+ \in \{0,1\}^m, z^- \in \{0,1\}^m,\ \begin{array}{l} z^+ + z^- \leq 1, \sum_i z_i^+ + z_i^- \leq \Gamma \\ a_i = \bar{a}_i + (a_i^+ - \bar{a}_i) z_i^+ + (a_i^- - \bar{a}_i) z_i^- \end{array} \right\}$$

where $\Gamma \in \{0, 1, 2, \ldots, n\}$ is the maximum number of parameters taking one of their extreme values. The idea behind the robustification of h is that the solution of the energy-economy problem should be feasible for any 'nature-controlled' realization of the uncertain parameters in e.g. the temperature constraint. Thus, we want to identify the worst-case combination of parameters in h constrained by the uncertainty budget Γ. For example, assuming we want to determine optimal economic mitigation choices to limit global warming below 2 °C, we need to identify trajectories that meet the temperature target even though some of the climate parameters were wrongly estimated. We assume that decisions shall be taken before the actual values of the parameters are known, to reflect the current status of political discussions and scientific progress in the climate science.
Under linearity conditions of $h(x,a)$ with respect to a, the uncertainty set $\mathbb{U}(\Gamma)$ can be equivalently replaced with its convex hull[2]:

$$\mathbb{U}'(\Gamma) = \left\{ a \in \Re^m \,\middle|\, \exists\, z^+ \in [0,1]^m, z^- \in [0,1]^m,\ \begin{array}{l} z^+ + z^- \leq 1, \sum_i z_i^+ + z_i^- \leq \Gamma \\ a_i = \bar{a}_i + (a_i^+ - \bar{a}_i) z^+ + (a_i^- - \bar{a}_i) z^- \end{array} \right\}$$

and the robust constraint can be reformulated using strong duality as:

$$\begin{cases} h(x,\bar{a}) + \sum_i \max\left((a_i^- - \bar{a}_i) h_i'(x) - v;\ 0;\ (a_i^+ - \bar{a}_i) h_i'(x) - v \right) + \Gamma v \leq 0 \\ v \geq 0 \end{cases} \tag{4.3}$$

where $v \in \Re$ is an additional decision variable that need to be optimized jointly with x, and where $h_i'(x)$ is the derivative of $h(x,a)$ with respect to a_i.

The robust problem can then be reformulated by incorporating this new set of constraint in the original problem (see Bertsimas and Sim, 2004, for the original discussion about such a reformulation). Unfortunately, such reformulations are not always possible. Beyond the strictly linear case, Ben-tal et al. (2012) proposes a methodology to reformulate robust programs in the more general case of nonlinear but still convex constraints when using convex uncertainty sets such as $U'(\Gamma)$. Yet, these conditions typically involve that both $h(x,a)$ be concave in a and that the uncertainty set be a convex set. Unfortunately, the mere fact that $h(x,a)$ be a concave function prevents one from replacing $\mathbb{U}(\Gamma)$ with its convex hull. This therefore implies that such reformulation are unlikely to be obtainable for robust non-linear climate constraints when an uncertainty set as $\mathbb{U}$ is used.

[2]Refer to example 14.3.2.B in Ben-tal et al. (2009) for a proof of this representation.

As an illustration, let us consider that temperature follows some linear dynamics, i.e., Eq. (4.2.1) can be written as:

$$T_{at}(t) = a_1 F(t) + a_2 T_{at}(t-1) + a_3 T_{oc}(t-1)\,,$$

where (a_1, a_2, a_3) are three parameters that might be considered uncertain. When unfolding this expression in order to assess the long term effect of the parameters on the temperature level, we get expressions that resemble

$$T_{at}(t) = \sum_{\tau=1}^{t} a_2^{t-\tau} a_1 F(\tau) + a_2^t T_{at}(0) + \sum_{\tau=1}^{t} a_2^{t-\tau} a_3 T_{oc}(\tau)\,,$$

which is a polynomial function of (a_1, a_2, a_3) and does not in general satisfy structural assumptions such as monotonicity, convexity or concavity. This makes the hope of obtaining a compact reformulation as in (4.3) somewhat unrealistic.

Note that it is possible to avoid the need of a compact reformulation by including additional constraints that exhaustively enumerate all possible combination of deviations that need to be verified for a given choice of Γ. Unfortunately, the number of such combinations increases exponentially with respect to m, the number of uncertain parameters. To avoid the exponential growth in the problem size, we suggest employing a constraint generation method that will attempt to identify a small subset of such extreme value combinations that are sufficient to obtain the optimal robust solution of the problem. This approach is fairly generic as it relies entirely on two modest (as we will see) assumptions: i) the ability to identify a worst-case combination of extreme value for a fixed decision x; and ii) the ability to solve the RC problem where the robust constraint is replaced by:

$$h(x, a) \leq 0\,,\ \forall\, a \in \{\hat{a}_1, \hat{a}_2, \ldots, \hat{a}_K\} \tag{4.4}$$

Let us now detail our proposed constraint generation algorithm:

1. Set $\hat{\mathbb{U}}_1 = \{\bar{a}\}$ and $k = 1$
2. Solve the master problem $(MP(\hat{\mathbb{U}}))$ which consists in maximizing the social surplus under a robust temperature constraint that accounts only for instances of the parameters a contained in $\hat{\mathbb{U}}$:
$$(MP(\hat{\mathbb{U}})) : \begin{cases} \max\limits_{x} f(x) \\ s.t. \\ g(x) \leq 0 \\ h(x, a) \leq 0\,,\ \forall\, a \in \hat{\mathbb{U}} \\ x \in \mathbb{R}^n \end{cases}$$
Capture the optimal trajectories in this problem with x_k^*
3. Given some optimal trajectories, identify the worst-case scenario in $\mathbb{U}$ for the parameters of the temperature constraint function by solving the $SP(x_k^*)$ worst-case analysis problem:
$$(SP(x_k^*)) : \left\{ \max_{a \in \mathbb{U}(\Gamma)} h(x_k^*, a) \right.$$
Capture the worst-case value of this problem as h_k^* and one of the assignments that achieve the worst-case value as a_k^*.
4. If $h_k^* \leq 0$, terminate the algorithm and return x_k^* as the optimal robust trajectories of problem (P) in Eq. (4.1). Otherwise, add a_k^* in the set $\hat{\mathbb{U}}$, increase k by one, and go to step 2

4.3 Application to TIAM-World

4.3.1 TIAM-World

The TIAM-World model

The TIMES Integrated Assessment Model (TIAM-World) is a detailed, global, multi-region technology-rich model of the energy/emission system of the world. It is based on the TIMES (The Integrated MARKAL-EFOM System) economic paradigm, which computes an inter-temporal dynamic partial equilibrium on energy and emission markets based on the maximization of total surplus[3]. TIAM-World is described in Loulou (2008) and in Loulou and Labriet (2008). It is used in many international and European projects (for recent applications see: Babonneau et al. (2011); Labriet et al. (2012)). The multi-region partial equilibrium model of the energy systems

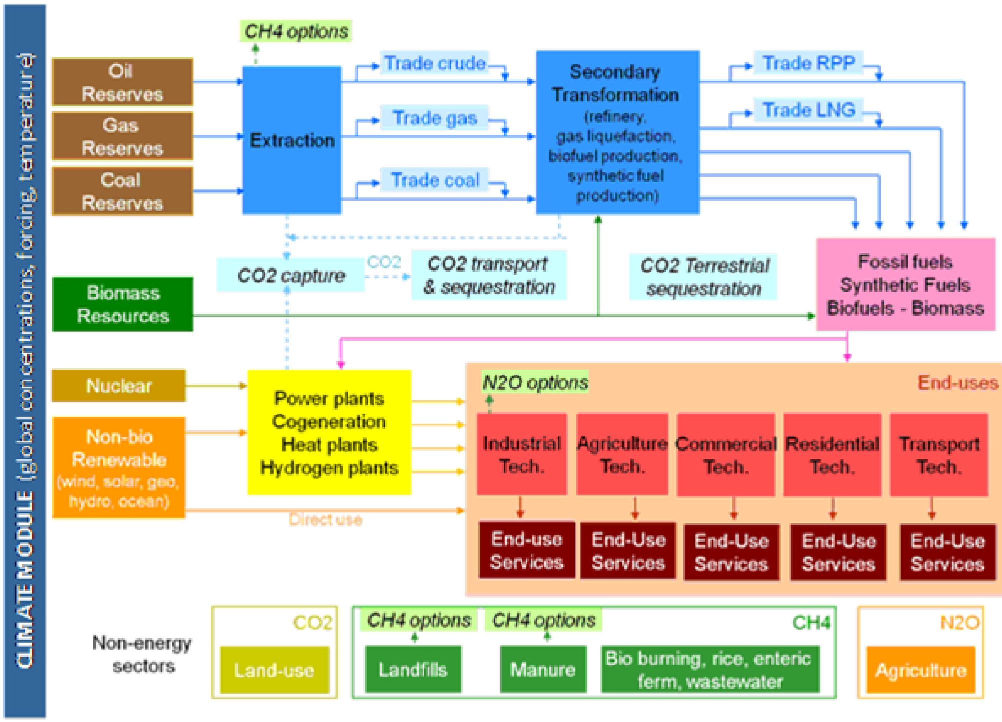


Figure 4.2: TIAM Reference Energy System

of the entire World is divided in 16 regions. Regions are linked by trade variables of the main energy forms (coal, oil, gas) and of emission permits. TIAM's planning horizon extends from 2000 to 2100, divided into periods of varying lengths.

In TIMES, an intertemporal dynamic partial equilibrium on energy markets is computed, where demands for energy services are exogenously specified (only in the reference case), and are sensitive to price changes in alternate scenarios via a set of own-price elasticities at each period. Although TIMES does not encompass all macroeconomic variables beyond the energy sector, accounting for price elasticity of demands captures a major element of feedback effects between

[3]A complete description of the TIMES equations appears in www.etsap.org/documentation.

the energy system and the economy. Thus, the equilibrium is driven by the maximization (via linear programming) of the discounted present value of total surplus, representing the sum of surplus of producers and consumers, which acts as a proxy for welfare in each region of the model (practically, the LP minimizes the negative of the surplus, which is then called the system cost).

The maximization is subject to many constraints, such as: supply bounds (in the form of supply curves) for the primary resources, technical constraints governing the creation, operation, and abandonment of each technology, balance constraints for all energy forms and emissions, timing of investment payments and other cash flows, and the satisfaction of a set of demands for energy services in all sectors of the economy.

The nominal formulation of the TIAM problem is a cost minimization and can be written as follows (with some simplifications):

$$\begin{cases} \min \sum_t c_t^T x_t \\ s.t. \\ L_t x_t \geq b_t, x_t \in \mathbb{R}^n, L_t \in \mathbb{R}^{m*n} \text{ , (technological constraints)} \\ D_t x_t \geq d_t, x_t \in \mathbb{R}^n, D_t \in \mathbb{R}^{d*n} \text{ , (demand constraints)} \\ y_t \leq w_t, \text{ with } y_t = A y_{t-1} + F x_t \text{ , (recursive climate constraints)} \\ x_t \in \mathbb{R}^n, y_t \in \mathbb{R}^w, A \in \mathbb{R}^{w*w}, F \in \mathbb{R}^{w*n} \end{cases}$$

The objective function is the total cost of the system. It includes among others: investments costs, operating costs of the various sectors, taxes, transportation costs between geographical zones... Technological constraints cover capacity limits, supply limits, yields, the allowed growth rates of the processes in the various sectors. Demand constraints include energy service demands of each zone and climate constraints embrace constraints on GHG emissions or stocks in the atmosphere or the temperature increase.
TIAM-WORLD also includes an endogenous climate module that allows the user to impose climate targets, such as upper bounds on concentrations, on atmospheric radiative forcing, or on temperature increase. The CO_2, CH_4 and N_2O emissions related to the energy sector are explicitly represented by the energy technologies included in the model. The nonenergy-related CO_2, CH_4 and N_2O emissions (landfills, manure, rice paddies, enteric fermentation, waste water, and land use) are also included in order to correctly represent the radiative forcing induced by them, but they are exogenously defined. Emissions from some Kyoto gases (CFCs, HFCs, and SF6) are not explicitly modeled, but a special radiative forcing term is added in the climate module.

The climate module

The climate module used in TIAM-World for this work is an adapted version of the model developed by Nordhaus and Boyer (1999). Greenhouse gas concentration and temperature changes are calculated from linear recursive equations. We briefly present its characteristics here, a detailed description can be found in Loulou et al. (2010).
The climate representation in TIAM-World is characterized by three steps. First, the GHGs emitted by anthropogenic activities accumulate in the atmosphere; exchanges with the upper and deep ocean layers occur then for CO_2, while the dissipation of CH_4 and N_2O is described with single atmospheric decay parameters. The terrestrial carbon cycle of this climate module is depicted in figure 4.3. Formally, the one-year-lagged dynamics of the three detailed greenhouse

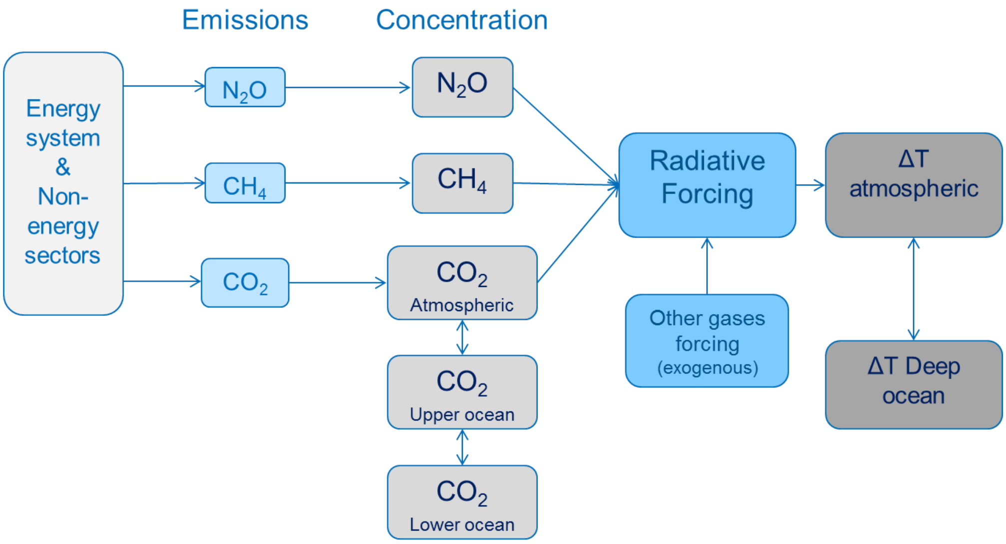


Figure 4.3: TIAM Climate Module

gases are the following (see A for detailed equations):

$$M_t^g = \Phi^g M_{t-1}^g + FE_t^g \tag{4.5}$$

where M_t^g is the vector of the mass of gas g across the different reservoirs in year t, E_t^g is the emission of gas g in year t (from the global energy model), $g \in G = \{CO_2, CH_4, N_2O\}$ and $r : reservoirs \in R = \{atmosphere, UpperLayer, LowerLayer\}$.
This set of equations defining the time profiles of atmospheric GHGs is then used to compute the radiative forcing. It is common to consider that forcings are additive, so that:

$$\Delta F_t = \sum_{g \in G} \Delta F_t^g + Exf_t \tag{4.6}$$

where ΔF_t^g is the forcing of gas g in period t and Exf_t corresponds to an exogenous assumption of forcing for all gases other than carbon dioxide, methane and nitrous oxide. The current knowledge on radiative forcing suggests that none of these terms is linear in the atmospheric stock of gas; the linearization used here is proposed by Loulou et al. (2010):

$$\Delta F_t^g = \gamma_g A^g + \gamma_g B^g M_t^g, \tag{4.7}$$

, where γ is a constant (the radiative forcing sensitivity to atmospheric CO_2 doubling for $g = CO_2$), and A's and B's are constant depending on pre-industrial concentration levels and linearization intervals.
At last, temperature elevation profiles are computed based on the following equations:

$$\begin{bmatrix} \Delta T^{up} \\ \Delta T^{lo} \end{bmatrix}_t = S \begin{bmatrix} \Delta T^{up} \\ \Delta T^{lo} \end{bmatrix}_{t-1} + \begin{bmatrix} \sigma_1 \\ 0 \end{bmatrix} \Delta F_t, \tag{4.8}$$

$$S = \begin{bmatrix} 1 - \sigma_1 \left(\frac{\gamma}{C_S} + \sigma_2 \right) & \sigma_1 \sigma_2 \\ \sigma_3 & 1 - \sigma_3 \end{bmatrix}.$$

C_S represents the climate sensitivity, i.e. the change in equilibrium atmospheric temperature due to a doubling of GHG concentration; σ_1 and σ_3 are the adjustment speeds for respectively atmospheric and oceanic temperature (lags, in $year^{-1}$); σ_2 is a heat loss coefficient from the atmosphere to the deep ocean.

4.3.2 Uncertainty sets

The concrete procedure for estimating min and max values for the climate system parameters differs across parameters. While most estimations are based on comparisons with existing literature (Stocker et al. (2013), Butler et al. (2014)), the construction of lower and upper bounds for the three-box carbon cycle parameters relies on a calibration against existing emission scenarios and the subsequent concentrations from MAGICC6 (Meinshausen et al. (2011)). More detail about the estimation procedures can be found in appendix B; table 4.1 lists the nominal values and upper/lower bounds for the TIAM climate model parameters. Instead of keeping an upper and a lower value for the parameters, a rapid pre-study provided us the worst-case value of the parameters (in bold letters in the table).

Parameter	Description	Nominal value	Lower bound	Upper bound
ϕ_{a-u}	Atmosphere to upper layer carbon transfer coefficient (annual)	0.046	**0.04393**	0.04807
ϕ_{u-a}	Upper layer to atmosphere carbon transfer coefficient (annual)	0.0453	0.04326	**0.0473**
ϕ_{u-l}	Upper to lower layer carbon transfer coefficient (annual)	0.0146	**0.0139**	0.01526
ϕ_{l-u}	Lower to upper layer carbon transfer coefficient (annual)	0.00053	0.00051	**0.00055**
γ	Radiative forcing from doubling of CO_2	3.7	2.9	**4.5**
C_S	Climate sensitivity from doubling of CO_2	2.9	1.3	**4.5**
σ_1	Adjustment speed of atmospheric temperature	0.024	0.0216	**0.0264**
σ_2	Heat loss from atmosphere to deep ocean	0.44	**0.396**	0.484
σ_3	Heat gain by deep ocean	0.002	**0.0018**	0.0022

Table 4.1: Nominal values and bounds for climate parameters

4.3.3 Approach implementation

Robust formulation of the climate problem

Based on the uncertainty that was described above, one can describe a robust counterpart of TIAM as follows :

$$\begin{cases} \min_x \sum_t c_t^T x_t \\ \text{s.t. } L_t x_t \geq b_t \quad \text{(technological constraints)} \\ \quad D_t x_t \geq d_t \ \text{ (demand constraints)} \\ \quad y_t(x, A, F) \leq w_t \,,\ \forall\, (A, F) \in \mathbb{U}(\Gamma) \ \text{ (robust temperature constraints)} \\ \quad x \in \mathbb{R}_+^n \end{cases}$$

where the climate equation is written as:

$$y_t(x, A, F) = \sum_{\tau=1}^{t} A^{t-\tau} F x_\tau + A^t y_0 \,.$$

and where intuitively the uncertainty set $\mathbb{U}(\Gamma)$ includes any pair of matrices (A, F) that can be obtained by setting less than Γ of the uncertain parameters described in Table 4.1 to one of their extreme values. The algorithm described in section 4.2.3 can be applied here as long as we are able to solve

$$(SP(x_k^*)) : \left\{ \max_{(A,F)\in\mathbb{U}(\Gamma)} h(x_k^*, A, F) := \max_{t=1,\ldots,T} y_t(x, A, F) - w_t \right. ,$$

and return the maximum value with a pair (A_k^*, F_k^*) that achieves this worst-case value for one of the time period in the horizon $t = 1, \ldots, T$.
This resolution will be done by enumerating through all t's and identifying a worst-case (A_t^*, F_t^*) pair for

$$\max_{(A,F)\in\mathbb{U}(\Gamma)} y_t(x, A, F) - w_t \,. \tag{4.9}$$

Given that the largest worst-case difference among all t's is achieved at t^*, the oracle will return $h_k^* := y_t(x, A, F) - w_t$ with the pair $(A_{t^*}^*, F_{t^*}^*)$ to be included in $MP(\hat{\mathbb{U}})$. While it might be possible to solve problem (4.9) by enumerating through all the possible scenarios for A and B, we present in appendix C the procedure that we employed which relies on the resolution of a mixed integer linear program which we believe might be more efficient when the number of uncertain parameters becomes large.

4.4 Numerical results

This section presents the results we obtained when we applied the methodology described previously to the TIAM-World model.

Using the uncertainty sets designed in section 3.2, we applied a temperature constraint on the model for the whole 2000-2200 horizon. We choose two levels for the temperature constraint: the well-known 2°C target and a 3°C target. The latter seems more realistic given the actual temperature deviation and the announced actions by the countries involved in the COP21 (even though the final COP21 agreement mentionned the 1.5 °C target, which we do not consider

realistic in view of the actual emission and technological pathways).
The uncertainty budget takes value in $[0-9]$, 9 being the number of uncertain parameters in the TIAM climate module.

4.4.1 Impact on climate and parameter sensitivity

We first present how uncertainty impacts the temperature trajectory. For low values of the uncertainty budget the impact is quite strong as shown on the figure 4.4. This figure represents the temperature trajectories obtained with the nominal values of the parameters when the trajectory with deviated parameters is under the 2 or 3°C threshold. These trajectories are the ones that should be followed in order to fulfill the temperature constraint even in presence of parameter uncertainty: these are in a way hedging trajectories. In order to ensure that the temperature

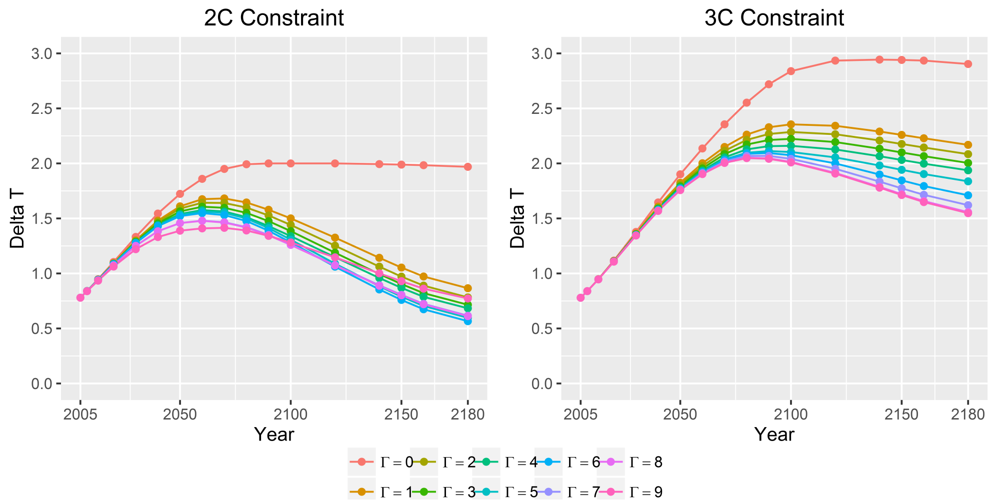


Figure 4.4: Atmospheric temperature delta for different values of the uncertainty budget

trajectory stays below 2°C (respectively 3°C), we should aim at temperature increase between 1.3 and 1.5°C (resp. between 2 and 2.3°C) with the nominal climate model. If we examine these results in light of the recent international negotiations on climate change (COP21), reaching a $\tilde{2}$°C target is consistent with *actually targeting* a 3°C one and accounting for some of the uncertainties surrounding the biophysical terrestrial system. Similarly, it is interesting to note that – according to these calculations – the newly evoked 1.5°C target is equivalent to a climate-uncertain 2°C objective. Second, it seems feasible to protect against climate uncertainty at the 3°C level without temperature overshoot, which means that the average temperature increase does not go above its 2100 level throughout the horizon[4]. At the 2°C level, overshoot is the rule: the temperature peaks between 2060 and 2070, before it cools down. This notably impacts the technology pathways deployed to reach the climate target (see section 4.4.3).
The robust optimization methodology also allows to rank the parameters or group of parameters by sensitivity. Table 4.2 shows the order in which the parameters deviate, traducing a diminishing negative impact on the constraint. Since the robust counterpart of the nominal problem maximizes the temperature deviation for a given emission profile, increasing the uncertainty

[4]Temperature curves are monotonically increasing

budget consists in finding parameters with the worst effect on the solution within the set of remaining (undeviated) parameters.

Parameters	C_S	ϕ_{a-u}	ϕ_{u-a}	σ_2	γ	σ_1	ϕ_{u-l}	ϕ_{l-u}	σ_3
Order 3 °C	1	2	3	4	5	6	7	8	9
Order 2 °C	1	2	3	4	9	7	5	6	8

Table 4.2: Deviation order of uncertain climate parameters

The first deviating parameter is the climate sensitivity (Cs). This can be explained by (i) its wide uncertainty range compared to the ones of the other parameters and (ii) the fact it is a central parameter of the climate module. This result is therefore consistent with scenarios from other studies which focus on the analysis of climate response sensitivity to derive 2°C-compliant mitigation pathways (Labriet et al., 2010, Vanderzwaan and Gerlagh, 2006, Ekholm, 2014). More interestingly, carbon cycle parameters are critical right after the climate sensitivity. The terrestrial carbon dynamics is of primary importance to assess the impact of anthropogenic GHG emissions: the amount of carbon present in the atmosphere at a given period depends on the exchange rates with the other biospheric reservoirs. Therefore, bad surprises on the climate cycle directly affect the carbon stock of the atmosphere, hence the forcing and temperature. It strengthens the importance of relying on appropriate uncertainty ranges for the climate parameters (see appendix B); it is likely that economists and system modelers working on long-term scenarios should pay more attention to the intricacies of the carbon cycle, including feedbacks and nonlinearities.

Looking at the two temperature targets, the parameter deviation order differs between the two series of runs as the temperature evolution is path dependent. While in the two cases, climate sensitivity and the carbon cycle appear as primary factors, second-order parameters are ranked very differently. This can be (at least partially) explained by the mitigation dynamics in the two climate scenarios: in the 2°C case, mitigation pathways *must* be implemented earlier anyway, so that the climate dynamics does not have the same impact. The CO_2 emission trajectories for the nominal scenarios and the emissions ranges in the hedging scenarios illustrate this point (figure 4.5).

With the 3°C scenarios, the shaded area – corresponding to the range of robust trajectories – expands over time to reach a maximum size by 2080: at this time, emission scenarios are more dispersed. On the contrary, in the 2°C case, the range of emissions widens around 2040 and then shrinks again. This means that below 2°C, the endpoint carbon footprint of the energy system is quite stable, and strong abatements occur in the first half of the century. This difference in timing of the mitigation strategies justify that some climate parameters do not play the same role in the two scenarios, as long as they contribute differently to the global climate dynamics. Hence different CO_2 emission profiles diversely weigh on the concentration and forcing trajectories and finally on the temperature constraint.

4.4.2 Robustness cost

Here we try to assess how the introduction of uncertainty impacts the objective function, or in other words what is the robustness cost.

