BRAIN-Energy: Bounded Rationality Agents Investments model

Online model documentation – March 2020

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1. Model overview

This document provides a description of the new Python-based version of **BRAIN-Energy (Bounded Rationality Agents Investments model)**, of its key equations, calibration data, agents, and their characteristics and strategies.

BRAIN-Energy is an **agent-based model (ABM)** of electricity generation and investment. Its strength and novelty lies in the sophisticated representation of agent behaviour and interactions. The model's aim is to represent heterogeneous agent characteristics in investment decisions and multi-agent interaction, and to explore the impacts of those aspects on the electricity sector's low-carbon transition to 2050.

BRAIN-Energy is implemented in Python using an object-oriented programming framework, it is calibrated to 2012 as a base year, and it proceeds to 2050. Eight time-slices per year (two seasons and each season is represented by a typical day with four intra-day periods) are adopted to represent the temporal variations of electricity supply and demand of the UK-wide and local electricity systems. The definition of the eight time-slices is shown in the table below.

Table 1 – Definition of time-slices in BRAIN-Energy

Season	Intra-day period	Time represented	Notes
Winter (W) Summer (S)	Night (N)	00:00–07:00	Lowest demand
	Day (D)	07:00–17:00	Includes morning peak
	Evening peak (P)	17:00–20:00	Peak demand
	Late evening (E)	20:00–00:00	Intermediate

BRAIN-Energy's initial version (Barazza and Strachan, 2020a; Barazza and Strachan, 2020b) was calibrated to the UK, German and Italian electricity supply sectors, while the updated version in Python is at present only calibrated to the UK. BRAIN-Energy gives a stylised representation of the UK electricity sector in terms of generation technologies to reach UK's net-zero target at 2050, installed capacity, agents (investor agents and policy agents on a national and local level), policies in the energy sector and climate change targets.

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 (Bergek et al., 2013; Iychettira et al., 2017; Wüstenhagen and Menichetti, 2012).

New developments in the Python-based version of BRAIN-Energy include:

- local energy system component (3 regions and local investor and policy agents)
- improved governance (new policy mechanisms at the local level)
- improved depiction of the technical side of the power system (8 time slices for electricity dispatch-side, demand response)
- Improved technology portfolio to reach UK's net-zero target at 2050 (BECCS has been added to the technology portfolio)

