

# Long-term issues with the energy-only market design in the context of electricity decarbonisation

Insights from a system dynamics simulation model

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13th Toulouse Conference on The Economics of Energy and Climate



# Outline

- ① Research question & main takeaways
- ② Modelling framework
- ③ Simulations
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Theoretically, wholesale electricity markets have a twofold objective

- ① (short-term) to ensure an optimal dispatch for existing assets
- ② (long-term) to provide the adapted investment/divestment signals required for long-term efficiency



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In practice, **the ability of current market design options to deliver adequate signals for long-term decisions is largely questioned** (Pollitt 2021, Joskow 2021). The problem is not new (Glachant et al. 2011) but the **unprecedented scale, pace and required coordination** of the necessary changes exacerbate this issue.



Traditional modeling approach in prospective analysis resorts to Generation Expansion Planning (GEP) models based on optimization. They can provide optimal decarbonization pathways under a variety of constraints. However, GEPs are not suited for a comprehensive discussion on two crucial aspects: **investors' behavior** and **available information** (Petitet et al. 2017, Tao et al. 2021).

- Their outcome correspond to **perfect competition with fully rational and informed agents**
- No **explicit** representation of the decision making process.



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Equilibrium models constitute another option. They allow to relax perfect assumptions about market functioning and derive general analytical results. However, they demand specific mathematical properties and leave aside the overlooked out-of-equilibrium dynamics (Léautier 2018), albeit important in a transition phase.



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Simulation models complement the toolbox by allowing to explicitly model investors' behavior evolving in a given market structure.

# Research questions and takeaways

Questions addressed:

- ① which assumptions about investor behaviour and available information are needed to ensure that an EOM induces the target mix trajectory, i.e. that which achieves decarbonisation objectives at least cost?

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- ② how robust is an EOM (as measured by deviations between realized vs. optimal mix trajectories) when different assumptions are considered?

First findings based on an illustrative case inspired by the Californian power system:

- ① EOM (completed with a carbon price signal) is able to reproduce the optimal mix trajectory **but required assumptions are demanding and do not fit with reality.**
- ② **When relaxing some of these theoretical assumptions (to switch to more realistic ones), mix trajectory of the energy-only market can considerably deviate from the optimal trajectory.**

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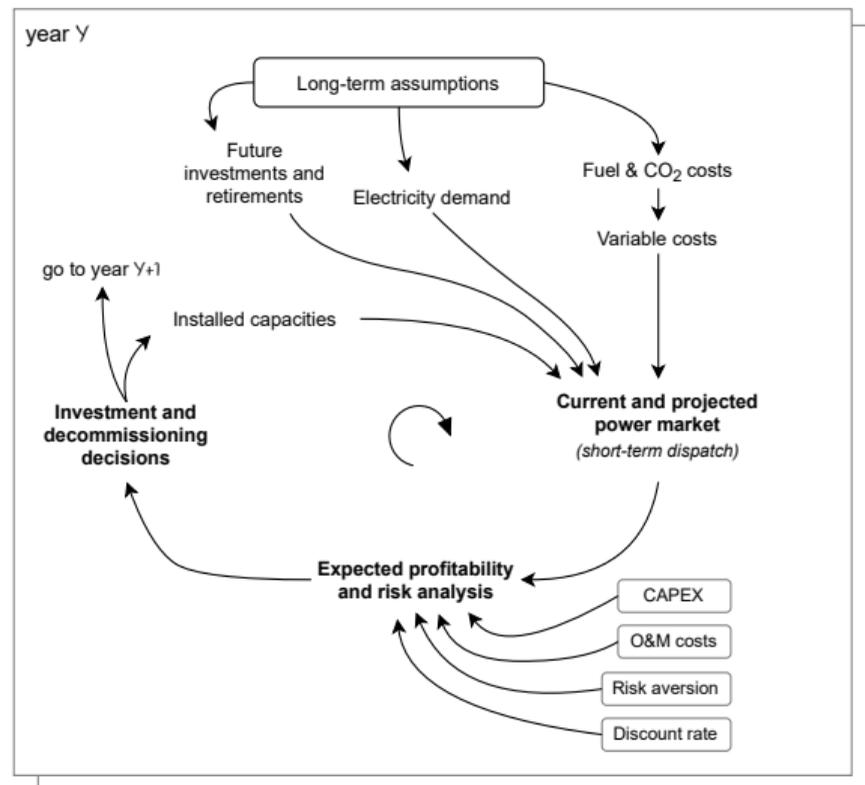
# Overview of the simulation model

Market Simulation with System Dynamics also has a long tradition for long-term policy evaluation (Ford 1983, Bunn et al. 1996, Petit et al. 2017, Ousman Abani et al. 2018).

