Energy Policy 170 (2022) 113241

Contents lists available at ScienceDirect

Energy Policy

journal homepage: www.elsevier.com/locate/enpol

The influences of non-optimal investments on the scale-up of smart local energy systems in the UK electricity market

Pei-Hao Li [*], Elsa Barazza, Neil Strachan

UCL Energy Institute, University College London, Central House, 14 Upper Woburn Place, London, WC1H 0NN, UK

A R T I C L E I N F O

Keywords:
Long-term decarbonisation
Electricity market
Smart local energy system (SLES)
Non-optimal decision making
Investor heterogeneity
Agent-based model (ABM)

A B S T R A C T

Rapid and deep decarbonisation of electricity systems is critical in many pathways to meet net-zero emissions by 2050. Smart local energy systems (SLES) have been touted as key for both a rapid scale-up of renewable electricity and flexibility for stability in decarbonised electricity systems. A novel agent-based model – incorporating local investor and governance agents, improved temporal resolution, and demand-side flexibility – was used to investigate strategic decision making in the scale-up of SLES. From the perspective of this model, key modelling insights include: SLES investors, initially supported by local governments, can successfully boost the uptake of renewable energy up to 80% of total generation; SLES scale-up significantly erodes the market share and profitability of incumbent utilities, however national level agents are still key for capital-intensive low carbon plants; Demand-side response facilitates balancing electricity supply and demand, but it can result in non-optimal policy agents postponing required incentives for heterogeneous investor agents to build new low carbon plants; National carbon prices (in conjunction with local SLES and technology support mechanisms) are needed to maintain overall system stability. Therefore, understanding the critical role of non-optimal investor decision making is key to fully understand the drivers and implications of a rapid scale-up of SLES.

1. Introduction

1.1. Importance of electricity decarbonisation and smart local energy systems

To achieve the goals of the Paris Agreement (UNFCCC, 2015), global energy systems should be deeply decarbonised in the coming decades to reach net-zero greenhouse gas (GHG) emissions by 2050 (IPCC, 2018). Many countries have thus set and legislated ambitious long-term GHG emissions reduction targets to align with the Paris Agreement. For instance, the European Union, France, Germany, UK, and New Zealand, have adopted net-zero targets by 2050 (European Commission, 2022).

For two reasons, the early and rapid reduction in CO_2 emissions from the electricity sector is the foremost measure to enable the pathway to net-zero GHG emissions from the energy system. First, electricity generation is the largest global emission source (International Renewable Energy Agency, 2019), accounting for about 32% of total CO_2 emissions in 2018, which is mirrored by its importance at national level. For instance, electricity generation contributed about 27% and 23% of total GHG emissions in the United States (US EPA, 2020) and the UK (BEIS, 2020) respectively in 2018. Second, electrification is a key strategy to reduce GHG emissions in the end-use sectors (e.g. the residential and transport sectors) (CCC, 2019; IPCC, 2018). With the sharp increase in electricity consumption due to the extensive electrification of those sectors, low-carbon electricity is even more pressing for the success of achieving net-zero targets. Hence the full decarbonisation of the global electricity sector is essential to limit temperature increase to 1.5°C across all pathways with a wide range of socio-economic and technology assumptions (IPCC, 2018). This pivotal role is also seen at the national level. For example, the Committee on Climate Change (CCC) estimates that the carbon intensity of the UK power sector needs to drop below 100 gCO_2/kWh by 2030, followed by full decarbonisation by 2050 (CCC, 2015a).

Low or zero carbon technologies must be deployed at scale to dramatically decarbonise the electricity sector. With the sharp drop in costs of variable renewable energy (VRE) (i.e. solar PV, onshore wind, and offshore wind) in recent years (International Energy Agency, 2017), the introduction of VRE is thus crucial to transform the electricity sector cost-effectively. According to National Grid (2021), to achieve the UK's net-zero target with minimum total costs by 2050, all four pathways

* Corresponding author.
E-mail address: p.li@ucl.ac.uk (P.-H. Li).

https://doi.org/10.1016/j.enpol.2022.113241

Available online 13 September 2022

considered have VRE contributing over 78% of total electricity generation in the UK. Such a high share of intermittent VRE (combined with less flexible nuclear power) brings new challenges in balancing electricity supply and demand. Hence, system flexibility measures (e.g. demand-side response (DSR)) also need to be widely adopted to ensure system stability in the future low-carbon electricity systems (CCC, 2015b).

Smart local energy systems (SLES) that comprise renewable energy (i.e. VRE and biomass plants) and system flexibility measures in sub-national regions (Morstyn et al., 2020) have been seen as a potential approach to scaling-up the adoption of renewable energy for electricity provision (Ford et al., 2019). SLES is touted to expand and diversify the energy investor base, and hence increase the flow of finance into renewables and other transition technologies (Braunholtz-Speight et al., 2020; McInerney and Bunn, 2019). Local investors in SLES might include municipal utilities and households. These investors can have a lower investment risk when investing in decentralised renewable energy (Wilson et al., 2020). Additionally, SLES could maximise the use of renewable energy since households are more likely to engage with DSR schemes as system flexibility measures, such as smart appliances and smart heating controls (Carmichael et al., 2018). SLES can thus potentially accelerate the energy transition towards a low-carbon future.

1.2. Contribution of this paper

The scale-up of SLES heavily relies on the investment decisions of heterogeneous investors both at national and sub-national levels (Ford et al., 2019), such as investments in decentralised renewable energy (Kraan et al., 2018). This is especially true in liberalised electricity markets (e.g. the UK's electricity market (Grubb and Newbery, 2018)). Investors have limited ability to gather and process relevant information so that they primarily seek satisfactory rather than optimal solutions (Hall et al., 2017). These investors hence have varied expectations on the future investment environment – such as fuel prices, technology costs, and electricity demands – and also exhibit different investment strategies and risk-taking tendencies (Kraan et al., 2018). Consequently, with their limited foresight of the future electricity market, investors employ strategies that are "good-enough" and "acceptable" (i.e. non-optimal) in their investment decisions (Barazza and Strachan, 2020a; Chappin et al., 2017).

However, investors' heterogeneity and non-optimal decision-making strategies are too complicated to be represented in most energy system models, such as partial equilibrium optimisation models (Daly and Fais, 2014), that assume a homogeneous system planner with perfect market foresight (Barazza and Strachan, 2020b). Agent-based models (ABM), on the other hand, that simulate multiple agents with different behaviours to interact with one another and the environment, are ideal for representing market players' complicated investment behaviours in liberalised electricity markets (Ringler et al., 2016). Several agent-based models (ABMs), such as EMLab (Chappin et al., 2017) and BRAIN-Energy (Barazza and Strachan, 2020b), have been developed to gain insights into the role of market players in the decarbonisation of electricity systems. Nonetheless, those past studies only focused on investment decisions of national investors, such as incumbent utilities, in national electricity markets without considering local investors and SLES.

This study thus extends the BRAIN-Energy model (Barazza et al., 2020), an ABM for electricity system investments, to explore how the scale-up of SLES can influence the decarbonisation of the electricity sector to gain new policy and investment insights, considering non-optimal investment behaviours of heterogeneous market players. Unlike previous studies, this study considers both national (e.g. incumbent utilities) and local investors (e.g. municipal utilities and households). To better represent SLES, the temporal and spatial resolutions of the model have also been further refined, along with the incorporation of DSR capabilities to evaluate system flexibility improvement. The UK's electricity market, a typical liberalised electricity market, is adopted as the study case.

Therefore, this study's primary contributions cover the following three aspects in an integrated way. First, we have improved an (energy) ABM by having significantly more diverse agents – notably adding local investors and policymakers to national players. Then, second, we discuss how there is a lack (compared to other model types) of ABMs being applied to energy transition issues (policy design and investment) and that ABMs have significant advantages over usual optimisation modelling approaches, including a range of decision-making criteria, learning/responding to other strategies and having imperfect views of future trends/drivers. Finally third, the use of an electricity ABM, therefore, allows us to provide new policy and investment insights, especially related to smart local energy systems.

This paper is structured as follows: Section 2 reviews the literature on the decarbonisation of the electricity sector using both optimisation models and ABMs. Section 3 describes the BRAIN-Energy model, including the extensions to incorporate local investors and SLES uptake. The results of four scenarios are discussed to reveal the influences of the scale-up of SLES in Section 4. Finally, Section 5 draws out the main conclusions from the study.

