Modeling the Transition to a Low-carbon Energy System - How can an Agent-based Model Approach Complement an Optimization Model Approach

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Abstract

When modeling the energy transition, the agent-based model (ABM) approach is far less used compared to the optimization model approach. However, an ABM has the advantage of including important features of the energy transition such as heterogeneous characteristics of decision-makers, bounded-rationality, historic path-dependency, etc. This article illustrates and discusses how an agent-based model can complement an optimization model.

Modeling the transition to a low-carbon electricity system

When studying the energy transition towards zero CO_2 emissions, a wide range of computational models have been employed for assessing its feasibility, consequences and costs. These models are useful as they may help decision-makers understand the potential consequences of various policy proposals and make informed decisions.

Among different modeling approaches, an optimization model approach is the most commonly used one in the field of energy system studies, because it shows the potentially optimal decisions and how a least-cost solution can be reached. Compared to an optimization approach, an agent-based model (ABM) approach is far less used, but its application has been growing, partly because the existing mainstream modeling tools are limited in their ability to include features such as heterogeneous characteristics of decision-makers, bounded-rationality, historic path-dependency of the energy system, imitation and interaction among market players. But all these features can be captured in ABMs in a reasonably simple way.

An agent-based model is typically composed of individual agents and an environment. In an energy system model, an agent can be anything from a (or a group of) power plant(s), investor(s), household(s), bank(s), government(s), social group(s), etc. Each agent individually assesses their situation and makes decisions based on its goals. The observed overall outcome, such as the transition of the energy system, is the emergent phenomena resulting from individual agents' actions and interactions.

One aspect in which the ABM can complement the optimization model is that the ABM captures the heterogeneity of agents and can investigate how does this heterogeneity impacts the agents' actions and interactions, and thereby, impacts the overall system. For example, in the field of energy transition study, one group of agents that embodies heterogeneity is the investors. Different investors can have different levels of risk averseness, they may have preferences for different types of technologies, and they may have different beliefs about the future climate policies, etc... In the following section, we demonstrate the implementation of such heterogeneity in an ABM and show the individual investors' different investment choices.

A simple example of using an ABM

We have developed the HAPPI (**H**eterogeneous **A**gent-based **P**ower **P**lant **I**nvestment) model and explore the transition to a low carbon energy system[1]. The agents in this model are power companies who make investment decisions in new power plants. The goal of a company is to maximize its profit for each investment. Companies are heterogeneous as they have different levels of risk averseness (represented by the hurdle rate value used by a company). In addition, companies have limited information about how future carbon tax levels and different companies expect different growth rates of future carbon taxes. Some companies underestimate the "real" carbon price, while some other companies overestimate and some correctly estimate the tax price that is implemented in the model.

Figure 1 shows that under an increasing carbon tax scenario, the system transits from a coal- and gas-based to a low-carbon electricity system. Figure 2 shows that heterogeneous companies make heterogeneous investment decisions. Companies that are using lower hurdle rates (first two rows of Figure 2) are in general more willing to invest, and they invest more heavily in wind and nuclear compared to companies that use higher hurdle rates. This is because a low hurdle rate lowers the investment cost of wind and nuclear plants more than the coal-fired power plant. It is interesting to notice that, after an initial expansion, the installed capacity of wind declines some twenty years later due to competition from nuclear, which then expands significantly. The impact of a low hurdle rate is thus different for wind and nuclear in the long run (Yang et al., 2021).

Another observation is that in the beginning years, while those companies who underestimate carbon tax (the first two columns in Figure 2) invest in coal power plants, companies that expect high carbon prices (the last two columns in Figure 2) start early in investing in

