# Agent-based modelling of investment decisions in the electricity sector

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***Abstract*—The energy transition requires coherent and consistent investments in new carbon-neutral generation and storage technologies. These investments and the subsequent capacity expansions are not centrally orchestrated, but come mainly from private companies focusing on their business interests. Policy measures aimed at guiding the capacity expansion process often fall short of reaching their goals. To address this, we introduce an agent-based approach to model investment decisions in the electricity sector according to current business practices. We couple this model with an agent-based dispatch model of the electricity market to investigate the interplay of investment, policy, and market. The resulting simulation model is shown to replicate key features of the investment and generation expansion process in two test cases. First, a company's risk assumptions, policy support, and prognosis about future electricity prices are varied. This influences the investment decisions and capacity expansions. Second, two companies invest large amounts of capital and add a substantial amount of renewable generation capacity. This leads to lower and more volatile electricity prices at the simulated electricity market. The consistent application of agent-based modelling for the investment and market operation of renewable energy technologies allows new analyses on policies regarding the capacity expansion process.**

***Index Terms*—agent-based modelling, investment decisions, electricity market, AMIRIS, policy support, transition pathways**

## I. INTRODUCTION

### *A. Motivation*

To combat climate change, the electricity system has to undergo a rapid transformation from technologies based on fossil fuels towards clean, renewable energy sources. The success of this energy transition relies largely on private actors who finance, build, and operate new generation and storage facilities. The underlying motivation for these actors is not predominantly the political goal of a climate-neutral society, but the economic necessity to generate profit from their investments. Importantly, they take decisions that serve their business interests. Investments in the electricity sector are driven by expectations about the performance of specific plants on the electricity market. At the same time, the dynamics of the electricity market change rapidly due to the ramp up of variable, non-dispatchable electricity generation sources, such as photovoltaics (PV) and wind energy. Policy makers need to navigate this complex interplay of investment behaviour and market dynamics. They face the challenge to design effective and efficient incentives to increase the share of renewables in the electricity system. To assist policy makers, computationally modelling the energy system and evaluating different scenarios has become a cornerstone of energy system research.

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### *B. Existing modelling approaches*

Multiple ways exist to model the energy system and its adjunctive markets. Three main approaches can be observed: Energy system optimization models (ESOM), agent-based models (ABM), and hybrid models. Optimization models represent the power system as a set of equations derived from the underlying techno-economic characteristics of system components [1]. Their goal is to find a set of model parameters to optimize a specific output, like minimum carbon dioxide emissions or system costs. By doing so, they take a system perspective and assume that actions of the entities within the system are aligned with the system goals. This approach is the dominant one in energy system analysis and capacity expansion planning with great modelling efforts [2]–[5]. A central criticism to ESOMs is the observation that entities of the real world often do not act in order to contribute to overarching systemic goals, but to reach their own goals. This line of thought has fuelled the development of agent-based models. ABMs represent the power system as a set of prototypical agents with behaviour rules derived from technical conditions and social science. Some models focus on investments and policy measures [6]–[8], while others concentrate on the electricity market [9], [10]. They share a bottom-up approach where the characteristics of the overall system emerge from the linked but uncoordinated actions of the entities within the system. This can give insight into the current market dynamics and interactions. One shortcoming is that they often lack a clear approach for the long-term development of the system. To fill this gap, hybrid models [11] have emerged which use optimization to obtain a future state of the energy system and then apply agent-based models to investigate the market dynamics at this future state. This mix of methodology indicates that ABMs are valuable for the evaluation of capacity expansion, but currently lack the ability to model it consistently.

### C. Research gap

The real-world capacity expansion process does not follow the path indicated by the strict optimization of techno-economic models [12]. Instead it is driven by the combined impact of individual investment entities and dependent on complex market interdependencies. Understanding the dynamics of this process, and how it can be influenced by policy, is crucial for the success of the energy transition. Existing models often come short in capturing this at a time when policy makers increasingly depend on models to inform their decision making [13]. The fact that many past policy interventions which aimed to reduce emissions in the electricity system had no major effect [14] underscores this impression.