2. Literature review

2.1. Energy system modelling for long-term decarbonisation

Conventional equilibrium and optimisation energy system models have long been the main tool to study the decarbonisation of the energy sector and have been used as the main decision support tools for energy policy (Trutnevyte, 2016). Because of their mathematical precision and high level of technological detail, such models have focused on the techno-economic details of the energy sector, exploring the full range of technological pathways for future energy systems, or providing detailed spatial and temporal resolution in balancing electricity demand and supply in the electricity sector (Zeyringer et al., 2018). However, energy system optimisation models are weaker in addressing the complexity and non-linearity of the energy system long-term low-carbon transition (Bale et al., 2015) while more progress has been made to model agent heterogeneity and non-optimal choices in other fields (Bilbiie, 2020; Farhi and Werning, 2019). Specific criticisms include aggregating decision-makers, assuming these to act in a rational and profit-maximising way (Hoekstra et al., 2017), and not capturing their interactions. As a result, such models poorly represent a real system made of heterogeneous agents, which have limited capability to gather and process essential information to support decision-making (e.g. imperfect foresight) and rely on habits and past-experiences in their investment choices, given their limited foresight of the future (Keppo and Strubegger, 2010). This makes real-world agents' choices non-optimal, entangled with other agents' choices and path-dependent, which conventional energy models are not able to capture (Mercure et al., 2016).

However, it is key to represent heterogeneous actors especially when studying the development of SLES, which involves new types of actors and investors such as municipal utilities and local authorities (Busch et al., 2017). Local actors have different and broader motivations for investing in energy infrastructure compared to incumbent actors in the energy sector (Seyfang et al., 2013) including on social and environmental outcomes besides economic ones when investing in new energy infrastructure (Foxon et al., 2015).

2.2. Agent-based modelling for long-term decarbonisation of the power sector

ABMs are a suitable modelling approach to deal with the increasing complexity and non-linearity of the energy sector's long-term decarbonisation (Bale et al., 2015). ABMs are bottom-up simulation models

(Tesfatsion, 2006), where agents are the main unit of analysis. In ABMs agents can be boundedly rational, with interactions with one another and path-dependent behaviour, and their heterogeneous decision rules and interactions give rise to a system's emergent properties. ABMs thus make it possible to model the complexity inherent in agents' decision-making process as it is the real world (Ma and Nakamori, 2009), including co-evolution in the energy system's long-term decarbonisation. ABMs can represent future diversity of investors (and governance) in the energy system (Hansen et al., 2019), a key element to study local investments in the scale-up of SLES (Busch et al., 2017).

Given these distinctive advantages, the application of ABMs to study the energy sector's decarbonisation has increased in recent years (Hansen et al., 2019). ABM studies of the electricity sector focusing on the supply side mainly concentrate on national electricity producers as key agents, and study a stylised electricity sector (Kraan et al., 2018). Socio-technical ABMs – e.g., of the long-term decarbonisation pathways of the German electricity sector (Deissenroth et al., 2017) also focus on national electricity generators.

A key electricity decarbonisation ABM has been EMLab (Chappin et al., 2017), which has been used to analyse the long-term decarbonisation of two interconnected European electricity markets as a result of national electricity generators' investments under different policy conditions (Richstein et al., 2014). Extensions of the EMLab model have been used to analyse the impacts on social welfare of renewable energy support schemes (Iychettira et al., 2017), to explore the need for electricity storage and other flexibility options in an electricity market with a capacity market (Khan et al., 2018), and finally to study the impacts of a capacity market and flexibility options on the electricity sector's long-term decarbonisation (Bhagwat et al., 2016).

Another key electricity decarbonisation ABM has been BRAIN-Energy which has a greater focus on the heterogeneity of agents and their non-optimal investment behaviours and myopic strategies (Barazza and Strachan, 2020b), and on capturing the co-evolutionary dynamics between the market players' investment strategies and the institutional and policy dimensions (Barazza and Strachan, 2020a).

Many past ABM studies also oversimplified the necessary operational aspects of the electricity systems – including diurnal patterns and demand responses – that are needed for a balanced modelling approach that gives useable insights to policy and decision makers (Li and Strachan, 2019).

2.3. Agent-based modelling for smart local energy systems

The incorporation of SLES aspects into ABMs has been much less developed (Ringler et al., 2016), with work just starting on incorporating aspects such as distributed generation, demand response, and how prosumers in local markets integrate in centralised markets. Exploratory work has studied residential agents, including their technology adoption choices (Robinson and Rai, 2015), the role of communication and imitation (Palmer et al., 2015), and assessment of storage-based demand response (Zheng et al., 2014). A further ABM study explores the development of district heating focusing on the governance barriers which heterogeneous local actors with diverse motivations and capabilities face (Busch et al., 2017). However, the role of local actors in the development of SLES for the transition to a low carbon economy still remains largely overlooked in ABM studies (Foxon et al., 2015).

3. Modelling methodology

3.1. Model overview and technical operations

BRAIN-Energy is an ABM of electricity generation and investment (Barazza and Strachan, 2020b), with a detailed representation of agent behaviour and interactions. The model's yearly simulation procedure over the modelling horizon is briefly explained in Appendix A. In the following, we only focus on extensions that are relevant to local investments and SLES for conciseness. For more detailed information, please refer to the model documentation (Barazza et al., 2020).

To better model SLES, it has recently been extended as regards to its temporal resolution, improved depiction of sub-national regions, estimation of future electricity demand, local investors and their strategies (see section 3.2), and finally demand-side flexibility (section 3.4).

BRAIN-Energy is calibrated to 2012 as a base year (this allows to validate the model against historical data) and proceeds to 2050. The temporal resolution (Table 1) has been refined to eight time-slices in a year (i.e. 4 time-slices in a typical day in two seasons), based on the temporal representation of the UK TIMES model, a key whole energy system model supporting policy-making in the UK (Daly and Fais, 2014). Electricity loads at the evening peak time-slice are scaled up by a factor to reflect possible fluctuations of electricity demand on extreme days.

As regards to the spatial depiction, BRAIN-Energy offers a stylised representation of the UK electricity market, which has been divided into three regions based on their different renewable energy potential and governance structures. The three regions are London (with a dense population, high PV potential and mayoral powers), Scotland (with high potentials for onshore and offshore wind power and an executive government), and the rest of UK to allow further diffusion of renewable energy technologies.

The estimation of future national electricity demand has been updated to reflect the results of the UK TIMES model (Daly and Fais, 2014) for a scenario which achieves the net-zero GHG emission target by 2050. National electricity demand is allocated to the three regions based on historical trends and official projections. The details of the allocation and technical operations of the power market can be found in the model documentation (Barazza et al., 2020).

3.2. Agents

Agents and their strategies are at the core of BRAIN-Energy. There are two types of agents in BRAIN-Energy: (1) investor agents and (2) policy agents.

Investor agents can be national (incumbent utilities and new-entrants) and local (municipal utilities and households). Investors are heterogeneous based on the type of organisation and on their strategies (Barazza and Strachan, 2020b), and all have different initial financial endowments and risk-return considerations (see section 3.3.1). Moreover, investors are likely to adopt non-optimal decision-making strategies, represented by the fact that: (1) they have limited foresight of the future (further explained in section 3.3.1), (2) their investment choices are based on their own heterogeneous expectations of electricity demand, fuel and technology costs, and (3) own past-experience and imitation of other investors' successful strategies also affect their investment choices. Table 2 summarises the investors' main strategies, also highlighting the number of investors of each type in BRAIN-Energy at the base year. Investor agents can be forced to exit the market when their equity becomes negative. Further details can be found in the model documentation (Barazza et al., 2020).

Policy agents in BRAIN-Energy are the national government, the national regulator, and local government.

The national government aims to decarbonise the UK power sector. It does this by using Contracts for Difference (CfD) (section 3.3.2) to encourage new investments in renewable energy plants, and by applying

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

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

Table 2
Overview of investor agents and their strategies in BRAIN-Energy.

