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Investment in the future electricity system - An agent-based modelling approach

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A B S T R A C T

Now that renewable technologies are both technically and commercially mature, the imperfect rational behaviour of investors becomes a critical factor in the future success of the energy transition. Here, we take an agent-based approach to model investor decision making in the electricity sector by modelling investors as actors with different (heterogeneous) anticipations of the future. With only a limited set of assumptions, this generic model replicates the dynamics of the liberalised electricity market of the last decades and points out dynamics that are to be expected as the energy transition progresses. Importantly, these dynamics are emergent properties of the evolving electricity system resulting from actor (investor) behaviour. We have experimented with varying carbon price scenarios and find that incorporating heterogeneous investor behaviour results in a large bandwidth of possible transition pathways, and that the depth of renewables penetration is correlated with the variability of their power generation pattern. Furthermore, a counter-intuitive trend was observed, namely that average profits of investors are seen to increase with carbon prices. These results are a vivid and generic illustration that outcome-based policy cannot be solely based on market instruments that rely on perfect rational and perfectly informed agents.

1. Introduction

The energy transition is gaining momentum in the last several years, due to rapidly falling prices of renewable energy technology and substantial institutional consensus on climate change created at the Conference of Parties in Paris in December 2015. The electricity sector is expected to take a leading role in the decarbonisation of the energy sector as it is crucial for a low-carbon energy system. The energy transition will therefore have a large influence on the electricity system, as it entails a transition from the centralised and homogeneous fossil fuel-based system to a much more distributed and heterogeneous system based on intermittent renewable sources [1–4].

Furthermore, the need for instantaneous balancing and limited storability of electricity, in combination with the intermittent nature of renewables will further increase the complexity of the electricity system. The liberalisation of the electricity system in many countries [5] has led to entry of investors, further increasing the complexity of the system as these new actors are now expected to play a key role in the transition.

Liberalised electricity markets are designed on the assumption that dispatchable electricity generation with a range of positive marginal costs can be ranked, which is the case for thermal generators such as coal or gas fueled power generation assets [5]. This merit order in which the electricity price is set ensures economic efficient allocation of resources. With massive deployment of renewable energy sources, the market assumptions are undermined as renewable power generators cannot be dispatched and have zero marginal costs [7].

In electricity markets designed as 'energy-only market', electricity generators receive revenues for selling electricity but not for providing capacities [8,9]. In theory these energy-only markets in which electricity prices should be covering capital investment, guarantee security of supply [10]. In practice, market imperfections and inadequate regulation can lead to 'the missing money problem', the problem that insufficient investments can lead to concerns around the security of supply [7,8].

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1.1. Modelling electricity markets

Modelling the development of the electricity mix within energy-only markets can give insight in the mechanisms taking place during the energy transition [11–13]. Many techno-economic studies on the energy transition have been carried out that can be classified in optimisation, equilibrium and simulation models [14–19].

Large scale bottom-up optimisation models in general show cost-optimal pathways of the energy transition (e.g. Refs. [18,20,21]) and answer the question of 'what should be' [22]. Results from these studies are useful to depict an 'ideal' world in which a central actor with control power must be active that implements these multi-decade systems to achieve cost-optimal pathways. Western democracies however have deliberately moved away from centralised planning with the liberalisation of (electricity) markets. If we want to increase our understanding of these systems, we therefore should focus more on the incorporation of heterogeneous actors with bounded rationality and imperfect information.

Whereas optimisation models rely on detailed bottom-up technologies, equilibrium models (e.g. Refs. [23–25]) try to model the overall market behaviour top-down with algebraic and/or differential equations (e.g. Worldscan [26]). However, when the problem under consideration is too complex to be addressed within a formal equilibrium framework, simulation models are an alternative to equilibrium models [14].

These and other neoclassical models that depend on economic rational behaviour have provided key insights for business decisions and policy makers [27]. Literature and simple observation of the real world suggest however, that these assumptions do not hold and that decision makers in the system are heterogeneous and exhibit bounded rationality in their decision making behaviour [28–30]. Including bounded rationality relaxes the assumptions of perfect foresight and maximising utility [31]. Modelling these aspects requires different tools [22,30,32].

1.2. An agent-based approach to electricity sector investment

Agent-based modelling (ABM) can be used to simulate complex adaptive systems (CAS) such as the electricity system and is well suited to model adaptive heterogeneous actors (agents) such as investors that can be part of emergent system behaviour.[1] Modelling the energy transition this way is therefore expected to give important new insight that complements the insights obtained from more traditional energy systems modelling.

Several large-scale ABM studies have been looking at the transition of the electricity system, focusing on the role of consumers (e.g. Refs. [33,34]) and investors [35]. In these studies, the added value of modelling the role of investors in the energy transition and more specifically in the electricity system has been recognised (e.g. Refs. [36–38], for an overview: [11,39]). Because previous ABM studies on the role of investors mainly focus on detailed behaviour (see e.g. Ref. [40] on detailed improvements to the EU Emission Trading System), there is a gap in the understanding of the impacts of investor behaviour on the fundamental dynamics of the electricity system in transition.

The goal of this study is thus to elucidate the fundamental processes that underline the transition of the electricity system. We have taken a conceptual approach aimed at identifying the minimum set of agent-types, behaviour rules and assumptions that could replicate the fundamental dynamics of the first phase of the transition and show possible concerns for the future. This approach has strengthened the transparency, tractability and reproducibility of model results as these are three fundamental challenges in ABM studies [41,42].

We will focus on exploring the emergence of the deep decarbonisation of the electricity sector based on the interactions and individual investment decisions of heterogeneous bounded rational investors in the electricity market. The model represents a typical liberalised Western European electricity market designed as energy-only market [9] such as The Netherlands [43]. As this is a common feature of modern electricity markets, conclusions are potentially generalisable.

The organisation of this paper is as follows: in Section 2 the starting set of assumptions are discussed. The conceptualisation of our model is described in Section 3. In Section 4 we describe our results and in Section 5 we reflect on recent developments and present our main observations. We conclude in Section 6 with a reflection on our modelling approach.

2. Investment decisions in an evolving electricity system

Our model focuses on the role of investors and assesses the influence of their behaviour on the dynamics that drive the development of the electricity system. To avoid the trap of an over-parameterised model we aimed to keep our model as simple as possible. We argue that a reasonable starting set of assumptions for an investor-focused agent-based model, is the following:

1. Future electricity market prices, fuel prices and technology learning rates are unknowable.
2. Investors make investment decisions based on heterogeneous expectations about the future.
3. Past performance of investors affects their investment capacity (and may colour their outlook) but there is the possibility of new investors entering the market.
4. Investment opportunities in power generation assets are diverse with regards to the energy resource, capital lay-out, running cost (including fuel) and CO_2 intensity.

