# BRAIN-Energy: Bounded Rationality Agents Investments model

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## 1. Overview

This model documentation provides a description of BRAIN-Energy, it's key equations, actors and strategies, a description about the actors' investment process, and of the data used to calibrate the model.

BRAIN-Energy is implemented in Netlogo (Wilensky and Northwestern University, 1999), a specific software for agent-based and system dynamics modelling. It is calibrated to 2012 as a base year, and it proceeds to 2050 in yearly time-steps. BRAIN-Energy's yearly resolution is justified by the fact that actors' investment decisions and interactions are better captured on an annual basis.

BRAIN-Energy analyses the strategic investment decisions in power generation assets of different market players with bounded-rationality, and the effects of their myopic and path-dependent choices and their interactions on the long-run evolution of the electricity sector to 2050. BRAIN-Energy aims to address a gap in existing energy-modelling literature, where most studies assume homogeneous and perfectly rational agents, and lack attention to the actors' heterogeneity and bounded-rationality. Case studies are the UK, the German and the Italian electricity markets.

## 2. Brief description

BRAIN-Energy is an agent-based model of electricity generation and investment. It gives a stylised representation of the UK, German and Italian electricity sectors in terms of generation technologies, installed capacity, actors, policies in the energy sector and climate change targets.

BRAIN-Energy is based on evolutionary economics and its main building blocks (Safarzynska and Van den Bergh, 2010; Nelson and Winter, 1982). In fact, in BRAIN-Energy agents have bounded rationality, they are heterogenous (which leads to diversity in the model, another important concept in evolutionary economics), and the investment choices of the agents are influenced by path-dependency, leading to adaptive investment choices. Moreover, imitation, hence learning, influences agents' investment decisions. This leads to selection of the best strategies, even though this process is not perfect due to agents' bounded-rationality. Finally, the investment choices of the market players and their outcomes co-evolve with the surrounding policy environment and governance structure.

Table 1 summarises the main exogenous variables and outcomes of BRAIN-Energy.

| Exogenous variables | Outcomes |
|---|---|
| • Electricity demand<br>• Fuel costs<br>• Capital costs of technologies<br>• Fixed and variable operational and maintenance (O&M) costs of technologies<br>• CO2 price (only in the scenarios where the government agents doesn't adjust the CO2 price, and in all other scenarios only the "no-increase trajectory, see Table 2) | • Aggregated and yearly capital investments (by technology and by agents)<br>• Electricity price<br>• Electricity production (amount and share of production by technology)<br>• Installed capacity (total and split by technology)<br>• Average and peak supply-demand gaps<br>• CO2 emissions from the power sector and carbon intensity of electricity generation<br>• Generators' and investors' market shares |

Table 1- BRAIN-Energy's exogenous variables and outcomes

## 3. Model flow

Figure 1 illustrates BRAIN-Energy's flow and the main feedback loops between agents and dimensions. The different strategies of the market players and the different strategies of the government agents are the drivers of change in BRAIN-Energy. Each year market players take short-term operational decisions (electricity production from their stock of assets), and bid electricity into the market. As a result of their electricity sales, the market players' equity and cash positions are updated. The market players' financial position then constrains (or encourages) their long-run investment decisions.

As a next step, the government checks the amount of CO2 emissions (or emission intensity) produced by the power sector. If the interim decarbonisation targets are not me, the government agent can increase the prevailing CO2 price, according to the level of his environmental commitment and strategy (see Table 2). t the Government agent can increase the prevailing CO2 price, according to the level of his environmental commitment and strategy. The regulator agent also intervenes in the market to manage eventual supply gaps by enforcing capacity auctions (in the UK and Italian versions of BRAIN-Energy only). Therefore, the policy changes which the government/regulator agents enforce in BRAIN-Energy are endogenous, and co-evolve with the emergent techno-economic properties of the sector through the years.

Market players then reassess the profitability of their prior investments and switch-off unprofitable power plants. This can give rise to supply- demand gaps, creating for new investments. As a last step, market players decide about new investments. Newly committed investments start being operational after a planning- and construction lag, and the generation mix is, therefore, an emergent result of the agent's investment and decommissioning decisions.