To illustrate the trade-off between optimality (a low objective function value) and robustness (when the uncertainty budget is high), we draw the evolution of the objective function with the

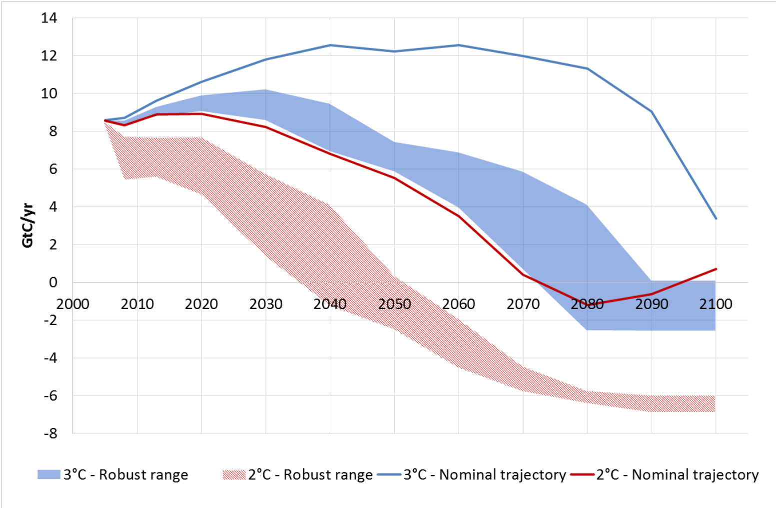


Figure 4.5: CO_2 emissions profiles

level of "insurance" (figure 4.6).
To do so, we realized Monte-Carlo simulations using the emission trajectories obtained for each value of Γ with a temperature constraint. The climate model parameters considered are uniformly distributed on the previously defined uncertainty sets. We then are able to derive the VaR and the CVaR for the temperature deviation in 2100 for both constraints. On the abscissa, we report the temperature deviation against which we "insure" ourselves using the optimal robust pathway: $x(T_{constraint}, 2100, \Gamma) = CVaR(T_{constraint}, 2100, \Gamma = 0) - CVaR(T_{constraint}, 2100, \Gamma)$ (see appendix D for plots of the distributions obtained). The ordinate represents the objective function obtained for different value of the protection level normalized by the deterministic case objective function.
Figure 4.6 depicts how the world energy system and its emissions adapt to increasing protection levels with respect to a reference temperature target. It reads as the cost increase to support in order to "buy" a certain amount of protection level given the uncertain response of the climate system: insuring against the risk that the 5%-CVaR of the average temperature increase will not be higher than xx (or reducing it by xx compared to the nominal case).

This function aggregates two elements, namely (i) the evolution of the total energy system cost with an increasing uncertainty budget and (ii) the CVaR-computed protection level associated to the change in global GHG emissions trajectory. Both are by construction concave functions of the uncertainty budget Γ. Indeed, the robust hedging strategies are driven by a worst-case logic, which implies that the incremental cost of increasing the uncertainty budget is necessarily diminishing. The same principle applies to GHG emissions. Interestingly, the process of composing these two functions to make the additional cost a function of the temperature protection yields a convex-shaped function. This implies that although both the temperature-expressed protection level and the incremental cost are concave shaped, the incremental cost still grows faster than the temperature hedge acquired.
Overall, this plot is comparable to a "standard" temperature-based marginal abatement cost curve, except that it embeds a consistent risk perspective which combines robust optimization and a simple CVaR metrics for the output GHG emissions pathways. Comparing the two series

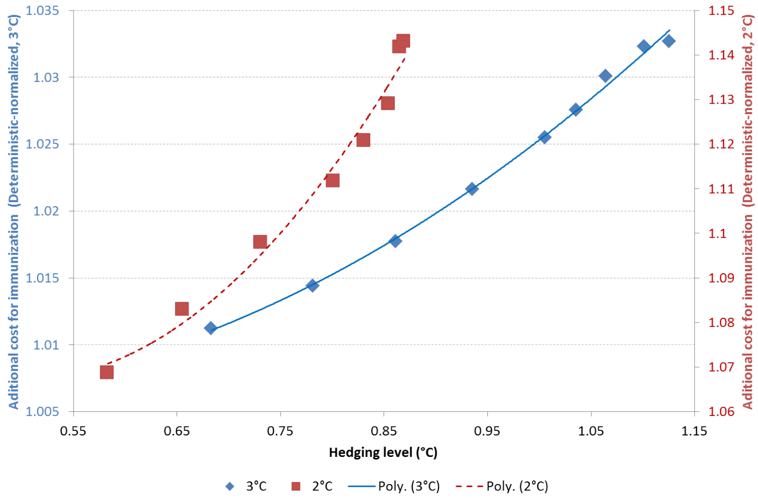


Figure 4.6: Costs of insurance

for different climate constraints, it appears naturally that costs of protection are higher for the 2°C series, and also more convex, yielding higher marginal costs.

4.4.3 Robust energy transition pathways

Increasing the required protection level for a given nominal temperature target implies an adaptation of the energy system towards reducing GHG emissions. Some salient elements of these robust energy transition pathways are described in this section.

Robust decarbonization challenges – a mesoscopic view

Figure 4.7 plots the world primary energy[5] intensity of GDP, in 2050 and 2100, for the 3°C and 2°C targets (2050: plain lines, 2100: dashed lines; 3°C: blue dot markers, 2°C: red square markers) as a function of the protection level and 2008 normalized [6]. With the same convention, figure 4.8 plots the evolution of the carbon intensity of primary energy with the protection level [7].

The evolution of the primary energy intensity of GDP and carbon intensity of primary energy show very different strategies for the 3 and 2°C constraints. Hedging against climate uncertainty at the 3°C level shows a balanced used of energy efficiency and decarbonization of primary energy in 2050; the two indicators show comparable abatement levels (more or less 50%) compared to the 2008 reference. In 2100, the 3°C scenario hedges with a stronger reduction of carbon intensity, at the expense of primary energy intensity: carbon intensity drops 10% more (-50 to -60% with hedging). This is especially true for higher protection levels for which CCS massively penetrates the decarbonization mix (see below). This yields negative carbon intensities, indicating

[5]Primary energy consumptions are computed as the sum of coal, crude oil, natural gas, enriched uranium, biomass, solar and wind energy consumed in the whole energy system.

[6] $PEI_{ratio} = \dfrac{Primary\_Energy(Yr)}{GDP(Yr)} * \dfrac{GDP(2008)}{Primary\_Energy(2008)}$

[7] $CI_{ratio} \dfrac{Primary\_Energy(2008)}{CO_2(2008)} * \dfrac{CO_2(\bar{Y}r)}{Primary\_Energy(Yr)}$

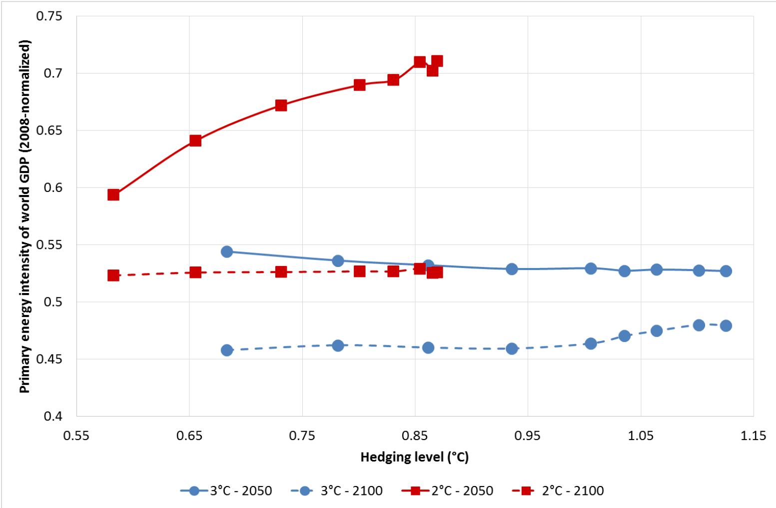


Figure 4.7: Primary energy intensity of GDP against protection level

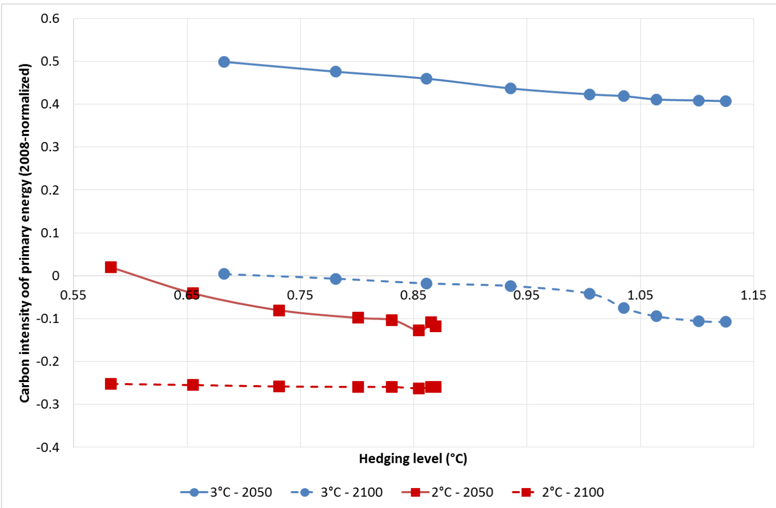


Figure 4.8: Carbon

negative net emissions. CCS-ready technologies are less efficient than their non-CCS equivalents, therefore the primary energy requirements increase (moderately) with hedging.
At the 2°C level, the tradeoff between energy intensity and carbon intensity is anticipated as early as 2050. The fall of primary energy intensity of GDP is lower (from -40% to -30% compared to 2008) while the carbon intensity of GDP is reduced by an additional 10% with the protection level, going to negative values and hence negative net emissions. By 2100, protection strategies have reached a status-quo situation with the amount of climatic uncertainty. Both the primary energy intensity and the carbon intensity have become insensitive to the protection level. The maximum abatement potential is reached (model limit).
Overall, between the two climate scenarios, comparable strategies (tradeoff between energy intensity and carbon intensity: necessity to spend more energy to store carbon) with a large difference

in timing. This result is consistent with the observation of the temperature and CO_2 emissions paths, which show that protection at the 3°C level is an *endpoint* issue (mitigation occurs in the second half of the century), while protection at the 2°C level is a *midpoint* question (mitigation is extremely strong by 2050, but final states – 2100 – show less variability). This raises the question of the decarbonization speed of the economy to reach e.g. COP21 compliant objectives.

Robust energy portfolios

While the previous results show an aggregate picture of reduction and mitigation strategies in an uncertain climate context, further desagregating the primary energy consumption level (figure 4.9) offers additional insights. Both the 3°C and the 2°C scenario groups show similarities. Naturally, increasing protection and/or imposing a more stringent climate objective tend to reduce the use of the most carbonized energy sources (coal, gas) for renewable energy sources (solar, wind, biomass) (see table 4.10).

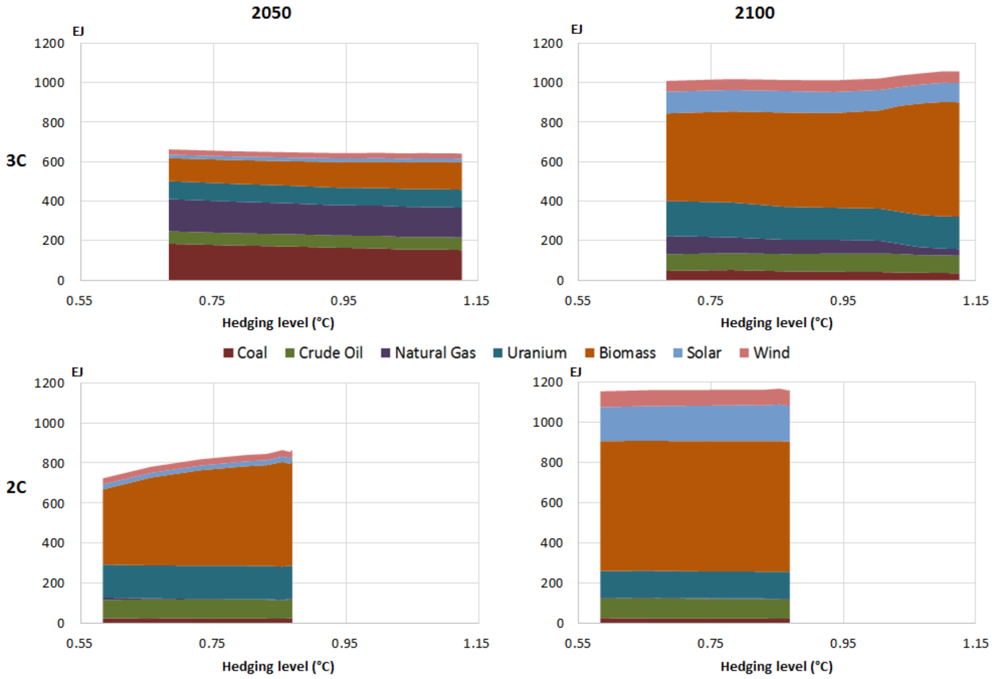


Figure 4.9: Primary energy consumption by type against protection level

As primary energy sources with high carbon contents, gas and coal uses are highly elastic to the protection level; gas use decreases between 13 and 20% in 2050 and between 32 and 75% in 2100 in the 3°C scenarios (always compared to the deterministic case in the same target scenario group). At the same time, coal use is diminished by 22 to 36% in 2050 and 53 to 65% in 2100. The scenarios for the 2°C target show a comparable albeit amplified tendency: both energy source uses diminish by 75 to 90% in 2050 and 2100. At the same time, the use of renewable energy raises in any case, up to 200% in 2050 for the 2°C scenario. While for the 3°C scenarios, renewable use is tripled between 2050 and 2100.
In the renewable group, biomass plays a particular role as its use coupled with Carbon Capture

EJ/yr		Natural Gas	Crude Oil	Coal	Uranium	Biomass	Solar	Wind	Non Renewable	Renewable	Total
3°C target											
2050	Deterministic	189	62	237	54	97	16	26	542	139	681
2050	Lowest Protection level (0.68°C)	163	63	185	91	116	17	27	502	160	663
2050	Highest Protection level (1.13°C)	151	63	153	91	139	18	26	458	184	642
2100	Deterministic	135	55	100	191	304	97	52	482	453	935
2100	Lowest Protection level (0.68°C)	93	84	47	177	444	110	55	401	608	1009
2100	Highest Protection level (1.13°C)	34	89	36	164	580	98	58	322	735	1057
2°C target											
2050	Deterministic	49	140	90	176	154	20	26	455	200	655
2050	Lowest Protection level (0.58°C)	12	91	24	164	376	25	30	292	431	723
2050	Highest Protection level (0.88°C)	3	95	22	165	521	27	32	286	580	866
2100	Deterministic	34	131	58	133	409	105	60	356	574	930
2100	Lowest Protection level (0.58°C)	3	97	25	134	647	168	79	259	894	1153
2100	Highest Protection level (0.88°C)	3	96	21	134	649	179	77	254	905	1159

Figure 4.10: Primary energy consumption by type

and Storage is a critical pathway for decarbonization (because it generates negative emissions).

Nuclear is an option for decarbonizing the economy, and more precisely an electro-intensive economy which relies more on carbon-neutral sources. The use of uranium gradually increases by 2100 in the 3°C scenarios, and much faster in the 2°C scenarios (up to 2050) before stabilizing. Lastly, oil plays a particular role: while the use of other fossil energy decreases, the amount of crude oil consumed in the primary energy mix is rather stable across scenarios and protection levels. This tendency to maintain the use of oil products is to be related to the difficulty to reduce transport emissions (high abatement costs) combined with the large availability of low-carbon alternatives in other sectors(nuclear, CCS).

A sectoral view – The "backstop" negative emissions pathways against low-elastic transport

Figure 4.11 helps assessing the role of the various sectors in the decarbonization process.
Whichever the scenario, transport remains the main CO_2 emitter worldwide. In the 3°C case, all emissions peak around 2040 before falling – at the exception of the transport sector – alternative technologies penetrate the mix. Electricity and industry are the main contributors to abatement, essentially between 2050 and 2100. In 2100, transport emissions represent between 60 and 90% of the end-use emissions; they are rather stable in absolute terms, so that technology improvements (efficiency, low-carbon fuels) compensate for the demand growth. While CCS is deployed by 2050 as a hedge for about 10 Gt/yr, transport emissions in the 2nd part of the horizon are compensated by credits from CCS captured from biomass (negative emissions).
The 2°C picture differs from this by three main elements. First, the need to reduce emissions

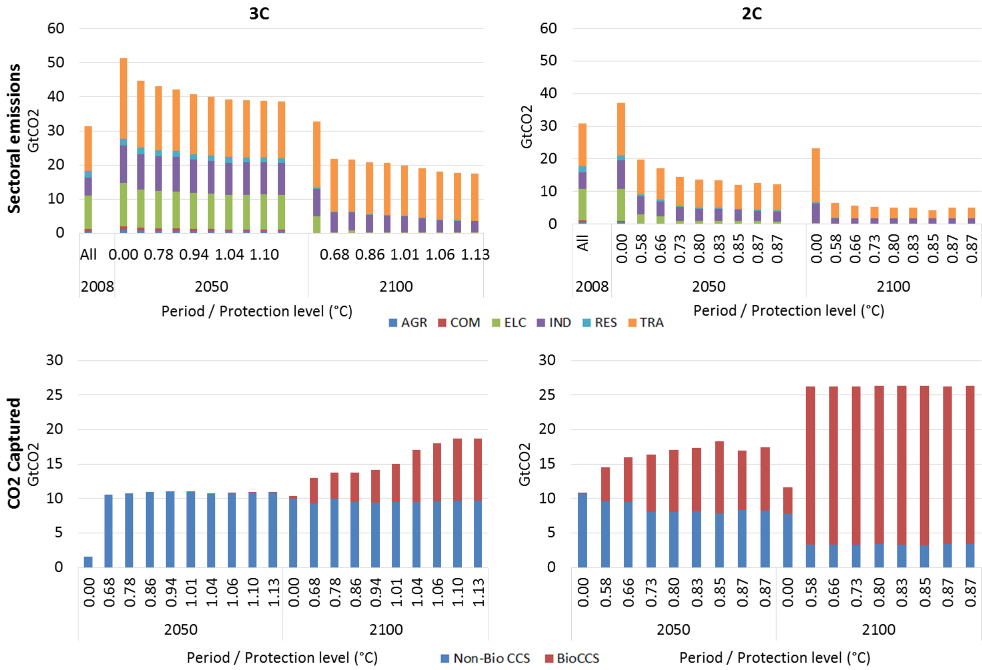


Figure 4.11: Sectoral emissions and Stored Carbon (from biomass and fossil fuels)

further to remain compliant with a 2°C target with uncertainty forces to reduce emissions from the power and industry sectors much faster (by 2050). Second, even transport emissions go down sharply to get to a 1.5°C average elevation level. At this timescale, only transport and industry have some residual emissions. Third, the additional use of CCS from biomass fueled power plants is not only incremental but also comes as a substitute for fossil CCS pathways. The importance of bioCCS in this picture reveals the importance of estimating biomass potentials and assessing relevant sensitivity analysis on the subject (insert ref to Claire's paper on BioCCS here).

The clear-cut arbitrage strategy between biomass-CCS and transport emissions can be explained at the technology level. The analysis of the energy mix for transport shows a strong reliance on fossil-based fuels, which represent a large part of the mix except in the longer term for the 2°C target. In that case, transport fuels have become almost carbon free with a strong reliance on hydrogen. Since transport is a sector with high abatement costs (cite there), it is only when uncertainty is high that the oil trajectory is impacted. The vehicle fleet is progressively electrified, diesel and gasoline losing market share with time and uncertainty. Electric vehicles appear as a relevant way to mitigate the risk induced by climate uncertainty.
Besides, in energy terms, the moderate penetration of electricity as a transportation fuel minimizes a wider reality: while electricity can represent up to 30% of the energy used in transport, the relative efficiency of electric vehicles compared to conventional ICEs (2 to 2.5, cite) implies that more than 50% of the total world mobility is actually electromobility, in 2050, near a 2°C temperature path. Yet, the commercial transportation fleet sticks with diesel trucks, leading to a stable diesel consumption.
In the power sector, the introduction of uncertainty leads to an early use of CCS, as early as 2030 in most cases (see Figures 4.11 and 4.12). The nuclear and the CCS trajectories under

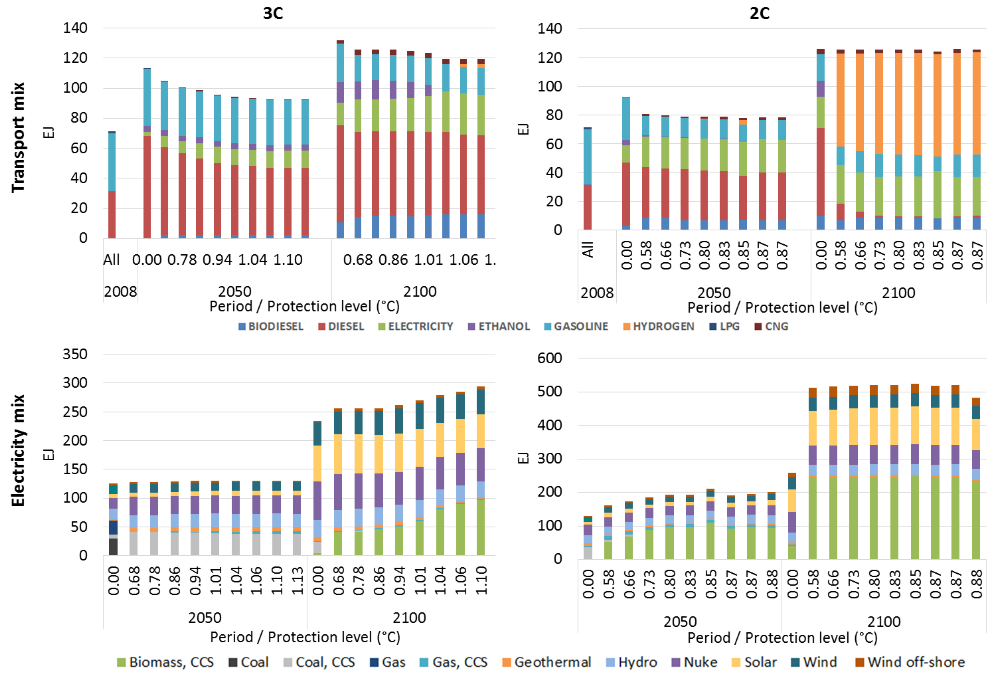


Figure 4.12: Transport and electricity production energy mix

uncertainty have large consequences in terms of policy decision. For example, given the current R&D going on on CCS (various projects shut down this last decade), this result suggests that we should maybe rethink and modify the R&D budget allocation. The importance of nuclear in the energy mix is also at odd with some country policies like Germany which decided some years ago to close all the nuclear plants in a near future (unlike Japan, where nuclear plants are planned to restart in the next 3 years). This negative emission possibility is something quite abstract and subjected to lots of uncertainty (see the thesis appendix for more details) as no commercial scale of biomass fueled power plant with CCS has ever been built.

4.5 Conclusion

Climate modeling is hampered by a considerable amount of uncertainty because of the lack of knowledge of the climate system. As it impacts significantly climate policy making, the need for tools to evaluate robust transition pathways is more and more urgent. In this paper, we present a robust approach to handling climate uncertainty in Integrated Assessment Models.
We find that the most sensitive parameters of the climate module is the climate sensitivity. This is consistent with the existing literature on the subject. Yet, it is important to remember that climate sensitivity is the most studied parameters and that its value estimations are numerous. Hence the determination of the climate sensitivity uncertainty range is quite straightforward. Another important point is that this range relies on a large information set unlike the other parameters, for which data is scarce. It is indeed quite complicated to find information on the carbon cycle parameters (few studies in the IAMs climate module literature) and yet the global climate system behavior is very sensitive to them. Also, the parameters impact diversely the

timing of the adaptation: the radiative forcing sensitivity multiplies directly the CO_2 concentration, hence even a small variation of this parameter leads to a strong impact on the CO_2 abatement timing. We then believe that a stronger focus should be put on the other climate model parameters.
To ensure that we comply with the 3°C constraint, the temperature trajectories we should aim at with the nominal parameters should not exceed 2.4°C, leading to zero net carbon emissions at the end of the century. With the 2°C constraint, we should aim at 1.6°C with negative carbon emissions as soon as 2050. If the insurance cost is quite reasonable for the higher constraint (from 1.5 to 4% of the system total discounted cost), it is less the case of the 2°C objective. In this latter situation, the system total discounted cost increases by 7% when uncertainty is low to up to 14% when it is high. Indeed, in order to comply with a stringent target, sectors with high abatement costs have to participate in the global reduction effort. Transport is little impacted by the 3°C target (but as uncertainty grows, the vehicle fleet is slightly modified) when the introduction of uncertainty leads to major fuel consumption changes for the 2°C constraint. The abatement strategies are quite different between the two temperature targets. For the 3 degree one, both the carbon intensity and the primary energy intensity of the economy decrease with uncertainty while for the 2 degree target, the energy intensity increases and the carbon intensity decreases. This stringent goal is reached by investing massively in carbon removal technologies such as bioenergy with carbon capture and storage (BECCS) which have yields much lower than traditional fossil fueled technologies. Another interesting fact of the 2°C hedging trajectories is the drastic increase of the nuclear electricity production. The massive use of nuclear or carbon removal technology is highly uncertain as BECCS is a very expensive technology that is not competitive in the absence of a high CO_2 price while the development of the nuclear industry could be hampered by social acceptance issues. The 1.5°C objective mentioned during the COP21 is obviously very ambitious and reaching it would necessitate strong political and societal ambitions and actions (much stronger than the ones decided during COP21).
By taking a robust approach to study ways of complying with ambitious climate targets, we were able to bring to light hedging technological trajectories without excessive computational issues. The method presented being quite generic, it could be interesting to perform similar exercises with other IAMs. It would help strengthen the knowledge on technological transition pathways with uncertainty and would allow a better understanding and awareness of the costs of the risks linked to the climate system partial knowledge.

Bibliography

Andrey, C., Babonneau, F., Haurie, A., Labriet, M., 2015. Modélisation stochastique et robuste de l'atténuation et de l'adaptation dans un système énergétique régional. Application à la région Midi-Pyrénées. Natures Sciences Sociétés 23 (2), 133–149.

Anthoff, D., Tol, R. S. J., 2013. The uncertainty about the social cost of carbon: A decomposition analysis using FUND. Climatic Change 117 (3), 515–530.

Babonneau, F., Kanudia, A., Labriet, M., Loulou, R., Vial, J.-P., Jul. 2011. Energy Security: A Robust Optimization Approach to Design a Robust European Energy Supply via TIAM-WORLD. Environmental Modeling & Assessment 17 (1-2), 19–37.

Bahn, O., Haurie, A., Malhamé, R., Jun. 2008. A stochastic control model for optimal timing of climate policies. Automatica 44 (6), 1545–1558.

Ben-tal, A., El Ghaoui, L., Nemirovski, A., 2009. Robust Optimization. Princeton Series in Applied Mathematics. Princeton University Press.

Ben-tal, A., Hertog, D. D., Vial, J.-P., 2012. Deriving robust counterparts of nonlinear uncertain inequalities.

Ben-tal, A., Nemirovski, A., 2000. Robust solutions of Linear Programming problems contaminated with uncertain data. Mathematical Programming 88 (3), 411–424.

Ben-tal, A., Nemirovski, A., 2002. Robust Optimization — Methodology and Applications. Mathematical Programming 92 (3), 453–480.

Bertsimas, D., Brown, D. B., Caramanis, C., 2010. Theory and applications of Robust Optimization. SIAM Review 53 (3), 464–501.

