Experience-based Exploration of Complex Energy Systems

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Abstract

In our energy-restricted world, planners and engineers have to cope with problems of CO_2 emissions and oil- and gas-shortages. Many planning activities not captured under the heading of "futures studies" share common goals like dealing with an uncertain, complex future. We focus on two novel approaches: agent-based modelling and serious games. These approaches, even though they stem from the same general systems theory roots, allow its users to experience "reality" in different ways. This has implications for when and how to use these methods in scanning future developments and how these are communicated.

Keywords: Complexity, agent-based modelling, serious gaming, exploration, energy systems

Introduction

We are increasingly becoming aware that our world is complex (Sardar, 2010) and value-laden (Funtowicz & Ravetz, 1993). This means that although we want to tackle wicked problems such as the economic and climate crises, we cannot rely any more on simplistic understanding of our socio-technical systems: they are constantly adapting, evolving, and the players in this game of life are reflexive and sometimes unpredictable (Emery & Trist, 1965). While researchers in the engineering sciences may not explicitly refer to futures studies, they also try to cope with change and uncertainty in a multitude of possible futures. In management-oriented engineering, for example, real-options thinking tries to exploit uncertainty by emphasising a more flexible approach to planning and building (Herder et al., 2011). The upcoming field of asset management emphasises taking a broader systems-perspective when planning for building infrastructures and networks: a short-term, local solution may have a detrimental effect on the system as a whole.

To deal with complex systems problems, researchers have traditionally relied on increasingly complicated mathematical models of the world. Whereas these models have led to insight in complex systems, they increasingly relied on computing power, and became intractable and opaque electronic oracles (Meadows & Robinson, 2002) that people visit to be told what to do, not to gain additional insight in how the world works. In this article we describe two approaches that, while still relying on mathematical models, aim to help decision-makers gain more insight through their own and other people's experience. These approaches, agent-based modelling and serious gaming, allow for simulation that is open to some experimentation and thus are more useful than "closed box" reasoning for communicating and tackling complex problems.

We first describe the ideas behind and the merits of the two approaches, then we contrast their premises and discuss how they help in communicating complex problems.

Agent-based Modelling (ABM)

Have you ever tried to reason how a system – say a market with buyers and sellers, or an ecosystem – works? Apart from very vague notions like "the invisible hand" or "Mother nature's balance", a top-down approach to understanding systems requires simplification that is not easily tractable. When looking at a high abstraction level, details that matter are necessarily overlooked (Scott, 1998). The Club of Rome's famous report "The Limits to Growth" and the underlying systems dynamics models reduced everything that matters in the world to interactions of five global economic subsystems: population, food production, industrial production, pollution, and consumption of non-renewable natural resources (Turner, 2008). To understand the world at such a high abstraction level is very difficult – it relies on insight in systemic behaviour that is non-intuitive (Forrester, 1971).

Agent-Based Modelling (ABM) is presented as an alternative to or logical follow-up of system dynamics (computer) modelling (Heath et al., 2009). Instead of arguing from the point of view of large systems, ABM starts with its smallest constituents: agents. From an abstract perspective "an agent is a thing that does things to other things" (Shalizi, 2006). For modellers trying to build a simulation of our socio-technical world, agents often represent humans or organisations of humans. An agent-based model is "a collection of heterogeneous, intelligent, and interacting agents, that operate and exist in an environment, which for its part is made up of agents" (Epstein and Axtell, 1996; Axelrod, 1997a). With its focus on individual agents/actors, ABMs are often applied in the social sciences (Axelrod, 1997b; Köhler, 2006; Gilbert, 2007).

Agent-based computer models take agents (components) and their interactions as central modelling focus points. The interacting agents, through their built-in rules, generate emergent (unexpected, unforeseeable) patterns of complex dynamic behaviour (Borshchev and Filippov, 2004), and serve as an in *silico* experimental device (Epstein, 1999). They are a laboratory for capturing evolving and learning systems in models. Therefore, an ABM is a *playground* for scientists, to *explore* emergent outcomes of the interaction of a set of autonomous agents (computer algorithms). This approach provides for construction of models in the absence of the knowledge about the global interdependencies: you may know very little about how things affect each other at the aggregate level, or what the global sequence of operations is, but if you have some notion of how the individual participants of the process behave, you can construct the model and then obtain the global behaviour.