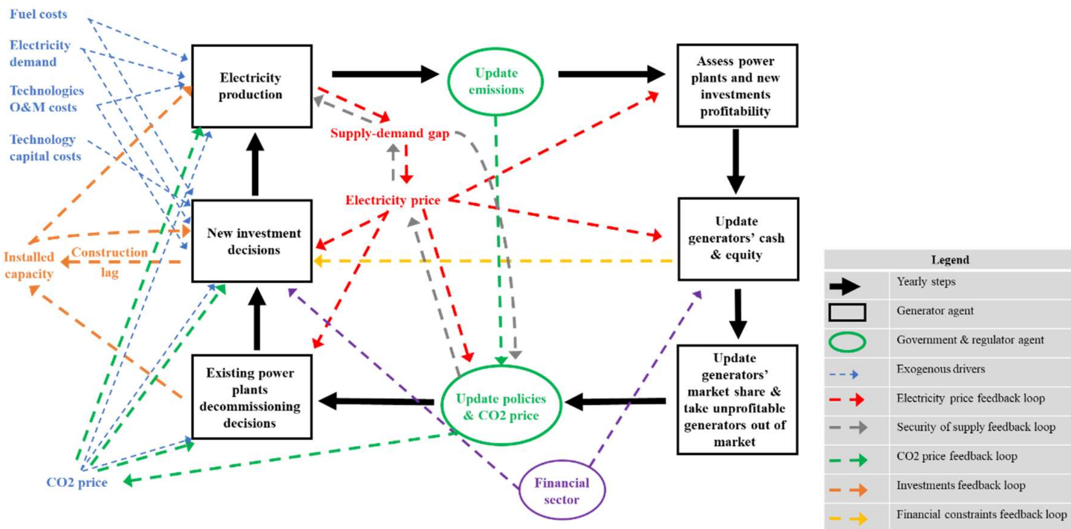


*Figure 1 - BRAIN-Energy's flow*

## 4. Actors and strategies

### a. Market players in the electricity sector

The main market players in the UK version of BRAIN-Energy are:

- Incumbent electricity generators
- Independent power producers
- New-entrants

In the German and Italian version of BRAIN-Energy also the following market players have been modelled:

- Municipal utilities
- Institutional investors
- “Civic” sector actors: “Civic” sector actors (as defined by Hall et al., 2016) are households and energy cooperatives, and are very important investors in renewable energy assets in Germany and in Italy. These actors invest mainly in small scale renewable energy facilities, to cover self-consumption, and might sell surplus locally.

In BRAIN-Energy market players have bounded rationality and take myopic investment decisions in accordance with evolutionary economics theory, not having perfect foresight about the future, and not knowing what the other market players’ future decisions are. On top of path-dependency and imitation in investment decisions, the most important strategic parameters of the market players are:

- technology preferences: this means that market players only operate or invest into determined types of technologies.
- length of the foresight used to evaluate possible investment options: this means that different types of market players evaluate future investment options over a different number of years in the future. This reflects the fact that the myopic foresight of the market players depends on their investment strategies, risk propensity and return expectations

- length of time during which generators and investors are willing to absorb losses from operating power stations before closing unprofitable plants down.
- interest rate that market players pay on their financial loans and the associated expected rate of returns of new investments: interest rates charged to market players are based on values found in the literature (HM Treasury, 2011; Hermelink and De Jager, 2015; Global Capital Finance, 2014; Steinbach and Staniaszek, 2015) and on the financial statements of the major European utilities. These reflect the risk profile of each type of actor also taking into account the risk profile of the country in which they operate, and represent a company's weighted average cost of capital (WACC). As a result of their interest rates, heterogeneous generators and investors expect different returns on their investments which match the level of the interest rate they pay.
- expectations about renewable technologies capital costs, fuel prices and level of future electricity demand: these reflect the future views of the market players about the evolution of the electricity market, depending on their expected level of electrification in the transport and heating sectors.

