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# LONG-TERM ISSUES WITH THE ENERGY-ONLY MARKET DESIGN IN THE CONTEXT OF ELECTRICITY DECARBONIZATION: INSIGHTS FROM A SYSTEM DYNAMICS SIMULATION MODEL

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# Long-term issues with the energy-only market design in the context of electricity decarbonization: Insights from a system dynamics simulation model

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**Abstract**

Decarbonization of energy systems is challenging but needs to happen. Despite a rich literature on energy transitions and electricity markets, there is a scant literature analyzing (1) how an energy-only market (EOM) design may yield energy mix trajectories that are compatible with decarbonization objectives and (2) the role of underlying investor behavior assumptions. This paper intends to bridge this gap and illustrate both aspects through electricity market model simulations. We study an illustrative case inspired by the Californian power system and highlight two main findings. First, an EOM complemented with a carbon price signal can reproduce the optimal mix trajectory but required assumptions are demanding and unrealistic (e.g. perfect rationality, full information about fundamentals, perfect coordination between decommissioning and investment decisions). Second, we characterize how the EOM-induced mix trajectory can considerably deviate from optimality when we relax these assumptions. We conclude that the desirable theoretical properties of an EOM are not robust to practical investor behaviors. Meeting decarbonization targets thus calls for a change in market design paradigm toward hybrid markets that combine a dedicated long-term investment module with short-term wholesale markets as we know them today.

**Keywords:** Electricity Markets, System Dynamics, Energy-Only Market, Investments

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## I. INTRODUCTION

The energy transition has become a common trend over the world and poses mounting challenges to energy systems with various interrelated facets including decarbonization, renewables integration, energy efficiency improvement and electrification. In practice, these aspirations translate in more or less binding targets for different time horizons. In the EU for instance, key targets for 2030 are to cut greenhouse gas (GHG) emissions by at least 55% below 1990 levels and the longer-term vision aims at the much more ambitious objective of a net-zero GHG emissions economy by 2050 [7]. The US state of California is another example of ambitious energy transition objectives where the Senate Bill 100 requires 60% and 100% of electric retail sales to end-use customers to be zero-carbon by 2030 and 2045 respectively [4].

In the electricity sector, decarbonization prospective analysis mostly resorts to generation expansion models (GEP) which cost-optimize over time to determine efficient pathways that reach given end-point targets. There is a rich literature discussing the underlying optimization techniques and technological assumptions (e.g. integration of renewable energy sources, representation of short-term issues, long-term seasonal storage) behind such analyses such as Shirizadeh et al. [20] and Tejada-Arango et al. [22]. Yet, they are to a large extent oblivious to market design and agent behavior issues, i.e. economic and behavioral factors that have a bearing on investment decisions [e.g. 21]. This blind spot becomes a particularly salient shortcoming in a context of growing concerns about the ability of current institutional framework and market design choices to meet deep decarbonization and security of supply objectives that necessitate profound changes in power system structures and technology mixes [e.g. 18, 12, 9, 11, 17].

Specifically, an increasing number of voices have been raised to claim that the energy-only market (EOM) model[1], which is held up as the target market design model in many jurisdictions including the EU, is structurally ill-equipped to support adequate investments to deliver on these objectives. These analyses show that the EOM rests on idealistic assumptions about market functioning and behavior (e.g. complete markets, perfect rationality) that do not hold in practice and is subject to several externalities (e.g. learning spillovers, social or industrial preferences, pollution). Additionally, existing corrective policies and market design patches fall short of ensuring that targets will be met as economically as possible and on schedule, notably for lack of systemwide coordination. Crucially, the literature offers limited qualitative and quantitative insights on the role of investor behavior and associated modeling assumptions in this situation.

In this paper, we seek to partially fill this gap in the literature and quantitatively illuminate two related aspects in the case of a pure EOM design. First, we explore which behavioral and informational assumptions are needed to ensure that the resulting investment decisions align with the optimal mix trajectory, i.e. that which achieves decarbonization objectives at least overall cost. We find these assumptions to be demanding

[1]The traditional *energy-only market* terminology used in the literature can sometimes be misleading as it may include markets for ancillary services. In this paper, this is how we refer to market designs exclusively based on short-term wholesale markets.

and unrealistic, which underpins the diagnosis that the purported EOM properties fail to materialize in practice. Second, we characterize the robustness of the EOM-induced mix trajectory to these assumptions by relaxing them gradually. We find that substantial deviations from the optimal one can occur when investors exhibit limited sophistication in making adequate projections for future states of the world (e.g. $CO_2$ price, installed asset fleet) that govern expected market prices, revenue streams and in turn investment profitability.

To embed these issues at the core of our analysis, we develop an electricity market model based on *System Dynamics* (SD). Such an approach allows for the incorporation of a variety of behavioral factors in the investment-closure decision-making process of a representative agent [e.g. 26, 16, 14, 21]. Importantly, we also build a bridge with the traditional GEP modeling approach whose output we use as a benchmark for the SD model simulation results and as a possible source of information when investors make projections in the SD model.

The remainder proceeds as follows. Section 2. lays out the modeling framework with a strong focus on the SD market model. Section 3. describes the case study, the underlying assumptions and the reference optimal trajectory obtained with the GEP approach. Section 4. presents and discusses the simulation results from the SD market model. Finally, section 5. concludes and offers important implications for policy and market design.

## II. METHODOLOGY

### 2.1. Modeling framework

For decades, economists and engineers have used a rich toolbox of complementary approaches to gain understanding on long-term power system issues . The different modeling options are generally classified into three categories, namely optimization, equilibrium, and simulation models [25, 21] with distinct and complementary areas of relevance. In this paper, we choose to develop a modeling framework consisting of two models[2]:

1. A System Dynamics (SD) model similar to Petitet et al. [16] which is a tool that aims at simulating industry representative agents' decisions and operations.
2. An optimization model in the form of a traditional Generation Expansion Planning (GEP) model (see Kagiannas et al. [10] for historical perspective). The goal of this class of model is to determine the optimal capacity development plan by jointly minimizing investment and operating costs with respect to a variety of constraints. Alongside usual ones, one notable constraint is a cap on $CO_2$ emissions detailed in section II.22..

The choice of System Dynamics is first motivated by the necessity to focus on decision-making process by considering explicit assumptions for investors' rationality and fore-

[2]The two models presented herafter were developed in the open-source coding language Python and can be reproduced based on the equations and descriptions provided in the article.

cast evolving in a certain market environment. Both optimization and equilibrium models fail to represent these aspects. The first category does not represent any agent nor market and the latter relies on solvers and thus does not explicitly exhibit the dynamic decision-making process and fail to cover common out of equilibrium situations. Useful review of SD models for power systems are found in Teufel et al. [23] and Ahmad et al. [1]. Among simulation models, agent-based modeling and system dynamics are generally considered as the two main sub approaches, although their definition and perimeter may differ from one to another. As well as SD, agent-based modeling has been applied to power system and is particularly well-suited to analysis heterogeneous behaviors among market participants. dos Santos and Saraiva [19] provide a latest review of agent-based modeling applied to power systems. This article focuses on identifying investor's behaviors and assumptions that are necessary to obtain mix trajectory in coherence with energy-only market paradigm. It does not aim at analysing heterogeneous investors. This explains why SD appears as the relevant modeling approach for our purpose. This part of our modeling exercise is in continuation with the SD literature initiated in the 1990s (see Bunn and Dyner [2]) and that still provides useful insights in the context of energy transition (see Ousman Abani et al. [14]).

Moreover, several considerations led us to expand our modeling exercise with a GEP model. The primary motivation is to use this second model to compute the optimal investment and retirement trajectories regardless of market considerations[3]. This optimal solution constitutes a benchmark to assess the outcome of our SD simulation model.

Then, we also built a linkage between the two models by feeding the SD model with different information from the GEP model. Firstly, as the carbon market functioning is not within the scope of this paper, the shadow price of the constraint on $CO_2$ emissions is used as an exogenous carbon price signal for the SD model. Secondly, as detailed in Tao et al. [21], simulation models are very sensitive to price projection methods and in particular to the way future capacities are projected in the case of a virtual market clearing. To this end, the SD model can possibly use some information from the optimal trajectory, especially concerning future investment or retirement decisions. Section II.33. provides more details on these modeling assumptions.

Before diving deeper into the implementation of the two models, the end of this section will provide some general assumptions of our modeling framework. First, the exercise covers a typical time horizon of 25 years with an hourly resolution (8760 hours per year). We consider one representative scenario for each year with respect to weather conditions. We represent an isolated power system which we assume to be a copper plate. We focus on wholesale electricity market (ancillary services are not in our scope). The generating fleet is modelled by discrete units with standard capacities.

Abbreviations and notations are exposed in tables 1 and 2. They are shared in the GEP and SD sections. In case of ambiguities, superscript $\star$ will refer to the GEP and superscript $\circ$ to the SD. For greater clarity, we occasionally use a condensed notation where, for example, $q$ denotes the vector of all $q_{t,n,h}$.

[3]The results of linear/convex GEP models can be interpreted as the outcome of a market equilibrium in a perfectly competitive configuration with fully rational and informed agents. However, markets are not explicitly represented.