Since our interest lies in the evolving electricity sector as ever more intermittent renewables enter the generation mix, an additional assumption is:

5. Renewable power generation assets have seasonal variable supply and there is no seasonal storage solution.

Finally, we make one additional assumption which is only true in specific liberalised markets, namely that:

6. The electricity market is as an energy-only market.

We will discuss these assumptions in more detail in the next sections.

2.1. Investors' heterogeneous view on the future and their investment decisions

To elaborate on the first assumption; because, (i) the future is fundamentally unknowable and inherently and irreducibly uncertain, (ii) the pace of the transition is unknown, (iii) the preferred technology options are unknown (because future costs and performance are unknown), and (iv) the future price-setting mechanisms in the market are unknown, one naturally expects different investors to have different expectations about the future

[1] A list of acronyms can be found in Table 3 which can be found at the end of this study.

(assumption 2). This can be understood as investors with different corporate strategies and different risk appetites. This leads to a heterogeneity of views on the development of the electricity market and the business environment which influences investment decisions.

Investors' expectations are related to capital providers that asses these expectations companies have. Besides this external component, investors also have an internal component that expresses their required return on capital invested. This internal component is also heterogeneous among investors; while incumbent investors may require a high return on capital invested for new projects, other investors may require a lower rate.

All investors evaluate opportunities by assessing the discounted cash flows in relationship with the size of the investment. The combination of the heterogeneous external expectations and internal requirements investors have, determines the discount rate with which they evaluate these cash flows.

2.1.1. Influence of past performance on new investment decisions

Because investors assess future investments heterogeneously, they will make different investment decisions. Their performance, based on the development of the electricity market and the choices investors have made, is reflected in the average profitability of the assets an investor owns and influences future decisions (assumption 3).

Although the electricity market is composed by a limited number of existing power producers, there is a possibility of new investors that can enter the market (e.g. Qurrent in The Netherlands [44]. We assume they are able to raise capital not based on past performance (which is non-existent), but on the basis of a business vision that is sufficiently new and appealing [45]. For the case at hand that means that renewable power companies can enter the market which are unburdened by a fossil legacy portfolio.

2.2. Power generation assets

The electricity system in most European countries is predominantly based on thermal power generation fueled by fossil resources. However, new, scalable renewable technologies have come available which produce electricity from intermittent resources (assumption 4). These renewable assets, (offshore) wind parks or solar PV-farms, have near-zero operating costs and near-zero CO_2-emissions but are variable on different scales; seasonal, day to day and second to second. The variability of electricity output from these renewable assets depends on the regional location, weather conditions and the mix of PV and wind turbine capacity. Especially the variability of these resources on a seasonal scale is of importance as there is limited possibility for large scale seasonal storage [46] (assumption 5).

2.2.1. Learning rate of renewable technology

The capital lay-out mentioned in assumption 5 with regards to renewable energy technology is especially relevant as renewable energy technology have shown large cost reductions in the last decades [2]. This reduction in turnkey costs can be explained by learning by doing which is a common process; unit costs follow learning curves and go down over cumulative investment. Internationally onshore wind power generators have shown a learning rate of 9% [2] while solar PV-panels have shown learning rate of around 20% percent per year [1,2]. In Section 4.2.4. details can be found of the learning curves for our experiments.

2.3. Electricity markets and the incentive to invest

Assumption 6 treats the electricity market design. We will first discuss the electricity market and then take a closer look at energy-only markets.

Pro-market reforms in the electricity sector that took place in the 1980's and 1990's resulted in liberalised electricity markets, both in OECD and non-OECD countries and regions [9]. In these liberalised electricity markets, power generators offer different quantities of electricity at various prices that are ranked from the lowest to the highest Short Run Marginal Costs (SRMC). The market-clearing price is set by the SRMC of the marginal producer. The SRMC of an asset consists of the fuel and other variable operation and maintenance costs (OPEX) but excludes the costs of capital. The margin for electricity producers is defined by the infra-marginal rent, the difference between the SRMC of the marginal producer and their own SRMC. Via this infra-marginal rent, investors need to regain their investment costs.

2.3.1. Energy-only markets and the scarcity rent

In energy-only markets, marginal producers at peak demand can use their market power to increase prices. This is caused by the fact that in electricity markets power buyers accept price premiums (scarcity rents) to prevent black-outs. The marginal producer at peak demand recovers its capital costs via this premium. This pricing mechanism therefore creates an incentive to invest in the marginal producer at peak demand.

The scarcity rent is the quantification of the market power of the marginal producer when capacity is scarce and is crucial to maintain security of supply in an energy-only market. This market power has been observed in reality and its effect has been studied in several studies e.g. Ref. [7]. Because of this scarcity rent in electricity markets, electricity wholesale prices spike at moments of scarce capacity. In most western countries, consumers are protected against these price spikes but as smart meters are rolled out, there is discussion between policy makers if these prices spike should be fed back to consumers. For example the Netherlands has chosen for an energy-only market [43,47], while in Germany and the United Kingdom elements of a capacity market are being introduced.

3. Conceptualisation

The agent-based model in this study is developed by applying the 10-step framework as proposed by Van Dam et al. [48] and is written in the software environment of Netlogo [49]. Literature research combined with semi-structed interviews with experts at Shell and The Copernicus Institute of Sustainable Development have led to the conceptualisation of the model. The model has been extensively verified and has been validated with recording and tracking behaviour, single-agent testing and multi-agent testing [48]. The model, as well as the description, is open source and is published on openabm.org.[2] The software package R has been used for analysis [50]. During the model development best practices for scientific computing have been pursued [51]. For the mentioned detailed description of the model, the ODD protocol is followed [52,53].

Based on our understanding of the electricity market and investor behaviour we developed the conceptualization of our model. Fig. 1 shows our conceptualisation which will be discussed in more detail in the following sections.

3.1. Investors

In the model investors use Net Present Value (NPV) as the key

[2] https://www.openabm.org/model/5361/version//view.