Investor agents	Description	Region and number	Technology
Incumbent utility	Main players in the electricity sector, whose main business is electricity generation. They aim to provide stable dividends to their shareholders.	2 national agents	All: nuclear, gas, biomass, PV, onshore-and offshore wind
New-entrant	These are new types of investors in electricity generation assets (for example institutional investors). These agents intend to invest in renewable energy to maximise their profits.	2 national agents	Renewable energy only: biomass, PV, onshore-and offshore wind
Municipal utility	Directly or indirectly owned by a municipality or city or local authority. These companies operate only in their regions. Their objective is to supply affordable and reliable energy to local consumers, and some also have an environmental focus.	1 in London region, 1 in Scotland region, 1 in the rest of UK region	London: PV Scotland and the rest of UK: biomass, PV, onshore and offshore wind
Household aggregator	Households invest in small scale renewable energy plants and participate in demand response programs. They invest in renewable energy to cover self-consumption, and for environmental reasons.	1 in London region, 1 in Scotland region, 1 in the rest of UK region	London: PV Scotland and the rest of UK: PV and onshore wind

a carbon price and setting emission reduction targets to further steer the decarbonisation of the power system (section 3.3.2). The national regulator agent uses a capacity market (section 3.3.2) to promote security of supply by encouraging investments in gas and nuclear power plants. Finally, local government can implicitly subsidise technologies through guaranteeing they receive electricity prices set at the national level, as well as providing initial capital loans to allow new local entrants to enter the market.

3.3. Investments and market mechanisms

3.3.1. Investments

Investment choices come after the operational activities (electricity production and dispatch) of each investor. Investors in BRAIN-Energy decide each year whether to invest in new electricity production plants according to their technological preferences, highlighted in Table 2. Each investor agent takes investment decisions independently. Local investors' investments in new local renewable energy plants are prioritised over proposals bided by national investors, as local investors are more likely to have advantages of land ownership or community engagement. Local investors are guaranteed to receive the national electricity price for selling electricity to the grid to incentivise their participation.

Investors base their investment decisions on an NPV calculation (full details of the investment procedure are provided in (Barazza and Strachan, 2020b)). Non-optimality in investment decisions is reflected in the fact that investors have limited foresight of the future and base their NPV calculation on n years ahead (n is different by type of investor) (Hall et al., 2017), and by the fact that they use heterogeneous expectations about future electricity demand, fuel and technology costs in their NPV calculations. A further element of heterogeneity lies in the fact that different types of investors use different discount rate r in their NPV calculation, which reflects their cost of capital and have been calibrated based on previous studies (Helms et al., 2015; Salm, 2018; Salm et al., 2016; Steinbach and Staniaszek, 2015). National investors such as incumbent utilities and local investors such as municipal utilities (for whom electricity generation is the main business) have a longer foresight n, while new-entrants (such as institutional investors) prefer to invest in liquid assets and hence have a shorter foresight n (Hall et al., 2017). Moreover, while incumbent utilities are willing to take on riskier projects with high returns (reflected by a higher discount rate r in BRAIN-Energy), new-entrants prefer low-risk investments with lower but stable returns (hence have a lower r in BRAIN-Energy) (Helms et al., 2015; Salm, 2018). Local households have the lowest r in BRAIN-Energy between 3% and 6% (Steinbach and Staniaszek, 2015).

The investment choices of the investors give raise to the electricity system's emergent properties (generation technologies, CO_2 emissions and electricity price). These properties of the electricity system influence all investors' future investments, their revenues and market shares. Hence, investors are confronted with the outcomes of their own and the others' investments and interact through those. Moreover, based on the emerging characteristics of the electricity sector, such as CO_2 emissions and security of supply, policy agents update their policy decisions. This co-evolution between investment choices and the policy dimension within BRAIN-Energy model can be found in the previous study (Barazza and Strachan, 2020a).

Investors' investment decisions in BRAIN-Energy are also affected by self-learning and imitation. Self-learning is represented by the fact that the investment choices of the investors are affected by their past-performance, and are adaptive in the sense that investors learn from their own unsuccessful past investments. Moreover, past investments affect the investors' financial performance which helps or constrains new investments. Imitation leads investors to learn from other investors' successful investments and is a further element of interaction between investors in BRAIN-Energy. Further details about the self-learning and imitation mechanisms can be found in the model documentation (Barazza et al., 2020).

3.3.2. Market mechanisms to support investments

There are three market mechanisms in BRAIN-Energy at the national level which either encourage renewable energy investments (CfDs and the CO_2 price), or support investments in gas, nuclear, and biomass plants for system security.

CfD auctions in BRAIN-Energy take place every three years, to match the historical frequency in the UK electricity market (Grubb and Newbery, 2018). Auctions cover investments in onshore and offshore wind, biomass and PV plants, and the winners receive a fixed price (which is an auction's strike price) for 15 years, providing stability to investors' future revenues.

Furthermore, the national government agent in BRAIN-Energy sets carbon budgets. These are defined in terms of carbon intensity of the power system, which has to drop to 100 gCO_2/kWh by 2030, to 50 gCO_2/kWh by 2035, and eventually to full decarbonisation by 2050 (CCC, 2015c). The national government agent applies a CO_2 price to reach those budgets, and can increase the CO_2 price by up to 200% over the "no-increase" CO_2 price if those budgets are not met. The "no-increase" price is based on the CO_2 price used in an official report (BEIS, 2017). If the desired carbon intensity is reached, the government decreases the CO_2 price again to the "no-increase" price. Hence, policy decisions are the result of the investment choices of the investors, and the two dimensions (i.e. policy decisions and investment choices) co-evolve in BRAIN-Energy (Barazza and Strachan, 2020a). It is worth noting that in BRAIN-Energy, due to the fact that investors have imperfect foresight and that their investment choices are not-optimal, carbon budgets may be missed and scenarios may not reach a full decarbonisation by 2050.

The regulator agent, who also has imperfect foresight, enforces a capacity market by forecasting every year the maximum potential electricity production four years ahead. If this is lower than the expected peak demand at the same future point in time, it calls a capacity auction to which gas, nuclear and biomass technologies can participate. Winners of the auction receive a guaranteed price for 15 years. In BRAIN-Energy the capacity market calculation is based on Bhagwat et al. (2017).

The mathematical formulations behind the CfDs and the capacity market are provided in the model documentation (Barazza et al., 2020).

3.4. Demand-side response

System flexibility in BRAIN-Energy has been improved through DSR, which can become crucial as the share of renewable energy becomes higher in the future low-carbon electricity system. In BRAIN-Energy households in SLES can participate in DSR. Smart appliances are assumed to be controlled collaboratively at the local level to balance the local electricity demand and electricity generation from local renewable energy plants. The potential of shiftable demand at each time-slice is estimated based on the participation rate of local households in the DSR scheme and the physical shiftable potential of individual smart appliances. The participation rate is assumed to increase from 0% in the base year (2012) to 100% by 2050 linearly, and only appliances that can be controlled via direct local control schemes are considered. As the residential sector will be dramatically electrified approaching 2050 to reduce GHG emissions, the DSR potential is assumed to increase considerably over the modelling horizon due to the penetration of controllable appliances into UK households. For more details of the settings of the DSR modelling, please refer to Li and Pye (2018).

4. Results and discussion

4.1. Scenarios

Four scenarios, as defined in Table 3, are investigated to understand the influences of local investors, carbon prices, and system flexibility on the role of SLES within the transition of the UK electricity system. The reference scenario (National-only) is to show how the power system transits to a low-carbon system with a traditional setting where only national agents can take part in the electricity market with carbon pricing. The rest three scenarios with local investors show the impact of the scale-up of SLES, considering various settings of carbon prices and DSR. The SLES-NoDSR and SLES-DSR scenarios incorporate local investors and local policy agents, without or with (respectively) the option of DSR to maximise the use of renewable energy. Finally, the SLES-NoCarbon scenario contrasts the role of local investors in the market without carbon pricing.

This study highlights key differences between these four scenarios; focusing on the operation of the electricity system, investments in renewable energy, overall emissions, which market players make the key investments, and which market players win or lose.

The results from BRAIN-Energy show that the strategies and decisions of investors and policy-makers make a critical difference to both SLES and then overall national efforts to decarbonise the electricity sector. In the discussion below, we step through: (1) How SLES can help ensure the electricity system is stable (section 4.2); (2) How SLES can significantly boost investments in renewable energy (section 4.3); (3) How SLES can enact faster emission reductions (in the 2030s) but not quite as low by 2050 (section 4.4); and (4) How incumbent national investors see their market share and profitability erode under SLES and even further with SLES plus DSR (section 4.5).