Bertsimas, D., Sim, M., Feb. 2004. The Price of Robustness. Operations Research 52 (1), 35–53.

Block, K., Mauritsen, T., 2013. Forcing and feedback in the mpi-esm-lr coupled model under abruptly quadrupled co2. Journal of Advances in Modeling Earth Systems 5 (4), 676–691.

Butler, M. P., Reed, P. M., Fisher-Vanden, K., Keller, K., Wagener, T., 2014. Identifying parametric controls and dependencies in integrated assessment models using global sensitivity analysis. Environmental Modelling & Software 59, 10–29.

Cao, L., Bala, G., Caldeira, K., Nemani, R., Ban-Weiss, G., 2010. Importance of carbon dioxide physiological forcing to future climate change. Proceedings of the National Academy of Sciences of the United States of America 107 (21), 9513–9518.

Criqui, P., Mima, S., Viguier, L., 1999. Marginal abatement costs of {CO2} emission reductions, geographical flexibility and concrete ceilings: an assessment using the {POLES} model. Energy Policy 27 (10), 585 – 601.

Ekholm, T., 2014. Hedging the climate sensitivity risks of a temperature target. Climatic Change 127 (2), 153–167.

El Ghaoui, L., Oustry, F., Lebret, H., 1998. Robust solutions to uncertain semidefinite programs. Society for Industrial and Applied Mathematics 9 (1), 33–52.

Hof, A. F., Hope, C. W., Lowe, J., Mastrandrea, M. D., Meinshausen, M., van Vuuren, D. P., 2012. The benefits of climate change mitigation in integrated assessment models: The role of the carbon cycle and climate component. Climatic Change 113 (3-4), 897–917.

Hope, C. W., Anderson, J., Wenman, P., 1993. Policy analysis of the greenhouse effect: An application of the PAGE model. Energy Policy 15, 328–338.

Hu, Z., Cao, J., Hong, L. J., 2012. Robust Simulation of Global Warming Policies Using the DICE Model. Management Science 58 (December 2012).

IPCC, 2014. Summary for policymakers. In: Field, C., Barros, V., Dokken, D., Mach, K., Mastrandrea, M., Bilir, T., Chatterjee, M., Ebi, K., Estrada, Y., Genova, R., Girma, B., Kissel, E., Levy, A., MacCracken, S., Mastrandrea, P., White, L. (Eds.), Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, pp. 1–32.

Joos, F., Roth, R., Fuglestvedt, J. S., Peters, G. P., Enting, I. G., Von Bloh, W., Brovkin, V., Burke, E. J., Eby, M., Edwards, N. R., Friedrich, T., Frölicher, T. L., Halloran, P. R., Holden, P. B., Jones, C., Kleinen, T., Mackenzie, F. T., Matsumoto, K., Meinshausen, M., Plattner, G. K., Reisinger, a., Segschneider, J., Shaffer, G., Steinacher, M., Strassmann, K., Tanaka, K., Timmermann, a., Weaver, a. J., 2013. Carbon dioxide and climate impulse response functions for the computation of greenhouse gas metrics: A multi-model analysis. Atmospheric Chemistry and Physics 13 (5), 2793–2825.

Knutti, R., Hegerl, G. C., 2008. The equilibrium sensitivity of the Earth's temperature to radiation changes. Nature Geoscience 1 (11), 735–743.

Labriet, M., Kanudia, A., Loulou, R., Dec. 2012. Climate mitigation under an uncertain technology future: A TIAM-World analysis. Energy Economics 34, S366–S377.

Labriet, M., Loulou, R., Kanudia, A., Nov. 2010. Uncertainty and Environmental Decision Making. Vol. 138 of International Series in Operations Research & Management Science. Springer US, Boston, MA.

Labriet, M., Nicolas, C., Tchung-Ming, S., Kanudia, A., Loulou, R., 2015. Energy decisions in an uncertain climate and technology outlook : how stochastic and robust analyses can assist policy-makers. In: Giannakidis, G., Labriet, M., Gallachóir, B. O., Tosato, G. (Eds.), Informing energy and climate policies using energy systems models, springer s Edition. Springer, Ch. 03.

Loulou, R., 2008. ETSAP-TIAM: the TIMES integrated assessment model. part II: mathematical formulation. Computational Management Science, 5 (1), 41–66.

Loulou, R., Labriet, M., 2008. ETSAP-TIAM: the TIMES integrated assessment model Part I: Model structure. ComputationalManagement Science, Special issue "Managing Energy and the Environment 5 (1).

Loulou, R., LEHTILA, A., Labriet, M., 2010. TIMES Climate Module (Nov. 2010). TIMES Version 2.0 User Note (November).

Manne, A., Mendelsohn, R., Richels, R., 1995. MERGE A model for evaluating regional and global effects of GHG reduction policies. Energy Policy 23 (I), 17–34.

Meinshausen, M., Raper, S. C. B., Wigley, T. M. L., 2011. Emulating coupled atmosphere-ocean and carbon cycle models with a simpler model, MAGICC6 - Part 1: Model description and calibration. Atmospheric Chemistry and Physics 11, 1417–1456.

Nordhaus, W., Sztorc, P., 2013. DICE 2013R : Introduction and User ' s Manual with (April), 1–102.

Nordhaus, W. D., 1994. Managing the Global Commons: The Economics of Climate Change. The MIT Press, Cambridge.

Nordhaus, W. D., 2008. A Question of Balance: Weighing the Options on Global Warming Policies. Vol. 87.

Nordhaus, W. D., 2014. Estimates of the social cost of carbon: Concepts and results from the DICE-2013R model and alternative approaches. Journal of the Association of Environmental and Resource Economists 1 (1/2), 273–312.

Nordhaus, W. D., Boyer, J., 1999. Warming the World. The MIT Press, Cambridge.

Pindyck, R. S., 2013. Climate Change Policy : What Do the Models Tell Us ? Journal of Economic Literature 51, 860–872.

Schmidt, H., Alterskjæ r, K., Alterskjæ r, K., Bou Karam, D., Boucher, O., Jones, a., Kristjánsson, J. E., Niemeier, U., Schulz, M., Aaheim, a., Benduhn, F., Lawrence, M., Timmreck, C., 2012. Solar irradiance reduction to counteract radiative forcing from a quadrupling of CO 2: Climate responses simulated by four earth system models. Earth System Dynamics 3 (1), 63–78.

Smith, M. J., Vanderwel, M. C., Lyutsarev, V., Emmott, S., Purves, D. W., 2012. The climate dependence of the terrestrial carbon cycle; including parameter and structural uncertainties. Biogeosciences Discussions 9 (10), 13439–13496.

Soyster, L. A., 1973. Convex Programming with Set-Inclusive Constraints and Applications to Inexact Linear Programming. Operations Research 21 (5), 1154–1157.

Stern, N., 2007. The Economics of Climate Change: The Stern Review. Cambridge University Press.

Stern, N., 2013. The structure of economic modeling of the potential impacts of climate change: Grafting gross underestimation of risk onto already narrow science models. Journal of Economic Literature 51 (3), 838–59.

Stocker, T., Qin, D., Plattner, G.-K., Tignor, M., Allen, S., Boschung, J., Nauels, A., Xia, Y., Bex, V., Midgley, P., 2013. IPCC, 2013: Summary for Policymakers. Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change.

Syri, S., Lehtila, A., Ekholm, T., Savolainen, I., Holttinen, H., Peltola, E., Feb. 2008. Global energy and emissions scenarios for effective climate change mitigation—Deterministic and stochastic scenarios with the TIAM model. International Journal of Greenhouse Gas Control 2 (2), 274–285.

United Nations, 2015. Paris agreement to the united nations framework convention on climate change.

van Asselt, M. B. A., Rotmans, J., 2002. Uncertainty in integrated assessment modelling: From positivism to pluralism. Climatic Change 54 (1/2), 75–105.

van Vuuren, D. P., Lowe, J., Stehfest, E., Gohar, L., Hof, A. F., Hope, C., Warren, R., Meinshausen, M., Plattner, G.-K., Dec. 2009. How well do integrated assessment models simulate climate change? Climatic Change 104 (2), 255–285.

Vanderzwaan, B., Gerlagh, R., nov 2006. Climate sensitivity uncertainty and the necessity to transform global energy supply. Energy 31 (14), 2571–2587.

Zhang, M., Huang, Y., 2014. Radiative forcing of quadrupling co2. Journal of Climate 27, 2496–2508.

Appendix

A TIAM World Climate Module

The terrestrial carbon cycle of this climate module is depicted in figure 4.3. Formally, the one-year-lagged dynamics of the three detailed greenhouse gases are the following:

$$\begin{aligned}
\begin{bmatrix} M^{CO_2,a} \\ M^{CO_2,u} \\ M^{CO_2,l} \end{bmatrix}_t &= \Phi^{CO_2} \begin{bmatrix} M^{CO_2,a} \\ M^{CO_2,u} \\ M^{CO_2,l} \end{bmatrix}_{t-1} + \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix} E_t^{CO_2}, \\
\begin{bmatrix} M^{CH_4,a} \\ M^{CH_4,u} \end{bmatrix}_t &= \Phi^{CH_4} \begin{bmatrix} M^{CH_4,a} \\ M^{CH_4,u} \end{bmatrix}_{t-1} + \begin{bmatrix} 1 \\ 0 \end{bmatrix} E_t^{CH_4}, \\
\begin{bmatrix} M^{N_2O,a} \\ M^{N_2O,u} \end{bmatrix}_t &= \Phi^{N_2O} \begin{bmatrix} M^{N_2O,a} \\ M^{N_2O,u} \end{bmatrix}_{t-1} + \begin{bmatrix} 1 \\ 0 \end{bmatrix} E_t^{N_2O}, \\
\Phi^{CO_2} &= \begin{bmatrix} 1-\varphi^{a-u} & \varphi^{u-a} & 0 \\ \varphi^{a-u} & 1-\varphi^{u-a}-\varphi^{u-l} & \varphi^{l-u} \\ 0 & \varphi^{u-l} & 1-\varphi^{l-u} \end{bmatrix}, \\
\Phi^{CH_4} &= \begin{bmatrix} \varphi^{CH_4} & 0 \\ 0 & 1 \end{bmatrix}, \Phi^{N_2O} = \begin{bmatrix} \varphi^{N_2O} & 0 \\ 0 & 1 \end{bmatrix},
\end{aligned}$$

where $M_t^{g,r}$ is the mass of gas g in reservoir r in year t, E_t^g is the emission of gas g in year t (from the global energy model), φ^{r_o,r_i} is the transfer coefficient for CO_2 from reservoir r_o to reservoir r_i, φ^{CH_4} and φ^{N_2O} are the decay rates of methane and nitrous oxide in the atmosphere, $g \in G = \{CO_2, CH_4, N_2O\}$ and $r \in R = \{atmosphere, UpperLayer, LowerLayer\}$.
This set of equations defining the time profiles of atmospheric GHGs is then used to compute the radiative forcing. It is common () to consider that forcings are additive, so that:

$$\Delta F_t = \sum_{g \in G} \Delta F_t^g + Exf_t$$

, where ΔF_t^g is the forcing of gas g in period t and Exf_t corresponds to an exogenous assumption of forcing for all gases other than carbon dioxide, methane and nitrous oxide. The current knowledge on radiative forcing () suggests that none of these terms is linear in the atmospheric stock of gas; the linearization used here is proposed by ():

$$\Delta F_t^{CO_2} = \gamma A^{CO_2} + \gamma B^{CO_2} M_t^{CO_2,a},$$
$$\Delta F_t^{CH_4} = A^{CH_4} + B^{CH_4} M_t^{CH_4,a},$$
$$\Delta F_t^{N_2O} = A^{N_2O} + B^{N_2O} M_t^{N_2O,a}$$

, where γ is the radiative forcing sensitivity to atmospheric CO_2 doubling, and A's and B's are constant depending on pre-industrial concentration levels and linearization intervals.
At last, temperature elevation profiles are computed based on the following equations:

$$\begin{bmatrix} \Delta T^{up} \\ \Delta T^{lo} \end{bmatrix}_t = S \begin{bmatrix} \Delta T^{up} \\ \Delta T^{lo} \end{bmatrix}_{t-1} + \begin{bmatrix} \sigma_1 \\ 0 \end{bmatrix} \Delta F_t,$$
$$S = \begin{bmatrix} 1 - \sigma_1 \left(\frac{\gamma}{C_S} + \sigma_2 \right) & \sigma_1 \sigma_2 \\ \sigma_3 & 1 - \sigma_3 \end{bmatrix}.$$

C_S represents the climate sensitivity, i.e. the change in equilibrium atmospheric temperature due to a doubling of GHG concentration; σ_1 and σ_3 are the adjustment speeds for respectively atmospheric and oceanic temperature (lags, in $year^{-1}$); σ_2 is a heat loss coefficient from the atmosphere to the deep ocean.

B Estimation of lower/upper bounds for climate parameters

Overall, and in the course of this estimation exercise, we may classify the climate parameters at stake in this study into three groups. First, *one group contains the parameters for the carbon cycle*. The terrestrial carbon cycle itself is a rather large field of study in geophysics (see e.g. Smith et al. (2012), Joos et al. (2013) for a multi-model approach). One can also find sensitivity analysis on the carbon cycle in IAM-based research (Butler et al. (2014), Hof et al. (2012)), or are least clues on how uncertain these parameters are (Nordhaus (2008)). One way of assessing the behavior of carbon cycle models is to perform the so-called "doubling experiment", where the evolution of an atmospheric CO_2 doubling-concentration pulse in year 0 is followed across the various carbon sinks for the next 100-400 years. Existing multi-models experiments (Joos et al. (2013), van Vuuren et al. (2009)) point out large response spectra; van Vuuren et al. (2009) additionally shows that simple carbon models (few boxes, simple linear recursive dynamics) such as DICE end up in the low range of possible outcomes: they have, compared to the rest, relatively optimistic carbon cycles. Such an experiment seems to be a good starting point to calibrate a carbon cycle. However, the uncertainty it traduces covers both parametric and structural uncertainty. For example, van Vuuren et al. (2009) argue that the PAGE model behaves very differently from the rest of the test population because it includes feedbacks on the carbon cycle. This limitation – carbon cycle models have different structures, hence different parameters – makes it difficult to adopt such a calibration procedure. Therefore, we adopt a calibration procedure similar to that Nordhaus and Sztorc (2013), but for the four IPCC-RCP emissions scenarios ran under the multi-ensemble simulation mode of MAGICC6 (Meinshausen et al. (2011)). To this purpose:

- the nominal values of the parameters in the climate module in TIAM-World was left as described in Loulou et al. (2010);

- the upper bound of the inter-boxes transfer coefficients were estimated to get close to the 83rd percentile of the MAGICC6 inter-model simulations for the four RCP scenarios. This is done by changing the parameters by identical relative amounts, and computing a simple distance measure (the sum of squares of annual relative distances between the TIAM-climate simulation and the MAGICC6-RCP benchmark).

The result of this experiment is shown in figure 13.

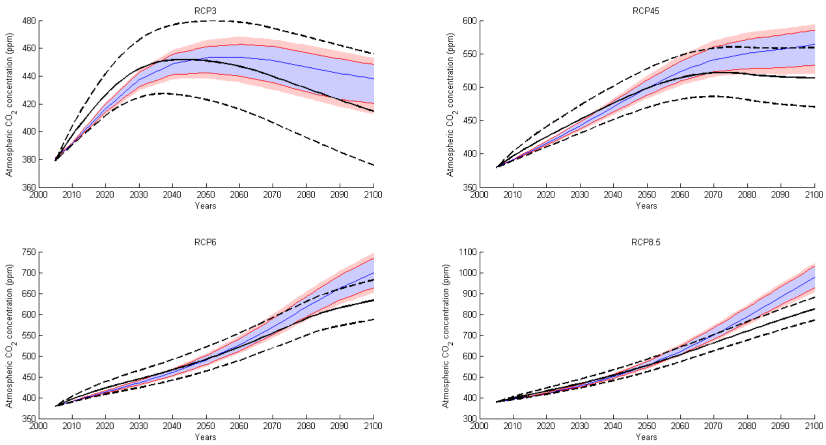


Figure 13: TIAM-World climate module: uncertainty in the carbon cycle agains MAGICC6 ranges, 4 RCP scenarios

These variations allow to capture only a minor part of the carbon cycle model variations described by Joos et al. (2013) or van Vuuren et al. (2009). Hof et al. (2012) show that the variations in climate change benefits from a set of IAMs due to the carbon cycle are lower than the MAGICC6 ranges, which seems to indeed indicate that simple carbon cycles do not capture all the "volatility" of outcomes.

A *second set of parameters includes the forcing and climate sensitivities*, which are likely to be the most well-documented parameters in the climate literature. They traduce the global equilibrium surface forcing and warming after a doubling of atmospheric CO_2 concentration; any climate models includes these parameters. The importance of the equilibrium radiative forcing is widely acknowledged (Cao et al. (2010)); multi-models comparisons and simulations are also frequent (Schmidt et al. (2012)). If issues such as climate feedbacks arise in the estimation of forcing (Block and Mauritsen (2013)), available comparisons indicate plausible range for the forcing parameters (using doubling or quadrupling experiments), with the the last IPCC report (AR5-WG1, Stocker et al. (2013)) providing a central value of 3.7 with a +/- 0.8 99% confidence interval. This estimation is consistent with Zhang and Huang (2014), and is retained for this study. As for the climate sensitivity, the initial value of the TIAM-World calibration corresponds to the Knutti and Hegerl (2008) synthesize plausible sensitivity ranges for the climate sensitivity for different lines of evidence, and demonstrate how critical it is if the policy objective is to prevent damages caused by certain levels of warming. The IPCC most likely value and upper bound are 3 °C and 4.5 °C respectively, which is consistent with other papers such as Syri et al. (2008). Butler et al. (2014) make a different choice, and end up with a range (upper bound of 8 °C) closer to what Knutti and Hegerl (2008) refer to as "expert elicitation". Combining different lines of evidence, these authors obtain a range close to the one of IPCC, which we will

retain as a basis. Compared to existing literature on IAM-SCM sensitivity analysis in Butler et al. (2014), these ranges are high for forcing and low for the climate sensitivity.
Finally, the rest of the parameters, traducing the *temperature dynamics, are part of a third group constituted of apparently less studied parameters.* There seems to be considerably less available work on these. By default, we proceed as Butler et al. (2014), and apply a 10% variation to the annual heat transfer coefficients. The range of temperature responses of TIAM-World are compared against MAGICC6 for the 4 RCPs scenarios, accounting for the uncertainty of all parameters. The results are presented in 14

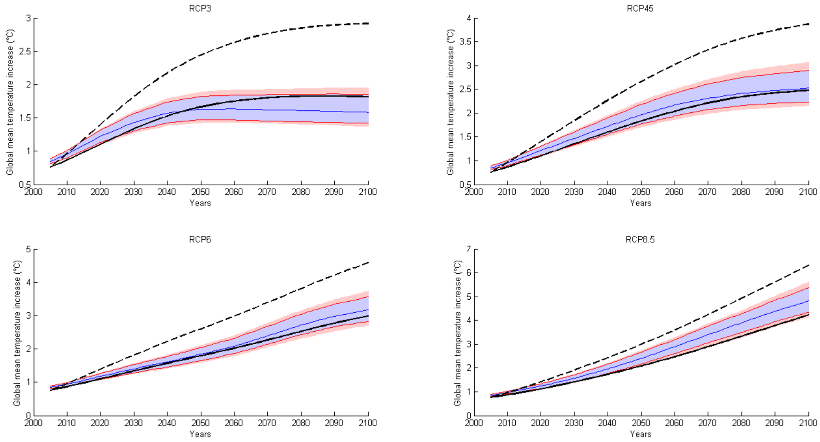


Figure 14: TIAM-World climate module: uncertainty in the global Mean Temperature against MAGICC6 ranges, 4 RCP scenarios

The final nominal values and ranges for the climate parameters are presented in 3 along with the values kept in Butler et al. (2014) for comparison purposes.

Parameter	Description	Nominal value	Lower/ Upper bound	Nominal value (Butler et al. (2014))	Lower/ Upper bound (Butler et al. (2014))
ϕ_{a-u}	Atmosphere to upper layer carbon transfer coefficient (annual)	0.046	0.044	0.189	0.223
ϕ_{u-a}	Upper layer to atmosphere carbon transfer coefficient (annual)	0.0453	0.0473	0.0972	derived
ϕ_{u-l}	Upper to lower layer carbon transfer coefficient (annual)	0.0146	0.01394	0.05	0.025
ϕ_{l-u}	Lower to upper layer carbon transfer coefficient (annual)	0.00053	0.00055	0.00312	derived
γ	Radiative forcing from doubling of CO_2	3.7	4.5	3.8	3.9
C_S	Climate sensitivity from doubling of CO_2	2.9	4.5	3	8
σ_1	Adjustment speed of atmospheric temperature	0.024	0.0264	0.22	0.24
σ_2	Heat loss from atmosphere to deep ocean	0.44	0.396	0.3	0.27
σ_3	Heat gain by deep ocean	0.002	0.0018	0.05	0.045

Table 3: Nominal values for climate parameters and comparison with Butler et al. (2014)

C Appendix : Implementation details for the worst-case oracle in TIAM-World model

For simplicity of exposure, we describe the procedure for solving problem (4.9) when the respective worst-case extreme value (between minimum and maximum) for each parameter can be identified a-priori (either analytically or using common sense). Following the information presented in Table 4.1, we can describe the uncertainty as follows:

$$
\begin{aligned}
\psi^{a-u} &:= \bar{\psi}^{a-u} - \hat{\psi}^{a-u} z_1 & \psi^{u-a} &:= \bar{\psi}^{u-a} + \hat{\psi}^{u-a} z_2 \\
\psi^{u-l} &:= \bar{\psi}^{u-l} - \hat{\psi}^{u-l} z_3 & \psi^{l-u} &:= \bar{\psi}^{l-u} + \hat{\psi}^{l-u} z_4 \\
\gamma &:= \bar{\gamma} + \hat{\gamma} z_5 & (1/C_s) &:= (1/\bar{C}_s) - (\hat{C}_s/(\bar{C}_s^2 + \bar{C}_s\hat{C}_s)) z_6 \\
\sigma_1 &:= \bar{\sigma}_1 + \hat{\sigma}_1 z_7 & \sigma_2 &:= \bar{\sigma}_2 + \hat{\sigma}_2 z_8 \\
\sigma_3 &:= \bar{\sigma}_3 + \hat{\sigma}_3 z_9 \,, & &
\end{aligned}
$$

where the "bar" annotated parameter refers to the nominal value and the "hat" annotated parameter refers to the magnitude of the perturbation needed to get to the chosen extreme value. We also modeled the perturbation on the term $1/C_s$ using an additive formulation, namely

$$
1/C_s := \left\{ \begin{array}{cl} 1/\bar{C}_s & \text{if } z_6 = 1 \\ 1/(\bar{C}_s + \hat{C}_s) & \text{otherwise} \end{array} \right. .
$$

Based on the definitions of A and F, one should notice that these two matrices are not linear functions of the uncertainty z_1, z_2, ..., z_9. This can be remedied by replacing the nonlinearities with additional binary variables. In particular, when studying the effect of z on each term of A, one might realize that the following expressions come into play:

$$
\left\{ \begin{array}{l}
\gamma\psi^{a-u} = \bar{\gamma}\bar{\psi}^{a-u} - \bar{\gamma}\hat{\psi}^{a-u} z_1 + \bar{\psi}^{a-u}\hat{\gamma} z_5 - \hat{\gamma}\hat{\psi}^{a-u} z_1 z_5 \\
\gamma\psi^{u-a} = \bar{\gamma}\bar{\psi}^{u-a} + \bar{\gamma}\hat{\psi}^{u-a} z_2 + \bar{\psi}^{u-a}\hat{\gamma} z_5 + \hat{\gamma}\hat{\psi}^{u-a} z_2 z_5 \\
\sigma_1\gamma\psi^{a-u} = \bar{\sigma}_1\bar{\gamma}\bar{\psi}^{a-u} - \bar{\sigma}_1\bar{\gamma}\hat{\psi}^{a-u} z_1 + \bar{\sigma}_1\hat{\gamma}\bar{\psi}^{a-u} z_5 + \hat{\sigma}_1\bar{\gamma}\bar{\psi}^{a-u} z_7 \\
\qquad\qquad - \bar{\sigma}_1\hat{\gamma}\hat{\psi}^{a-u} z_1 z_5 - \hat{\sigma}_1\bar{\gamma}\hat{\psi}^{a-u} z_1 z_7 + \hat{\sigma}_1\hat{\gamma}\bar{\psi}^{a-u} z_5 z_7 + \hat{\sigma}_1\hat{\gamma}\hat{\psi}^{a-u} z_1 z_5 z_7 \\
\sigma_1\gamma\psi^{u-a} = \bar{\sigma}_1\bar{\gamma}\bar{\psi}^{u-a} + \bar{\sigma}_1\bar{\gamma}\hat{\psi}^{u-a} z_2 + \bar{\sigma}_1\hat{\gamma}\bar{\psi}^{u-a} z_5 + \hat{\sigma}_1\bar{\gamma}\bar{\psi}^{u-a} z_7 \\
\qquad\qquad + \bar{\sigma}_1\hat{\gamma}\hat{\psi}^{u-a} z_2 z_5 + \hat{\sigma}_1\bar{\gamma}\hat{\psi}^{u-a} z_2 z_7 + \hat{\sigma}_1\hat{\gamma}\bar{\psi}^{u-a} z_5 z_7 + \hat{\sigma}_1\hat{\gamma}\hat{\psi}^{u-a} z_2 z_5 z_7 \\
\sigma_1\gamma/C_s = \bar{\sigma}_1\bar{\gamma}\bar{\theta} + \bar{\sigma}_1\hat{\gamma}\bar{\theta} z_5 - \bar{\sigma}_1\bar{\gamma}\hat{\theta} z_6 + \hat{\sigma}_1\bar{\gamma}\bar{\theta} z_7 \\
\qquad\qquad - \bar{\sigma}_1\hat{\gamma}\hat{\theta} z_5 z_6 + \hat{\sigma}_1\hat{\gamma}\bar{\theta} z_5 z_7 - \hat{\sigma}_1\bar{\gamma}\hat{\theta} z_6 z_7 - \hat{\sigma}_1\hat{\gamma}\hat{\theta} z_5 z_6 z_7 \\
\sigma_1\sigma_2 = \bar{\sigma}_1\bar{\sigma}_1 + \hat{\sigma}_1\bar{\sigma}_1 z_7 + \bar{\sigma}\hat{\sigma}_2 z_8 + \bar{\sigma}_1\bar{\sigma}_2 z_7 z_8 \,,
\end{array} \right.
$$

where $\bar{\theta} := 1/\bar{C}_s$ and $\hat{\theta} := \hat{C}_s/(\bar{C}_s^2 + \bar{C}_s\hat{C}_s)$. By making the replacement $v_{0jk} := z_j z_k$ and $v_{ijk} := z_i z_j z_k$, one would instead get the following set of linear representations:

$$
\left\{ \begin{array}{l}
\gamma\psi^{a-u} = \bar{\gamma}\bar{\psi}^{a-u} - \bar{\gamma}\hat{\psi}^{a-u} z_1 + \bar{\psi}^{a-u}\hat{\gamma} z_5 - \hat{\gamma}\hat{\psi}^{a-u} v_{015} \\
\gamma\psi^{u-a} = \bar{\gamma}\bar{\psi}^{u-a} + \bar{\gamma}\hat{\psi}^{u-a} z_2 + \bar{\psi}^{u-a}\hat{\gamma} z_5 + \hat{\gamma}\hat{\psi}^{u-a} v_{025} \\
\sigma_1\gamma\psi^{a-u} = \bar{\sigma}_1\bar{\gamma}\bar{\psi}^{a-u} - \bar{\sigma}_1\bar{\gamma}\hat{\psi}^{a-u} z_1 + \bar{\sigma}_1\hat{\gamma}\bar{\psi}^{a-u} z_5 + \hat{\sigma}_1\bar{\gamma}\bar{\psi}^{a-u} z_7 \\
\qquad\qquad - \bar{\sigma}_1\hat{\gamma}\hat{\psi}^{a-u} v_{015} - \hat{\sigma}_1\bar{\gamma}\hat{\psi}^{a-u} v_{017} + \hat{\sigma}_1\hat{\gamma}\bar{\psi}^{a-u} v_{057} + \hat{\sigma}_1\hat{\gamma}\hat{\psi}^{a-u} v_{157} \\
\sigma_1\gamma\psi^{u-a} = \bar{\sigma}_1\bar{\gamma}\bar{\psi}^{u-a} + \bar{\sigma}_1\bar{\gamma}\hat{\psi}^{u-a} z_2 + \bar{\sigma}_1\hat{\gamma}\bar{\psi}^{u-a} z_5 + \hat{\sigma}_1\bar{\gamma}\bar{\psi}^{u-a} z_7 \\
\qquad\qquad + \bar{\sigma}_1\hat{\gamma}\hat{\psi}^{u-a} v_{025} + \hat{\sigma}_1\bar{\gamma}\hat{\psi}^{u-a} v_{027} + \hat{\sigma}_1\hat{\gamma}\bar{\psi}^{u-a} v_{057} + \hat{\sigma}_1\hat{\gamma}\hat{\psi}^{u-a} v_{257} \\
\sigma_1\gamma/C_s = \bar{\sigma}_1\bar{\gamma}\bar{\theta} + \bar{\sigma}_1\hat{\gamma}\bar{\theta} z_5 - \bar{\sigma}_1\bar{\gamma}\hat{\theta} z_6 + \hat{\sigma}_1\bar{\gamma}\bar{\theta} z_7 \\
\qquad\qquad - \bar{\sigma}_1\hat{\gamma}\hat{\theta} v_{056} + \hat{\sigma}_1\hat{\gamma}\bar{\theta} v_{057} - \hat{\sigma}_1\bar{\gamma}\hat{\theta} v_{067} - \hat{\sigma}_1\hat{\gamma}\hat{\theta} v_{567} \\
\sigma_1\sigma_2 = \bar{\sigma}_1\bar{\sigma}_1 + \hat{\sigma}_1\bar{\sigma}_1 z_7 + \bar{\sigma}\hat{\sigma}_2 z_8 + \bar{\sigma}_1\bar{\sigma}_2 v_{078} \,,
\end{array} \right.
$$