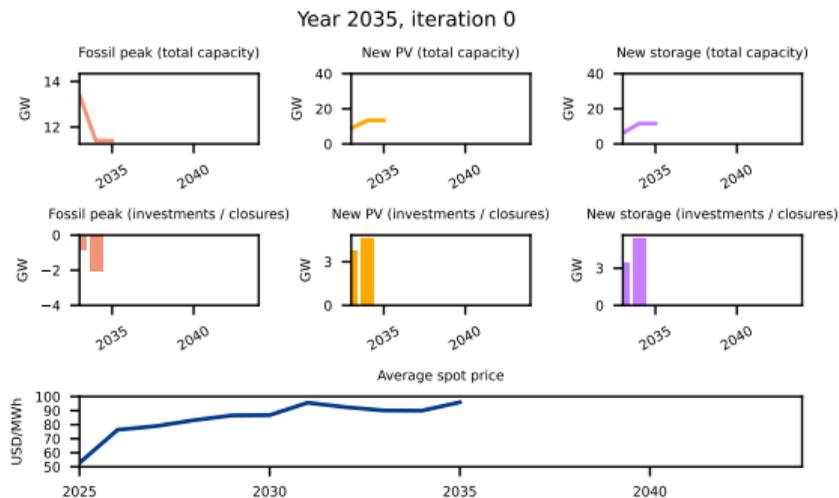
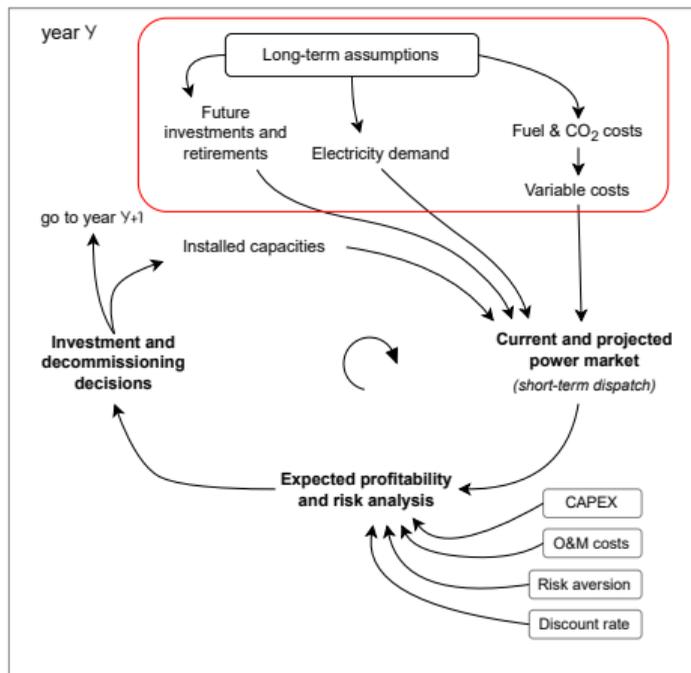
Key elements:

- Endogenous investment and decommissioning in thermal, variable renewables and storage technologies
- Particular emphasis on anticipated capacities (Tao et al. 2021)

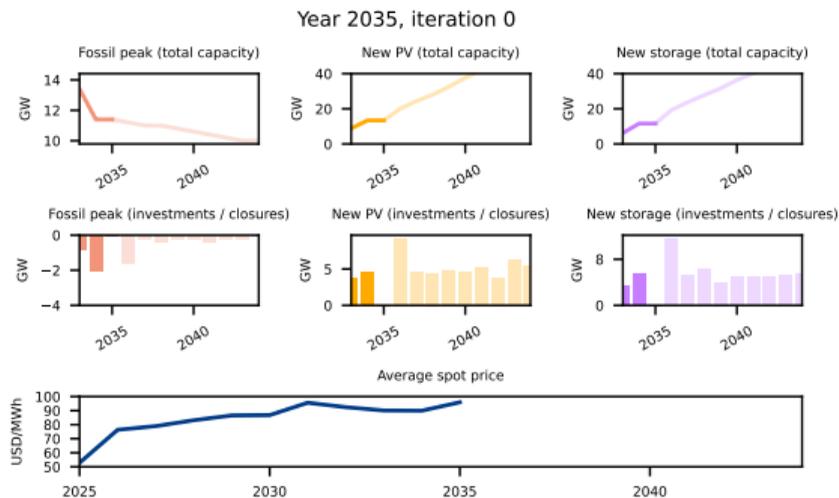
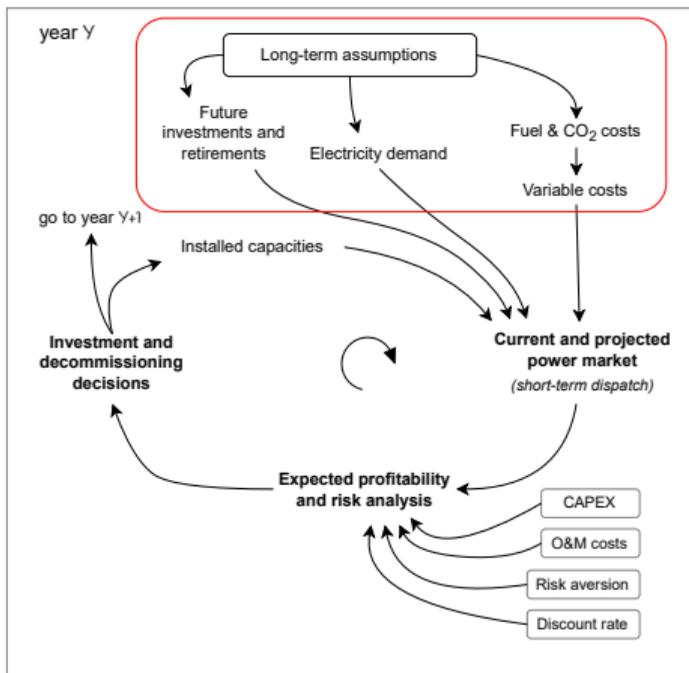
**Investment and decommissioning decisions are represented year by year, project by project.**



