Environmental Modelling & Software 96 (2017) 421–431

Contents lists available at ScienceDirect

Environmental Modelling & Software

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

Simulating climate and energy policy with agent-based modelling: The Energy Modelling Laboratory (EMLab)

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ARTICLE INFO

Article history:
Received 29 November 2016
Received in revised form
12 July 2017
Accepted 13 July 2017
Available online 18 August 2017

Keywords:
Agent-based modelling
Energy transition
Energy and climate policy
Energy modelling laboratory
Investment

ABSTRACT

We present an approach to simulate climate and energy policy for the EU, using a flexible and modular agent-based modelling approach and a toolbox, called the Energy Modelling Laboratory (EMLab). The paper shortly reviews core challenges and approaches for modelling climate and energy policy in light of the energy transition. Afterwards, we present an agent-based model of investment in power generation that has addressed a variety of European energy policy questions. We describe the development of a flexible model core as well as modules on carbon and renewables policies, capacity mechanisms, investment behaviour and representation of intermittent renewables. We present an overview of modelling results, ongoing projects, a case study on current reforms of the EU ETS, and we show their relevance in the EU context.

1. Introduction

We face inherent uncertainties regarding how our energy infrastructures can be shaped towards our policy objectives of a sustainable, affordable and secure supply of energy. While policy objectives are becoming more ambitious and firm, i.e. the COP21 agreement in Paris, it is yet unclear what would constitute the best set of policies for an effective and efficient transition. We cannot just rely on targets and we cannot expect the market to act by itself (Stern, 2006). The question is how to intervene in the complex dynamics of our energy infrastructures (Chappin and Dijkema, 2015).

In this paper, we present an agent-based modelling approach for designing and evaluating energy and climate policy. We do so with modular approach aiming to represent much detail of European electricity systems (cf. a complicated model as described in (Sun et al., 2016)). Therefore, the core objective of this paper is to illustrate how agent-based modelling can support energy and climate policy analysis. We focus on our model of the decarbonisation of the power sector, in particular on how energy and climate policy affects investment in electricity generation. The effects of policies, such as the European emissions trading scheme (Zhang et al., 2011), are core to the analysis. The Energy Modelling Laboratory (EMLab) was developed to complement existing approaches in analysing policies for improving the EU emissions-trading scheme (EU ETS). This includes national CO_2 price restrictions, the interaction of the EU ETS with national renewables policies and policy schemes for maintaining security of electricity supply under large scale renewables deployment. At the end of the day, we aim to contribute to the methodological question of how to model the impacts of interventions in complex dynamic systems.

The decarbonisation of the power sector requires large investments. These investments are risky: they are capital intensive, the regulatory framework is in flux and the costs of resources such as fuel and CO_2 are uncertain. The long lead times of investments (due to permitting and construction times) and the long life cycles of power sector assets create a delayed response and a physical path dependence. As a result, the power system is never in a long-term economic equilibrium. Imperfect behaviour of actors, such as investor and consumer risk aversion complicates the sector

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http://dx.doi.org/10.1016/j.envsoft.2017.07.009
1364-8152/

dynamics. Policy instruments may affect the objectives of other instruments; for example, renewable energy support affects generation adequacy as well as CO_2 policy. These instruments may also create spill-over effects into adjacent markets with which electricity is exchanged, e.g. in the form of cheap exports and/or price volatility.

These factors need to be modelled in order to analyse the expected effectiveness of policy interventions. A policy that is aimed at stabilizing the system such as a capacity market or the Market Stability Reserve in the European Emission Trade System cannot be modelled with an equilibrium model. Such a model would assume the problem away, rendering an intervention by definition useless. Compound effects of multiple instruments, risk aversion of actors, physical path dependence and cross-border effects are also difficult to model with conventional models. Agent-based modelling can handle these aspects more easily. In this paper, focus on how to design an ABM that is suited for answering these types of questions.

The structure of this paper is as follows: we illustrate the modelling questions that matter for the energy transition and outline the complementarity of agent-based modelling to current approaches (section 2), we describe the modelling laboratory (section 3), the main research projects and results were obtained with using it (section 4), supported by a case study about the improved proposal for the Market Stability Reserve (section 5) and end with conclusions (section 6).

2. Modelling policies for the energy transition: existing approaches, challenges and the need for an agent-based toolbox

Currently the policy objective in Europe is to decarbonize the electricity sector in the next decades. In this section, we highlight the challenges for energy and climate policy modelling, we introduce three dimensions to analyse existing modelling approaches, we shortly review the existing approaches and the need for an agent-based toolbox. We start from the desire to explore what the likely consequences are of (proposed) energy and climate policies with respect to achieving the policy objective(s) of energy saving, renewables and CO_2 reduction. At the same time the energy and climate goals shall be in line with preserving affordability and security of energy supply. Numerous climate and energy policy instruments are needed to drive these radical changes; the most important climate policy in Europe is the EU emissions-trading scheme (EU ETS). The ongoing efforts to improve the performance of the EU ETS (Richstein, 2015), and the debate around the German ‘Energiewende’ (Buchan, 2012) illustrate the huge challenge of getting the ‘right’ policies in place for achieving the said objectives.

2.1. The need for policy modelling

For the case of climate and energy policy, it is difficult to determine without modelling what the side effects of policies are, because of the following sources of complexities in the system:

- **Cross-policy effects.** The performance of various policies may be affected because they interact with others, for instance renewables policies interact with decarbonisation policies, because renewables are also options that reduce carbon emissions.
- **Cross-border effects.** The various physical infrastructures and markets of European countries are linked, which means that cross-border effects of neighbouring countries may influence policies in place and should be considered.
- **Imperfect foresight.** Substantial reductions in CO_2 emissions need to be achieved by investments in low carbon technologies. Investments are made by heterogeneous actors, each deciding on the basis of their own preferences, on the basis of interactions with others, on the basis of their own belief system of the policies in place. Decisions to reduce energy consumption or invest in low carbon technologies are, therefore, not based on perfect forecasts and only financial reasons.
- **Lumpiness of investment.** Furthermore, investment decisions are highly capital intensive, so each individual decision matters: any investment made influences additional opportunities to invest.
- **Differences in actor behaviour.** In reality, significant differences exist between actors with respect to their preferences and assets (Groot et al., 2013). These differences affect their investment decisions.
- **Path dependence.** Climate and energy policies essentially target long-term changes in large-scale systems. All effects that play out dynamically over time need to be taken into account in order to have a realistic analysis of any of the policies. Over the course of decades, unwanted side effects may emerge out of the decisions made over time. In the long run, path dependency creates lock-in effects (Chappin and Dijkema, 2015), which, in turn, could make the energy transition costly and slow.