We propose to combine an agent-based investment model with an agent-based dispatch model. With this framework, both the performance of the investments made as well as the long-term effect of aggregated capacity expansions on market dynamics can be evaluated under the influence of policy interventions. Hence, it enables analysis on the interface between policy, market, and investment.

## II. METHODOLOGY

### A. Modelling of investment decisions

Empirical evidence[1] suggests that most real-life investors in the German electricity sector follow a similar decision logic. Investments are based on few key financial metrics like the Net Present Value (NPV), Return on Equity (ROE), or the internal rate of return. All of them estimate the profitability of a project over its lifetime. They rely heavily on the future electricity price prognosis, which together with the production profile of a generation plant can be used to calculate the expected return. We model the decision logic as a process with three steps. First, the NPV is calculated for all available investment options. We then use the ROE to filter out options not fulfilling the minimum return requirements. Finally, the most profitable alternatives are selected and portfolio considerations are applied.

*1) Net Present Value:* The Net Present Value is used to discount future expected profits to the present day and offset them against the initial investment. It is defined as

$$NPV = -I_0 + \sum_{n=0}^{N} \frac{R_n - C_n}{(1+i)^n} \tag{1}$$

Here, $I_0$ is the initial investment and the summation term describes the expected profit over the projected service life of the project $N$. Annual revenue and cost flows $R_n$ and $C_n$ are balanced every year and discounted with the imputed interest rate $i$. The weighted average cost of capital (WACC) is used as the imputed interest rate to reflect the financing conditions and intended returns. The WACC weighs different profitability expectations for equity and borrowed capital. We use the definition described in [15]:

$$i = wacc = r_{eq} \cdot \frac{c_{eq}}{c_{tot}} + r_{bor} \cdot (1 - s) \cdot \frac{c_{bor}}{c_{tot}} \tag{2}$$

In this formula, $r_{eq}$ and $r_{bor}$ are the interest on equity and borrowed capital, while $c_{tot}$ and $c_{bor}$ describe the total and borrowed capital and $c_{eq}$ is the equity used. The variable $s$ describes the income tax share on earnings. Following [15], we further calculate the internal interest on equity as

$$r_{eq} = r_{rf} + (r_m - r_{rf}) \cdot \beta \tag{3}$$

Here, $r_{rf}$ is the interest of a risk-free investment alternative while $r_m$ is the typical interest rate of the considered market. Importantly, this formulation includes $\beta$, a company-specific risk factor with values $\beta \in [0, 2]$.

*2) Minimum return requirements:* Investments need to achieve a minimum profitability to be viable options. One implementation for this is the use of the return on equity (ROE):

$$ROE = \frac{NPV}{N} \cdot \frac{1}{c_{eq}} \tag{4}$$

As the ROE is the annual mean of the NPV over the project lifetime $N$, divided by the equity $c_{eq}$, it can be interpreted as the interest on equity. Companies usually have a clear expectation of what minimum value this interest rate should have, leading to

$$ROE > ROE_{min} \tag{5}$$

*3) Portfolio determination:* The investor now has multiple options that are all profitable and above the minimum return requirements. The naive approach would be to invest all available investment capital in the most profitable option. However, most investors diversify their investments and choose a portfolio strategy with target shares for different options. We model this strategy by giving each investor a maximum capital share $s_{max,tech}$ for each technology. The technologies are then ranked by declining NPVs. $I_{tech} = s_{max,tech} \cdot c_{tot}$ is invested into the most profitable technology. The rest of the capital is invested into the second-most profitable technology up to its specific maximum portfolio share. This continues until the investment capital is fully used. As a final step, the allocated money is translated into the capacity expansion for each technology by considering the technology costs: $P_{tech} = \frac{I_{tech}}{C_{tech}}$.

For modelling the investment decision, two types of data are used. Global data like commodity prices or technology costs is equal for all modelled agents and includes assumptions about the economy at large. Agent-specific data like equity, risk factor, or portfolio shares characterize a single agent. They allow to create a set of heterogenous agents with differing investment decisions.

