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Document de Travail
Working Paper
2016-29

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

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Highlights

• We assess the impact of cost uncertainty on energy transition pathways in the French transportation sector by 2050.
• We introduce in a simple French energy system model (Times paradigm) recent robust optimization techniques.
• We account for uncertainty for both primary energy costs and technology costs, using two different models of uncertainty propagation.
• We find original results regarding total system costs and technology diversification.

Abstract

To improve energy security and ensure the compliance with stringent climate goals, the European Union is willing to step up its efforts to accelerate the development and deployment of electrification, and in general, of alternative fuels and propulsion methods. Yet, the costs and benefits of imposing norms on vehicle or biofuel mandates should be assessed in light of the uncertainties surrounding these pathways, in terms of e.g. cost of these new technologies. By using robust optimization, we are able to introduce uncertainty simultaneously on a high number of cost parameters without notably impacting the computing time of our model (a French TIMES paradigm model). To account for the different nature of the uncertain parameters we model two kinds of uncertainty propagation with time. We then apply this formal setting to French energy system under carbon constraint. 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. 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.

Keywords: Robust optimization; Climate change; Energy transition; Transportation policy
JEL classification: C61, O33, Q47, R40

☆We are grateful to xxxx and yyyy for insightful comments and suggestions. Of course, any remaining errors are ours. The views expressed herein are strictly those of the authors and are not to be construed as representing those of IFP Énergies Nouvelles.

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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 to (i): reduce its Greenhouse gas (GHG) emissions by 20% below 1990 levels for the year 2020, (ii): get a 20% improvement in energy efficiency and (iii): 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 the 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 debates 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 fuel decarbonization, and a better management of the mobility demand are the three levers countries can use to abate CO_2 emissions (Alazard-Toux et al., 2015, 2014) and to conjointly reach other objectives, such 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 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 simulations 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. Pragmatically, 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 embraces 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, tech-

nology 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 in ways the stochastic optimization has more difficulty doing (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. In the transportation sector, low-carbon alternatives (CNG, electricity) appear consistently as hedges against cost variations, along with biofuels. Yet, as uncertainty increases technological diversification is close to the one of the deterministic case. At a more macro level, uncertainty introduction leads to an increase of the total system cost; which is partly due to technological substitutions taking 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.

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.

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, such as 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 the 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).

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 no matter the parameter realization in the set. The major modeling 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:

$$\textbf{(P)} : \begin{cases} \min c^T x \\ s.t.\ Ax \leq b \\ x \in \mathbb{R}^n_+, A \in \mathbb{R}^{m*n} \end{cases} \tag{1}$$

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):

$$\textbf{(Prob)} : \begin{cases} \min c^T x \\ s.t. \\ \sum\limits_j \overline{a_{i,j}} x_j + \max\limits_{z_{i,j}} \sum\limits_j z_{i,j}\widehat{a_{i,j}} x_j \leq b_i, \forall i \in I \\ |z_{i,j}| \leq 1, \forall i, j \\ \sum\limits_j |z_{i,j}| \leq \Gamma_i, \forall i \in I \\ x \in \mathbb{R}^n_+ \end{cases} \tag{2}$$

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) :

$$\textbf{(P2)} : \begin{cases} \max\limits_z \sum\limits_j z_{i,j}\widehat{a_{i,j}} x^*_j \\ \text{s.t.} \\ 0 \leq z_{i,j} \leq 1, \forall j & (\mu) \\ \sum\limits_j z_{i,j} \leq \Gamma_i, & (\lambda) \end{cases} \qquad \textbf{(D2)} : \begin{cases} \min\limits_{\lambda,\mu} \lambda_i \Gamma_i + \sum\limits_j \mu_{i,j} \\ \text{s.t.} \\ \lambda_i + \mu_{i,j} \geq \widehat{a_{i,j}} x^*_j, \forall j \\ \lambda_i \in \mathbb{R}_+, \mu_{i,j} \in \mathbb{R}_+ \end{cases} \tag{3}$$

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:

$$\textbf{(Prob)} : \begin{cases} \min c^T x \\ s.t. \\ \sum_j \overline{a_{i,j}} x_j + \lambda_i \Gamma_i + \sum_j \mu_{i,j} \leq b_i, \forall i \in I \\ \lambda_i + \mu_{i,j} \geq \widehat{a_{i,j}} x_j, \forall j \in J, \forall i \in I \\ \lambda \in \mathbb{R}_+, \mu \in \mathbb{R}_+ \\ x \in \mathbb{R}_+^n \end{cases} \tag{4}$$