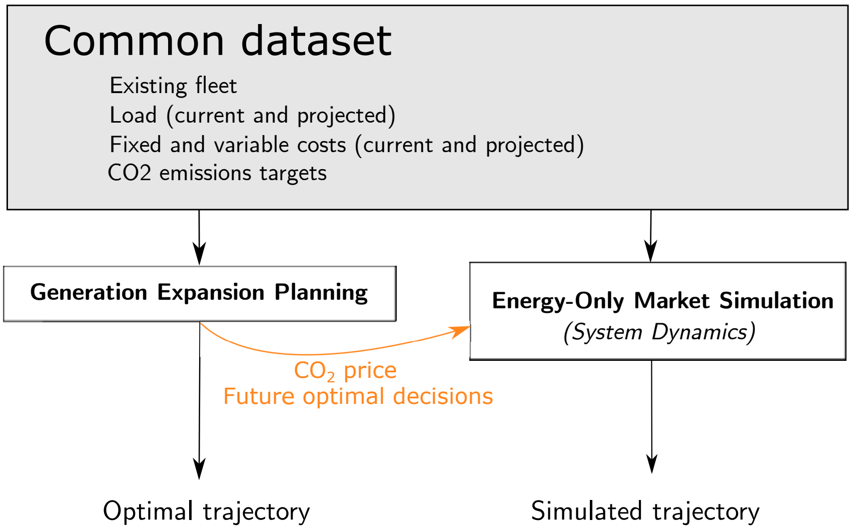


Figure 1: Overview of the modeling framework

| | |
|---|---|
| CCGT | Combined Cycle Gas Turbine |
| CHP | Combined Heat and Power |
| EOM | Energy-Only Market |
| GEP | Generation Expansion Planning |
| NPV | Net Present Value |
| O&M | Operating and Maintenance |
| RES | Renewable Energy Source |
| RPS | Renewable Portfolio Standard |
| SD | System Dynamics |
| VoLL | Value of Loss Load |
| WACC | Weighted Average Cost of Capital |

Table 1: Abbreviations

### 2.2. GEP model

The GEP model is a traditional deterministic multi-annual cost-minimization problem where the objective function is made up of both operating costs and investment costs with decision variables consequently pertaining to operations on one side and invested and retired capacities on the other side. All equations are provided in appendix A.11.. We will highlight a few features of interest for this study in the remainder of this section. First, the GEP model can invest and divest in three types of technology with dedicated modeling objects:

1. Conventional dispatchable units characterised by a variable cost of generating electricity and an availability profile. For sake of simplicity, dynamic generation constraints are not represented.
2. Variable renewables which have an hourly capacity factor and zero variable cost.
3. Short-term storage units which have a power and an energy components linked by a duration parameter and a round-trip efficiency. These technologies are modelled in a deterministic way (dispatched over the different time steps thanks to perfect foresight).

| | |
|---|---|
| **Sets, indices and set-related notations** | |
| $h \in \mathcal{H}$ | set of hours in a year |
| $y \in \mathcal{Y}$ | set of years |
| $g \in \mathcal{G}$ | conventional dispatch technologies |
| $v \in \mathcal{V}$ | variable renewable energy technologies |
| $s \in \mathcal{S}$ | storage technologies |
| $\mathcal{T} = \mathcal{G} \cup \mathcal{V} \cup \mathcal{S}$ | set of all technologies (indexed $t$) |
| $u \in \mathcal{U}_t$ | set of units of a certain technology |
| # | Number of elements in a set |
| **Parameters and variables** | |
| $\Delta$ | time step duration (i.e. one hour) |
| $D_{y,h}$ | Load in year $y$ at hour $h$ [MW] |
| $\gamma$ | Discount factor |
| $\lambda_{y,h}$ | Marginal cost of electricity [USD/MWh] |
| $OC_{y,t}$ | Annual fixed O&M cost [$/MW/Yr] |
| $IC_{y,t}$ | Investment cost annuity [$/MW/Yr] |
| $VC_{y,t}$ | Generating cost [$/MWh] |
| $\rho_t$ | Carbon intensity [$tCO_2$/MWh] |
| $Q_y$ | $CO_2$ emissions target [$tCO_2$] |
| $\ell_t$ | Lifespan [Yr] |
| $\mathcal{L}_u$ | Year of initially scheduled closure |
| $P_y^{CO_2}$ | Carbon price [$/$tCO_2$] |
| $n_{y,t}$ | Number of operating units |
| $n_{y,t}^+$ | Number of developed units |
| $n_{y,t}^-$ | Number of closed units |
| $\alpha_{t,h}$ | Hourly availability [%] |
| $k_t$ | Power capacity [MW/unit] |
| $q_{t,y,h}$ | Production [MW] |
| $c_{s,y,h}$ | Power charged into storage units [MW] |
| $soc_{s,y,h}$ | State of Charge of storage units [MWh] |
| $\rho_s$ | Charging and discharging efficiency [%] |
| $d_s$ | Storage duration [hours] |
| $f_{y,h}$ | Lost Load [MW] |
| $VoLL$ | Value of Lost Load [$/MWh] |

Table 2: Modeling notations

Each technology is represented by homogeneous units (*i.e.* the decision variables are expressed in terms of number of units).

Second, with respect to long term decisions (investments and retirements), technologies can be either fully exogenous (installed capacity trajectory is an input), partially endogenous (initial capacity is an input, new investments are not allowed but economic retirements are) or fully endogenous (investments and retirements are both allowed). Finally, the GEP model features $CO_2$ constraints in the forms of an upper limit on annual emissions to which each technology can contribute trough a carbon intensity parameter. The dual variable of this constraint (shadow price) is interpreted as the optimal carbon price to reduce emissions accordingly to the trajectory fixed as input, and is used to feed the SD market model.

## 2.3. System Dynamics market model

### 2.3.1. Overview

The SD model focuses on representing investors' behavior and does not aim at providing the optimal mix trajectory. It simulates new investments and decommissioning decisions in electricity generation units over several decades. Decisions are obtained endogenously each year of the simulation based on estimated profitability of various projects for a range of anticipated future patterns. It can also model investors with risk aversion, which differ by the criterion based on which their investment/decommissioning decisions are made. An algorithmic overview of the model is provided in Algorithm 1. The SD causal-loop diagram is also presented in Figure 2. Our SD market model is made of four main modules: the energy price module (briefly detailed hereafter) which takes assumptions from the anticipation module (presented in subsection 2.3.22.), the investment module (presented in subsection 2.3.33.) and the decommissioning module (presented in subsection 2.3.44.). Note that the investment and decommissioning modules are executed sequentially for each simulated year, as presented in Algorithm 1.

Regarding market design representation, this version of the SD model corresponds to the EOM paradigm: the economic assessment is done by anticipating future market conditions with a projected short-term dispatch implemented trough a cost-minimization problem. This implies that short-term operations are supposed to be perfectly competitive. We also assume that the price cap is matching the consumers' opportunity cost of not being served (in other words, the Value of Loss Load (VoLL)). With this configuration and without representing behavioral bias such as risk aversion, no missing money issue should be present and a capacity mechanism is not necessary. We therefore do not represent any mechanism of this kind in the model. Our goal is to analyse conditions required to obtained optimal mix trajectory from the EOM design, and thus this should be done within a modeling framework of perfect EOM marked design with an energy price that can jump to the VoLL.

As explained before, the $CO_2$ market is not within the scope of our SD market model. We use an exogenous $CO_2$ price that corresponds to the $CO_2$ price from the GEP model, but we do not endogenously represent its price formation.

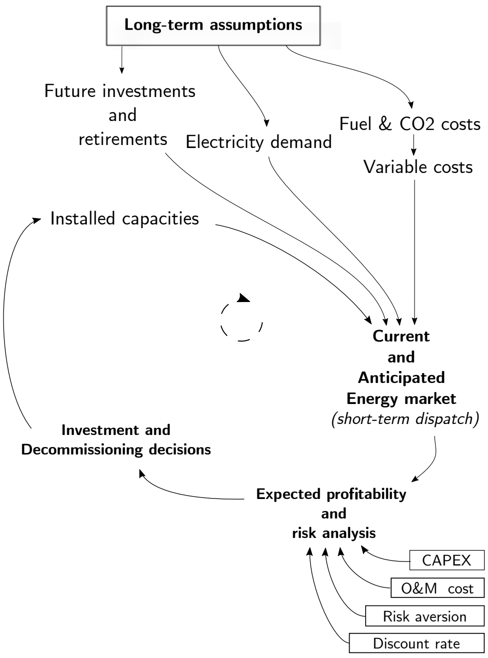


Figure 2: Causal-loop diagram of the SD model

#### 2.3.2. Focus on anticipation

In order to perform their investment decisions, investors need to anticipate relevant future market situations. Future anticipations requires both exogenous parameters (*e.g.* demand, fuel and carbon costs) but also endogenous variables such as the projected capacity mix. As highlighted by Tao et al. [21], the latter is of prime importance. When using multi-annual optimization models such as the GEP model exposed in section II.22., the formulated problem is processed by a numerical solver that provides optimal values for all decision variables at once. However, one specific purpose of the SD model is to detail every decision explicitly and chronologically.
Our SD model can accommodate three different options regarding anticipation of investment/decommissioning decisions that will occur in the future. Figure 3 illustrates the three options.

**Option A `[no anticipation]`:** The first and simplest option is to not consider any subsequent decisions: for a given year, existing units are projected in the future until they reach their lifespan and retire, without any further projected investments or early economic retirements. This is done endogenously in the SD market model without the need for any exogenous assumptions.
The two following options B and C are based on an anticipation of future decisions, and thus require exogenous assumptions of investment and decommissioning decisions for each year. Options B and C differ by the way to deal with deviations from the exogenous mix trajectory.