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[1] https://www.dlr.de/en/ve/research-and-transfer/projects/project-investagent/online-survey (visited 03.02.2025)

### *B. Modelling of the short-term electricity market*

To model the short-term electricity market, we use the agent-based dispatch model AMIRIS [10]. AMIRIS uses prototypical agents to represent the different actors on the electricity market. Real-world actors are grouped as follows:

- Power plant operators provide their production capacity to traders but don't trade themselves.
- Traders sell the production capacity following a certain strategy, eg. to maximize profit.
- Policy agents implement support instruments which can affect a trader's marketing decision.
- Demand agents place time-dependent demand offers.
- Storage and flexibility agents control their dispatch following a certain strategy, eg. to maximize profit. They rely on a model-endogenous electricity price forecast to do so.

For example, a wind plant operator provides its capacity to a trader agent. The trader offers the electricity generation on the market on the basis of the plant's marginal cost, taking into account support schemes provided by the policy agent. The market is represented by an electricity exchange where the offers of all agents form the supply curve or merit-order. Demand bids set from the demand agents are combined with the merit-order curve to clear the market, i.e. to satisfy demand with the lowest possible price. This possibly leaves out producers with higher prices. The newly formed electricity price together with the operation profiles of all plants is the main output of the market model. Such a bottom-up approach allows to approximate characteristics and emergent features of electricity markets with high shares of renewables. The ability to directly define agent behaviour and interaction makes AMIRIS a well-suited tool for research on market design and policy intervention.

### *C. Simulation of investments in the electricity market*

We described the methods to model the investment decision of a single prototypical investor as well as the electricity market independently. In the real world, multiple investors are active over many years, and their investments have a direct influence on the short-term market outcome. To reflect this, we use the simulation workflow shown in Algorithm 1. First, all investors make their investment decisions according to the decision model described above. The individual expansion projects are aggregated to a total capacity expansion plan. This capacity is then added to the installed capacities in AMIRIS, the dispatch model of the electricity market. Note that we use a brownfield approach where the initial state of AMIRIS reflects the energy system and market conditions of the first simulated year. AMIRIS is executed and simulates the German electricity market for one year. The profit of each plant installed by the investors is calculated and distributed. This cycle is repeated for all years in the scenario time frame whereby new investments can take place every year.

**Algorithm 1** Simulation workflow

```
for year $in$ years do
    for investor $in$ investors do
        Select investments
    end for
    Aggregate capacity expansion
    Run dispatch model AMIRIS
    Return profits to investors
end for
Store results
```

## III. PROOF OF CONCEPT

### *A. Factors influencing the investment decision*

The aim of this section is to show how assumptions and policies affect the modelled investment decisions and therefore the capacity expansion. The simulation setup consists of a single investor specializing mainly in utility-scale PV, but also building onshore wind parks. It has a fixed annual budget for new investments, but is too small to affect the overall market dynamics with its actions. The investor has certain assumptions about market developments like the cost and risk of a technology, electricity price developments, and interest rates. Given these assumptions, the investor applies the decision algorithm described in chapter II-A to allocate its investments. We consider the German electricity system and use its state in 2019 as starting point for the simulations, which cover the time frame from 2020 until 2030. The input data and the resulting assumptions about the developments of technology costs, interest rates, and other parameters are adapted from [16]. An overview of the central assumptions in the model is given in the Appendix.

The following three cases compare a baseline scenario against a scenario with modified assumptions and policies. We focus on how these stylized modifications change the amount and composition of the capacity expansion. The goal of this section is to demonstrate the capabilities of the model.

*1) Risk factor influence:* The risk factor $\beta$ from the capital asset pricing model [17] is considered in the WACC calculation (eq. 2) and has an impact on the expected return of an investment option. A changed evaluation of this factor, for example due to the geopolitical dependencies of a technology or new operation risks, should therefore have an impact on the investment behaviour. An increase of $\beta$ should lead to less investments in a technology due to a lower NPV, while a decrease should lead to more investments. We test this by changing the risk factor from $\beta_{PV,b} = 0.9$ and $\beta_{Wind,b} = 1.3$ in the baseline scenario to $\beta_{PV,m} = 1.3$ and $\beta_{Wind,m} = 0.9$ in the modified scenario. The results in Figure 1 show the capacity expansion decisions for the baseline scenario (opaque) and the modified scenario (solid). They confirm our assumption, at least during the first two years: Wind is evaluated as more profitable in the modified run and receives a larger share of investments than previously. PV is neglected completely in the first investment round in 2020 and receives a smaller share of investments in 2021. For the following years, PV becomes more profitable again than wind. This is due to our assumption that the rapidly falling technology costs of PV outperform the learning curve for wind energy (Appendix, Fig. 9).