**b. Government and regulator**

The government agent in BRAIN-Energy is responsible for making sure that the legally binding CO2 reduction targets are met, and that the low-carbon transition of the electricity sector is on track to meet the interim carbon budgets. The level of the government activity and its commitment to meet climate change targets is measured by the degree to which the government agent increases the carbon price over the prevailing "no-increase" trajectory when the interim carbon budgets are not met. There are three CO2 price trajectories which the government agent can apply, which are explained in Table 2. If in between carbon budgets the carbon intensity of electricity generation falls below the desired level, the government decreases the CO2 price again to the "no-increase" trajectory

| CO2 price trajectory | Description and calibration |
|---|---|
| **"No-increase"** | This is the prevailing CO2 price at the onset of all scenarios in BRAIN-Energy. When the government is not committed to meet decarbonisation targets, it maintains the CO2 price at this level even if interim carbon budgets are not met. It is calibrated as:<br><br>**UK:**<br>• Historical: EU ETS + Carbon Price Floor according to the "Reference" scenario in BEIS (2016)<br>• Future: "Reference" scenario in BEIS (2016)<br><br>**Germany and Italy:**<br>• Historical: EU ETS (BmWi Energiedaten database[1])<br>• Future: "Referenzprognose" scenario and "Trendszenario" (Prognos, 2014) |
| **"Weak"** | This trajectory represents a weak commitment by the government to meet decarbonisation targets. Under the "weak" trajectory, when interim carbon budgets are not me, the government increases the CO2 price by 100% over the "no-increase" trajectory . |
| **"Strong"** | This trajectory represents a strong commitment by the government to meet decarbonisation targets. Under the "strong" trajectory, when interim carbon budgets are not me, the government increases the CO2 price by 200% over the "no-increase" trajectory |

*Table 2- CO2 price trajectories in BRAIN-Energy*

[1] https://www.bmwi.de/Redaktion/DE/Binaer/Energiedaten/energiedaten-gesamt-xls.html

The frequency of the carbon budgets in the three countries can be found in Table 3 for the UK, Table 4 for Germany and Table 5 for Italy.

| Year | Carbon intensity of power generation |
|---|---|
| 2020 | 250 gCO2/kWh |
| 2025 | 200 gCO2/kWh |
| 2030 | 100 gCO2/kWh |
| 2035 | 50 gCO2/kWh |
| 2040 | 25 gCO2/kWh |
| 2045 | 15 gCO2/kWh |
| 2050 | Near-zero |

*Table 3- Carbon budgets in UK BRAIN-Energy*

| Year | Share of renewables in electricity production |
|---|---|
| 2020 | 20% |
| 2025 | 45% |
| 2035 | 60% |
| 2045 | 70% |
| 2050 | >=80% |

*Table 4 - Carbon budgets in German BRAIN-Energy*

| Year | Share of renewables in electricity production |
|---|---|
| 2020 | 20% |
| 2030 | 55% |
| 2040 | 70% |
| 2050 | >=80% |

*Table 5 - Carbon budgets in Italian BRAIN-Energy*

Moreover, the Government agent subsidises investments in new renewable generation assets either through Contracts for Difference (CfDs) in the UK, or through feed-in tariffs (FITs) in Germany and in Italy. CfD auctions take place every three years, and winners of the auctions are paid the difference between an auction's strike price and the prevailing market price for 15 years, hence providing stability and predictability to investors' revenues for 15 years. In BRAIN-Energy the strike price (expressed in MWh) which agents bid into the market is calculated as the price which allows them to recover capital expenditures for a given project *p* ( $CAPEX\ p$ ), interest costs on the loan raised to finance the project *p* ( $r$ ), and O&M, fixed and variable costs associated to the expected level of electricity generation from project *p* in a given year *t* ( $g_{p,t}$ ) , hence to have an net present value (NPV) equal to zero.

$$SP_{x,p,t} = \frac{\left(\frac{CAPEX_p}{l_p} \times (1+r)\right) + \ c_{p,t}}{g_{p,t}}$$

where:

$SP_{x,p,t}$ is the strike price required by generator or investor *x* for plant *p* at time *t*
$l_p$ is the lifetime of plant *p*
$c_{p,t}$ is the expected cost of generation of plant *p* in year *t* based on fixed, O&M and variable costs

In the German and Italian versions of BRAIN-Energy the government agents use Feed-in-tariffs (FITs), according to the laws in these two countries. In BRAIN-Energy FITs are modelled as fixed price which market participants receive on their low-carbon investments for 15 years ahead. Hence, when generators and investors calculate the expected profitability of future investments (as described later in point 6.a), instead of using the expected electricity price they based their calculation on the level of the FITs which the government agents provide for each technology.

