1 INTRODUCTION

Coupled climate-economy systems are complex adaptive systems. While changes and out-of-equilibrium dynamics are in the essence of such systems, this dynamics can be of a very different nature. Specifically, it can take a form of either gradual marginal developments along a particular trend or exhibit abrupt non-marginal shifts (Filatova, Polhill, & van Ewijk, 2015). Nonlinearities, thresholds and irreversibility are of particular importance when studying coupled climate-economy systems. Strong feedbacks between climate and economy are realized through energy: economy needs energy for development in literary any sector, while emissions need to stabilize and be even reduced to avoid catastrophic climate change (IPCC, 2014). Possibilities of passing some thresholds that may drive these climate-energy-economy (CEE) systems in a completely different regime need to be explored. However, currently available models are not always suitable to study nonlinearities, paths involving critical thresholds and irreversibility (Stern, 2013). To be able to formulate an appropriate energy policy for this complex adaptive CEE system, policymakers should ideally have decision support tools that are able to foresee changes in energy market over the coming decades to plan ahead accordingly. Many macro models, that assume rational representative agent with static behavior, are designed to study marginal changes only. So there is a need for models that are able to capture nonlinear changes and their emergence. An Integrated System of Models (ISM) can be used to address policy questions and methodological challenges when assessing CEE dynamics in the presence of nonlinearities (Voinov and Shugart, 2013). This research is aimed to elicit equilibrium and disequilibrium model integration feasibility and to explore how an agent-based energy market could link with a computable general equilibrium (CGE) model within ISM. The integration of an ABM and a CGE in the energy domain is a new approach in CEE systems.
ABMs are simulating human social behavior more realistically and can capture human variability and other nonlinear processes (Arto et al., 2013; Bonabeau, 2002; Castel & Crooks, 2006; Chappin & Dijkema, 2007; Gilbert, 2008; Tesfatsion, 2006; Tran, 2012). Since ABMs are not directly used to model climatic systems, there are no climate system thresholds considered directly. Irreversibility, however, is addressed in ABMs. The ABM of the carbon emission trading impact on shifting from carbon-intensive electricity production (Chappin & Dijkema, 2007) suggested that as soon as investments in new technology are made, the switch from the old technology is irreversible. Various scenarios produced by the ENGAGE ABM by Gerst et al. (2013) all produce irreversible transitions to low-carbon economy. While depending on a policy, the transition can be swift or more gradual, the return back to carbon-intensive economy is unforeseeable.

2 AGENT-BASED ENERGY MARKET

ABM aims to investigate nonlinearities and to trace potential discontinuities in energy markets driven endogenously from within the economic ABM or triggered by changes in the environment. The quantities and prices of different energy sources and corresponding greenhouse gas emissions resulting from the microeconomic choices are indicators of an aggregated AMB energy market dynamics.

In this paper we focus on the retail electricity market. The flow of the activities of our ABM is presented in Figure 2.

**Demand:** Demand side of our ABM consists of heterogeneous households with different preferences, awareness of climate change, and socio-economic characteristics, which lead to various energy consumption choices. Households choose a producer and energy type by optimizing utility they expect to receive ($u_{exp}$) given price expectations ($q_{hce}/q_{hff}$) under budget constraints. Households receive utility from consuming energy ($E$) and a composite

![Figure 1: agent-based energy market- conceptual model](image-url)
good (z) between which its budget is shared (equation 1). Moreover, households have awareness about the state of climate and environmental preferences (γ), which could potentially be heterogeneous and change over time.

Eq1. \[ U = z^\alpha \cdot E^{(1-\alpha)} \cdot C^\gamma \]

Later on we plan to implement various energy saving actions selecting from the following pool: switching to energy efficient equipment, installing solar panels, energy saving bulbs, or change in electricity usage habits (e.g. switching off the lights).

