# Moving Forward Blindly: Capacity Planning, Uncertainty, and Environmental Targets

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**Abstract**

The energy industry currently faces significant uncertainty in future demand and supply. Despite this, policies for decarbonizing the power sector are often based on predetermined scenarios. In this paper, we develop a dynamic stochastic model of generation capacity investment to evaluate the consequences of neglecting uncertainty under ambitious environmental targets. The model is calibrated using hourly data from the German electricity system for the period 2015-2020. The results show that disregarding uncertainty results in vastly underestimating the cost of decarbonization and hinders reaching environmental targets. Our study suggests a practical approach of focusing on a more pessimistic, predetermined scenario as a better solution.

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# 1 Introduction

Decarbonizing the power sector is crucial for the energy transition, but current European national roadmaps rely heavily on *deterministic* scenarios for future electricity systems, future electricity systems, with little consideration to future uncertainty. However, the distant future remains highly uncertain, as exemplified by recent major events such as the COVID-19 crisis, war in Ukraine, and climate disasters, which have caused unforeseen fluctuations in electricity demand and supply, resulting in significant consequences.

This paper argues that neglecting uncertainty in long-term capacity planning can result in significant economic and environmental consequences. We quantify the economic costs and environmental impacts of capacity planning under mispecified uncertainty regarding future supply and demand conditions using a dynamic stochastic model of capacity investment under uncertainty. We consider three sources of uncertainty: (1) future demand, (2) natural gas prices, and (3) renewable energy availability. To study the consequences of misestimating uncertainty, we calibrate our model for Germany.

Specialized government research centers regularly conduct prospective studies to determine energy transition policies that meet environmental targets. These studies focus on optimizing production costs in a deterministic environment, assessing the feasibility and cost-effectiveness of different renewable energy and energy efficiency measures. The resulting reports are used to establish environmental targets and develop appropriate policy tools, such as carbon pricing and renewable support policies. Examples of such reports include the European Union's 2050 Energy Strategy, the French TSO report "Futurs énergétiques 2050," which outlines necessary investments in renewable energy infrastructure and considers policy and market developments needed to support the deployment of renewable energy sources. The German government's Energiewende plan also relies on this deterministic modeling approach.

Power generation is fraught with uncertainties, including operational issues like unplanned outages, as well as cost uncertainties, particularly fuel costs. With the energy transition and the increasing penetration of renewable power, new uncertainties arise. Firstly, renewable production is weather-dependent and less predictable than conventional power plants. Secondly, there is technological uncertainty surrounding backup technologies, such as large-scale storage (IEA, 2022). Finally, as many European countries phase out coal and nuclear power plants, they rely more on gas production, which is concerning given the volatility of gas prices that drive spot market prices and affect the profitability of all production assets.

Investment in future power plants requires annual projections of electricity demand, with a goal of exceeding anticipated levels. However, maintaining adequacy of electricity supply is critical and requires precise matching of supply to demand every second. Economic trends and shocks, such as the COVID-19 pandemic, can significantly impact electricity consumption, as evidenced by the 12% reduction in consumption during the quarantine period in France (Benatia, 2022). Additionally, electricity demand is heavily influenced by weather and seasonal variations, which are expected to become more unpredictable with climate change. As a result, investment decisions must factor in significant uncertainty.

Scenario-based techniques are commonly utilized to integrate uncertainty into demand and production forecasts. This involves using optimistic to pessimistic scenarios to facilitate straightforward calculations and technical assumptions, without depending on intricate probabilistic models. While this method can effectively optimize investment trajectories for each scenario, it has some limitations and disadvantages. One significant drawback is that it neglects additional costs linked with excess or shortfall generation fleets. This includes the cost of amortizing extra investments or the cost of a significant generation shortfall. Thus, when using scenario-based techniques to make investment decisions, it's important to consider these costs.

Policymakers prioritize matching electricity demand, even at the expense of environmental concerns during unforeseen events. Transmission System Operators (TSOs) provide emergency reserves to adjust power supply, but these reserves only cover a small portion of planned production, which is not always sufficient. For instance, in response to soaring gas prices during the Ukraine crisis, France and other European nations reopened coal plants to protect consumers from higher electricity costs and potential blackouts [1]. However, this decision had significant environmental repercussions that must be taken into account in future policymaking. On the other hand, investors need to anticipate future asset profitability years in advance to build new capacities and assess spot market

[1] https://www.lemonde.fr/en/economy/article/2022/09/02/despite-climate-commitments-the-eu-is-going-back-to-coal_5995594_19.html

revenues. As a result, forecasts remain necessary.

**Main contributions.** In this paper, we demonstrate the significant impact of uncertainty on optimal energy transition paths. Specifically, we make three key points: Firstly, failure to account for uncertainty leads to substantially different optimal energy transition paths. Secondly, neglecting uncertainty can result in a significant underestimation of the cost of a successful transition or can further delay the transition and increase the failure rate of the system. Thirdly, setting an environmental target without properly accounting for uncertainty can be highly inefficient in negative shock scenarios. Our findings underscore the importance of taking into account uncertainty when designing policies for energy transition. By doing so, we can ensure that we achieve a successful and sustainable transition, even in the face of unexpected challenges.

**Literature review.** We developed a model based on the Generation Expansion Planning (GEP) approach used in previous reports, aimed at optimizing the expansion of power generation systems, particularly centralized systems. The literature frequently includes reviews of GEP modeling, such as Koltsaklis and Dagoumas (2018). Two main methods are used to model uncertain elements in the generation expansion planning problem: deterministic and probabilistic approaches. Deterministic models produce a single optimal solution that represents the best expansion plan based on given assumptions. In contrast, probabilistic models directly account for uncertainty during the optimization process. Many studies have argued for the increased robustness of probabilistic approaches over deterministic methods (Conejo et al., 2016; Scott et al., 2021). However, as noted by Scott et al. (2021), only 20% of papers published on this topic use stochastic modeling for production or demand, with many still opting for sensitivity analysis of parameters used (Shirizadeh et al., 2022). This approach is not sufficiently robust, as it neglects forecast errors and their consequences. Our paper aims to quantify the consequences of choosing a deterministic rather than probabilistic approach.