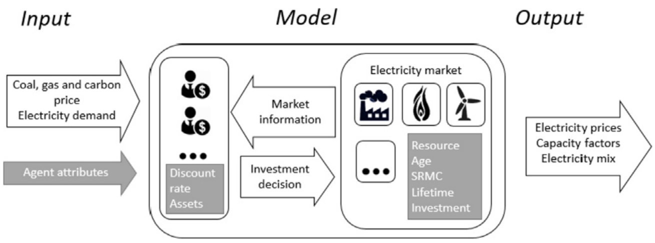

Fig. 1. Model description. Investors invest in power generation units based on market information and their heterogeneous discount rate. These assets are part of the electricity market. Investors and assets are initialised with agent attributes (grey). Other inputs and outputs of the model are depicted (white).

metric in the evaluation of investment opportunities in power generation assets of different types. An NPV in excess of zero triggers investment action. The fact that investors have differing (*i.e.* heterogeneous) views about the future is expressed through a discount rate in the NPV calculations. These different discount rates are given to investors at initialisation. Additionally, at initialisation, investors are given an existing portfolio of gas and coal assets.

There also is the possibility for new 'green' investors not burdened by a legacy portfolio of fossil assets to enter the market; these are initialised with a random discount rate, and have no existing portfolio of assets. It is *a priori* not clear if this is an attractive business model, or that it adds anything to the dynamics of the transformation. But it is obviously of importance to at least be *open to it*, not the least because in the real world there are such players.

The adaptivity of investors is expressed in the model by making the discount rate of each individual investor dynamic. That is: each investor will see its discount rate increase or decrease over time, based on the profitability of its asset portfolio. During the model run the discount rate an investor applies reflects therefore its expectations about the future, expressed by the discount rate at initialisation and its performance during the model run. This adjustment is made once a year after investments decisions have been made.

A visual representation of the decision-making process of investors is given in Fig. 2.

3.2. Assets

At initialisation assets have a heterogeneous age and efficiency within threshold values. Gas and coal assets have a constant dispatchable production, renewable assets have a variable supply on a seasonal scale.

For simplicity, but without loss of generality, we assume that investors can invest in assets of one GW name-plate capacity. In our model, we have three types of assets: gas-fired power stations, coal-fired power stations, and renewable assets. These three asset-types have different properties with regards to their investment costs, their SRMC (based on the fuel costs), and the CO_2-intensity of the resource they are using. These properties (such as cost and efficiency) may drift over time, reflecting technology learning. The attributes of renewable assets can vary so as to reflect a particular mix of solar and wind assets. At initialisation, assets have a heterogeneous age and efficiency.

In the specific runs discussed in this paper, gas and coal assets have constant dispatchable production. Renewable assets have a variable supply on a seasonal scale modelled as a variation of a cosine function, based on empirical data [54–57]. In the present case, we look at seasonal variation of renewables and accordingly use time slicing with 10 slices in the year, thus representing 'months'.[3] Also, in this paper we keep the unit cost of gas and coal assets constant; the unit costs of renewable assets decrease over time as a function of the cumulative investment in the technology. These costs follow a standard learning curve of the form given in Equation (1), where $C(t)$ is the cost of a renewable asset at time t, C_0 is the cost of renewable asset at initialisation, n is the number of renewable power generation assets of 1 GW_p and l is the learning rate.

$$C(t) = C_0 * n^{\log l / \log 2} \tag{1}$$

3.3. Electricity market

In the electricity market, during a year, assets produce electricity that satisfies the electricity demand. As said, the electricity market is modelled as energy-only market. In this paper, we are interested in the supply side and have assumed demand to be constant over time.

In our model, the electricity price is set by the merit-order, the actual market price is the SRMC of the marginal producer, plus a mark-up for generation scarcity, the 'scarcity rent'. This scarcity rent, $S(t)$, is taken to be a function of the excess capacity-factor as defined in Equation (2), where $S(t)$ is the scarcity rent at time t, S_{min} is the minimum scarcity rent, S_{max} is the maximum scarcity rent and α is the scarcity rent variable that determines curvature (see Fig. 3).

$$S(t) = \frac{S_{max} - S_{min}}{\alpha - 1} * \alpha^{e(t)} + S_{min} - \left(\frac{S_{max} - S_{min}}{\alpha - 1}\right) \tag{2}$$

The time-dependent excess capacity, $e(t)$, is defined in Equation (3) as the *potential* power generation of all the assets in the system, i.e. the summation of the *nameplate capacity* of the coal and gas assets (1 GW) and the *momentary* power from renewable assets, relative to the (momentary, but here constant) demand. In Equation (3), D represents the (constant) demand D and $G(t)_i$ potential production at time t of all assets with resource i, including the variability of renewable assets $G(t)_{ren}$. Note that the excess capacity as we define it here is related to what in the power sector is called the 'adequacy margin'. The adequacy margin is simply $1 - e(t)$.

The scarcity rent approaches zero when enough capacity is available and no market player can use their market power to raise the price about the SRMC. On the other hand, the scarcity rent will be high at moments capacity is scare (low $e(t)$) to incentivise investment. The maximum electricity price, including the maximum scarcity rent, reflects the value of lost load (VOLL). We have chosen the functional form and parameterisation of the relation between the scarcity rent and the excess capacity factor such that outages do not occur.

3.4. Model narrative

Our model describes the time-evolution of the power system over years and decades. Within each year, the 'clock tick' of the model (the shortest time step in an ABM) is a month. Every month electricity prices are calculated based on existing assets. After a year has passed, the following steps are followed:

Investors calculate their profitability. Based on production and the monthly electricity price, investors calculate their income from each of the assets in their portfolio. The profitability of investors'

[3] Note that there is no loss of generality. By going from 12 time slices in the year to 365 one would model days, by going to 8760 h, etc.