The regulator agent in BRAIN-Energy manages security of supply through a capacity market in the UK and in the Italian models. The way the capacity market works in the UK version of BRAIN-Energy is represented by the fact that the regulator agent, who also has bounded-rationality, forecasts every year the maximum potential electricity production at *t+4* ($maxs_{t+4}$) by estimating the maximum potential electricity production of all active power plants with plant life of at least or greater than *t+4.* If the maximum potential electricity production at *t+4* ($maxs_{t+4}$) is lower than peak demand at year *t+4*, then the regulator agent sets a capacity auction into place at year *t* with capacity to be delivered at *t+4*. The capacity to be auctioned ( $CA_t$) is then:

$$CA_t = PeakDemand_{t+4} - maxs_{t+4}$$

In BRAIN-Energy, the capacity market functions for new capacity investments only and is modelled following Hach et al. (2015). The price that market players bid into the market is the annual payment from which a negative NPV turns to zero ( $CP_{p,t}$ ) . If the NPV of a project is already greater than zero, than generators and investors bid zero into the capacity auction.

$$CP_{p,t} = \max(0; -NPV)$$

where:
$CP_{p,t}$ is the annual capacity payment for plant *p* at time *t* which agents participating into the capacity auction bid into the market. It is capped at £75/kW a year in accordance with regulation in the UK market.

## 5. Power sector operations

Electricity demand, an exogenous variable in BRAIN-Energy, has been divided into average yearly day demand and average yearly night demand, to account for diurnal variations in electricity load. In the UK model this has been done based on half-hourly national Grid data for historical data. Also, a yearly peak demand in GW has been defined, which is calculated as the yearly average day demand multiplied by the peak factor. For all the three countries, the peak factor ($PF$) has been calibrated on historical observations of the absolute yearly peak electricity demand in the UK, Germany and Italy, and is defined as a percentage of the average yearly day demand. The peak factor ($PF$) is assumed to be constant through the years from 2012 to 2050.

$$PeakDemand_t = AverageYearlyDayDemand_t \times PF$$

To account for the intermittency of renewable generation assets, their installed capacity has been de-rated by their load-factor. Moreover, renewable plants in this model have a declining "contribution to peak", which means that the marginal contribution of each new renewable generation asset in meeting peak demand is declining the more renewables are installed in the system.

Electricity production bidding strategy ($b_t$) of market players:

$$b_t = f(SRMC_{p,t,}, ep_{p,t})$$

Where:
$SRMC_{p,t,}$ is the short-run marginal cost of plant p at time t
$ep_{p,t}$ is the potential available production capacity of power plant $p$ in MWh at time $t$

Short-run marginal cost of generators:

$$SRMC_{p,t} = \frac{(p_{f,t} + p_{CO\ ,t}) \times ep_t + fc_{p,t}}{ep_{p,t}}$$

where:
$p_{f,t}$ is the price of fuel $f$ at time $t$ for a MWh of electricity, $p_{CO2,t}$ is the CO2 price at time $t$ for a MWh of electricity, $ep_t$ is the potential available production of plant $p$ at time $t$ in MWh, $fc_{p,t}$ are the fixed O&M costs for plant $p$ at time $t$

The wholesale electricity price at year $t$ ( $p\ t$ ) is equal to the short run marginal cost of the last and most expensive bid accepted into the market, which is required to meet electricity demand in that year.