4.2. System stability

System stability (i.e. ensuring supply always meets demand) heavily relies on future investment activities in the market. The de-rated capacity margin – the effective extra capacity of a power system there is compared to its peak load, can thus give insights into how investment activities impact the overall stability of the electricity system through time. This is illustrated in Fig. 1. High levels of de-rated capacity margin show the impact of new (low carbon) investment, while the drops of de-rated capacity margin are majorly caused by decommissioning the existing power plants from the base year (i.e. 2012).

As capacity margins fall as old plants retire, the regulator agent foresees possible further closures of power plants a few years ahead and holds a capacity market auction in order to stimulate construction of power plants. In the years following the base year, the incumbent investors tend to invest in gas power plants since they have a short construction period and this maintains the de-rated capacity margin at a sufficient level (i.e. 5%). However, as carbon prices increase over time (in the three scenarios with carbon pricing), different dynamics play out to ensure there is sufficient capacity of power plants for generation at all times. In the reference case (National-only), a few incumbent investors profitably dominate the market and are able to invest in power plants that have high capital costs, such as nuclear and biomass power plants. Due to the longer construction period of these plants, the de-rated capacity margin is mainly lower than those for SLES-NoDSR and SLES-DSR. In contrast, when local investors can participate in the market (e.g. SLES-NoDSR), they invest in new renewable energy plants, including biomass, wind, and solar plants, with a shorter construction period, and the de-rated capacity margin rebounds faster.

The influence of DSR, including demand-shifting and -shedding, is seen by comparing SLES-NoDSR and SLES-DSR. When there is no DSR, electricity demands cannot be shifted to reduce peak loads. Policy agents thus hold capacity market auctions earlier and more frequently. As a result, new power plants are deployed earlier so that the de-rated capacity margin for SLES-NoDSR is mostly higher than that for SLES-DSR.

However, in the scenario with no carbon price (SLES-NoCarbon), the de-rated capacity margin is volatile and insufficient to fulfil the electricity demands after 2030. This scenario has the lowest electricity

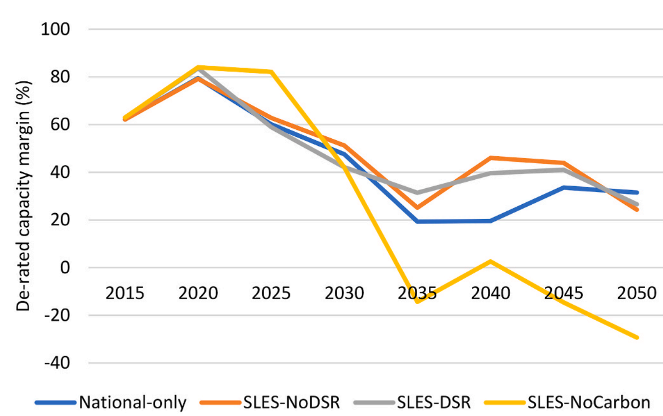

Fig. 1. Five-year average de-rated capacity margin over the modelling horizon for four scenarios.

Table 3
Definition of scenarios.

Scenario	Investor	Carbon price	Demand-side response
National-only	National investors only	With carbon price; two times higher if carbon budget is not met	No
SLES-NoDSR	Both national and local investors	With carbon price; two times higher if carbon budget is not met	No
SLES-DSR	Both national and local investors	With carbon price; two times higher if carbon budget is not met	Yes
SLES-NoCarbon	Both national and local investors	No carbon price	Yes

prices and investors struggle to recoup their investment capital. The lowest electricity prices are due to no carbon price being introduced to increase electricity production costs in the market. Although the CfD regulatory mechanism, and local investors are boosting renewables, this doesn't happen fast enough with supply-demand gaps opening up despite the best efforts of the capacity market plus the use of DSR.

4.3. Power mix

As shown in Fig. 2, the existence of local investors in sub-national regions changes which low-carbon technologies are invested in. The SLES scenarios dramatically increase the share of renewable energy in the system, compared to the scenario with only national investors (National-only) where these incumbent investors with a high level of equity invest more in nuclear power plants to bring in more revenues, with less capital remaining for investment in renewable energy plants. In contrast, in all scenarios with local investors, revenues from selling electricity to sub-national regions enable local investors to further invest in more renewable energy plants, such as wind, PV and even biomass power plants. Locally driven renewable energy deployment can occur without carbon pricing (i.e. SLES-NoCarbon) but is further boosted (higher renewable energy share in a larger overall system) with carbon pricing (i.e. SLES-NoDSR and SLES-DSR). More detailed electricity production by technology for the four scenarios can be found in Appendix B.

4.4. GHG emissions

Investor agents' investments in various technology mixes (Fig. 2 and Appendix B) have significant impacts on GHG emissions from the power system (Fig. 3). The reference case (National-only) has the highest GHG emissions between 2031 and 2040, but then the lowest emissions in the last decade among the four scenarios. This is due to the lowest share of renewable energy with more gas power plants retained in the medium term for generation, but by the 2040s more nuclear power plants are gradually deployed into the power system to dramatically reduce GHG

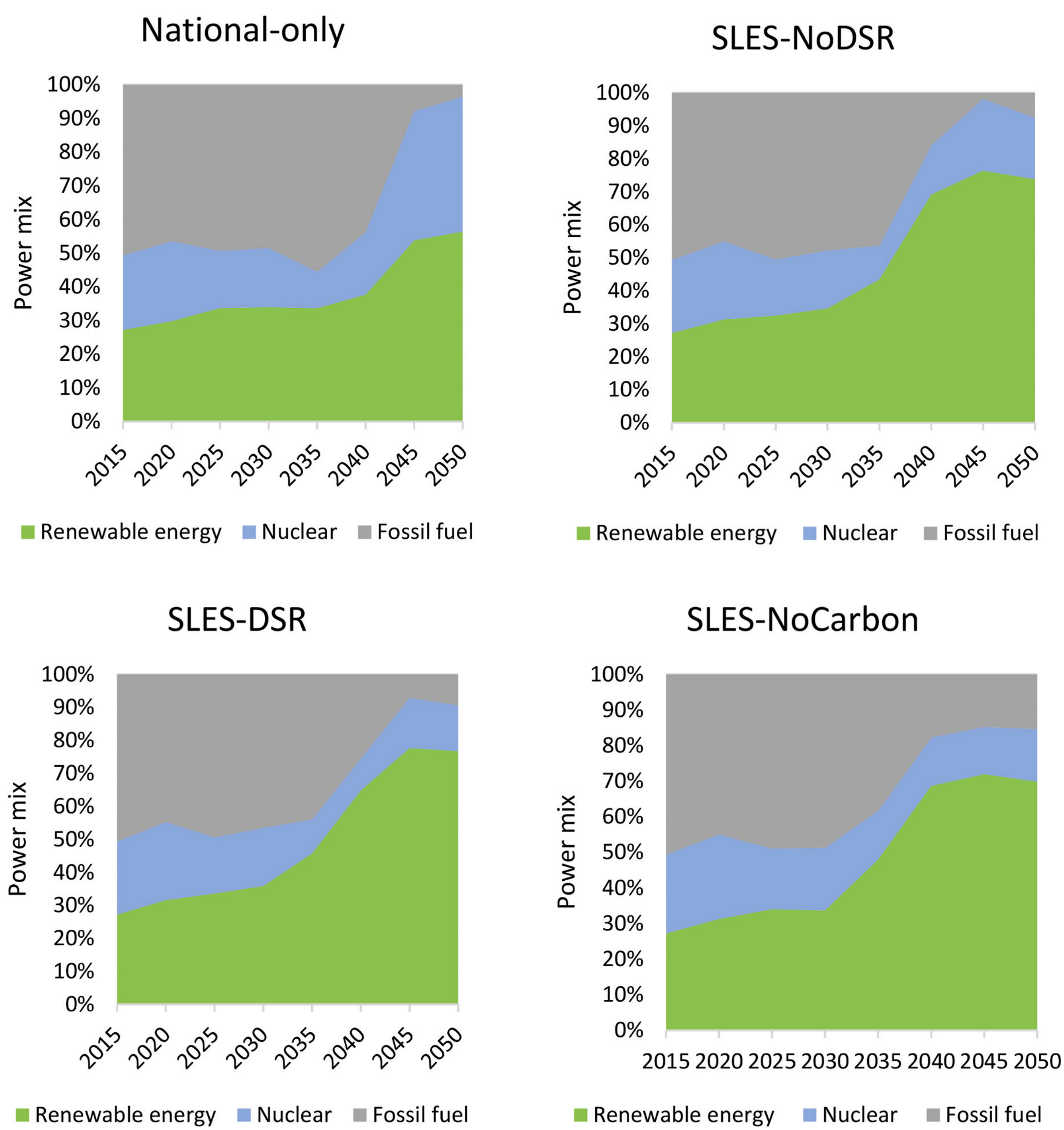

Fig. 2. Five-year average power mix over the modelling horizon for four scenarios.