We also examine the impact of uncertainty on policy design choices. In their study, Weitzman (1974) compared two policy instruments, namely quantity regulations and price instruments, to control externalities. They concluded that in the presence of uncertainty, price instruments, such as taxes or subsidies, are generally more efficient than quantity regulations. For the transition to renewable energy, a variety of policy instruments have been proposed and implemented, including carbon emission regulations, such as carbon taxes, cap and trade systems, and emissions targets, as well as support for renewable energy, such as Renewable Portfolio Standards, Feed-in Tariffs, and Research and Development Funding. Several studies have examined the effectiveness of these policy instruments. For instance, Gugler et al. (2021) concluded that carbon taxes are more effective than renewable subsidies in reducing carbon emissions, as they internalize the use of fossil fuel plants and are less costly. Petitet et al. (2016) advocated for a significantly high carbon price to encourage wind investments, while Gawel et al. (2014) and del Río (2017) discussed policy tool interactions. Fischer and Newell (2008) argued that a combination of environmental and technology policies is necessary for mitigating climate change, while Gerlagh and Van der Zwaan (2006) compared different policy instruments and concluded that the carbon intensity target is the most cost-efficient approach. Finally, Fischer and Preonas (2010) and Borenstein and Kellogg (2022) found that combining policies can increase the deployment of renewable energy technologies, but also noted that there can be diminishing returns from policy interactions.

In this paper, we investigate the impact of demand and production uncertainty on energy transition policy, and how they interact with public policies. We review prior research in this area, including Aïd et al. (2020) who examined the optimal timing for renewable market entry under a stochastic cost process, and Alonzo et al. (2021) who quantified revenue uncertainty for wind producers to determine the need for support mechanisms. de Vries and Heijnen (2008) were pioneers in introducing a stochastic demand process, showing that the socially optimal volume of generation exceeds the theoretical optimum in the presence of perfect knowledge. Meanwhile, Scott et al. (2021) demonstrated that including uncertainty in the analysis leads to underestimation of the market price level and overestimation of the carbon dioxide avoided. Schröder (2014) applied a combined investment and dispatch model to the German electricity market, comparing a stochastic and deterministic path to show how fuel and carbon price risks impact investment decisions. Finally, Lecuyer and Quirion (2019) studied the interactions between carbon emissions trading systems and renewable energy subsidies under uncertainty, concluding that renewable subsidies are necessary as a complement to carbon tax when uncertainty is substantial. In our paper, we extend this literature by assessing the impact of external uncertainty on the efficacy of policies to decarbonize the electricity sector.

Finally, our paper introduces a study of the consequences of unforeseen extreme events. The electricity demand is mainly influenced by weather factors, such as temperature sensitivity, and also by macroeconomic conditions, including the growth of industries, development of public and tertiary services, access to energy, and the digitalization of the economy, among others. This uncertainty factor plays a significant role in the future energy transition. To compensate for the intermittency of renewable energies, controlling the demand is one of the main levers. This control allows the demand to align with the availability of renewable production resources instead of following its historical cycles (day/night, peak/off-peak). Therefore, it is common to assume in engineering or operations research literature that the demand curve is smoothed over time and increasingly predictable. However, historically, the demand has regularly experienced unanticipated shocks (Craig et al., 2002). It has proven to be particularly vulnerable to black swan events (Benatia, 2022). Therefore, we introduced random extreme shocks in our modelling to account for this phenomenon.

This paper is structured as follows. Section 2 describes the model construction. Section 3 outlines a calibration exercise and simulation strategies. Section 4 analyzes the implications of uncertainty for energy transition modeling. Finally, Section 5 presents the conclusion.

# 2 The Model

A central planner is in charge of organizing the supply of electricity throughout the energy transition. It takes investment and production decisions in discrete time $t = 1, ..., T < \infty$ in order to minimize the long-run system cost while accounting for operational constraints and environmental objectives.

The timing of decisions and uncertainty is as follows:

1. At the beginning of year $t$, all uncertainties about demand and supply conditions for the entire year are resolved and are known to the central planner.

2. Investment: Upon observing the realizations of uncertainties, the central planner decides how much new capacity to install of each generation technology, which will

become available at the beginning of year $t+1$. These decisions must account for the uncertainty about the demand and supply conditions in years $t+1, t+2, ..., T$.

3. Production: For each hour $h = 1, ..., 8760$ of year $t$, the planner seeks to minimize the cost of supplying electricity given the realization of uncertainties for the current year.

## 2.1 Main parameters

In this section, we present the main parameters for demand, investment and production costs, and the costs of supply shortages.

**Demand.** The demand for electricity in year $t$ and hour $h$ is specified as

$$Q_{th}^{D} = \tilde{\alpha}_h A_t + D_{th}, \tag{1}$$

where $\tilde{\alpha}_h A_t$ is a deterministic time-varying component and $D_{th}$ is a random demand shock following a known probability distribution presented in due time. Both components are exogenous to supply conditions, and there is no demand-response technology.

The deterministic demand for electricity is characterized by hourly, daily, and monthly variations, captured by the $\tilde{\alpha}_h$ coefficients, and a long-run trend component $A_t$. This trend is useful to model the long-run structural changes associated with the electrification of the economy (e.g., the adoption of electric vehicles, the decarbonization of industry, changes in heating practices, etc.).

**Investment costs.** There are two main types of generation plants: conventional power plants and renewable power plants. We specify investment costs as follows.