Hence it becomes possible to represent $\mathbb{U}$ as

$$\mathbb{U} := \left\{ (A,F) \in \Re^{w\times w} \times \Re^{w\times n} \;\middle|\; \begin{array}{c} \exists z_0 = 1\,,\, z \in \{0,1\}^m\,,\, v \in \{0,1\}^{|\mathcal{S}|} \\ \sum_{i=1}^m z_i \le \Gamma \\ A = \bar{A} + \sum_{i=1}^m \hat{A}_i z_i + \sum_{(i,j,k)\in\mathcal{S}} \tilde{A}_{ijk} v_{ijk} \\ F = \bar{F} + \sum_{i=1}^m \hat{F}_i z_i + \sum_{(i,j,k)\in\mathcal{S}} \tilde{F}_{ijk} v_{ijk} \\ z_i + z_j + z_k - 2 \le v_{ijk} \le (1/3)(z_i + z_j + z_k)\,,\, \forall\,(i,j,k) \in \mathcal{S} \end{array} \right\}$$

where

$$\mathcal{S} := \{(0,1,5),(0,1,7),(0,2,5),(0,2,7),(0,5,6),(0,5,7),(0,6,7),(0,7,8),(1,5,7),(2,5,7),(5,6,7)\}\,,$$

and where $\bar{A}+\sum_i \hat{A}_i z_i+\sum_{(i,j,k)\in\mathcal{S}} \tilde{A}_{ijk} v_{ijk}$ and $\bar{F}+\sum_i \hat{F}_i z_i+\sum_{(i,j,k)\in\mathcal{S}} \tilde{F}_{ijk} v_{ijk}$ are the respective linear matrix representations of A and F. Furthermore, the set of linear constraints that take the form

$$z_i + z_j + z_k - 2 \le v_{ijk} \le (1/3)(z_i + z_j + z_k)\;,$$

are simply a convenient way of representing the nonlinear equality constraint $v_{ijk} = z_i z_j z_k$.

Having this representation for $\mathbb{U}$ in hand, problem (4.9) can be described as

$$\begin{cases} \max\limits_{y,z,v}\; y_t - w_t \\ \quad \text{s.t}\; y_{\tau+1} = (\bar{A} + \sum\limits_i \hat{A}_i z_i + \sum\limits_{(i,j,k)\in\mathcal{S}} \tilde{A}_{ijk} v_{ijk}) y_\tau \\ \qquad\qquad\qquad + (\bar{F} + \sum\limits_i \hat{F}_i z_i + \sum\limits_{(i,j,k)\in\mathcal{S}} \tilde{F}_{ijk} v_{ijk}) x_\tau\,,\, \forall\,\tau = 1,\ldots,t \\ \qquad \sum\limits_i z_i \le \Gamma \\ \qquad z_i + z_j + z_k - 2 \le v_{ijk} \le (1/3)(z_i + z_j + z_k)\,,\, \forall\,(i,j,k) \in \mathcal{S} \\ \qquad z \in \{0,1\}^m,\; v \in \{0,1\}^{|S|} \end{cases}$$

which is still a mixed integer nonlinear program due to the cross-terms $z_i y_\tau$ and $v_{ijk} y_\tau$.

In order to facilitate the resolution, we apply a second step of linearization by employing additional variables $Z \in \Re^{m\times t}$ and $V \in \Re^{|\mathcal{S}|\times t}$ such that $Z_{i,\tau} := z_i y_\tau$ and $V_{ijk,\tau} := v_{ijk} y_\tau$. This leads to the following mixed integer linear program:

$$\begin{cases} \max\limits_{y,z,v,Z,V}\; y_t \\ \quad \text{s.t.}\; y_{\tau+1} = \bar{A} y_\tau + \sum\limits_i \hat{A}_i Z_{i,\tau} + \sum\limits_{(i,j,k)\in\mathcal{S}} \tilde{A}_{ijk} V_{ijk,\tau} + \bar{F} x_\tau + \sum\limits_i \hat{F}_i x_\tau z_i + \sum\limits_{(i,j,k)\in\mathcal{S}} \tilde{F}_{ijk} x_\tau v_{ijk} \\ \qquad\qquad\qquad \bar{F} x_\tau + \sum\limits_i \hat{F}_i x_\tau z_i + \sum\limits_{(i,j,k)\in\mathcal{S}} \tilde{F}_{ijk} x_\tau v_{ijk} \\ \qquad -M_1 z_i \le Z_{i,\tau} \le M_2 z_i \\ \qquad y_\tau - M_2(1 - z_i) \le Z_{i,\tau} \le y_\tau + M_1(1 - z_i) \\ \qquad -M_1 v_i \le V_{i,\tau} \le M_2 v_i \\ \qquad y_\tau - M_2(1 - v_i) \le V_{i,\tau} \le y_\tau + M_1(1 - v_i) \\ \qquad \sum\limits_i z_i \le \Gamma \\ \qquad z_i + z_j + z_k - 2 \le v_{ijk} \le (1/3)(z_i + z_j + z_k)\,,\, \forall\,(i,j,k) \in \mathcal{S} \\ \qquad z \in \{0,1\}^m,\; v \in \{0,1\}^{|S|}, \end{cases}$$

where M_1 and M_2 are large enough constants that are known to capture $-M_1 \leq y^*_\tau \leq M_2$. One can easily verify that the "big M" constraints on $Z_{i,\tau}$ and $V_{ijk,\tau}$ ear equivalent to imposing that $Z_{i,\tau} := z_i y_\tau$ and $V_{ijk,\tau} := v_{ijk} y_\tau$.

D Monte-Carlo simulations of the temperature

For readability reasons, we plot only 100 trajectories (to calculate the CVaR, we realized 2000 draws).

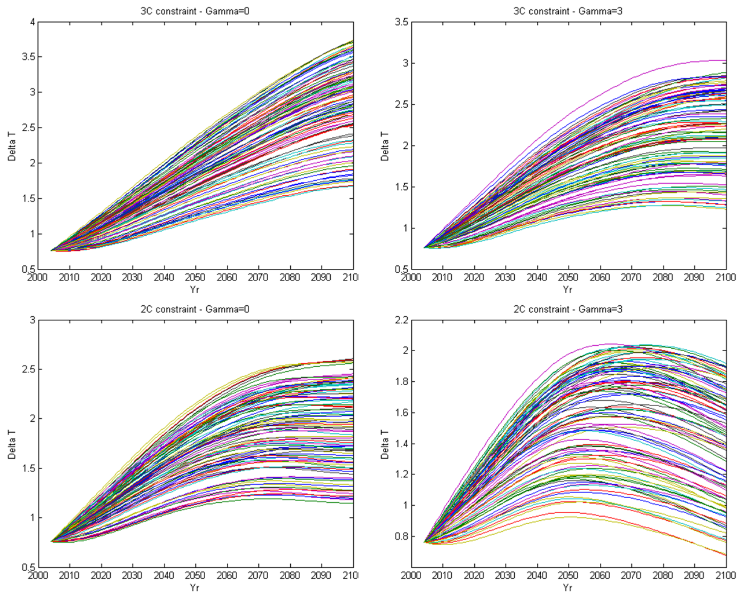


Figure 15: Temperature trajectories (2 °C and 3 °C emission pathways with $\Gamma = 0$ and $\Gamma = 3$)

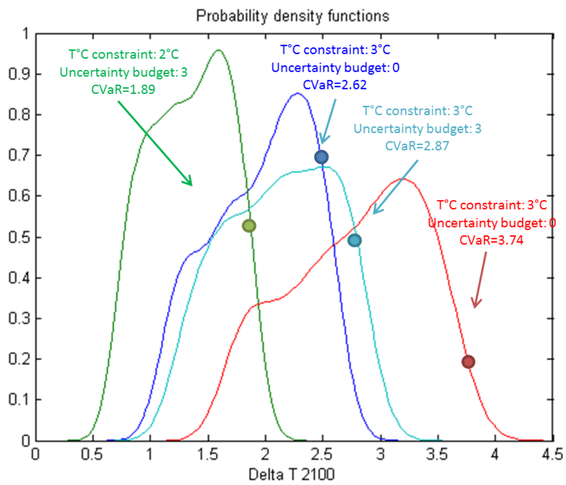


Figure 16: 2100 Temperature delta (2 °C and 3 °C emission pathways with $\Gamma = 0$ and $\Gamma = 3$)– Density functions and CVaR

5

Bioenergy with carbon capture and storage: key issues and main uncertainties

Emissions from fossil fuel combustion are recognized as a primary cause for the current and future increases in global greenhouse gas (GHG) concentrations and Earth's temperature (IPCC, 2014). Reducing GHG emissions require drastic changes in the global energy systems as emphasized by the various modeling exercises (e.g., Clarke et al. 2014, Kriegler et al. 2014). The most ambitious scenarios, those aiming at not exceeding a 2°C warming above pre-industrial levels, almost always involve the use of bioenergy with carbon capture and storage (BECCS), one of the techniques that is used to generate negative emissions. The notion of BECCS is to integrate planting trees and crops (that remove CO_2 from the atmosphere during their growth), harvesting them and using this biomass to obtain energy, in a process that also applies carbon capture from the exhaust and stores that carbon in geological formations. The concept of BECCS's negative CO_2 emissions is based on a usually assumed carbon neutral bioenergy, where CO_2 captured from the air while the plant is growing equals to CO_2 released during the plant combustion/processing. Hence the subsequent capture and storage of CO_2 emitted during the energy production/consumption phase leads to a negative CO_2 balance. BECCS is then "a net transfer of CO_2 from atmosphere into geological layers, providing in addition a non-fossil fuel source of energy" (Fuss et al., 2014). Even when the net GHG emissions related to bioenergy production are positive rather than neutral, BECCS is a negative CO_2 technology if the amount of carbon captured and stored is larger than the amount of carbon (or carbon-equivalence) produced during the process of energy production.

Despite such a sound presence in the climate stabilization forecasts, currently no commercial BECCS facility exists. Even more, the pace of carbon capture and storage (CCS) development has been slow in the recent years with only one commercial scale facility online (Boundary Dam in Canada) and several potential projects being cancelled. The resistance to CCS is particularly notable in Europe, where public confrontation to demonstration projects and picturing of CCS as a technology benefiting fossil fuels have led to a closure of a majority of the CCS-related projects. It seems that BECCS are currently missing its crucial component - CCS, in addition to concerns about land availability and impacts of food prices for the biomass production part.

We contribute to the existing literature by providing a review of the current knowledge about the necessary components for BECCS technology, its global potential in terms of energy production, related costs and likely constraints. We then use a global energy economic model, the MIT

Economic Projection and Policy Analysis (EPPA) model (Chen et al., 2015), to illustrate the challenges to capture the necessary details for assessing the long-term potential of the BECCS technology. Compared to previous studies (e.g., Kemper 2015, Gough and Vaughan 2015), we provide a consistent approach to evaluate all of the components of the technology, from growing biomass to CO_2 storage assessment. We also offer a discussion of the key issues that are needed to be considered in the integrated assessment models that produce long-term scenarios of the future development.

The paper is organized in the following way. In Section 2 we start with an overview of scenarios for the 21st century to illustrate the need for BECCS for climate mitigation policy. In Section 3 we discuss the determinants of biomass production: land requirements and agricultural yields. Section 4 focuses on bioelectricity production and Section 5 presents carbon capture technologies and their costs. In Section 6 we focus on carbon transportation and storage. Section 7 summarizes the estimates of costs for bioenergy with biomass. In Section 8 we provide suggestions for necessary components of BECCS to represent in the long-term modeling systems and illustrate the issues by providing the modeling results. Section 9 offers some concluding remarks.

5.1 Need for negative emissions technologies

Bioenergy with CCS (which sometimes also referred as Bio-CCS or biomass with CCS) does not have a consistent definition throughout the literature, as emphasized by Kemper (2015). The International Energy Agency's GHG Research and Development Program (IEAGHG) describes the following six Bio-CCS pathways (Koornneef et al., 2011): four pathways in power generation, which include standalone or co-firing of biomass in power stations (with and without gasification), and two pathways in liquid transportation fuel production, including CCS from advanced ethanol or Fisher-Tropsch biodiesel production. The negative emission potential in CCS-enabled liquid biofuel production is substantially smaller than the use of CCS in biomass-based power plants (Gough and Vaughan, 2015, Kemper, 2015). In our study, we follow Gough and Upham (2010) and use the term BECCS (Bioenergy with Carbon Capture and Storage) to refer exclusively to the process of direct or co-combustion of biomass fuels (liquid, solid or gaseous) in a power plant fitted with CCS.

BECCS technology plays a major role in the most stringent long-term mitigation pathways. The Intergovernmental Panel on Climate Change (IPCC) in its Fifth Assessment Report (AR5) provides more than a hundred scenarios consistent with limiting global temperature increase below 2°C, and BECCS are present in 101 of the 116 scenarios (Fuss et al., 2014, Clarke et al., 2014). The scale of BECCS development can be illustrated in several ways, like the amount of carbon captured or the amount of energy produced. One of the primary reason for BECCS use is to provide a carbon sink, hence the amount of captured carbon is a useful metric. For example, Figure 5.1 provides information on the amount of carbon captured by BECCS in the LIMITS model comparison exercise (Kriegler et al., 2014). Another important metrics is the amount of energy produced by BECCS. A quick look at the IPCC AR5 Database shows that for the 450 ppm scenarios, most models end up with a massive use of BECCS in 2100 (between 150 and 200 EJ for most cases). Most models envision BECCS introduction in the global energy mix in 2030-2040 and a substantial deployment after 2050. By 2100, BECCS capture from 7 to 21 gigatonnes (Gt) CO_2 per year. For a comparison, current global CO_2 emissions are in the order of 30-35 GtCO_2.

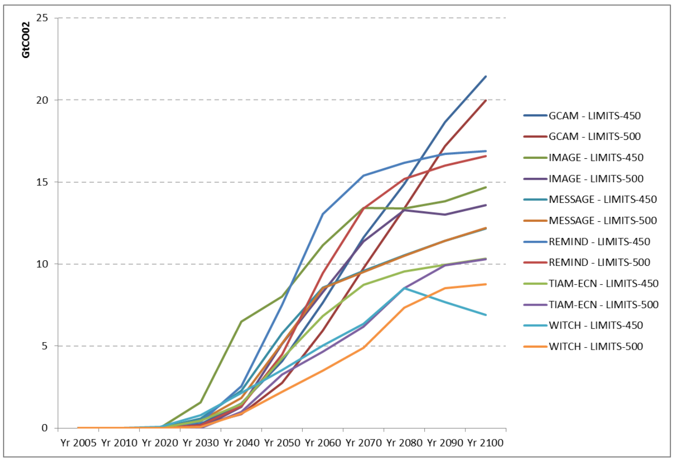


Figure 5.1: Carbon captured by BECCS across models for the 450 and 500 ppm eq policies (Data source: LIMITS, Kriegler et al. (2014))

Many researchers consider the 2°C target as impossible to reach without carbon sink, or negative emissions (provided by BECCS, direct air capture, or other technology). BECCS is regarded as the least uncertain and having the best potential among the negative emission generating technologies (McGlashan et al., 2012). A common theme in the mitigation literature is not only awareness about the necessity of negative emissions, but also the warnings about the huge uncertainties surrounding the availability and development of BECCS. Indeed this technology is in its early stages of development and no commercial scale plant has ever been tested. Yet, the BECCS technological feasibility is not the main concern and uncertainty source: biomass availability seems to be a much bigger issue as there are competing claims for this resource from food and feed production, timber production and bioenergy production. Moreover, the expansion of biomass production for energy use is a controversial subject discussed to a large extent in the LUC/ILUC (land-use change/Indirect land-use change) impacts literature (Faaij, 2015).

The second source of uncertainty is the CCS technology: even though many demonstration and pilot plant have been tested in the last decade, the number of commercial scale plants is still small (14 large-scale CCS projects in operation). Among these 14 projects only one is a power plant (Boundary Dam project in Canada) and only two projects inject the CO_2 in dedicated geological storage and do not use it to do EOR (enhanced oil recovery). The other projects are mostly gas processing plants or fertilizer production plants, the CO_2 retrieved being used for EOR. Hence the uncertainties on the costs of CCS are still large as well as the one on the geological storage potential.
These large technical uncertainties weighing on the potential development of BECCS are met with social uncertainties. The social acceptability of on–shore CCS is far from being granted as demonstrated by the abandonment of two projects due to a strong local opposition (the Barendrecht project in the Netherlands and the project in Jaenschwalde, Germany). BECCS also face criticisms as this technology is sometimes viewed as a way of prolonging the use of fossil fuels and of delaying mitigation actions (Smolker and Ernsting, 2012). With a constant cumulative carbon budget, one can make an argument that a future negative technology leads to not as strong action today because these current emissions can be canceled in the future by negative emissions.

To comply with a stringent climate constraint, most studies evaluate the need for BECCS to capture and store by 2100 between 10 and 20 GtCO_2/yr. This range implies the production of a large amount of biomass for energy use. Yet, Slade et al. (2014) state that studies usually provide limited insights into the level of deployment that might be achievable for energy crops and they highlight the need for caution in using global estimates provided by these studies. Rose et al. (2014) study comprehensively how well the agricultural sector is described in 15 Integrated Assessment Models (IAMs), a table summarizing their findings can be found in the appendix (Table 20). The large diversity in the model paradigms and differences in regional biomass production explains the large differences in the estimates of biomass potential, which represent the upper limit of energy that can be obtained from biomass (see Table 5.1).

Bioenergy	**Imaclim**	**DNE-21**	**Poles**	**Merge**	**Remind**	**Message**	**TIAM**
EJ	99 (75 woody biomass, 24 biomass for biofuels) (low)	40.2 (2000)	200 (2100)	188.64 (2050)	370 (2100) with 300 EJ/yr of energy crops	145	2050 technical potential: 240
	362 (302, 60) (high)	29.3 (2050)				technical potential: 160-270	2100 technical potential: 255

Table 5.1: Estimates of bioenergy potential. Sources: Bibas and Méjean 2014, Kitous et al. 2010, Marcucci 2014, Luderer et al. 2013, Sterling and Gregg 2013

5.2 Bioenergy

The availability of biomass is a critical factor of BECCS deployment. There are competing claims on scarce land resources from food production (expected to grow during the century), timber production (for construction and other industries) and bioenergy production. Different final usages also compete for the biomass produced for energy: heating, biofuels (for cars and planes) and electricity generation. These competitions introduce uncertainty on the future biomass availability for BECCS, uncertainty that is increased by the lack of knowledge on the effect of global warming on crop yields and local climate change which impedes a good evaluation of future biomass availability (Azar et al., 2013).

Besides the competition with other usages, an increased production of biomass raises concerns regarding food prices, water availability, biodiversity protection and prevention of soil degradation. And the real impact of BECCS on CO_2 emissions is under scrutiny as it will depend a lot on the type of biomass used in the power plant and on the land-use changes associated with its production (directly or indirectly) (van Vuuren et al., 2013). A review of studies on the bioenergy potential reveals huge differences in estimates (see Figure 5.2). As a comparison, bioenergy use is estimated to be around 50 EJ/yr nowadays and total primary energy consumption was around 567 EJ in 2013.

Bioenergy availability: the main factors

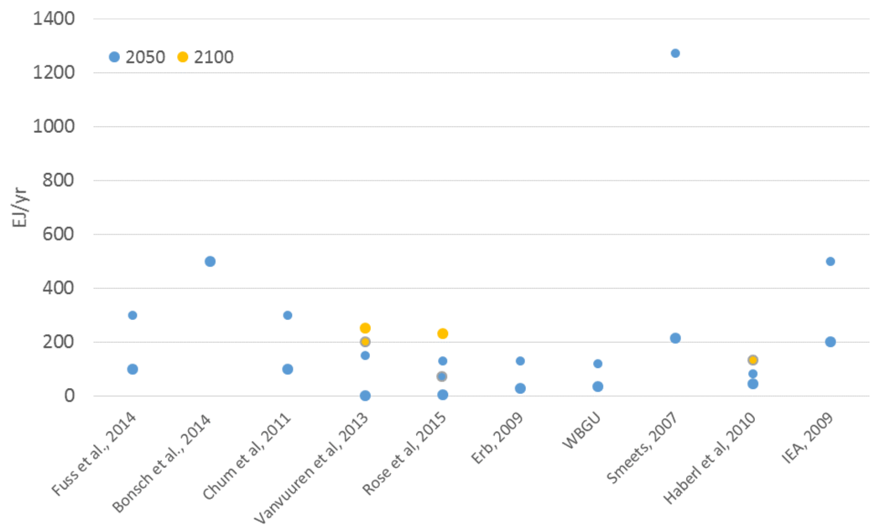


Figure 5.2: Bioenergy potential estimates. Source: Compiled by the authors based on IEA 2009, Rose et al. 2014, Haberl et al. 2010, Chum et al. 2011, Fuss et al. 2014

Biomass availability for energy use mainly comes from two sources: residues and dedicated energy crops (e.g., miscanthus, switchgrass, jatropha). In a recent paper, Slade et al. (2014) review a large number of studies on biomass contribution to primary energy supply and found out that the most important source of biomass are energy crops (between 22-1272 EJ), agricultural, forestry residues and wastes (25-221 EJ) and forestry (60-230 EJ). They also try to explain how assumptions are driving these estimates and find out that the most controversial assumptions relate to the future role of energy crops. Indeed, energy crops are potentially the most important source of biomass for energy yet many uncertainties weigh on their development. Their potential is determined by land availability, crop yields and water resource availability.

Land availability
The existing studies usually find that land availability for energy crops is a key determinant of bioenergy potential (Rose et al., 2014, Azar et al., 2013). It is important to note that most studies evaluating bioenergy potential assume that expansion of biofuels does not affect food demand (Slade et al., 2014). Future population and diets are hence critical assumptions to estimate land availability for energy crops. A common hypothesis is that energy crops will be grown on abandoned or agriculturally degraded lands (allowing avoiding issues as growth in food prices or CO_2 emissions linked to land use changes e.g. when forest lands are cleared for bioenergy crops).

A strong assumption is that lands are abandoned when global agricultural yields improve (resulting in a smaller land need), when the land yield diminishes due to soil degradation or to local climate change (Campbell et al., 2008) or when pastureland are freed of livestock because of changing diets. Yet, the link between an increase of yields and a decrease of the cultivated land areas is not direct because these studies usually assume that food demand is not affected by availability of additional land (inelastic demand). However, yield improvements could lead to lower food prices and an increase of the food demand. In some cases, it could lead to a rebound effect and to an increase of the cultivated area. Slade et al (2014) conclude that the link between crop intensification and land sparing is uncertain and that bioenergy potential estimates relying heavily on this link (mostly those assuming more than 300EJ of bioenergy potential) should be considered with caution.

Figure 5.3 presents estimates of land availability for energy crops. Most estimates are concentrated around 400 Mha, the most optimistic ones being driven by very ambitious assumptions as high yield increases, low meat diets and high use of fertilizers. To compare with the current situation, Rosegrant and Msangi (2014) estimate that the actual area used for bioenergy production is around 30 million hectares, approximately 2% of the cultivated surface (Fischer et al., 2008).

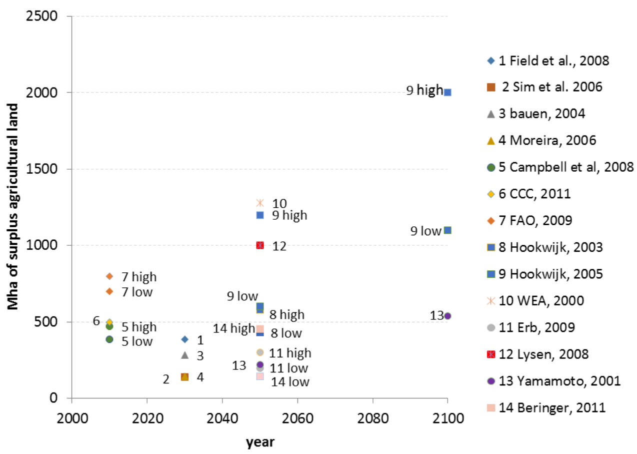


Figure 5.3: Land availability for energy crops estimates. Data Source: Compiled by the authors based on Slade et al. 2014, Campbell et al. 2008, CCC 2011

Yields

Assumptions on yields are also central for bioenergy estimates. When detailed agricultural models are not available, assumptions regarding the type of plant grown, the area where it grows, the irrigation, the management practices and the climate - have to be made and translated for modeling in more aggregated IAMs.