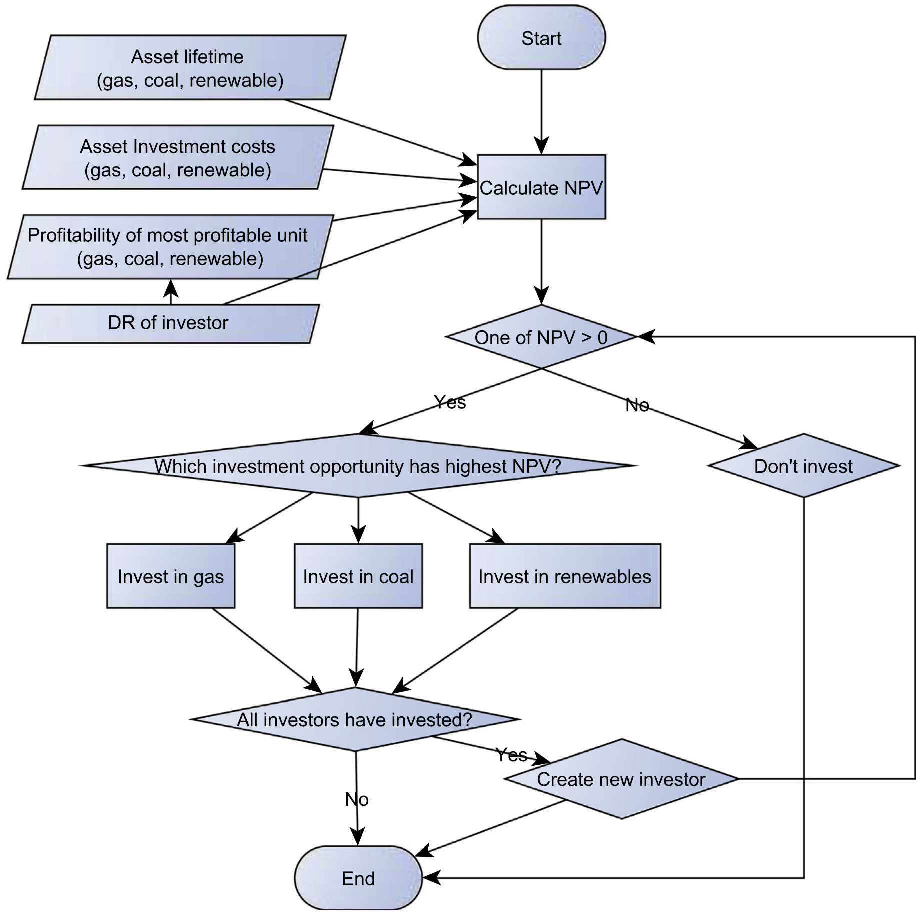

Fig. 2. Decision-making process of investors.

assets determines whether their discount rate will increase (low profitability) or decrease (high profitability). If the discount rate rises above a threshold, the investor goes bankrupt.

Investors evaluate new investment opportunities. Investors make NPV calculations based on their individual expectations about the profits an investor can anticipate to make from a new asset. This profit will depend on the place of that investment in the (future) merit order. Although coal- and gas-based electricity production is mature technology, new units will have a slightly higher efficiency than older units. Thus, a new unit, with a slightly higher efficiency, will be ahead of the currently most profitable unit (of the same type, gas or coal) in the merit order.

After evaluating all the options, investors decide to invest in an asset with the highest positive NPV (provided there is one). These assets are then placed in the system instantaneously and will generate power (and income) from that same year on. (That is, for the sake of simplicity we ignore investment lead times.)

New investors. New investors can enter the market when an investment opportunity has a positive NPV. New investors are initialised with a random discount rate within threshold values. Because only a limited number of investors in the world can raise the capital needed to invest in these large-scale electricity production units, only one new investor can enter the market each year.

Finally, assets may be taken out of operation and removed from the system: **Asset elimination.** Finally, assets may be taken out of operation and removed from the system when their lifetime is reached.

4. Experimental setup and results

In this section, we describe the setup of the various experiments we conducted with the model and we give a brief overview of the results these experiments have produced.

4.1. Experimental setup

Four experiments have been carried out around the key exogeneous parameters of the model to explore their effect on the dynamics of the electricity market.

- Carbon price development.
- Heterogeneity of investors.
- Variable production patterns of renewable power generation.
- Cost decline of renewable power technology.

We have setup the model to represents the Dutch electricity system, with approximate Dutch generation capacity and demand (20 GW and 15 GW), with 5 investors (the utility companies), and a representative age distribution of assets and resource mix. Power plant efficiencies, resource prices and investment prices of a 1 GW asset are based on order of magnitude numbers from literature and experts. The model runs for 780 months representing the years 2000–2065, a realistic time frame for the transition of the electricity system. Carbon prices are modelled to historic prices of the EU-ETS between 2000 and 2015. Power generation by renewables is modelled to realistic power generation by a mix of wind and solar

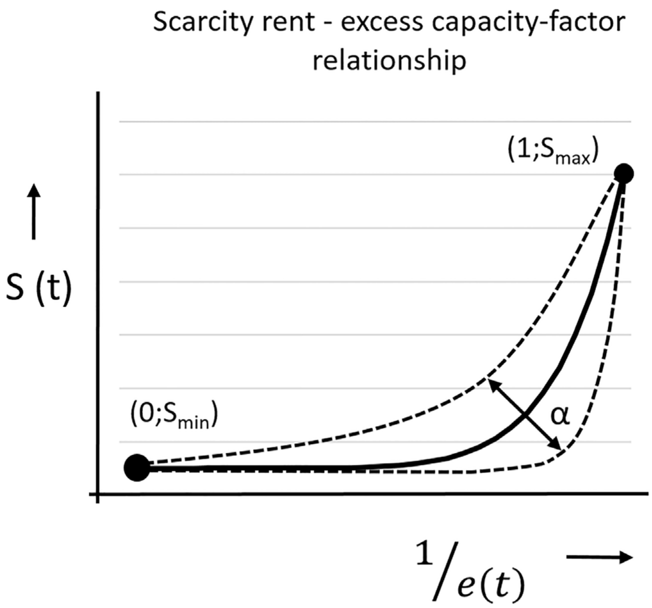

Fig. 3. Relationship between scarcity rent and excess capacity factor, where *S(t)* is the scarcity rent at time t, *Smin* is the minimum scarcity rent, *Smax* is the maximum scarcity rent and α is the scarcity rent variable that determines curvature. The time-dependent excess capacity, $\boldsymbol{e}(\boldsymbol{t})$, is defined as the potential power generation of all the assets in the system divided by demand *D*.

$$e(t) = \frac{\sum G(t)_{ren} + \sum G(t)_{gas} + \sum G(t)_{coal}}{D} \tag{3}$$

assets (see Section 4.2.3). The learning rate for renewable assets is assumed to be 20% (see Section 4.2.4). In all our experiments we have initialised the model to represent the Dutch electricity system in 2000 [58]. An overview of the most important values at initialisation are given in Table 1.

4.2. Results

Results of four experiments are discussed in the following sections. Graphs in these sections show results from 30 model runs in each of the scenarios; shaded areas show the first quartile on both sides of the median while the thick lines show the median.

4.2.1. Carbon price

Fig. 4 shows the development of the electricity mix under two carbon price scenarios. In the left graph the carbon price has been kept constant at 6 €/tonneCO_2, the approximate carbon price in the EU ETS program between 2010 and 2015 [63]. In the right graph, we linearly increased the carbon price from 6 €/tonneCO_2 after 15 years with 2 €/tonneCO_2 to 34 €/tonneCO_2 in 2030. After thirty years, the carbon price remains constant till the end of the model run. This carbon price scenario will be our ‘base case (BC)’.