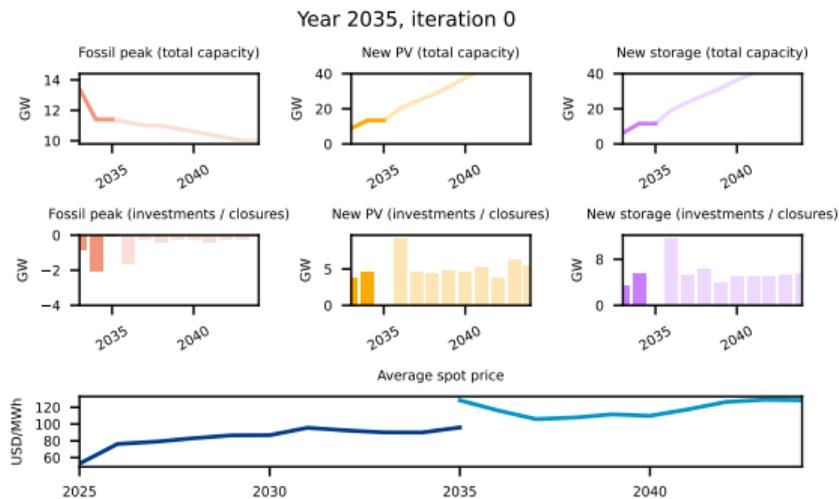
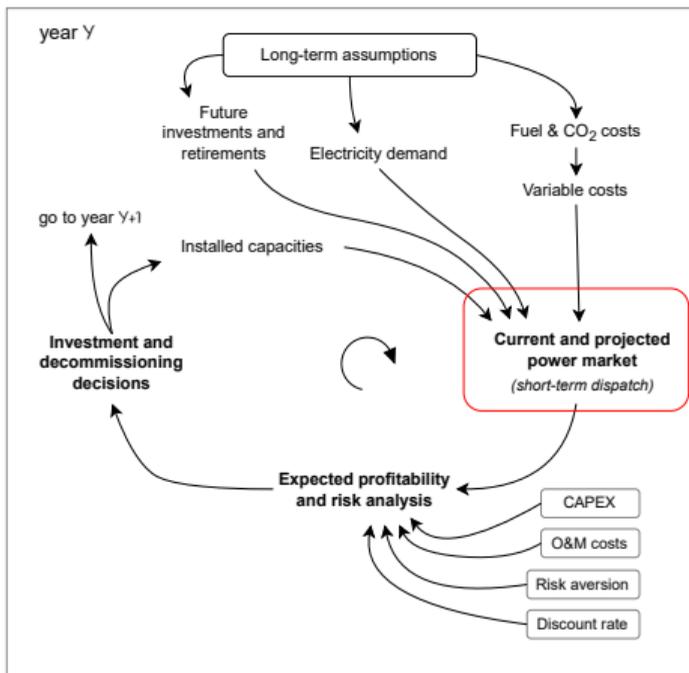
# Step 1: long term assumptions (1/2)



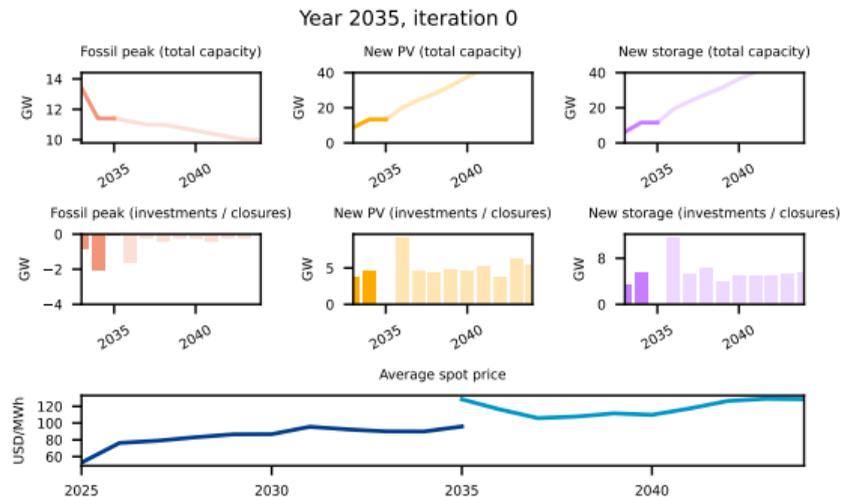
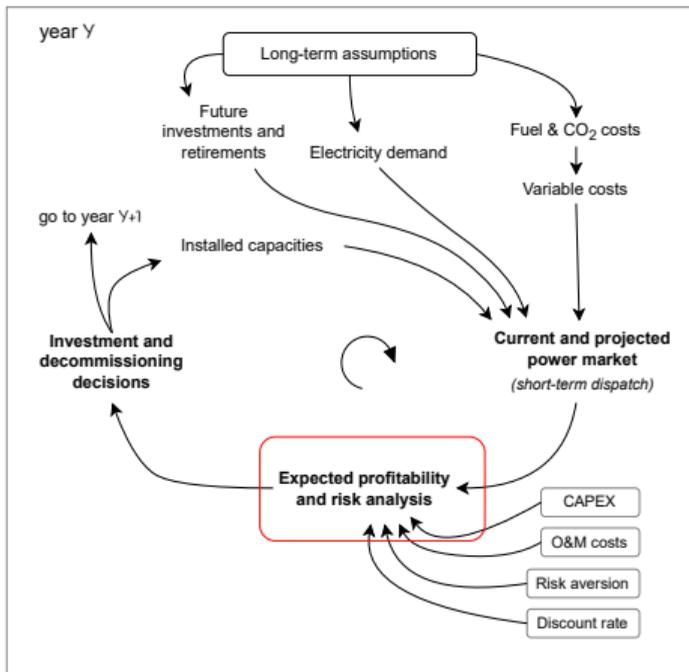
# Step 1: long term assumptions (2/2)