At time $t$, the conventional capacity of fuel $f$ corresponds to the existing capacity $K_{t-1}^{f}$ in $t-1$, augmented by the net capacity additions decided in $t-1$, as given by

$$K_t^f = K_{t-1}^f + I_{t-1}^f, \tag{2}$$

where $I_{t-1}^f$ represents capacity additions, net of retirements, entering production in period $t$.

Capacity additions of conventional capacity of fuel $f$ are associated with a construction cost of $\gamma_r$ per MW. Only a fraction $\pi$ of the initial investment is recovered in case of retirements. The corresponding investment cost function writes as

$$\mathcal{I}_t^f(I_t^f) = \gamma_t^f I_t^f \left( \mathbb{1}_{I_t^f \geq 0} - \pi \mathbb{1}_{I_t^f < 0} \right), \tag{3}$$

where the parameter $\gamma_t^f$ changes in time and $I_t^f \geq -K_{t-1}$. Similar law of motion and investment cost functions hold for renewable capacity of source $r$.

**Short-run costs.** Conventional power plants are perfectly controllable up to their capacity limit. Let $q_t^f$ denote the output at time $t$ of conventional plants with fuel $f \in \{\text{gas}, \text{coal}, \text{oil}\}$, which production is constrained by the corresponding installed capacity at time $t$, denoted $K_t^f$.[2]

The cost function of conventional plants of fuel $f$ at time $t$ is defined as

$$C^f(q_t^f) = a_f K_t^f + q_t^f (b_f + h_{ft} + c_{ft}\tau_t), \tag{4}$$

which includes both fixed and variable components. The former is the fixed maintenance cost $a_i K_t^i$ that varies with installed capacity. The variable cost has three components: a variable maintenance cost $b^i q_t^f$, a fuel cost $h_{ft} q_t^f$, and a carbon cost $c_{ft}\tau_t q_t^f$. The latter depends on the carbon intensity $c_{ft}$ of the plant and the carbon price $\tau_t$. The marginal cost is hence equal to $MC_t^f = b_f + h_{ft} + c_{ft}\tau_t$.

Renewable power plants are constrained by random weather conditions, but their production can be curtailed if needed. The production $q_t^r$ of renewable plants of source $r \in \{\text{wind}, \text{solar}\}$ is constrained by $\epsilon_t^r K_t^r$, where $\epsilon_t^r$ denotes the maximum capacity factor in $t$ for renewable energy source $r$, and $K_t^r$ denotes the corresponding installed capacity. The cost function of renewable plants of source $r$ at time $t$ is defined as

$$C^r(q_t^r) = a_r K_t^r + q_t^r b_r, \tag{5}$$

where $a_r K_t^r$ represents the fixed maintenance cost, and $q_t^r b_r$ is the variable operation and maintenance cost. The marginal cost $MC_t^r = b_r$ is hence constant through time.

[2]Our model abstracts from planned and forced outages.

**Failure costs.** A supply shortage, or failure, occurs if the total available capacity $K_{ht}$ at a given time is insufficient to cover the realized demand $Q_{ht} > K_{ht}$. We assume that, in such event, the central planner is able to ration consumption by the excess demand $Q_{ht} - K_{ht} > 0$ through rolling blackouts.

Rationing demand has however welfare implications for unserved consumers. The welfare cost is specified as an affine function of the *default* quantity, and is given by

$$C^{fail}(Q_{ht} - K_{ht}) = p + (Q_{ht} - K_{ht}) \times VOLL, \tag{6}$$

if $Q_{ht} > K_{ht}$, and 0 otherwise. The key parameter $VOLL$ corresponds to the *Value Of Lost Load*, i.e. the consumers' marginal willingness to pay to avoid rationing of one MWh, and $p$ is the lump-sum penalty faced by the planner for reaching a positive default quantity.

**Uncertainty.** We model three sources of uncertainty: (1) demand shocks $D_{th}$, (2) renewable production shocks $\epsilon^r_{th}$, and (3) fuel prices $h^f_{th}$ at the hourly level. For numerical tractability, we specify these uncertainties by using a joint discrete probability distribution of annual trajectories of hourly random shocks for each component, denoted $\Omega_{tt} = (D_t, \epsilon^{wind}_t, \epsilon^{solar}_t, h^{gas}_t)$. These trajectories are drawn from two sets of possible realizations: normal years and extreme years. Note that there is only uncertainty about demand and supply conditions in the following years, which thus affect investment decisions but not current year's production decisions. We give a brief description of our modelling choices here, and provide more details in the empirical section.

Annual trajectories of hourly random shocks drawn from normal years are designed to correspond to historical realizations of demand, renewable capacity factors, and fuel prices. In opposition, extreme years are artificial trajectories with distinctive features. We consider two cases: "good news" and "bad news" years, each built around the same reference historical year.

The motivation behind this modelling choice is driven by the recent events with large consequences on electricity markets, such as climate disasters, the COVID-19 crisis, and the war in Ukraine. In "good news" years, the electricity demand and natural gas prices are lower than in the reference year, but renewable capacity factors are higher. During these years, system costs and CO2 emissions are smaller by construction. "Bad news" years are the symmetrical opposites, and drive the risks of supply shortages and missing environmental objectives.

## 2.2 The central planner's objective

The central planner's problem can be separated into a static problem about production decisions given realized supply and demand conditions, and a dynamic problem about investments decisions in a uncertain environment about future years' supply and demand conditions.

**The static problem.** In each hour $h$ of any year $t$, the sum of total supply $Q^S_h = \sum_f q^f_h + \sum_r q^r_h$ and the unserved energy due to shortages $q^{fail}_h$ must equate the realized demand $Q^D_{th}$. This problem being the same for any $t$, we neglect the $t$ subscript for clarity. We further assume that there is no dynamic cost components at the production stage.