In order to explore the possible effects of energy and climate policies, these complexities need to be somehow explored.

2.2. Framework for energy policy modelling traditions

Modelling traditions differ with respect to the methodology and logic with which they evaluate policy instruments. We distinguish the approaches among the three dimensions in Fig. 1: how models deal with time (x-axis) because of the strong path dependence of investments, how they deal with scope (y-axis) because decarbonisation involves strong interdependencies between different subsystems and depends on many factors, and how they deal with uncertainty (z-axis) because large investments are strongly dependent on uncertain future developments.

With respect to the **time horizon and resolution**, some models are used to study today's energy systems and evaluate their dynamics with a focus on short time scales. These models thus focus on how to get the energy transition going, rather than the structural changes that need to follow along the way. For instance, what can we expect from the CO_2 price in the near future and what investment incentive for low carbon technologies can we expect. This can lead, for instance to an estimation of the need for or the cost of a policy instrument in the short to medium term. Models those are strong at representing todays energy systems often have a high resolution, and contain a large amount of data, which limits their scope to the short and medium term.

At the other end, modelling studies can simulate a possible future end-state of an energy system. These essentially are similar to the short and medium time scale questions, but placed in the future. Simulations include technological choices under ideal, minimal societal cost conditions and determine the technological composition of the energy system in a particular future year. This results in visions on the energy mix in the next decades after the energy transition, and how a hypothetical energy system may function: what dynamics of the system can be expected, what electricity prices may be, how welfare may be distributed. It also allows a reference for parts of the system, such as the business case for energy storage, demand response, or grid expansion.

In between are the models that deal with energy transition pathways, which need to consider long-term dynamics. Typical are

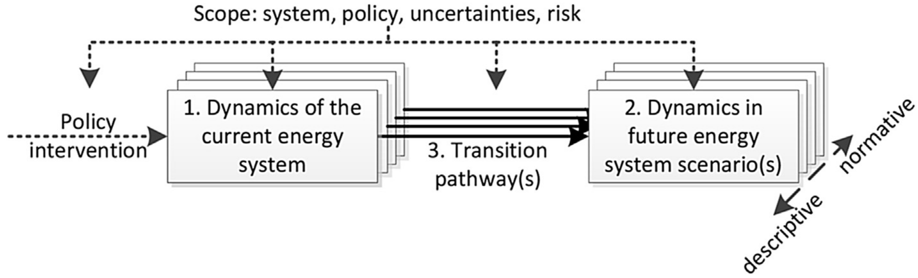

Fig. 1. A framework for energy policy modelling traditions. Questions vary in time, scope and uncertainty.

studies that include the search for the set of investments and actions that lead a particular energy transition vision. This gives insight into minimal or expected costs of the energy transition, it gives body to the pathway and the possibilities of achieving it. It also provides a baseline to compare real-world investments. These analyses may include an estimate of the policy consequences: for example shifts in the optimal pathway provoked by the interplay of subsidy and cost decrease of a technology. It also enables to implicitly estimate the costs for the policies. Some analyses with large models would also predict the effects on macro-economic parameters, such as jobs created.

An important consideration is which aspects are dominant determinants of the long-term dynamics. For a variety of questions time scales from hours (if not minutes) to years are relevant and this poses significant difficulties to simulate validly, because of computational limitations. An example of such a question is what could be expected of the business case of storage in combination to demand response.

Modelling questions vary widely in **scope**, in terms of the system and policy affected. A rather broad scope could be called 'modelling the system'. In general, the 'system' covered in the model should be large enough so all aspects crucial for the policy are covered, and no crucial interactions with elements outside of the system boundaries are lost. This implies that the physical electricity system, power generators, demand, the grid and the interfaces to other systems (demand sectors, natural environment) are included in the scope. It also suggests that the behaviour of the main actors (e.g. power producers and system operators) are covered.

Typically, a more focused scope is to 'model the problem'. If for instance the problem is how to maintain grid stability when more wind is implemented, all system elements needed (the infeed from more wind, the grid and demand) needs to be included in the system scope. Though focusing on the particulars of a problem reduces the scope, developing a specific model for *each* problem may be infeasible, in terms of time and resources. This is particular the case when problems become more intertwined.

Modelling the problem affects the system that needs to be represented. The other way around, how the system is modelled determines what kinds of policy interventions that can be modelled and how they can be assessed. Questions that aim to determine which policies would be needed to achieve a certain level of demand response, for instance, implicitly require the modelling of all actors offering demand response, i.e. small consumers and industrial sectors. If then we consider long-term dynamics, it means that a solid representation of these dynamics for those sectors becomes essential.

Various **types of uncertainties**, such as exogenous drivers and actor behaviour do not only affect the modelling outcomes, but also how the modelling questions are phrased. For instance, possible side effects of policies, such as the ones emerging from the heterogeneity of actors in their response to policy interventions, the consequences of imperfect forecasting such as 'pig cycles' can be essential to the question as to how to judge a particular policy. This means that the modelling question may be formulated according to those phenomena. This includes effects of inertia and lock-in, perceptions and habits of actors, and so on. These uncertainties point at the systemic risks for the energy transition. This also includes the risk of and need for capacity mechanisms and revised market models in a system with high levels of renewables.

The examples in Table 1 illustrates how to deal with uncertainties and risks, by varying the specificity of the modelling question. On the one hand there are rather specific questions that lead to particular outcomes. The examples show point-estimates of parameters at a particular point in the future. Though the result may have much detail, a disadvantage may be the limited validity: only under a strong set of assumptions the result is valid. It may also provide an extreme case and function as a reference. A broader perspective is embraced by questions that take into account some degree of uncertainty in the input and represent the potential consequences as ranges or distributions in the outcomes. Even broader are modelling questions strive for finding patterns in the outcomes, for instance finding the set of conditions under which a policy performs sufficiently. This provides insight into the robustness of the findings.

2.3. Current approaches to study energy and climate policy

Computational analysis is widely accepted as a tool for problems that can be solved by making accurate system predictions (Bankes, 2002). The dominant approach for climate and energy policy has been to use optimization and equilibrium techniques, predominantly the class of computational general equilibrium (CGE) models (cf., the review by (Capros et al., 2014)) for top-down analysis of economy wide effects, as well as partial-equilibrium models and techno-economic optimization models for more detailed bottom-

Table 1
Examples of specific and broader modelling questions.