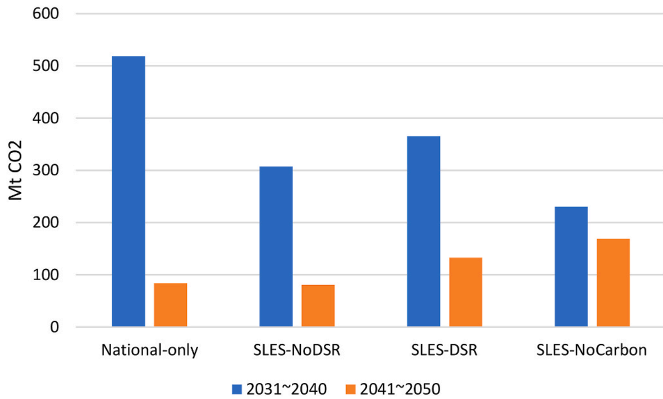

Fig. 3. Cumulative GHG emissions in last two decades for four scenarios.

emissions. In fact, National-only is the only scenario that fully decarbonises the power sector by 2050 based on the stylised settings of the model. As for the cases with local investors (SLES-NoDSR and SLES-DSR), the opposite timing occurs with much lower GHG emissions in the 2030s (40% and 30% less respectively) due to the higher investments in renewable energy. In the 2040s, however, the uptake rate of renewable energy doesn't match with the sharp rise in electricity demand, with existing gas power plants thus being used to provide additional electricity. The sharp increase in electricity demand is due to the dramatic electrification of the end-use sectors for decarbonisation. As for the lower GHG emissions in the 2030s in SLES-NoCarbon, this is due to the underinvestment in power plants so that there is a shortage of electricity generation to fulfil the demand, as shown in Figure B4.

Perhaps surprisingly, the case with DSR (i.e. SLES-DSR) has relatively higher GHG emissions than the case without DSR (i.e. 19% and 64% higher in the 2030s and 2040s respectively). The lower emissions in SLES-NoDSR is due to the earlier adoption of more nuclear plants, as policy agents are more likely to foresee a shortage of capacity earlier (with no DSR to manage peak demand). On the other hand, in SLES-DSR, less low-carbon power plants, such as nuclear and biomass plants, are introduced into the system as peak loads can be reduced with DSR, with gas plants then used as an additional option to fill the supply shortage, as shown in Figure B3. As a result, higher GHG emissions are seen in both the early and late periods in the DSR case (SLES-DSR) than the no-DSR case (SLES-NoDSR).

4.5. Cumulative investments, and remaining capital

The investment trends across the four scenarios are shown in Fig. 4. In the reference case (National-only), incumbent utilities provide 79% of total investments over the whole period, while 21% is provided by new entrants. Incumbent investors actively participate in the capacity market to invest in high capital expenditure plants (e.g., nuclear and biomass), that can yield more revenue from electricity provision than other plants as well as ensuring sufficient capacity in the power system. In contrast, with the presence of new local investors, the investments in renewable energy increase significantly, rising from 21% in SLES-NoDSR to 46% in SLES-DSR. The higher renewable energy investments are driven by preferences of local investors for renewable energy in sub-national regions.

Additionally, DSR encourages more investments in renewable energy with inherent variability, such as onshore wind and PV plants, as shown in SLES-DSR in Fig. 4(b). As the demand profile can be transformed by demand-shifting to match with the supply profile of these variable renewable sources, local investors can realise higher revenues and therefore increase investments in renewable energy. As a result, the role of incumbents is lower in SLES-NoDSR, where they create only 50% of total investment compared to 79% in National-only. Investment by incumbents falls further still in SLES-DSR to only 39%, with one incumbent utility leaving the market entirely, while local agents are delivering 33% of total investments, the highest level across all scenarios.

The success (or failure) of investments leads to investor agents' financial performance in terms of capital (Fig. 5). Without the competition from local investors in the National-only scenario, incumbent investors dominate the market with their fleet of gas, nuclear, and biomass plants. On the other hand, the scenarios with the participation of local investors in the market show two major impacts: (1) the dominance of incumbent investors diminishes dramatically; (2) overall capital is much higher than the reference case. As the deployment of SLES grows over time, local investors' plants gradually become the primary electricity sources, leaving a limited supply gap for incumbent utilities to fill. National investors' capital thus shrinks significantly over time. The dominance of local investors can even force incumbent utilities to leave the

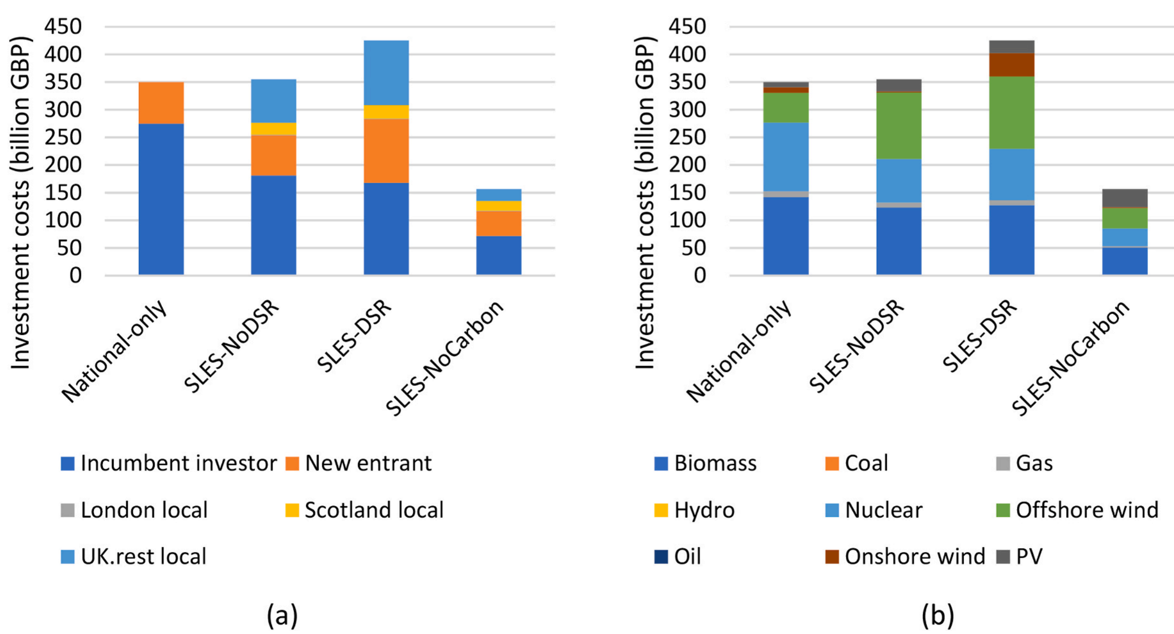

Fig. 4. Cumulative investments (a) by investor type and (b) by technology for four scenarios.