**Supply:** The supply side is presented by heterogeneous energy suppliers, which may deliver either electricity based on low-carbon energy sources (LCE) or on fossil fuels (FF). The ABM model is being integrated with a macro-economic CGE model (Filatova et al., 2014). Thus, at this stage we do not go into the details of modeling the various energy producers where ABM can be instrumental in simulating the potential diffusion of alternative energy technologies. Instead, we simulated suppliers with different share of LCE and FF electricity production. In retail electricity market, form expectations are calculated regarding to prices \( (q_{lce}/q_{ff}) \), and shares (LCE vs. FF), to deliver next time step in order to optimize supplier’s profits. Through literature, total revenue and total cost is used for maximizing profit. Therefore we calculated supplier’s profit expectation by using the cumulative price growth \( (cpg) \), market prices of electricity \( (p_{lce}/p_{ff}) \), electricity production \( (q_{lce}/q_{ff}) \), and total cost of production (Eq2).

Eq2. \[ \text{Pro} = (cpg \cdot p \cdot q^*) - \text{cost} \]

![Figure 2: Flow of activities in the agent-based energy market](image-url)
Market clearing: due to the reasons widely discussed in the literature (Arthur, 1999; Kirman, 2011; LeBaron, 2006; Tesfatsion, 2006) agent-based markets try to distance from the traditional Walrasian auctioneer. Thus, the equilibrium price determination is replaced with alternative market structures. Different methods of market clearing evolved in the agent-based computational economics practice, which can be categorized in four main groups (LeBaron, 2006; Rekike, Hachicha, & Boujelbene, 2014).

The first category, which can be labeled “gradual price adjustment”, assumes a simple price which market-maker announce it and the demands are submitted at this price. Then if we have an excess demand, the price is increased, and if there is an excess supply the price is decreased. The price is often changed as a fixed proportion of the excess demand as in Eq4 (LeBaron, 2006).

\[
pt+1 = pt (1) + \alpha(D(pt) - S(pt))
\]

This price adjustment method is used in Alvarez-Ramirez, Suarez, and Ibarra-Valdez (2003); Beja and Goldman (1980); Day and Huang (1990); Dieci and Westerhoff (2010); Farmer (2002); Farmer and Joshi (2002); Martinez-Echevarria (2007); Zhu, Singh, and Manuszak (2009) models.

In second approach is temporary market clearing which the price is determined so that the total demand equals the total number of shares in market (Arthur, 1999; Brock & Hommes, 1998; Ke & Shi, 2009; LeBaron, 2006; Levy, Levy, & Solomon, 1995; Rekike et al., 2014). The advantage of this approach in compare with the “gradual price adjustment” method is there is no need to deal with market-maker. However, two critical problems is mentioned for this approach. First, it may impose too much market clearing, and it may not well represent the continuous trading situation of a financial market. Second, it is often more difficult to implement. It either involves a computationally costly procedure of numerically clearing the market, or a simplification of the demands of agents to yield an analytically tractable price (LeBaron, 2006).

Third category which is the most realistic approach and is labeled “order book” market structure, simulated where demand and supply are crossed with using a certain well defined procedure. One of the most common examples within this category if price formation mechanism is a double-auction market (Chiarella & Iori, 2002; Chiarella, Iori, & Perello, 2009; Farmer, Patelli, & Ilija, 2005; LeBaron, 2006; Lux & Marchesi, 2000; Ponta, Raberto, & Cincotti, 2011; Rekike et al., 2014). This method is not only very realistic but also allows to analyze and trace more in detail. However, these institutional details need to be built into the market architecture, and learning specification of agents (LeBaron, 2006).

The fourth approach is bilateral trade. In this method the new price comes up when agents meet randomly and trade if they reach a deal. It seems this trade appear more realistic for informal markets, where trading institutions defined not very well or buyers and sellers meet less randomly (Albin & Foley, 1992; LeBaron, 2006).

We choose the first approach “gradual price adjustment” as the price determination of agent-based electivity market model. As it seems to represent the retail electricity market more accurately (Federico & Vives, 2008).
New energy prices ($p_{ec}/p_{rf}$) and market shares of green and grey energy are an emergent outcome of this agent-based energy market. After the market clearing, households update their price expectations and utility when comparing them to the actual market outcomes. If the total energy spending for a household are more than was expected, it stimulates a household to reconsider either an energy supplier and a type of energy source, or an investment leading to energy savings, or a change in energy consumption pattern.