**Option B `[anticipating initial pace]`:** Only the future pace of investments and retirements from the exogenous trajectory is considered. In others words, anticipated capacities are obtained in a given year by virtually adding future investments and retirements of the exogenous trajectory to the system current state.

**Algorithm 1:** SD market simulator

**Result:** Vector of simulated $n, n^+, n^-, q, f, c$

**for** $y \in \mathcal{Y}$ **do**
  # *disinvestment sequence*
  Remove all units reaching the end of their lifespan
  Build anticipation for the disinvestment sequence
  continue = True
  **while** *continue* **do**
    Compute net revenues $\mathcal{R}_{y,u}$ in current year for all existing units of technologies eligible for decommissioning. If $\mathcal{R}_{y,u} < 0$, compute $NPV^{deco.}_{u,y}$ too.
    **if** $\min(NPV^{deco.}_{\bullet y}) < 0$ **then**
      Remove unit $u$ corresponding to the minimum NPV
    **else**
      continue = False
    **end**
  **end**
  # *investment sequence*
  Build anticipation for the investment sequence
  **while** *continue* **do**
    Compute $NPV^{invest.}_t$ of a new project for each technology candidate for investment.
    **if** $\max(NPV^{invest.}_{\bullet}) \geq 0$ **then**
      Add one unit of technology x corresponding to the maximum NPV
    **else**
      continue = False
    **end**
  **end**
**end**

**Option C** `[anticipating with perfect catch up]`: Future paces are updated so that they always try to catch up with the exogenous trajectory in case of a deviation. It may not always be feasible – *e.g.* when a technology only eligible for decommissioning already had too much retirements, it is not possible to re-invest – but the representative agent anticipates the closest possible trajectory as illustrated in Figure 3.

For each year, the sequential implementation of the disinvestment sequence (executed first) and the investment sequence (executed as a second step) led us to add one modeling assumption. Indeed, the three options described above are relative to *future* decisions, *i.e.* in the years following the year for which investment and retirements are being decided. However, this sequential setup induces the need to discuss if investment decisions of the current year are foreseen in the disinvestment module or not. This is translated in an optional parameter to decide if this is the case, and if so, what assumption is made regarding anticipated capacities (*i.e.* initial pace vs. perfect catch up).

As a final remark, we highlight that the exogenous reference trajectory required in options B and C can typically be the optimal ones computed by the GEP model but they may also be altered for study needs.

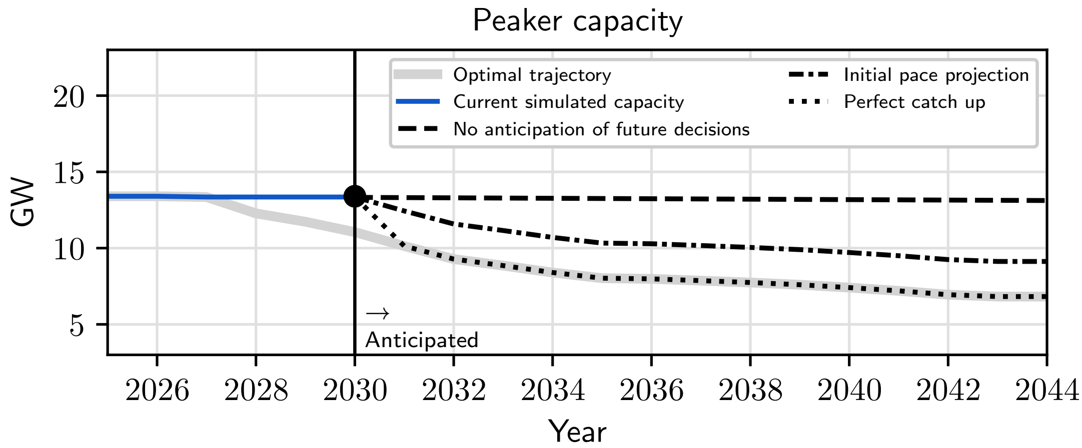


Figure 3: Anticipating future decisions in the SD model

#### 2.3.3. Investment sequence

In the investment sequence, the value of a new project is assessed for each candidate technology. To do so, we explicitly consider how the addition of a new project of a given technology would impact future energy prices. In other words, we adjust assumptions from the anticipation module by adding one generation unit and then, the short term market module is virtually run over all the anticipated year to estimate future energy prices ($\lambda$) and hourly volumes of energy ($q$) produced by each units. The model then computes energy revenues of the considered generation unit based on future energy prices and hourly generation dispatch, for every anticipated future scenario. The anticipation horizon on which revenues are estimated can correspond to the entire lifetime of the project or can also be reduced on purpose to represent myopia of agents. Myopia issue is not addressed in this paper and thus all our simulations consider the maximum available look-ahead horizon to assess economic value of projects.

The SD market model embeds several economic metrics to compare candidate technologies and to base investment decisions. In this paper, simulations are carried out with the classical Net Present Value (NPV), expressed relatively to one additional MW of installed capacity.[4] Equation 1 details the NPV formula used to this purpose, with $y$ being the current year in the simulation and $t$ the considered candidate technology.

$$NPV_{t,y} = \sum_{k=y}^{\min(\#\mathcal{Y},\mathcal{L}_u)} \gamma^k \sum_{h\in\mathcal{H}} \left( \frac{q_{t,k,h}}{n_{k,t} k_t} (\lambda_{k,h} - VC_{k,t}) - OC_{k,t} - IC_{k,t} \right) \tag{1}$$

This NPV formulation is a little bit altered compared with textbooks since it does not assess the value of the project on its whole lifetime but only on the part covered by the study horizon. This approach, also used by Tao et al. [21], has two benefits: (1) it is

[4]The profitability index (*i.e.* the ratio between the NPV of the project and its investment cost) and the internal rate of return are two other economic metrics embedded in our SD market model

consistent with the GEP approach that only sums annualized and discounted costs over this same period and (2) it avoids making hazardous choices on the value of projects beyond the end of the study horizon.

Sensitivity tests were conducted with the profitability index and results presented below are robust to the investment-decision metrics.

Once the investment metric is computed for each candidate technology, all profitable projects (in our case, profitable means having a positive NPV) are ranked and the one that produces the greatest investment return is selected and one unit is being invested in. This investment decision is then taken into account and is added to the fleet. The investment sequence proceeds by sequential loops and is terminated when no more profitable investment project is detected.

#### 2.3.4. Decommissioning sequence

The decommissioning sequence will assess the net revenue $\mathcal{R}_{u,n}$ for each existing unit eligible for decommissioning in the current year. It consists in the margin earned on the energy market minus fixed O&M costs as detailed in equation 2). Note that CAPEX are not considered in this assessment because they are already engaged and can no longer be saved (sunk costs).

$$\mathcal{R}_{t,y} = \sum_{h \in \mathcal{H}} \left( \frac{q_{t,y,h}}{n_{y,t} k_t} (\lambda_{y,h} - VC_{y,t}) \right) - OC_{y,t} \tag{2}$$

For all units experiencing losses in the current year $y$ (*i.e.* $\mathcal{R}_{t,y} < 0$), a complete assessment is made from the current year $y$ to its initially scheduled closure or at the end of an anticipation horizon (equation 3)[5].

$$NPV^{deco.}_{u,y} = \sum_{k=y}^{\min(\#\mathcal{Y}, \mathcal{L}_u)} \gamma^k \mathcal{R}_{u,k} \tag{3}$$

When different technologies have a negative $NPV^{deco.}$, the unit that generates the greatest losses is first retired. The decommissioning sequence is repeated and ends when no technology has a negative $NPV^{deco.}$.

## III. CASE STUDY

Our case study represents the evolution of a stylised system inspired by the Californian power system between 2025 and 2045. Most of our assumptions come from the 2019-2020 Integrated Resource Planning (IRP) exercise from the California Public Utilities Commission (CPUC) [6]. The three main features that make this case interesting and

[5] The time horizon can also be reduced to take into account investors' myopia

[6] We used the "30MMT_base_20191001_2045" scenario.

insightful are:

- A grid demand stagnating up to 2030 followed by a strong increase pushed by electrification although moderated by decentralized solar generation.
- A strong commitment to drastically reduce GHG.
- An existing fleet including a substantial share of gas-fired dispatchable technologies and investment candidates consisting of non-dispatchable renewable energy sources alongside storage solutions. In the CPUC scenario we used as a reference, massive developments are expected for solar and storage while a certain amount of the gas fleet will retire economically before the end of its lifespan.

As regards market design, we consider the EOM with price that can jump to the VoLL, completed with an exogenous carbon price that drives decarbonization. Our case study is an illustrative power system to draw broad features, but it is by no means a prospective exercise for California. In that sense, the market design layer of our case study diverges significantly from the real market design in California[7].

For sake of simplicity, our illustrative power system is considered as isolated (no interconnections) and the internal electricity network is not represented (*copper plate*). The modeling framework could be extended to an interconnected situation but at an important computational cost and would require further methodological developments.

### 3.1. Dataset overview

The dataset is adapted from three data sources: the 2019-2020 IRP study from the CPUC [5], Ninja Renewables [13] and historical data from CAISO [3].

First, we consider an exogenous gross load slightly increasing up to 2030 (0.4% p.a.) before taking off (2.3% p.a.) for the rest of the study horizon. A growing amount of decentralized solar generation is subtracted from the gross load (+2TWh p.a., starting from 28 TWh in 2030). The annual targets here exposed are converted into hourly time series by scaling the 2019 historical gross load and a distributed generation time series from Ninja Renewable.