Specific questions – specific outcomes	Broader questions – robust findings
What price for commodity electricity can we expect next year?	How are electricity prices in the Netherlands affected by German RES levels?
What is the expected cost of a feed-in tariff between 2020 and 2030 for transition pathway to 30% offshore wind?	How do regional renewable policies interact within and across borders?
What is the lowest-cost scenario in 2050 that meets the technical potentials?	How can investment risks be reduced in order to make the EU ETS more effective?

Table 2
Existing approaches to study energy and climate policy.

Axis	Computational general equilibrium	Partial equilibrium	Techno-economic energy system models
Time	Equilibrium (either static, recursive-dynamic, or dynamic)		Pathway or end-state (least-cost)
Scope	The economy as a whole with aggregates, and more details for particular sectors	Individual sector in detail	Individual sector with high technology detail
Uncertainty	Some uncertainties are included. Ignores uncertainties caused by system being out of equilibrium and the dynamics caused by policy uncertainty.		

up analysis of specific sectors. We describe these here according to the three axes defined above. The overview can be found in Table 2.

Computational general equilibrium (CGE) models describe the overall economy by using representative agents (described by equations that define equilibrium conditions, not algorithmic descriptions of their behaviour) that represent a number of sectors in a highly aggregated manner (one example being the GEM-E3 model, in some models specific sectors are described with a bit more detail (Capros et al., 2013)). They answer policy questions by determining an equilibrium that would happen for a particular set of policies and exogenous assumptions, where the policies are modelled close to the theory. Alternatively, they are used to produce insight in what policy (results) would be needed (e.g. degree of RES support) to achieve certain objectives, or even to identify an optimal policy mix. For cap-based policies, such as emission-trading systems or renewable-certificate trading schemes, a simple constraint is imposed, thus it is implicitly assumed that the policy in place would lead to that target in a cost-effective way. Depending on whether the equilibrium is obtained respectively for a single period (static), sequentially over several periods (where past periods influence future periods, recursive-dynamic) or a full equilibrium over all periods (fully dynamic), CGE models vary widely in their assumptions regarding future expectations. Only the full dynamic approach describes an optimal pathway for transitions.

Partial equilibrium models are similar to CGE models in that they are defined by stating equilibrium conditions for which a solver finds a (unique) solution. However, they are focussed on individual sectors, thus ignoring feedback loops to the overall economy, for example via income effects of households. Due to their limited scope they can incorporate greater technological detail, and more heterogeneous behavioural assumptions, for example limited banking capabilities of actors in the EU ETS (Schopp et al., 2015) or stochastic foresight of agents. As with CGE models, they will compute an optimal equilibrium (point or pathway, depending on whether the model is static or dynamic).

Techno-economic energy system models focus exclusively on the energy sector and model individual technologies in great detail. A pathway or final state of the energy system is computed via optimization, finding a least cost solution to provide a predefined amount of (end-)energy to society, and usually ignoring the effect of prices on demand. An example of such a model is OSeMOSYS (cf. (Howells et al., 2011)).

Despite the fact that some of these models include uncertainties and risks, they are not designed to adequately describe the system out of equilibrium. These typical approaches answer those policy questions that relate to what we may expect under the assumption that we are able to implement the proposed policies very effectively, i.e. with perfect foresight, risk-neutral investment, no regulatory uncertainty etc. However, if the model assumes that the policy target will be reached, it will not give you any reasons for it or conditions under which you would not reach it. Any relaxation of the assumption of optimality is left for the analysist, who then needs to, somehow, translate that into his policy advice. We see that interpretation as a crucial step in policy modelling, which is currently *not* at the heart of the approach.

These modelling approaches have in common that they tend to be *optimization* models. As a result, their outcomes should be interpreted in a normative way: they show how things (investment, policy choices) should be done, given certain assumptions and scenarios. As a consequence, these approaches tend to overlook side effects and the assumption of equilibrium ignores core dynamics − the process in which the equilibrium emerges remains black-box. While policies can be evaluated with traditional models using shocks, these shocks remain exogenous and do not endogenously develop out of the model itself: policies can thus not be endogenously investigated for their robustness to typical market movements, such as investment cycles, which are frequently observed in markets. This matters for policy design because a policy that is robust against movements away of the optimum/equilibrium is probably more effective in reality.

Emergent side effects or risks of policy proposals are, therefore, essentially beyond the scope of existing policy modelling. This includes possible policy risks, the consequences of uncertainties, the heterogeneity of actors, the interaction effects of policies that make them move away from the optimum. How can the real-world levers for the decision makers be identified and how he can minimize possible issues; what interventions can the decision maker use? All of these are beyond the scope of the modelling method (or what modellers with this method tend to include).

2.4. The need for an agent-based toolbox

Research now takes up the challenge of using non-predictive models for policymaking (Lempert, 2002). The objective of modelling and simulation changes towards the search for good arguments on the basis of computational experiments instead of the perfect predictions (Bankes, 2002). Models then change from determining optimal trajectories to exploring what-if questions regarding how the sector could respond to policy interventions. This counts also outside the optimum (Chappin, 2011), which is key for the many challenges in section 2.1. For this type of analysis, a *descriptive* approach is needed, one that does not assume optimal (investor) behaviour and that is not predicated on the assumption that the market is in equilibrium.

Agent-based models (ABMs) are a promising approach for policy support (Farmer and Foley, 2009) that can take up the challenges without relying on perfect predictions (Chappin, 2011). In contrast to more traditional approaches ABM captures the emergence of system level behaviour out of the individual behaviour of its actors (Chappin and Dijkema, 2015), which complements all existing approaches in section 2.3. As (Bankes, 2002) justifies, ABM can be used because of “(i) the unsuitability of competing modelling formalisms to address the problems of social science, (ii) agents as a natural ontology for many social problems, and (iii) emergence” (Bankes, 2002). The challenges for the energy transition, as mentioned above, essentially contain strong social aspects (heterogeneous actors, various types of decisions), for which ABM is suitable. “With ABM, it is possible to design irrational agents with incomplete information in relatively uncertain situations” (Ghorbani et al., 2014).

