Robust technological and emission trajectories for long-term stabilization targets with an energy-environment model

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Widespread use of energy-economy-environment system models
- Energy security and climate change: insights regarding the cost and benefit of policy objective and system effects
- These models grow bigger and bigger
  - Sectoral and geographical coverages, coupling with other models, Higher level of details/complexity...
- And are subject to criticisms (too complex, validation issue, hidden values issue)
- The main criticism: uncertainty handling (Pindyck, 2013)

Uncertainty treatment
- Uncertainty not considered because of model size & complexity
- A polymorphous uncertainty:
  - growth, technical parameters, backstop technology, climate system...

Methods
- Exogenous ways
  - Extensive scenario analysis (Babaee et al, 2014)
  - Sensitivity analysis (Hope, 2006)
  - Monte Carlo analysis (MIT 2011)
- Endogenous ways
  - Stochastic programming (requires density functions)
  - Robust optimization: set-based uncertainty models, large cardinalities allowed (distributional robustness) (Babonneau et al, 2011)
Climate models in IAMs

- Small Climate models deriving from Global Circulation Models and/or Earth System Models of Intermediate Complexity (Van Vuuren et al, 2009)

- Lots of approximations / calibration methods which can impact the model results
- Idea: assess the robustness of the model to climate parameters uncertainty and understand which parameters or combination of parameters are the most sensitive
- Problem: a classic sensitivity study would take too long (with 10 parameters to study and only 2 values for each parameters, more than 1000 runs)
- Hence the use of robust optimization
ROBUST OPTIMIZATION: what is it?

- **Principle**
  - Immunize solutions of mathematical programs to adverse realizations of uncertain coefficients

- **Initial approach**
  - Soyster (1973): pessimistic « worst-case » solution

- **Many improvements since the end of 90s**
  - Lots of efforts on linear formulations: Bertsimas and Sim (2004) – generalization of Soyster’s approach
  - Ongoing extensions to general constraints (Ben-Tal et al, 2012)

Very well established results for LP
ROBUST OPTIMIZATION: what is it?

- Nominal LP problem
  \[
  \begin{align*}
  \min & \quad C^T x \\
  \text{s.t.} & \quad Ax \leq b \\
  & \quad x \in \mathbb{R}^n_+, b \in \mathbb{R}^m
  \end{align*}
  \]

- Some parameters are uncertain, we assume they deviate in the “uncertainty set”
  \[
  a_{i,j} \in \left[\overline{a}_{i,j} - \overline{\alpha}_{i,j}, \overline{a}_{i,j} + \overline{\alpha}_{i,j}\right], \\
  a_{i,j} = \overline{a}_{i,j} + z_{i,j} \overline{\alpha}_{i,j}, \quad z_{i,j} \in [-1, 1]
  \]

- The “worst” case is unlikely hence:
  \[
  \sum_j |z_{i,j}| \leq \Gamma_i, \Gamma: \text{uncertainty budget}
  \]

- Primal deviation problem
  \[
  \begin{align*}
  \max & \quad \sum_j z_{i,j} \overline{a}_{i,j} x_j \\
  \text{s.t.} & \quad \sum_j z_{i,j} \leq \Gamma_i (\lambda) \\
  & \quad x \in \mathbb{R}^n_+, b \in \mathbb{R}^m
  \end{align*}
  \]

- Dual deviation problem
  \[
  \begin{align*}
  \min & \quad \Gamma_i \lambda + \sum_j \mu_{i,j} \\
  \text{s.t.} & \quad \lambda + \mu_{i,j} \geq \overline{a}_{i,j} x_j \\
  & \quad \mu_{i,j} \in \mathbb{R}_+, \lambda \in \mathbb{R}_+
  \end{align*}
  \]

- Using strong duality arguments

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Why using this methodology?

- **Input-based reasons**
  - Tackling the computational burdens of large bottom-up IAMs
  - Being able to consider a lot of parameters at the same time

- **Output based reasons**
  - Proposing alternative model of uncertainty within IAMs
  - Obtaining trajectories robust to most parameter realizations

- **Other potential applications**
  - Cost uncertainty, technical parameter uncertainty, demand uncertainty
Application with the TIAM-World model

- The TIMES climate module is adapted from Nordhaus & Boyer (1999) (Loulou et al, 2010)

**Parameters**

- Carbon cycle: $\varphi_{au}$, $\varphi_{ua}$, $\varphi_{lu}$, $\varphi_{ul}$ annual CO2 flow coefficients between the three reservoirs
- Radiative forcing: $\gamma$ is the radiative forcing sensitivity to a doubling of the atmospheric
- Temperature
  - $\sigma_1$: speed of adjustment parameter for atmospheric temperature.
  - $\sigma_2$: ratio of the thermal capacity of the deep oceans to the transfer rate from shallow to deep ocean
  - $\sigma_3$: transfer rate (per year) from the upper level of the ocean to the deep ocean
  - $CS$: a feedback parameter, representing the equilibrium impact of CO2 concentration doubling on climate.