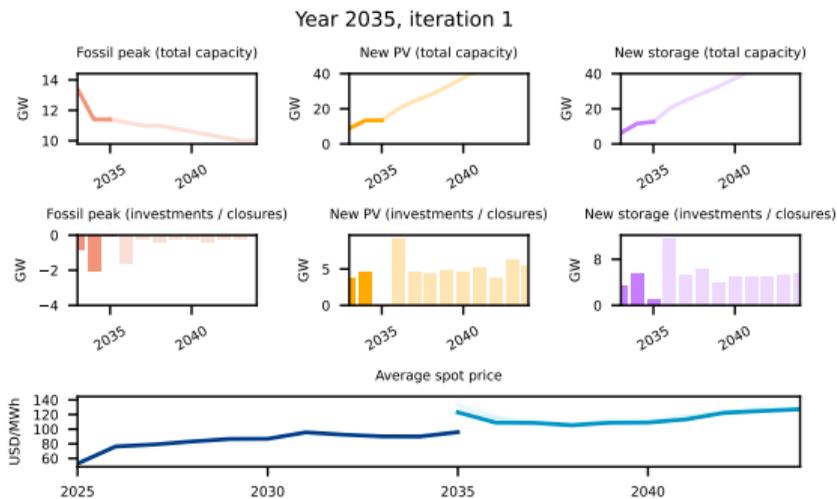
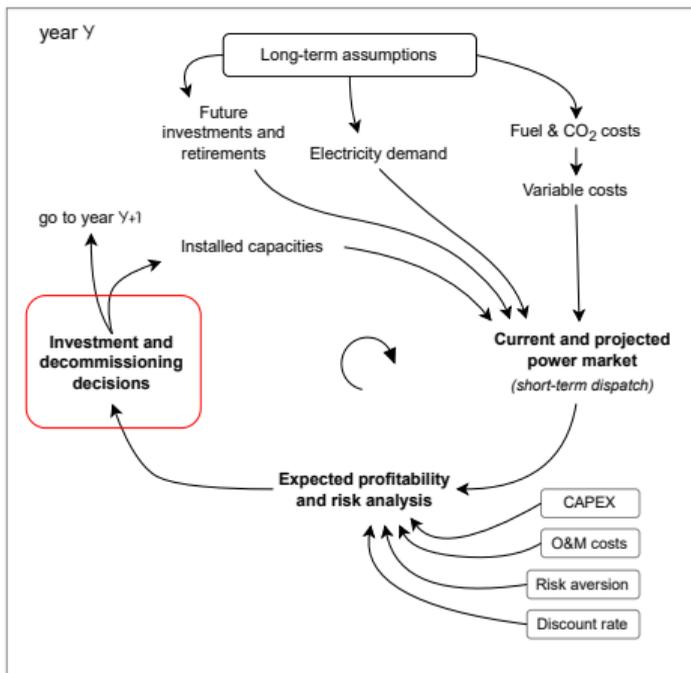
# Step 2: current and projected power market



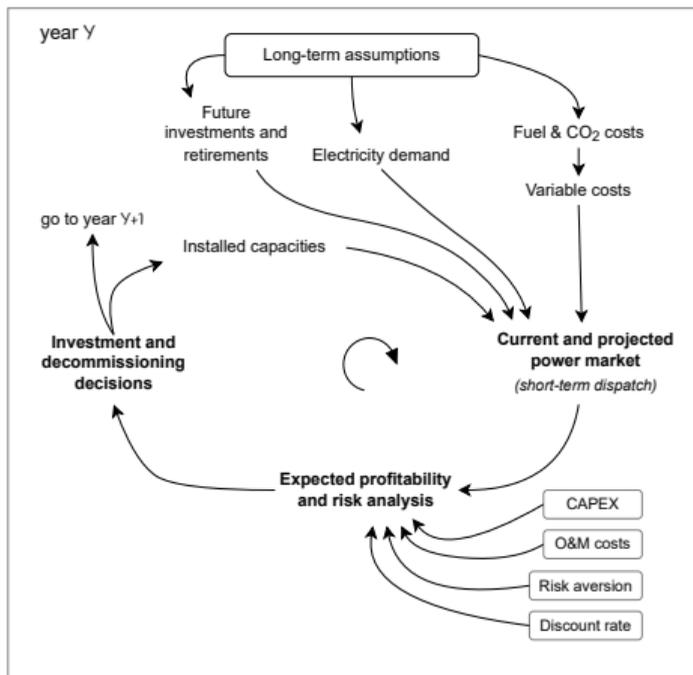
# Step 3: economic assessment of possible decisions