Most studies do not identify specific energy crop species and assume that the best adapted crop for each area and land type will be used (Slade et al., 2014). One issue with the above-mentioned assumption on land use is that usually abandoned lands are not the most productive; hence the yields cannot be too optimistic. Haberl et al. (2010) review various studies on bioenergy potential and find that yield expectations of bio-crop differ widely from 3.5 to 32 odt/ha (6.9 to 60 MJ/m2) when Slade et al (2014) report values between 3 and 21 odt/ha (up to 60 odt/ha for one study) most values being in the 4-12 odt/ha range. The larger values are usually obtained by researchers that consider irrigated and fertilized lands as well as dedicated energy crops (e.g., short rotation willow, sugarcane), while the lower values for food crop yields are obtained by assuming growing on rain-fed, non-fertilized lands (e.g., wheat in South America). Johnston et al. (2009) analyze yield assumptions in a set of bio-energy studies and conclude that yields are often largely overestimated, sometimes by more than 100%. This overestimation has multiple causes: a lack of regional data, the yields are chosen on the optimistic end of the range by researchers, cultivating practices assumed are the best management practices, distinction between developed and developing countries are not made, the water availability issue is not considered.

It is therefore quite complicated to pick a representative yield even if different kinds of area are modeled (see Table 21 in appendix for yield values). The second issue is the selection of the yields improvement rate. In the Global Agro-Ecological Zone (GAEZ) methodology, developed conjointly by the FAO (Food and Agricultural organization) and IIASA (International Institute for Applied Systems Analysis), three levels of agricultural management are distinguished, each determining agro-climatically attainable areal yields: 1) Traditional: subsistence based, not market oriented, no fertilizer or pesticide application, no conservation measures; 2) Improved: partially market oriented, manual labor with animal traction and some mechanization, some fertilizer and pesticide application, some conservation measures; 3) Advanced: mainly market oriented, high yielding varieties, fully mechanized, optimum application of nutrients and pesticides.

The traditional management can be disregarded for the BECCS estimates as we consider biomass destined for the bioenergy market. Yet, depending on the time horizon of the study and of the geographical zones considered, the two other types of management should be considered, leading to different yield improvement rates. Fischer (2009) states that at the global level grain yields increased by an average of about 2 percent annually in the period 1970 to 1990 but since then the rate of yield growth has halved. And the crop yields for most commodities are much lower in developing countries than in developed ones as yields and fertilizer consumption are closely correlated. Hence, most of the yield improvements should certainly take place in the developing countries and not necessarily in the most advanced ones (Fischer et al., 2011). Another factor limiting the potential yield growth is a shared belief that "for some major crops, yield ceilings have been, or are rapidly being reached", this belief being strengthened by the fact that yield growth has slowed these last two decades (see Figure 22 in the appendix). Yet, according to Alexandratos and Bruinsma (2012) the growth slowdown of yields can be explained by the slowing population growth and not by natural constraints. Winchester and Reilly (2015) consider yield improvements between 0.75% and 1% per year between now and 2050 which is close to the value considered by FAO, 0.8% (FAO 2009) but lower than improvement yields considered by Fischer (2009) for lignocellulosic feedstocks (between 1.45% and 3.5%).
Modelers have to make many crucial assumptions for estimating the biomass availability for energy use, but perhaps the most important thing is to ensure internal consistency of different assumptions. A fact that is well illustrated by Figure 5.4 where Slade et al (2014) represent the bioenergy potential estimated by various studies as a function of the assumed crop yields and land area available.

Sustainability of bioenergy

Biomass production for energy use should not result in higher food prices nor in new GHG emissions, water shortages or increased pollution.

Deforestation and land-use changes

One of the risk of an increased energy crop production is that the need for more agricultural land leads to native forests clearing, thus releasing a lot of stocked CO_2 into the atmosphere and threatening biodiversity. Bioenergy feedstocks can be divided in two categories: those requir-

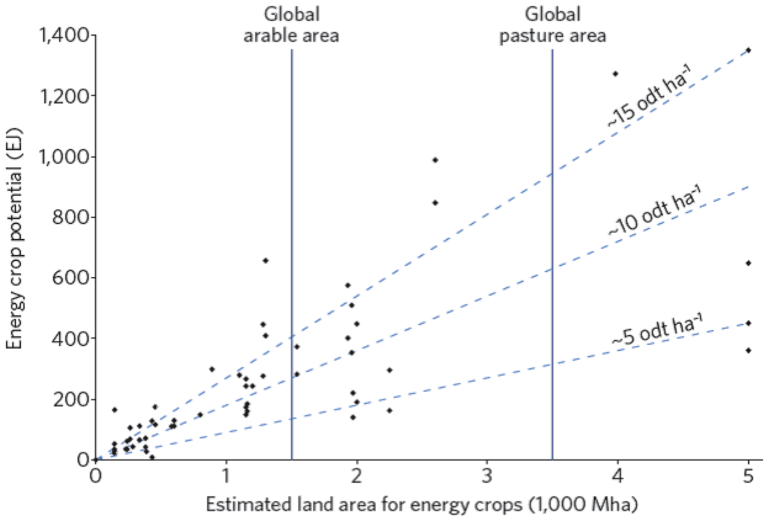


Figure 5.4: Estimated land area for energy crops (Gha) Source: Graph from Slade, Bauen and Gross 2014

ing land use change (sugary, starchy, lignocellulosic and oily energy crops) and those who don't (MSW, residues, and some wood).
This is an important thing to consider in models when allowing land use change for bioenergy production purposes. One way of avoiding LUC issues when the model is not detailed enough to integrate a precise description of lands, crops and GHG emissions related to LUCs, is to consider available for energy crop cultivation only lands with a LUC emission factor under a certain threshold.

Water availability
Climate change, rising food demand and water pollution are three factors that could induce water scarcity and therefore limit the expansion of energy crops. There will indeed be a trade-off between high energy crop yields with irrigation or lower yields with rain-fed cultures (but then larger land area for energy production).

5.3 Bioelectricity production

Biomass burning is an ancient technology with a long history of development, however, its efficiency is still lower in comparison to modern coal and natural gas plants. Combining biomass with CCS provides an additional challenge. Pilot plants of biomass with CCS as ethanol production or pulp and paper production with CCS exist but at this date no biomass fired power plant has been coupled with CCS.

For biomass-only fired plants, BECCS is not the most suited technology as the economics of CCS generally assumes large scale units and high thermal efficiency. The bulkiness of biomass usually leads to high fuel handling logistics costs. The issues of biomass availability as well as the risks of high temperature corrosion when using high temperature and pressure steam (a prerequisite for high efficiency) (Johnsson et al., 2012) can be resolved by co-firing biomass with

coal or natural gas. Most coal and natural gas power facilities with CCS could substitute some or all of the fossil fuel feedstock with biomass fuels. Yet in most cases allowing to burn biomass in a fossil designed power plant would require large investments and retrofitting. An easy option is then to co-fire biomass in coal power station, but the potential rates of co-firing are not really high and vary a lot (they are typically in the 10-30% range)[1]. Some authors envision an increase in co-firing rate in the future, for example, Koornneef et al. (2011) discuss an increase in the co-firing rate up to 50% for 2050.
Co-firing is doable with a large variety of biomass and given the high thermal efficiency of a large coal fired plant the economics is often better than for the biomass-only plant. The main challenges to co-firing lie in the different properties of the fuels (calorific value, moisture content) (Gough and Upham, 2010). At low co-firing ratios the impacts on plant performance are modest for most biomass materials. At higher co-firing ratios, the concerns about impacts on plant are increasing and this affects biomass fuel flexibility. When converting coal plant to 100% biomass, the range of fuels that can be fired is generally limited to high quality wood materials. The principal technical concerns are associated with the increased risks of excessive ash deposition, and high temperature corrosion of the boiler tubes (Livingston, 2013). Two projects of biomass co-firing with CCS are planned to start in 2019: the White Rose CCS project (426MW) and the CGEN North Killingholme project (470MW), both located in the UK.

Another issue linked to biomass fired power plant is the transport infrastructure needed to convey the biomass from the harvesting place to the plant. Due to the bulkiness of the biomass and the large size of the plant (required for economic reasons, because CCS is more effective at scale), the fuel handling logistics costs risk to be quite high. A second key point to limit the costs of the whole chain is to build the power plant close to a storage site. Hence, the biomass fired power plant with CCS needs to be close to a biomass harvesting site and to a potential CO_2 storage site which somehow hampers the site selection.

5.4 Carbon Capture

In its last report, IPCC's Working Group III worked with more than 900 mitigation scenarios and shows that if the CCS technology is not available/used, mitigation costs are multiplied by 2.5 (median value, the 25th -75th percentile range is 1.5-3.5) for the RCP2.6 and by 1.5 for the RCP4.5. The same kind of results are obtained by other studies: in its 2012 report (ETP 2012), the International Energy Agency considers that achieving the 2°C target without CCS is possible but will be 40% more expensive than if CCS is available (Bassi et al., 2015). Gasser et al. (2015) have a different approach than the aforementioned studies as they use an Earth System Model and not an Integrated Assessment Model to assess the tradeoff between conventional mitigation and negative emission in RCP2.6. They reach an even more unequivocal conclusion: even in the "best" cases, CO_2 capture is required at a significant level (>1GtC per year from now on) to meet the 2°C target.

Yet, these modeling exercises are mostly prospective ones aiming to find the best solution to reach a given climate target. The reality of CCS technology deployment is far from being as good as these studies could lead to think. Nowadays less than 20 commercial scale CCS projects are operating and only one of them is a power plant (the others are mainly natural gas processing plant with pre-combustion capture technology). Moreover in most of these projects the CO_2 is used for enhanced oil recovery (EOR), participating in revenue generation. The last issue re-

[1]http://hub.globalccsinstitute.com/publications/global-status-beccs-projects-2010/4-beccs-projects

garding the current CCS deployment is the project localization: most of them (2/3) are located in North America which is not necessarily a good thing as CCS will be needed globally.
Deployment lagging behind is not the only challenge faced by CCS: it also faces various criticisms. CCS detractors accuse the technology of allowing a longer use of fossil fuels and of capturing subsidies that would be better employed to fund the research on renewable energies. On the other side, CCS supporters argue that it would help avoid the stranded assets effect and that unlike renewables, power plants with CCS can provide dispatchable electricity.

The main reason why CCS is not used is its cost and the loss of efficiency it involves. Adding CCS to a power plant decreases the plant efficiency and at the same time increases its costs since the whole CCS process is not only energy consumer but also quite expensive as it requires heavy investments. The cost of CCS depends on the capture technology (the most costly step) chosen, three technologies being currently available.

Capture Technologies
Capture is the most expensive step of the CCS process. Three alternative ways of capturing CO_2 are still largely studied in order to reduce the whole process cost:

- Pre-combustion process: the fuel is converted in a gaseous mixture of CO and hydrogen and goes through a water gas shift reaction in order to form a CO_2-H2 mixture. The high CO_2 concentration (>20%) allows an easy CO_2 separation from hydrogen that can then be burnt without CO_2 production. The separated CO_2 is compressed and processed for transportation and storage. This technology is not used in existing power plant because the fuel pre-processing units are quite cumbersome and usually do not fit in pre-existing plant. Yet this technology can be used for new power plant in particular IGCC and NGCC. See Figure 5.5.

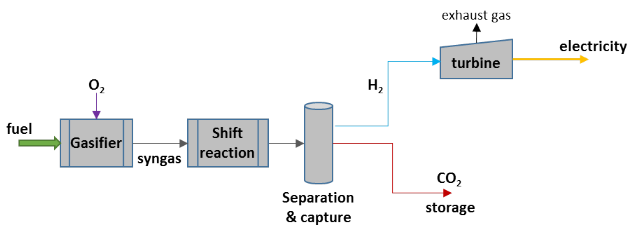


Figure 5.5: Pre-Combustion process

- Post-combustion process: the CO_2 is separated from combustion exhaust gases. The separation can be done with an amine-based solvent, a membrane, a membrane and solvent combination or through a chemical looping combustion. This technology is the most adapted to existing power plants. Yet, the low concentration of CO_2 in the exhaust gases (7-14%) is an issue as the concentration of the CO_2 aimed at being stored is above 95.5%. Hence the energy consumption to separate the CO_2 from the rest of the exhaust gases is quite high (Leung, Caramanna, and Maroto-Valer 2014). See Figure 5.6.

- Oxy-combustion process: the fuel is burnt in oxygen rather than in air (See Figure 5.7). The combustion exhaust gases are mainly water, CO_2, SO_2 and particulates and above all

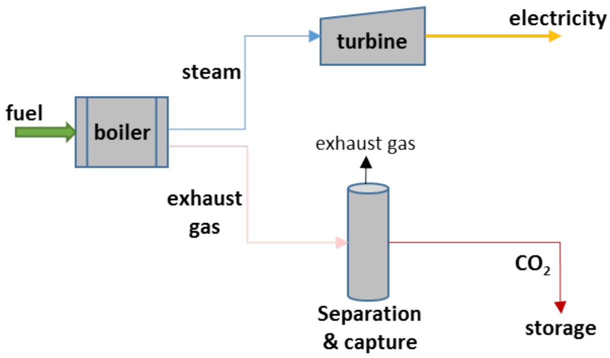


Figure 5.6: Post-Combustion process

do not contain nitrogen (a component that badly affects the separation step in the post-combustion case) nor NOx. After separation from SO_2 and particulates, the high concentrated CO_2 stream can be processed for storage. This process is not cost-competitive with the two previous ones as the O_2 production is energy-intensive, hence expensive. Moreover, the high SO_2 concentration in the exhaust gas may intensify the system's corrosion problems leading to more costs. Yet the elements of the oxy-combustion technology all exist and are used in e.g. the metal and glass melting industries.

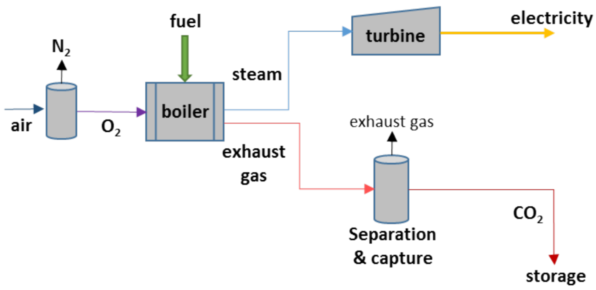


Figure 5.7: Oxy-Combustion process

A study undertaken in 2014 by IEAGHG allows comparing the different capture technology investment costs (table 5.2). When referring to BECCS, oxy-combustion is not a process that seems realistic (neither it is at the moment for regular power plant with CCS). The most mentioned ideas are to co-fire biomass with coal in "regular" power plant or to gasify the biomass in Bio-IGCC power plant (so using post and pre-combustion capture processes).

Regarding the capture techniques used with biomass fired power plants, both the post and the pre-combustion are compatible but the efficiency penalty is worst in the post-combustion case as the biomass has to be dried (else more steam is in the flue gas, lowering the CO_2 concentration). The loss of efficiency in the case of post-combustion biomass-only fired plant is estimated between 13-16%, leading to overall efficiency around 23-26% (Koornneef et al., 2011). The capture

	Plant efficiency	Total Capital Requirement (TCR)	TCR increase vs reference plant
Pulverised Coal	*%*	*\$2014/kW*	*%*
No Capture (Reference Plant)	44.1	2503	
Post Combustion Capture	35.2	4775	191
Oxy-Combustion	35.7	4752	190
IGCC			
Shell, Oxygen-Blown	35.5	5769	231
GE, Oxygen-Blown	34.9	5621	225
MHI, Air-Blown	34.8	5570	223

Table 5.2: Capital costs and efficiency of electricity generation plants (Source: Ieaghg (2014a))

of CO_2 from biomass fired oxyfuel power plants have not been studied a lot. Few studies have been realized on the pre-combustion case with biomass IGCC but the main processes involved in CO_2 capture should stay the same, independently of the fuel used. As the composition of the syngas exiting the gasifier has an impact on the subsequent water gas shift reaction, the use of biomass will result in energy penalty but this penalty is assumed to be quite low compared to the post-combustion case (Koornneef et al., 2011).
Hence Biomass Integrated Gasification Combined Cycle (BIGCC) with CCS seems to be the most promising technology.

5.5 Carbon Transportation and storage

Transportation
Efficient large scale transportation of CO_2 is realized thanks to pressurized pipelines both on and off-shore. For large distances (when CO_2 sources are located too far from the storage area), oversea tanker transportation would be the best solution but even though conceptual designs of such ships have been made, no CO_2 tanker ship exists at the time (IEAGHG 2014b). Transportation of CO_2 is not a technical issue as the pipeline industry already knows quite well how to do it in an efficient way (Bassi et al., 2015). Enhanced oil recovery (EOR) with CO_2 exists since the 1970s and in 2013 around 5000 km of pipeline transporting 60 Mt of CO_2 per year were installed on the globe. (European Technology Platform for Zero Emission Fossil Fuel Power Plants 2010). However, this infrastructure is clearly not sufficient to transport the large CO_2 amounts (up to 10 GtC/yr) that would need to be stored if CCS were to be largely deployed.
The issues regarding CO_2 transportation deployment are hence more regulatory and planning issues than technical ones as the scale of the needed investment is huge: as a comparison the current gas pipeline infrastructure has a capacity of 1.5 GtC.

The main issue regarding transportation is the fact that CO_2 sources are not necessarily located near the storage capacities. A network of pipeline would hence be necessary to convey the gas in an efficient manner. The second point is the fact that many storages or at least admissible storages are located off-shore which implies a greater transportation cost. As the technology is quite mature, the uncertainties on transportation costs are not numerous (but for the offshore costs for which cost numbers can vary a lot, see section 5.6.3).

Storage
Of the whole CCS chain, large scale CO_2 storage and monitoring is the least developed stage.
CO_2 storage: reservoir and storage mechanisms
Carbon dioxide can be stored underground in different kinds of storage reservoirs. Usually 3 types of storage are distinguished:

- Oil and gas fields (empty or partially empty)
- Unmineable coal seams to which enhanced coal bed methane recovery can be applied (ECBM)
- Deep saline aquifers

The principal characteristics needed for a geological formation to securely store CO_2 are the following according to IEAGHG (Ieaghg, 2014b). The rock must:

- Be permeable (allow the flow of injected CO_2 into and through the formation);
- Be deep, at least 800 meters (2600 feet), the depth below which, due to high pressure and temperature conditions, CO_2 becomes a "supercritical fluid" that takes up much less space than a gas and flows much better than gases through the tiny pore spaces;
- In most cases, be covered by thick layers of impermeable "cap rock" that can withstand any pressures or stresses due to the injection or movement of CO_2 or natural geologic processes and that will not allow the upward flow of the injected CO_2
- Have secure trapping mechanisms to hold the CO_2 in the desired formation

Once injected, the CO_2 will stay underground thanks to one or several mechanisms. The first and most obvious one is the classical geological trapping which can be structural or stratigraphic. In this case, the CO_2 is held in place by an impermeable rock. The second kind of trapping that can occur is the residual trapping: after injection, the CO_2 migrates with the formation water and at the tail of the CO_2 plume, the falling CO_2 concentration leads to the trapping of the gas in the tiny pores between rocks by the water capillary pressure. The third mechanism is the solubility trapping: the CO_2 dissolves in the saline water forming a dense solution that migrates ate the bottom of the reservoir. The last trapping (which is also the longest one to occur) is the mineral trapping: the CO_2 chemically combines with the reservoir rocks to form minerals.
In a geological storage site, these mechanisms are usually combined which ensures that the CO_2 stays underground.

The safety and permanence of geological storage is a big concern which explains the large number of studies led worldwide (see the appendix for a map of the various monitoring projects).

CO_2 storage: estimating the capacity
Given the diversity of reservoirs and storage mechanisms, it is not easy to determine the CO_2 storage capacity. First of all, as it is the case for fossil fuels or mineral availability estimates, CO_2 storage capacity are distinguished between resources and reserves (Bachu et al., 2007). Resources, which can be discovered or undiscovered, are the theoretical quantity of CO_2 storage estimated by geologists while reserves are the known and commercially quantity of CO_2 storage exploitable at a given time. Reserves hence fluctuate over time as technical, economic, environmental, societal and regulatory factors change while resources evolve as new discoveries are made.

In the case of CO_2 storage, experts distinguish between theoretical capacity, effective capacity, practical capacity and matched capacity. The theoretical capacity is an upper bound of the resources, the effective capacity represents that part of theoretical storage capacity that can actually be physically accessed, the practical capacity is what we usually consider as the reserves while the matched capacity is a subset of the practical capacity that is obtained by detailed matching of large stationary CO_2 sources with adequate geological storage sites (Bachu et al., 2007). These distinctions between capacity estimates explained partly the large discrepancies sometimes found between studies as the kind of capacity estimated is not always clearly detailed. Another issue when searching for data regarding storage capacity is the few regionalized data. Most of the time, the estimated capacity are aggregated (see table 23 in the appendix for a table with regional data).

Capacity estimates from various sources are reported in table 5.3 :

Gt CO2	**IFPEN** (low-high)	**IPCC** 2005 (low-high)	**IIASA** 2012 (low-high)	Hendricks et al, 2004 (low-medium-high)	Edmonds 2012
Oil and gas fields	920	675-900	996 – 1150	446-1152-3320	800
Coal seams	5-150	15-200	93 – 150	0-267-1480	
Deep saline aquifers	400-10000	1000-10000	3963 – 23,171	30-240-1081	5000 (onshore) 1300 (offshore)

Table 5.3: Storage capacity estimates

The large differences in estimates, in particular between recent studies and the ones realized before 2005, are mainly due to deep saline aquifers. Dooley (2013) explains that previous estimates were assuming that the storage in deep saline aquifers would necessitate the presence of geological trapping which seems now considered as an overly restrictive constraint that ignores the role of other trapping mechanisms.

What seems to be a consensus among CCS experts is that storage should not be a limiting factor for CCS (Clarke et al., 2009, Koornneef et al., 2011) except in a few places like Japan or South Korea where underground storage is nonexistent (that is why the Japanese worked on deep ocean storage of CO_2 but this alternative does not seem really realistic).

5.6 Economics of bioenergy with CCS

5.6.1 Cost of biomass

It is quite complex to agree on a biomass cost per region as the economics of biomass is strongly dependent upon the type of biomass considered and also upon the assumptions made for the yields, the fertilizer use, the land availability, the harvesting techniques and the transportation mode used to gather the biomass. Studies like the one realized by Perlack et al. (2011) try to derive supply curves for various scenarios for these parameters in the US. In this work, biomass cost is in the 40-60 $/ODT (oven dry ton) range and lowers through time as yields are due to improve. IRENA (2012) comes up with similar prices (40-55 $/ODT) as well as (Kyle et al., 2011) who use for the GCAM models prices ranging between 35 and 65$/ODT (the price vary with the type of bioenergy crop). But in other regions the cost could be very different (lower yields, less land potential, more transportation, less good harvesting techniques...), as shown by the cost difference between industrial wood pellets in Europe (around 10 $/GJ) and in the US (around 4$/GJ) (IRENA, 2012). The assumptions regarding biomass cost are critical to discuss BECCS economical potential and they should be clearly exposed and the consistency of the biomass cost and the amount of biomass used in BECCS should be monitored closely (it is quite easy to forget that the cost parameters used where valid only for some part of the supply curve).

5.6.2 Cost of capture

CCS costs

Carbon Capture and Storage deployment is really uncertain as it mainly relies on political decisions. If a carbon price/market were to be implemented, then CCS would maybe have a chance of being profitable. Hence a question that many people try to answer is: what CO_2 price level would allow CCS to emerge or to reformulate, what is the cost to avoid emitting one ton of CO_2 with CCS? A rapid literature study provides price ranges that are quite wide (Table 5.4): Another metric often looked at when the CCS issue is raised is the levelised cost of electricity

Abatement cost (\$2014/tCO_2)	**Bassi et al 2015**	**IEAGHG (2015)**	**NETL (2015)**	**SBC Institute (2012)**
CCS coal	47-122	49	79	55-95
Coal Oxy-Combustion		81		
IGCC		126-132.6	86	
CCS gas	87-167			69-109

Table 5.4: Cost of an avoided ton of CO_2

(LCOE) and in particular its increase due to the addition of CCS (see Table 5.5). The hope that the uncertainty ranges on the costs narrow down and that the general level of the cost goes down is still high as most of the technologies used in CCS are still working their way up the cost curve (see Figure 5.8). Yet, the low number of CCS demonstration and large-scale projects should not enable the technologies to evolve rapidly on this curve. The lack of CCS projects is partly due to the fact that CO_2 avoidance is in most cases the only purpose of CCS. Hence, even if CCS

LCOE (increase % reference)	Bassi et al 2015	IEAGHG (2015)	IPCC (2014)	NETL (2015)	IPCC (2005)	
Coal (No capture) ($2014/MWh)	65-115	69	29 / 66 / 104	86.1	52-63	
CCS coal (post combustion)	69%	82%	80%	62%	46%-90%	%
Coal Oxy-Combustion		76%	64%			
IGCC		123%	64%	31%	25%-50%	
Gas (No Capture) ($2014/MWh)	61-110		34/773		37.5-60.5	
CCS gas	50%		21%-50%		50%	

Table 5.5: LCOE increase with CCS for various types of power plant

abatement costs are not really high when compared with those of Off-shore wind, solar PV and thermal or geothermal energy; these technologies are better appreciated by project developers.

5.6.3 Cost of transportation

As stated in Table 5.6, pipeline transportation costs per ton of CO_2 increase a little less than proportionally with the distance because most of the cost is driven by investment costs in the pipeline infrastructure (which is proportional to the pipeline length). It is not the case with CO_2 transportation by ship as in this case, investment cost is not correlated with the distance the ship travels to transport the CO_2 to the storage site.

Cost in $2014/ t$CO_2$	European Technology Platform for Zero Emission Fossil Fuel Power Plants 2011			Hendriks et al. 2004		
Distance in km	180	500	750	50-200	200-500	500-2000
Onshore	1.72	4.64	6.88			
Offshore	2.96	6.48	9.43	4.62	7.69	15.38
Ship	13.52	15.03	16.39			

Table 5.6: Transportation costs

5.6.4 Cost of storage

The cost of storage can be divided into 5 cost categories: regional evaluation and site selection, site characterization, permitting, operations and post injection site care and site closure. Operations and post injection site care and site closure stand for half of the costs in real value but in discounted value site characterization and operations are the two most important costs (according to NETL exercise on CO_2 saline storage).