On the supply side, we model four endogenous technologies in terms of investment and retirement decisions completed by a set of exogenous generating technologies. Data relative to endogenous technologies are exposed in table 3. Note that they are divided into two groups with respect to available decisions: (1) a first group made up of existing fossil-fired dispatchable technologies and (2) a second group of technologies candidate for investment made up of solar generation and a storage technology. PV and storage assets are available for investment with no build time, *i.e.* they are build and start to generate electricity on the same year of the investment decision. The storage technology that we considered is generic and congruent with a Li-ion 4 hours Battery Energy Storage System (BESS) with a 85% roundtrip efficiency. A common WACC of 8 % is

[7] The Californian market design consists in a nodal energy market with soft offer cap at $1,000/MWh, completed with a $CO_2$ price, a mandatory resource adequacy requirement (but no formal capacity market), and a Renewable Portfolio Standard (RPS) program. However, in the 2019-2020 IRP exercise from the CPUC, the RPS constraint is not binding (the associated shadow price is zero) and the decarbonization trajectory is driven by the constraint on GHG emissions.

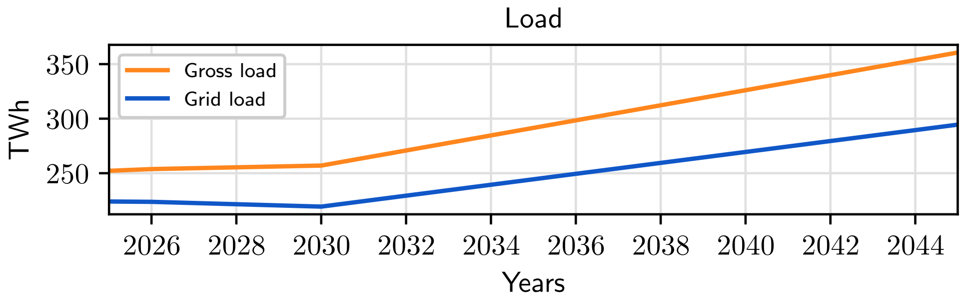


Figure 4: Load assumptions (grid load corresponds to the gross load minus decentralized solar generation)

| **Technology** | **Available decision** | **CAPEX** | **Fixed O&M** | **Fuel cost** | **Carbon intensity** |
|---|---|---|---|---|---|
| - | - | [USD/kW-Yr] | [USD/kW-Yr] | [USD/MWh] | [$tCO_2$/MWh] |
| CCGT | Decommissioning | 126 | 11 | Average: 31 | 0.37 |
| Peaker | Decommissioning | 46 | 14 | Average: 51 | 0.61 |
| PV | Investment & decommissioning | 70 | 9 | 0 | 0 |
| Storage | Investment & decommissioning | 82 | 10 | 0 | 0 |

Table 3: Technical and economic parameters for endogenous technologies

taken for all technologies.
The initial capacities in 2025 for fossil capacities and storage are determined by running the GEP model on this first simulated year in order to start the simulation with a balanced and economically optimized fleet. They amount to 10 GW for CCGT, 13.4 GW for peakers and 6.4 GW for storage. Initial values for endogenous solar is set to 0 since the existing and already planned fleet is accounted for exogenously. All endogenous technology have a representative capacity of 200 MW per unit. All lifespans are assumed to be longer than the simulation duration (25 years).

Exogenous technologies consist of CHP, nuclear, existing and already planned wind and solar and finally Geothermal, Biomass and Small Hydro-power combined in one category labelled "Other RES". Hourly availability factors of these technologies is modelled by using data from CPUC [5], converted to an hourly resolution with Ninja Renewables [13] if necessary.

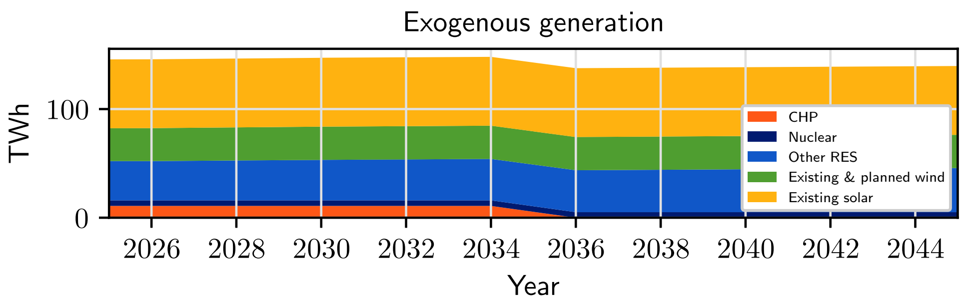


Figure 5: Exogenous generation

The $CO_2$ emissions annual targets are presented in Figure 6. This trajectory depicts a 60% reduction in emissions throughout the study horizon.

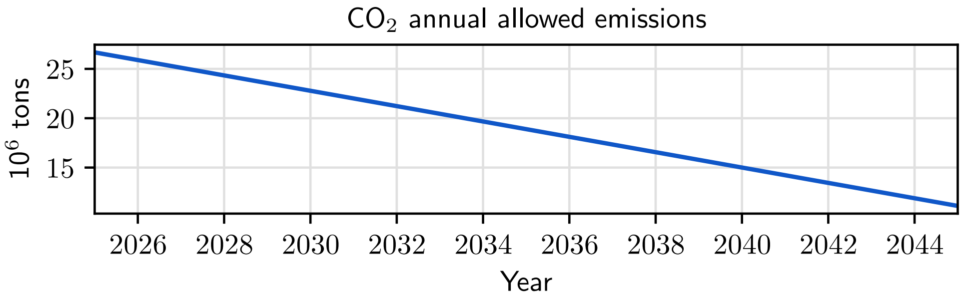


Figure 6: Allowed $CO_2$ emissions

### 3.2. Results from the GEP

The optimal trajectories for endogenous capacities are presented in Figure 7. Regarding new developments, large scale solar reaches an amount of 68 GW installed capacity in 2045 and 74 GW for storage. Fossil peaker capacity is divided by two (-6.6 GW between 2025 and 2045) and CCGT capacity remains steady.

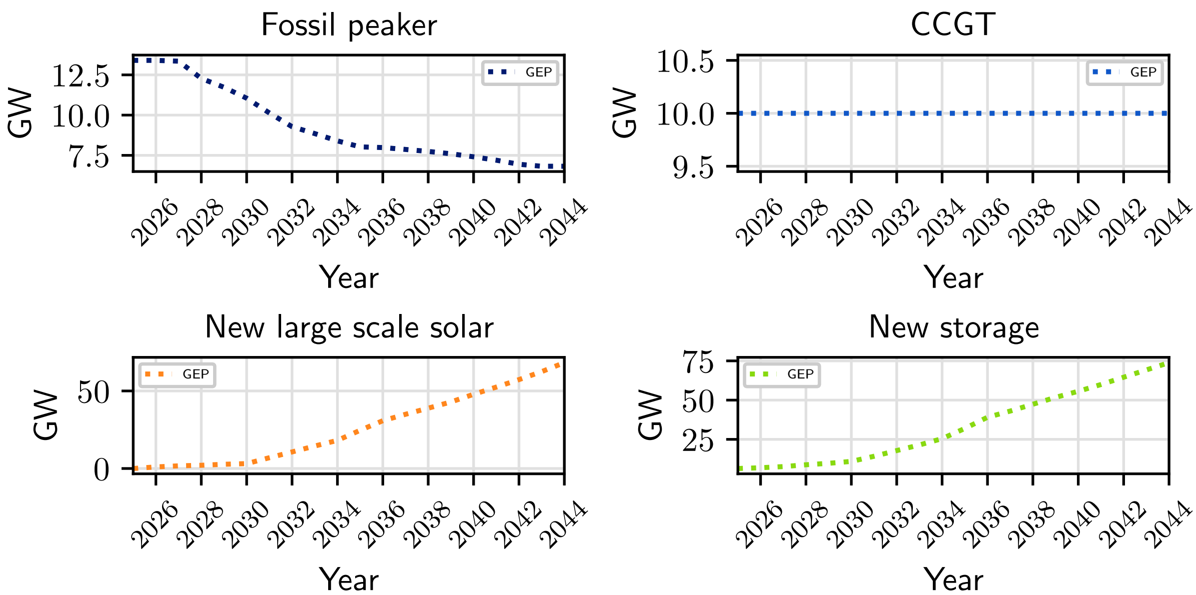


Figure 7: Optimal capacity trajectories for endogenous technologies derived from the GEP model

The constraint on $CO_2$ emissions is binding during the full trajectory (Figure 8) and its shadow price reaches the level of 363 $\$/tCO_2$ in 2045 (see Figure 9 for full path).

In the CPUC's exercise, initial capacities in peaker plants and CCGT are respectively 8.6 GW and 16.2 GW. They are respectively reduced by 4.2 GW and 1.8 GW. Solar is developed to the extent of 64.3 GW and storage 50.8 GW. Regarding the $CO_2$ shadow price, it reaches 403 $\$/tCO_2$.
We thus argue that although the exact figures deviate from the the CPUC's exercise, the broad landscape depicted in our exercise is very comparable.