So far, the real impact of agent-based models is limited and this paper aims to further develop their potential. There are a number of important challenges to current ABMs. First, they are typically developed as one-offs, tailored to very specific problems, in contrast to the existing models, which have broader scope, (they 'model the system') and are reusable. As a consequence, the development process is rather slow and tedious. Gained insights are hard to translate to other problems. Second, although intuitive in nature, they are not easy to develop and the implications of ABMs are not easy to understand: they include more uncertainty and this needs to be represented in the outcomes. Third, since specifying individual agent behaviour lies at the core of the ABM process, and since specification of such behaviour maybe based on different theoretical or empirical foundations and a diverse practices specific to modelling tools, the models ultimately appear to be diverse, and lacking clearly validated conventions. This makes modelling choices for individual projects appear arbitrary. ABMs are criticized for the assumptions on which they rely; however, they allow the relaxation of certain structural assumptions regarding the optimality of actor behaviour that underlie optimization models. Fourth, ABMs make it possible to provide a rich analysis of the effects of uncertainty upon the long-term development of a system. This enriches the nature of the outcomes and insights presented. It also affects their relevance in the policy process, in which policy makers and politicians would like to rely on clear, tangible and intuitive judgements of policy proposals. With EMLab-Generation, we use agent-based modelling to provide insight in the expected long-term effects of policy interventions in a system in which heterogeneous decision-makers make key decision under uncertainty and develop this into an approach with various projects in the context of the energy transition.

3. The Energy Modelling Laboratory (EMLab) approach

In this section, the broad objectives of EMLab are outlined. The architectural framework of the model, AgentSpring, is introduced. Further, notions of time, scope, and uncertainty within modelling of the energy transition are translated into specific architectural and representational choices in the model.

In order to represent time in both the short and the long term, certain algorithms (e.g., electricity spot market clearing) apply to a short-term time scale, while other algorithms (e.g., investment in power plants) apply to longer time scale. Scope on the other hand is treated 1) with a combination of distinction between the data, and the core processes or the 'agent layer', and 2) with modularity between implemented policies. The distinction between data and 'agent layer' is explained in greater detail in section 3.2. The modularity between policies is described in section 3.3. Uncertainty is managed by two ways, one by incorporating randomness in the data sets, and conducting statistically sufficient repetitions during execution, and another by modularity. The modularity of the code is vital to allow for numerous configurations and consequently a thorough scenario analysis. Thereby, it aids robustness of the results. This is also described in section 3.3.

3.1. The long-term development of the power sector

The EMLab-Generation model describes the impact of policy instruments on investment in the electricity sector in the EU. Therefore it focuses on the long-term development. At the same time, short-term dynamics are also included, as they affect investment decisions. Energy companies base their investments on their individual imperfect forecasts. For investments, interacting policies matter, as do cross-border effects. We aim to support the exploration of policy proposals and policy improvements.

The contribution of this ABM toolbox can be found in evaluating policies on the basis of their effects emerging out of the interactions of investors, each with their own portfolio of assets, information and investment profile.

3.2. The agent spring framework

Fig. 2 summarizes the EMLab framework in three layers. The framework was developed with and alongside the AgentSpring agent-based modelling framework (Chmieliauskas et al., 2012; De Vries et al., 2013), and makes use of it.

The top layer is the **engine layer**, which contains a variety of user interfaces and contains the simulation controller. Three *user interfaces* are implemented: a web-based user interface in which model runs can be observed, an interface to run the model from R statistical computing, and a command-line interface for running the model in batch runs, for instance on high performance clusters. The user interface taps into the database of the model and allows for developing custom views while the model is running. The R interface allows running of specific analyses directly during a model run. The command line interface allows for capturing any data from the model for multi-run analysis.

All user interfaces tap into the *simulation controller*, which is the model application that actually runs. It implements features to handle all user interventions coming from the interfaces, i.e. to initiate particular scenarios and to start and stop the simulation.

The middle layer is the **data layer**, which contains the system state and possible configurations of the model. The domain language is implemented as a Java class structure with object classes and their properties. These properties may be other objects, which creates an object graph. This is reflected in a *graph database* that is configured to capture the objects in the simulation. The complete system state is contained in this graph database, which uses nodes and edges and properties to store the data in the system. The object

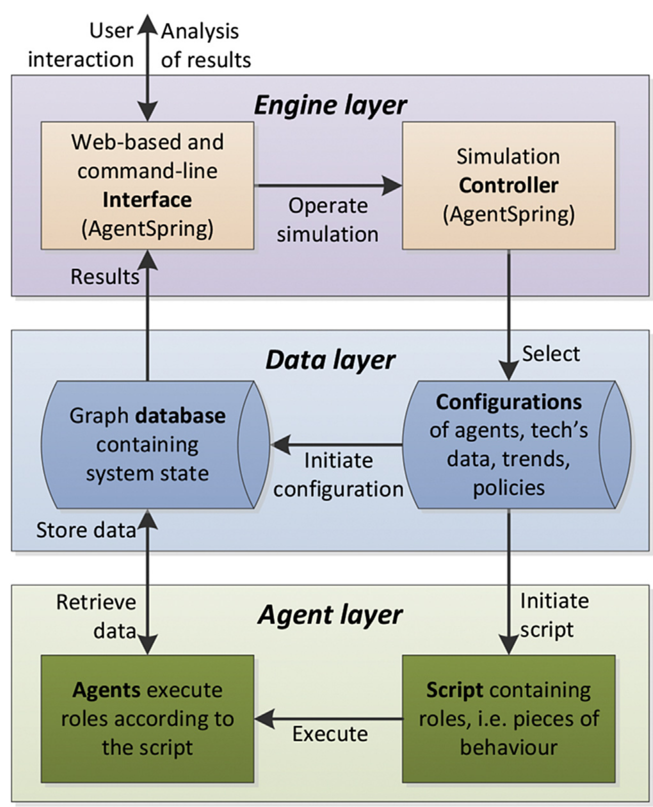

Fig. 2. Energy Modelling Laboratory overview.

types (including agents) are reflected as nodes in the database and all links between objects become edges (according to the relations defined in the Java class structure). This means that graph data depends on the actual agents and other objects in the model and allows for semantic queries. Different query languages can be used to write the agent behaviour. The graph database also provides the link between to all user interfaces during the simulation.

In addition to the database, the data layer contains customizable *configurations* using XML files, which includes all data needed to initialize the model: which agents are there, which decision mode do they use (if multiple options exist), the definitions of technologies (efficiencies and learning curves), how exogenous trends are defined (data in CSV files, or geometric trends), policy options and detailed policy choices. At the model start, the engine uses a selected XML file to initialize the model run and populate the database.

