Modelling the Transition to a Low-Carbon Energy Supply

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1 Background and Research Question

Due to the threat of climate change, a transition from a fossil-fuel based system to one based on zero-carbon is required. However, this is not as simple as shutting down all fossil-fuel based power plants and replacing them with renewable energy; careful decisions need to be made to reduce economic impact and lapses in electricity supply. Decision makers therefore need a way of assessing the consequences of decisions in different possible scenarios.

Due to a deliberate move away from centralised planning, and to the liberalisation of electricity markets in many western democracies, heterogenous actors with bounded rationality and imperfect information should be focused on to increase understanding [1].

I propose a method of modelling these heterogenous actors in electricity markets and explore potential pathways to transition to a low-carbon economy. For this goal, I have created a new open-source agent-based model named ElecSim. ElecSim is a stochastic electricity market simulation tool which enables practitioners to alter scenarios and assess the outcomes of possible interventions in an electricity market.

I propose the use of artificial intelligence and optimisation techniques to gain a more realistic representation of an electricity market, and better aid policy makers and electricity market players. Specifically, this will involve the use of reinforcement learning techniques such as Deep Deterministic Policy Gradients (DDPGs)[2], or Deep Q Networks [3]. These algorithms will be used to learn optimal bidding and investment strategies.

1.1 Literature Review

Live experimentation of an electricity market is not practical. The time scales are long and there is a significant risk that changes can have detrimental impacts. This can often lead to minor tweaks being made [4]. A solution to this is simulation, where simulation is the substitution of a physical process with a computer model.

A number of different simulations and computer models have been used to aid policy makers and energy market developers in coming to informed conclusions. Energy models can typically be classified as top-down macroeconomic models or bottom-up techno-economic models [5]. To explicitly model types of technology such as the intermittency of renewables we have focused on bottom-up techno-economic models.

Tool name	Open Source	Long-Term Invest-ment	Market	Stochastic Inputs	Country General-isability
SEPIA [10]	✓	×	✓	Demand	✓
EMCAS [11]	×	✓	✓	Outages	✓
NEMSIM [12]	?	✓	✓	×	×
AMES [13]	✓	×	Day-ahead	×	×
GAPEX [14]	?	×	Day-ahead	×	✓
PowerACE [15]	×	✓	✓	Outages Demand	✓
EMLab [16]	✓	✓	Futures	×	✓
MACSEM [17]	?	×	✓	×	✓
ElecSIM	✓	✓	Futures	✓	✓

Table 1: Features of electricity market ABM tools.

It is possible to further categorise bottom-up models into optimisation and simulation models. Optimisation energy models minimise costs or maximise welfare, defined as the material and physical well-being of people, from the perspective of a central planner [6]. Examples of optimisation models are MARKAL/TIMES [7] and MESSAGE [8].

However, electricity market liberalisation in many western democracies has changed the framework conditions. Centralised, monopolistic, decision making entities have given way to multiple heterogeneous agents acting for their own best interest [9]. Policy options must therefore be used to encourage changes to attain a desired outcome. It is proposed that these complex agents are modelled using ABMs due to their non-deterministic nature.

A number of dedicated tools have been created for this regard, however by referring to Table 1 it can be seen that these do not suit the needs of an open source, long-term market model.

1.2 Background and Research Question

- Introduction to problem of climate change and requirement for decarbonization.
- Requirement of shift in heating, transport, and industry to electricity.
- Inability to use traditional machine learning and statistical tools to project into future due to rapid disruption.
- Use of long-term agent-based model to simulate into the future (eg. 2050) allowing policy makers and energy market players to assess effect of decisions made.
- Agent-based models can be used to model the impact of heterogenous investors
- Enable policy makers to assess the impact of market power and collusion
- Ability to use reinforcement learning to give agents intelligence

1.3 Literature Review

- Literature review on state-of-the-art models and applications
- Agent-based model tools
    1. Absence of open-source tool with stochasticity (table).
- Optimisation tools

1.4 Work Completed

- Short-term load forecasting
- Completion of agent-based model at yearly granularity
- Results of yearly granularity of agent-based model
- Use of Northern Ireland scenario for optimisation of carbon tax using reinforcement learning (preliminary results)

2 Research Outputs

- Note-paper at e-Energy '18
- Poster at e-Energy '19
- Paper at 2nd International Workshop on Electricity Market Engineering at e-Energy '19?

3 Remaining Work

Whilst the agent-based model, ElecSim, has been designed and parametrised, it has been designed to cater for a temporal granularity of a yearly time-step. That is, decisions for bidding into an electricity market and investing in power plants happens every year. The goal is to increase the granularity temporally, which will enable the modelling of sudden fluctuations in wind speed and solar irradiance. Collins *et al.* showed that a low temporal resolution results in overestimation of intermittent renewable energy technology, and underestimation in dispatchable energy sources [18].

To further increase the validation accuracy of ElecSim, I propose the use of optimisation such as mixed integer linear programming and genetic programming to further parametrise the model. I propose the use of the NSGA-II algorithm, which enables multi-objective optimisation, and approximates the pareto frontier [19]. I propose the minimisation of the difference between real and modelled electricity prices and real and modelled energy mix. Where the energy mix is defined as percentage share of different renewable types.

I propose the use of reinforcement learning techniques to control the behaviour of agents. For instance, controlling and optimising the behaviour of investment decisions and bidding strategies. I would also like to model collusion between agents through the means of parameter sharing between agents. This would enable the comparison between scenarios where collusion is present and those where it is not.

Whilst I have completed preliminary work on optimising the carbon price using reinforcement learning techniques using DDPG, I would like to do improve this when I have designed a higher granularity model which may improve results.

I propose the modelling of further scenarios using this model and change variables such as cost of technologies, change in demand, uncertainty in fuel prices, differing countries, and changing availability and capacity factors.