- 9 parameters calibrated with more complex climate models (e.g. MAGICC)
Experimental setting

- Climate constraint: 3°C over the whole 2010-2200 horizon (no overshoot)
- 2 sets of climate parameter deviations

Set 1: 10% set

- Simple: Parameters can deviate of 10% of their nominal value
- \(a_{i,j} \in [\overline{a}_{i,j} - 0.1\overline{a}_{i,j}, \overline{a}_{i,j} + 0.1\overline{a}_{i,j}]\)

Set 2: literature set

- Use deviation values found in literature
- Difficulty to find homogenous data for all parameters

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Value</th>
<th>Deviation</th>
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<tbody>
<tr>
<td>(\varphi_{au})</td>
<td>0.046</td>
<td>10%</td>
</tr>
<tr>
<td>(\varphi_{ua})</td>
<td>0.0453</td>
<td>10%</td>
</tr>
<tr>
<td>(\varphi_{lu})</td>
<td>0.00053</td>
<td>10%</td>
</tr>
<tr>
<td>(\varphi_{ul})</td>
<td>0.0146</td>
<td>10%</td>
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<tr>
<td>(\sigma_1)</td>
<td>0.024</td>
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</tr>
<tr>
<td>(\sigma_2)</td>
<td>0.44</td>
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</tr>
<tr>
<td>(\sigma_3)</td>
<td>0.002</td>
<td>10%</td>
</tr>
<tr>
<td>CS</td>
<td>2.9</td>
<td>10%</td>
</tr>
<tr>
<td>(\gamma)</td>
<td>3.71</td>
<td>10%</td>
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</tbody>
</table>
Most sensitive parameters

- Uncertainty set: 10%
  - Delta T atm - Set 10%

- Uncertainty set: literature
  - Delta T atm - Set literature

<table>
<thead>
<tr>
<th>Deviation</th>
<th>φau</th>
<th>CS</th>
<th>φua</th>
<th>φlu</th>
<th>φul</th>
<th>σ1</th>
<th>σ2</th>
<th>σ3</th>
<th>γ</th>
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<tr>
<td>10%</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>5</td>
<td>4</td>
<td>7</td>
<td>6</td>
<td>9</td>
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<td>Literature</td>
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<td>5</td>
<td>2</td>
<td>3</td>
<td>9</td>
<td>8</td>
</tr>
</tbody>
</table>

Parameter deviation order

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CO₂ Captured

CO₂ Captured – Set 10%

CO₂ Captured – Set literature
Conclusion

- Use of robust optimization for large bottom-up model with non-linear constraint
- Need to be careful with Small Climate Model results given the parameter diversity across models
- Adapt calibration? Generalize sensitivity study?

- Next step: going further with the robust optimization methodology. Trying to understand how we can interpret the robust trajectories (hedging, attitude towards risk...).
Robust technological and emission trajectories for long-term stabilization targets with an energy-environment model

Thank you for your attention
Application with the TIAM-World model

- Implementation obstacle
  - The climate module is not linear in the parameters:
    - We linearized it using binary variables, the problem becomes a MIP
    - Implementation of a column and constraint generation algorithm using a MIP oracle

Diagram:

- Master Problem: TIAM-World (LP)
  - Emission trajectories
  - $E_{GHG,it}^*$
  - New constraint for the new variable: $y_{it+1}$ (climate variable with the deviated parameters)

- SubProblem: Max climate deviation (MIP)
  - Find worst parameter deviations

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Times climate module

\[ M_{atm}(y) = E(y) + (1 - \varphi_{atm-up}) M_{atm}(y-1) + \varphi_{up-atm} M_{up}(y-1) \]
\[ M_{up}(y) = (1 - \varphi_{up-atm} - \varphi_{up-lo}) M_{up}(y-1) + \varphi_{atm-up} M_{atm}(y-1) + \varphi_{lo-up} M_{lo}(y-1) \]
\[ M_{lo}(y) = (1 - \varphi_{lo-up}) M_{lo}(y-1) + \varphi_{up-lo} M_{up}(y-1) \]

\[ M_t = P \cdot M_{t-1} + E_t, \]
\[ P = \begin{pmatrix} 1 - \varphi_{a-u} & \varphi_{u-a} & 0 \\ \varphi_{a-u} & 1 - \varphi_{u-a} - \varphi_{u-l} & \varphi_{l-u} \\ 0 & \varphi_{u-l} & 1 - \varphi_{l-u} \end{pmatrix}, \quad F_t = \gamma \left[ f_1 + f_2 \left( m^T P^t M_0 + \sum_{\tau=1}^t m^T P^{t-\tau} E_\tau \right) \right] \]
\[ M_t = P^t \cdot M_0 + \sum_{\tau=1}^t P^{t-\tau} E_\tau, \]
\[ M^a_t = m^T M_t \]

\[ \Delta T_t = S \Delta T_{t-1} + sF_t, \]
\[ S = \begin{pmatrix} 1 - \sigma_1 (\lambda + \sigma_2) & \sigma_1 \sigma_2 \\ \sigma_3 & 1 - \sigma_3 \end{pmatrix}, \quad s = \begin{pmatrix} \sigma_1 \\ 0 \end{pmatrix} \]

\[ \Delta T_t = S^t \Delta T_0 + \sum_{\tau=1}^t S^{t-\tau} s F_\tau \]
The TIAM Model

- A multi-regional and inter-temporal partial equilibrium model of the entire energy/emission system of the World
- 16 Regions
- Driven by a set of 42 demands for energy services in all sectors
Cost of robustness

Objective function
- Set 10%

Objective function
- Set literature
Contributions

- Use of a recent technique developed in the operations research field: robust optimization. Application to tackle the climate module parameter uncertainty.
- This technique allows to derive robust trajectories
- And to highlight the most sensitive parameters or parameter combinations.