The lower layer is the **agent layer** that contains the coded agent behaviour, called *Roles,* coded in Java classes. Particular to EMLab is the fact that agent behaviour is split up in parts, i.e. that an agent can have various Roles for different aspects of his behaviour (e.g. one for doing investments, one for bidding in the market, and one for paying for fuels), which makes the model as a whole modular and flexible. When agents execute a role, they query the graph database to retrieve information regarding the system state, 'do' something (a calculation, make a change) and save the result back to the database, which finishes the role. Roles can initiate others, and, as such, they form the *script* of the model. Typically, the script is worked through, finishing one simulation tick. Composing the scripts provides for modularity, where pieces can be combined, as desired and different alternative implementations for similar functionalities may co-exist in the code base.

In addition to these layers, the framework includes code developing practices such as revision control, branching and merging on GitHub. The code is open access in order to allow for collaboration and retracing all assumptions and extend the model in various modelling projects.

3.3. Model description: model core, agents and configurations

This paper focuses on the EMLab-Generation model, which makes use of this framework and is built up out of the following elements:

- There is a core of behavioural roles that was developed as a starting point and forms the basis for all modelling projects. This core is conceptualized with care to be efficient and enable various directions for development. The core model is specific enough to capture the short-term processes in the electricity sector, such as market clearing and dispatch and the long-term processes of the electricity sector, investment and dismantling.
- A collection of modules that extend this core to make it applicable for particular modelling questions. Mostly this means additional behaviour that captures the response to particular policy proposals.
- A number of data sets and scenarios connected to the model core and to the modules.
- The system state, including the 'objects' in the system, in particular the power plants, are affected by the operation of the core module in each iteration, and, if applicable, the policies present.
- Different representations of the core modules can also be implemented and tested.

This section contains an excerpt from the full model description, which is published elsewhere (Richstein, 2015; De Vries et al., 2013). We will first describe the model core, the data used and the agents represented and their behaviour. Afterwards we describe the various modules and configurations that were developed in the project, and their findings.

3.3.1. The model core

We describe the main model core (see Table 3). The **electricity sector** in EMLab-Generation is conceptualized as (one or) two interconnected electricity markets and a common CO_2 market. The electricity markets are effectively price zones, and the markets are cleared via market splitting. Each zone can represent either a country or a set of countries that each have one electricity price at a time. The choice to have two interconnected markets is that it is the simplest system that allows for exploration of policy difference between countries or regions that are interconnected but where the interconnection is limited. The effects of policy differences are crucial for understanding contributing to the energy policy debate in the EU that is primarily composed of different policies in the various EU member states, but with shared policy goals. There is a common CO_2 market that represents the EU ETS, scaled down to the electricity sector (so other sectors are excluded). The most important elements in the model are the electricity markets, the energy producer agents and the power plants.

Developments in fuel prices and demand are modelled as exogenous stochastic trends, with a time step of one-year length and a horizon until 2030 or 2050. The choice to have a yearly time step is necessary to limit run time. Additionally, this is in line with the focus on investment in power generation capacity, which is a long-term process. Nevertheless, some aspects within a year are represented, primarily to provide input to investment decisions. Electricity load is approximated via a load duration curve, which is

Table 3
The modelling choices and assumptions in the model core.

Component	Core modelling choices and assumptions
Time	ABM with a yearly time step, using a segmented load duration curve, which is based on ENTSOE data. Model choices focus on how they fit the long term processes in the model, in particular investment.
Electricity sector	Two price regions are modelled as a power pool, governed by emissions-trading system. Electricity spot markets and ETS are assumed to be in equilibrium. The two price zones typically represent Central Western Europe (CWE, consisting of Belgium, France, Germany, Luxembourg and the Netherlands) and Great Britain (GB). Other configurations are possible and data has been collected for all these combinations.
Investment	Agents have different portfolios of assets. They invest based on NPV estimates in target year, which differs between agents (mostly by varying interest rates and forecasting horizons). Dismantling based on age and being out of the money.
Operation	Includes consumption of fuels and maintenance.
Exogenous variables	Fuel prices are based on triangular distributions for lignite, biomass and uranium (Richstein et al., 2014). Hard coal and gas prices are correlated stochastic Ornstein-Uhlenbeck processes (Richstein et al., 2014), based on data from UK Department of Energy and Climate Change (Department of Energy and Climate Change, 2012).
Technologies	Power plant technology data is based on the World Energy Outlook 2011 New Policies Scenario (IEA, 2011) and additional assumptions (Richstein et al., 2014).

segmented in a reasonable number of load levels that represent the different hours of the year, each with their corresponding demand.

Each year, the **energy producer agents** submit bids to the electricity markets based on the fuel mix and efficiency of power plants and a mark-up representing their market power. They also pay for maintenance and loans, and dispatch their power plants based on what they sold on the electricity market. Energy producers invest endogenously in new generation capacity, based on bottom-up forecasts of the net present value (NPV) for each generation type. The NPV is determined for a reference year, varying between agents from 6 to 8 years ahead. NPVs are determined on the basis of a merit order analysis, using regressions for fuel prices, demand and CO_2 price. Investors take turns and investments are reflected in subsequent NPV calculations of other agents. When no energy producer is willing to invest any more the investment rounds are stopped. The agents also decide on dismantling old plants that have passed their technical lifetime or that have not returned an operational profit for several years.

The **electricity spot market** clears the joint electricity and CO_2 market, including modelling the joint banking behaviour of the energy producers in the CO_2 market. As modelled, it forms the bridge between equilibrium-style modelling and agent-based modelling, assuming that the short-term actions provide equilibrium in electricity and CO_2 prices within the year. The choice to do this is to represent the processes within the year, but not focus on it. We come to reasonable electricity and CO_2 prices that are input to the rest of the model. The process works by merging the two electricity spot markets into one, and clearing them for all segments of the load duration curve. For each of the segments, it is checked wither the existing interconnected capacity is not exceeded. If that is the case, the market is considered as cleared. Otherwise the two markets are cleared separately with the market loads adjusted by the interconnector capacity and, as a result, price differences between the markets. This clearing of the electricity markets is nested in an iterative price search for a CO_2 emissions price that clears the CO_2 market. The price search is done when the CO_2 cap is just met for the emissions in the current year and for expected emissions in the next three years, as well as fulfilling the hedging strategy of energy producers (which is to bank 80%, 50% and 20% of expected emissions in the coming three years ahead, respectively with some flexibility to deviate from these goals).

The **other processes** in the model are implemented by other agents. The fuels are sold to the energy producers by commodity suppliers and the electricity is purchased by an energy consumer. Power plants can be purchased from the power plant manufacturer and maintenance is done by the power plant maintainer. Energy producers get loans from the bank. Each of these agents is relatively simple, but enable areas for expanding the model.