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 the problem is always re-writable with an auxiliary variable (e.g α) and we can minimize α subject to an additional constraint that we could make robust:

$$\min_{\alpha,x} \left\{ \alpha : c^T x \leq \alpha, Ax \leq b, x \in \mathbb{R}_+^n \right\} \tag{5}$$

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 is 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 cost 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). In the long-run, technology investment costs depend on the intensity and effectiveness of R&D, learning effects, costs of raw materials, or organizational issues Alazard-Toux et al. (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 inter-temporal perspective on uncertainty propagation (figure 1, left-hand side);
- *persistent, inter-temporal 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 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 (see below).

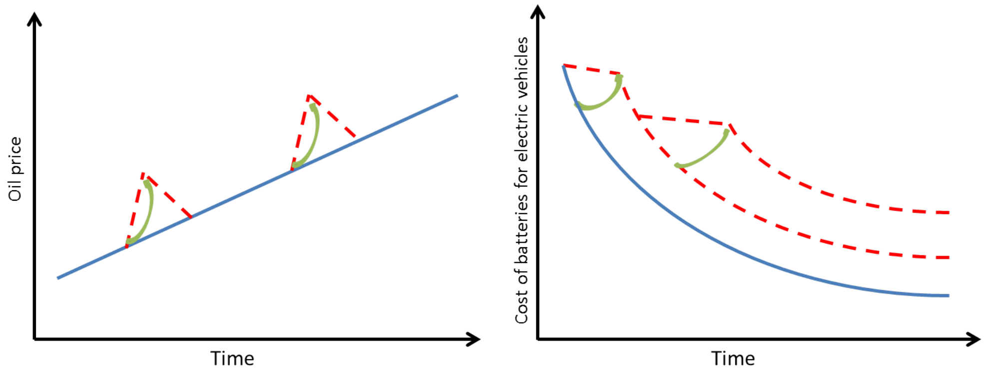


Figure 1: Uncertainty models: transitory (left-hand side) and permanent (right-hand side)

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).
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:

$$(P_{rob}): \begin{cases} \min \alpha \\ s.t.\ c^T x + \lambda\Gamma + e^T\mu \leq \alpha \\ Ax \leq b\ (y) \\ \lambda + \mu_j \geq \widehat{c}_j x_j, \forall j \in J\ (z_j) \\ x \in \mathbb{R}^n_+, \lambda \in \mathbb{R}_+, \mu \in \mathbb{R}_+ \end{cases} \tag{6}$$

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

$$\Delta_{rob} = \underbrace{[\bar{c}^T(x^*_{rob} - x^*_{det})]}_{\text{Technical substitutions}} + \underbrace{[\lambda^*\Gamma + \sum_j \mu^*_j]}_{\text{Captive costs}} \tag{7}$$

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:
$f^*_{rob} = (\bar{c}_J + z^*\widehat{c}_J)^T x^*_J + \bar{c}^T_{\bar{J}} x^*_{\bar{J}}$,
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 sub-problem). 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 with various cost regimes[1].

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

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*.

2.4. Robust optimization: Integration in an inter-temporal 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 (inter-temporal optimization under perfect foresight), the decision has to be made before the realization of the parameters is known (here and now decisions). Since the whole model is inter-temporal, we must discuss how the uncertainty propagates.
In what follows, we will see different ways of allowing uncertainty to propagate over time.
As a general introduction, we shall formulate the original LP model in its inter-temporal shape as follows:

$$\mathbf{(P)}: \begin{cases} \min \sum_{t\in\tau}\sum_{j\in J} c_{j,t}x_{j,t} \\ s.t.\ Ax \leq b \\ x \in \mathbb{R}^n_+, A \in \mathbb{R}^{m*n} \end{cases} \tag{8}$$

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 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 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 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, inter-temporal 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

$$
\textbf{(P)}: \begin{cases} \max\limits_z \sum_{t\in\tau} \sum_{j\in J_t} z_{j,t}\hat{c}_{j,t}x_{j,t} \\ s.t.\ z_{j,t} \leq 1,\ \forall (t,j) \in \tau \times J_t^{NP},\ (\mu_{j,t}) \\ \sum_{j\in J_t} z_{j,t} \leq \Gamma_t,\ \forall t \in \tau,\ (\lambda_t) \\ \sum_{t\in\tau} z_{j,t} \leq \Gamma^j,\ \forall j \in J_t^{NP},\ (\lambda^j) \\ x_{j,t} \in \mathbb{R}^+, \forall (j,t) \end{cases} \tag{9}
$$