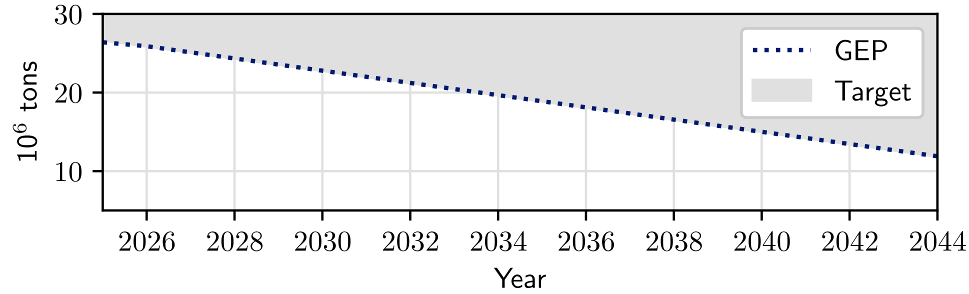


Figure 8: $CO_2$ emissions compared with its target

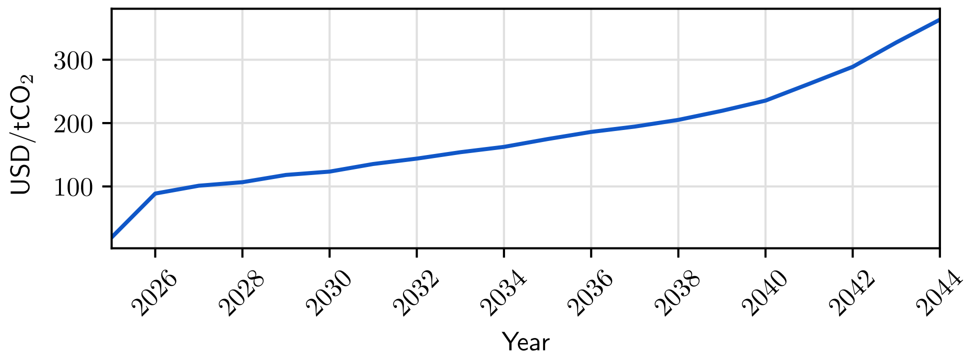


Figure 9: $CO_2$ shadow price derived from the GEP model

In this configuration, it is interesting to note that a few hours with unserved load are experienced in the first years but quickly vanish afterwards (see Figure 11). This is due to the combination of new capacities developed to meet the decarbonization constraint and the fact that the fixed O&M costs needed to maintain gas resources are low compared to the VoLL ($11–14/kW-yr vs. $20/kWh), i.e. it is cost-efficient to retain 1 MW of existing gas to avoid 1 MWh of lost load. Still, some price spikes occur within each year (for instance when available capacity is perfectly equal to load) and allow the different technologies to recover their costs.

Indeed, running the GEP model allows us to observe how costs are recovered with this approach. This can be done by using the Cost Recovery Ratio (CRR) metric that consists in computing the ratio between net revenues earned on the power market and the invested capital for each vintage. For a given vintage of a technology $t$ invested in year $y$, the CRR is detailed in equation 4. We can note that each vintage recovers exactly 100% of its costs in the GEP in accordance with theoretical results (see Figures 18 and 17).

$$CRR_{t,y} = \sum_{k=y}^{\min(\#\mathcal{Y},\mathcal{L}_u)} \frac{\sum_{h\in\mathcal{H}} \left(\frac{q_{t,k,h}}{n_{k,t}k_t}(\lambda_{k,h} - VC_{k,t}) - OC_{k,t}\right)}{IC_{k,t}} \tag{4}$$

## IV. RESULTS AND DISCUSSION

Our simulation exercise is structured in two phases. First, Section IV.11. examines the conditions under which the SD market model can track the optimal trajectory described in Section III.22.. Then, Section IV.22. explores how the simulated EOM outcomes change when we relax some of theses conditions.

### 4.1. EOM outcomes with idealistic assumptions

It is well known that it is theoretically possible to reach the long-run equilibrium when fully informed and rational agents compete on perfect and complete markets. Here, we investigate how these conditions translate in the SD framework and find that EOM-induced investment and retirement decisions reproduce the optimal path only when the four assumptions below 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 $CO_2$ price over the whole horizon. This price is assumed to coincide with the shadow price computed with the GEP model.
**A3.** 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.[8]
**A4.** Future anticipated decisions catch up with the optimal trajectory in case of deviation.

Figure 10 depicts the simulated EOM outcomes when assumptions A1–A4 hold. Visual inspection shows that the mix trajectory closely tracks the optimal one provided by the GEP model.

Some slight deviations are observable and can be attributed to the lumpiness of units. Indeed, cost recovery is not ensured in the optimal solution with discrete units, but only when capacities can be continuously adjusted to optimal values. Therefore, small discrepancies occur because the SD model is based on discrete representation of units and uses a decision criteria ensuring cost recovery. To correct for these unavoidable deviations, we assume that anticipated decisions catch up with the optimal trajectory (hence A4 assumption).

This can be further illustrated by the cost recovery analysis. The extra revenues – 105% for PV and 107% for storage units on average – that can be observed for some vintages, even in this idealistic case, are induced by the presence of a few additional hours with unserved energy (see Figure 11) induced by the presence of price spikes that can reach the VoLL and investment options with discrete capacities. However, this does not indicate any significant adequacy issue since these numbers of hours remain low and close to the optimal.

[8] Assumption A3 echoes with Section 2.3.22. and calls for the implementation of an anticipation module that represents future optimal decisions.

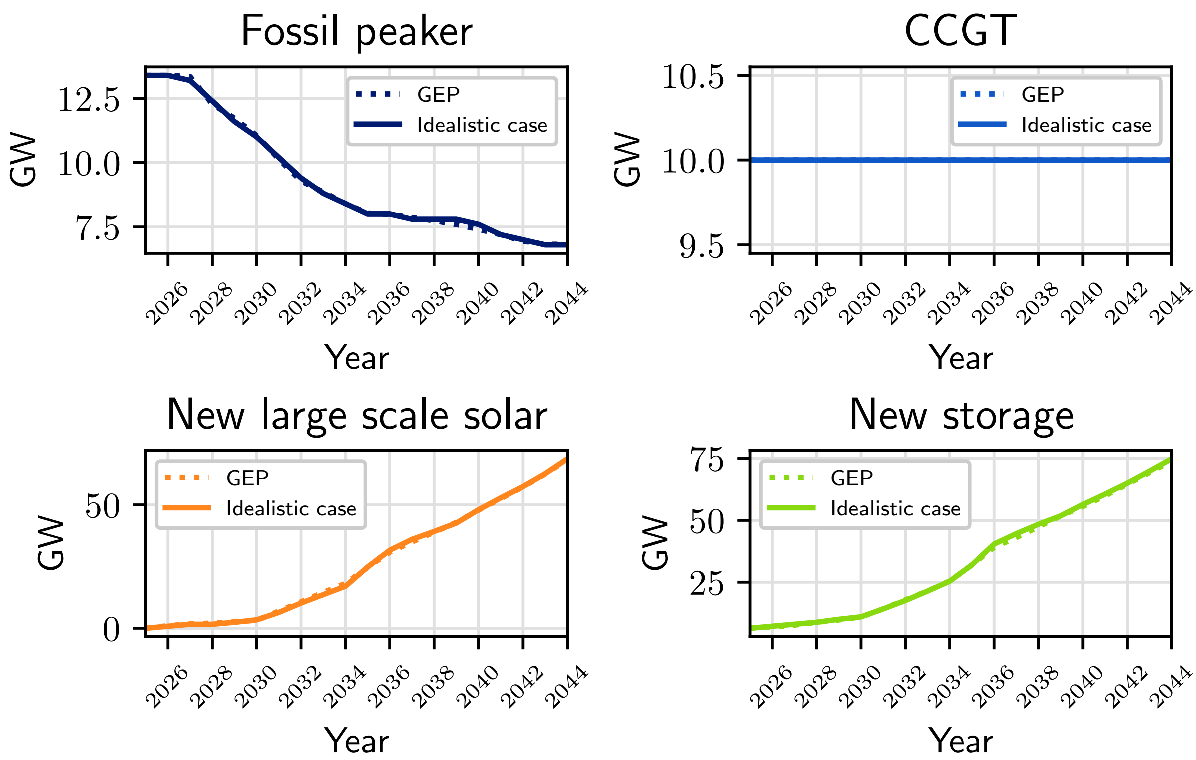


Figure 10: SD market simulation results in the idealistic case (i.e. assumptions A1–A4 hold)