3.3.2. Software availability

The agent-based model and underlying framework are developed by TU Delft (the authors of this paper) and are Java applications. Both are open source and available on GitHub under https://github.com/EMLab/emlab-generation. This includes running instructions (which makes use of maven) and all data used for the papers published with the model. This paper does not present new model runs, but it presents the overall framework and a synthesis of earlier modelling results and conclusions. This means no new data was added to the GitHub repository particularly for this paper. All versions and extensions are available on GitHub and references in other papers describing individual modelling results.

4. Results

This section pertains to the question of how EMLab can support energy and climate policy analysis. It includes therefore, a list of research questions that have been tackled and answered using this approach, with detailed explanations of three specific projects, and the limitations of the approach in each project.

The model has been used in various projects, using and expanding on the model core, which are summarized in Table 4. This indicates that developing larger models is indeed a team effort. The findings have been presented in one PhD thesis (2 more ongoing), various journal and conference articles and a series of MSc thesis reports. Describing all results is beyond the breadth of this paper, but the overall projects structure and key highlights — both in terms of content and the approach taken — are provided in the following table.

4.1. Improving the EU ETS requires price stability

The first module is on the workings of the EU ETS and various improvements to the current design and the links with renewables policies, which in Europe are implemented on the country level. In general, the main pitfall of the EU ETS is that price stability is required for proper investment. At the same time prices are sensitive to allocation schemes, developments in demand and other policies. For instance, regional renewables policies tend to introduce more CO_2 price volatility. Interactions between the different (renewables and carbon) policies are not intuitive. Delays in price stability may well trigger long delays in investment, longer than socially optimal — it is a system that remains out of equilibrium for a long time. In particular, we evaluated the Market Stability Reserve in the form of the original proposal by the EU commission and the refined form. This is the topic of the case study in section 5.

In addition, some effects that differences between countries cause were explored. With two price zones — essentially two electricity markets and two different policy designs — we already showed what dramatic long-term consequences may be expected - a CO_2 price floor in a smaller set of countries may have a long-term destabilizing effect on the prices in Europe (Richstein et al., 2014). These effects do not emerge in theory or in many model studies, as it is typically assumed investors would be able to accommodate for these future developments in their plans. But when they are not fully able to do so, the side effects of a policy proposal that aims to stabilize prices may actually lead to the opposite.

4.2. Capacity mechanisms functioning in a dynamic context

The second module deals with security of supply policies. In various projects the effects of a capacity market, a strategic reserve and an increase in interconnection have been evaluated under different conditions, such as high penetration levels of renewables. In this module, it is vital that policies can be enabled and disabled at will, in order to provide for experimentation with different sets of policies. Some of these are developed in this module, some in others. The merits of various capacity mechanisms that aim to improve security of supply (by providing for sufficient capacity) are determined. This is done in particular in the context where multiple countries have different security of supply policy, where we include the long term dynamics in a system that is undergoing transition and where we explore them under varying levels of intermittent renewables. One capacity mechanism is a strategic reserve, where the system operator contracts some of the capacity to remain in reserve. Contracting a strategic reserve when sized according to theory does not necessary succeed in attracting sufficient investment when investment decisions are imperfect. Also, a high share of intermittent renewable generation would likely require a redesign or replacement.

An alternative is a capacity market, where the operator has a

Table 4
The projects using the model, main assumptions and usage.

Module	Modelled additions	Configurations	Projects
Carbon and renewables policies	Hedging demand of power generators Investor meeting governments renewable targets	Two price zones, CWE & GB	Evaluating minimum and maximum prices on CO_2 auction, either in one price region or both (Richstein et al., 2014) Testing EU ETS Market Stability Reserve (Richstein et al., 2015a) Adjusting the CO2 cap for subsidized renewables (Richstein et al., 2015b)
	Renewable tender system		Harmonized tenders for renewables (De Jeu, 2015)
Security of supply policies	Capacity market A CO_2 tax	Single price zone modelled after the Netherlands	Capacity market under dynamic conditions, with and without renewable target (Iychettira, 2013; Bhagwat et al., 2014)
	Energy storage	Two price zones, CWE & GB	Capacity market under dynamic conditions, with penetrating renewables, and interconnection (Swager, 2014)
		Single price zone modelled after the Netherlands	Influence of a capacity market on energy storage (Kerckhoffs, 2015)
	Strategic reserve	Single price zone modelled after the Netherlands	Strategic reserve under penetrating renewables (Bhagwat et al., 2016)
	Hydropower Investment in interconnection	Two price zones, Scandinavia & North-Western Europe	The development of interconnection capacity between and the stimulation of renewable energy (Veldman, 2014)
Investment models	Alternative investment models, including various risks, technology preferences, credit-risk considerations and risk-averse behaviour	Single price zone, modelled after the Germany or CWE	Potential effects of risk aversion on technology choices and security of supply (Gielis, 2016) Including various uncertainties in the investment (Nebel, 2015) Including hard and soft factors for investments (Verweij, 2013)
	Local opposition Permitting process	Single price zone modelled after the Netherlands	Impact of power plant location decisions (Paling, 2013)
Improved representation of intermittency	Load duration curve based on regional hourly production of renewables	Single price zone modelled after the Netherlands	Questions related to the role of energy storage, the role of the market at high penetration levels of renewables (Chappin et al., 2012; Soukop et al., 2015)
	Short term optimization model	Single price zone modelled after the Netherlands	Development of an hourly dispatch and operational model using optimization (on-going)

demand and willingness to pay for generators having capacity provided. The system to trade in capacity is difficult to setup properly. Nevertheless, it does not show the difficulty in dealing with growing renewables. It does suppress investment in neighbouring markets if they don't have a similar capacity market.

These results point at the fact that the electricity market model may need overhauling under high levels of capital intensive, low variable costs technologies (wind, solar, and to a lesser extent nuclear and even coal). Other market models could be explored and tested.

4.3. Different rule sets for investment behaviour

Essentially, much of the dynamics that can be expected in the energy transition, are about investments, such as those in power generators. Therefore, the investment behaviour is a crucial component of the model core. In various projects, alternative investment models have been proposed, implemented and evaluated. This shows the modularity of the modelling approach: master students were able to develop a different set of investment rules, translate them to code, push them as their own model branch on GitHub and develop a model configuration that runs the model with their own investment behaviour. All this code can exist side by side, some of it only in student projects, and the rest in a flexible, shared core. It also points to the modularity of the model core in that it is able to accommodate well for quite a variety of projects. This also implies that not all code needs to be taken up in the main model. Therefore, the project keeps as a whole manageable.