  The dual version of this problem is then

$$
\textbf{(P)}: \begin{cases} \min\limits_{\mu,\lambda} \sum_{t\in\tau} \Gamma_t\lambda_t + \sum_{j\in J_t} \Gamma^j\lambda^j + \sum_{t\in\tau}\sum_{j\in J_t} \mu_{j,t} \\ s.t.\ \mu_{j,t} + \lambda_t + \lambda^j \geq \hat{c}_{j,t}x_{j,t},\ \forall (t,j) \in \tau \times J_t^{NP},\ (z_{j,t}) \end{cases} \tag{10}
$$

  Here, we use the two kinds of uncertainty budgets, one inter-temporal 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

$$
\textbf{(P)}: \begin{cases} \max\limits_z \sum_{t\in\tau} \sum_{j\in J_t} \sum_{t'\leq t} z_{j,t'}\hat{c}_{j,t'}x_{j,t} \\ s.t.\ z_{j,t} \leq 1,\ \forall (t,j) \in \tau \times J_t^{P},\ (\mu_{j,t}) \\ \sum_{j\in J_t} z_{j,t} \leq \Gamma_t,\ \forall t \in \tau,\ (\lambda_t) \\ \sum_{t\in\tau} z_{j,t} \leq \Gamma^j,\ \forall j \in J_t^{P}\ (\lambda^j) \\ x_{j,t} \in \mathbb{R}^+, \forall (j,t) \end{cases} \tag{11}
$$

  This yields the following dual formulation:

$$
\textbf{(P)}: \begin{cases} \min\limits_{\mu,\lambda} \sum_{t\in\tau} \Gamma_t\lambda_t + \sum_{j\in J_t} \Gamma^j\lambda^j + \sum_{t\in\tau}\sum_{j\in J_t} \mu_{j,t} \\ s.t.\ \mu_{j,t} + \lambda_t + \lambda^j \geq \hat{c}_{j,t}\sum_{t'\geq t} x_{j,t'},\ \forall (t,j) \in \tau \times J_t^{NP},\ (z_{j,t}) \end{cases} \tag{12}
$$

The final cost-robust problem takes the form :

$$
(P_{rob}): \begin{cases} \min\limits_{x,\lambda,\mu} \sum_{t\in\tau}\sum_{j\in J} c_{j,t}x_{j,t} + \sum_{t\in\tau} \Gamma_t\lambda_t + \sum_{j\in J_t} \Gamma^j\lambda^j + \sum_{t\in\tau}\sum_{j\in J_t} \mu_{j,t} \\ s.t.\ Ax \leq b \\ \mu_{j,t} + \lambda_t + \lambda^j \geq \hat{c}_{j,t}x_{j,t}, \forall (t,j) \in \tau \times J_t^{NP} \\ \mu_{j,t} + \lambda_t + \lambda^j \geq \hat{c}_{j,t}\sum_{t'\geq t} x_{j,t'}, \forall (t,j) \in \tau \times J_t^{P} \\ x \in \mathbb{R}_+^n, A \in \mathbb{R}^{m*n} \end{cases} \tag{13}
$$

3. Implementation in an energy-transport system model

3.1. MIRET

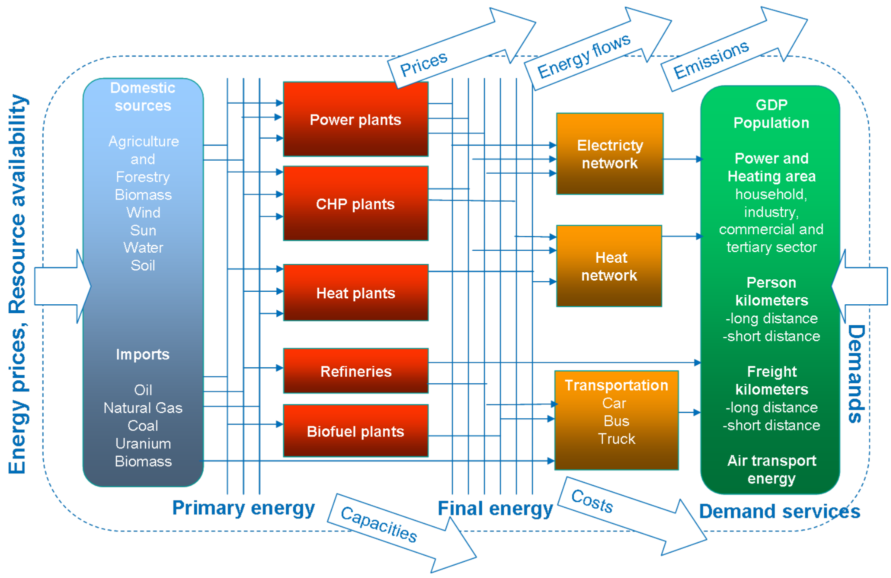
In this section, we present MIRET, a TIMES model developed by IFPEN.
TIMES (The Integrated MARKAL-EFOM System) is a technology rich, bottom-up model generator, which uses linear-programming to produce a least-cost energy system, optimized according