Because we are interested in the decarbonisation of the electricity system from the current mix towards a renewable-based energy system and prevent a near-technicality with regards to run-up effects of initialisation, three outcomes parameters are depicted. The blue colour depicts the traditional fossil generation mix as it installed at initialisation and shows whether the current mix is sustained during the model run. The red colour depicts the percentage of production delivered by the extra only-gas assets that are added, which contribute to the decarbonisation because of their lower emission intensity. The green colour indicates the mix

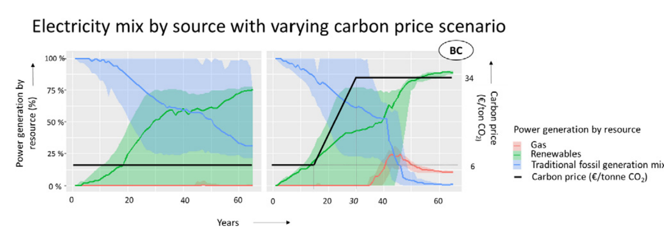

Fig. 4. Electricity production in percentage by resource with two carbon price scenarios. Carbon price starts at 6 €/tonneCO_2 at initialisation and is after 15 years, either constant (left) or 15 years linearly increased till 34 €/tonneCO_2, our base case (BC) (right). Graphs show that with an increased carbon price, the variation of outcomes percentages in 2060 is substantially reduced. Model runs represent the years between 2000 and 2065.

Table 1
Variables of parameters at initialisation.

Variables per model component	Initialisation	Type	Based on source
Electricity market			
Number of investors	5	dynamic	[59]
Demand	15 GW	constant	[58]
Installed capacity	20 GW	dynamic	[58]
Time resolution	Months	constant	
Runtime	65 years	constant	
Investors			
Discount rate	Uniform distribution (6%–20%)	dynamic	
Number of assets per investor	4 assets of 1 GW	dynamic	[59]
Discount rate at bankruptcy	>20%	constant	
Assets			
Lifetime fossil assets	30 years	constant	
Lifetime renewable assets	25 years	constant	
Natural gas price	4,5 €/GJ	constant	[60]
Coal price	2 €/GJ	constant	[60]
Gas asset eff	42%	dynamic	[61]
Coal asset eff	38%	dynamic	[61]
Age fossil assets	Uniform distribution (0–30 years)	dynamic	[59]
Investment coal asset	1.2 €/W	constant	[62]
Investment gas asset	0.6 €/W	constant	[62]
Investment renewable asset	1.6 €/W	dynamic	[1,56]
Load factor renewable asset	[0.15–0.42]	constant	[54–57]

of renewables in the electricity mix.

Firstly, comparing the two graphs we see that with an increased carbon price, the variation of renewable generation percentages in 2060 is substantially reduced compared to the scenario with no further increase of the carbon price. However, although an increased carbon price reduces the bandwidth of possible pathways from 2050 onwards, there is a very large range of possible pathways in the intermediate period. This is mainly due to the distribution and development of discount rates that the (relatively few) investors use in their financial evaluation and that heavily impacts on the start of the learning curves of renewables.

Secondly, we see in the right graph (with the increased CO_2 price), that the penetration of renewable power generation stalls before full conversion to renewables (the stalling point is at ca. 87%). This emerging 'penetration limit' is higher with an increased carbon price.

Thirdly, the choice between gas and coal assets is based on their relative investment and fuel costs and their subsequent performance in the last year. In all carbon price scenarios, these costs are related to their relative carbon intensity. This is shown by Equation (4), where p_{gas} is the profitability of a gas asset, p_{coal} is the profitability of a coal asset, P_{gas} is the price of gas (€/MWh), P_{coal} is the price of coal (€/MWh), η_{gas} is the carbon intensity of gas ($kgCO_2/m^3$) and η_{coal} is the carbon intensity coal ($kgCO_2/kg$).

$$p_{gas} = p_{coal} \leftrightarrow P_{gas} - P_{coal} = P_{CO_2}\left(\eta_{coal} - \eta_{gas}\right) \quad (4)$$

Fourthly, if we increase the yearly carbon price, renewables enter the market earlier. Gas can come back into the system if carbon prices are further increased and electricity from gas assets becomes cheaper than electricity from coal assets.

In Table 2 and Fig. 5 results of our model are compared with two influential scenario studies about The Netherlands: Scenarios for the Dutch Electricity Supply System (SDESS) by Frontier Economics commissioned by the minister of Economic Affairs [64], and 'Nationale Energieverkenning 2016' (NEV) by major governmental related organisations (Energie Centrum Nederland (ECN), Centraal Bureau voor de Statistiek (CBS) and Plan Bureau voor de Leefomgeving (PBL) [65]).

The comparison of our model results with mentioned conventional scenario studies shows that results from these studies are in the range of our results. Although these conventional modelling studies show sensitivity analyses in their reports, a notable difference is the large bandwidth of possible pathways in our results.

The average electricity price in Fig. 5 shows the effect of the penetration of renewable power generation on the average electricity prices over the year. Because renewable assets have near-zero SRMC they decrease the electricity price on average. The increased carbon price however increases the price of electricity from fossil assets. Therefore, with variable supply by renewables, electricity price decrease when renewables produce and increase the price when they don't produce. The combined effect makes electricity prices more volatile during the year. With further penetration of renewables between 2040 and 2060, the decreasing effect becomes stronger than the effect of the carbon price and therefore electricity prices on average go down.

If we define the price volatility as the difference between the minimum and maximum electricity price over the period and compare the price volatility in this study with the SSDES study, the bottom graph in Fig. 5 shows that this price volatility increases with the penetration of renewable power. (The price volatility in the NEV- scenario study is not publicly available). These results are in line with conventional scenario studies, although with our ABM-approach we can show the bandwidth of possible pathways.

4.2.2. Heterogeneity of investors

To explore the effect of heterogeneity of investors on our model results in Fig. 6 the effect of this heterogeneity on the development of the electricity mix is depicted. While in model runs that are depicted in the right graph all investors have a discount rate of 10%,

Table 3
List of acronyms and symbols.