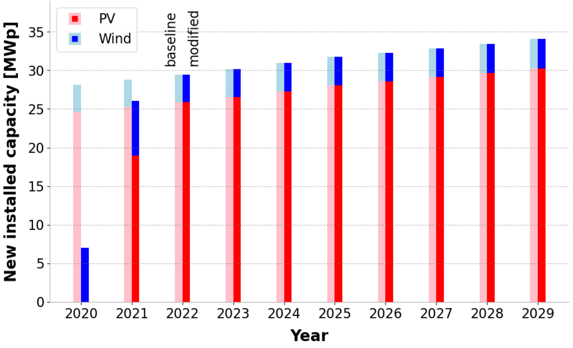

Fig. 1. Influence of the risk factor $\beta$ on the capacity expansion decisions of a single investor. The modified scenario (solid) with $\beta_{PV} = 1.3$ and $\beta_{Wind} = 0.9$ shows a shift of investments away from photovoltaics and towards wind energy during the first two years. This is due to a lower return expectancy for PV compared to the baseline scenario (opaque) with $\beta_{PV} = 0.9$ and $\beta_{Wind} = 1.3$. From 2022 onwards, falling technology costs have a bigger influence than the risk factor.

*2) Support scheme influence:* A capacity premium or subsidy is a policy tool often used to stimulate investments. It describes a lump sum payment per installed capacity. It can be interpreted as lowering the cost of technology, therefore increasing the capacity one can buy for the same amount of money. A higher capacity premium should increase the installed capacity. Figure 2 shows the results for an increase of the capacity premium from $cp = 10\%$ of the specific technology costs in the baseline scenario (opaque) to $cp = 20\%$ in the modified scenario (solid). The newly installed capacity is consistently higher for both technologies in the modified run, confirming our assumption.

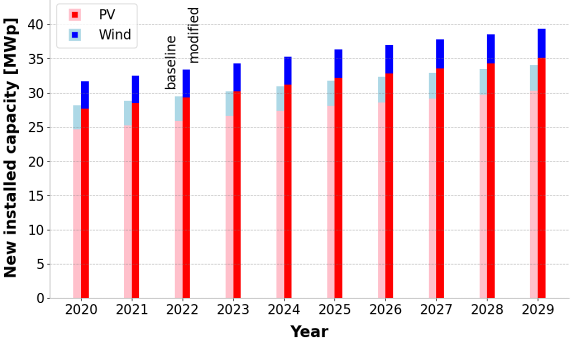

Fig. 2. Influence of the capacity premium on the capacity expansion decisions of a single investor. The modified scenario (solid) with a capacity premium of $cp = 20\%$ of the specific technology costs shows increased capacity expansion for both technologies. This is due to lower installation costs compared to the baseline scenario (opaque) with a capacity premium of $cp = 10\%$.

*3) Electricity price prognoses influence:* The expected profitability of a new plant is directly affected by the price for which its electricity will be sold. The electricity price depends on many uncertain parameters, making its accurate long-term prediction nearly impossible. However, using energy market models, one can approximate the characteristics and capture trends of the price curve under given assumptions. Such exogenous electricity price series are used as prognoses in the investment model. We use AMIRIS to generate the electricity price prognoses until 2050 for our cases. For this case, we need to prepare two different price prognosis. First, the electricity price for the baseline case is calculated with the assumptions given in the Appendix. Second, the the electricity price for the modified case is calculated with an energy system that contains $\Delta P_{PV} = 5\%$ more installed photovoltaic capacity. All other assumptions remain equal. The computed price series are given to the investors as basis for their decision. By this, we mimic two investors with a different outlook on how the energy system will evolve. Such assumptions can have a direct impact on their own profitability: In the modified case with increased PV capacity, PV becomes the price-setting technology. We assume zero marginal cost and neglect policy support for PV. Hence, PV generation is offered at a price of zero. The increase in cheap electricity from photovoltaic plants decreases the overall electricity price and results in a lower expected profitability. Additionally, we assume the same production profile for all PV plants. Hence, photovoltaic investments are especially affected as the photovoltaic modules cannibalize each other due to a high degree of simultaneous electricity production.