2. Model flow

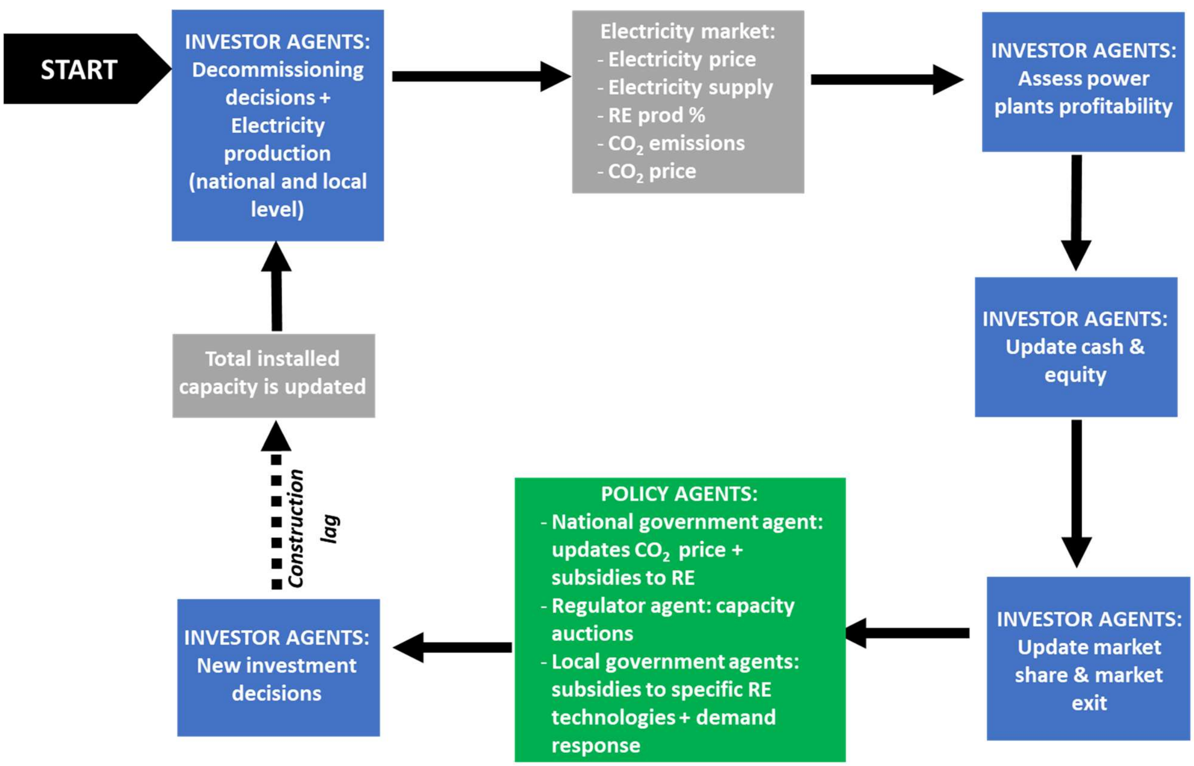

Figure 1- BRAIN-Energy's yearly flow

Figure 1 depicts BRAIN-Energy's annual flow and how it iterates through its different main procedures. Each year investors decommission unprofitable power plants, and then take short-term operational decisions (electricity production from their stock of assets), and bid electricity into the market at a national and local level. As a result of their electricity sales, the yearly national and local electricity price is created (section 4), as well as the electricity supply curve (section 4) and the CO_2 emissions from the power sector (section 4). Based on their electricity sales and on the electricity price investors assess the profitability of their stock of assets and their market share is updated. Investors whose equity is negative exit the market.

Policy agents (these are explained in section 5.2 and are the national government agent, the regulator agent and local government agents) are active at the next step: the national government agent checks the amount of CO_2 emissions (or emission intensity) produced by the power sector at the national level. If the interim decarbonisation targets are not met, the national government agent can adjust the prevailing CO_2 price (section 5.2) at the national level. The national government agent also subsidises investments in renewable technologies through Contracts for Difference (section 5.2) at the national level. The regulator agent also intervenes in the market to manage eventual supply gaps by enforcing capacity auctions (section 5.2) at the national level. Local government agents take the necessary policy measures at the local level (subsidising specific renewable technologies and managing demand response programs). Therefore, the policy changes which the policy agents (the national government, regulator and local government agents) enforce in BRAIN-Energy are endogenous, and co-evolve with the emergent techno-economic properties of the sector through the years.

Finally investors decide about new investments (section 6). Newly committed investments start being operational after a planning- and construction lag, and the resulting generation mix is, therefore, an emergent result of the investment and decommissioning decisions of the investors.

3. Regions

The UK has been divided into 3 regions to better represent the differences in the energy systems of different parts of the UK: these 3 regions are London, Scotland, and the rest of UK. These regions have unique characteristics in terms of their socio-economic profile, energy use patterns, deployment potential for energy technologies, investor profiles and government actors.

London is the largest urban region in the UK and contributes almost a quarter of the UK's GDP. In addition, the Greater London Authority and the Mayor of London's Office hold significant authority and have defined more ambitious climate targets than the UK and constituted local energy programmes to meet these goals.

Scotland's devolved government has independent control over large parts of the Scottish economy and society, and has its own Climate Change Plan with annual CO_2 targets and a Scottish Energy Strategy that sets the long-term goals for the Scottish Energy System.

The Rest of UK forms the third region, which like Scotland is composed of large areas with a rural population interspersed with cities of a much smaller size as compared to London.

BRAIN-Energy simulates the electricity market using a hierarchy-based approach by determining electricity supplies in the local regions first. Power plants in the local regions (i.e. London and Scotland) are firstly applied to supply electricity to meet the local electricity demands. Whenever there is a shortage of electricity supply, electricity will be imported from the national region (i.e. UK) to meet the demand. In contrast, if there is surplus electricity from variable renewable energy (VRE) in the local regions, the surplus electricity can be exported to the national system. The same hierarchy-based approach is also applied to prioritise new investments in the local regions made by local agents (i.e. households).