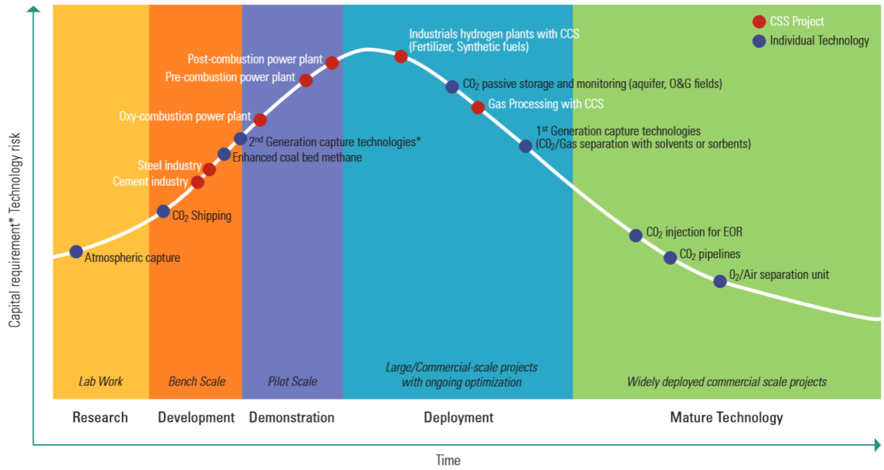


Figure 5.8: Investment-risk curve of individual CCS technologies (Source: SBC Energy Institute, 2012)

In a study performed in 2014 (Grant et al., 2013), NETL built a cost supply curve for the US saline formation (figure 5.9). If we make the assumption that all coal power plants actually

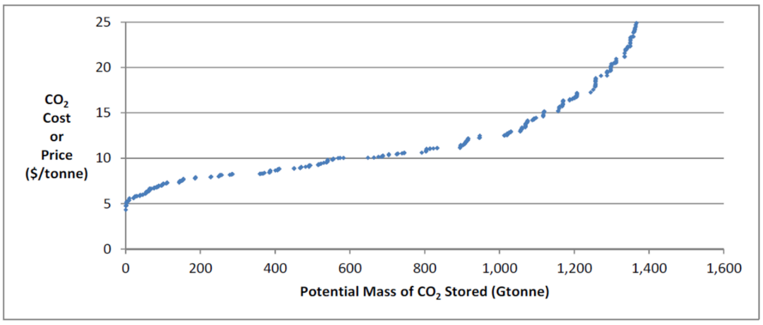


Figure 5.9: Cost-supply curve for Baseline Case, costs below \$25/tonne in \$2011 (Source: NETL/DOE)

installed in the US are equipped with CCS and using usual hypotheses (80% capacity factor, 90% capture rate), a little bit less than 2 GtCO_2/yr would be stored. Which means that the potential storage under 10\$/ton would be plenty enough in the US for quite a long time.

5.6.5 LCOE for BECCS technologies

It is even more complicated to derive future LCOE prices for BECCS than for other power plant with CCS technologies as no pilot has ever been done. Estimates of the level of the necessary CO_2 tax have been realized in recent studies are quite varied. They range between 200-290 \$2014/t CO_2 (Akgul et al., 2014), 61-114 \$2014/t CO_2 (McGlashan et al., 2012) and 167 \$2014/t CO_2 (Humpenöder et al., 2014).

5.7 Modeling of bioenergy with CCS in EPPA

5.7.1 The EPPA Model

The Emissions Prediction and Policy Analysis (EPPA) model is the part of the MIT Integrated Global Systems Model (IGSM) that represents the human systems (Paltsev et al., 2005). EPPA is a recursive-dynamic multi-regional general equilibrium model of the world economy, which is built on the GTAP dataset and additional data for the greenhouse gas, urban gas emissions, taxes and details of selected economic sectors. Prevision is made for analysis of uncertainty in key human influences, such as the growth of population and economic activity and the pace and direction of technical advance... It is designed to develop projections of economic growth and anthropogenic emissions of greenhouse related gases and aerosols.
The model projects economic variables (GDP, energy use, sectoral output, consumption, etc.) and emissions of greenhouse gases (CO_2, CH_4, N_2O, HFCs, PFCs and SF6) and other air pollutants (CO, VOC, NOx, SO_2, NH_3, black carbon, and organic carbon) from combustion of carbon-based fuels, industrial processes, waste handling, and agricultural activities. Different versions of the model have also been formulated for targeted studies to provide consistent treatment of feedbacks of climate change on the economy, such as effects on agriculture, forestry, bio-fuels and ecosystems and interactions with urban air pollution and its health effects (see appendix B for more detail).

5.7.2 BECCS implementation

In EPPA, production technologies are described using nested CES functions (see Paltsev et al. (2005)). Figure 5.10 illustrates the nest for bioelectricity production without CCS while figure 5.11 illustrates the implementation of BECCS in EPPA.
Where pbcrop is the price index for biocrop, pk and pl are respectively the price indices for

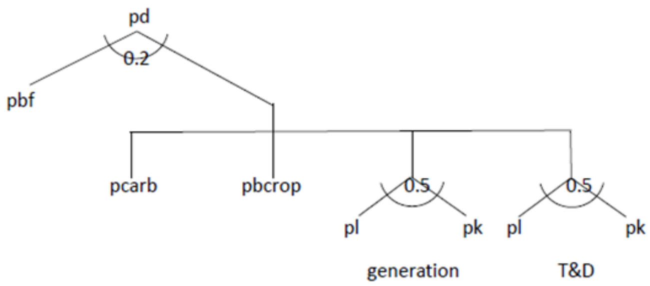


Figure 5.10: EPPA: electricity generation from biomass no CCS

capital and labor, pbf is the technology specific factor input cost share (used to limit the rate of penetration of a new technology in its early phases of deployment) and pcarb is the CO_2 permit price index for the technology. Finally, pd is the price index for bioelectricity production. The main difference between the 2 structures is that without CCS, CO_2 price is an input (if the technology emits fossil CO_2 at some point on the value chain, it will cost) while with CCS this price is an output, the technology "earns" money by storing carbon dioxide from biomass.

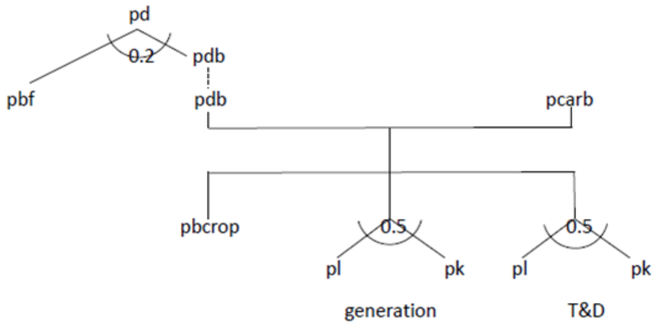


Figure 5.11: EPPA: BECCS

5.7.3 Modeling biomass production

Our parametrization of feedstock costs assumes that a representative energy grass is grown in each region and follows Winchester and Reilly (2015). Based on a literature review of switchgrass and Miscanthus yields in the US, the authors assign a base energy grass yield of 16.8 oven dry tons per hectare (ODT/ha) in this region. Base yields for other regions are calculated by multiplying the US yield by net primary productivity for C3-C4 grasslands estimated by the Terrestrial Ecosystem Model (TEM)[2] divided by net primary productivity for the same grasslands in the US. As several yield estimates surveyed by Winchester and Reilly (2015) involved field trials and we wish to evaluate large-scale bioelectricity production, we classify energy grass yields used by these authors as a "high yield" scenario and consider two alternative cases with lower yields. Thomson et al. (2009) estimate that on all continental US cropland, switchgrass an average switchgrass yield of 5.6 ODT/ha. Mann and Spath (1997) estimate American yields to be between 9 and 11 odt/ha in most part of the US, while Perlack et al. (2011) use yields for energy crops around 5-7 odt/ha (with low scenarios around 2-3 odt/ha and high ones at 11-12 odt/ha for the US).. Informed by these estimates, we multiply the base yields estimated by Winchester and Reilly (2015) by one-half in a 'medium yield' and one-third in a 'low yield' case. For each case, base yields are combined with crop land rents to estimate land costs per ODT. Production cost for other inputs required for delivered biomass – including growing, storage and transportation – are assigned using estimates from Duffy (2008). The production structure for the representative energy grass is shown in Figure 5.12 . The nesting structure facilitates endogenous yield responses to changes in land prices by allowing substitution between land and the energy materials composite (e.g., fertilizer) and between the resource-intensive bundle and the capital-labor aggregate. The model also includes compounding exogenous yield improvements of 1% per year for all crops (including food crops), which is applied to the base yields in each case and is consistent with estimates by Ray et al. (2013).

5.7.4 The Cost of Bioenergy Generation Technologies

For the EPPA model, we must define the relative costs of all technologies in the base year of the model. We do so using "markups", or the cost of a technology relative to the cost of the conventional technology (e.g. coal) against which it competes in the base year of the model. A markup of 1.5 therefore means the technology is 50% more expensive in the base year. Over time, the relative costs will change endogenously as the cost of inputs change and substitution of

[2] see http://ecosystems.mbl.edu/tem/

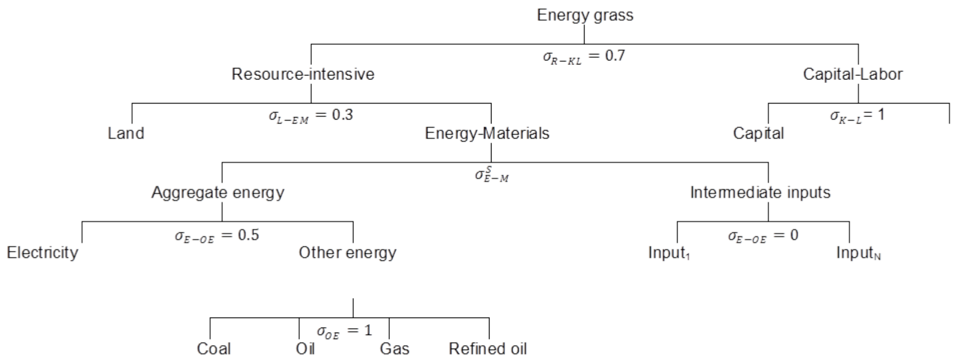


Figure 5.12: Production of energy grass in the EPPA model

inputs occurs. The base markups are based on a levelized cost of electricity (LCOE) calculation. We use a standard equation for calculating LCOE:

$$LCOE = \frac{TCR * CRC}{OH} + \frac{FOM}{OH} + VOM + FC + CTS \tag{5.1}$$

where TCR is the total capital requirement (overnight capital costs & construction schedule cost), CRC is the capital recovery charge: $CRC = \frac{r}{1-(1+r)^{-n}}$ (r: discount rate, n:project life (20 yr)), OH is the operating hours, FOM is fixed O&M, VOM is variable O&M per kWh, FC is fuel cost per kWh ($/BTU * Heat Rate (BTU/kWh)) and CTS is the cost of transportation and storage of captured CO_2 per kWh (for CCS technologies).
The resulting LCOE and markups are shown in Table 5.13 for the bioenergy generation technologies and the main technologies against which it competes. The data sources used for the bioenergy generation technologies include EIA (2015), Cuellar and Herzog (2015) and Bibas and Méjean (2014), see appendix C for details. These data result in the LCOEs found in line 19 (which includes transmission and distribution costs) and the markups in line 20 of the table. Those markups are then put into the base year of the EPPA model.

		Units	New Pulverized Coal	Pulverized Coal with CCS	Biomass plant	Biomass plant with CCs	BIGCC	BIGCC with CCS	NGCC	NGCC with CCS	IGCC	IGCC with CCS
[1]	"Overnight" Capital Cost	$/kW	2821	3850	3538	6507	5314	7988	983	2003	3604	6277
[2]	Total Capital Requirement	$/kW	3272	4620	4104	7809	6165	9585	1062	2244	4036	7533
[3]	Capital Recovery Charge Rate	%	10.6%	10.6%	10.6%	10.6%	10.6%	10.6%	10.6%	10.6%	10.6%	10.6%
[4]	Fixed O&M	$/kW	30.1	50.9	102.1	159.6	110.1	130.8	14.9	30.7	49.7	70.4
[5]	Variable O&M	$/kWh	0.0043	0.0055	0.0051	0.0063	0.0070	0.0082	0.0032	0.0066	0.0070	0.0082
[6]	Project Life	years	20	20	20	20	20	20	20	20	20	20
[7]	Capacity Factor	%	85%	85%	80%	80%	80%	80%	85%	80%	80%	80%
[8]	Capacity Factor Wind											
[9]	Capacity Factor Backup											
[10]	Operating Hours	hours	7446	7446	7008	7008	7008	7008	7446	7008	7008	7008
[11]	Capital Recovery Required	$/kWh	0.0464	0.0656	0.0619	0.1177	0.0930	0.1445	0.0151	0.0338	0.0609	0.1136
[12]	Fixed O&M Recovery Required	$/kWh	0.0040	0.0068	0.0146	0.0228	0.0157	0.0187	0.0020	0.0044	0.0071	0.0100
[13]	Heat Rate	BTU/kWh	8740	10663	11373	16891	10200	11373	6333	7493	7450	8307
[14]	Fuel Cost	$/MMBTU	3.15	3.15	2.61	2.61	2.61	2.61	8.18	8.18	3.15	3.15
[15]	Fraction Backup	%										
[16]	Fuel Cost per kWh	$/kWh	0.0275	0.0336	0.0297	0.0441	0.0266	0.0297	0.0518	0.0613	0.0235	0.0262
[17]	Levelized Cost of Electricity	$/kWh	0.0823	0.1206	0.1112	0.2055	0.1423	0.2109	0.0720	0.1097	0.0984	0.1651
[18]	Transmission and Distribution	$/kWh	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
[19]	LCOE with T&D	$/kWh	0.1023	0.1406	0.1312	0.2255	0.1623	0.2309	0.0920	0.1297	0.1184	0.1851
[20]	**Markup Over New Pulverized Coal**		**1.00**	**1.37**	**1.28**	**2.20**	**1.59**	**2.26**	**0.90**	**1.27**	**1.16**	**1.81**
For CCS												
[21]	Amount Fossil Fuel	EJ/KWh		1E-11		2E-11		1E-11		8E-12		9E-12
[22]	Carbon Content	mmtC/EJ		24.686		24.975		24.975		13.700		24.686
[23]	Carbon Emissions	mmtC/KWh		0.0000		0.0000		0.0000		0.0000		0.0000
[24]	Carbon Dioxide Emissions	tCO2/KWh		0.0010		0.0016		0.0011		0.0004		0.0008
[25]	CO2 Emissions after 90% Capture	tCO2/KWh		0.0001		0.0002		0.0001		4E-05		8E-05
[26]	Cost of CO2 T&S per ton	$/tCO2		10		10		10		10		10
[27]	CO2 Transportation &Storage Cost	$/KWh		0.0092		0.0147		0.0099		0.0036		0.0071

Figure 5.13: LCOE and Markups of Bioenergy Generation and Main Competing Technologies in EPPA (in 2007$)

5.7.5 Scenarios

In this study, we aim at assessing the impact of the introduction of BECCS technology on decarbonization pathways under climate constraint and also at evaluating the sensitivity of the various uncertainties mentioned earlier (biomass availability, technology) on the BECCS deployement. We hence build 13 scenarios to test with the EPPA model.
We consider 4 uncertain parameters and for each of them 3 possible values (low, base, high):

- biomass availability through crop yield
- technology costs of biomass power plants
- technology cost of CCS
- Renewable energy costs

For the crop yields we used the numbers and hypotheses discussed in the previous section. For the high and low technological costs, we used expert judgment (see appendix **??**) while for the renewable costs we made a change of 20% (lower and higher).
For 13 combinations of these parameters, we run the model with a 2°C constraint over the whole century [3] and a no-policy case (called the reference run).
Scenarios:

- $Reference\_base$: no policy, all the costs/parameters at their nominal value
- $Policy\_base$: 2°C, all the costs/parameters at their nominal value
- $Policy\_low$: 2°C, all the costs/parameters at their "best" value (low costs, high yields)
- $Policy\_high$: 2°C, all the costs/parameters at their "worst" value (high costs, low yields)
- $Policy\_nobioCCS$: 2°C, all the costs/parameters at their nominal value, no BECCS technology
- 8 sensitivity runs: 2°C, all the costs/parameters at their nominal value, except one.

5.7.6 Results (preliminary)

Macro-indicators
Figure 5.14 represents the evolution of the primary energy intensity of GDP and of the carbon intensity of the world economy. While the energy intensity decreases monotonously for the reference case, it is interesting to see that for the policy cases it stabilizes around 2060 and begins increasing after 2080. This phenomenon is due to the fact that most renewable or carbon-free technologies have lower yields than the fossil ones. It is particularly true for BECCS (see part 5.4). In order to comply with the carbon constraint (or rather because of the increasing price of CO_2), the carbon intensity decreases sharply for the policy cases and becomes even negative at the end of the time horizon. It is due to the high level of CO_2 storage and particularly of bio-CO_2 storage.

CO_2 emissions and storage
Figure 5.15 presents carbon emissions for various scenarios. As stated previously, for the policy

[3] Starting from 2020, there is a price constraint: a GHG tax scheme increasing at 4%/year in each region. For each period, the GHG tax levels are the same across regions. The policy target is to achieve a cumulative emissions level consistent to the two-degree target with a 480-530 ppm atmospheric concentration (see Chen et al. (2016) for details))

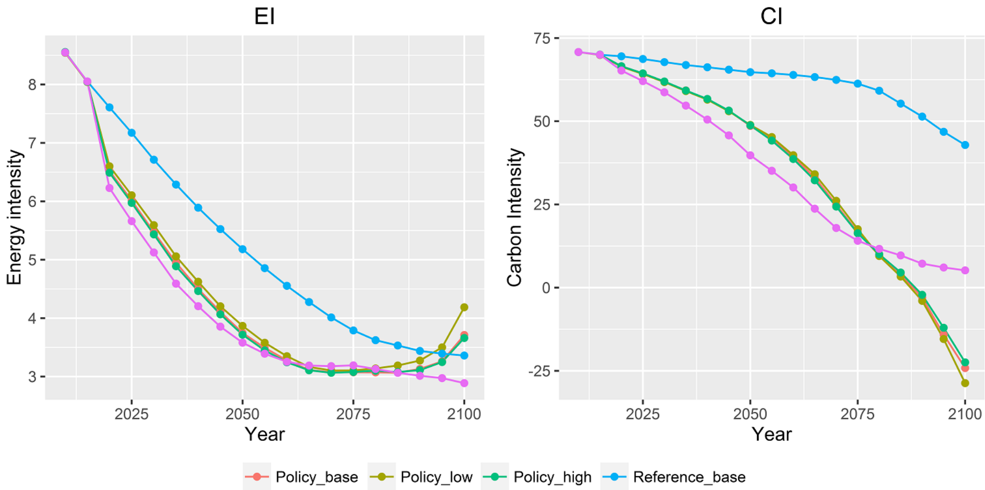


Figure 5.14: Energy intensity of GDP (TJ/G$) and Carbon Intensity of energy (Mton/EJ)

runs, emissions decrease rapidly and become negative around 2085 while for the no bioCCS case they also decrease sharply but stay positive.

CCS technologies

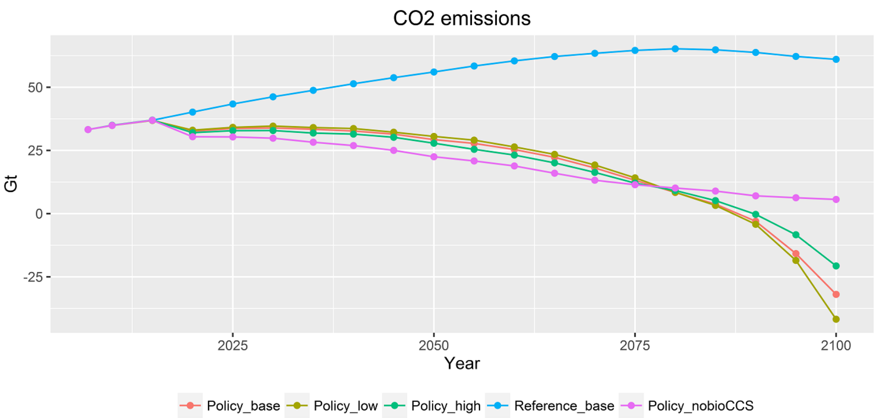


Figure 5.15: Carbon dioxide emissions

The negative emissions at the end of the period are due to an intensive use of BECCS technologies. We can see on Figure 5.16 that CCS and stored carbon increase notably from 2060. Up until 2080, regular CCS technology is mostly used while for the last 20 years of the century, BioCCS becomes the dominant technology and CCS use decreases. Unlike other studies and models (see 5.1), BECCS deployment begins quite late within EPPA and is quite fast. Moreover, at the end of the horizon, the amount of negative CO_2 is quite impressive since it is around 40 Gton/yr (more than today annual emissions).
The consequence of this huge need for BECCS at the end of the horizon is a complete mod-

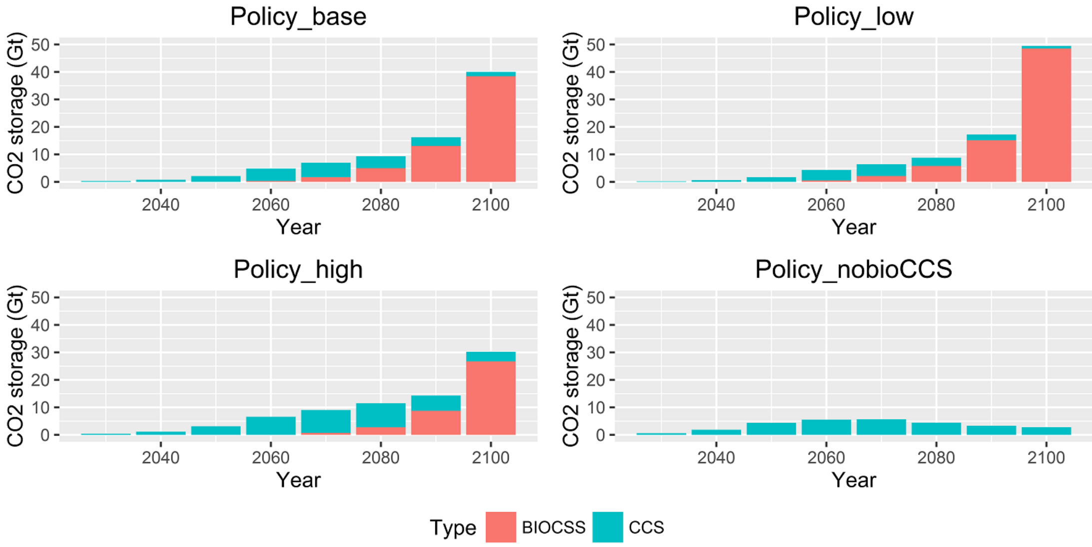


Figure 5.16: CO_2 stored by type of technology

ification of the electricity production structure (see figure 5.17). For all the policy cases, the electricity production is much higher than in the reference case. Yet the impact is stronger for the policy base and the *policy_low* (when BECCS is cheaper), in those cases electricity production by BECCS is huge and all other technologies almost disappear. It is less the case for the *policy_high* scenario where BECCS are less competitive compared for example to nuclear or gas.

BECCS deployment: parameter sensitivity
The following graph (5.18) represents the difference of CO_2 storage in 2100 between the policy scenarios with one deviating parameters and the *policy_base* scenario. The cost of renewable has a very low impact on BECCS. Given the various values chosen for the uncertain parameters, we find that BECCS deployment in EPPA is more sensitive to the CCS costs, then to crop yields and finally to the LCOE value of bioelectricity.

Primary energy consumption
In the policy case, when negative CO_2 emissions are not allowed, bioenergy, nuclear, wind & solar and bio oils are used to reduce CO_2 emissions (comparison with the no policy case) while the use of coal, oil and gas decreases notably. With the BioCCS option, the same energies increase or decrease yet in different proportions. Bioenergy use increases a lot, while the impact on nuclear and renewable is very small. Around 2070, the consumption of oil in the *policy_case* is around 60 EJ higher than in the no BioCCS case (around 40% higher) which validates the fact that using negative emission technologies allows for a longer use of fossil fuels (yet not in huge proportions).

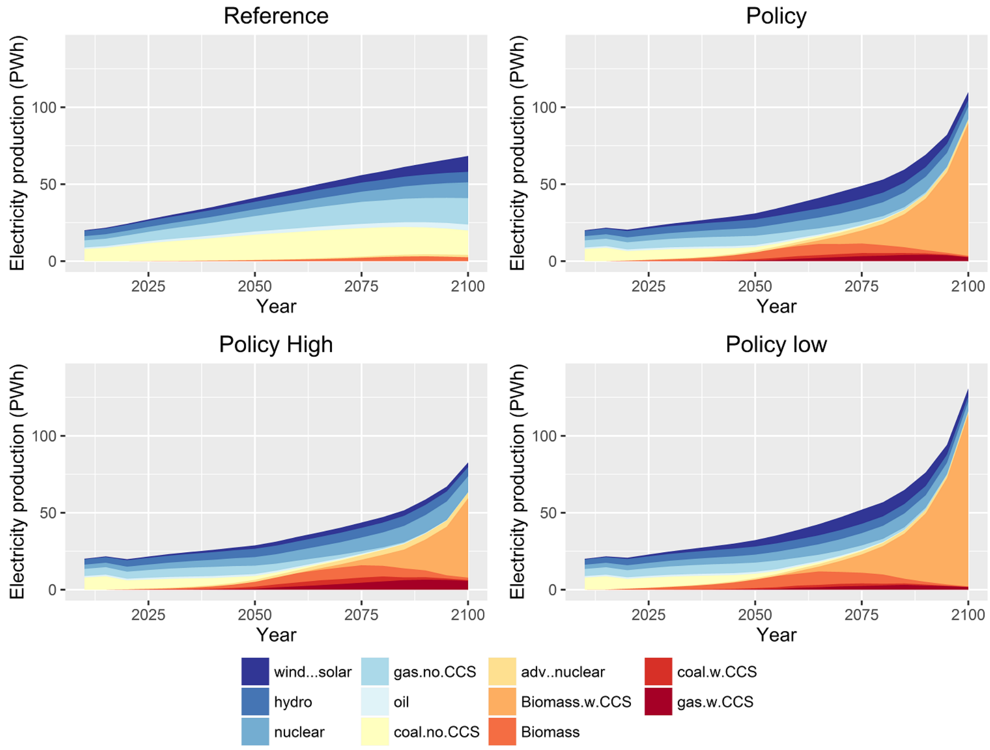


Figure 5.17: Electricity generation

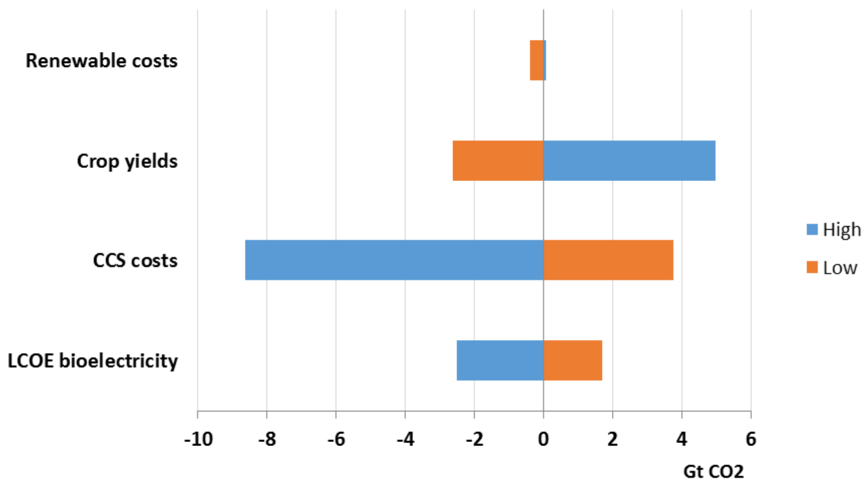


Figure 5.18: Sensitivity of bioCO2 storage in 2100 to various parameters

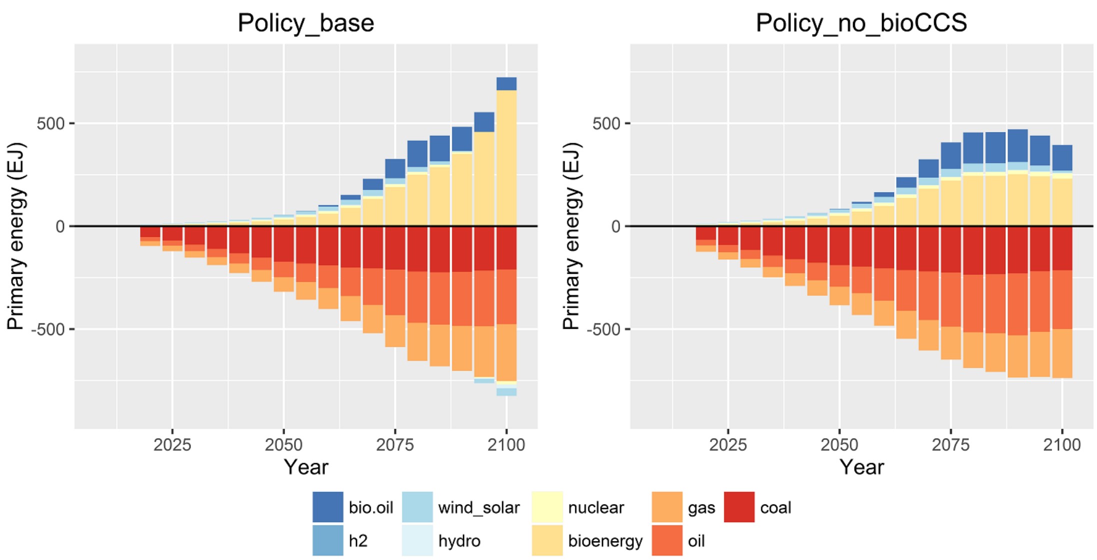


Figure 5.19: Primary energy consumption (difference with the reference case)

5.8 Conclusions

The agreement achieved at the UN climate conference in Paris in 2015 calls to hold "the increase in the global average temperature to well below 2°C... and to pursue efforts to limit the temperature increase to 1.5°C above preindustrial levels...." A majority of the scenarios in the UN FCCC database (IIASA, 2014) designed to achieve such an outcome requires negative emission technology. However, it seems that for the BECCS technology logistics and land use constraints will limit BECCS to less than what is needed.