The central planner solves the least-cost dispatch problem, i.e. it seeks to minimize the cost of achieving this equilibrium condition under operational constraints, defined as

$$\begin{aligned} \min_{q^f_h, q^r_h, q^{fail}_h, \forall f,r} \quad & \textstyle\sum_f C^f_h(q^f_h) + \sum_r C^r_h(q^r_h) + C^{fail}_h(q^{fail}_h) \\ \text{s.t.} \quad & \begin{cases} 0 \leq q^f_h \leq K^f, \forall f \\ 0 \leq q^r_h \leq \epsilon_h K^r, \forall r \\ 0 \leq q^{fail}_h \\ \sum\limits_f q^f_h + \sum\limits_r q^r_h + q^{fail}_h = Q^D_h \end{cases} \end{aligned}$$

Solving this problem is simple given the assumption of constant marginal cost functions. Technologies are ranked in ascending order of their marginal costs, and each technology enters production sequentially only after the previous technology's capacity is depleted. We impose assumptions on the cost parameters so that the solution can be characterized as follows:

1. Renewable plants have relatively small marginal costs. Wind plants enter production before all other plants because they have the smallest marginal cost, $b_{wind} < b_{solar} < b_f$. Solar plants start producing when $Q^D_h > K^{wind}$. Both types of renewable

plants produce up to available capacity $q_h^r = \epsilon_h^r K^r$ for each $r$ as soon as $Q_h^D \geq \epsilon_h^{wind} K^{wind} + \epsilon_h^{solar} K^{solar}$.

2. Conventional plants enter production sequentially using the same approach as early as $Q_h^D \geq \epsilon_h^{wind} K^{wind} + \epsilon_h^{solar} K^{solar}$. The merit-order depends on the carbon price and fuel prices.

3. Supply shortage is so expensive that it only occurs if the realized demand exceeds the total available capacity, i.e. $q_h^{fail} > 0$ if and only if $Q_h^D > \sum_f K_h^f + \sum_r \epsilon_h^r K_h^r$. In that case, it is equal to $q_h^{fail} = Q_h^D > \sum_f K_h^f + \sum_r \epsilon_h^r K_h^r$.

Using this characterization, we obtain the optimized cost functions in each hour as functions of the installed capacity of each technology and realized supply and demand conditions. Then, we sum these cost functions across the hours of a given year to obtain the annual-level optimized cost function conditional on the realization of the annual trajectory of random shocks, denoted $C^*(K_t, \Omega_t)$, where $K_t = \{K_{t,\forall f}^f, K_{t,\forall r}^r\}$ is the vector of installed capacities. This function is finally used to write the dynamic problem.

**The dynamic problem.** The planner's objective is to determine an optimal investment path that minimizes the discounted sum of annual supply costs and investment costs. The corresponding optimization problem is given by

$$\min_{\{I_t^f \forall f, I_t^r \forall r\}_{t=0,..,T}} \sum_{t=0}^{T} \beta^t \mathbb{E}_\Omega \left[ C^*(K_t, \Omega_t) + \sum_f \mathcal{I}^f(I_t^f) + \sum_r \mathcal{I}^r(I_t^r) \right], \tag{7}$$

and subject to the transition laws described above. At each time $t$, the state of the system is fully characterized by the vector of installed capacities $K_t$ and the realizations of random shocks $\Omega_t$. Denoting the associated value function by $V_t(K, \Omega)$, we obtain the equivalent recursive formulation

$$V_t(K_t, \Omega_t) = \min_{(\{I_t^f, I_t^r\})} \{C^*(K_t, \Omega_t) + \sum_f \mathcal{I}^f(I_t^f) + \sum_r \mathcal{I}^r(I_t^r) + \beta \mathbb{E}[V_{t+1}(K_{t+1}, \Omega_{t+1})]\} \tag{8}$$

We solve this problem numerically using the backward induction algorithm. To alleviate computations, we assume that random shocks are independent across years, so the expectation about next period's state does not depend on the current's state realization.

**Environmental objectives.** We consider three possible policies aimed at achieving environmental objectives: (1) carbon pricing, (2) renewable energy targets, (3) carbon emissions reduction targets. Carbon pricing affects directly the marginal cost of production of conventional plants in the static problem through the value of $\tau_t$, but it only affects the dynamic problem indirectly. However, incorporating the targets requires some modifications to the dynamic problem. We proceed as follows.

Renewable energy targets are interpreted as constraints on the total renewable capacity installed at specific dates, denoted as a sequence $\{\underline{K}_0^r, \underline{K}_1^r, ..., \underline{K}_T^r\}$. We model this into the dynamic problem by augmenting the contemporaneous cost in (8) with the penalty term $\sum_r \kappa_r(\underline{K}_t^r - K_t^r)\mathbb{1}_{\underline{K}_t^r > K_t^r}$, where $\kappa_r$ measures the stringency of the targets associated with technology $r$.

Similarly, emissions reduction targets are interpreted as constraints on the total reduction in year $t$ with respect to year 0, denoted $E_t$. This sequence of constraints $\{\underline{E}_0, \underline{E}_1, ..., \underline{E}_T\}$ is used to enforce the targets in the dynamic problem. We add the penalty term $\lambda(\underline{E}_t - E_t)\mathbb{1}_{\underline{E}_t > E_t}$ to the contemporaneous cost in (8). $\lambda$ captures the stringency of the emissions reduction targets.

These environmental constraints may not be satisfied if the stringency policy parameters $\kappa$ and $\lambda$ are not large enough. We use this feature to model the fact that governments sometimes miss legally-binding environmental targets.

# 3 Case study: Germany 2030

Our proposed simulation exercise models the German electricity mix for the period of 2021 to 2030. We will study the consequences of neglecting uncertainty and the effects of policy instruments over a 10-year horizon.

### 3.1 Empirical strategy

To study the effects of public policies on investment strategies, we will represent three strategies for the monopoly (planner) that choose an investment path considering uncertainty in the state of the future $\Omega$.