3 CGE

CGE model (developed by TNO) is a large scale and highly detailed world CGE model built on the detailed environmentally-extended database EXIOBASE. The model divides the global economy in 44 countries and a rest of world, and 164 industry sectors per country. The model includes 5 types of households, a representation of 29 types GHG and non-GHG emissions and different types of waste. The model is presently calibrated on the data for 2007. The model currently uses the period 2013-2050 as the time horizon for its calculations. The model equations tend to be neo-classical in spirit, assuming cost-minimizing behavior by producers, average-cost pricing, and household demands based on optimizing behavior (Filatova et al., 2014). In following the general plan of linking ABM with CGE is described.

4 ABM-CGE INTEGRATION ATCHITECTURE

On the demand side, our ABM will disaggregated only residential sector demand taking the energy demand of all other sectors from CGE (Figure 3). When modeling changes in individual energy demands in between annual equilibria of the CGE we would like to explicitly trace changes in preferences and energy consumptions choices driven by individual assessments, pro-environmental attitudes and social interactions (norms). This will result in the new budget shares a households spend on (i) energy vs other goods, and (ii) LCE vs. fossil fuel energy sources. On the supply side we will differentiate between energy production based on fossil fuels and low-carbon energy sources taking the aggregate supply equations structurally similar to the ones in the CGE. Ideally, this process will result in new elasticities, which could serve as inputs to the CGE.
Figure 4 shows ABM-CGE integration on demand side of energy market. As it is illustrated, ABM is focused on “Electricity” and “Heating” as the households energy consumption. Households can reduce their CO2 footprint by means of one of three actions: (1) investing in energy efficient devices and equipment, (2) reducing energy consumption through behavioral change, and (3) by switching to low-carbon energy.

The lowest scale of operation of the CGE model is NUTS1, while the highest scale of the ABM would be NUTS2. Therefore, the ABM outputs to CGE are going to be scaled up to NUTS1. We envision doing that by means of endowing households agents in the ABM with the key attributes of households groups following the structure of the EU Household Budget Survey. Thus, changes in behavior with respect to energy consumption in the ABM
can be scaled up to bigger groups of households in other NUTS2 regions in CGE, attributes of which are also harmonized with the EU HBS. While the CGE simulates the connections across economic sectors as an annual equilibrium, ABM run quarterly to investigate non-marginal changes in energy market.

Following diagrams (Figure 5) is illustrated the exchange variables and input/output of ABM and CGE. We aim at integrating the ABM with the CGE model to assure direct feedbacks between behavioral change with consequent changes in market shares of LCE vs. FF and impacts of these on other sectors of economy (ABM=>CGE), as well as accounting for non-residential electricity demand and changes in households incomes as economy evolves (CGE=>ABM). The linkage is take place in two phases. The first phase, ABM is getting data e.g. electricity prices, share of LCE vs. FF, electricity consumption and production (LCE vs. FF) as initialization from CGE. The second phase, after ABM market clearing the new shares (LCE vs. FF) and price will update CGE.

Figure 5: ABM-CGE integration framework

5 RESULTS AND FUTURE WORK

We present a work in progress with an application of the retail electricity market ABM to the Navarre region of Spain as one of our case studies. Currently the demand and supply sides of energy (electricity) market are simulated using NetLogo with GIS and R extensions. We explored the dynamics of market shares of low-carbon electricity in the scenario where a household’s choice on the type of electricity (grey or green) is driven exclusively by preferences vs. when market-clearing mechanisms is explicitly modeled. We also contrast the results for a population of household with homogeneous vs. heterogeneous preferences and awareness of climate change as well as incomes.

At the conference we plan to present the simulation results of the first version of this energy market with a focus on the detailed modeling of the demand side. We present the trends in
prices for low-carbon-energy and fossil fuels. Moreover, we test the feasibility of data exchange between CGE and ABM, where quantities (i.e. shares) of LCE and FF emerge as the outcome of the energy market.

The future work will go on in two directions. Firstly, we aim to improve and expand the integration points of agent-based energy market with CGE model. Secondly, we plan to study behavioral changes and socio-economic characteristics of households via a survey. The main goal of the survey is to elucidate the information on behavioral changes, which includes not only change in choices but also in preferences and opinions, potentially affected by social influence on the demand side (households) to feed it into the ABM.

Acknowledgements: Funding from the EU FP7 COMPLEX project 308601 and the Netherlands Organization for Scientific Research (NWO) VENI grant 451-11-033 is gratefully acknowledged.

References:


IPCC. (2014). Fifth assessment report: Climate change.