Acronym	Full form
ABM	Agent-based Modelling
BC	Base case
$C(t)$	Cost of renewable asset at time t
C_0	Cost of renewable asset at initialisation
CAS	Complex adaptive systems
CBS	Centraal Bureau voor de Statistiek
D	Demand
$e(t)$	Excess capacity factor
EU-ETS	European Union Emissions Trading System
$G_i(t)$	Potential power generation of asset i at time t
GW_p	GigaWatt-peak
l	Learning rate
n	Number of renewable power generation assets
NEV	Nationale Energieverkenning
NPV	Net Present Value
ODD protocol	Overview, Design concepts, and Details protocol
OECD	Organisation for Economic Co-operation and Development
OPEX	Operating Expenditures
PBL	Plan Bureau voor de Leefomgeving
p_i	Profitability of asset with resource i
P_i	Price of resource i
PV	Photovoltaic
$S(t)$	Scarcity rent at time t
SDESS	Scenarios for the Dutch Electricity Supply System
S_{max}	Maximum scarcity rent
S_{min}	Minimum scarcity rent
SRMC	Short Run Marginal Costs
VOLL	Value of lost load
α	Scarcity rent variable

Table 2
Comparison of scenarios of the Dutch Electricity system: Scenarios for the Dutch electricity supply system (SDESS), 'Nationale Energieverkenning 2016' (NEV) and Current model – Increased carbon price.

	SDESS			NEV 2016			Current model – Base case		
	Carbon	Renewable	Renewable	Carbon price (€/tonneCO_2)	Renewable	Renewable production (%)	Carbon price (€/tonneCO_2)	Renewable	Renewable
	Price (€/tonneCO_2)	Capacity (GW)	Production (%)		Capacity (GW)			Capacity (GW)	Production (%)
2015	7	4	9	8	7	9	6	0 - 19 [9.4]	0–27 [12,5]
2020	10	16	28	11	12	27	16	0–31.5 [16]	0–67,5 [37,5]
2030	20	23,5	44	26	30	47	30	0–43.8 [22.5]	0–67,5 [60]
2035	30	27	50	39	39	60	30	0 - 40 [24]	0–67,5 [60]
2050							30	15–52.5 [47.5]	85–90 [87,5]

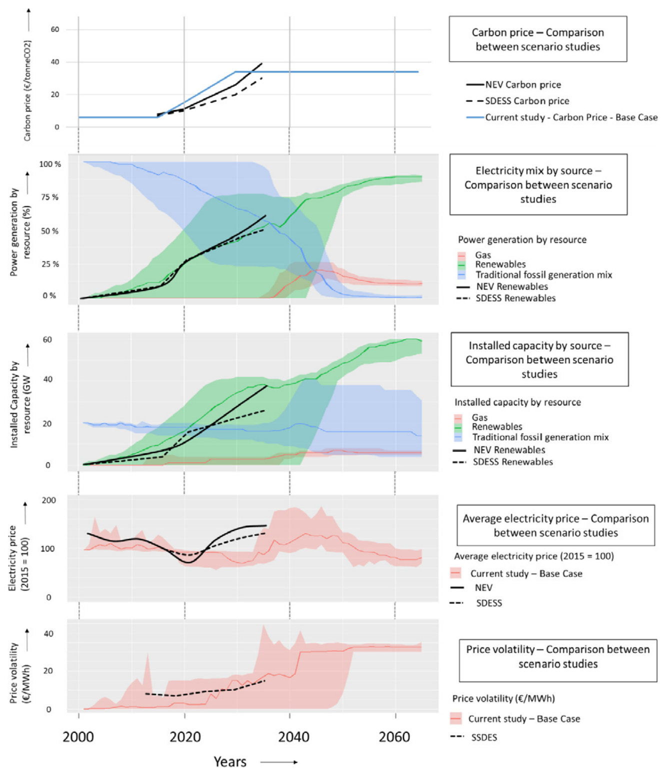

Fig. 5. Comparison between current study and two other scenario studies, SDESS and NEV. Graphs depict Renewable power production percentage, Installed capacity, Average electricity prices, and Price volatility in the period 2000–2065. Price volatility is defined as the difference between maximum and minimum electricity prices in a year. Graphs show conventional scenario studies are in range of outcomes of our agent-based model but the current study shows large bandwidth of possible pathways.

in the right graph, investors have a heterogeneous discount rate with an uniform distribution between 4% and 20%. In both scenarios, the low carbon price scenario is used as depicted.

The left graph shows that the electricity mix stays constant over time if we assume homogeneous investors: with the given discount rate (at initialisation) and carbon price, investors will not invest in renewable or gas assets. The main difference in the outcome of the model runs is caused by the initialisation of the learning process. Because the learning process is initialised at different moments due to the heterogeneity of investors, different pathways are taken. If we exclude this heterogeneity, investors will make the same decisions and will basically behave as one.

4.2.3. Variability of renewable energy sources

To explore the effect of the variability of renewable energy sources in our model, we experimented with three electricity generation (load factor) patterns (based on empirical data [54–57]).

Three power generation patterns are tested: a scenario (i) with no variability and constant production, (ii) with solar variability patterns associated with only renewable solar assets and (iii) with a realistic combination of wind and solar assets (i.e. 70% wind and 30% solar).

Fig. 7 shows the development of the electricity mix with three different renewable power generation patterns. The left graph shows that renewable electricity is favourable over other sources if it would be able to produce constant over time since they are in front of the merit-order. The middle graphs show the development of the electricity mix if renewable assets would have a full intermittent load factor pattern. This would be the case if all renewable capacity would be supplied by solar assets, as their minimum power output goes to zero in winter. In this case fossil back-up power generation capacity is necessary to be able to fulfill demand. Therefore, a technical decarbonisation limit emerges. Whether this back-up power will be supplied by the traditional mix or by gas depends on the carbon price.

If, on the other hand, a mix between wind and solar assets is used, renewables (a mix between wind and solar assets) would show reduced variability which results in a higher emerging penetration limit as the right graph shows (our base case). This

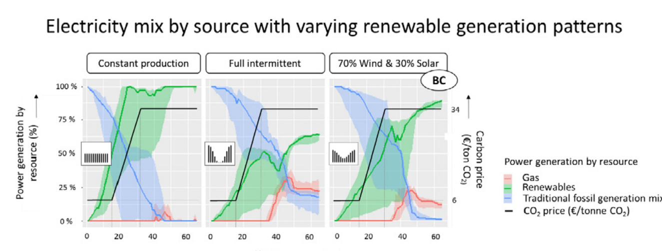

Fig. 7. Electricity mix with varying power generation from renewable generation. Left graph shows mix when renewables have no seasonal variability, middle graph shows mix when only renewable generation is only provided by solar (i.e. when electricity production is full intermittent), right graphs shows mix with realistic production pattern, our base case (BC). Small graphs indicate load-factor pattern.