1. **Unsuspecting planner**: The unsuspecting planner makes their investment decision by selecting a future scenario $\widetilde{\Omega}$ as a reference The unsuspecting planner does not revise their predictions since the future's state is independent of the past.

$$V_t^U(K_t,\Omega_t) = \min_{(\{I_t^f, I_t^r\})\in\mathcal{C}_t} \{C^*(K_t,\Omega_t) + \sum_f \mathcal{I}^f(I_t^f) + \sum_r \mathcal{I}^r(I_t^r) + \beta[V_{t+1}^U(K_{t+1},\widetilde{\Omega}_{t+1})]\} \tag{9}$$

2. **Counterfactual: The Perfect foresight planner**: The Perfect Foresight planner serves as a counterfactual scenario, enabling us to calculate the optimal outcome in the absence of uncertainty.

$$V_t^{PF}(K_t,\Omega_t) = \min_{(\{I_t^f, I_t^r\})\in\mathcal{C}_t} \{C^*(K_t,\Omega_t) + \sum_f \mathcal{I}^f(I_t^f) + \sum_r \mathcal{I}^r(I_t^r) + \beta[V_{t+1}^{PF}(K_{t+1},\Omega_{t+1})]\} \tag{10}$$

3. **Alternative strategy: The Stochastic planner**: The stochastic planner calculates a closed-loop solution and anticipates future uncertainty. Unlike the deterministic planner, it weighs each scenario and makes decisions based on the probability of making mistakes.

$$V_t^S(K_t,\Omega_t) = \min_{(\{I_t^f, I_t^r\})\in\mathcal{C}_t} \{C^*(K_t,\Omega_t) + \sum_f \mathcal{I}^f(I_t^f) + \sum_r \mathcal{I}^r(I_t^r) + \beta\mathbb{E}[V_{t+1}^S(K_{t+1},\Omega_{t+1})]\} \tag{11}$$

## 3.2 Calibration

We conducted a Monte-Carlo exercise with 100 simulations, and a 8% discount factor, using the following parameters.

**Modelled technologies** The planner can invest in gas and wind power plants. Oil power plants proportion remains constant. Short-run costs are calibrated using Kost (2021). The investment costs for gas power plants are assumed to be constant, while wind power investment cost decreases over time. Coal and oil prices are based on IEA Net Zero Emission scenario. Gas prices come from Dutch TTF historical data.

**Scenario calibration** We modelled 7 future realisations $\Omega_t$, using 5 historical years (from 2015 et 2019), and 2 synthetic extreme scenarios using COVID-19 and Gas crisis in Europe.

To create the "Good news" scenario, we used the estimation of -12% decrease of demand during COVID-19 based on the estimation from Benatia (2022), applied to the winter period. Gas prices correspond to 2020 prices (lowest historical year in our dataset). The renewable production was scaled to recover the third quartile of the historical distribution, allowing us to represent higher production than usual. This is a favorable scenario for the planner.

The "Bad news" scenario is the counterpart of the previous scenario. In this case, an event led to a +12% increase in demand during winter, and the renewable production was scaled to recover the first quartile of the historical data. We used the 2022 gas price data, considering the exceptional price peaks this year.

We assigned a uniform probability to each state, i.e., there is over 70% chance of drawing an historical scenario each year. As a reference scenario for the unsuspecting planner, we chose historical year 2018 because in our data, the renewable production was lower than usual, and the demand higher, giving us a precautionary scenario.

**Public policies calibration** We calibrated 4 cases of public policies, in which both the coal phase-out plan and solar energy investment path were shared and exogenous: In all simulations, the capacity additions of solar PV and the phasing out of coal capacity are both set on the Germany's energy transition roadmap.

1. **No additional policy**: Only coal phase-out plan and solar energy plan are considered, conterfactual scenario

2. **Carbon pricing policy**: Carbon tax $\tau_t$ increase linearly over time and reach 130€ by the year 2030, based on the International Energy Agency's (IEA) Net Zero Emissions scenario

3. **Renewable targets policy**: Increase of at least 10GW of onshore wind per year starting in 2025, in concordance with the latest objective set by the German government

4. **Carbon emissions targets**: Standard of -48% on emissions in 2030 compared to 2021 is proposed, calibrated on the average emission reduction level achieved with the binding constraint on renewables

**Electricity demand** We used historical hourly demand data for Germany from 2015 to 2021 to model the projected demand. To estimate the predictable deterministic share based on this data, we use the following econometric equation:

$$demand = \beta_0 + \beta_1 season + \beta_2 peakweek + \beta_3 peakweekend + \beta_4 year + \epsilon_t \tag{12}$$

The equation was estimated using a classical OLS estimator. The estimation revealed that 31.8% of the variance in the data could be explained by predictable seasonal variations. Residual is assumed to be an exogenous shock.

In addition, we have added a 2% upward trend in the predictable component of demand, representing the electrification of the economy.

**Capacity factor construction** We have developed our own aggregated load factor for wind energy in Germany, as historical data does not represent *curtailment phenomena*, which refers to the voluntary interruption of wind generation when it becomes economically profitable.

We reestimated the national renewable generation potential in several steps. First, we compiled a list of the 50 most geographically representative clusters from the wind farms in Germany, using a k-means clustering algorithm. We obtained a potential of production for these clusters using Renewable Ninja website (Staffell and Pfenninger, 2016). We used the following econometric equation to compute for the weights of the representative clusters on the national capacity factor:

$$nationalproduction_t = \alpha_0 + \alpha_1 cluster_1 production + ... + \alpha_{50} cluster_{50} production + \zeta \quad (13)$$

The equation was estimated using non-negative least squares (NNLS) estimators. Similar exercise was conducted to obtain a corrected solar capacity factor.

**Failure cost estimation** To get a representative VOLL estimation for the country, we computed a weighted average of estimated VOLL per sector from Growitsch et al. (2013). We obtained a parameter of 7621€ per MWh of missing production.