It should be noted that ABMs are not used to predict the future or identify optima; their generative nature allows to explore *possible futures* through asking "what-if?" type questions.

ABM: Decarbonization of the Power Sector

To clarify what we mean, we present the example of the long-term impact of policy interventions on CO_2 emissions and prices in the power sector. After lengthy scientific deliberation, scientists joined under the IPCC have identified CO_2 emissions as an important factor to global warming (IPCC, 2007). To curb the effects of global warming, politicians in most countries and at different levels of government have agreed that CO_2 emissions need to be reduced. The questions is which governmental instruments (an emissions-trading scheme, carbon taxation, or no intervention) are most suitable for attaining this goal? Given assumptions about market behaviour, how do electricity producers in a liberalized market respond to these policy incentives?

The model we used reflects a (hypothetical) country in which six independent electricity producers who have different generation portfolios make different decisions regarding the operation of their generators, investments, and decommissioning. The agents in the model have operational behaviour: power producers need to negotiate contracts for feedstock, the sales of electricity, and emission rights. They also exhibit strategic behaviour: in the long-term the agents need to choose the moment of investment, the amount of capacity, and the type of power generation technology. Agents interact through negotiated contracts and organized exchanges and are subject to the physical flows, their characteristics and constraints. In the model, the following actions are repeated yearly:

- Acquire emission rights. The 'willingness to pay' for CO_2 for a generator is based on its CO_2 intensity and the expected electricity price.
- Offer electricity to the market. Each generator offers at variable generation cost (i.e. fuel cost, variable operating and maintenance cost, and expected CO_2 cost). In case insufficient CO_2 rights have been obtained, CO_2 cost equals to the penalty for non-compliance.
- Acquire fuels.
- Use CO_2 credits. Pay the penalty in case there is a shortage of CO_2 rights.

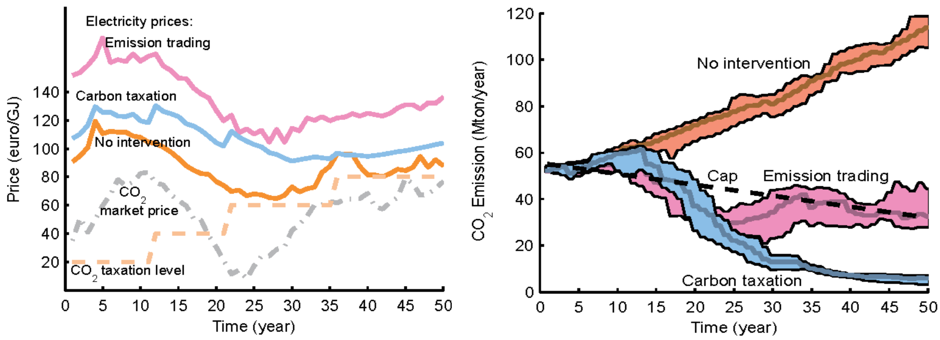

Figure 1. Electricity and CO_2 prices and CO_2 emission levels for three carbon policies (Chappin et al., 2010)

Instead of using trend extrapolation, the characteristics of the modelled system are emergent: the generation portfolio, fuel choice, abatement options, as well as electricity and CO_2 prices and emissions emerge as a result of the decisions of the agents. Typical results from simulation are shown in figure 1. Without intervention, emissions rise. Neither carbon policy guarantees a continuous and rapid decrease of emissions. Emissions increase in the first 10-15 years, even at high CO_2 prices.

The three carbon policies cause significant, structural differences in the electricity prices. Under emissions trading, CO_2 prices are highly volatile for the first three to four decades. Under emissions trading, the CO_2 price is strongly correlated with the electricity price, while the correlation between a carbon tax and electricity prices is much weaker. Given a certain CO_2 cost to producers – whether it be due to a tax or the price of CO_2 emission rights – carbon taxation leads to lower electricity prices than emissions trading.

Identified advantages of a tax can be used to improve the EU-ETS: a carbon tax could be used *in addition* to the EU-ETS, a carbon tax could be issued for sectors outside the EU-ETS, and a minimum price could be implemented on the credit auctions.