However, fossil fuel and biomass power plants are always operated co-ordinately at the national level due to the size of those plants is usually too large for local demands.

4. Power sector operations

Electricity demand, an exogenous variable in BRAIN-Energy, has been divided into eight intraday demands for two typical days in two seasons respectively based on historical data, to account for diurnal variations in electricity load.

A yearly peak demand in GW has been defined, which is calculated as the demand at the evening peak time-slice (P) in the winter season multiplied by the peak factor. The peak factor (PF), as shown below, has been calibrated on historical observations of the absolute yearly peak electricity demand in the UK, and is defined as a percentage of the evening peak demand in the winter season.

Table 2 – Peak factors (source: same sources as for electricity demand see section 8)

	% of yearly average day demand
UK	125%

The peak factor (PF) is assumed to be constant through the years from 2012 to 2050.

$$PeakDemand_t = WinterEveningPeakDemand_t \times PF$$

To account for the intermittency of renewable generation assets, their installed capacity has been de-rated by their load-factor.

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. The same mechanism is applied to both national and local regions to determine regional electricity prices. In other words, regional wholesale electricity price is determined by the technology mix in the corresponding region.

Total CO_2 emissions and carbon intensity of the power sector: 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*

5. Agents

Agents in BRAIN-Energy have been defined based on an extensive literature search. Agents in BRAIN-Energy are heterogeneous: they are of different types (different types of organisations) and have different characteristics. Types of agents in BRAIN-Energy include:

- **Investor agents**
- **Policy agents**

Both investor and policy agents can be national or local agents.

All agents in BRAIN-Energy have bounded-rationality. This means that investors have limited foresight of the future, and that they take satisificing rather than maximising investment decisions (Simon, 1953, 1955; 1956; Nelson and Winter 1982), which are based on routines, habits, past experience and on their own heterogeneous expectations of electricity demand, fuel and technology costs.

5.1 Investor agents

Table 3 contains a description of the different types of investor agents represented in BRAIN-Energy. Those investors aim to represent the most important private investors in renewable energy technologies based on various literature sources (CPI, 2019; IRENA/CPI, 2018; European Commission, 2017).

Table 3- Description of investor agents in BRAIN-Energy

AGENTS	DESCRIPTION	REGION
Incumbent utility	Main players in the electricity sector, whose main business is electricity generation. These are sophisticated players, some are vertically integrated companies, which also own the supply business. They focus on large scale projects.	National
New-entrant	New-entrants players in the UK electricity market are new types of investors in electricity production assets, whose main business is however not electricity generation (as for incumbent utilities). Examples of new-entrants include institutional investors, who can invest directly or indirectly in renewable energy projects.	National
Municipal utility (local supplier)	Directly or indirectly owned by a municipality or city or local authority. These companies operate only in their regions, to which they are strategically committed. Their objective is to supply affordable and reliable energy to local consumers, and some also have an environmental focus.	Local
Household aggregator	Households invest in small scale renewable energy plants such as PV and participate in demand response programs. They invest in PV to cover self-consumption, and for environmental reasons.	Local

Different types of investor agents have different characteristics which are summarised in Table 4.

Table 4 – Characteristics of investor agents in BRAIN-Energy

INVESTOR AGENTS	Technology	Location of project	Risk (Cost of capital in BRAIN-Energy)	Return (ROI in BRAIN-Energy)	Time horizon of investments
Incumbent utility	• Fossil fuel (gas) • Nuclear • RE (no PV)	National	High risk	High returns	Long
New-entrant	• RE (all)	National	Low risk	Low returns	Short
Municipal utility (local supplier)	• Fossil fuel (gas) • RE (all)	Local	Medium risk	Medium return	Long
Household aggregator	• PV • Demand response • Small onshore wind for rural/UK households	Local	Low risk	Low returns	Short

Technology choices and location of projects for the different investor agents have been calibrated based on CPI (2014). As regards to risk and return considerations, cost of capital ranges for the different types of investors have been calibrated based on Steinbach and Staniaszek (2015), Diacore (2015), Salm (2018), Helms et al. (2015), Salm et al. (2016), Broughel and Hampl (2016) and are as follows:

- Incumbent utilities: 8%-12%
- New-entrants: 6%-7%
- Municipal utility (local supplier): 8%-9%
- Households: 3%-6%