Finally, I would like to compare my model to another open source model, OSeMOSYS [20]. OSeMOSYS is an optimisation based model. I believe that a comparison between agent-based models and optimisation model will help to elucidate the strengths and weaknesses of these models in comparison to one another, and discover the scenarios in which the models are better suited.

1. Increase granularity to hourly.

   (a) Selection of best representative days for long-term - Comparison to literature that selects best day for single year.

2. Parametrise model using genetic algorithm or other optimisation tool.

3. Add intelligence to agents using reinforcement learning for:

   (a) Investment decisions.

   (b) Bidding strategy.

   (c) Impact of collusion (variable sharing between two or more agents).

4. Complete work on carbon tax optimiser

5. Comparison of optimisation and agent-based model in different scenarios.

   (a) Same intialisation parameters and project to future (form of cross-validation).

   (b) Collusion.

6. Further scenarios and results as examples

   (a) Decreasing costs of technology over time

   (b) Different countries

   (c) Improving availability and capacity factors

   (d) Uncertainty in fuel prices

   (e) Changing demand curve shape due to increase in electric vehicles

4 Progress against First Year Plan

Review A literature review has been undertaken and a greater understanding of energy market models has been developed. With a distinction between top-down macroeconomic models and bottom-up techno-economic models shown. Also the differences between traditional centralised optimisation models and new simulation techniques developed. I have developed a table which positions my research in relation to the literature.

Design of System and Validation The fundamental components of the system have been designed. A model of an electricity market with a yearly time-step has been completed with generation company and demand agents, with example scenarios. The model has been calibrated with data from the UK, however designed in such a way that other countries can be used. For instance, by providing an optimisation framework in which individual cost parameters can be estimated from a simple average cost of electricity.

I am currently testing the design of a 30 minute time step. Representative days of weather and load have been selected to reduce overall computation time by testing different techniques such as k-means clustering, genetic programming and Fourier resampling.

The model has been validated through the comparison of actual electricity prices with modelled electricity prices. The model has also been validated through the means of observation of a process. Specifically, an increase in carbon tax leads to a proportionally higher uptake in low-carbon technology and vice-versa.

I have researched the use of reinforcement learning to optimise carbon tax to reduce electricity price and carbon emissions. However, this has not provided the expected results of a rapid increase in reward. I am increasing the temporal granularity to aid in this, and further investigation is required.

I am yet to implement agent intelligence through the use of reinforcement learning for bidding and investment strategies. However, I have identified the necessary algorithms for this.

Scenario Testing I have undertaken various scenario tests by increasing and decreasing electricity demand and varying carbon taxes to observe the behaviour.

5 Remaining Work Plan

Parameter Tuning I plan to tune the parameters with respect to a minimisation of the difference between actual and modelled electricity price as well as electricity mix. The parameters to tune will be:

Multi-agent Intelligence

Carbon-tax Optimiser

Collusion

Optimisation and Agent-Based Model Comparison

Thesis

Alexander Kell PhD Gantt Chart

TITLE	Modelling the Transition to a Low-Carbon Energy Supply	**AFFILIATION**	Newcastle University
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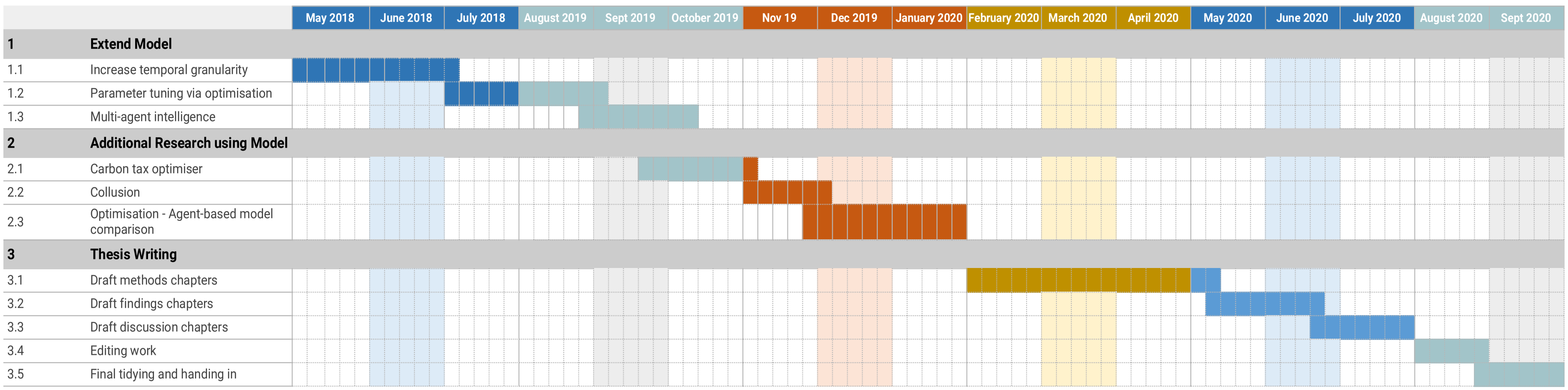

6 Thesis Outline

6.1 Chapters

1. Introduction
2. Literature review
3. Data analytics of smart meter data
   (a) Short-term
   (b) Long-term load forecasting (inadequacy of long-term load forecasting)
   (c) Demand segmentation
4. ElecSim: An open-sourced agent-based model
   (a) Yearly granularity
   (b) Hourly granularity
5. Adding Intelligence to Agents
   (a) Reinforcement learning techniques for agents
   (b) Collusion
   (c) Optimisation of Carbon Tax using reinforcement learning
6. Scenarios
7. Agent-based model and Optimisation tool: A comparison
8. Conclusion and future work

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