The main uncertainties weighing on BECCS development are bioenergy availability, CCS development, policy incentives and social acceptance. Bioenergy availability is subjected to many uncertainties such as the rate of improvement in agricultural management, choice of crops and their yields, changes in food demands and human diets, use of degraded land, competition for water, use of agricultural/forestry by-products, protected area expansion, water use efficiency, climate change impacts, carbon neutrality of the biomass.

CCS is a proven technology, but it is not a mature one yet. The costs performance is expected to improve but some aspects of the CCS chain are still unknown, such as global CO_2 storage capacity, maximum annual rate of CO_2 storage, the BECCS/CCS deployment rate.
Policy incentives and social acceptance is a huge driver of BECCS development but here again many uncertainties remain, such as CO_2 price, negative emissions accounting, global governance system, clear framework for the storage and monitoring of CO_2, regional differences in attitude towards carbon storage.

The efforts to improve public knowledge about CCS projects should be enhanced as in many cases the opposition is based on inaccuracy in understanding the nature of CO_2 properties and its storage. To overcome these challenges, policy makers need to support the accelerated development of BECCS, including the advanced methods to increase biomass productivity.

Bibliography

Akgul, O., Mac Dowell, N., Papageorgiou, L. G., Shah, N., 2014. A mixed integer nonlinear programming (MINLP) supply chain optimisation framework for carbon negative electricity generation using biomass to energy with CCS (BECCS) in the UK. International Journal of Greenhouse Gas Control 28, 189–202.

Alexandratos, N., Bruinsma, J., 2012. WORLD AGRICULTURE TOWARDS 2030 / 2050 The 2012 Revision PROOF COPY (12), 146.

Azar, C., Johansson, D. J. a., Mattsson, N., 2013. Meeting global temperature targets—the role of bioenergy with carbon capture and storage. Environmental Research Letters 8 (3), 034004.

Bachu, S., Bonijoly, D., Bradshaw, J., Burruss, R., Holloway, S., Christensen, N. P., Mathiassen, O. M., 2007. CO2 storage capacity estimation: Methodology and gaps. International Journal of Greenhouse Gas Control 1 (4), 430–443.

Bassi, S., Boyd, R., Buckle, S., Fennell, P., 2015. Bridging the gap : improving the economic and policy framework for carbon capture and storage in the European Union. Tech. Rep. June, Grantham Research Institute on Climate Change and the Environment, London.

Bibas, R., Méjean, A., 2014. Potential and limitations of bioenergy for low carbon transitions. Climatic Change 123 (3-4), 731–761.

Campbell, J. E., Lobell, D. B., Genova, R. C., Field, C. B., 2008. The global potential of bioenergy on abandoned agriculture lands. Environmental Science and Technology 42 (15), 5791–5794.

CCC, 2011. Bioenergy Review. Tech. Rep. December, Committee on Climate Change.

Chen, Y.-H. H., Babiker, Paltsev, S., Reilly, J., 2016. Costs of Climate Mitigation Policies. Tech. Rep. 292, MIT Joint Program, Cambridge, MA.

Chen, Y.-H. H., Paltsev, S., Reilly, J., Morris, J., 2015. The MIT EPPA6 Model: Economic Growth, Energy Use, Emissions, and Food Consumptions. Tech. Rep. 278, MIT Joint Program, Cambridge, MA.

Chum, H., Faaij, A., Moreira, J., Berndes, G., Dhamija, P., Dong, H., Gabrielle, B., Goss Eng, A., Masera Cerutti, O., Mcintyre, T., Minowa, T., Pingoud, K., 2011. Bioenergy. In: Edenhofer, O., Pichs-Madruga, R., Sokona, Y., Seyboth, K., Matschoss, P., Kadner, S., Zwickel, T., Eickemeier, P., Hansen, G., Schlömer, S., von Stechow, C. (Eds.), IPCC Special Report on Renewable Energy Sources and Climate Change Mitigation. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, Ch. 2, pp. 209–332.

Clarke, L., Jiang, K., Akimoto, K., Babiker, M., Blanford, G., Fisher-Vanden, K. Hourcade, J.-C., Krey, V., Kriegler, E., Löschel, McCollum, D., Paltsev, S., Rose, S., Shukla, P. R., Tavoni, M., van der Zwaan, B. C. C., van Vuuren, D., 2014. Assessing Transformation Pathways. In: Climate Change 2014: Mitigation of Climate Change. Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change, cambridge Edition. Cambridge, United Kingdom and New York, NY, USA, Ch. 6, WP3.

Clarke, L., Wise, M., Edmonds, J., Placet, M., Kyle, P., Calvin, K., Kim, S., Smith, S., 2009. CO2 Emissions Mitigation and Technological Advance : An Updated Analysis of Advanced Technology Scenarios (Scenarios Updated January 2009). Technology, 1–82.

Cuellar, A., Herzog, H., 2015. A Path Forward for Low Carbon Power from Biomass. Energies 8 (3), 1701–1715.

Dooley, J. J., 2013. Estimating the Supply and Demand for Deep Geologic CO2 Storage Capacity over the Course of the 21st Century: A Meta-analysis of the Literature. Energy Procedia 37, 5141–5150.

Duffy, M., 2008. Estimated Costs for Production, Storage, and Transportation of Switchgrass. Iowa State University Extension, Ag Decision Maker Document (A1-22), 1–8.

Faaij, A. P., 2015. Food for All and Biobased Economy: Fundamental Conflict or Essential Synergy for Sustainable Development. In: 2015 CRC LCA of Transportation Fuels Workshop. No. October.

Fischer, G., 2009. How do climate change and bioenergy alter the long-term outlook for food, agriculture and resource availability? Expert Meeting on How to feed the World in 2050 (June), 24–26.

Fischer, G., Hizsnyik, E., Wiberg, D., 2011. Scarcity and abundance of land resources: competing uses and the shrinking land resource base. SOLAW Background Thematic Report - TR02, 58.

Fischer, G., Nachtergaele, F., Prieler, S., van Velthuizen, H., Verelst, L., Wiberg, D., 2008. Global Agro-ecological Zones Model documentation, 179.

Fuss, S., Canadell, J. G., Peters, G. P., Tavoni, M., Andrew, R. M., Ciais, P., Jackson, R. B., Jones, C. D., Kraxner, F., Nakicenovic, N., Le Quéré, C., Raupach, M. R., Sharifi, A., Smith, P., Yamagata, Y., 2014. Betting on negative emissions. Nature Climate Change 4 (10), 850–853.

Gasser, T., Guivarch, C., Tachiiri, K., Jones, C. D., Ciais, P., 2015. Negative emissions physically needed to keep global warming below 2c. Nature Communications 6, 7958.

Gough, C., Upham, P., 2010. Biomass energy with carbon capture and storage (BECCS): a review. Tyndall Working Paper 147 (December).

Gough, C., Vaughan, N., 2015. Synthesising existing knowledge on the feasibility of BECCS. Tech. Rep. 1104872, Avoid 2 programme (DECC).

Grant, T., Morgan, D., Poe, A., Lawrence, R., 2013. FE / NETL CO 2 Saline Storage Cost Model.

Haberl, H., Beringer, T., Bhattacharya, S. C., Erb, K.-H., Hoogwijk, M., dec 2010. The global technical potential of bio-energy in 2050 considering sustainability constraints. Current opinion in environmental sustainability 2 (5-6), 394–403.

Humpenöder, F., Popp, A., Dietrich, J. P., Klein, D., Lotze-Campen, H., Bonsch, M., Bodirsky, B., Weindl, I., Stevanovic, M., Müller, C., 2014. Investigating afforestation and bioenergy CCS as climate change mitigation strategies. Environmental Research Letters 9 (6), 064029.

IEA, 2009. Bioenergy – a Sustainable and Reliable Energy Source. Tech. rep.

Ieaghg, 2014a. ASSESSMENT OF EMERGING CO2 CAPTURE TECHNOLOGIES AND THEIR POTENTIAL. Tech. Rep. December, IEAGHG.

Ieaghg, 2014b. CARBON CAPTURE AND STORAGE: Proven and it Works. Tech. rep., IEAGHG.

IRENA, 2012. Biomass for Power Generation.

Johnsson, F., Kjärstad, J., Odenberger, M., 2012. The importance of CO2 capture and storage: A geopolitical discussion. Thermal Science 16 (3), 655–668.

Johnston, M., Foley, J. a., Holloway, T., Kucharik, C., Monfreda, C., 2009. Resetting global expectations from agricultural biofuels. Environmental Research Letters 4 (1), 019801.

Kemper, J., aug 2015. Biomass and carbon dioxide capture and storage: A review. International Journal of Greenhouse Gas Control 40, 401–430.

Kitous, A., Criqui, P., Bellevrat, E., Chateau, B., 2010. Transformation patterns of the worldwide energy system - Scenarios for the century with the POLES model. Energy Journal 31 (1), 49–82.

Koornneef, J., van Breevoort, P., Hamelinck, C., Hendriks, C., Hoogwijk, M., Koop, K., Koper, M., 2011. Potential for Biomass and Carbon Dioxide Capture and Storage. Tech. Rep. July, IEAGHG.

Kriegler, E., Weyant, J. P., Blanford, G. J., Krey, V., Clarke, L., Edmonds, J., Fawcett, A., Luderer, G., Riahi, K., Richels, R., Rose, S. K., Tavoni, M., van Vuuren, D. P., jan 2014. The role of technology for achieving climate policy objectives: overview of the EMF 27 study on global technology and climate policy strategies. Climatic Change 123 (3-4), 353–367.

Kyle, P., Luckow, P., Calvin, K. V., Emanuel, W., Nathan, M., Zhou, Y., 2011. GCAM 3.0 Agriculture and Land Use : Data Sources and Methods. Agriculture (December), 58.

Livingston, B., 2013. The firing and co-firing of biomass in large pulverised fuel boilers Doosan Biomass Co-firing Experience. In: IEA Exco Workshop Jeju.

Luderer, G., Leimbach, Bauer, N., 2013. Description of the REMIND model (Version 1.5). Tech. rep., PIK Potsdam.

Mann, M. K., Spath, P. L., 1997. Life Cycle Assessment of a Biomass Gasification Combined-Cycle System. Fuel and Energy Abstracts 2009 (Journal Article), 100.

Marcucci, A., 2014. THE MERGE-ETL MODEL : 2014 ASSUMPTIONS AND MODEL CALIBRATION.

McGlashan, N. R., Workman, M. H. W., Caldecott, B., Shah, N., 2012. Negative Emissions Technologies. Grantham Institute for Climate Change Briefing Paper No.8 (8).

Paltsev, S., Reilly, J. M., Jacoby, H. D., Eckaus, R. S., Mcfarland, J., Sarofim, M., Asadoorian, M., Babiker, M., No, R., 2005. MIT Joint Program on the Science and Policy of Global Change (EPPA) Model : Version 4. Policy Analysis Report No (125), 78.

Perlack, R. D., Stokes, B. J., Eaton, L. M., Turnhollow, A. F., 2011. US Billion-ton update. Biomass Supply for a Bioenergy and Bioproducts Industry. Tech. Rep. August, US DoE.

Ray, D. K., Mueller, N. D., West, P. C., Foley, J. A., 2013. Yield Trends Are Insufficient to Double Global Crop Production by 2050. PLoS ONE 8 (6).

Rose, S. K., Kriegler, E., Bibas, R., Calvin, K., Popp, A., van Vuuren, D. P., Weyant, J., 2014. Bioenergy in energy transformation and climate management. Climatic Change 123 (3-4), 477–493.

Rosegrant, M. W., Msangi, S., 2014. Consensus and Contention in the Food-Versus-Fuel Debate. Annual Review of Environment and Resources 39 (1), 271–294.

Slade, R., Bauen, A., Gross, R., 2014. Global bioenergy resources. Nature Climate Change 4 (2), 99–105.

Smolker, R., Ernsting, A., 2012. BECCS (Bioenergy with Carbon Capture and Storage): Climate saviour or dangerous hype? biofuelwatch (October).

Sterling, J., Gregg, J. S., 2013. Issues and Assumptions Relevant to Biomass Modeling.

Thomson, A. M., Izarrualde, R. C., West, T. O., Parrish, D. J., Tyler, D. D., Williams, J. R., 2009. Simulating Potential Switchgrass Production in the United States (December), 1–22.

van Vuuren, D. P., Deetman, S., van Vliet, J., van den Berg, M., van Ruijven, B. J., Koelbl, B., 2013. The role of negative co2 emissions for reaching 2 c-insights from integrated assessment modelling. Climatic Change 118 (1), 15–27.

Winchester, N., Reilly, J. M., sep 2015. The feasibility, costs, and environmental implications of large-scale biomass energy. Energy Economics 51, 188–203.

Appendix

A Biomass

Model	1st generation	Dedicated lignocellulosic	Residues	Biomass feedstock sustainability considerations/constraints (e.g., feedstock supply, land use/conversion)	Bioenergy international trade (primary or secondary, i.e., biomass or bioenergy)
AIM-Enduse*	Yes, but not independently	Yes, but not independently	Crop residues, MSW and animal manures, and forestry residues	Supply capacity constraints	Primary
DNE21+	Sugar cane, oil crops, and cereals (maize, wheat and rice)	Generic cellulosic	Residential & Commercial, agriculture, and forestry	Available lands for biomass production are constrained: (1) cropland for food and feed production and pasture are excluded from the available lands for biomass production, (2) forests and water-stressed areas are also excluded from the available lands for biomass, and (3) biomass yields and land accessibility considered as economic feasibility.	Secondary
GCAM	Maize, sugar cane, oil crops	Switchgrass, miscanthus, willow, jatropha, eucalyptus	Agriculture and forestry	Food/feed/timber demands given priority. Residue extraction somewhat limited to prevent erosion/preserve soils. Bioenergy can expand on any land, but yields are differentiated regionally (and very low in some places)	Primary
IMACLIM	Sugar cane, beet, starch crops	Herbaceous (e.g., miscanthus) and woody (e.g., poplar or eucalyptus)	Agriculture and forestry	Woody biomass grown on abandoned agricultural land. Other biomass competes with agriculture for land based on supply curves derived from WEO (2006).	Primary and secondary
IMAGE	Maize, sugar cane, oil crops	Woody bio- energy	Agriculture and forestry	Land-use constrained to abandoned agricultural land and part of natural grasslands. Nature reserves are excluded. Depending on scenario, additional sustainability constraints can be introduced.	Secondary
MERGE	No	Switchgrass	Agriculture and forestry	Supply constraints associated with food/feed/timber priority with residues a by-product. Residue extraction that preserves soil health. Dedicated energy crops limited to surplus agricultural lands, and additional deforestation prevention.	No
MESSAGE**	No	Woody bio- energy	Agriculture and forestry	Supply constraints due to joint production of timber, biomass and food. Sustainability constraints for land (e.g., preserved areas) and bioenergy is limited to marginal (non-cropland) lands.	Secondary
POLES	Non- cellulosic (rape, sunflower, maize/wheat-corn)	Cellulosic (short rotation crops, miscanthus, switchgrass, sweet sorghum, maize/wheat-plant, straw, log wood)	Agriculture and forestry (e.g., wood chips, fellings, black liquor)	Constraints on the share of each land type (agriculture, grassland, forest) that can be dedicated to bioenergy.	Secondary
ReMIND/MAgPIE	Maize, sugar cane, oil crops	Herbaceous (e.g., miscanthus) and woody (e.g., poplar or eucalyptus)	Agriculture and forestry	Food/feed/timber demands given priority. Nature conservation areas are excluded for cropland expansion.	Primary
TIAM-WORLD	Sugar, starch, and oil crops aggregated in to one category "first-generation crops"	Herbaceous (e.g., miscanthus) and woody (e.g., poplar or eucalyptus)	Agriculture and forestry	Use of first-generation biofuels is limited (upper bound) to represent a default preference for second-generation over first generation biofuels. Prices of second-generation bioenergy based on MAgPIE assumptions.	Primary and secondary
WITCH	Sugar cane	Woody bio- energy	Agriculture and forestry	Limited supply.	No

Figure 20: Biomass feedstock and trade modeling details Biomass (Source:Rose et al. 2014)

Region	Potential rain-fed yield		
	Average yield (dry t/ha)	Low yield (dry t/ha)	High yield (dry t/ha)
North America	9.3	6.7	21.4
Europe & Russia	7.7	6.9	14.5
Pacific OECD	9.8	6.5	20.0
Africa	13.9	6.7	21.1
Asia, East	8.9	6.4	19.0
Asia, South	16.7	7.6	21.5
Latin America	15.6	7.1	21.8
Middle East & N. Africa	6.9	6.3	10.6
Developed	8.9	6.7	21.0
Developing	14.5	6.8	21.5
World	12.5	6.8	21.5

Figure 21: Lignocellulosic yields (Source: Fischer et al. 2008)

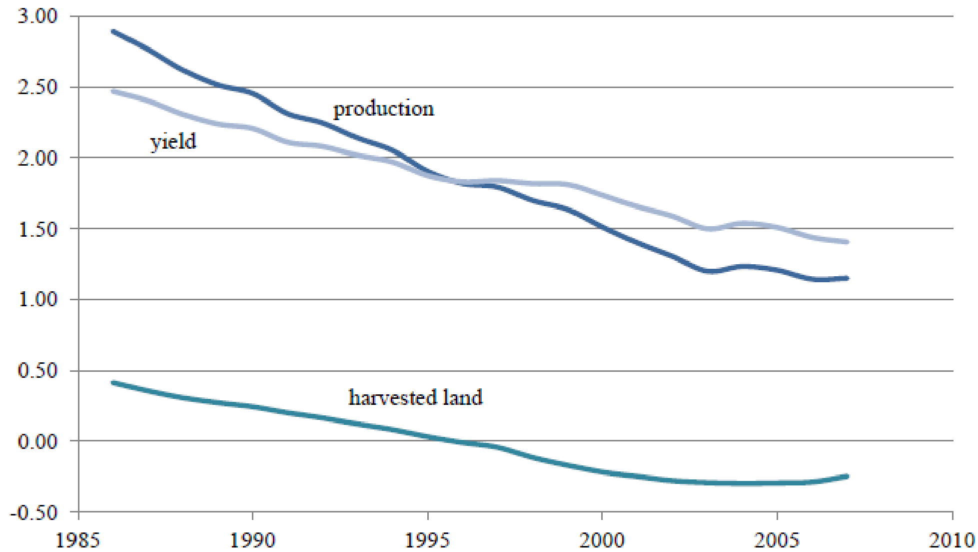


Figure 22: Annual growth rates of world cereal production and yields (over preceding 25-year period; historical 1961 - 2007) source: Alexandratos and Bruinsma, 2012

Estimated Storage Capacity (GtCO2)	Depleted Oil and Gas Reservoirs	Saline Formations	Coal Seams	TOTAL
North America	226	2102-22000	56-114	1856–20,473
Latin and South America (incl Brazil)	89	30.3	2	NA
Brazil	NA	2000	0.2	2000.2
Australia	19.6	28.1	11.3	59
Japan	0	1.9–146	0.1	2–146.1
China	9.7–21	110–360	10	1445 -3080
Indonesia	56–188	NA	NA	56–188
South Asia (India, Pakistan, Bengladesh)	6.5–7.4	NA	0.36–0.39	6.86–7.79
Former Soviet Union (FSU)	177	NA	NA	177
Sub-Saharan Africa	36.6	34.6	7.6	48.3
Middle East and North Africa	439.5	9.7	0	449.2
Europe	20.22–30	95.72–350	1.08–1.5	117–381
World	996 – 1150	3963 – 23,171	93 – 150	

Figure 23: Estimated storage capacity (GtCO2) Source: (Iiasa 2012)

B EPPA

To assess BECCS development scenarios, we use the MIT EPPA model (Chen et al., 2015), which is a multi-region, multi-sector dynamic model of the global economy. It has been widely applied to evaluation of climate and energy policies. The EPPA model provides an examination of the economy-wide effects of different policies, and incorporates numerous technologies to provide details about the resulting technology mix for different policy approaches. The GTAP data set provides the base year (2007) information on the input-output structure for regional economies, including bilateral trade flows. The GTAP data are aggregated into 18 regions and 24 sectors. Figure 24 shows the geographical regions represented explicitly in the model. EPPA represents

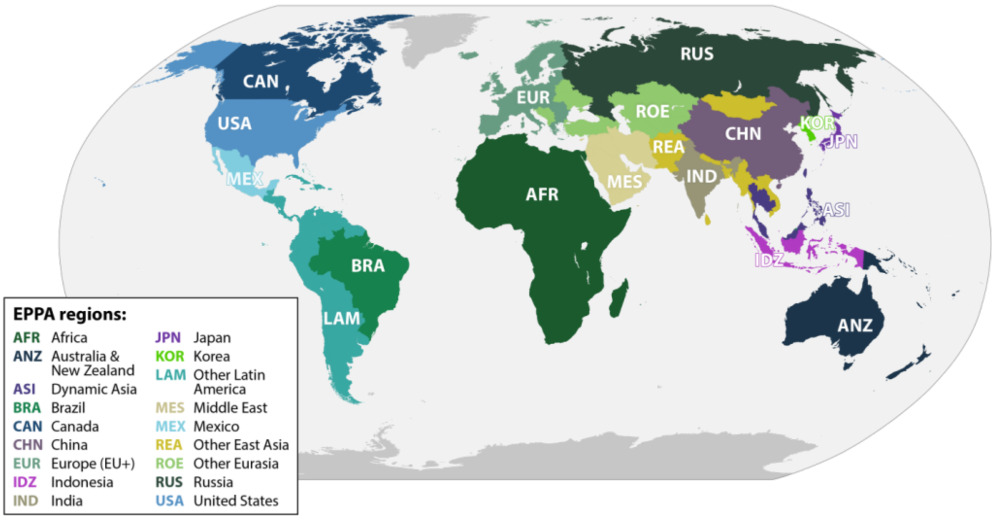


Figure 24: Regions in the EPPA model.

interactions among sectors (through inter-industry inputs) and regions (via bilateral trade flows). It simulates production in each region at the sectoral level. Sectoral output is produced from primary factors including multiple categories of depletable and renewable natural capital, produced capital, and labor (Table 25). Intermediate inputs to sectoral production are represented through a complete input-output structure. The EPPA model projects CO_2 emissions and other greenhouse gases (GHGs) such as methane, nitrous oxide, hydrofluorocarbons, perfluorocarbons and sulfur hexafluoride. The model also projects pollution emissions from sulfates, nitrogen oxides, black carbon, organic carbon, carbon monoxide, ammonia, and non-methane volatile organic compounds. Mitigation options are also represented in the model. [4]

[4]1 Natural Gas production includes production from conventional resources, shale gas, tight gas, coal-bed methane, and coal gasification.
2 Electricity production technologies include coal, natural gas, oil, advanced natural gas, advanced coal, hydro, nuclear, biomass, wind, solar, wind with natural gas backup, wind with biomass backup, advanced coal with carbon capture and storage, advanced natural gas with carbon capture and storage, and advanced nuclear.
3 Other Household Consumption is resolved at the production sectors level. Source: Adopted from Chen et al. (2015).

Sector		Primary Factor Inputs
Production Sectors		**Depletable Natural Capital**
Agriculture - Crops	CROP	Conventional Oil Resources
Agriculture - Livestock	LIVE	Shale Oil
Agriculture - Forestry	FORS	Conventional Gas Resources
Food Products	FOOD	Unconventional Gas Resources
Coal	COAL	Uranium Resources
Crude Oil	OIL	Coal Resources
Refined Oil	ROIL	Renewable Natural Capital
Natural Gas[1]	GAS	Solar Resources
Electricity[2]	ELEC	Wind Resources
Energy-Intensive Industries	EINT	Hydro Resources
Other Industries	OTHR	Land
Services	SERV	Produced Capital
Transport	TRAN	Conventional Capital (Bldgs & Mach.)
Household Sectors		Labor
Household Transport	HHTRAN	
Ownership of Dwellings	DWE	
Other Household Consumption[3]	HHOTHR	

Figure 25: Sectors and Factor Inputs in the EPPA model

C LCOE

For the overnight capital for biomass with CCS we start with the overnight cost for biomass (from EIA, 2015) then add an additional capital cost for CCS (888 in \$2014, from Cuellar & Herzog, 2015), and then adjust for the decrease in efficiency from adding CCS (which we assume drops from 30% to 20.2%, by applying the 9.8% efficiency penalty Rubin et al. 2015 found for adding CCS to pulverized coal to the 30% biomass efficiency from Cuellar & Herzog, 2015). Efficiencies are converted to heat rates by dividing the number of BTUs in one kWh of electricity (3412) by the efficiency. Fixed costs and variables costs come from EIA (2015) for biomass and from Cuellar and Herzog (2015) for biomass with CCS. The overnight cost and fixed costs for BIGCC with CCS are from Bibas and Mejean (2014), scaled by the ratio between EIA's costs for IGCC with CCS and those from Bibas and Mejean, which is 2.27 for overnight costs and 1.55 for fixed costs. The overnight cost and fixed costs for BIGCC are then the costs for BIGCC with CCS minus the difference in cost between IGCC with CCS and IGCC (from EIA, 2015). Variable costs for BIGCC are set equal to those for IGCC and for BIGCC with CCS are set equal to variables costs IGCC with CCS. Heat rate for BIGCC with CCS is from the 30% efficiency in Bibas and Mejean (2014), while the heat rate for BIGCC is equal to the heat rate of BIGCC with CCS divided by the ratio between IGCC with CCS and IGCC (1.12). The cost of transportation and storage of captured CO2 is assumed to be \$10/tonCO2, consistent with Hamilton (2009). The CO_2 transportation and storage cost per kWh is added to the LCOE. The fuel costs for the bioenergy technologies come from base year feedstock costs in the EPPA model. These feedstock costs vary by region as the biomass crop yields vary by regions. The following table includes the fuel cost for the U.S. as an example, for this work we use costs parameterized with an other model (see section 5.7.3).