The effect of this changed prognosis for electricity prices is visible in Figure 3. PV installations in the modified scenario (solid) stay below the installations in the baseline scenario (opaque) until 2024. For the period between 2021 and 2024 increased investment in wind energy can be observed, as it is not affected by the cannibalization effect of PV.

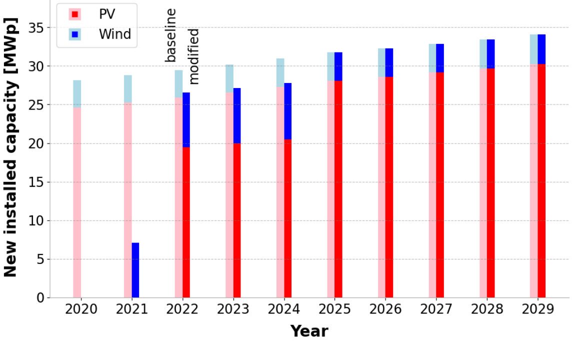

Fig. 3. Influence of the electricity price estimation on the capacity expansion decisions of a single investor. The modified scenario (solid) assumes a future energy system with an installed capacity of photovoltaic that is $\Delta P_{PV} = 5\%$ higher than in the baseline scenario (opaque). The resulting lower electricity prices, especially during hours of high PV production, lead to a lower return expectancy and shift investments towards wind energy until 2024.

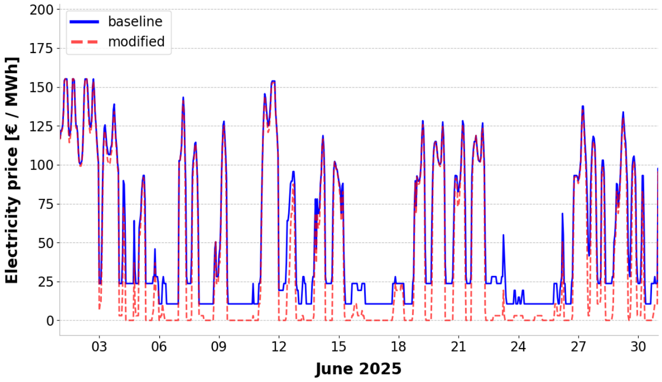

Fig. 4. Influence of capacity expansion decisions on the electricity price. The modified scenario (red) computes lower electricity prices than the baseline scenario (blue), here shown for the illustrative month of June 2025. This is due to an annual capacity expansion of PV and wind energy of $\Delta P_a \approx 2\% \cdot P_{baseline}$, which changes the market dynamics.

| | **Baseline** | **Modified** |
|---|---|---|
| Mean | 52.89 | 44.39 |
| Median | 40.14 | 30.26 |
| Std | 44.21 | 46.77 |
| 25th percentile | 12.18 | 0.00 |
| 75th percentile | 93.20 | 88.31 |

TABLE I
STATISTICAL ANALYSIS OF THE ELECTRICITY PRICE FROM 2020-2030

### B. *Effect of investments on the electricity market*

While the previous section focused on the effect of certain assumptions and policies on the investment decisions, this section investigates the effect of investment decisions on the electricity market. We verify that sufficiently big investments can change the dynamics of the market and the resulting electricity price. The simulation scenario is similar to the one in chapter III-A. Again, we study the German electricity market from 2020 to 2030. The baseline scenario does not include any new investments or endogenous changes in generation capacity over this period. Exogenous capacity changes are contained in the input data set for both scenarios. For the modified scenario we consider two investors, one specializing in PV and the other in wind energy. Both are equipped with enough financial means to increase the installed capacity of their respective technology by $\Delta P_a \approx 2\% \cdot P_{baseline}$ every year. Both technologies are assumed to have zero marginal prices and policy support is neglected. This leads to both technologies bidding at zero. The assumption is that such a big capacity expansion should have measurable effects on the electricity price. Figure 4 displays the computed electricity price for an illustrative month. The results of the modified scenario (red) are clearly different from the results of the baseline scenario (blue). The increase in generation capacity lead to lower prices with many events of zero pricing. This impression is confirmed by the statistical analysis of the results from 2020 to 2030 in Table I. Compared to the baseline scenario, the modified scenario shows a lower mean and median electricity price and a higher standard deviation. The 25th percentile of the modified scenario is equal to 0, indicating a large number of zero pricing events.