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 inter-temporal 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 a base year. MIRET was developed by IFPEN[3], and has been used in national case studies (Alazard-Toux et al., 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 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 2 diagram: primary energy supply, technology, final energy/energy services demand and policy.

Figure 2: Model schematics



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

[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.

- *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.

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. 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.

3.2. 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).
Fossil fuel price scenarios

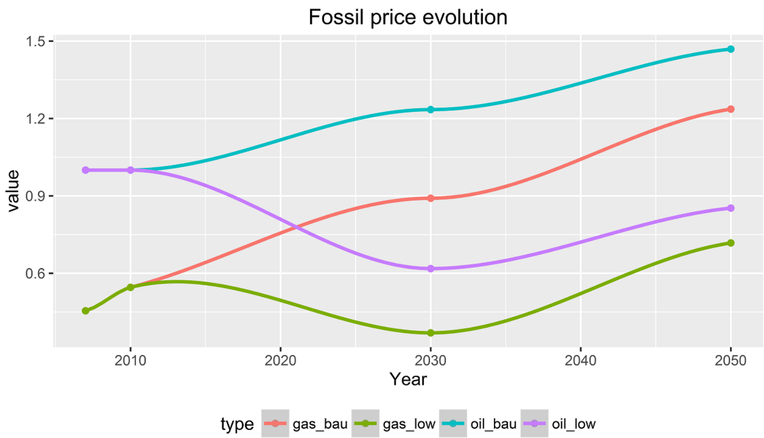


Figure 3: Oil and gas prices evolution

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 standpoint, this scenario takes into account the return of Iran in the global 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 non-conventional oil production 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 anticipates a conflict resolution in the medium-term in Libya, in Syria and in Iraq, a strong ability for producing countries facing financial turmoil since 2015 (OPEC

countries, Brazil, Russia ...) to maintain political stability, and a favorable economic investment and diversification process despite the strong collapse of 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, at around 2.5%, driven by Asia, Africa and Latin America. In this context, global oil demand will not record any major rebound and will remain at 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 subsidy 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 until 2050. On the supply side, the oil market experienced a sharp collapse of the prices between June 2014 and early 2016 which induced 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 thus decide to end this market share gains policy with the implementation of a new agreement on the level of production within the organization. These factors - cyclic shift investment and production agreement in the OPEP - restrict the possibilities of a sharp rebound in oil supply.
On 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 down and operates its transition to a low carbon economy, but its economic and demographic weight still continues 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. 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 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 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 and Freight)	Investment Cost	Propagation
	Power plants	Investment Cost	Propagation

Table 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. Thus we only have one parameter, Γ, that controls the "level of uncertainty" in the model.

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.

4.1. Robustness cost

Uncertainty introduction leads to a higher total system cost. On figure 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 budget