Total CO2 emissions and carbon intensity of the power sector: At the end of each year, based on the production mix resulting from the merit order, hence on the share of electricity produced through renewable sources and through conventional sources, total emissions in the power sector ( $TotCO2_t$) at time $t$ and carbon intensity of electricity generation ( $CI\ _t$) at time $t$ are calculated.

$$TotCO2_t = \sum_{x}^{n}((s_{p,day,t} + s_{p,night,t}) \times EI_p)$$

$$CI_t = \frac{TotCO2_t}{\sum_x^n(s_{p,day,t} + s_{p,night,t})}$$

where:
$s_{p,day,t}$ total day electricity production of power plant $p$ at time $t$, $s_{p,night,t}$ total night electricity production of power plant $p$ at time $t$, $EI_p$ is the emission intensity of plant p, $n$ is number of active power plants at time $t$

## 6. Investment process

In BRAIN-Energy the investment choices of the market players co-evolve with the policy dimension and the governance structure. This is illustrated in Figure 2.

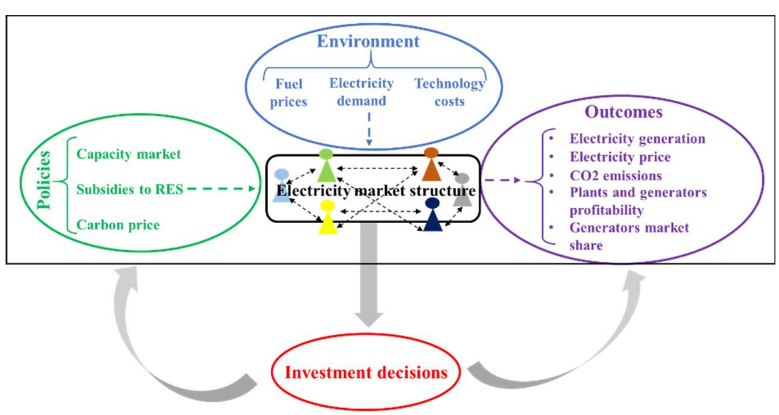


*Figure 2 - Investment process in BRAIN-Energy and co-evolution with other dimensions*

**a. Economic criteria in investment decisions**

Market players in the power market take yearly decisions to decommission unprofitable power plants, reassess the profitability of prior investments and take decisions about building new power stations. Such strategic decisions are taken by each market player independently and sequentially one after the other.

Investment choices come after the operational activities of each market player, as they also depend on the amount of revenues generated by their core business of electricity production. Each market player finances part of the capital investment costs for new power stations from own resources (cash generated from operating activities), and the remaining part through debt taken by banks at a market player's specific cost.

Every year, all market players evaluate the potential future profitability of each generation technology in which they are willing and able to invest given their technology preferences, by calculating its net present value ($NPV$) up to a future reference year $n$ years ahead. The value of $n$ depends on each market player's foresight. As market player have myopic foresight and don't have perfect information about the future, their $NPV$ calculations are based on their own micro-economic expectations and estimations about future electricity demand, fuel and technology prices, and cash-flow from future potential investment technologies.

Operating cash-flow ($CFop_p$) and NPV calculations:

$$CFop_p = \sum_{y=t}^{n} \frac{(ep_{p,t} \times p_{exp,t}) - ((vc_{f,c,p,t} \times ep_{p,t}) + fc_{p,t}}{(1+r)^y}$$

$$NPV_p = CFop_p - (\frac{CAPEX_{p,t}}{l_p} \times n)$$

Where:

$ep_{p,t}$ is the expected production of plant *p* at year *t*

$p_{exp,t}$ is the electricity price which each actor expects at time *t*

$vc_{f,c,p,t}$ are the variable costs of plant *p* as a function of fuel and carbon costs at time *t*

$fc_{p,t}$ are the fixed costs of plant *p* at time *t*

$r$ is the interest rate that market players pay on their liabilities

$CAPEX_{p,t}$ is the project capital cost for generation technology *p* at time

If NPV is greater than zero, market players select the investment option with the highest return on investment (ROI).

Institutional investors (in the German and Italian versions of BRAIN-Energy) are assumed to invest directly into projects, and not through equity or debt of other companies (Blyth et al., 2015; CPI, 2012), and use the same investment calculations and process explained above.