## IV. CONCLUSION AND OUTLOOK

We introduce a model to simulate corporate investment decisions in the electricity sector. The model is based on the key decision metrics NPV, WACC, and ROE. It can be used to investigate the effect of assumptions and policy interventions on investment decisions and the resulting capacity expansions. The investment model is connected to the electricity market dispatch model AMIRIS. This allows to explicitly depict new generation capacities in the simulated market and study their performance and effect on market dynamics. We present a simulation tool that consistently applies agent-based modelling for the different phases of renewable energy capacity expansion, from investment decisions to market dispatch. The model is uniquely positioned to investigate the impact of actor assumptions, policies, and market dynamics on the clean transformation of the electricity sector.

Further work will focus on expanding the model capabilities in three areas. First, investor agents will be enabled to evaluate the profitability of their investments. Unprofitable plants will be subject to a shut down decision, introducing an additional interaction between market conditions and installed capacity. Second, the electricity price prognosis will be made dynamically with an external fundamental model. This approach aims at incorporating investor-specific assumptions with a strong impact on the estimated electricity price, like the expectation of a higher carbon dioxide price. Third, investments in back-up power plants and large-scale storage systems will be considered. These technologies will play an important role in the future energy system, but if and how companies can turn them into profitable business cases in a large scale is far from clear. Overall, these changes will improve the modelling capabilities and possible analyses of investment decisions and their implications.

## ACKNOWLEDGMENT

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# APPENDIX

## A. Scenario data

This work uses AMIRIS in two ways: First, we couple it with the investment model to simulate the short-term electricity market until 2030. Second, we use it to generate electricity price prognosis until the year 2050. Hence, a full parametrization of AMIRIS until 2050 is needed. The following figures show the central assumptions of the parametrization in three key areas: development of plant capacities (Fig. 5, 6), electricity demand (Fig. 7), and prices (Fig. 8, 9). Electricity exchange with other countries via import and export is omitted. The assumptions were collected from multiple sources and harmonized using an open-source script[2]. Where the available data ends in 2045, input data from 2046 until 2050 is set to the last available value. For a full description of the data sources and how they were combined we refer to [16].

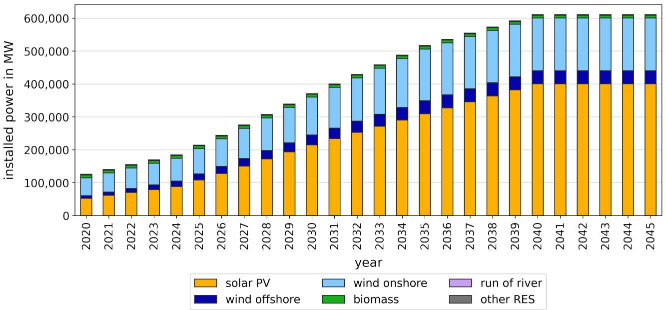

Fig. 5. Installed capacity of renewable energy sources in Germany until 2045. This data is used in AMIRIS to model the short-term electricity market. Investments done by the investment model are added to these capacities.

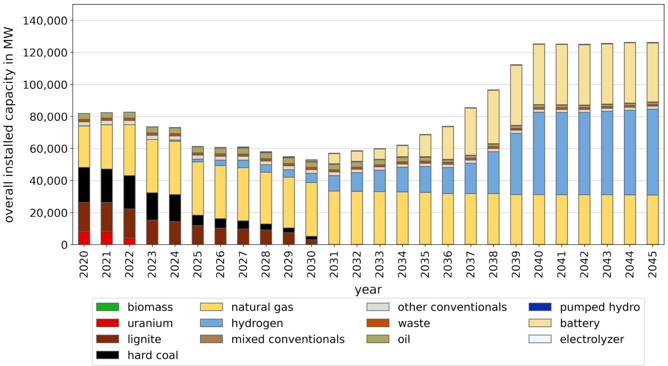

Fig. 6. Installed capacity of backup power plants in Germany until 2045.