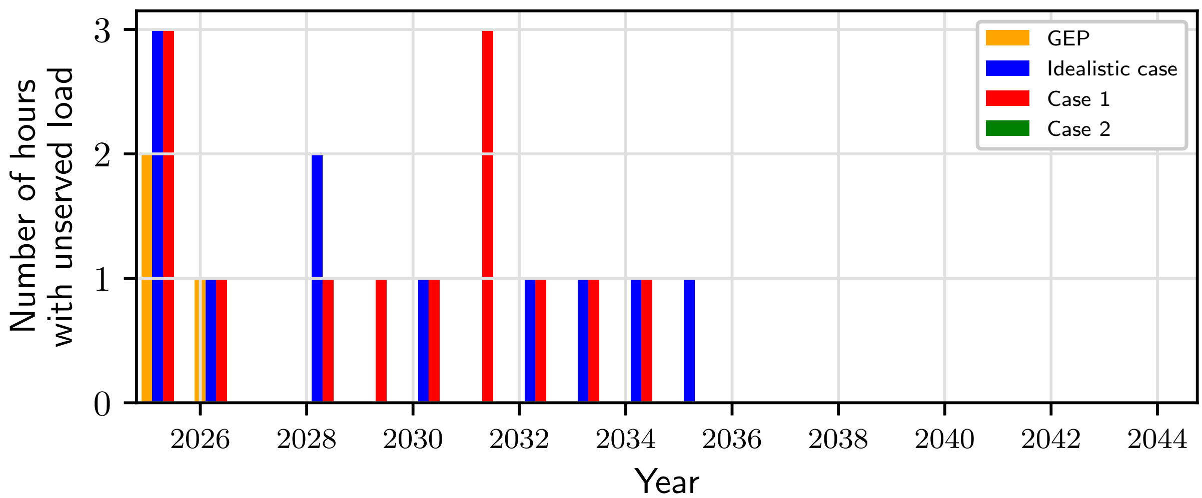


Figure 11: Number of hours with unserved load in the different simulations + GEP

### 4.2. EOM outcomes with relaxed assumptions

We now relax two of the above assumptions sequentially as presented in Table 4. First, in Case 1, we drop A2 and consider that investors and asset owners make conservative projections for the future $CO_2$ price compared to the high price levels that are required to meet deep decarbonization targets (Section 4.2.11.). This behavior is consistent with observations in existing carbon markets worldwide where prices have been too low and volatile to convey credible long-term investment signals in line with those targets (e.g. Tvinnereim and Mehling [24]; Joskow [9]; Perino et al. [15]). Since a deviation is

| | Idealistic case | Case 1 | Case 2 |
|---|---|---|---|
| **A1**: perfect information about demand, distributed generation and costs | ✓ | ✓ | ✓ |
| **A2**: perfect information about the $CO_2$ price | ✓ | | |
| **A3**: perfect information about future decisions | ✓ | ✓ | |
| **A4**: projected decisions catch up with optimal decisions | ✓ | | |

Table 4: Assumptions for the different cases.

expected, we assume that market participants anticipate the initial pace of investment and decommissioning decisions as per A3 but do not update their capacity mix projections when they observe inconsistencies compared with the optimal trajectory (i.e. A4 is not verified anymore).

Second, in Case 2, we further drop A3 (i.e. both A1 and A3 do not hold) and consider that investors and asset owners do not anticipate future investment and retirement decisions (Section 4.2.22.). That is, they have a static view of the asset fleet with given decommissioning dates. This assumption is motivated by the fact that anticipating competitors' decisions is a very difficult task with an uncertain outcome in liberalized electricity markets [e.g. 8, 6].

### 4.2.1. Case 1: Conservatism in $CO_2$ price projections

Case 1 considers that investors anticipate a lower $CO_2$ price than the realized one as shown in Figure 12. The anticipated $CO_2$ price begins at the same level than in the reference case but gradually deviates downwards (-2% p.a. compared with the reference). This lower trajectory is only used in the anticipation loop when making investment and decommissioning decisions but the actual realization remains the reference price.

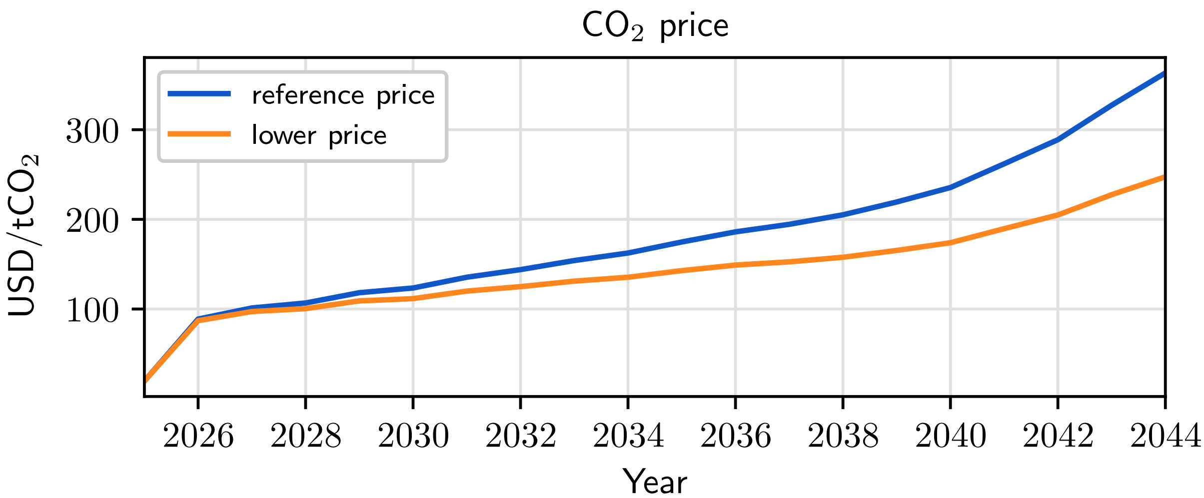


Figure 12: Anticipated carbon price trajectory in the optimal vs. conservative case. The reference trajectory (in blue) corresponds to the actual outcomes in all simulations.

Results depicted in Figure 13 show that all trajectories in Case 1 are significantly delayed compared with the reference idealistic case: fossil capacity remains too high, and PV and storage development is significantly reduced and delayed. Finally, Case 1 does not lead to the optimal mix trajectory in line with the decarbonization target. In particular, it does not allow to reach the targeted carbon emissions level (see Figure 14).

Regarding costs system-wide presented in Figure 15, the lower level of investments observed in Case 1 induces some savings on the CAPEX sides. However the fact that the resulting system in Case 1 is emitting more $CO_2$ and that the actual outcomes of the $CO_2$ price is the reference price leads to more generation costs. Consequently, the system total cost is increased by 1.6%.

Finally, the cost recovery analysis for this simulation shows extra-revenues for investors. In fact, since the carbon price used during the investment assessment is lower than the actual trajectory and because a higher carbon price is more beneficial to the candidate technologies, each vintage ends up having a cost recovery ratio greater than 100%. In particular, PV investments have an average 132 % cost recovery and 131 % for the storage units (see Figures 17 and 17).

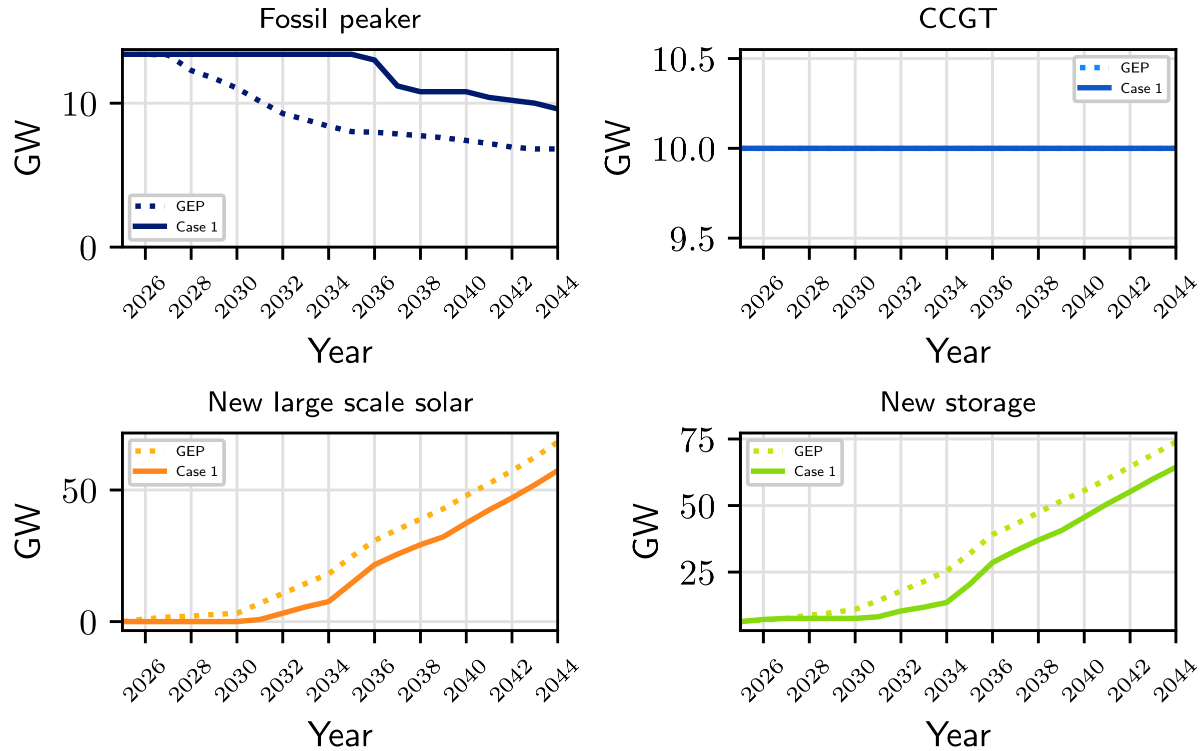


Figure 13: Simulated EOM outcomes in Case 1

#### 4.2.2. Case 2: identical to Case 1 + no anticipation of future decisions

Results for Case 2 depicted in Figure 16 significantly differ from both the idealistic case and Case 1. The energy transition observed in Case 2 shows a fast development of PV and storage early on which nonetheless achieves a too limited development of these technologies compared to the idealistic trajectory in the long run (similarly to Case 1).

