METHODOLOGICAL ANALYSIS OF INVESTMENT DECISION MAKING ALGORITHMS IN LONG-TERM AGENT-BASED ELECTRICITY MARKET MODELS

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Overview

Traditional long-term power system modelling techniques consist of optimization and equilibrium models. Optimization models typically aim to minimize the total system cost. The solution of such a model can be interpreted as the equilibrium established in competitive markets where agents aim to maximize surplus and are fully rational. In contrast, in equilibrium models, each agent is represented explicitly by its own optimization problem, and the aims is to find the equilibrium between these different agents interacting. This offers more flexibility to model for instance strategic or risk-averse behaviours. Such equilibrium models are computationally challenging to solve, and are still restricted in terms of the representation of agents and their decision making process.

However, the assumptions such as perfect information and rational players made by optimization and equilibrium are sometimes unrealistic. Moreover, due to the fact that investors are heterogeneous in the form of technology preferences, prior investment choices and financial status, agent level heterogeneity has to be modelled when the aforementioned assumptions do not hold. Agent-based modelling (ABM) has the flexibility to incorporate detailed descriptive components on agent level, enabling the modeller to carry out research under the situation of imperfect information and bounded rationality.

Over the past decades, several ABM frameworks have been developed to study electricity markets. Most ABM frameworks focused on the behaviour of agents in spot markets. A limited number of models have incorporated agent level investment decision making, for instance EMLab [1], EMCAS [2] and PowerACE [3]. One challenge for long-term ABMs is how to model the investment decision making of generation companies. Whereas the criteria used for making an investment decision are relatively clear (e.g., a positive net present value or an internal rate of return exceeding a certain threshold), the challenge specifically lies in determining a method to make the projections of future revenue streams, which are needed to evaluate the investment decision criterion. The investment methods (i.e., the assumptions relating to future revenue stream projections) used in different long-term ABMs described in the literature vary strongly. The influence of these assumptions on the modelling results has to our best-knowedge not yet been investigated.

The aim of this paper is to gain insight into the underlying assumptions regarding revenue projection of different agents, and assessing the impact and the sensitivities of different investment algorithms adopted in ABMs. To this end, the results of an ABM in which different investment algorithms are incorporated are compared, and a sensitivity analysis is performed. In addition, the results of all these simulations will be compared to those of an equilibrium model.

Methods

So as to compare the investment decision algorithms implemented in ABMs in the literature, we developed an agent-based model in which the system features will be kept unchanged except for the investment algorithms applied by energy producers. The theoretical basis of these investment decision algorithms can vary. A first option (as in [1]), is evaluating the profitability of possible investments using so-called virtual auction processes, i.e. a virtual market clearing of the electricity market in future years is perfomed to determine electricity prices and operating hours for different investment options. One key element is how to project the configuration of the future system. Given that it becomes more difficult to make good projections of the system configuration as one looks further into the future, an important parameter to consider is the time horizon used by the agent to base its investment decisions on. We will refer to this as the *look-ahead horizon* in the rest of the paper. In a second option (as in [2]), the investment algorithm introduces scenario trees to anticipate competitors' generation expansion, whereas the corresponding probabilities on different branches are exogenous input. In a third option [3], investment decisions are based on the assumption that electricity prices increase over time following a certain rate. This paper will mainly compare the first and second approach. These future revenue projection methods and the corresponding key parameters are summarized in Table 1. The results coming from these different models will be compared, as well as the sensitivity of the results to key parameters listed in Table 1.