The time horizon of investments for the different types of investor agents has been calibrated in BRAIN-Energy based on Hall et al. (2017) and Salm et al. (2016) and is as follows:

- Incumbent utilities: 10-12 years
- New-entrants: 5 years
- Municipal utility (local supplier): 12-15 years
- Households: 5 years

Within each type, of investor agents, there are:

- 2 incumbent utilities
- 2 new-entrants
- 2 municipal utilities (local suppliers): these match the regional split and are the London supplier and the Scotland supplier
- 3 household agents (one for each region in BRAIN-Energy: London household agent, Scotland household agent, rest of UK household agent)

These differ by:

- initial technology portfolio
- initial money endowment
- risk
- return
- time horizon of investments

Investor agents have other strategic behaviour:

- different expectations about future electricity demand, fuel and technology costs
- imitation of other investors' agents successful investments (section 6.3)
- learning: investors get out of technology type if poor investments (section 6.2)
- exit the market when money endowment is negative

5.2 Policy agents

The different types of policy agents in BRAIN-Energy are summarised in Table 5.

Table 5 – Description of policy agents in BRAIN-Energy

AGENTS	DESCRIPTION	REGION
National government agent	This policy agent is committed to reach the 2050 decarbonisation objectives and hence enforces a CO_2 price and subsidises investments in renewable generation assets.	National
Regulator agent	This policy agent is committed to guarantee a secure supply of electricity for all consumers. It hence enforces a capacity market to manage security of supply and guarantee that electricity demand is met at all times.	National
Local government agent	Local government agents are committed to radically reduce carbon emissions and achieve 100% clean energy in their areas by 2050. They provide subsidies to specific renewable technologies to achieve a more local and distributed energy system, and enforce demand response programs. Matching BRAIN-Energy's regional split, there is one London government agent and one Scotland government agent in BRAIN-Energy.	Local

There is one national government agent, one regulator agent and two local government agents in BRAIN-Energy to match the model's regional split (the London government agent for the London region, and the

Scotland government agent for the Scotland region). Local government agents have been introduced in the updated version of BRAIN-Energy, because local governments in the UK have set their own net-zero targets (London net-zero electricity by 2040 (GLA, 2018), Scotland to reach net-zero by 2045[1]).

Table 6 summarises the functionality of the policy agents in BRAIN-Energy.

Table 6 – Functionality of policy agents in BRAIN-Energy

POLICY AGENTS	Functionality in BRAIN-Energy
National government agent	CO_2 price (to national and local investors) + subsidies to all renewable technologies (Contracts for Difference) (to national and local investors)
Regulator agent	Capacity market (auctions and capacity payments) to national and local investors
Local government agents	**London government agent:** • Provides support to demand-side response for households • Subsidises investments in PV (to national and local investors) **Scotland government agent:** • Provides support to demand-side response for households • Subsidises investments in onshore wind (to national and local investors)

The national government agent can increase the CO_2 price by up to 200% over the “no-increase” trajectory (Table 7) whenever interim carbon budgets (Table 8) are not met. The level of the increase depends on the scenario.

Table 7- “No-increase” CO2 price trajectory in BRAIN-Energy

CO_2 price trajectory	Description and calibration
“No-increase”	This is the prevailing CO_2 price at the onset of all scenarios in BRAIN-Energy. • Historical: EU ETS + Carbon Price Floor according to the “Reference” scenario in BEIS (2016a) • Future: “Reference” scenario in BEIS (2016a)

Table 8- Carbon budgets in the UK in BRAIN-Energy (source: CCC, 2015)

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

The national government agent also subsidises investments in new renewable generation assets through Contracts for Difference (CfDs).

[1] https://www.gov.scot/policies/climate-change/reducing-emissions/

CfD auctions take place every three years (up to 6 GW of renewable technologies can be commissioned at each auction[2]), 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

BRAIN-Energy will track how much the national government agent spends on subsidising renewable investments through CfDs at the national level. The model will also track revenues from CO_2 from the national government agent.