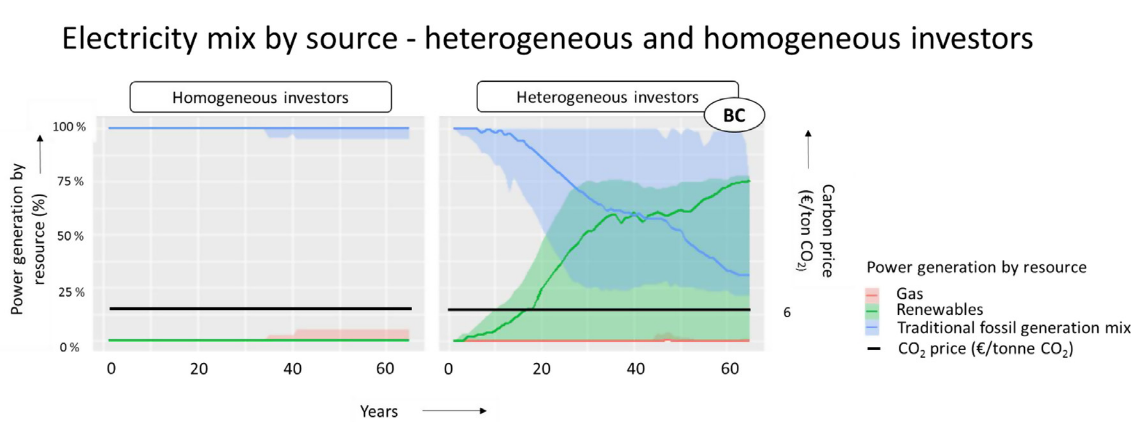

Fig. 6. The effect of heterogeneity of investors on the electricity mix. Left graph shows possible pathways with heterogeneous investors, while in the right graph all investors are initiated with the same discount rate.

however is not a ‘technical’ limit as production does not go to zero over the year.

4.2.4. Substantial cost decline of renewable power generation assets

Steep learning curves of renewable assets in the last decades, has had a large influence on the development of the electricity system. In Section 4.2.3 we saw that the fact that production does not go to zero over the year suggests that renewable power generation could supply full demand when enough renewable capacity is build. Therefore, we tested if a full renewable system can emerge if we assume that renewable power generation technology will continue to decrease in price.

Fig. 8 shows three renewable power generation costs curves with three different stabilisation levels, 1 €/W (our base case); 0.75 €/W and 0.25 €/W, which are based on empirical data and scenario studies [1,56].

Fig. 9 shows that with substantial further cost reduction of renewable assets, the penetration of renewable electricity mix can be increased. The left-hand graph shows that even a full renewable electricity mix can emerge when costs are reduced sufficiently. This would however require a substantial renewable capacity installment of ±6.5 times the peak load incorporating the load factor pattern of our base case

4.2.5. Profitability of investors

The effect of this penetration of renewable power generation on the profitability of investors is shown in Fig. 10. The figure shows the average discount rate of investors in the model in 30 model runs with different linear increasing carbon price scenarios. What we see is that increasing the carbon price gradient beyond the technical limit, increases the profitability of investors on average.

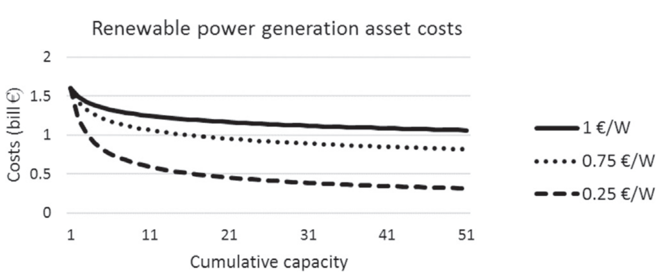

Fig. 8. Three scenarios for the cost development of a renewable power generation asset with a one GW name-plate capacity.

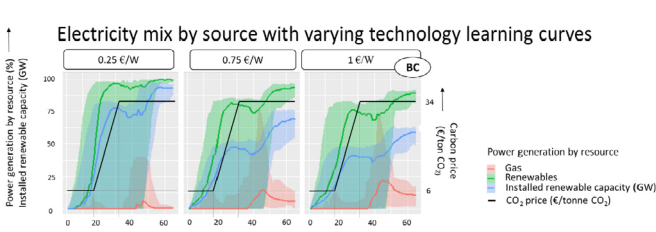

Fig. 9. Electricity mix by source with varying technology learning curves. The right graphs show our base case (BC). If, due to technological learning, the investment size of renewable power generation assets decreases substantially, they would be able to supply 100% of power demand. This would require substantial investment in renewable power generation capacity as depicted (in blue).

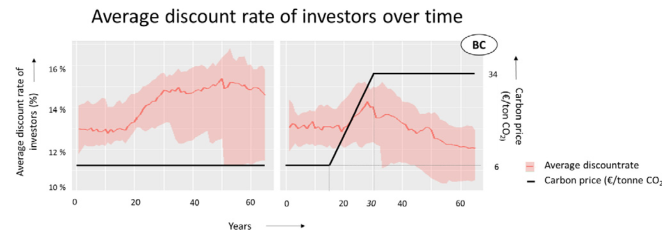

Fig. 10. shows the average discount rate of investors in the model in 30 model runs with different linear increasing carbon price scenarios. What we see is that increasing the carbon price gradient beyond the technical limit, increases the profitability of investors on average.

5. 5validation and discussion on model results

5.1. Qualitative validation

With our conceptual, simple model we have simulated the development of the electricity mix in the period 2000 till 2065. Because of the high-level, abstract nature of our approach, validation of the model is qualitative and semi-quantitative. We validated our model against the developments in the Netherlands electricity sector between 2000 and 2015.

This period saw an increase in electricity generation by wind and solar from less than 1% in 2000 to 8% 2015 [66], similar to the transition in other Northern Europe countries. Although we are aware that governmental incentives have influenced these developments we argue that we can relate model results to the following historical dynamics: (i) the increase of the share of coal in the electricity mix and gas fueled power stations being dismantled [15,67], (ii) on average decreasing electricity prices [68], (iii) increased electricity price volatility [8,47], and (iv) decrease of the profitability expressed by the Moody rating of large incumbent utilities [69]. Our investor-based model of the electricity sector was able to reproduce these trends as reported in the literature (e.g. Refs. [70,71]).