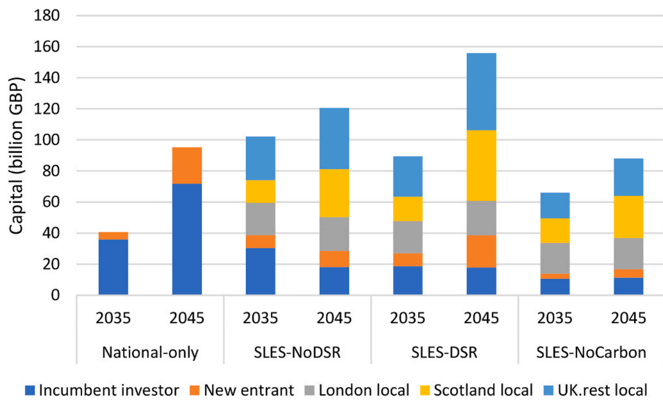

Fig. 5. Capital by investor type in 2035 and 2045 for four scenarios.

market as those investors' plants are not able to compete with local investors' renewable energy plants to make sufficient profits. Moreover, local investors can benefit from renewable energy plants' lower operation and maintenance costs to accumulate much more capital than national investors.

The capital of local investors in London remains at a similar level in both years across the three cases with local investors. This implies local investors in London exploit almost the full potential of PV in London before 2035 due to the highly competitive prices of PV plants in all three cases. On the other hand, local investors in Scotland and the rest of the UK have higher capital in 2045 since additional renewable energy plants can be deployed in these two regions.

It is noteworthy that although the scale-up of SLES allows local investors to thrive in the long run, local investors do need seed capital, which is given in the model, to participate in the electricity market at the beginning. Initial supports (e.g. subsidies, loans, and grants) from local or national governments are thus crucial to deploy SLES at scale (Braunholtz-Speight et al., 2020).

5. Conclusions and policy implications

The BRAIN-Energy agent-based model (ABM) was extended to study smart local energy systems (SLES), including the addition of local regions with both the incorporation of new local investor agents and local governance agents, combined with an improved temporal resolution and demand-side flexibility. This allowed the investigation of strategic decision making under non-optimal decision making for SLES, within a model that captures the operational characteristics of an electricity system. Four scenarios were created to explore the conditions in which SLES (with and without demand-side response (DSR)) play a significant role in the future electricity system.

This novel ABM modelling study of SLES has a number of limitations which could be addressed in future work. Some of the limitations are listed below, which are not exhaustive.

- Compared to a full electricity dispatch model it still has a relatively coarse temporal and spatial disaggregation.
- A simplified modelling of how local investors are incentivised and capitalised, without considering novel business models, new market mechanisms, and new regulations.
- The potential of DSR is estimated exogenously, considering households' participation rates and physical capability of demand-shifting activities.
- Further demand-side measures (e.g. adoption of energy-efficient appliances) are not considered explicitly (although are incorporated into future electricity consumption).
- A reduced menu of low carbon technologies is available, with (unproven at scale) negative emission technologies – such as bioenergy-fuelled carbon capture and storage (BECCS) – not taken into account. Unexpected systematic disruptions (e.g. fuel shortage and price hike due to geopolitical conflicts) could also be considered in scenarios in the future.

But this novel ABM modelling study of SLES generates a set of insights into the non-optimal strategic decisions of market players relevant to the scale-up of SLES. These insights, explained in the following sections, should be taken into account when policy-makers try to boost the share of renewable energy in a power system with SLES.

According to the analysis, SLES is important for the uptake of renewable energy. The enabling of SLES by local governments allows local investors (e.g. municipal utility and household aggregator) to actively participate in and then lead the electricity market. The share of renewable energy in the power system can hence be scaled-up faster and further. Renewable-based SLES systems can provide a secure supply of electricity, and while overall investment requirements to decarbonise the power system are higher with local agents and DSR, the transition's resulting variable costs are less expensive.

In addition, carbon prices are influential for system stability under market players' investment decisions for decarbonisation, from the perspective of this model. National government imposing carbon prices on the power system, works alongside local government support of SLES and the regulator running capacity markets to ensure supply and demand are balanced. The agent-led dynamics (incumbents vs. new entrants, with/without DSR) are different in each scenario. But without carbon pricing, the investment security in a decarbonising system is not enough for non-optimising investors.

However, DSR can give mixed messages and hence alternate strategies in a non-optimal electricity market, based on the modelling assumptions in this study. Despite the indisputable benefits of DSR in balancing electricity supply and demand, it can result in policy agents (who also act imperfectly) postponing the incentives that are required for heterogeneous investor agents to build new low carbon plants. Consequently, the uptake of low-carbon generation technologies could be delayed so that more dramatic investments in new plants approaching 2050 are needed.

Finally, the introduction of SLES significantly reduces but does not eliminate the market role of incumbents according to the findings. Even though SLES gains market share and develops profitable new local producers (municipal utilities and household aggregators), the generation from renewable energy may not always be enough to fulfil demands in sub-national regions, and certainly cannot always meet nationwide demand. Hence incumbent investors are still needed (and need to be incentivised) to invest in capital-intensive, dispatchable plants to ensure system stability. Without SLES, incumbents should play the utmost important role in deploying low-carbon generation technologies, such as nuclear power plants, to decarbonise the power system. However, in this case, consumers might not be able to enjoy low electricity prices as the share of renewable energy scales up at a much slower pace.

Smart local energy systems (SLES) hold the promise of flexible electricity decarbonisation pathways that fully engage with local communities. But as this novel modelling study shows, to realise the scale-up of SLES needs an understanding of the non-optimal strategic decision making of local investors and governance agents, and the resultant impacts on the emissions, costs and stability of the national electricity system.

CRediT authorship contribution statement

Pei-Hao Li: Conceptualization, Data curation, Formal analysis, Investigation, Writing – original draft, Writing – review & editing. **Elsa Barazza:** Conceptualization, Data curation, Formal analysis, Methodology, Writing – original draft, Writing – review & editing. **Neil Strachan:** Conceptualization, Supervision, Writing – original draft, Writing – review & editing, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Acknowledgements

This study was funded by EnergyREV Plus (EP/S031898/1) which is part of the Industrial Strategy Challenge Fund's Prospering from the Energy Revolution (PFER) programme. Additional project support was provided by UKERC 4 (EP/S029575/1). The authors like to thank Tim Green, Charlie Wilson, and Meysam Qadrdan for their valuable comments on the draft of the study, and Sumit Kothari for his contribution to the extension of the BRAIN-Energy model.

Appendix A. Model flow of the BRAIN-Energy ABM

To simulate the UK's liberalised electricity market, the BRAIN-Energy agent-based model simulates the operations of the power system, trading in the electricity market, individual investors' behaviours, and policy-makers' interventions sequentially in each model year (Figure A1). This procedure repeats iteratively until the target year (e.g. 2050) is reached. At the beginning of each year, investors decommission unprofitable power plants and then take short-term operational decisions (electricity production from their stock of assets), followed by bidding 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, as well as the electricity supply curve and the CO2 emissions from the power sector. Based on their electricity sales and 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.

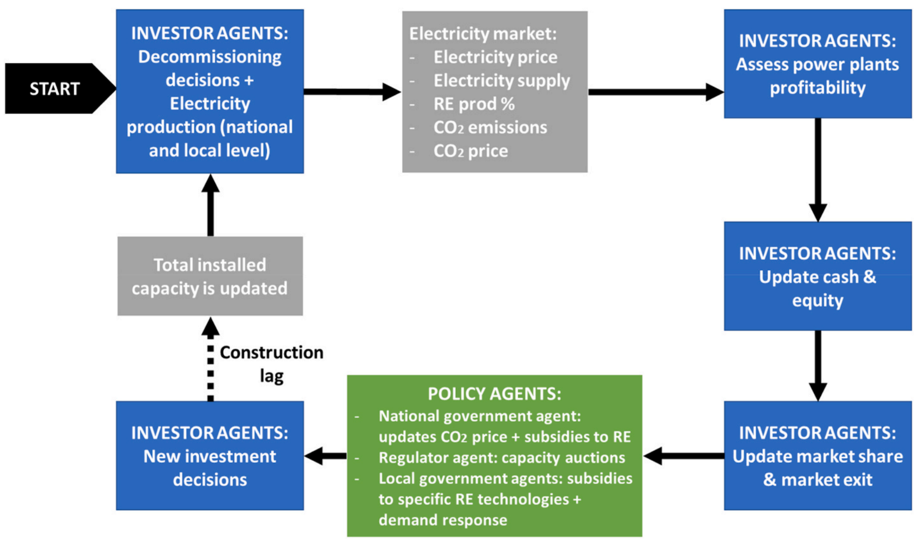

Fig. A.1. Yearly simulation procedure of the model

Policy agents (i.e. the national government agent, the regulator agent and local government agents) are active in 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 at the national level. The national government agent also subsidises investments in renewable technologies through Contracts for Difference at the national level. The regulator agent also intervenes in the market to manage eventual supply gaps by enforcing capacity auctions 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 that 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. 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.