ABMs require modellers to make explicit assumptions about agent behaviour. In complex systems the outcome of these assumptions cannot be predicted and therefore must be tried out using different assumptions and/or parameters. The assumptions could be traced and checked (although this is mostly left to the modellers' discretion). They allow for experts to challenge the actions of the agents: “A real company would never … in such a situation”. This allows for the modellers to improve on their assumptions and rules. However, the modellers remain in control of the research process. Serious gaming allows for more input from “outsiders”, as we describe below.

Serious Gaming and Simulation

In the performing arts (e.g. theatre or music) it is customary to organise try-out sessions and dress-rehearsals in front of a live audience (usually friends, family, or non-paying audience). The idea is to practice the performance in a more benign setting. Serious games are similar to try-out performances: they allow the player to practice in a situation in which the stakes are lower than in the “real” event. In addition to that, games are effective tools for studying, teaching, and understanding complex (socio-technical) systems. To make a distinction with games that are purely played for entertainment purposes, the term *serious* gaming is used. Although serious games have been played for more than 40 years, the term nowadays is also related to the increased use of computers to support learning. The exact ways in which computers are used varies: they can be used for providing a richer experience by adding graphics, for providing support to the game operator by automating calculation and representing outcomes (which is the way we use computers for our game), but also for tapping the vast *cognitive surplus* of users of the internet for generating ideas (see The Institute for the Future work presented by Jake Dunagan in this issue).

From the systems scientist's perspective serious games are a way to involve humans (laymen or topical experts) in simulations. Games have a special power to motivate and instruct (Meadows, 1999). They can present complex environments, are repeatable, produce high levels of immersion, and are fun (Garris et al., 2002). Serious games provide a basis for organized communication about a complex topic (Duke, 1974; Duke, 1980; Kelly et al., 2007) and are often developed for learning within organizations such as the military, and fields of business and management science, economics, and inter-cultural communication (Raybourn, 2007; Mayer, 2009). Games are used for education and for the exploration of strategies and policies (Gosen & Washbush, 2004) and, compared to other simulation techniques, games result in a high involvement of the users (Pang, 2010). How far this involvement goes is demonstrated by the highly free-form games described by McGonigal (2003a).

The main disadvantage of games is that there are strong limitations to the complicatedness and length of a game. Even stronger, a conceptually complex game needs to be relatively simple (in terms of activities) in order to be effective (Meadows, 1999). Although there is an elaborate literature on game design for non-educational purposes (Rollings & Morris, 2004; Salen and Zimmerman, 2004; Fullerton et al., 2008; Schell, 2008), there is less literature on serious game design. Essentially, the challenge is to design a game with a good game-*play*, an interesting model of *reality* (if simulation is the aim), and the correct underlying *meaning* (Harteveld, 2011).

Serious Game: Market Behaviour of Electricity Companies

The example we use is in the similar application field as the ABM: power generation. The players (usually forming a team of 2-3) represent the directors of five competing electricity companies that manage a portfolio of power plants and have to make electricity pricing and investment decisions given future uncertainties such as electricity demand, fuel prices, outages, and possibly CO_2 emissions trading (de Vries et al., 2009). Each round represents a year, and a period of approximately two decades is simulated in order to give the players insight in the long-term consequences of their actions. The company with the highest bank balance at the end of the game wins the game, because it achieved the highest return on investment.

The game is played and operated through the internet on a dedicated server (http://emg.tudelft.nl, see figure 2). Each company has its own website, part of which provides public information, such as news and market prices and part of which contains private information such as the company's assets and its bank account. Players do not have to be physically together to play the game. As a result, only a limited amount of contact time needs to be spent on the introduction and the final evaluation of the game, and the length of game rounds can be chosen to fit the players' schedule (de Vries & Chappin, 2010).