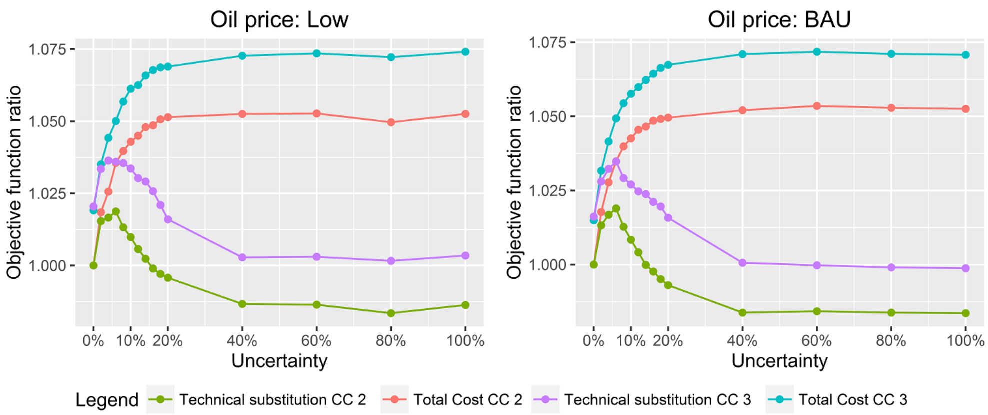


Figure 4: Total system cost evolution with uncertainty

is low and reaches an asymptote for a budget of 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 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 though their cost deviates and the "captive cost" share of the total cost increases with Γ.
The captive cost is quite low but not null 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 neither lead to an early-scrapping of all diesel and gasoline cars nor will it lead to a huge investment in biofuel production facilities, at least not in the short term).
Unsurprisingly, the objective function's shape is concave but more remarkably the cost decomposition's shape is also rather concave. One of the standard 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%).

[4]as described in 2.3, Total Cost Ratio: $TCR_{\Gamma,oilprice,Cap} = \dfrac{TC_{\Gamma,oilprice,Cap}}{TC_{0\%,oilprice,2}}$, Technical Substitutions ratio: $TSR_{\Gamma,oilprice,Cap} = \dfrac{\sum_t \overline{c_t}(x_t^*(\Gamma) - x_t^*(0\%))}{TC_{0\%,oilprice,2}} + 1$

4.2. Cost parameters

With the RO approach, we are able to rank the cost parameters by sensitivity. To observe which of the parameters are most sensitive, we look at the value of μ, the marginal value of the first constraint in the primal of 3. The higher the μ value, the higher the model sensitivity to this parameter. The sum of μ is also part of the robust objective function, it is expressed in euros and represents part of the additional robustness cost.
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 of the scenario studied (see figure 5).

On this figure, we plotted for the scenario BAU CC2: $\mu(i) = \sum_{j \in I} \mu(j)$, where I are the 5

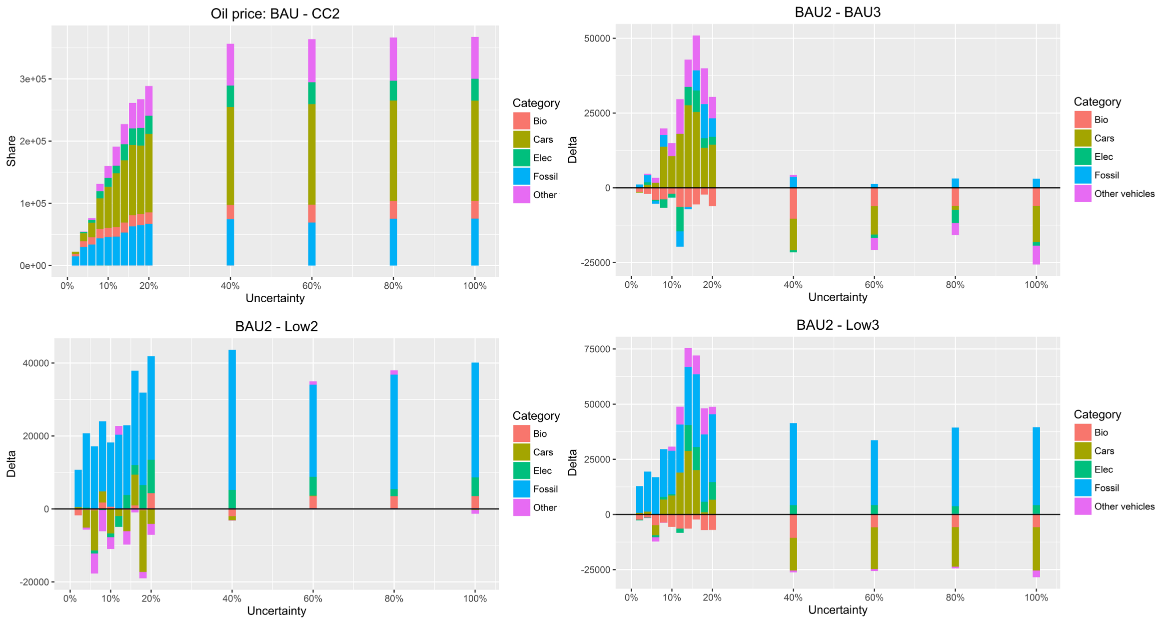


Figure 5: Weight of the cost parameters for different values of the uncertainty budget for the BAU CC2 case (top left) - Weight difference with BAU CC2 for the other scenarios

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 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 $\Gamma = 1.90\%$, 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.