# 4 Main results

We considered several policy scenarios and we compare the results under different assumptions about the central planner's approach to uncertainty. We start by presenting the reference, or *no policy* scenario.

**No policy.** In the reference scenario with no policies, the unsuspecting planner (UP) tends to under-invest in gas capacity because they have too optimistic expectations about renewable production and electricity demand. In contrast, the stochastic planner (SP) invests more in gas capacity so as to hedge against extreme scenarios. The planner with perfect foresight, or foresighted planner (FP), builds less capacity than SP, but more than UP, as shown in Figure 1.

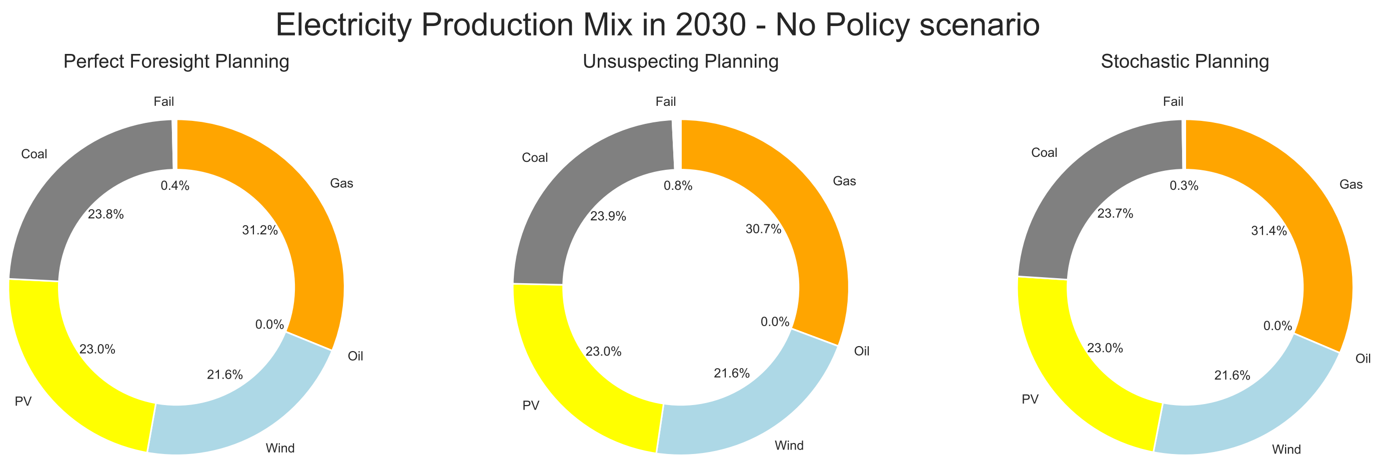


Figure 1: Production by technology (No policy)

Table 1 reveals that if the future is favourable, the minimum net present value (NPV) of SP is 5 Bn € higher than UP. However, Table 2 shows that the probability of failure is significantly higher for UP than SP, resulting in a maximum NPV that is 25 Bn € higher than SP due to the high failure cost in case of low renewable production. On average, SP results in an NPV that is closer to FP, despite an overcost of 3 Bn €.

Table 1: No policy scenario: Distribution of Net Present Values

| | Average Net Present Value (Billion euros) | | | | | |
|---|---|---|---|---|---|---|
| | Mean | Min | Max | Std. | $Q_{0.25}$ | $Q_{0.75}$ |
| Perfect Foresight | 68.05 | 53.64 | 91.26 | 8.59 | 61.51 | 72.70 |
| Stochastic | 71.43 | 59.90 | 100.36 | 8.83 | 65.22 | 75.37 |
| Unsuspecting | 75.29 | 54.46 | 125.78 | 16.13 | 62.30 | 86.17 |

Table 3 shows that SP relies less on coal for production and results in less carbon emissions than FP because of its higher installed gas capacity.

Table 2: No policy scenario Summary

| | Failure rate | -50% $CO_2$ probability | Coal production |
|---|---|---|---|
| Perfect Foresight | 0.03% | 0.89 | 23.72% |
| Stochastic | 0.04% | 0.89 | 23.59% |
| Unsuspecting | 0.06% | 0.89 | 23.77% |

This table reports failure probability, probabilities of reaching a reduction of 50% reduction in carbon emissions, and average share of coal production in 2030

Table 3: No policy scenario: Carbon emissions distribution

| | $CO_2$ emissions (% reduction from 2021) | | | | | |
|---|---|---|---|---|---|---|
| | Mean | Min | Max | Std. | $Q_{0.25}$ | $Q_{0.75}$ |
| Perfect Foresight | -25.81% | -58.96% | -11.53% | 12.64 | -25.24% | -18.61% |
| Stochastic | -25.94% | -58.96% | -11.57% | 12.88 | -25.24% | -18.62% |
| Unsuspecting | -25.79% | -58.00% | -11.78% | 12.59 | -25.22% | -18.56% |

**Carbon pricing.** Carbon pricing policy led to very similar installed capacities than the no policy scenario. However coal production share decreases for the three investing strategies. Table 5 shows that carbon pricing results in a 17-point drop coal production than under no policy. There is a *switching effect* in favor of gas production, that becomes less expensive, as long as no “Bad news” shock appears.

Table 5 shows that the carbon price policy doubled the NPVs compared to the reference scenario, and increased the gap between minimum and maximum values, from 38 Bn € to 74 Bn €. In particular, the gap between the maximum value and third quantile for FP is 36 Bn €: this can be explained by the strong difference in gas price between historical scenarios and extreme shocks. Two factors are at play here: firstly, carbon emissions are now taxed, which has a weight on the NPV, and secondly, the system costs now rely more than before on the gas price, which is stochastic. Therefore, the final costs are more volatile and may even lead to a switch back to coal production.