# Step 4: decision-making



# Iteration until no decision is profitable



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# Stylized California case study

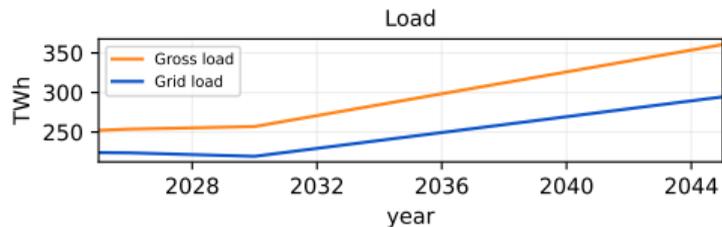


Figure 2: Load assumption → stagnating until 2030, followed by a strong increase (electrification) up to 2045

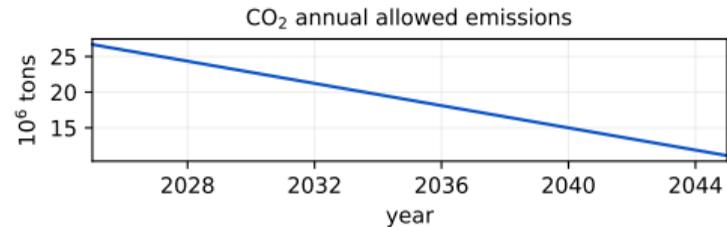


Figure 3: CO<sub>2</sub> annual emissions targets → strong reduction (- 60% throughout the study horizon)

## Data sources

All data adapted by authors from CPUC's RESOLVE (CPUC 2021), NINJA Renewables (Staffell et al. 2021, Staffell et al. 2016, Pfenninger et al. 2016) and historical data.

# California case study : endogenous generation

Four technologies endogenously represented (investment or decommissioning decisions).

| Technology | Available decision           | CAPEX       | Fixed O&M   | Fuel Cost                              | Carbon intensity        |
|------------|------------------------------|-------------|-------------|--|-------------------------|
|            |                              | [USD/kW-Yr] | [USD/kW-Yr] | [USD/MWh]                              | [tCO <sub>2</sub> /MWh] |
| CCGT       | Decommissioning              | 126         | 30          | Average: 31 <a href="#">▶ see app.</a> | 0.37                    |
| Peaker     | Decommissioning              | 46          | 20          | Average: 51 <a href="#">▶ see app.</a> | 0.61                    |
| PV         | Investment & decommissioning | 70          | 9           | 0                                      | 0                       |
| Storage    | Investment & decommissioning | 82          | 10          | 0                                      | 0                       |

- Units have a discrete size of 200 MW.
- The storage technology is assumed to have a 4 hours duration and a 85% round-trip efficiency.
- Common WACC: 8 %
- Price cap on the energy market: 15 USD/kWh
- Other (exogenous) generation: existing fleet, nuclear, CHP, biomass, etc.

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# Results from the CO<sub>2</sub>-constrained GEP model

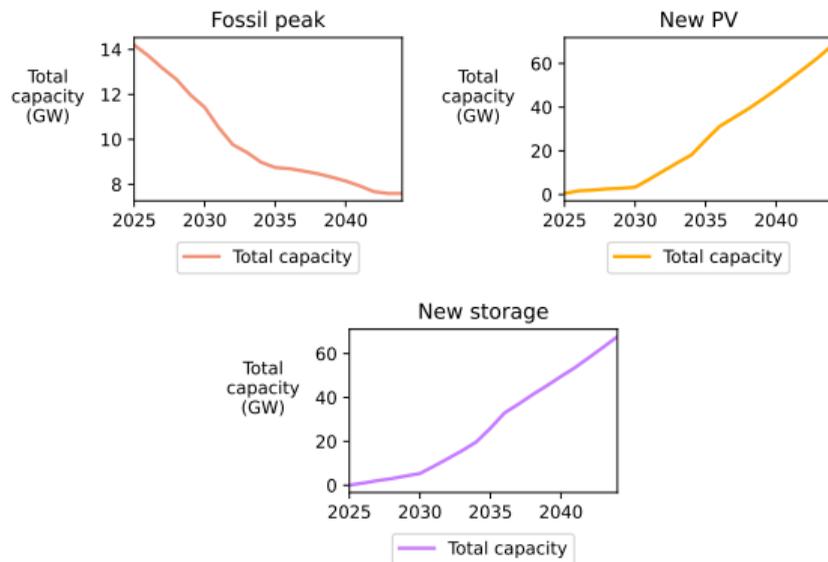


Figure 4: Optimal capacity trajectories from the GEP model

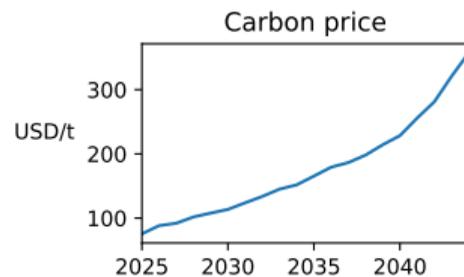


Figure 5: CO<sub>2</sub> shadow price from the GEP model

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Simulation results are organized in four batches:

- ① First batch illustrating the functioning of a **quasi-perfect Energy-Only Market Design**.
- ② A second batch pertaining to **coordination**.
- ③ A third batch pertaining to anticipation of future **entry/exit decisions anticipation**.
- ④ A final batch illustrating issues with the **carbon price anticipation**.