For more detailed information about how the model works, please refer to the model documentation (Barazza et al., 2020).

Appendix B. Electricity provision by technology in four scenarios

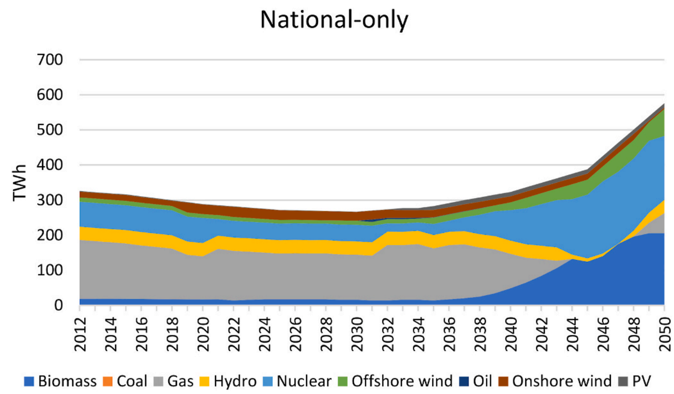

Fig. B.1. Electricity provision by technology for National-only scenario

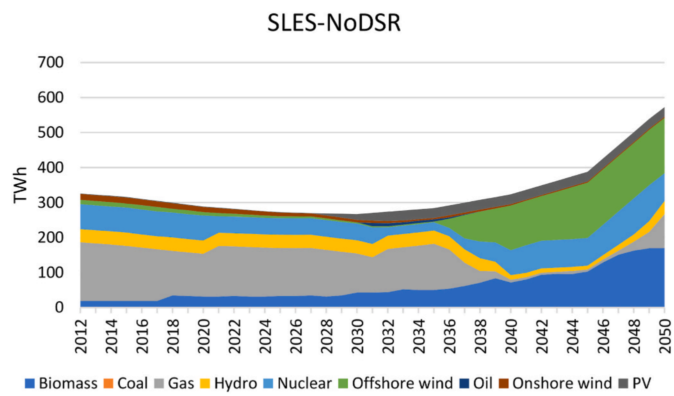

Fig. B.2. Electricity provision by technology for SLES-NoDSR scenario

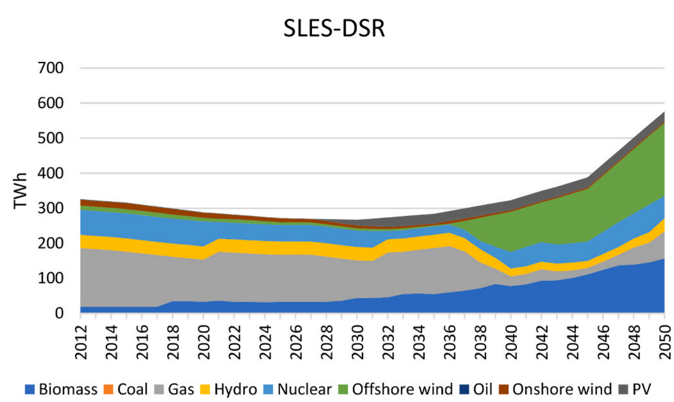

Fig. B.3. Electricity provision by technology for SLES-DSR scenario

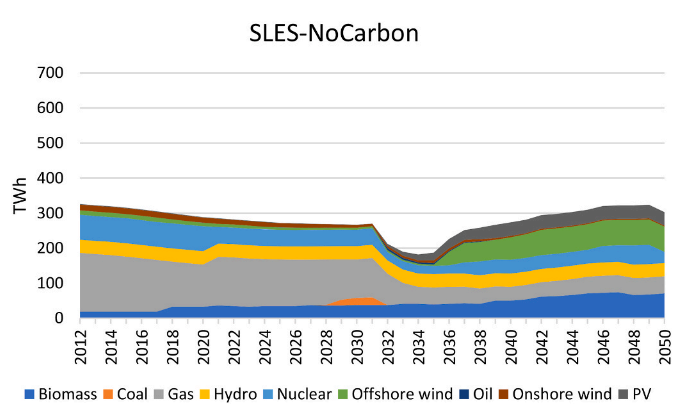

Fig. B.4. Electricity provision by technology for SLES-NoCarbon scenario

References

CCC, 2015a. The Fifth Carbon Budget: the Next Step towards a Low-Carbon Economy. Committee on Climate Change, London, London.
CCC, 2015b. The Fifth Carbon Budget. Committee on Climate Change, London, London.
CCC, 2015c. The Fifth Carbon Budget: the Next Step towards a Low-Carbon Economy. Committee on Climate Change, London, London.
CCC, 2019. Net Zero: The UK's contribution to stopping global warming, Committe on Climate Change.
Bale, C.S.E., Varga, L., Foxon, T.J., 2015. Energy and complexity: new ways forward. Appl. Energy 138, 150–159. https://doi.org/10.1016/j.apenergy.2014.10.057.
Barazza, E., Strachan, N., 2020a. The co-evolution of climate policy and investments in electricity markets: simulating agent dynamics in UK, German and Italian electricity sectors. Energy Res. Social Sci. 65, 101458 https://doi.org/10.1016/j.erss.2020.101458.
Barazza, E., Strachan, N., 2020b. The impact of heterogeneous market players with bounded-rationality on the electricity sector low-carbon transition. Energy Pol. 138, 111274.
Barazza, E., Li, P.-H., Kothari, S., 2020. BRAIN-energy : bounded rationality agents investments model [WWW Document]. URL. https://www.ucl.ac.uk/energy-models/sites/energy-models/files/brain-energy_model_documentation_-_march_2020.pdf.
BEIS, 2017. Updated Energy and Emissions Projections 2016.
BEIS, 2020. 2018 UK greenhouse gas emissions, provisional figures.
Bhagwat, P.C., Richstein, J.C., Chappin, E.J.L., de Vries, L.J., 2016. The effectiveness of a strategic reserve in the presence of a high portfolio share of renewable energy sources. Util. Pol. 39, 13–28. https://doi.org/10.1016/j.jup.2016.01.006.
Bhagwat, P.C., Marcheselli, A., Richstein, J.C., Chappin, E.J.L., De Vries, L.J., 2017. An analysis of a forward capacity market with long-term contracts. Energy Pol. 111, 255–267. https://doi.org/10.1016/j.enpol.2017.09.037.
Bilbiie, F.O., 2020. The new keynesian cross. J. Monetary Econ. 114, 90–108. https://doi.org/10.1016/j.jmoneco.2019.03.003.
Braunholtz-Speight, T., Sharmina, M., Manderson, E., McLachlan, C., Hannon, M., Hardy, J., Mander, S., 2020. Business models and financial characteristics of community energy in the UK. Nat. Energy 5, 169–177.
Busch, J., Roelich, K., Bale, C.S.E., Knoeri, C., 2017. Scaling up local energy infrastructure; an agent-based model of the emergence of district heating networks. Energy Pol. 100, 170–180. https://doi.org/10.1016/j.enpol.2016.10.011.
Carmichael, R., Gross, R., Rhodes, A., 2018. Unlocking the Potential of Residential Electricity Consumer Engagement with Demand Response. Energy Futures Lab, Imperial College London.
Chappin, E.J.L., de Vries, L.J., Richstein, J.C., Bhagwat, P., Iychettira, K., Khan, S., 2017. Simulating climate and energy policy with agent-based modelling: the Energy Modelling Laboratory (EMLab). Environ. Model. Software 96, 421–431. https://doi.org/10.1016/j.envsoft.2017.07.009.
Daly, H.E., Fais, B., 2014. UK TIMES model Overview [WWW Document]. URL. http://www.ucl.ac.uk/energy-models/models/uktm-ucl/uktm-documentation-overview.
Deissenroth, M., Klein, M., Nienhaus, K., Reeg, M., 2017. Assessing the plurality of actors and policy interactions: agent-based modelling of renewable energy market integration. Complexity 2017. https://doi.org/10.1155/2017/7494313.
European Commission, 2022. 2050 long-term strategy | Climate Action [WWW Document]. URL. https://ec.europa.eu/clima/policies/strategies/2050_en. accessed 8.4.20.
Farhi, E., Werning, I., 2019. Monetary policy, bounded rationality, and incomplete markets. Am. Econ. Rev. 109, 3887–3928. https://doi.org/10.1257/aer.20171400.
Ford, R., Maidment, C., Fell, M., Vigurs, C., Morris, M., 2019. A Framework for Understanding and Conceptualising Smart Local Energy Systems. EnergyREV, University of Strathclyde Publishing, UK.
Foxon, T.J., Bale, C.S.E., Busch, J., Bush, R., Hall, S., Roelich, K., 2015. Low carbon infrastructure investment: extending business models for sustainability. Infrastructure Complexity 2. https://doi.org/10.1186/s40551-015-0009-4.
Grid, National, 2021. Future Energy Scenarios.
Grubb, M., Newbery, D., 2018. UK electricity market reform and the energy transition: emerging lessons. Energy J. 39, 1–25. https://doi.org/10.5547/01956574.39.6.mgru.
Hall, S., Foxon, T.J., Bolton, R., 2017. Investing in low-carbon transitions: energy finance as an adaptive market. Clim. Pol. 17, 280–298. https://doi.org/10.1080/14693062.2015.1094731.
Hansen, P., Liu, X., Morrison, G.M., 2019. Agent-based modelling and socio-technical energy transitions: a systematic literature review. Energy Res. Social Sci. 49, 41–52. https://doi.org/10.1016/j.erss.2018.10.021.
Helms, T., Salm, S., Wüstenhagen, R., 2015. Investor-Specific Cost of Capital and Renewable Energy Investment Decisions. In: Renewable Energy Finance. IMPERIAL COLLEGE PRESS, pp. 77–101. https://doi.org/10.1142/9781783267774_0004.
Hoekstra, A., Steinbuch, M., Verbong, G., 2017. Creating agent-based energy transition management models that can uncover profitable pathways to climate change mitigation. Complexity 2017. https://doi.org/10.1155/2017/1967645.