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 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 scenario, the

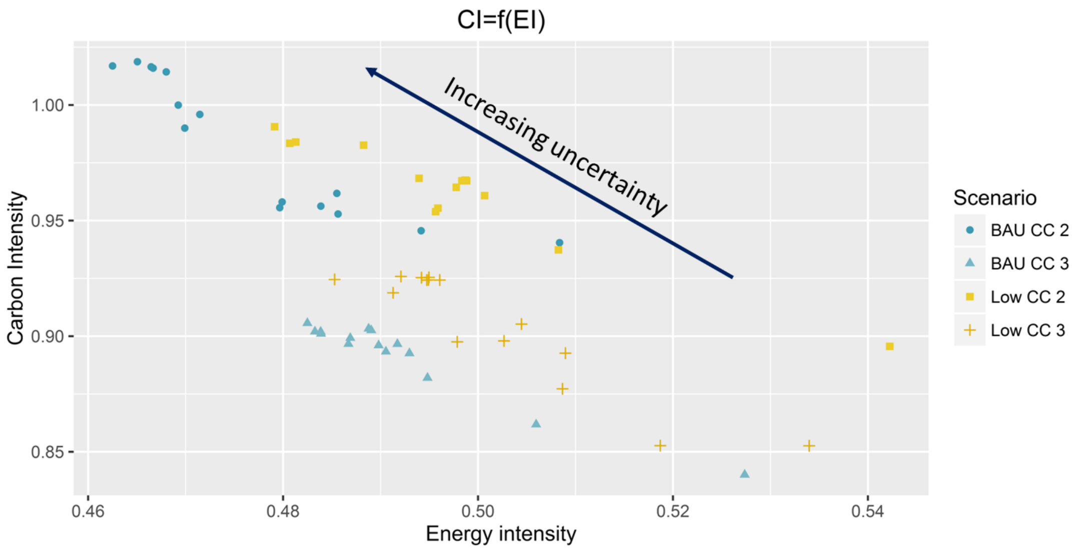


Figure 6: Carbon intensity (2010 normalized) as a function of French energy intensity of GDP (2010 normalized) for various values of the uncertainty budget in 2050

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 no matter 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 much less efficient than the 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 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 8 what we can call HHI_{act}:

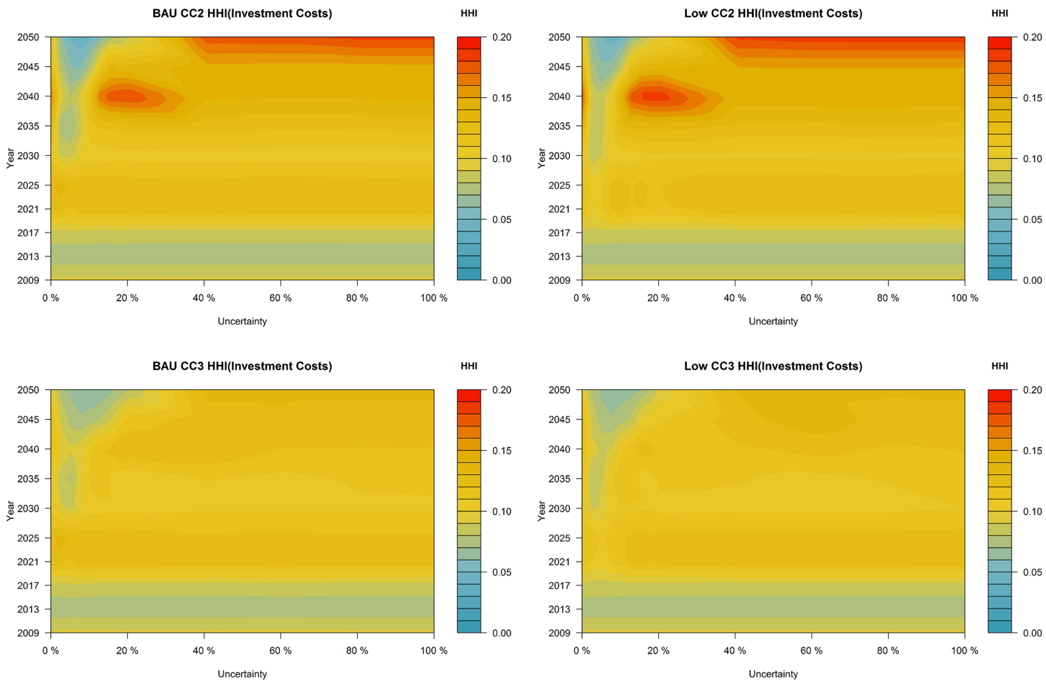


Figure 7: Diversification of investments with uncertainty and time

$HHI_{act} = \sum_i \frac{Activity(i)^2}{(TotalTranportACtivity)^2}$, 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 will 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 is inferior to 15%. For the low carbon constraint (CC2), the diversification exists, but it is not really high, while for the stringent carbon constraint (CC3), diversification is really present at the end of the period, and this is true irrespective of the uncertainty value.

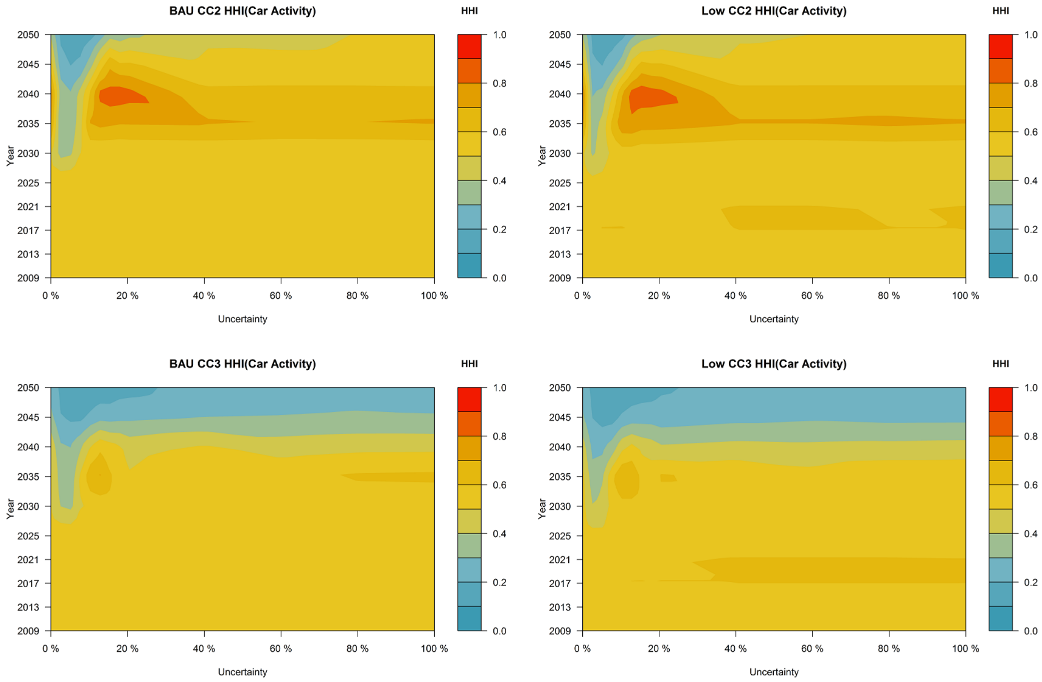


Figure 8: Transportation technology diversification with uncertainty and time

4.4. Transportation sector: transition pathways

The implementation of the technological diversification at the sectoral level 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 9 plots the car activity by technology in millions of passengers/km. In 2035, no matter 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 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 reasons why these two technologies penetrate the market simultaneously and quite fast. On the figure 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