"Civic" sector actors, instead, use a different process to evaluate future investment options. In fact, households (which can be found in both the German and the Italian model) and energy cooperatives (which can only be found in the German model) calculate the economic utility from future investments based on the length of the payback period, which is given by the year when the NPV of the new investment passes from being negative to being positive. This is based on Palmer et al. (2015) as this study is specifically focused on studying the adoption of solar PV between households in Italy.

**b. Non-economic criteria in investment decisions**

*Path-dependency*

Path-dependency in investment choices in BRAIN-Energy is represented by the fact that:

- Market players' investment choices are constrained by the performance of existing plants and investments, which dictate an agent's financial constraints

- Market players assess their investments, comparing actual with expected profitability of a new generation asset. If a new generation plant is less profitable than expected, it is flagged as an unprofitable investment, which dissuades agents to invest in the same technology at the next time-step, leading to experience-based adjusted investment decisions. After five years that a new investment has become operational agents start assessing every year the profitability of their new investment over the previous five years. If cumulative profits over the last 5 years ($\sum_{y=t}^{n} PF_{p,t}$) are lower than the 5-yearly share of the new investment's total capital costs (which means that the profits generated by the new plant are not able to recover capital and interest and cover operational and interest costs) then the new investment is flagged as unprofitable.

$$\sum_{y=t}^{n} PF_{p,t} < \frac{CAPEX_p}{l_p} \times n$$

  If the number of years during which the new investment is unprofitable in a row is greater than the number of years market players' are willing to absorb losses for, then the new plant is shut down. Once a new investment has been flagged as unprofitable, other generators and investors don't invest into the same generation technology up to the point when such technology becomes profitable again

- Market players shut down existing plants at the beginning of the simulations if they have been unprofitable for a given number of years in a row. the number of years after which unprofitable power plants are closed down depends on each agent's strategy and willingness to absorb losses

*Imitation*

In BRAIN-Energy investment choices are also influenced by other agents' successful investments.

The way that imitation works in BRAIN-Energy is based on the evolutionary economics model of imitation proposed by Nannen and Van den Bergh (2010). As in Nannen and Van den Bergh (2010) in BRAIN-Energy agents have bounded-rationality, and the only information which they have available are the investment strategies of the other agents and their expectations about future technologies capital costs, fuel costs and electricity prices. Agent *a* in BRAIN-Energy measures the outcomes of the investment strategies of the other agents in terms of growth or decline of their market share, hence they believe that there is a link between investment strategies and development of the market share. Agent *a* also assess the investment strategies of the other players' in terms of early closures due to unprofitability of their new investment. If an agent's *x* market share ($MS_x$) is growing compared to the previous year, hence if $MS_{x,t+1} > MS_{,t}$ , agent *a* chooses to imitate the agent *x* whose market share grew the most at year *t+1*, and who didn't close down any new power stations at year *t+1* due to unprofitability. Among the new investments of the agent *x* which agent *a* decides to imitate (given his technology preferences), agent *a* chooses to imitate investments in the generation technology with the highest expected ROI based on

its own myopic expectations (or the shortest pay-back period for “civic” sector actors) and invests in that generation technology. This is because agent *a* doesn't have perfect information about which exact power plant or generation technologies caused the imitated agent's market share to increase between *t* and *t+1*.
As imitation is not a perfect process and errors can take place during the imitation process, imitation can lead to the creation of a number of diverse successful or unsuccessful investment strategies.

The above described investment process (economic and non-economic criteria) are also shown in Figure 3.