		Units	New Pulverized Coal	Pulverized Coal with CCS	Biomass plant	Biomass plant with CCs	BIGCC	BIGCC with CCS	NGCC	NGCC with CCS	IGCC	IGCC with CCS	Advanced Nuclear	Wind	Solar Thermal	Solar PV	Wind Plus Biomass Backup [a]	Wind Plus Gas Backup [a]
[1]	"Overnight" Capital Cost	$/kW	2821	3850	3538	6507	5314	7988	983	2003	3604	6277	5189	1915	3918	3171	5452	2898
[2]	Total Capital Requirement	$/kW	3272	4620	4104	7809	6165	9585	1062	2244	4036	7533	7264	2068	4231	3424	5889	3130
[3]	Capital Recovery Charge Rate	%	10.6%	10.6%	10.6%	10.6%	10.6%	10.6%	10.6%	10.6%	10.6%	10.6%	10.6%	10.6%	10.6%	10.6%	10.6%	10.6%
[4]	Fixed O&M	$/kW	30.1	50.9	102.1	159.6	110.1	130.8	14.9	30.7	49.7	70.4	90.1	38.2	65.0	23.9	140.3	53.1
[5]	Variable O&M	$/kWh	0.0043	0.0055	0.0051	0.0063	0.0070	0.0082	0.0032	0.0066	0.0070	0.0082	0.0021	0.0000	0.0000	0.0000	0.0051	0.0032
[6]	Project Life	years	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20
[7]	Capacity Factor	%	85%	85%	80%	80%	80%	80%	85%	80%	80%	80%	85%	35%	35%	26%	42%	42%
[8]	Capacity Factor Wind																35%	35%
[9]	Capacity Factor Backup																7%	7%
[10]	Operating Hours	hours	7446	7446	7008	7008	7008	7008	7446	7008	7008	7008	7446	3066	3066	2277.6	3679.2	3679.2
[11]	Capital Recovery Required	$/kWh	0.0464	0.0656	0.0619	0.1177	0.0930	0.1445	0.0151	0.0338	0.0609	0.1136	0.1031	0.0713	0.1458	0.1589	0.1691	0.0899
[12]	Fixed O&M Recovery Required	$/kWh	0.0040	0.0068	0.0146	0.0228	0.0157	0.0187	0.0020	0.0044	0.0071	0.0100	0.0121	0.0125	0.0212	0.0105	0.0381	0.0144
[13]	Heat Rate	BTU/kWh	8740	10663	11373	16891	10200	11373	6333	7493	7450	8307	10479	0	0	0	11373	6333
[14]	Fuel Cost	$/MMBTU	3.15	3.15	2.61	2.61	2.61	2.61	8.18	8.18	3.15	3.15	0.50	0.00	0.00	0.00	2.61	8.18
[15]	Fraction Backup	%															8.8%	8.2%
[16]	Fuel Cost per kWh	$/kWh	0.0275	0.0336	0.0297	0.0441	0.0266	0.0297	0.0518	0.0613	0.0235	0.0262	0.0052	0.0000	0.0000	0.0000	0.0026	0.0043
[17]	Levelized Cost of Electricity	$/kWh	0.0823	0.1206	0.1112	0.2055	0.1423	0.2109	0.0720	0.1097	0.0984	0.1651	0.1225	0.0837	0.1670	0.1693	0.2149	0.1117
[18]	Transmission and Distribution	$/kWh	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.03	0.03
[19]	LCOE with T&D	$/kWh	0.1023	0.1406	0.1312	0.2255	0.1623	0.2309	0.0920	0.1297	0.1184	0.1851	0.1425	0.1037	0.1870	0.1893	0.2449	0.1417
[20]	Markup Over New Pulverized Coal		1.00	1.37	1.28	2.20	1.59	2.26	0.90	1.27	1.16	1.81	1.39	1.01	1.83	1.85	2.39	1.39

For CCS

		Units	Pulverized Coal with CCS	Biomass plant with CCs	BIGCC with CCS	NGCC with CCS	IGCC with CCS
[21]	Amount Fossil Fuel	EJ/KWh	1E-11	2E-11	1E-11	8E-12	9E-12
[22]	Carbon Content	mmtC/EJ	24.686	24.975	24.975	13.700	24.686
[23]	Carbon Emissions	mmtC/KWh	0.0000	0.0000	0.0000	0.0000	0.0000
[24]	Carbon Dioxide Emissions	tCO2/KWh	0.0010	0.0016	0.0011	0.0004	0.0008
[25]	CO2 Emissions after 90% Capture	tCO2/KWh	0.0001	0.0002	0.0001	4E-05	8E-05
[26]	Cost of CO2 T&S per ton	$/tCO2	10	10	10	10	10
[27]	CO2 Transportation &Storage Cost	$/KWh	0.0092	0.0147	0.0099	0.0036	0.0071

Figure 26: LCOE

A

Robust optimization

This chapter is devoted to briefly introduce Robust Optimization, a relatively recent methodology for handling optimization problems with uncertain data. In this part we do not compare RO to more traditional methodologies for handling data uncertainty as this is done in the thesis (see transition between chapter 2 and 3).
The rationale for robust optimization is the sensitivity of optimization models to data uncertainty. In Ben-tal and Nemirovski (2000), the authors show using NETLIB, a library of 90 linear programming problems from different applications of operations research, that a variation of only 0.01% of some coefficients was enough to result in constraint violations in more than 15% of the cases and when the variation reached 1%, almost a third of the cases were unfeasible. It leads the authors to conclude that "In real-world applications of Linear Programming one cannot ignore the possibility that a small uncertainty in the data (intrinsic for most real-world LP programs) can make the usual optimal solution of the problem completely meaningless from a practical viewpoint." The need to identify solutions that are immune to the actual realization of uncertain parameters explained the emergence of robust optimization.

Its first formulation by Soyster in 1973 has been since then largely improved. Soyster formulated the problem using a worst case approach to ensure that whatever the realization of the parameters in their uncertainty set, the problem would remain feasible hence introducing the idea of a robust constraint. This approach was condemned as it was considered too conservative.
Before Soyster, Abraham Wald already developed the "maximin" or "minimax" model in the context of game theory (Wald, 1945). The seminal paper of Ben-Tal & Nemirovski in (Ben-Tal and Nemirovski, 1998) is the first successful attempt to alleviate the conservatism of Soyster methodology and marks the beginning of the robust optimization revival. In this paper, the authors reintroduced the notion of robust convex optimization and show that when the uncertainty set is ellipsoidal, the robust counterpart of some of the well known convex optimization programs (LP, SDP...) is tractable and solvable in polynomial-time.
From that date on, the methodology gained interest and the number of works associated to this topic rose greatly as shown by the graphs on figure A.1 According to Delage (2015), the main reasons behind the rebirth of robust optimization are the following: (i) the discovery that when the uncertainty set is well chosen, the robust counterpart of the model is not much harder to solve than the initial problem, (ii) the computer science progresses as well as the apparition of fast method to solve convex optimization problems (other than linear) and (iii) the connection of robust optimization with the stochastic programming literature and the fact that RO is now

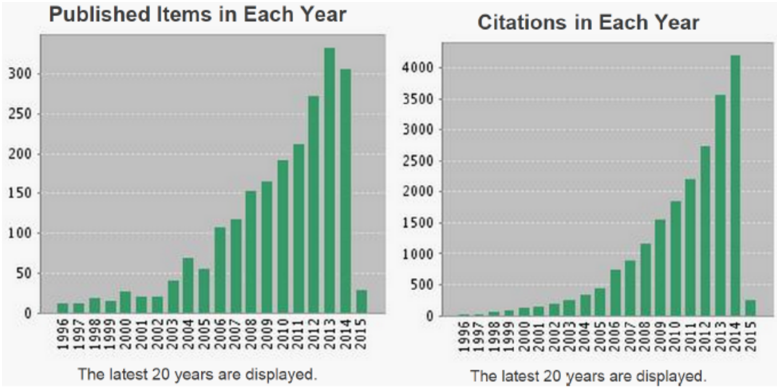


Figure A.1: Annual number of publications and new citations associated with Robust Optimization. Source: Delage, 2015

considered as a tractable way of solving a number of previously considered impossible stochastic programming models.
To these reasons, we can add the difficulty or the impossibility to calibrate a stochastic process when data are lacking (hence difficulty to apply stochastic programming techniques) and the fact that robust optimization offers parsimonious ways of dealing with problems of high dimensions requiring minimal information about the true probability distributions (Ben-tal and Nemirovski, 2002).

A.0.1 Robust optimization: general case

To present the general case, let's consider a decision model like the following:

$$\textbf{(P)} : \begin{cases} \min x f(x,a) \\ s.t.\ h_i(x,a) \geq 0, \forall i = 1,..,I \end{cases} \tag{A.1}$$

We wish to identify solutions (x being the vector of decision variables) that are "immunized" with respect to the actual realization of the parameters a, parameters affecting the solution and that can be uncertain.
Within the RO paradigm, we want to find solutions that are immunized against *any* realization of a in its uncertainty set A. We can then rewrite the previous problem to derive its robust counterpart:

$$\textbf{(P)} : \begin{cases} \min x \max a f(x,a) \\ s.t.\ h_i(x,a) \geq 0, \forall a in A, \forall i = 1,..,I \end{cases} \tag{A.2}$$

The two main issues of this formulation are: (i) how can we reformulate the robust counterpart to obtain a "computationally tractable" optimization problem or how we can approximate it by a tractable problem and (ii) how we can build reasonable uncertainty sets A. Ben-tal and Nemirovski (2002) provide answers to both question for particular cases: Linear, Conic Quadratic and Semidefinite Programming and work is still going on in the operations research community to extend their results and the RO scope. In what follows, we present the particular case of robust linear programming.

A.0.2 Mathematical formulation of robust linear programming

To introduce the mathematical representation of RO, we follow Bertsimas and Sim (2004) and consider the following linear problem:

$$\textbf{(P)} : \begin{cases} \min c^T x \\ s.t.\ Ax \leq b \\ x \in \mathbb{R}^n_+, A \in \mathbb{R}^{m*n} \end{cases} \tag{A.3}$$

As mentioned in the thesis introduction, while stochastic or Monte-Carlo frameworks require the definition of probability density functions, the principle of RO consists in set-based descriptions of uncertainties. As such, only the extent to which parameters are likely to vary needs to be known (although this information may be itself difficult to acquire). This corresponds to the support of the density functions.

We assume that the uncertainty only affects the coefficients $a_{i,j}$, $(i \in I, j \in J)$ of the matrix A and that all the coefficients are independent (for the sake of the exposition). The coefficients can vary in a symmetric range: $a_{i,j} \in [\overline{a_{i,j}} - \widehat{a_{i,j}}, \overline{a_{i,j}} + \widehat{a_{i,j}}]$ known by the decision maker, where $\overline{a_{i,j}}$ is the nominal value of the parameter and $\widehat{a_{i,j}}$ the uncertainty set half-length (and corresponds to the precision of the estimates). No specific probability distribution is needed.

The uncertainty budget

We can now introduce the parameter $\Gamma \in [0, |J|]$ named the budget of uncertainty whose role is to adjust the robustness of the methodology against the level of conservatism of the solution. By writing $a_{i,j} = \overline{a_{i,j}} + z_{i,j}\widehat{a_{i,j}}$, hence $z_{i,j} = \dfrac{a_{i,j} - \overline{a_{i,j}}}{\widehat{a_{i,j}}}$, $z_{i,j} \in [-1, 1]$ we can reformulate the problem (P) and write its robust counterpart (Prob):

$$\textbf{(Prob)} : \begin{cases} \min c^T x \\ s.t. \\ \sum\limits_j \overline{a_{i,j}} x_j + \max\limits_{z_{i,j}} \sum\limits_j z_{i,j} \widehat{a_{i,j}} x_j \leq b_i, \forall i \in I \\ |z_{i,j}| \leq 1, \forall i, j \\ \sum\limits_j |z_{i,j}| \leq \Gamma_i, \forall i \in I \\ x \in \mathbb{R}^n_+ \end{cases} \tag{A.4}$$

More generally, by limiting the number of parameters allowed to deviate or the extent of their cumulative deviation, Γ represents the degree of pessimism on the problem parameters. It relies on the fact that aggregate forecasts are usually more robust than individual ones as illustrated in the figure A.2.

In this figure, 1000 sample paths of a symmetric random walk are plotted over 100 time periods. At the beginning of the time horizon, when the uncertainty sources are not numerous (few time periods) the random walk is sometimes on its worst case path but as the uncertainty sources grow it is less and less frequent and the sample paths end up concentrated around the 0 mean value.

The concept of the uncertainty budget is based on the fact that it is highly unlikely that all the parameters take their worst case value at the same time. In the cases where Γ is an integer, it limits the number of parameters allowed to deviate. Its two extreme values are interesting as for $\Gamma_i = 0$, the robust problem is identical to the nominal one and for $\Gamma_i = |J|$, it is equal to the "worst case" problem (and we are back to the Soyster solution).

Linearization of the robust counterpart

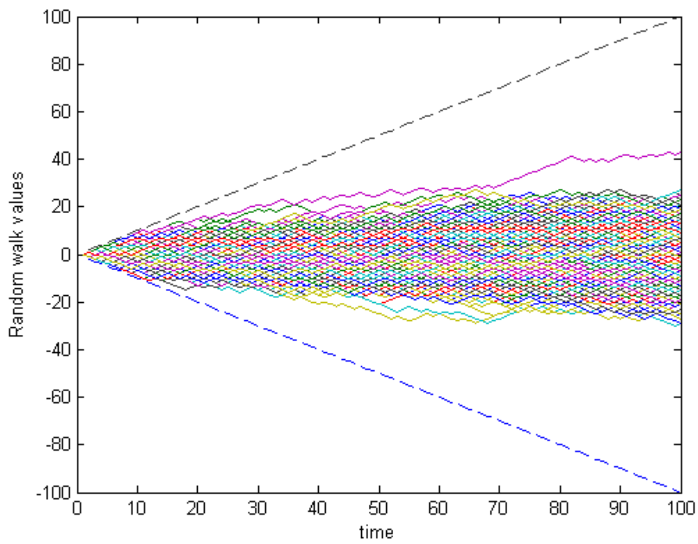


Figure A.2: Sample paths of a symmetric random walk

The problem (Prob) in its actual form is not linear. This issue can be overcome by reformulating it using the dual problem. Indeed, using strong duality arguments, the maximization problem in the constraint becomes a minimization problem (the dual and the primal feasible solutions are equal, the duality gap is nil).
We have $\forall i \in I$, the primal of the subproblem (P2) and its dual (D2) :

$$\textbf{(P2)} : \begin{cases} \max\limits_{z} \sum\limits_{j} z_{i,j}\widehat{a_{i,j}}x_j^* \\ \text{s.t.} \\ 0 \leq z_{i,j} \leq 1, \forall j \qquad (\mu) \\ \sum\limits_{j} z_{i,j} \leq \Gamma_i, \qquad (\lambda) \end{cases} \qquad \textbf{(D2)} : \begin{cases} \min\limits_{\lambda,\mu} \lambda_i\Gamma_i + \sum\limits_{j} \mu_{i,j} \\ \text{s.t.} \\ \lambda_i + \mu_{i,j} \geq \widehat{a_{i,j}}x_j^*, \forall j \\ \lambda_i \in \mathbb{R}_+, \mu_{i,j} \in \mathbb{R}_+ \end{cases} \tag{A.5}$$

The dual problem can be re-injected into the original problem allowing us to reformulate the robust problem (Prob) as a usual linear programming problem:

$$\textbf{(Prob)} : \begin{cases} \min c^T x \\ s.t. \\ \sum_j \overline{a_{i,j}}x_j + \lambda_i\Gamma_i + \sum_j \mu_{i,j} \leq b_i, \forall i \in I \\ \lambda_i + \mu_{i,j} \geq \widehat{a_{i,j}}x_j^*, \forall j \in J, \forall i \in I \\ \lambda_i \in \mathbb{R}_+, \mu_{i,j} \in \mathbb{R}_+ \\ x \in \mathbb{R}_+^n \end{cases} \tag{A.6}$$

Hence, the robust counterpart of the problem (P) is still a linear programming problem (a little bit bigger) and conserves the good properties of this class of model in terms of tractability and computational time (Bertsimas and Thiele, 2006). Note that the case with $x \in \mathbb{R}$ is a little less

straightforward[1].
The formulation above allows also to consider uncertain parameters in the objective function as we can always rewrite the problem with an auxiliary variable (e.g α) and minimize α subject to an additional constraint that we could make robust :

$$\min_{\alpha,x} \left\{\alpha : c^T x \leq \alpha, Ax \leq b, x \in \mathbb{R}^n_+\right\} \tag{A.8}$$

In the case presented here, the uncertainty set is polyhedral but the methodology can be generalized to convex uncertainty sets (ellipsoidal for example). For more details on the general formulation, proofs and applications to non linear programming see Ben-tal et al. (2009), Delage (2015).

A.0.3 Economic interpretation

In this section, we try to understand how we can interpret the robust optimization methodology in terms of hedging, insurance and costs and what it means to have a solution "more robust".
The uncertainty introduction leads to a "degradation" of the objective function (as new constraints are added to the program). The extra system cost due to robustness can be measured (for a given value of Γ and a maximum deviation of a) as the difference between the two optimal objective functions (the deterministic and the robust ones).
In the deterministic case, for the problem (P), we can write the optimal objective function as: $f^*_{det} = g(c, \overline{a}, b)$. In the case of (Prob), the expression is a little bit different as it is a linear function of λ and μ also: $f^*_{rob} = h(c, \overline{a}, b, \widehat{a}, \lambda, \mu, \Gamma)$.
In short the robust objective function integrates the cost linked to a change in the technological variables and a cost linked to the diversification to hedge against the uncertainty.
It is much clearer in the case where the objective function parameters are uncertain. If we go back to the last example with cost uncertainty,

$$(P_{rob}) : \begin{cases} \min \alpha \\ s.t.\ c^T x + \lambda\Gamma + e^T \mu \leq \alpha \\ Ax \leq b\ (y) \\ \lambda + \mu_j \geq \widehat{c_j} x_j, \forall j \in J\ (z_j) \\ x \in \mathbb{R}^n_+, \lambda \in \mathbb{R}_+, \mu \in \mathbb{R}_+ \end{cases} \tag{A.9}$$

the difference between the optimal robust and deterministic objective functions is the following:

$$\Delta_{rob} = \underbrace{[\overline{c}^T (x^*_{rob} - x^*_{det})]}_{\text{Technical substitutions}} + \underbrace{[\lambda^* \Gamma + \sum_j \mu^*_j]}_{\text{captive costs}} \tag{A.10}$$

---

[1] The case with $x \in \mathbb{R}$ is a little less straightforward, we have $\forall i \in I$:

$$\textbf{(P2)} : \begin{cases} \max\limits_{z} \sum\limits_j z_{i,j} \widehat{a_{i,j}} x^*_j \\ \text{s.t.} \\ |z_{i,j}| \leq 1, \forall j \\ \sum\limits_j |z_{i,j}| \leq \Gamma_i \end{cases} \Leftrightarrow \begin{cases} \max\limits_{z} \sum\limits_j z_{i,j} \widehat{a_{i,j}} y_j \\ \text{s.t. } 0 \leq z_{i,j} \leq 1, \forall j \\ \sum\limits_j z_{i,j} \leq \Gamma_i, \\ -y_j \leq x^*_j \leq y_j \\ y \in \mathbb{R}^n_+ \end{cases} \textbf{(D2)} : \begin{cases} \min\limits_{\lambda,\mu} \lambda_i \Gamma_i + \sum\limits_j \mu_{i,j} \\ \text{s.t.} \\ \lambda_i + \mu_{i,j} \geq \widehat{a_{i,j}} y_j, \forall j \\ -y_j \leq x^*_j \leq y_j, \forall j \\ \lambda_i \in \mathbb{R}_+, \mu_{i,j} \in \mathbb{R}_+ \\ y \in \mathbb{R}^n_+ \end{cases} \tag{A.7}$$

The whole Δ_{rob} can be interpreted as a risk premium against the level of robustness determined by the couple (Γ, U) where U is the uncertainty set in which cost deviations take values.
More precisely, the first bracketed term of Δ_{rob} accounts for the technical substitution cost due to uncertainty. It is linked to the technical substitutions operated in the energy system as a hedging strategy against a potential increase of some technology costs (the most sensitive ones). The second bracketed term consists in a pure financial cost, in the sense that it comes straightforwardly from the use of technologies that will be used although their cost may increase (in other words, the less substitutable technologies). It is the unavoidable cost the system will have to "support" if the most sensitive costs deviate. These unavoidable costs can be explained by previous investments in technology sensitive to cost uncertainty or by the fact that no alternative to these technologies/ energy sources are present in the model.

Second, we shall observe that varying the uncertainty budget actually corresponds to endogenously varying the costs coefficients of the objective function. At optimum, using the primal form of the deviation sub-problem, we get the following expression for the objective function : $f^*_{rob} = (\bar{c}_J + z^* \widehat{c}_J)^T x^*_J + \bar{c}^T_{\overline{J}} x^*_{\overline{J}}$,
where J and $\overline{J}$ are the sets of respectively the deviated costs and the ones that stay nominal at the optimum. This means that at optimum, the relative costs come as a solution of the problem. The term $(\overline{c_J} + z^* \widehat{c_J})$ corresponds to risk-adjusted costs according to a worst-case logic. The dual version of this observation is equally meaningful; the shadow prices of the technical constraints are now related by $\overline{c_J} + z^* \widehat{c_J} - A^T y \geq 0$ which means that the shadow prices of the commodities are likewise risk-adjusted for the pair (Γ, U).
This has an important implication: in the process of varying the uncertainty budget, we somehow endogenously generate different relative cost systems on the basis of a risk assessment (defined by the deviation subproblem). This interpretation gives a sense to performing a systematic sensitivity analysis on the uncertainty budget Γ, because it allows to test the model response to various cost regimes[2].

Risk preferences, risk measures
Finally, when it comes to uncertainty, one naturally expects to find some connections with *risk preferences*. A relationship exists between robust linear programs and risk-averse optimization; the link relies on the analysis of the uncertainty sets of the robust programs with respect to specific families of risk measures (Bertsimas and Brown, 2009, Natarajan et al., 2009). Taking risk measures as primitives, Bertsimas and Brown (2009) construct corresponding convex uncertainty sets for various class of risk measures (coherent risk measure, distortion risk measure). They show in particular that the entire space of polyhedral uncertainty sets can be generated by the class of CVaR [3] risk measures. Natarajan et al. (2009) perform the opposite exercise and try to find a correspondence between uncertainty sets regularly used in robust optimization (ellipsoidal, polyhedral, moment cone) and risk measures. They then propose a method for constructing coherent risk measure when the uncertainty set is known.

[2]Other approaches, e.g. Bertsimas and Sim (2004), Poss (2014), address the determination of an optimal uncertainty budget

[3]The CVaR is defined as the expected value of losses beyond the Value-at-Risk of a given position. The VaR itself is the value of losses that can be guaranteed at a given level, e.g. 95%. See Natarajan et al. (2009) for a proof in the case of a discrete uniform distribution, and Bertsimas and Brown (2009) in the general case.

Formally, the robust program (P_{rob}) defined above is equivalent to the risk-averse problem:

$$(P_{r_a}) : \begin{cases} \min \alpha \\ s.t.\ \rho_{r-a}(\alpha - \tilde{c}^T x) \leq 0 \\ Ax \leq b \\ x \in \mathbb{R}^n_+ \end{cases} \tag{A.11}$$

where ρ_{r-a} is a coherent[4] risk measure (Artzner et al., 1999), generated by a combination of Conditional-Value-at-Risk measures.
In the context of dynamic programming, Iyengar (2005) demonstrates that robust dynamic programming with dynamic uncertainty is equivalent to zero-sum games with perfect information. [5]

[4]A coherent risk- measure respects the following axioms: translation invariance, subbaditivity, positive homogeneity and monotonicity which ensure its convexity preservation.

[5]For applications of the RO methodolgy, see: Adida and Perakis (2005), Thiele and Bertsimas (2006), Andrey et al. (2015) for intertemporal problem, see Atamtürk and Zhang (2007), Zhao and Zeng (2012), Zeng and Zhao (2013) for two-stage problems , for robust dynamic programming see Iyengar (2005), Nilim and El Ghaoui (2005), for robust combinatorial optimization see Poss (2013)

Bibliography

Adida, E., Perakis, G., dec 2005. A Robust Optimization Approach to Dynamic Pricing and Inventory Control with no Backorders. Mathematical Programming 107 (1-2), 97–129.

Andrey, C., Babonneau, F., Haurie, A., Labriet, M., 2015. Modélisation stochastique et robuste de l'atténuation et de l'adaptation dans un système énergétique régional. Application à la région Midi-Pyrénées. Natures Sciences Sociétés 23 (2), 133–149.

Artzner, P., Delbaen, F., EBER Société Générale, J.-m., David Heath, P., 1999. Coherent Measures of Risk. Mathematical Finance 9 (3), 203–228.

Atamtürk, A., Zhang, M., aug 2007. Two-Stage Robust Network Flow and Design Under Demand Uncertainty. Operations Research 55 (4), 662–673.

Ben-tal, A., El Ghaoui, L., Nemirovski, A., 2009. Robust Optimization.

Ben-Tal, a., Nemirovski, A., 1998. Robust Convex Optimization. Mathematics of Operations Research 23 (4), 769–805.

Ben-tal, A., Nemirovski, A., 2000. Robust solutions of Linear Programming problems contaminated with uncertain data. Mathematical Programming 88 (3), 411–424.

Ben-tal, A., Nemirovski, A., 2002. Robust Optimization — Methodology and Applications. Mathematical Programming 92 (3), 453–480.

Bertsimas, D., Brown, D. B., dec 2009. Constructing Uncertainty Sets for Robust Linear Optimization. Operations Research 57 (6), 1483–1495.

Bertsimas, D., Sim, M., feb 2004. The Price of Robustness. Operations Research 52 (1), 35–53.

Bertsimas, D., Thiele, A., feb 2006. A Robust Optimization Approach to Inventory Theory. Operations Research 54 (1), 150–168.

Delage, E., 2015. Quantitative Risk Management Using Robust Optimization.

Iyengar, G. N., may 2005. Robust Dynamic Programming. Mathematics of Operations Research 30 (2), 257–280.

Natarajan, K., Pachamanova, D., Sim, M., 2009. Constructing Risk Measures from Uncertainty Sets. Operations Research 57 (5), 1129–1141.

Nilim, A., El Ghaoui, L., oct 2005. Robust Control of Markov Decision Processes with Uncertain Transition Matrices. Operations Research 53 (5), 780–798.

Poss, M., 2013. Robust combinatorial optimization with variable budgeted uncertainty. 4or 11 (1), 75–92.

Poss, M., sep 2014. Robust combinatorial optimization with variable cost uncertainty. European Journal of Operational Research 237 (3), 836–845.

Thiele, A., Bertsimas, D., 2006. Robust and data-driven optimization- modern decision-making under uncertainty. INFORMS Tutorials in Operations Research: Models, Methods and Applications for Innovative Decision Making.

Wald, A., 1945. Statistical decision functions which minimize the maximum risk. The Annals of Mathematics 46 (2), 265–280.

Zeng, B., Zhao, L., sep 2013. Solving two-stage robust optimization problems using a column-and-constraint generation method. Operations Research Letters 41 (5), 457–461.

Zhao, L., Zeng, B., 2012. An Exact Algorithm for Two-stage Robust Optimization with Mixed Integer Recourse Problems (1), 1–20.