Table 4: Carbon pricing scenario: Distribution of Net Present Values

| | Average Net Present Value (Billion euros) | | | | | |
|---|---|---|---|---|---|---|
| | Mean | Min | Max | Std. | $Q_{0.25}$ | $Q_{0.75}$ |
| Perfect Foresight | 136.24 | 108.76 | 182.35 | 13.25 | 126.36 | 146.08 |
| Stochastic | 138.70 | 112.98 | 190.83 | 13.34 | 128.80 | 147.11 |
| Unsuspecting | 139.91 | 110.68 | 200.09 | 13.19 | 127.26 | 148.15 |

Table 5: Carbon pricing scenario Summary

| | Failure rate | -50% $CO_2$ fail probability | Coal production |
|---|---|---|---|
| Perfect Foresight | 0.04% | 0.77 | 5.81% |
| Stochastic | 0.04% | 0.77 | 4.66% |
| Unsuspecting | 0.07% | 0.77 | 5.85% |

**Carbon target.** Figure 2 shows a significant difference in investment strategies. To ensure reaching the Carbon target even in unfavorable scenarios such as high demand or low renewable production, SP doubles its investment in wind power plants compared to the FP and UP (75%). Consequently, on average, more than 80% of the production is renewable in 2030. In contrast, FP increases gas capacity to hedge against higher demand.

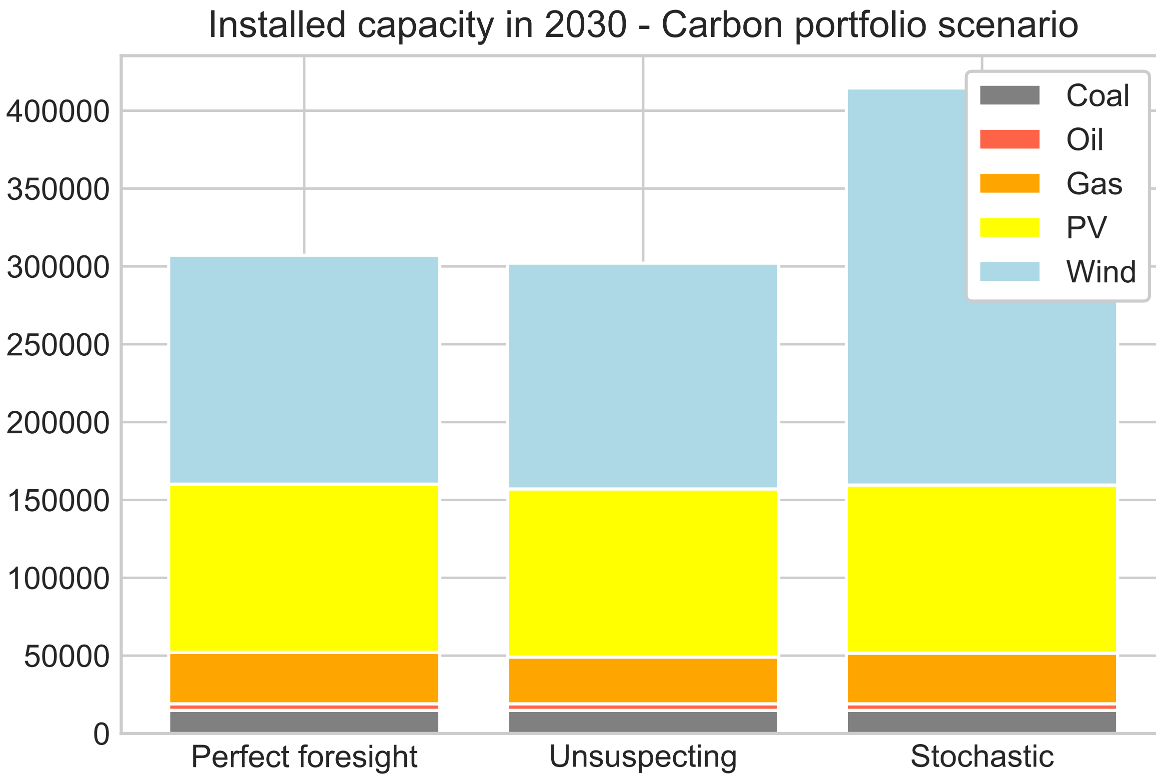


Figure 2: Installed capacity by technology (Carbon target)

As a result of this significant investment in renewable energy, the SP's average NPV is almost 100 Bn € higher than the FP and UP's NPVs (Table 6).

Table 6: Carbon target scenario: Distribution of Net Present Values

| | Average Net Present Value (Billion euros) | | | | | |
|---|---|---|---|---|---|---|
| | Mean | Min | Max | Std. | $Q_{0.25}$ | $Q_{0.75}$ |
| Perfect Foresight | 151.23 | 53.64 | 259.89 | 50.29 | 132.48 | 158.04 |
| Stochastic | 245.47 | 236.19 | 263.50 | 6.44 | 240.56 | 249.16 |
| Unsuspecting | 157.02 | 142.69 | 188.08 | 10.86 | 147.99 | 163.27 |

However, despite the direct specification of legal constraints on carbon emissions, Table 7 shows that the carbon target was missed in 15% of simulations for the UP, whereas SP always reached it. Table 7 also shows that without a direct carbon tax, coal marginal cost can be lower than gas marginal cost. As a consequence, the share of coal production is above 15% for FP and UP, and aound 10% for UP.

Furthermore, due to the high share of renewable production, Table 8 shows that SP decreases significantly more carbon emissions than both FP and UP, with an average of 73% reduction against less than 56%. Hedging strategy against low renewable production led to almost full decarbonization of the electricity mix when the simulation was more favourable.