Various investment projects dealt with uncertainty and risks. Investors typically do their own evaluation of the future, which implies that the modelled investors have their own model inside the simulation. This inherently limits what can be done. When investors take more risks into account with NPV calculations capturing various uncertainties, investors invest less, in particular in gas plants (Nebel, 2015). This finding reflects to recent developments in the Netherlands, where a brand new natural gas plants was unused and later sold and shipped. Taking these risks better into account in a dynamic context could have helped avoid the decision in the first place.

One of the projects takes into account detailed locational factors with respect to public opposition, the process of getting a permit. This has led to an overview of the most attractive power plant locations in the Netherlands over time, given the perspective of investors, the government and the public (Paling, 2013).

4.4. On-going work on representing intermittency

Higher levels of renewables have a dampening effect on electricity prices. More and more hours of the year, only technologies with very low marginal costs are running. Lower electricity prices prevent additional investment, in particular in capital-intensive technologies (such as wind turbines, which primarily have upfront costs). This effect may well limit the achieved renewables levels, something that was found in many EMLab simulation results.

Additionally, some analyses require to look at how the system develops hour after hour. For example, when looking at hydropower and other forms of energy storage. A second example is the study of ramping up and down of thermal power plants. A third is studying effects under high penetration levels of intermittent renewables. Results are imprecise with a base model that represents time as 20 different 'sets' of hours, which is required for limiting runtime. Some of the limitations were dealt with by rebuilding these 20 different sets of hours every simulated year, and this in some of the finished projects to take into account the short term slightly better. For instance, the role of energy storage has been explored in conjunction to a capacity market, which indicates that it is very challenging to gain insight in to what extent a capacity market will influence the business case for electrical energy storage. Reversely, if sufficient levels of energy storage are obtained, it may significantly lower the need for a capacity mechanism (Kerckhoffs, 2015).

Ongoing work deals with this limitation by developing a replacement for the short-term dispatch model, by translating all short-term processes into one optimization problem for a single year.

5. Case study: improving the proposed market stability reserve in the EU ETS

This section describes an application of EMLab-generation model to the proposed Market Stability Reserve in the EU ETS (adapted from (Richstein, 2015)). The EU ETS is a cap-and-trade system, with a (more or less) fixed, declining supply of emission allowances, which regulated companies need to obtain and hand in when they emit greenhouse gases. Allowances are, depending on the sector, freely allocated or auctioned to market participants, which are free to trade allowances or keep them for future time periods (so-called *banking*). The low prices in the European Union Emission Trading System (EU ETS) in combination with a large volume of allowances being banked (that is kept for use in later years), resulted in the European governments introducing the "Backloading" reform (European Commission, 2012), which delays the auctioning of a significant volume of EU emission allowances (EUA) for several years. The European Commission also proposed the establishment of a market stability reserve ((European Commission, 2014a), labelled "CommMSR", for Commission MSR), which is a policy instruments that withdraws and injects EUAs from the EU ETS auctions depending on the volume of EUAs in circulation. It aims to keep the volume of EUAs in circulation within a target corridor and thereby controlling the price.

In order to study the low emission prices — and the proposed interventions — banking behaviour needs to be considered. A cap-and-trade system will only be efficient in achieving a cumulative emission target over several years if unlimited banking and borrowing is permitted and the social discount rate is applied to banking decisions (Rubin, 1996). This description of banking behaviour usually does not differentiate between different actors in the market. Based on interviews, existing financial literature (Bailey, 2005) and industry reports (Eurelectric, 2009; Neuhoff et al., 2012), stipulates that at least two different market players are active on the market: hedgers and speculative bankers. Whereas the former are usually electricity producers and apply a lower discount rate (0—10%) to hedge their future sales, speculators need to take open positions regarding the carbon price development and apply a discount rate exceeding 10—15% to their trading decisions. This clearly exceeds typically assumed social discount rates of 0—3%. As a result, in a situation of oversupply of allowance (e.g. due to a recession or technological shock) once the banking capability of hedgers is exhausted, a very high discount rate is applied to further bank additional allowances.

The Market Stability Reserve aims to reduce the surplus to a level of the hedging corridor thus making the hedgers the marginal price setters again. The effects that it may have are still being debated. In (Richstein et al., 2015a) we reached the conclusion that the CommMSR might increase price volatility, mainly due to target corridors being set too low, because of the two year response time of the CommMSR and the late introduction time in 2021, which comes after the backloaded EUAs are returned to the market, which may lead to a price drop in the carbon market.

Based on criticism on the original design, the Committee on the Environment, Public Health and Food Safety of the European parliament (CEPF) proposed various amendments to the CommMSR and proposed by the European Commission (European Commission, 2014b). In this paper the amended MSR is labelled "ParlMSR" (for Parliamentary MSR). Three major revisions to the MSR were proposed by the (A8-0029/2015. 2015., 2015) and accepted by the member states of the European Union: 1) The backloaded credits should not be returned to the market, but instead placed in the market stability reserve. 2) The market stability reserve should start operating the latest on 31 December 2018. 3) The response time of the MSR should be shortened to one year, from two years.

The reform thus addressed points that we raised in our analysis. In the following we compare the newer MSR reform with the original proposal by the commission. We include a base case without any market stability reserve, labelled "PureETS".

Fig. 3 shows the development of CO_2 prices over time in the investigated scenarios. The black line depicts the median, the darker grey area the 50% envelope and the lighter grey area the 90%

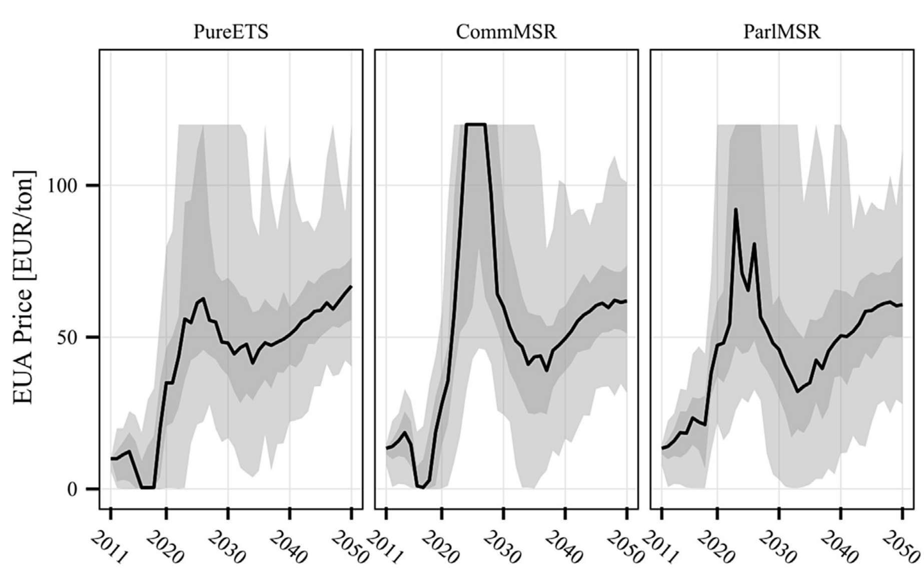

Fig. 3. Simulation findings: carbon prices in the simulations.