The regulator agent in BRAIN-Energy manages security of supply through a capacity market at the national level. The way the capacity market works in 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:

[2] His has been calibrated based on the total auctioned capacity at the Contracts for Difference Allocation Round 3 (AR3): https://www.gov.uk/government/publications/contracts-for-difference-allocation-framework-for-the-third-allocation-round-2019

$CP_{p,t}$ 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.

Local government agents are local agents in BRAIN-Energy and are committed to radically reduce carbon emissions and achieve 100% clean energy in their areas and net-zero emissions by 2050. They provide subsidies to specific renewable technologies to achieve a more local and distributed energy system, and enforce demand-side response programs. Table 5 summarises the functionality of two local government agents in BRAIN-Energy. Similarly as for the national government agent, BRAIN-Energy will also track how much local government agents spends on subsidising renewable investments in their local region.

6. Investment decisions

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

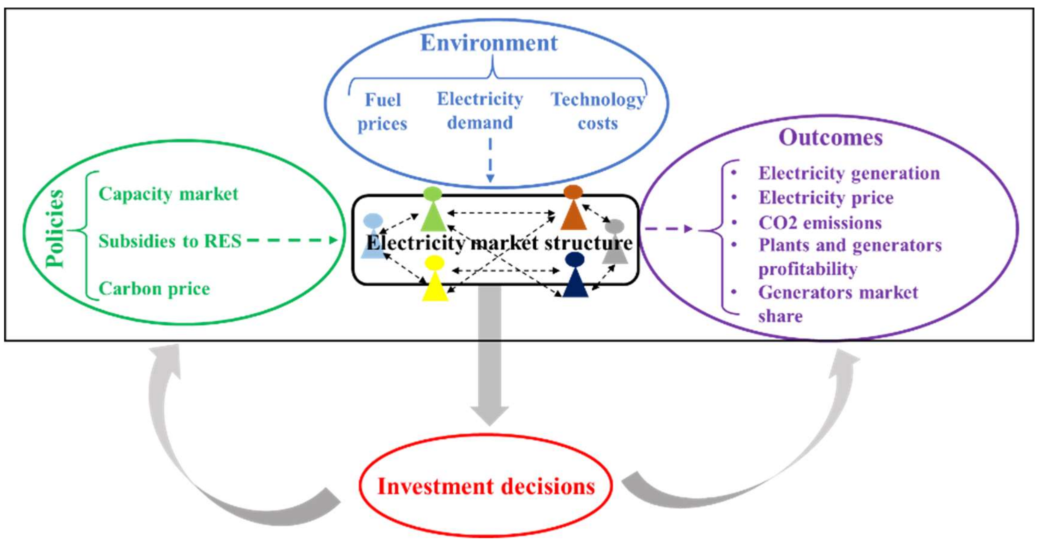

Figure 2 - Investment process in BRAIN-Energy and co-evolution with other dimensions

6.1 Economic criteria in investment decisions

Investors 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 investor independently and sequentially one after the other.

Investment choices come after the operational activities of each investor, as they also depend on the amount of revenues generated by their core business of electricity production. Each investor 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 an investor's specific cost.

Every year, all investors 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 investor's time horizon of investments. As investors 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 investor 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 cost of capital that investors pay on their liabilities

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

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

Household investors, instead, use a different process to evaluate future investment options. In fact, households 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.

6.2 Self-learning

Self-learning in investment choices in BRAIN-Energy is represented by the fact that:

- Investors' investment choices are constrained by the past performance of existing plants and investments, which dictate an investor's financial constraints. Hence, investment choices are adaptive and path-dependent. Learning from own successful past behaviour and investments is reflected in an investor's growing profit and improving financial situation.

- Investors learn from their own unsuccessful past investments. After five years that a new plant started operations, investors assess its profitability every year. If at any given year a plant's cumulative profits over the previous five years defined as:

$$\sum_{y=t}^{n} PF_{p,t} = (prod_{p,t} \times \ p_t) - \ totCost_{p,t}$$

are lower than the 5-yearly share of the new plant's total capital cost ($\frac{CAPEX_p}{l_p} \times n$) then the new investment is flagged as unprofitable.

Where:

l_p is the lifetime of plant p,

$prod_{p,t}$ is the electricity production of plant p at year t,

p_t is the electricity price at year t,

$totCost_{p,t}$ comprise variable and fixed production costs and yearly capital costs.