Table 1 Key features as well as pros and cons of the investment algorithms adopted in ABMs

Future revenue projection methods	**Key parameters**	**Reference example**
Run virtual auction based on anticipated capacity mix over a future horizon. The anticipation takes announced new projects and and generator reaching life expentancy into account.	Look-ahead time horizon	[1]
Use scenario trees to forecast competitors' investments in the corresponding year.	Probabilities over each branch in the scenario	[2]

Results

A simple test case with 3 types of technologies has already been carried out by using the first approach. The stabilized system capacity mix, under different look-ahead time horizon setting and the equilibrium solution derived from a screening curve method, are shown in Fig. 1. We found that overinvestment increases exponentially as the look ahead horizon becomes longer. This overinvestment is caused by the absence of an effective future capacity mix anticipation algorithm. In the first approach, agents project the capacity mix in a given future year by starting from the existing capacity mix and adding the already announced new capacity and subtracting the capacity reaching life expectancies before that given year. Thus, the agents assume no new investment decisions will be made between the current year, and a given future year. This assumption makes the simulation results sensitive to different look-ahead horizon in a way that short look-ahead horizon capture limited future information such as fuel price volatility and demand growth, while a longer look-ahead horizon lead to unrealistic expectation on future scarcities.

Adopting a time horizon between 10-15 years can be seen as a compromising solution as only a limited amount of existing capacities will reach their life expectancies within a relatively short horizon such that agent will expect realistic scarcities. While on the other hand, modellers are assuming that agents make decisions with limited future information. Fig. 2 shows the future capacity anticipation in a typical investment year with a look-ahead horizon of 20 years, during which a serious but unrealistic scarcity is expected after 15 years. These unrealistically high projections of scarcities and correspondingly high revenues drive the agents' overinvestment.

Another interesting fact observed in Fig. 1 is that overinvested capacities lie mostly on peak-load technologies. This is because scarcities are typically observed only in the last few years of the look-ahead horizon (see e.g. Fig.2), guiding the agents to select peak-load technologies, which are more cost-effective for short running hours thanks to their low capital costs. More results and analysis on such key parameters will be presented in the final paper.

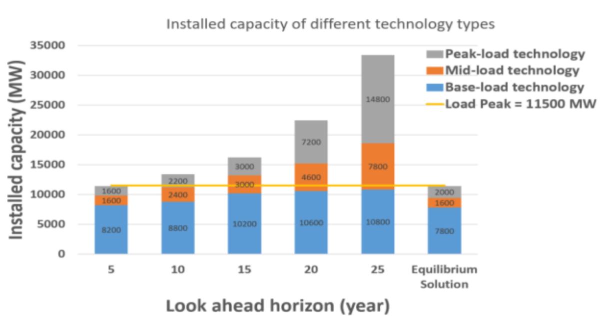

Figure 1 Sensitivity analysis on look ahead horizon

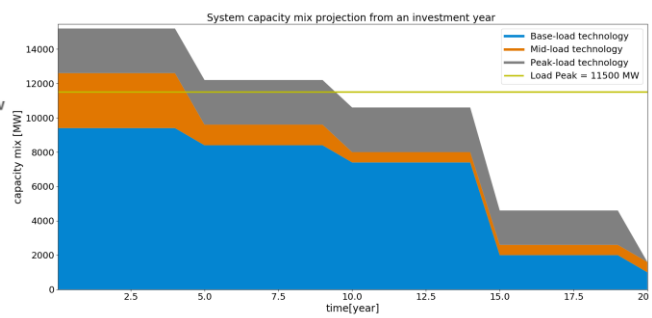

Figure 2 Expected capacity mix from an investment year

Conclusions

A simple test case already demonstrates that modellers should be well aware of the influences imposed by different assumptions and the corresponding key parameters in the investment algorithms adopted by long-term agent-based models, by which the credibility of modelling results and the conclusions drawn from these results can be guaranteed.

References

[1] L. De Vries, E. J. Chappin, and J. C. Richstein, "Emlab-generation-an experimentation environment for elec-tricity policy analysis (version 1.2),"Delft. http://emlab.tudelft.nl/generation/emlab-generation-report-1.2.pdf,2015.

[2]A. Botterud, M.R. Mahalik, T.D. Veselka, H.S. Ryu, and K.W. Sohn,"Multi-agent simulation of generationexpansion in electricity markets," inPower Engineering Society General Meeting. IEEE, 2007,pp.1–8.

[3] M. Genoese, F. Genoese, and W. Fichtner, "Model-basedanalysis of the impact of capacity markets on elec-tricity markets," in 2012 9th International Conference on the European Energy Market. IEEE, 2012, pp. 1–6