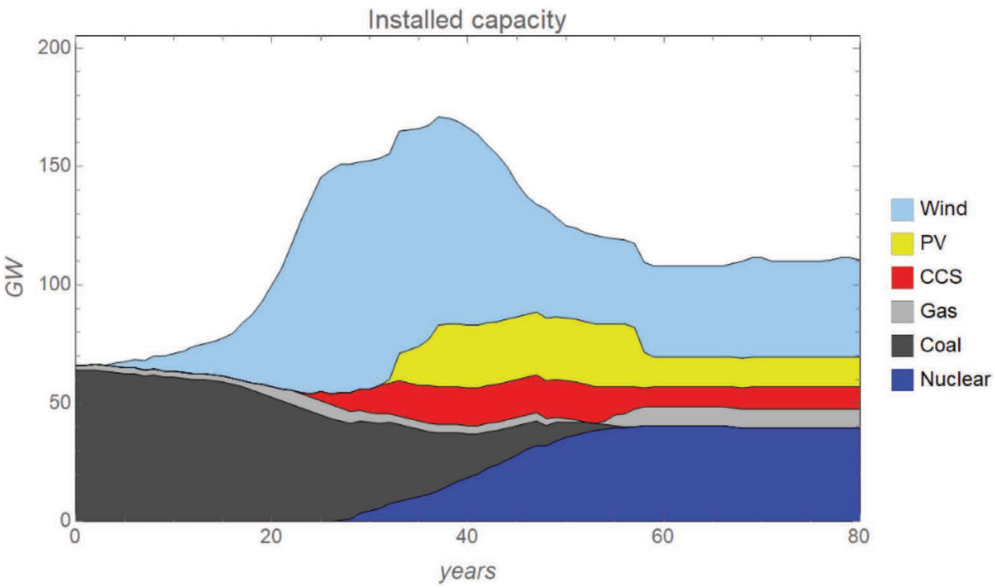

Figure 1 System installed capacity from year 0 to year 80 in the base case. The installed capacity of coal starts to decline around year 5, while wind starts to grow, and then decline some thirty years later due to competition from nuclear, which then expands.

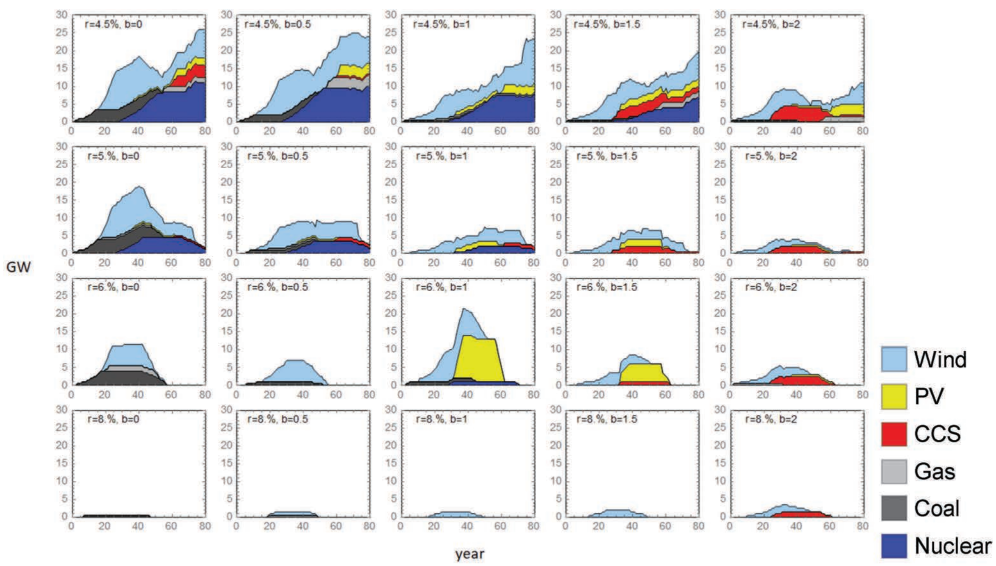

Figure 2 Installed capacity of 20 individual companies in the base case. ***r*** *is the hurdle rate agents use and* ***b*** *is the expected carbon tax parameter (for more detailed figure description and the model description, see: https://research.chalmers.se/publication/525564/file/525564_Fulltext.pdf)*

gas-fired plant with CCS, as they expect a higher carbon tax and therefore, estimate that the CCS technology would be profitable to invest.

How can ABM complement the optimization model approach?

This simple example above illustrates that the ABM can complement the optimization model approach by modeling the behavior and investigating the outcome on a micro-level. This micro-level modeling is important for the energy transition, because it is what happens on the micro-level that determines what will be observed on the macro level. As illustrated above, individual companies' investment choices determine what types of plants the system will have, therefore, depends on individual companies' investment choices, the transition to a low-carbon energy system may be accelerated or hampered.

Additionally, in an optimization model, it is usually assumed that decision-makers have perfect foresight, but, decision-makers have limited information, especially about the future, therefore, the optimal decisions showed in an optimization model may be hard to reach in reality. Hence, by comparing modeling results from an optimization model and an ABM, we may identify the differences and the reason for the inconsistancies. We may also identify difficulties or even infeasibilities of the transition pathways that an optimization demonstrated, and this might help to make more realistic model assumptions and even helps to make more effective policies for achieving the energy transition goals.

Footnote

[1] For more information about the study and the model, see: https://research.chalmers.se/publication/525564/file/525564_Fulltext.pdf

Reference

[1] Yang, J., Azar, C., Lindgren, K., 2021. Transition to a low-carbon electricity system — investment decisions under heterogeneity, uncertainty and financial feedback, https://research.chalmers.se/en/publication/?id=525564.