If the number of years during which the new plant is unprofitable in a row is greater than the number of years an investor is willing to absorb losses for, then it is shut down. An investor will only invest in the same technology when and if it becomes profitable again. This means that, if at any time the technology's NPV calculation is greater than zero, and if the ROI is equal or greater than the capital cost of the investor plus a threshold α which differs by type of investor, the investor will invest again in this technology. Thresholds α have been calibrated based on the wider characteristics and behaviours of the investors drawn from the literature. Threshold α can be between $1 \leq \alpha \leq 2$:

- new-entrants: α = 2
- incumbent utilities: α = 1.5
- municipal utilities: α = 1

6.3 Imitation

In BRAIN-Energy investor agents imitate the successful investments of other investor agents.

Incumbent utilities, new-entrants and municipal utilities (local suppliers) can all imitate each other, but not household investors. Household investors can only imitate other households.

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 investors have bounded-rationality, and the only information which they have available are the investment strategies of the other investors and their expectations about future technologies capital costs, fuel costs and electricity prices. Investor *a* in BRAIN-Energy measures the outcomes of the investment strategies of the other investor 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. Investor agent *a* also assess the investment strategies of the other investors' in terms of early closures due to unprofitability of their new investment. If an investor agent's *x* market share (MS_x) is growing compared to the previous year, hence if $MS_{x,t+1} > MS_{,t}$, investor agent *a* chooses to imitate the investor 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 investor agent *x* which investor agent *a* decides to imitate (given his technology preferences), investor 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 household agents) and invests in that generation technology. This is because investor agent *a* doesn't have perfect information about which exact power plant or generation technologies caused the imitated investor 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.

7. Demand-side response

Demand-side response (DSR) is regarded as an effective measure to provide system flexibility to balance the electricity supply and demand. DSR can be even more crucial as the share of VRE becomes higher in the future low-carbon electricity system. BRAIN-Energy thus incorporates DSR as a measure that can be adopted by household agents. The simulation approach proposed by Li and Pye (2018) is applied to model demand-shedding and demand-shifting between time-slices by demand types. Whenever electricity demand is higher than electricity supply at any time-slices, the model will try to shift the excess demand to another time-slice when there is surplus electricity from VRE, as illustrated in Figure 3. The amount of electricity demand that can be shifted or shedded depends on the participation rate of households in the DSR scheme and physical shifting potential of individual demand types, as shown in Table 9. In the model, only smart appliances that can be controlled via smart grid are taken into account in the DSR simulation.

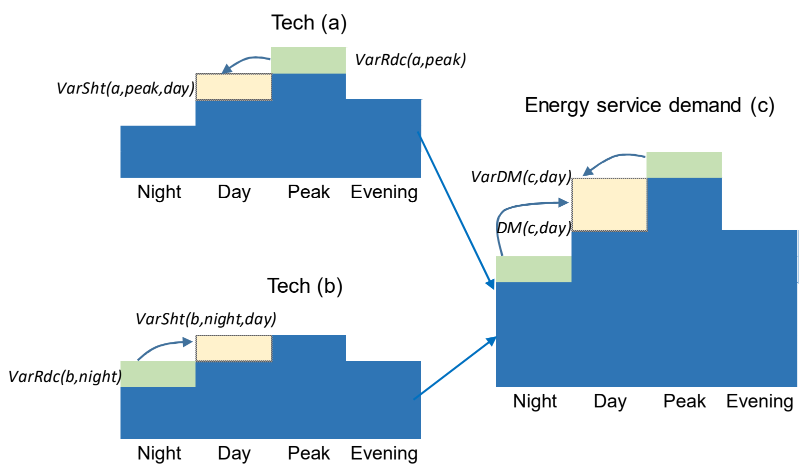

Figure 3- An illustration of how electricity demand is shifted across the diurnal profile by demand types (adopted from Li and Pye, 2018)

Table 9- Shiftable potentials and smart penetration rate of smart appliances (adopted from Li and Pye, 2018)

Technology	Shifting mechanism	Shiftable potential	Smart penetration rate in 2012	Smart penetration rate in 2050
Lighting	Consumer behaviour	0%	0%	0%
Oven/Stove	Consumer behaviour	0%	0%	0%
TV/Computer	Consumer behaviour	0%	0%	0%
Washing machine	Central control	100%	0%	100%
Tumble dryer	Central control	100%	0%	100%
Water heater	Central control	1 hour	0%	100%
Space heater*	Central control	1 hour	0%	100%
Refrigerator/ Freezer	Central control	1 hour	0%	100%

*Electric night storage heaters, heat pumps and district heating from electric heaters and heat pumps are included.