International Energy Agency, 2017. World Energy Outlook 2017.
International Renewable Energy Agency, 2019. IRENA (2019), global energy transformation: a roadmap to 2050, global energy transformation. A Roadmap to 2050.
IPCC, 2018. Global Warming of 1.5 °C. Intergovernmental Panel on Climate Change, Switzerland.
Iychettira, K.K., Hakvoort, R.A., Linares, P., de Jeu, R., 2017. Towards a comprehensive policy for electricity from renewable energy: designing for social welfare. Appl. Energy 187, 228–242. https://doi.org/10.1016/j.apenergy.2016.11.035.
Keppo, I., Strubegger, M., 2010. Short term decisions for long term problems - the effect of foresight on model based energy systems analysis. Energy 35, 2033–2042. https://doi.org/10.1016/j.energy.2010.01.019.
Khan, A.S.M., Verzijlbergh, R.A., Sakinci, O.C., De Vries, L.J., 2018. How do demand response and electrical energy storage affect (the need for) a capacity market? Appl. Energy 214, 39–62. https://doi.org/10.1016/j.apenergy.2018.01.057.
Kraan, O., Kramer, G.J., Nikolic, I., 2018. Investment in the future electricity system - an agent-based modelling approach. Energy 151, 569–580. https://doi.org/10.1016/j.energy.2018.03.092.
Li, P.-H., Pye, S., 2018. Assessing the benefits of demand-side flexibility in residential and transport sectors from an integrated energy systems perspective. Appl. Energy 228, 965–979.
Li, F.G.N., Strachan, N., 2019. Take me to your leader: using socio-technical energy transitions (STET) modelling to explore the role of actors in decarbonisation pathways. Energy Res. Social Sci. 51, 67–81.
Ma, T., Nakamori, Y., 2009. Modeling technological change in energy systems - from optimization to agent-based modeling. Energy 34, 873–879. https://doi.org/10.1016/j.energy.2009.03.005.
McInerney, C., Bunn, D.W., 2019. Expansion of the investor base for the energy transition. Energy Pol. 129, 1240–1244.
Mercure, J.F., Pollitt, H., Bassi, A.M., Viñuales, J.E., Edwards, N.R., 2016. Modelling complex systems of heterogeneous agents to better design sustainability transitions policy. Global Environ. Change 37, 102–115. https://doi.org/10.1016/j.gloenvcha.2016.02.003.
Morstyn, T., Collett, K.A., Vijay, A., Deakin, M., Wheeler, S., Bhagavathy, S.M., Fele, F., McCulloch, M.D., 2020. OPEN: an open-source platform for developing smart local energy system applications. Appl. Energy 275, 115397. https://doi.org/10.1016/j.apenergy.2020.115397.
Palmer, J., Sorda, G., Madlener, R., 2015. Modeling the diffusion of residential photovoltaic systems in Italy: an agent-based simulation. Technol. Forecast. Soc. Change 99, 106–131. https://doi.org/10.1016/j.techfore.2015.06.011.
Richstein, J.C., Chappin, E.J.L., de Vries, L.J., 2014. Cross-border electricity market effects due to price caps in an emission trading system: an agent-based approach. Energy Pol. 71, 139–158. https://doi.org/10.1016/j.enpol.2014.03.037.
Ringler, P., Keles, D., Fichtner, W., 2016. Agent-based modelling and simulation of smart electricity grids and markets - a literature review. Renew. Sustain. Energy Rev. 57, 205–215. https://doi.org/10.1016/j.rser.2015.12.169.
Robinson, S.A., Rai, V., 2015. Determinants of spatio-temporal patterns of energy technology adoption: an agent-based modeling approach. Appl. Energy 151, 273–284. https://doi.org/10.1016/j.apenergy.2015.04.071.
Salm, S., 2018. The investor-specific price of renewable energy project risk – a choice experiment with incumbent utilities and institutional investors. Renew. Sustain. Energy Rev. 82, 1364–1375. https://doi.org/10.1016/j.rser.2017.04.009.
Salm, S., Hille, S.L., Wüstenhagen, R., 2016. What are retail investors' risk-return preferences towards renewable energy projects? A choice experiment in Germany. Energy Pol. 97, 310–320. https://doi.org/10.1016/j.enpol.2016.07.042.
Seyfang, G., Park, J.J., Smith, A., 2013. A thousand flowers blooming? An examination of community energy in the UK. Energy Pol. 61, 977–989. https://doi.org/10.1016/j.enpol.2013.06.030.
Steinbach, J., Staniaszek, D., 2015. Discount rates in energy system analysis. BPIE, Fraunhofer ISI 6, 1–20 https://doi.org/NREL/TP-560-39181.
Tesfatsion, L., 2006. Chapter 16 agent-based computational economics: a constructive approach to economic theory. In: Handbook of Computational Economics. Elsevier, pp. 831–880. https://doi.org/10.1016/S1574-0021(05)02016-2.
Trutnevyte, E., 2016. Does cost optimization approximate the real-world energy transition? Energy 106, 182–193. https://doi.org/10.1016/j.energy.2016.03.038.
UNFCCC, 2015. The Paris agreement [WWW Document]. URL. https://unfccc.int/process-and-meetings/the-paris-agreement/the-paris-agreement.
US EPA, 2020. Sources of greenhouse gas emissions | greenhouse gas (GHG) emissions | US EPA [WWW Document]. URL. https://www.epa.gov/ghgemissions/sources-greenhouse-gas-emissions. accessed 8.4.20.
Wilson, C., Grubler, A., Bento, N., Healey, S., De Stercke, S., Zimm, C., 2020. Granular technologies to accelerate decarbonization. Science 368 (1979), 36–39. https://doi.org/10.1126/science.aaz8060.
Zeyringer, M., Price, J., Fais, B., Li, P.H., Sharp, E., 2018. Designing low-carbon power systems for Great Britain in 2050 that are robust to the spatiotemporal and inter-annual variability of weather. Nat. Energy 3, 395–403. https://doi.org/10.1038/s41560-018-0128-x.
Zheng, M., Meinrenken, C.J., Lackner, K.S., 2014. Agent-based model for electricity consumption and storage to evaluate economic viability of tariff arbitrage for residential sector demand response. Appl. Energy 126, 297–306. https://doi.org/10.1016/j.apenergy.2014.04.022.