5.2. Discussion on first phase dynamics

A well-known development that we observed in the first phase, which we define here as the phase till approximately 10% of renewables in the energy mix, is the merit-order effect [39,72,73]. When coal is cheaper than gas, it will go in front of gas in the merit order which leads to coal assets being profitable and gas assets ultimately being dismantled. The introduction of renewables reinforces this development in two ways; more capacity is added leading to overcapacity, and renewables capacity has a low SRMC and therefore pushes gas assets further up the merit order [40,73,74]. This development causes electricity prices to fall, and volatility to increase. Furthermore, we saw that in the first phase of the transition where renewables enter the market, profitability of existing assets decrease. This caused profitability of incumbent investors to decreases and their discount rate to increase which relates to their Moody ranking.

5.3. Discussion on later phase dynamics

Developments that emerge in our model in later phases (in systems with more than 10% renewables in the electricity mix) of the transition lead us to the following observations:

The end-point of the transition is fully determined by the renewable resource. In the absence of storage, the transition is *necessarily* incomplete as fossil back-up remains needed; a renewable penetration limit of ±87% emerges under the assumption that renewable assets consist of a mix between wind and solar power generation (Section 4.2.1). This penetration depth of renewables is correlated with the variability of their generation pattern and by the 'ultimate' cost level of renewables. Only with low or moderate seasonal intermittency (typical of wind) and *very* low cost (more typical of future PV) do renewables without fossil back-up or storage reach 100% penetration, but then only at the expense of significant curtailment.

Market incentives are inept tools for outcome-based policy. While conventional modelling methods show a limited number of possible pathways, our results show that incorporating more realistic investor behaviour results in a large bandwidth of possible outcomes. Therefore, caution should be taken in interpreting conventional techno-economic analyses as we have shown that incorporating heterogeneity and bounded rational behaviour of investors has a large influence on the probability distribution of outcomes (Section 4.2.2.). In the current market design, the mere setting of a carbon price will not always result in delivering on decarbonisation goals, to which governments have signed up. Therefore, we conclude that outcome-based policy cannot be solely based on market instruments that rely on perfect rational and perfectly informed agents.

Only with a very large cost decrease of renewable power generation can the electricity system be fully decarbonised and this is only possible with very high overcapacity. Full decarbonisation is possible if a mix between wind and solar assets is used but that would require substantial investment in (over)capacity of renewable power generation assets which is only attractive for investors if the investment size for renewable assets is substantially decreased (Section 4.2.2. and Section 4.2.4.).

The profitability for investors increases with the carbon price. This is a new and non-intuitive result which we attribute to the effect of the carbon price on the electricity price and infra-marginal rents investors receive. It follows logically from the reasoning that if we increase the carbon price, electricity prices increase in periods were fossil generations set the price. Therefore, infra-marginal rents increase and profitability of non-marginal producers increase (Section 4.2.1).

Energy-only markets become increasingly volatile. The implementation of energy-only markets requires political courage to allow price spike to occur to ensure enough investments are made. Such volatility increases with renewables penetration, making the market system – while theoretically 'efficient' – increasingly unappealing to electricity consumers – both corporate and private; a further reason why liberalized, energy-only markets are unattractive to policy makers and politicians.

Scarcity rent is not a technology neutral mechanism. Because only fossil assets are dispatchable they can use market power to supply demand when supply is scarce. As renewables power generation is non-dispatchable, it cannot use this market power and therefore the scarcity rent is not technology neutral mechanism.

5.4. Discussion on conceptualisation of decision making process

The conceptualisation of the decision-making process in an agent-based model is key. For this conceptualisation we have deliberately followed a keep-it-simple approach. For now (i.e. the present paper) that meant taking the long-term view (expressed by their heterogeneous discount rate) as sole differentiator between investors; the discount rate is the numeric pars pro toto of the investor's long-term outlook.

We realise full well that investor behaviour is more complex and that a vast variety of factors contribute to the investor's appetite for new investment [29,74]. We could think of factors such as preference for types of assets, previous experiences (i.e. company history), outlook for governmental intervention, risk appetite amongst others.

However, we argue that our simplification is justified, given the purpose of our model, since these factors would be impossible to quantify and extremely uncertain, even more so if we look at investment decisions decades from now. Therefore, we have decided not to do so, and solely refer to their long-term view with which we incorporate the mentioned factors.

5.5. Comparison to literature

The field of electricity market modelling is an active and fast-growing field of research. In Section 4 we showed how our results compare with influential conventional scenario studies. In general, there is lively discussion on the role of government and markets in the design of electricity markets [6,8,10,18,35,37,40,71,77]. What we argue here is that increasing reality in electricity market models (with agent behaviour), has implications for scenario studies and market design.

Some of these issues have been raised in earlier agent-based model studies. Increased volatility is a well-known phenomenon which has been reported earlier (e.g. Refs. [74–76]). Our result that profitability of investors increases with carbon prices has been reported once before but in a different context, i.e. carbon-trading [77].

Moreover, to our knowledge and based on a review of previous literature, there has been no other modelling effort that incorporated the endogenous investment in renewable generation and learning curve dynamics. Secondly, although market power has been analysed previously [7], this study goes further in analysing the effect of market power in energy-only markets.

To summarise, we would argue that within this complex field of research this modelling study has shown a novel conceptualisation which resulted in conclusions that could be supported with a comparatively simple and transparent approach.

6. Conclusion

We have shown that an agent-based model of investor behaviour is able to simulate the transition of the electricity system with only a very limited set of assumptions. The simulations bring out key challenges of the transition and link them back to the fundamental parameters of the technologies and investor behaviours. With this approach - which is transparent, tractable and reproducible - we have been able to simulate the influence of heterogeneous investors in the electricity market. This approach has shown great additional value to conventional techno-economic energy scenarios as it has given us a natural way to think about investors, their decision-making process and its effect on the system behaviour. In future research, we will extend this approach to include storage to resolve the intermittency problem.

Finally, we want to stress the importance of ABM in giving modellers a natural way to think about actors and actor behaviour. The great advantage of the 'keep-it-simple'-approach to agent-based model that we practiced in this paper is that it allows a wide range of stakeholders (not just scientist-modellers) to be actively engaged in the conceptualization of the model and in the discussion of its results. It thereby does full justice to the power of ABM, which is that modellers have a natural way to structure their thoughts about assumed agent behaviour, by allowing meaningful discussion of the agent assumptions with the agents or their representatives. This – we have found – is never a fully straightforward, one-way process but encourages stakeholder engagement throughout the process. In this way, ABM can give insights on problems related to complex adaptive systems such as the energy system as it gives us a tool to encompass essential features of these systems.

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