8. Data and calibration

Table 10 summarises the main exogenous variables and outcomes of BRAIN-Energy.

Table 10- BRAIN-Energy's exogenous variables and outcomes

Exogenous variables	Outcomes
• Electricity demand • Fuel costs • Capital costs of technologies • Fixed and variable operational and maintenance (O&M) costs of technologies • CO_2 price (the "no-increase trajectory, see Table 5))	• Aggregated and yearly capital investments (by technology and by market player) • Electricity price • Electricity production (amount and share of production by technology) • Installed capacity (total and split by technology) • Average and peak supply-demand gaps • CO_2 emissions from the power sector and carbon intensity of electricity generation • Market shares of the market players

BRAIN-Energy is calibrated for the UK electricity sector to 2012 using official government statistics (BEIS, 2016). Active generation technologies in BRAIN-Energy are based on the existing generation fleet at the base year 2012 (BEIS, 2016) and are detailed in Table 11.

Table 11 - Installed capacity in UK BRAIN-Energy at calibration year (source: BEIS, 2016)

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

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, 2016b). Other technical parameters of the generation plants, such as load factors, lifetime and emission intensity, are summarised in Table 12.

Table 12 - Technical power plant data in UK version of BRAIN-Energy source: BEIS, 2016b)

Technology	Average load factor	Lifetime	Emission intensity (gCO2/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	
BECCS (still to be calibrated)			

Fuel costs of gas and coal are based on historical gas and coal prices found in the BEIS (2016a) report. They can be found in Appendix A. Assumptions about fuel costs future evolution reflect the UK's government view and are based on the BEIS (2016a) "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. Further investment options also include BECCS (bioenergy carbon capture and storage) technologies.
Each generation technology has an associated capital cost (Table 13) expressed in EUR/kW (which is converted into £/kW).. 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), and has been double-checked against historical data from IRENA (2018).

Table 13 - Technologies capital costs in BRAIN-Energy in EUR/kW (source: 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
BECCS (still to be calibrated)									

Carbon costs (Figure 3) 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 (2016a) 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 national government agent can increase the CO_2 price when interim carbon budgets are not met is modelled according to the "Reference " scenario in the BEIS (2016a) report. The different CO2 price trajectories are shown in Figure 2.

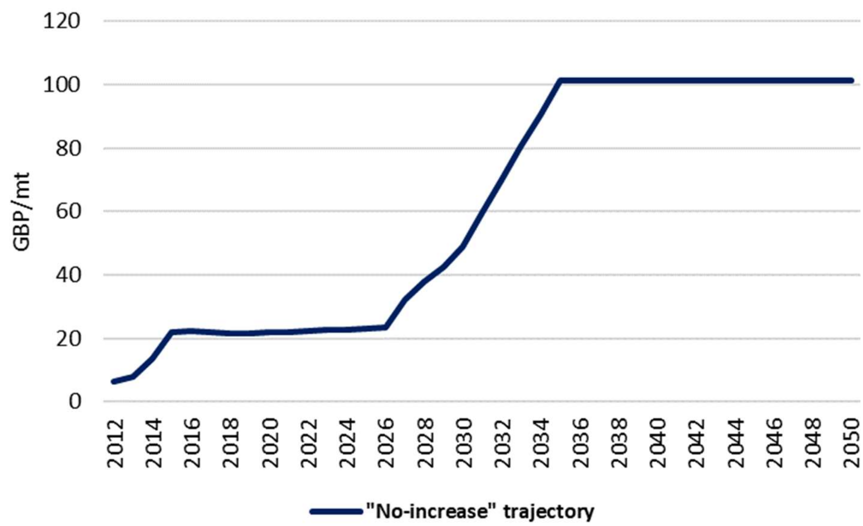

Figure 4 - CO2 price trajectories in BRAIN-Energy

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 modelling results of UK TIMES model (Daly and Fais, 2014), a whole energy system model adopted by BEIS and National Grid to investigate decarbonisation strategies for the UK. The electricity consumption is estimated for a scenario with net-zero GHG emission targets by 2050. The determined technology mix in the residential sector is used to further disaggregate the lump-sum demand profile into individual demand usages that can be used for the DSR simulation.

