# Transition to Low-Carbon Economy: Simulating Nonlinearities in the Electricity Market, Navarre Region, Spain

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## 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 nonmarginal shifts [1]. 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 requires energy for literary every sector, while emissions need to stabilize and be even reduced to avoid catastrophic climate change [2]. 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 [3]. 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.

ABMs are simulating human social behavior more realistically and can capture human variability and other nonlinear processes [4–9]. 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

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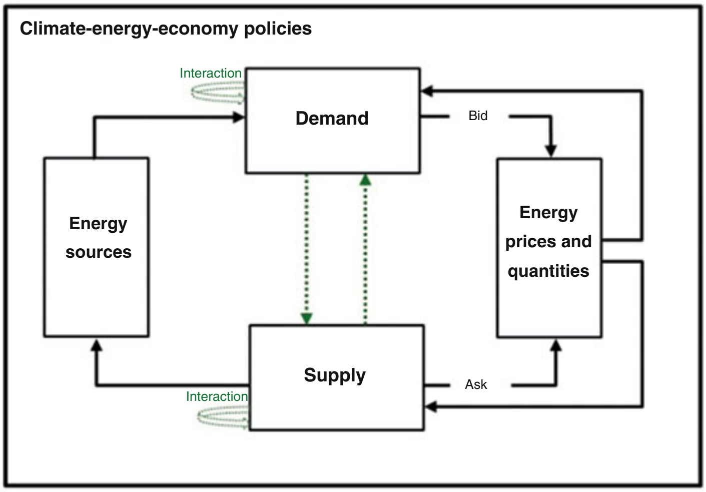


**Fig. 1** Agent-based energy market—conceptual model

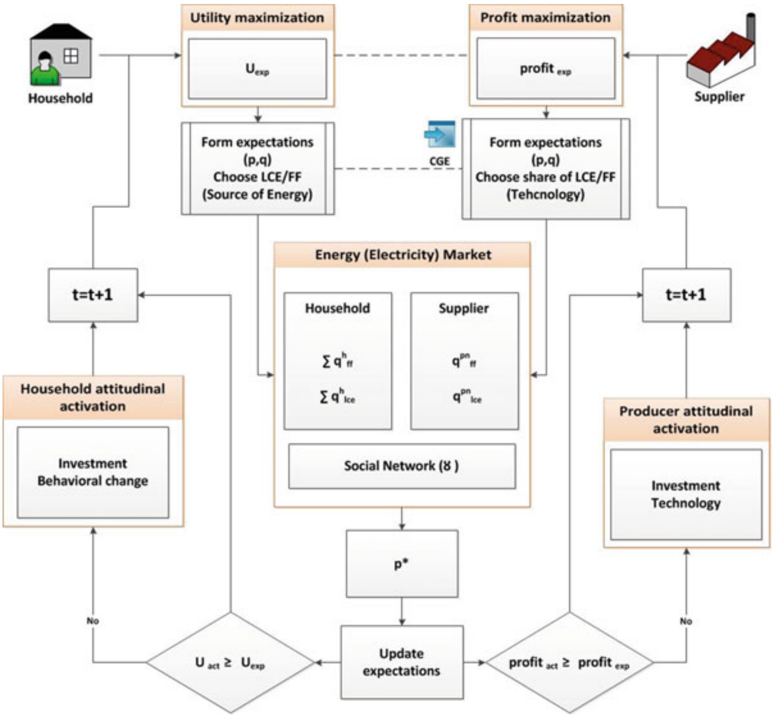


**Fig. 2** Flow of activities in the agent-based energy market

emission trading impact on shifting from carbon-intensive electricity production [7] 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. [10] 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

We designed and programmed an ABM with an aim to investigate nonlinearities in energy markets. It aims 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 namely low-carbon energy and fossil fuel and corresponding greenhouse gas emissions resulting from the microeconomic choices are indicators of an aggregated ABM energy market dynamics. Here we focus on the retail electricity market.

### *2.1 Demand*

Demand side of our ABM consists of heterogeneous households with different preferences, awareness of climate change, and socioeconomic characteristics, which lead to various energy-consumption choices. Households choose a producer and energy type by optimizing utility they expect to receive ($u_{\mathrm{exp}}$) given price expectations ($q_{\mathrm{hlce}}/q_{\mathrm{hff}}$) under budget constraints. Households receive utility from consuming energy ($E$) and a composite good ($z$) between which its budget is shared (Eq. 1). Moreover, households have awareness about the state of climate and environmental preferences ($\gamma$), which could potentially be heterogeneous and change over time.

$$U = z^{\alpha} \times E^{(1-\alpha)} \times C^{\gamma} \tag{1}$$

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).

## 2.2 Supply

The supply side is presented by heterogeneous energy providers, 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 [11]. 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 ($q_{\text{plce}}/q_{\text{pff}}$), and share of LCE vs. FF, to deliver next time step in order to optimize their profits.

New energy prices ($p^*_{\text{lce}}/p^*_{\text{ff}}$) 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 provider and a type of energy source, or an investment leading to energy savings, or a change in energy-consumption pattern.

## 2.3 Market Clearing

Due to the reasons widely discussed in the literature [12–15] 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 [14, 16].

The first category, which can be labeled "gradual price adjustment," assumes a simple price which the market-maker announces, 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 Eq. (2) [14].

$$\mathrm{pt} + 1 = \mathrm{pt}(1) + \alpha\,(D\,(\mathrm{pt}) - S\,(\mathrm{pt}\,)) \tag{2}$$

This price adjustment method is used in Alvarez-Ramirez et al. [17]; Dieci and Westerhoff [18]; Farmer [19]; Farmer and Joshi [20]; Martinez-Echevarria [21]; Zhu et al. [22] 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 [12, 14, 16, 23, 24]. The advantage of this approach when compared to the "gradual price adjustment," is that there is no need to deal with market-maker. However, two critical problems are mentioned for this approach. It may impose too much market clearing, and it may not well represent the continuous trading situation of a financial market. Also, 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 [14].

The 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 of price formation mechanism is a double-auction market [14, 16, 25–27].

The fourth approach is bilateral trade and it assumes that agents bump into each other randomly and trade if it benefits them. It would appear realistic. However it may not be very natural in places where trading institutions are well defined, and function to help buyers meet sellers in a less-than-random fashion [14].

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 [28].

## 3 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. Currently the demand and supply sides of energy (electricity) market are simulated using NetLogo with GIS and R extensions. We explore 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.

The future work will go on in constrain two directions. First, 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 nonresidential electricity demand and changes in households incomes as economy evolves (CGE=>ABM). Secondly, we plan to study behavioral changes and socioeconomic characteristics of households via a survey. The main goal of the survey is to elucidate the information on behavioral changes, which includes change not only in choices but also in preferences and opinions, potentially affected by social influence on the demand side (households) to feed it into the ABM.

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