Two effects going in opposite directions explain these results. First, the non-anticipation

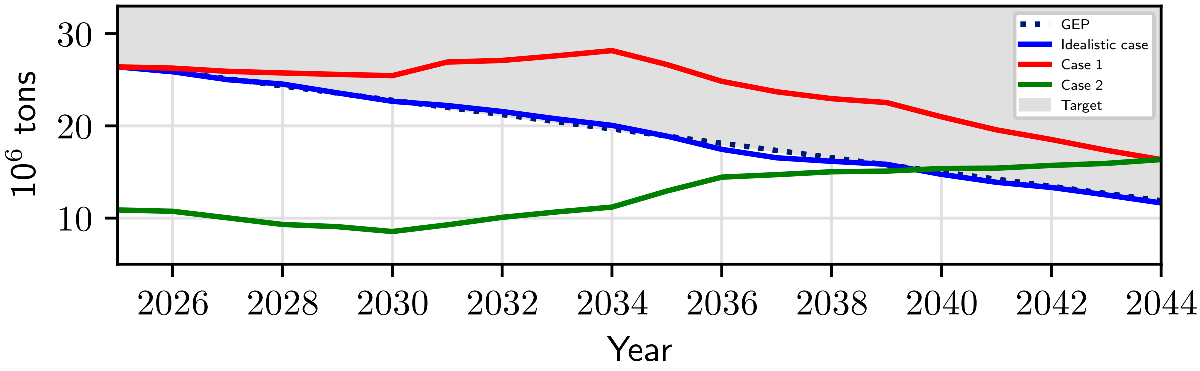


Figure 14: $CO_2$ annual emissions of power sector for the different simulations + GEP

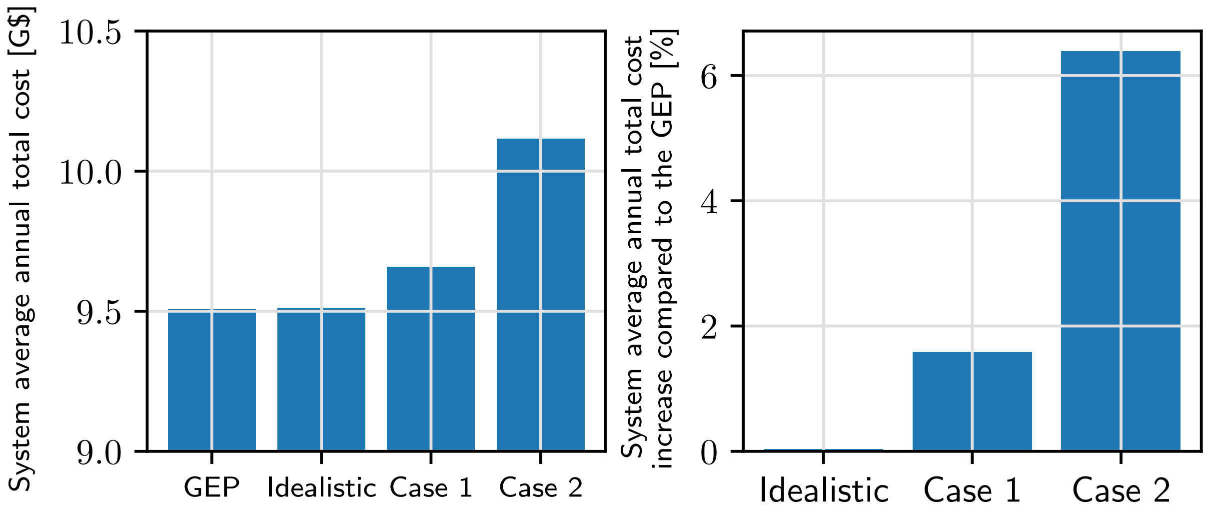


Figure 15: Comparison of system total cost from GEP + Simulations

of subsequent decisions in a context of growing capacity needs results in significant scarcities being (incorrectly) foreseen by investors. On the investment side, this leads to a significant amount of over-investment at the beginning of the horizon. In fact, investors do not anticipate that a substantial number of scarcity pricing hours, on which a sizable share of their project profitability is based, will vanish as additional investments materialize in the following years and alleviate capacity shortage. Similarly, projected price ranges and asset profitability will also be negatively impacted by other future developments (e.g. 'cannibalization effect').

Interestingly, the effect is similar for retirements. That is, even if asset owners experience losses in a given year, what turns out to be an over-optimistic view of future capacity needs leads them to keep their plants online to capture future anticipated benefits that would offset their current losses (but again incorrectly foreseen). This effect gradually fades away over time as the planning horizon (over which future decisions are not anticipated correctly) mechanically shrinks (edge effect).

The second effect we observe chronologically is due to the long-run underestimation of the carbon price (Section 4.2.11.). We find that while the dynamic is impacted towards early over-investment and over-capacity, installed capacity levels will eventually reach

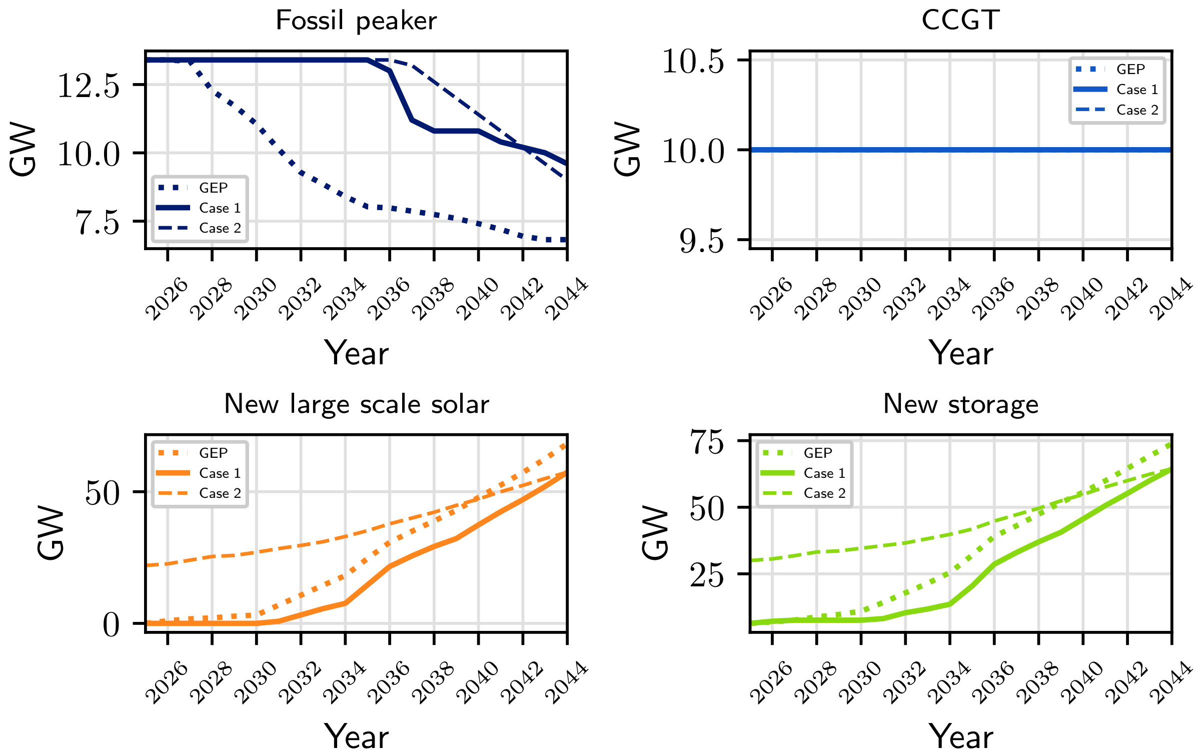


Figure 16: Simulated EOM outcomes in Cases 1 and 2

those induced by the lower carbon price signal.

Crucially, this effect is not only a matter of taking different paths to reach the same point. As Figures 17 and 18 show, this significantly affects cost recovery for installed capacities. Specifically, vintages from the beggining of the horizon experience significant losses (e.g. 75% CRR for PV invested in the first year) when non-anticipation issue is dominant. Going forward in the simulation, this effect fades out and the latest vintages experience extra-revenues in the same way as Case 1. Regarding system costs presented in Figure 15, they are increased by 6.3 % in this simulation, amounting to 10.1 G$ per year on average.

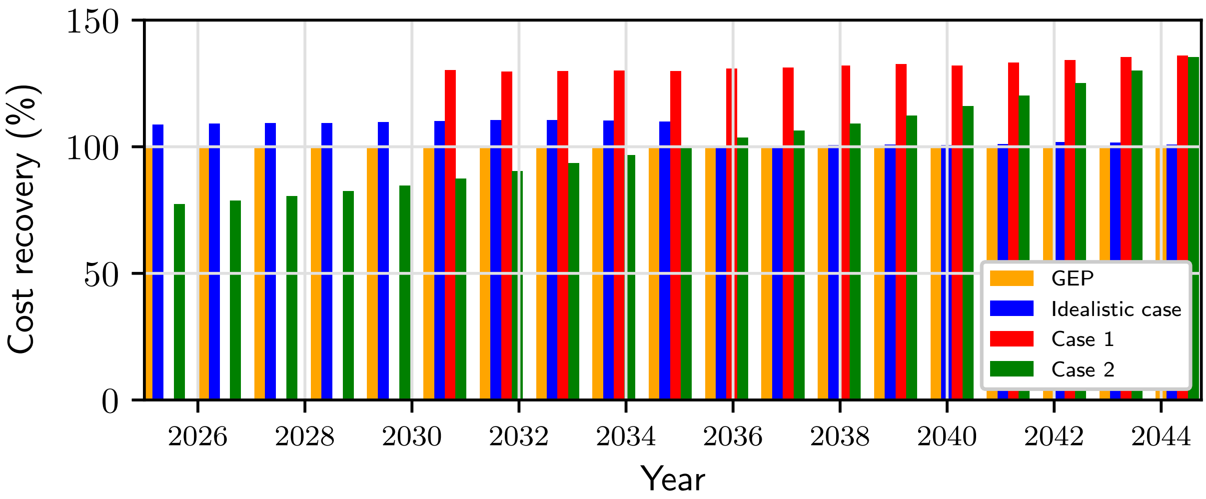


Figure 17: Cost recovery for each PV vintage in different simulations and in the GEP results