National electricity consumption is allocated to three regions (i.e. London, Scotland, and Rest of UK) using the following method:

- For the period 2010-2017, the UK demand has been split into regional demand in the proportion of actual demand as reported by the Sub-national total final energy consumption statistics: 2005 to 2017 (BEIS, 2019)
- For Scotland, the demand estimates from the Scottish TIMES model as published in the Climate Change Plan (The Scottish Government, 2018) and the Scottish Energy Strategy (Electrification scenario) (The Scottish Government, 2017) are used to generate the demand profile to 2050
- For London, the demand estimates to 2050 are obtained from London's Zero Carbon Pathways Tool (High Electrification scenario) (GLA, 2018) developed by the Greater London Authority in support of the London Environment Strategy
- For Rest of UK, the demand estimates to 2050 are obtained by subtracting the demands for Scotland and London from the aggregate UK demand

The demand profiles for three regions in the BRAIN-Energy are illustrated in Figure 5.

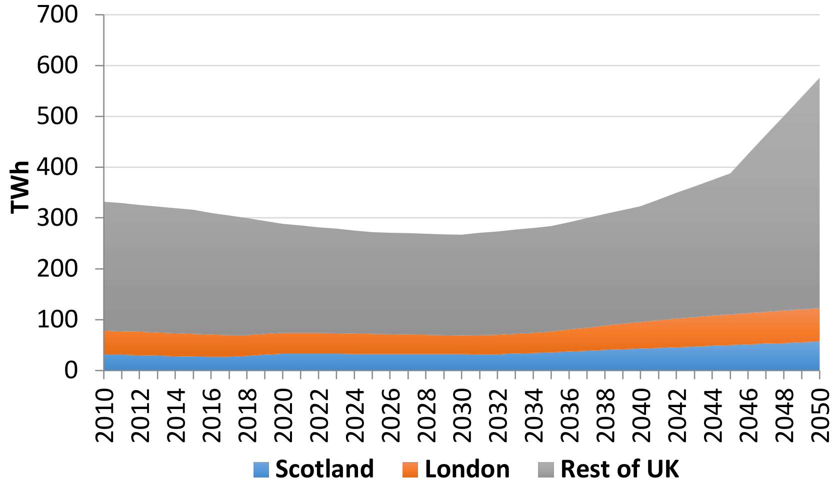

Figure 5- Electricity demand in UK BRAIN-Energy

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Appendix A

	Gas Prices	
Year	price (p/th)	Price (£/GWh)
	Reference	Reference
2012	59.64	20,349.5
2013	67.88	23,159.0
2014	49.93	17,036.0
2015	42.58	14,526.6
2016	29.00	9,894.3
2017	32.00	10,917.8
2018	32.00	10,917.8
2019	32.00	10,917.8
2020	32.00	10,917.8
2021	35.00	11,941.4
2022	38.00	12,964.9
2023	41.00	13,988.5
2024	44.00	15,012.0
2025	47.00	16,035.6
2026	50.00	17,059.1
2027	53.00	18,082.7
2028	56.00	19,106.2
2029	59.00	20,129.8
2030	62.00	21,153.3
2031	62.00	21,153.3
2032	62.00	21,153.3
2033	62.00	21,153.3
2034	62.00	21,153.3
2035	62.00	21,153.3
2036	62.00	21,153.3
2037	62.00	21,153.3
2038	62.00	21,153.3
2039	62.00	21,153.3
2040	62.00	21,153.3
2041	62.00	21,153.3
2042	62.00	21,153.3
2043	62.00	21,153.3
2044	62.00	21,153.3
2045	62.00	21,153.3
2046	62.00	21,153.3
2047	62.00	21,153.3
2048	62.00	21,153.3
2049	62.00	21,153.3
2050	62.00	21,153.3

Table A: Historical and projected gas prices in UK model (source: "Reference" scenario in BEIS (2016a)