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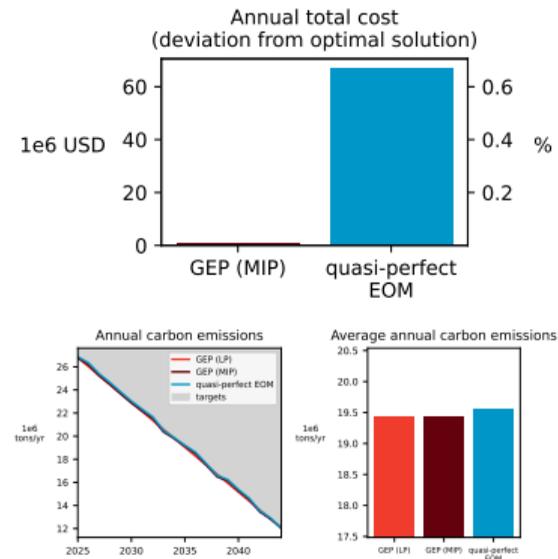
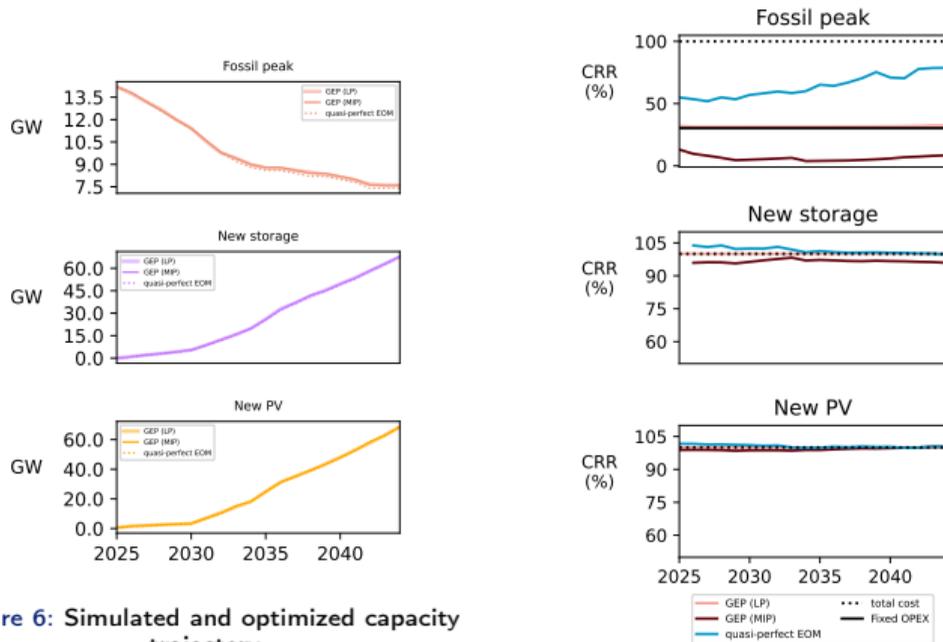
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## Assumptions A1–A4

In order to trigger the optimal investment and decommissioning decisions, the four following assumptions need to jointly hold:

- A1.** Perfect information about all exogenous parameters over the whole horizon including gross demand, distributed generation and costs (fuel, O&M and CAPEX).
- A2.** Perfect information about the CO<sub>2</sub> price over the whole horizon. This price is assumed to coincide with the shadow price computed with the GEP model.
- A3.** Perfect information about all concurrent decisions taken in a given year.
- A4.** When making investment and retirement decisions in a given year, future optimal decisions need to be known for all subsequent years until the end of the horizon.

# Quasi-perfect EOM simulation (compared with optimization results)



Trajectories are close, with a little less fossil peak that enables cost recovery.

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# Entry/exit coordination and anticipation of future decisions

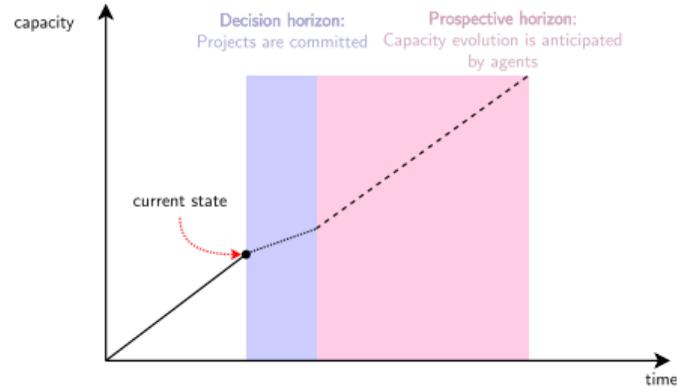


Figure 9: Decision and prospective horizons

## Terminology used:

- coordination issue: no information exchange between market participants in the decision horizon (decisions are taken simultaneously)
- entry/exit anticipation issue: no anticipation of future decision in the prospective horizon.