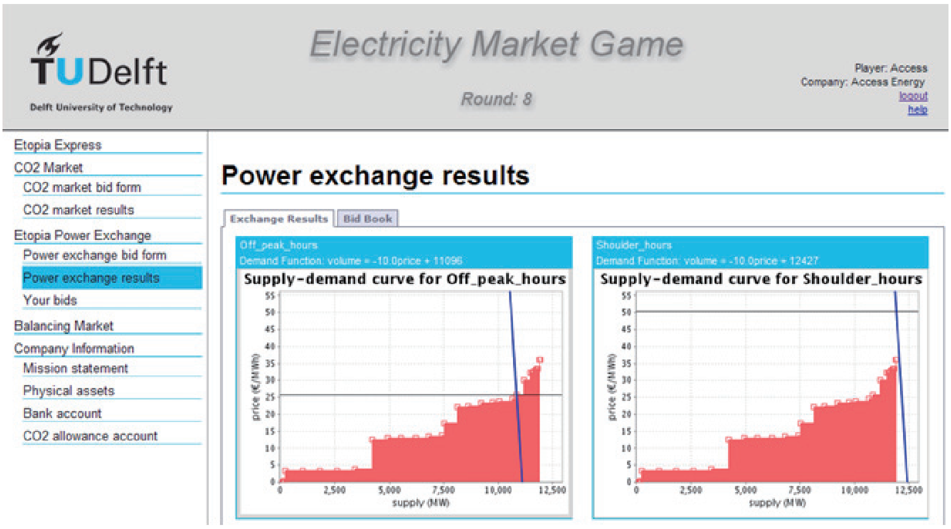

Figure 2. Snapshot of the electricity market game: Player/team "Access" observes the power prices in round 8 (Chappin et al., 2010).

When the game operator starts a new round, the power market is cleared (supply meets demand) and information is processed: which plants ran, how much power they sold, and accounting all revenues and costs. As the simulation package performs all administrative tasks for the game operator, he can concentrate on analysing the game while it is played and on coaching the participants.

Each round, companies have to perform a set of tasks. First, they have to offer electricity to the power exchange. Second, they decide whether to build new power plants and/or to dismantle old ones. Third, they have to acquire CO_2 credits, after the CO_2 market has been turned on, which is usually around round 6 or 7. To be able to perform these tasks, data and information are available throughout the web pages. The main information sources include a history of prices of fuels, CO_2 prices, and electricity prices. News items, written by the game operator, provide some hints of future energy price developments and a partial analysis (based on public data available to all participants) of what is happening in the market. In addition, detailed characteristics are available on the power plants in their portfolio and the availability of new generators. All revenues and expenses of the companies appear in their bank account: revenues from selling electricity and the costs of each power plant, including fuel costs. The stock values of the companies are plotted in the game's news bulletin, so the players can see how well they are doing.

The power companies all start with a comparable set of generators, including coal, gas, wind, and nuclear generators. However, power plants differ with respect to load cost, age, size, capacity, fuel efficiency, and reliability. Existing plants deteriorate with respect to reliability: the chance they fail during a particular round increases. Technology becomes more fuel-efficient and cheaper over time.

All the produced electricity is sold on the power exchange, modelled after European power exchanges. There are two main differences with reality. First, there are no contracts outside the exchange, so the price on the market is uniform for all players. Second, within one round, representing one year, the market is split up in three segments, one containing 5000 hours with base demand, one containing 3600 hours with shoulder demand, and one containing 160 hours with peak demand. This means that there are three electricity prices each year: a base, a shoulder, and a peak price.

Power producers place bids for all their available power plants in each of the market segments. To calculate their bids, players use information on the cost structure of the power plants, the fuel prices, and the wind factor. Bids can be different in the three segments, so they can try to manipulate the market. Sources for uncertainty are the availability of competitors' generators and the exact levels of demand, while historical data, given to the players, provide an indication only.

The game is set up such that the participants experience the following benefits (Chappin, 2011):

- Understanding the effects of competition
- Understanding investments in an uncertain environment
- Understanding the need for policies and evaluating policy designs
- Understanding how CO_2 markets work and how they impact the power market
- Understanding the increased investment risk caused by volatility in CO_2 prices
- Expectations stemming from irrational behaviour can shift the whole market
- Understanding that there is not a single optimal strategy
- Participants learn to deal with conflicting assumptions

Confronting Models and Games

We find that both agent-based simulation and serious gaming provide an interesting mix of creating a “fixed” model of the world on one hand (based on sophisticated cause-effect relationships), but allowing for behavioural surprise on the other. In both approaches abstractions and assumptions have to be made in order to capture the salient elements of the system of interest: system boundaries have to be defined. Whereas ABM starts from the assumption that behaviour can be captured in rules (computer algorithms) and the surprise lies in the interaction of these rules, gaming allows for surprise in the behaviour of the players. In fact, free-form games can be used to explore the different types of unexpected behaviour that humans portray.