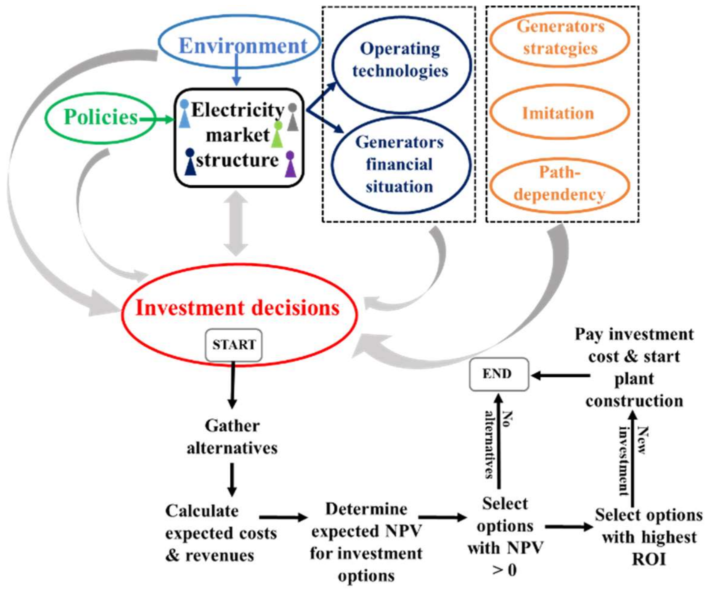


*Figure 3 - Economic and non-economic criteria in investment process in BRAIN-Energy*

## 7. Data and calibration

### UK model

The UK model is calibrated to 2012 using official government statistics (BEIS, 2016). Active generation technologies in the UK model are based on the existing generation fleet at the base year 2012 (BEIS, 2016) and are detailed in Table 6.

| Technology | GW |
|---|---|
| Gas CCGT | 35 |
| Coal | 30 |
| Nuclear | 9 |
| Onshore wind | 6 |
| Offshore wind | 3 |
| PV | 2 |
| Hydro | 4 |
| Biomass | 3 |
| Peaking plants (e.g. oil) | 2 |

*Table 6 - Installed capacity in UK BRAIN-Energy*

The technical and operational performance of the different technologies is expressed in terms of variable operational costs (fuel costs), carbon costs, and fixed operations and maintenance costs (O&M costs) per unit of electricity produced. O&M costs are based on the fixed operations and maintenance costs components of the levelized cost of electricity production (LCOE) of each technology (BEIS, 2016,b). Other technical parameters of the generation plants are summarised in Table 7.

| Technology | Average load factor | Lifetime | Emission intensity ($gCO_2/kWh$) |
|---|---|---|---|
| Gas CCGT | 93% | 25 years | 365 |
| Coal | 90% | 30 years | 907 |
| Nuclear | 90% | 60 years | |
| Onshore wind | 32% | 24 years | |
| Offshore wind | 43% | 23 years | |
| PV | 11% | 25 years | |
| Hydro | 40% | 35 years | |
| Biomass | 84% | 25 years | |
| Peaking plants (e.g. oil) | 22% | 25 years | |

*Table 7 - Technical power plant data in UK version of BRAIN-Energy*

Fuel costs of gas and coal are based on historical gas and coal prices found in the BEIS (2016,a) report. Assumptions about fuel costs future evolution reflect the UK's government view and are based on the BEIS (2016,a) "Reference scenario" estimates, because this scenario is based on central estimates of fossil fuel prices and economic growth for the UK, which are based on all agreed (hence also "planned" policies) and existing policies as of BRAIN-Energy's calibration year.

Existing generation technologies also provide future investment options for electricity generation in BRAIN-Energy, except for hydro which capacity is assumed to remain constant through the years. Each generation technology has an associated capital cost (Table 8) expressed in EUR/kW (which is converted into £/kW in the UK version of BRAIN-Energy). Data about technologies' capital costs and their expected evolution to 2050 in BRAIN-Energy is based on data from DIW's Current and Prospective Costs of Electricity Generation until 2050 report (DIW, 2013).