# Simulation results with coordination issues

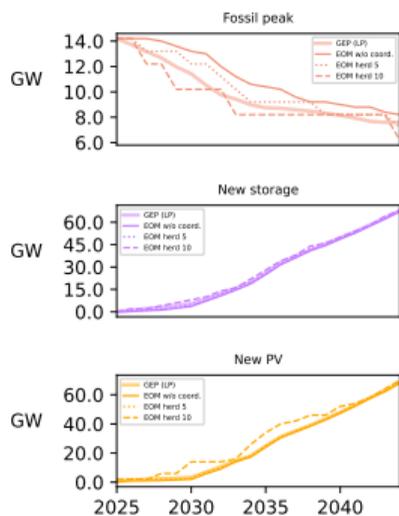


Figure 10: Simulated and optimized capacity trajectory

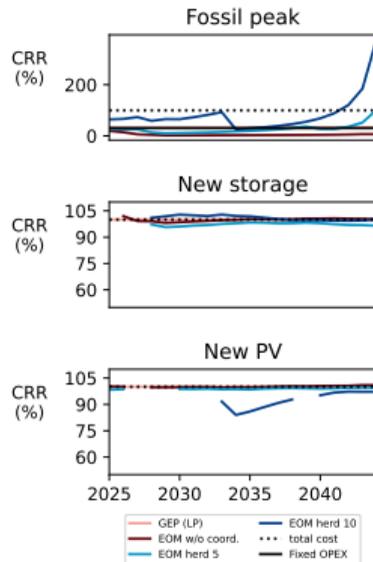


Figure 11: Cost Recovery Ratio

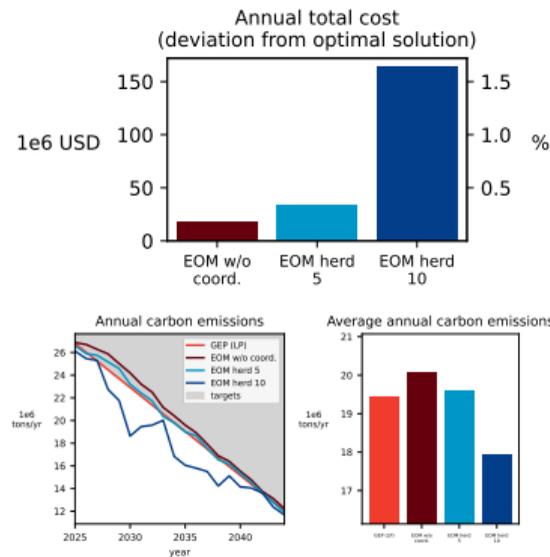


Figure 12: Total cost and carbon emissions

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# Simulation results without anticipation of subsequent decisions and myopia

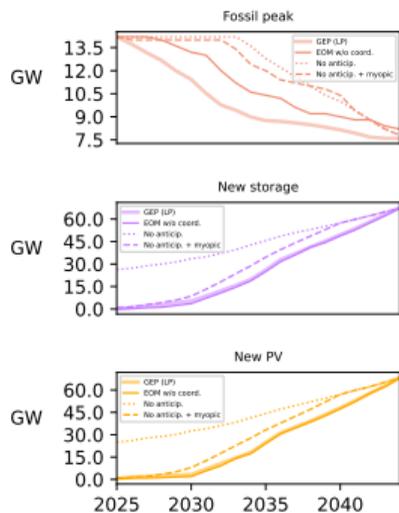


Figure 13: Simulated and optimized capacity trajectory

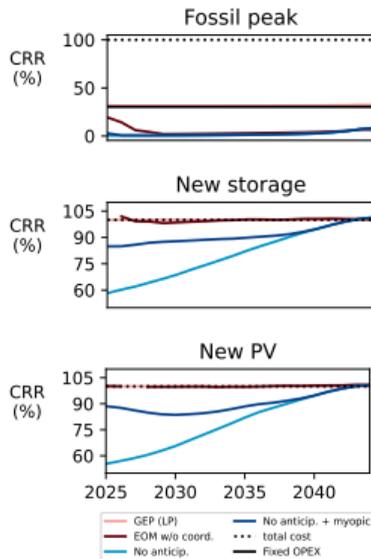


Figure 14: Cost Recovery Ratio

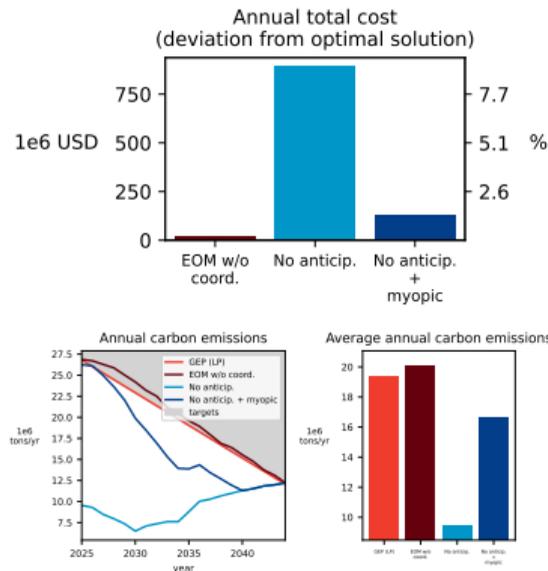


Figure 15: Total cost and carbon emissions

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## Figure 16

Narrative: carbon market prices are too low and volatile to convey credible long-term signals (Tvinnereim et al. 2018; Perino et al. 2021; Joskow 2021)