We try to capture the different characteristics of these two methods in Table 1. We have chosen to caricaturize the differences somewhat; individual instances of models or games may vary, of course.

Table 1. *Characteristics of ABM and serious gaming compared*

characteristics	agent-based modelling	serious gaming
focus	technical	social
main elements	pipes, poles, machines	trust, friendship, bargaining

level of detail	only limited by modelling capabilities, inclination to complexity	needs to be manageable by players, simplicity required
rules	rules are fixed	rules are negotiable in some games
decisions	captured in agent description	outcome of player interaction
uncertainties	can/must be captured	cannot be captured beforehand
model, system abstraction	closed, black box	open, explicit
dynamics	shown by repeated simulation	revealed by game-play
scenarios	several, up to millions	generally one per game
learning by	researchers and clients, as an application or presentation	participants and researchers, in debriefing discussion
goal	outcomes, understanding	understanding, engaging

First of all, agent-based simulation is more geared toward the mechanical regularities that technology embodies, than the subtle pallet of inter-human conduct. Whereas physical realities (pipes, poles, machines) can be confidently captured by a limited set of equations, social phenomena (trust, friendship, bargaining) are dependent on a wide range of inputs that can hardly be specified in detail. Of course, they can be represented by variables and serve as input to models, which can then become one-dimensional or intractable. As computers are very effective in crunching large amounts of data, the researchers are not hampered in their desire to capture more detail and thus to enhance complexity (Lee, 1973; Meadows & Robinson, 2002). Game participants, on the other hand, can navigate complex interactions, subtle meanings, implied rules, and many other relationships, but cannot crunch large amounts of data within the time span of a game: therefore, the game design needs to embody simplicity (a limited set of information).

When a computer simulation is run, all elements of the model are specified: rules are explicitly stated, decisions are explicit, and uncertainties have to be captured in a certain way to allow for quantification and calculation. The world the model represents is necessarily closed. Gaming is more geared towards allowing the knowledge and experience of the participants to directly influence the process of the game (if the rules of the game allow this freedom). First of all, the outcome of the game is strongly dependent on the will of participants to play along. Often, details of the rules are still negotiable while gaming, allowing for a more realistic setting. Thus, behaviour-related uncertainties cannot be captured or prevented in a game. The model should be open to "irregularities" taking place.

Simulations often hide many of the assumptions and abstractions that underlie the calculations - this is often necessary as the parameter space is very large and the details are many. Although gaming, as indicated, can also rely on such mathematical models, the abstractions are often more explicit, as participants are in closer contact with the representation of the world: it is easier to trace outcomes of activities (and then either accept or reject the abstractions).

The learning aspects of simulations lie predominantly with the researchers themselves (although the models are often made for policy makers or other clients). In designing a valid simulation model, many details need to be considered, researched, and verified which constitutes a learning process (i.e. Modelling as a way of organising knowledge (Wierzbicki, 2007)) for outsiders, the simulation quickly turns into a black box. Gaming potentially allows for the same learning experiences for researchers or designers, but is also often specifically focused on a learning experience for the participants. We would suggest that gaming therefore is more geared towards understanding social intricacies and engaging players in a discovery process, whereas simulations are often expected to produce quantitative outcomes.

Using ABMs and Serious Games for Communicating Futures

When using these methods for communicating possible future developments, the goals (e.g. advertising, legitimising action, demonstration of consequences, facilitating discussion, thinking in alternatives, insight in uncertainties, exploring policy) determine the means. The modelling approach builds strongly on the expertise of the modellers; the model itself is – for most users – a black box that should be trusted because of the reputation of its maker(s). When large policy institutes such as the World Bank and International Energy Agency publish results based on their computational general equilibrium models[2], the outcomes are treated as predictions rather than hypotheses. Often challenging the model can not be done for the following reasons:

- Closed data: the owner of the data typically considers it a valuable asset that should not be shared;
- Closed model: the institutes develop the models over a long period, building block upon block, which makes the full ensemble opaque;
- Modelling paradigm: fundamental assumptions that drive modelling choices are not debated, nor can they be adapted without dramatic changes.