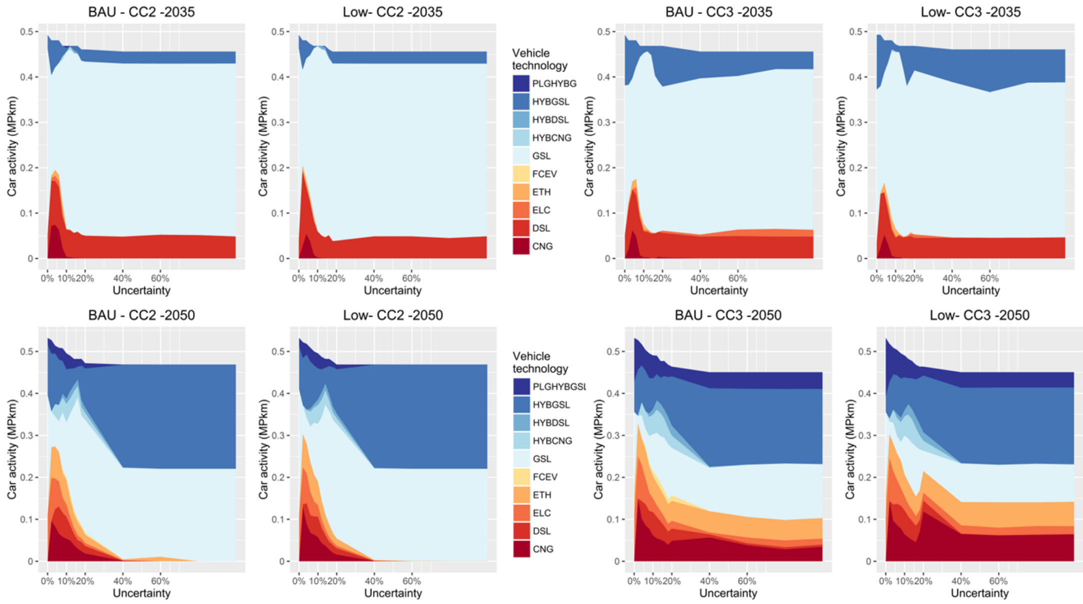


Figure 9: Car activity by technology in 2035 and 2050

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. Yet, with the CC3 ceiling, liquid fuel consumption is more important when the fossil price is low and especially diesel consumption.

For all scenarios, the introduction of biofuels occurs mostly in the commercial fleet, where substitution options are very expensive.

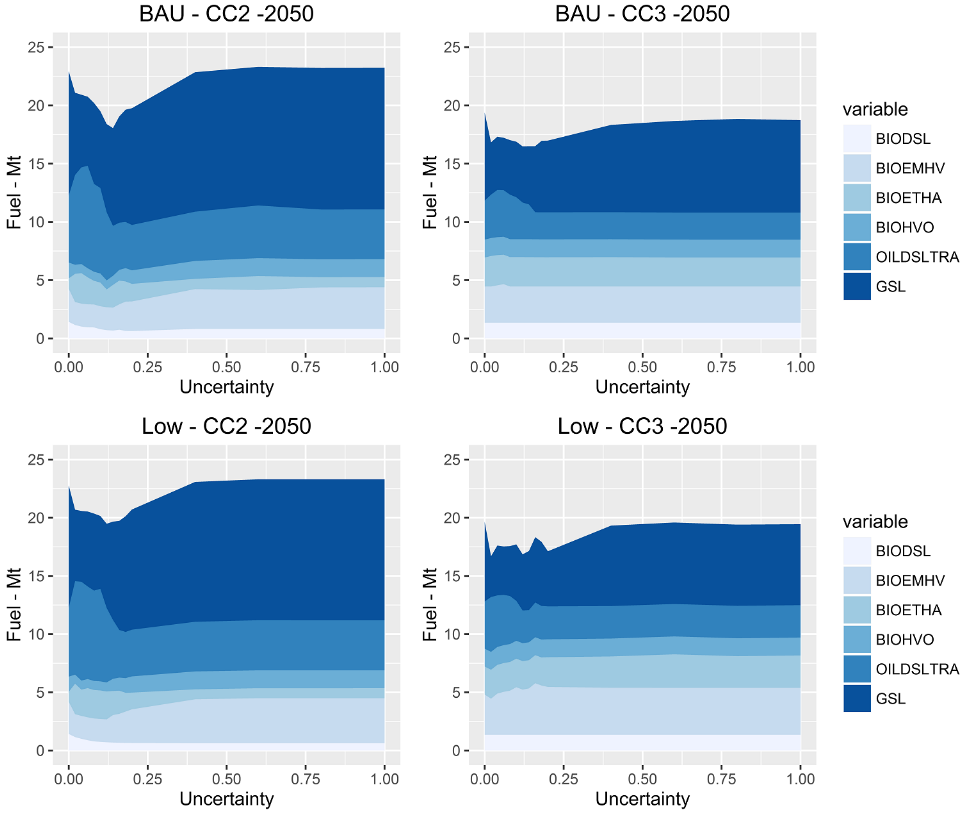


Figure 10: Liquid fuels used in transportation

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 there is no other choice than to keep using cost-drifted energy sources and technologies.
Second, results can be analyzed at the technological 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 no matter what our final decision is, 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 thus 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, since 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 of the model parameters are the most sensitive. 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.

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