# Simulation results with weak carbon price anticipations

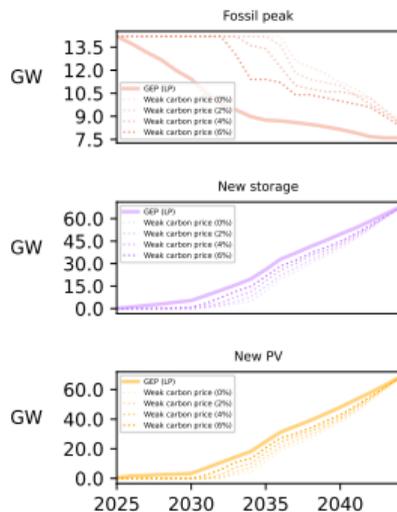


Figure 17: Simulated and optimized capacity trajectory

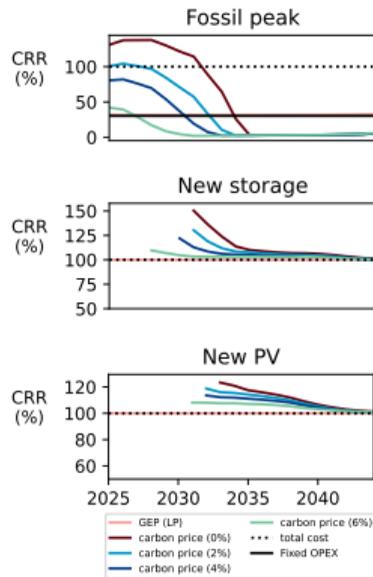


Figure 18: Cost Recovery Ratio

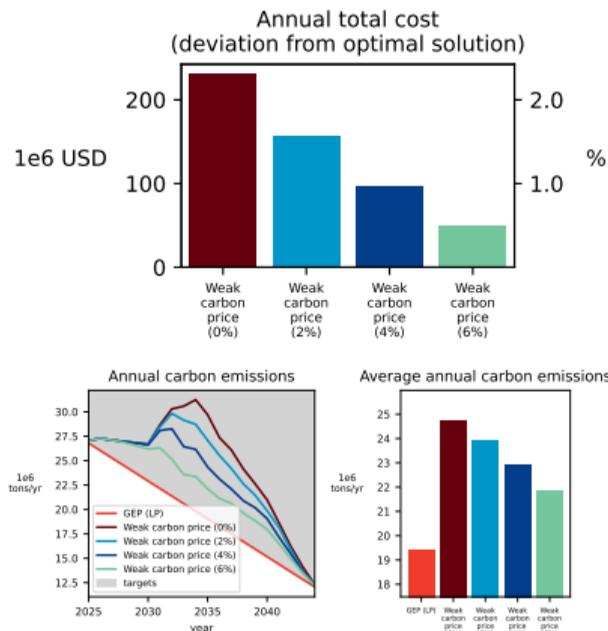


Figure 19: Total cost and carbon emissions

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# Conclusions

- ① EOM (completed with a carbon price signal) is able to reproduce the optimal mix trajectory **but required assumptions are demanding and do not fit with reality.**
- ② **When relaxing some of these theoretical assumptions (to switch to more realistic ones), mix trajectory of the energy-only market can considerably deviate from the optimal trajectory.**

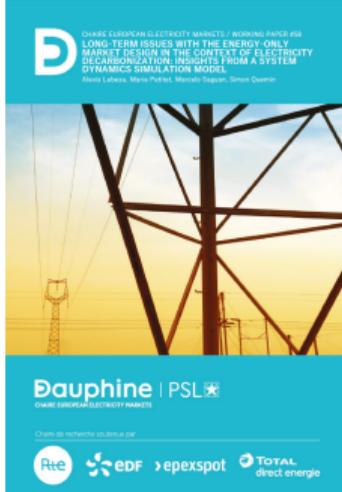
→ | This work highlights the importance of dynamic and out-of-equilibrium aspects that should not be overlooked in a transition phase.

→ | While an EOM looks appealing in theory, its desirable properties suffer from a **lack of robustness** with regard to practical investor behaviors.

→ | In turn, it is necessary to define a more adapted market design, e.g. in the form of hybrid markets (Roques and Finon 2017, Joskow 2021) that rely on long-term arrangements alongside short-term markets as we know them today.

Models and methods developed here allow to extend our work in several ways:

- **Multiple scenarios & risk preference**
- **Alternative market designs**
- **Market design robustness to unexpected trend changes**



The Working Paper is online on the CEEM website ([click here](#)).

Thank you for your attention !

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