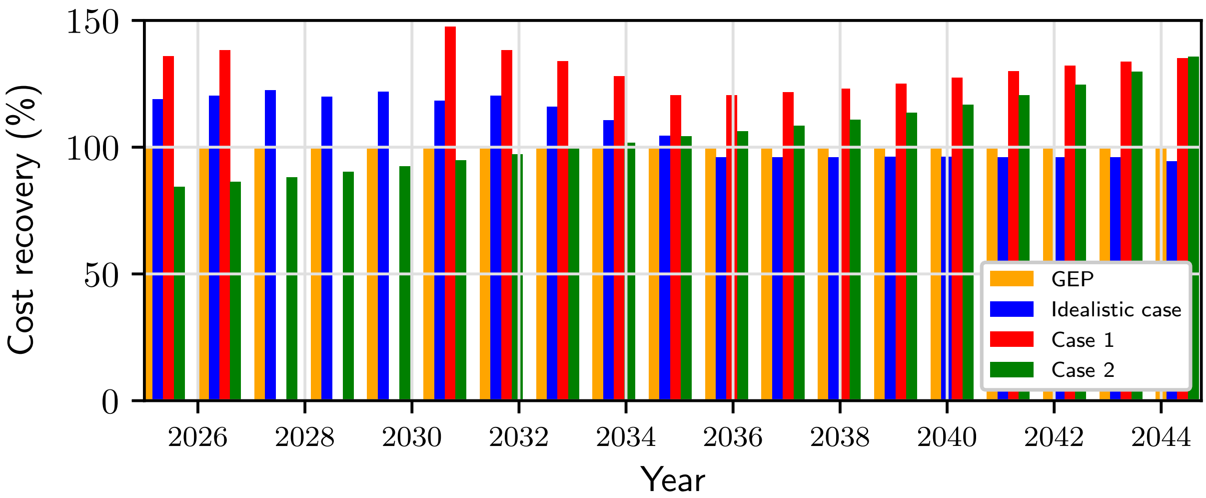


Figure 18: Cost recovery for each storage vintage in different simulations and in the GEP results

### 4.3. Summary of modelling results

The key metrics for the different cases previously exposed are summerized in Table 5. The main takeaway of this exercise is that the EOM simulation requires a certain number of strong assumptions to reproduce the optimal trajectory. Relaxing this assumptions can have damaging effects on the decarbonization trajectory (i.e. annual emissions targets are not met), the system total cost and cost recovery for investors.

## V. CONCLUSIONS AND POLICY IMPLICATIONS

In this paper, we first investigate what are the requirements behind the core assumption of 'perfectly competitive markets with fully informed and rational agents' required for the energy-only market design to reproduce cost-effective decarbonization pathways

| | System Average Total Cost [G$/Yr] | $CO_2$ emissions in 2045 [$GtCO_2$] | Cost Recovery for PV [%] | Cost Recovery for storage [%] |
|---|---|---|---|---|
| **GEP** | 9.5 | 12 | 100% | 100% |
| **Idealistic case** | 9.5 | 12 | 105% | 107% |
| **Case 1** | 9.7 | 16 | 132% | 131% |
| **Case 2** | 10.1 | 16 | 100% [75%-135%] | 104% [82%-136%] |

Table 5: Key metrics for the different cases

generated by traditional GEP models. To this end, we develop a SD market simulation model to (1) study how market participants make investment and retirement decisions and (2) compare simulated market outcomes with the results from a GEP model. The comparison exercise has clear implications and shows that the aforementioned requirements are numerous and demanding, i.e. unlikely to be met in practice.

Besides perfect information about all relevant exogenous parameters in the SD simulation, we emphasize the two following conditions:

1. A strong carbon price signal consistent with decarbonization targets is required. It has to be acknowledged and used by market participants in their decision making process. This however seems highly uncertain in practice as market prices for carbon are to a large extent too volatile and inconsistent with policy objectives.
2. Market participants must anticipate all subsequent investment and retirement decisions when assessing a project opportunity or a closure at a given date. This would probably require too high a level of information sharing and coordination among them.

Second, we relax these assumptions to appraise how the EOM design responds. It appears that the EOM lacks intrinsic counter-force and the generation mix can considerably deviate from optimality. Effects are mixed in terms of dynamics and end points but damaging impacts are observed in terms of decarbonization level and cost recovery for investors.

Our analysis calls for more robust market designs to ensure power system decarbonization at least cost, e.g. in the form of hybrid markets that rely on long-term arrangements alongside short-term markets as we know them today [18, 9]. Strength of investment and retirement signals should be a key point to assess the different available options with a specific attention to their robustness *vis-à-vis* practical investor behaviors in a context of deep uncertainty.

The models and methods developed in this paper outline relevant alleys for future work. First, our SD market model embeds alternative risk-adjusted decision criteria that can account for multiple forecasts and scenarios. This allows for further analysis of the robustness of market designs with a broader range of investor behavior (e.g. risk aversion). Second, SD modeling allows for the representation of alternative market designs (our model already incorporates some of them) including tenders and long-term contracts. Finally, using a more disruptive simulation context in terms of demand or cost evolution would offer further insights on market design robustness.

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# APPENDICES

## A. APPENDIX

### 1.1. GEP model equations

#### 1.1.1. Objective function

The objective function is the discounted total cost over the study horizon.

$$
\begin{aligned}
\min_{n,n^+,n^-,q,f,c} \sum_{y\in\mathcal{Y}} \gamma^y \Bigg( & \sum_{h\in\mathcal{H}} \sum_{t\in\mathcal{T}} q_{t,y,h}.VC_{y,t} \\
& + \sum_{t\in\mathcal{T}} n^+_{y,t}.IC_{y,t}. \sum_{i=0}^{\min(\ell_t,\#\mathcal{Y}-y)} \gamma^i \\
& + \sum_{t\in\mathcal{T}} n_{y,t}.OC_{y,t} \\
& + \sum_{h\in\mathcal{H}} VoLL.f_{y,h} \Bigg)
\end{aligned} \tag{A.1}
$$

#### 1.1.2. Constraints

Constraints (A.2-A.5) pertain to the hourly dispatch modelling:

(A.2) imposes load balance
(A.3) imposes the upper limit on generation
(A.4) imposes the upper limit on stored energy
(A.5) is the storage dynamics

$$
\begin{aligned}
& \forall y \in \mathcal{Y}, h \in \mathcal{H}, \\
& \sum_{t\in\mathcal{T}} q_{t,y,h} + f_{y,h} = D_{y,h} + \sum_{s\in\mathcal{S}} c_{s,y,h}
\end{aligned} \tag{A.2}
$$

$$
\begin{aligned}
& \forall y \in \mathcal{Y}, h \in \mathcal{H}, t \in \mathcal{T}, \\
& q_{t,y,h} \leq n_{y,t} k_t \alpha_{t,h}
\end{aligned} \tag{A.3}
$$

$$
\begin{aligned}
& \forall y \in \mathcal{Y}, h \in \mathcal{H}, s \in \mathcal{S}, \\
& soc_{s,y,h} \leq n_{y,s} k_s d_s
\end{aligned} \tag{A.4}
$$

$$
\begin{aligned}
& \forall y \in \mathcal{Y}, h \in \mathcal{H}^*, s \in \mathcal{S}, \\
& soc_{s,y,h} = soc_{s,y,h-1} + \rho_s c_{s,y,h-1} - \frac{1}{\rho_s} q_{s,y,h-1}
\end{aligned} \tag{A.5}
$$

Constraints (A.6 - A.7) pertain to investment and retirement dynamics.

(A.6) Number of units dynamics
(A.7) Lifespan limit: each endogenous investment can be associated with a decommissioning decision during its lifespan.

$$\begin{aligned} &\forall y \geq 1, h \in \mathcal{H}, t \in \mathcal{T}, \\ &\quad n_{y,t} = n_{y-1,t} + n^{+}_{y,t} - n^{-}_{y,t} \end{aligned} \tag{A.6}$$

$$\begin{aligned} &\forall t \in \mathcal{T}, \forall y \in \mathcal{Y}, \\ &\text{if } y + \ell_t \leq \#\mathcal{Y} : \\ &\sum_{i=y}^{\#\mathcal{Y}} n^{-}_{i,t} \geq n^{+}_{y,t} - \end{aligned} \tag{A.7}$$

Constraint (A.8) imposes an annual cap on $CO_2$ emissions.

$$\begin{aligned} &\forall n \in \mathcal{N}, \\ &\sum_{t \in \mathcal{T}} \sum_{h \in \mathcal{H}} q_{t,n,h} \leq Q_n \end{aligned} \tag{A.8}$$

Each decision variables can be constrained in an *ad-hoc* manner with an upper/lower bound or with a specific value. This feature is used to model the existing fleet for which $n$ can be fixed at the beginning of the simulation and $n^+$ can be constrained to $0$ afterwards if the technology is not candidate for new developments.

Finally, all decision variables (i.e. $n, n^+, n^-, q, f, c$) have non-negativity constraints.