| Technology | 2012 | 2015 | 2020 | 2025 | 2030 | 2035 | 2040 | 2045 | 2050 |
|---|---|---|---|---|---|---|---|---|---|
| Gas CCGT | 400 | 400 | 400 | 400 | 400 | 400 | 400 | 400 | 400 |
| Coal | 1,800 | 1,800 | 1,800 | 1,800 | 1,800 | 1,800 | 1,800 | 1,800 | 1,800 |
| Nuclear | 6,000 | 6,000 | 6,000 | 6,000 | 6,000 | 6,000 | 6,000 | 6,000 | 6,000 |
| Onshore wind | 1,300 | 1,269 | 1,240 | 1,210 | 1,182 | 1,154 | 1,127 | 1,101 | 1,075 |
| Offshore wind | 3,000 | 2,868 | 2,742 | 2,621 | 2,506 | 2,396 | 2,290 | 2,189 | 2,093 |
| PV | 1,560 | 950 | 750 | 675 | 600 | 555 | 472 | 448 | 425 |
| Biomass | 2,500 | 2,424 | 2,350 | 2,278 | 2,209 | 2,141 | 2,076 | 2,013 | 1,951 |
| Peaking plants (e.g. oil) | 400 | 400 | 400 | 400 | 400 | 400 | 400 | 400 | 400 |

*Table 8 - Technologies capital costs in UK, German and Italian versions of BRAIN-Energy in EUR/kW*

Carbon costs (Figure 4) for conventional generation technologies comprise the EU ETS price plus the Carbon Support Price component of the Carbon Price Floor (CPF), and are based on historical data found in the BEIS (2016,a) report also in the "Reference" scenario as for fuel prices. The "no-increase" $CO_2$ price trajectory, which is the prevailing $CO_2$ price over which the government agents can increase to a different degree the $CO_2$ price when interim carbon budgets are not met (the different $CO_2$ price trajectories which the government agents can apply are explained in Table 2), is modelled according to the "Reference " scenario in the BEIS (2016,a) report. The different $CO_2$ price trajectories are shown in Figure 4.

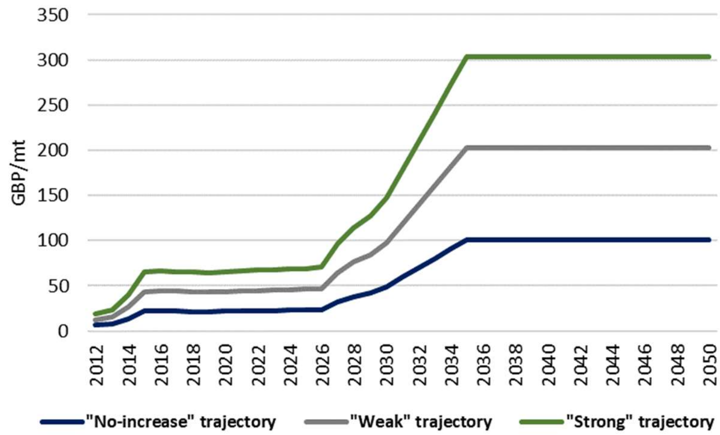


*Figure 4 - CO2 price trajectories in UK BRAIN-Energy*

Electricity demand (an exogenous variable in BRAIN-Energy) is calibrated until 2016 on historical half-hourly National Grid data. Assumptions about future demand evolution are based on the National Grid's Future Energy Scenarios 2016 report (National Grid, 2016). These scenarios have been chosen for the calibration of future electricity demand, in order to be consistent with historical data, and because of their level of detail and disaggregation until 2050. Figure 5 shows the calibration of electricity demand in the UK version of BRAIN-Energy.

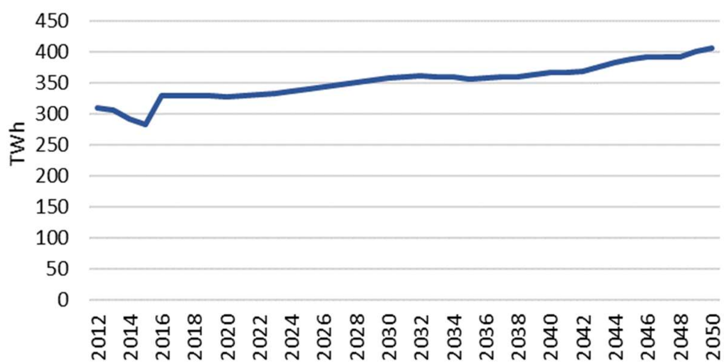


*Figure 5 - Electricity demand in UK BRAIN-Energy*

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