Thus, challenging the model limits itself to adjusting predetermined variables. The users of the model are presented with a “package deal” and can either accept or reject the artefact as a whole. Various developments in the modelling world attempt to remedy this fundamental flaw: open data initiatives enable scrutiny of underlying data[3], modelling practitioners are developing mechanisms for opening up and verifying models[4], and the use of open source software that allows for sharing and collectively improving the programming fundamentals[5]. Moreover, the combined use of these open models with serious games can further improve the understanding of complex systems (Chappin, 2011).

The advantage of serious games is a more active involvement of stakeholders in the discovery of patterns. Therefore, the assumptions of a game need to be clear from the beginning for players to actually get engaged (unless finding out the rules is part of the game-play (see McGonigal (2003b)). By living through the experience, the players are triggered to understand the underlying logic or at least compare their own actions with those of other players and the success or failure it means to them. That, in combination with the fun and excitement involved in some games, leads to strong involvement and faster and deeper learning. Because the outcome of a single game could just be the happy coincidence of players and rules – and thus have limited scientific meaning – the rich insight gained by playing games should be augmented by insights from multiple rigorous agent-based simulations.

From the players' perspective, still a leap of faith is required, namely the leap of faith that the assumptions of the game designer are correct. What is interesting to see is that deeply involved game players may not even be interested in the question whether the game reflects reality (McGonigal, 2006); they are generally oblivious to the hidden rhetoric of the game (Bogost, 2008), thus leading to a similar type of acceptance as we saw with ABMs.

The systems oriented nature of both approaches allow both researchers and participants or clients to move beyond simple linear cause-and-effect thinking, and get closer in touch with complex systems' emergent behaviour and systemic surprises. The agent-based modeller is, however, restricted to a certain world view or logic as the agents require behavioural scripts to follow. As indicated, there are few opportunities to challenge the assumptions of the modeller – both with regard to input parameters and fundamental design choices. The game design may allow for further investigation. In the example we presented here, there are few opportunities for the players to challenge the market's logic of demand and supply and marginal cost pricing. There are, however, games (e.g. the fishing game explained by Meadows (1999)) that are built to allow the players to transcend a competitive one-winner stance and to invent new cooperative rules that make everyone a winner.

Conclusions

What has already been commonplace in futures studies is now also advocated by (systems) engineers: when dealing with an uncertain, complex future one cannot predict, but should try to explore it. We find that agent-based models and serious games are useful approaches when exploring the future. They both allow for experiencing and exploring future scenarios with the aim of better understanding them. They are both built on the premise that some elements of uncertainty exist and that these uncertainties influence the outcome of the system under investigation. Both methods take a systems perspective and underline that complex futures are to be explored in a systematic fashion. Only some serious games allow for investigating futures beyond the researchers' intended frame of reference. ABM can develop further in incorporating different perspectives by allowing the intended users to co-create the agents and their behaviour. Thus, a model can be made that is more transparent and based on the world views of more than a handful of researchers. Serious games are thrilling and exciting, especially when combined with the graphical shock and awe of modern computers; the rigorous proof that games can lead to different insights is, however, often lacking.

Neither the use of agent-based models nor the use of serious games is sufficient to provide a comprehensive set of insights. Therefore, they should not be adopted in isolation. Different approaches provide different glasses through which the world can be explored. Both gaming and ABM allow for the input of other sources of knowledge to enhance the researcher's model. There is still much to learn in the exploration of complex systems, but these combinations look promising, both for researchers and their clients.

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Notes

1. Corresponding author: a.ligtvoet@tudelft.nl
2. World Bank: LINKAGE model, IEA: World Energy Model
3. See for example http://enipedia.tudelft.nl which is becoming the largest open database of energy related statistics.
4. See for example http://www.openabm.org which is a platform for sharing ABM applications.
5. See for example https://github.com/alfredas/AgentSpring which is an open source platform for developing ABMs.

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