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[2] https://github.com/pommes-public/pommesdata/blob/dev/pommesdata/data_preparation.ipynb (last visited 08.04.2025)

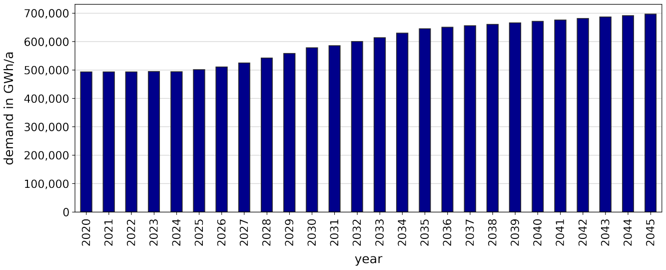

Fig. 7. Electricity demand in Germany until 2045.

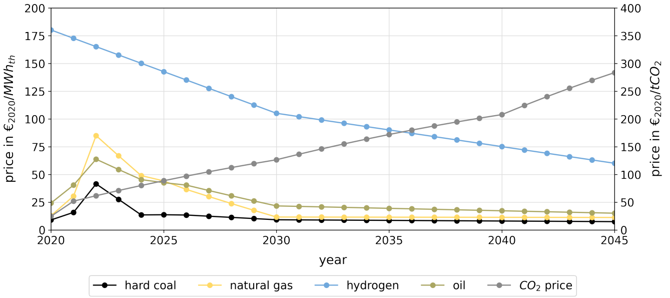

Fig. 8. Price assumptions for fuels and $CO_2$ emission permits in Germany until 2045.

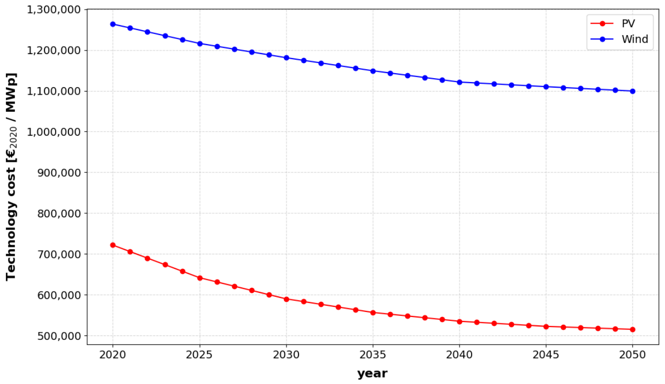

Fig. 9. Technology costs with learning curve for PV and Wind until 2050.

### B. Investment data

The tables II and III show the baseline parametrization for the investment model in the simulation cases of section III. Deviations from this parametrization are stated in the respective case descriptions.

| Description | variable | value | unit |
|---|---|---|---|
| Invested capital per year | $I_0$ | 20 000 000 | € |
| Lifetime of plant | $N$ | 20 | years |
| Minimum RoE | $ROE_{min}$ | 1 | % |
| Income tax share | $s$ | 30 | % |
| Interest rate (risk free) | $r_{rf}$ | 2 | % |
| Interest rate (borrowing) | $r_{eq}$ | 4 | % |
| Market return rate | $r_m$ | 7 | % |
| Equity share of capital | - | 20 | % |

TABLE II
BASELINE PARAMETRIZATION FOR ALL INVESTMENTS IN SECTION III

| Description | variable | PV | Wind | unit |
|---|---|---|---|---|
| Maximum portfolio share | $s_{max,tech}$ | 80 | 40 | % |
| Risk factor | $\beta$ | 0.9 | 1.3 | - |

TABLE III
TECHNOLOGY-SPECIFIC BASELINE PARAMETRIZATION FOR ALL CASES IN SECTION III