Table 7: Carbon target scenario Summary

| | Failure rate | -50% $CO_2$ fail probability | Coal production |
|---|---|---|---|
| Perfect Foresight | 0.03% | 0 | 16.01% |
| Stochastic | 0.03% | 0 | 9.63% |
| Unsuspecting | 0.06% | 0.15 | 15.34% |

Table 8: Carbon target scenario: Distribution of Carbon emissions

| | Distribution of $CO_2$ emissions (% reduction from 2021) | | | | | |
|---|---|---|---|---|---|---|
| | Mean | Min | Max | Std. | $Q_{0.25}$ | $Q_{0.75}$ |
| Perfect Foresight | -54.96 | -58.96 | -52.96 | 1.91 | -56.32 | -53.03 |
| Stochastic | -73.34 | -89.85 | -53.06 | 9.96 | -76.14 | -72.66 |
| Unsuspecting | -56.82 | -81.79 | -34.86 | 12.36 | -60.35 | -53.02 |

**Renewable targets.** Because of the optimistic expectation of renewable production, the UP does not invest in more gas capacities at all. The SP and FP invest, but less than the carbon price scenario.

Without the carbon price, there is no incentive to transition from coal to gas production. As a result Table 9 shows the average share of coal production is still above 18% for the three scenarios.

Table 9: Renewable target scenario Summary

| | Failure rate | -50% $CO_2$ fail probability | Coal production |
|---|---|---|---|
| Perfect Foresight | 0.03% | 0.15 | 18.58% |
| Stochastic | 0.04% | 0.15 | 18.56% |
| Unsuspecting | 0.07% | 0.15 | 18.62% |

# 5 Discussion

In our framework, we observe that the NPV ranges produced by the stochastic approach (SP) are proximal to the outcomes realized under perfect foresight, outperforming the results produced by the UP approach for the majority of policy scenarios considered. This finding lends support to previous research and implies that the SP approach is more optimal. The SP approach adopts a hedging behavior through over-investing in power plants. This strategy entails the construction of power plants in excess of average requirements, allowing the SP approach to anticipate potential negative outcomes in the future such as suboptimal renewable energy production or higher-than-anticipated demand. Notwithstanding the additional expenditure, this strategy serves to reduce the failure rate when confronted with "bad news" shocks. Conversely, the UP approach underinvested in power plants, resulting in increased costs when faced with such shocks.

The implementation of the direct carbon target policy has engendered considerable investments in renewable energy sources by the SP, thereby ensuring ample production to satisfy the demand sans resorting to fossil fuel power plants. As a result, the NPV has doubled, constituting the sole instance in which the UP approximated the optimal NPV. Nevertheless, in 15% of the simulations, the UP failed to achieve the carbon target, whereas the SP and PF consistently fulfilled it. This disparity can be ascribed to the

NPV calculation's omission of the costs of non-compliance with the policy. Thus, it is imperative to integrate the cost of non-compliance or exhibit vigilance towards possible extreme shocks that could deviate from the policy's course during the implementation of a direct carbon target policy.

We have found that a carbon price is a potent instrument in reducing the usage of coal, regardless of the planning strategy employed. However, we have observed that our framework has led to a greater reliance on gas power plants, as we have invested significantly more in them under the Strategic Plan (SP). Our decision was motivated by the desire to decrease production costs, as gas emits only half the amount of emissions compared to coal. Additionally, we took into consideration the possibility that the installed renewable power may not suffice in case of a high demand shock.

Despite the specified carbon price following the trajectory set by the International Energy Agency (IEA), we have noticed that it has not been sufficient in deterring the utilization of fossil fuels and encouraging the transition to renewable energy production. To address this matter, we intend to conduct a sensitivity analysis in the future.

But relying on gas has a drawback: because of gas price uncertainty, the final NPV is also highly uncertain. In case of gas price extreme upward shock, coal can become cheaper even with a high carbon price. Therefore if the policy objective is to reduce carbon emissions, this should be taken into account especially in light of the skyrocketing prices experienced in Europe in 2022.

In the end, although prioritizing investments in renewable energy sources showed promise, it failed to effectuate a complete transition from coal to gas in the context of remaining energy production. Notwithstanding, the judicious management of these investments effectively curtailed the impact of any ambiguities or variances that may have arisen in relation to the three approaches under consideration.

The results of our framework should be interpreted with caution, as several limitations may constrain the validity of our findings. Notably, we did not incorporate storage technologies or Demand Side Management (DSM) systems, such as smart grids, which could reduce the uncertainty associated with renewable energy production and electricity demand, thereby diminishing the attractiveness of gas power plants for controllable production. However, the addition of these technologies would also augment the complexity of the computation and introduce new sources of uncertainty. Moreover, there is no guarantee that storage will play a crucial role in the energy transition before 2030 (IEA, 2022).

Our model would benefit from several refinements. Specifically, our results reflect a central planning perspective, which is consistent with government reports on energy transition planning. However, future work should explore the impact of uncertainty within a competitive market framework. Additionally, the representation of the future remains simplistic and would benefit from enhancements such as introducing path dependency or increasing the likelihood of extreme shocks.

# 6 Conclusion

In this paper, we propose a stochastic approach for optimizing capacity expansion planning problems. Our approach has been shown to be more economically efficient on average than deterministic strategies, although it may require overinvestment in installed capacity that is not always utilized. Nevertheless, deterministic planning strategies may overlook the higher failure costs associated with incorrect anticipations of future renewable energy production or electricity demand.

Failing to consider future uncertainties risks non-compliance with legal emission targets. Ensuring compliance with these policies may require overinvestment, resulting in significantly higher costs. To reduce the volatility between planning strategies and simulations, more ambitious renewable energy targets can be set. However, to effectively reduce carbon emissions, a carbon price is still necessary to incentivize the transition from coal to gas-fired generation and to manage the intermittency of renewables in the absence of storage. Yet, a policy based solely on carbon pricing may be insufficient to stimulate investment in renewables, which is crucial for mitigating gas price shocks.

Our future work will concentrate on introducing a market framework and analyzing its interactions with various sources of uncertainty. Nevertheless, our findings underscore the importance of considering uncertainty in policy-making to accomplish the energy transition.

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