envelope. It is visible that in the PureETS case the initial years have very low CO_2 prices, which are followed by a rapid price increase around the year 2026. After a price drop over the next decade, the CO_2 price rises until the end of the simulate period. The CommMSR does not prevent the initial price collapse, since it only starts operating in the year 2021. It leads to an exaggeration of the peak CO_2 price in 2020–2030 (see also (Richstein et al., 2015a)). The ParlMSR avoids the initial price collapse in the years 2011–2020, due to the earlier start date in 2017. As a result, the price peak in the years 2021–2028 is lower and shorter than in the CommMSR case.

In terms of emissions and mitigation costs further differences between the scenarios exist. As in the simulation period banking levels do not fall below the lower trigger levels of the CommMSR and ParlMSR they effectively lead to lower emissions levels than the PureETS, and more spread out emissions as the MSR mechanisms bring some flexibility to the emission certificate supply (see Fig. 4). In terms of mitigation costs over the simulation horizon the CommMSR does not represent an improvement over the PureETS (compare Fig. 5). The ParMSR however does reduce mitigation costs. This is due to the avoided price slump in the beginning of the scenario, which causes the other two scenarios to have stranded assets (coal power plants) that increase the system cost compared to the abated emissions.

This case study illustrates that EMLab-Generation can adequately compare different policy scenarios in electricity and emissions markets. By analysing the original carbon market and the two scenarios for reforms of that system, we deduce the expectation that the improved proposal is better capable of stabilizing the carbon price than the original improvements. The fact that we analysed this on the basis of agents that invest in power generators under myopic conditions and that we test the robustness of the findings with an uncertainty analysis over different fuel price and demand scenarios illustrate the added value of this approach: these prove to be key ingredients to assess the robustness of the policy instruments that Europe has to curb our carbon emissions.

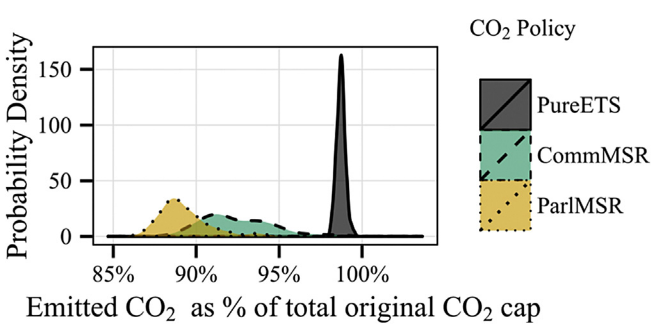

Fig. 4. Simulation findings: CO2 emissions in the simulations.

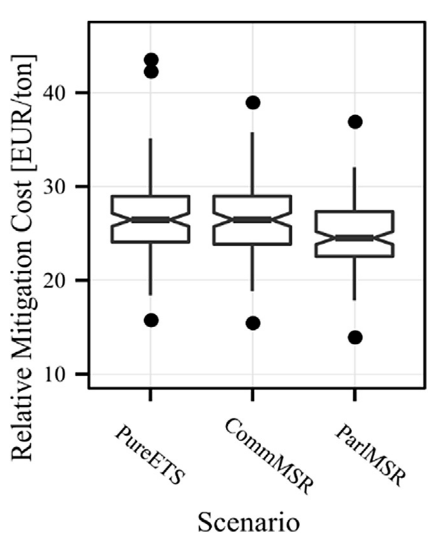

Fig. 5. Simulation findings: costs for mitigation of CO2.

6. Conclusions

We present a method for designing climate and energy policy for the EU, using a flexible and modular agent-based modelling approach and toolbox, called the Energy Modelling Laboratory, or EMLab.

Input to this process is a systematic overview of the policy design options, and the traditions of how this has been translated to modelling approaches. This indicates the need for a modular and flexible approach that is able to explore how to decide between various policies, which in turn interact with each other, beyond borders and systems, driving the energy transition. This leads to possible side effects, which, we argue, need to be taken seriously.

We have developed a flexible model core and worked on modules that focus on carbon and renewables policies, capacity mechanisms, investment behaviour and representing intermittent renewables. Each of those was developed and used in various modelling projects. The results suggest that the policy questions related to the ongoing energy transition in Europe more and more interrelate with other sectors and countries and are surrounded by fundamental uncertainties that cannot be taken away. As a consequence, scoping policy advice has become much more difficult, if not impossible. Only a flexible modelling approach that makes side effects of imperfect investment behaviour explicit, combined to other types of studies (including normative ones, such as development of qualitative and quantitative scenarios) is able to address todays questions. We show that agent-based modelling can fill this need by developing this large-scale, open source agent-based model of the electricity sector.

We have chosen a particular technical setup with a graph database and behavioural rules in pieces, to enable developing a model suite: an approach that allows for flexible configurations. This does affect runtime – making simulations slower than necessary (if all would be more tightly integrated). So far, we see the choices beneficial – reflecting the reality of a tangled web of research projects.

EMLab-Generation led to a wide range of policy scenarios in electricity and emissions markets. The case study illustrated three scenarios for the EU ETS market reforms. Factoring in agent-behaviour, especially myopia, as well as uncertainty analysis over different fuel price and demand scenarios are key ingredients to assess the robustness of such policy instruments.

Future developments may include a representation of electricity grids, expanding the number of price zones, and interconnections to other sectors, further developing EMLab as a platform for open source, multi-tool, multi-model, multi-level energy modelling.

Acknowledgements

This work has been supported by the European Commission through the Erasmus Mundus Joint Doctorate Fellowship in Sustainable Energy Technologies and Strategies (SETS), the Energy Delta Gas Research program, project A1 – Understanding gas sector intra-market and inter-market interactions and by the Knowledge for Climate program, project INCAH – Infrastructure Climate Adaptation in Hotspots.

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