Modelling Carbon Tax in the UK Electricity Market using an Agent-Based Model

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ABSTRACT

Impacts on natural and human systems have already been observed due to anthropogenic greenhouse gas emissions [16]. To reduce these emissions, a transition to a low-carbon economy is required. Carbon taxes can be used as a tool for pricing in the negative externalities of pollution and enabling a more rapid transition to a low-carbon economy.

This paper proposes the use of agent-based models to simulate an electricity market based in the United Kingdom. We vary carbon tax to observe the effects on investment up until 2050. We find that a carbon tax of £70 per tonne of CO_2 is sufficient in driving investment to an almost 100% renewable energy supply. A less aggressive option, however, of setting a carbon tax at £20 would lead to a 50% low-carbon 50%, traditional generation energy mix.

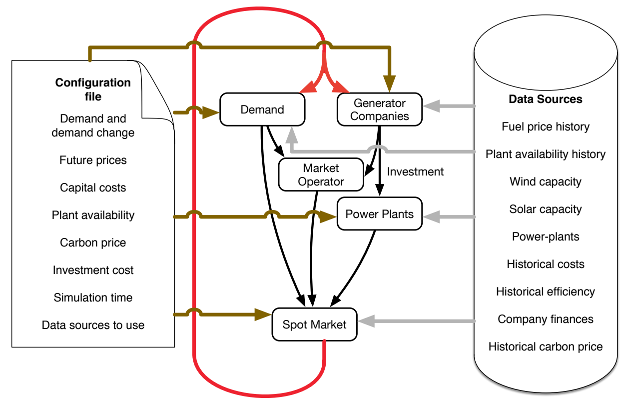

Figure 1: System overview of agent-based market model.

1 INTRODUCTION

Governmental policy is a tool that can be used to aid the transition to a low-carbon economy to prevent the worst effects of climate change. Options include a tax on all carbon emissions or subsidies in low-carbon technologies. In this paper, we propose the varying of carbon taxes to assess the long-term impacts on investment in the electricity market using an agent-based model simulation.

Simulation is a technique to create a physical system in a virtual model. In this context a model is defined as a set of mathematical formulas and algorithms which are designed to mimic real life [9]. Simulation allows practitioners to rapidly prototype high risk ideas in this virtual model and assess their outcome before implementation in the real world.

The electricity market in many western democracies consists of multiple heterogenous actors acting for their own best interest [17]. Agent-based modelling is a technique which allows for the simulation of these heterogenous actors with different risk profiles, profit requirements and preferences. A number of agent-based models have been used to model the impact of carbon tax on long term investments [3, 4, 22]. ABMs have been utilised in this field to address phenomena such as market power [20].

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We model the realisation of the wholesale electricity market in the United Kingdom and adjust carbon tax in our agent-based model to see the effect of long-term investment. We posit that decisions made today can have complex long-term consequences, the process of which can be observed through simulation.

This paper details our model, ElecSIM. We contribute a new open-source framework, and test different scenarios with varying carbon taxes to provide advice to stakeholders. Section **??** is a literature review of the models currently used in practice. Section 2 details the model and assumptions made, and Section **??** details how we validated our model, and displays performance metrics. Section 3 details our results, and explores ways in which ElecSIM can be used. We conclude the work and propose future work in Section 4.

2 MODEL ARCHITECTURE

The agent-based model is made up of five significant parts: the agents which are the generation companies (GenCos) and demand agents; power plants and a market operator which controls the spot market. How these parts interact are displayed in figure 1 with the relevant data sources.

We initialise the United Kingdom with every single power plant in operation in the year 2018, owned by their respective generation companies . Individual historical power plant costs are estimated from levelized cost of electricity (LCOE) [5] calculations [11, 12], whereas future power plants are taken from the department of business and industrial strategy [6]. The variable operation and maintenance cost was defined stochastically to model the changing costs per project. A uniform distribution was chosen to provide sufficient variance between projects.

The demand agent is modelled as a single aggregated demand, split up into 20 segments of a load duration curve (LDC), enabling us to increase speed of computation whilst maintaining accuracy. A LDC is defined as the load within a year, ordered in order of magnitude.

We model the influence of outages using availability data for gas, coal, photovoltaic, offshore and onshore power generators [2, 10, 15]. Historical availabilities are modelled for older gas, coal and hydro power plants [1]. Capacity factors were taken as an average of the UK for solar and wind [19, 21]. Where capacity factors is defined as the ratio of electrical output over a given time period over the maximum possible electrical energy output.

The generation companies make electricity bids each year for each of their power plants. The market operator then matches demand with supply in order of price, also known as merit-order dispatch. We model a uniform pricing market, where each of the companies are paid the highest accepted bid.

GenCos have the ability to invest every year in new power plants based on the expected net present value (NPV) of each power plant type. NPV is a summation of the present value of a series of present and future cash flow. The NPV calculation is dependent on a stochastic representation of GenCos predictions of fuel, carbon and electricity price and demand.

Each GenCo has a separate weighted average cost of capital (WACC), which is the rate that a company is expected to pay on average for its stock and debt, this is used as the discount rate in the NPV calculation [13]. The WACC is modelled as a stochastic variable, with a Gaussian distribution and a ±3% standard deviation, with values of 5.9% for non-nuclear power plants, and 10% for nuclear power plants [14, 18].

The model took yearly time-steps to limit the impact on computation time, however, to model the intermittency of renewable generation, we correlated demand with the respective capacity factor, enabling for example, solar and wind to only contribute a certain capacity to their load curve.

Stochasticity of fuel price within a year was also modelled, to take into account difference in hedging strategies and chance. An ARIMA model [7] was fit to historic coal and natural gas prices.

3 RESULTS

We experimented with the following levels of carbon tax: £10, £20 and £70.

This section describes scenario runs using ElecSIM. Here, we vary the carbon tax and either grow or reduce total electricity demand. This was done to observe the effects of carbon tax policy on long-term investment.

We assume that carbon tax is set by the government, and not subject to market forces such as the EU Emissions Trading Scheme [8].

We run 16 different scenarios 8 times each, with demand increasing and decreasing by 1% per year and varying carbon prices. In this section we explore a decreasing demand of 1% a year. We chose this due to the increasing efficiency of homes, industry and technology, and due to the recent trend in the UK. Demand, however, did not display a large effect on the optimum carbon price. We select a burn-in period of 6 years, due to the fact that the majority of power plants take 6 years to go from investment to operation.

It can be seen from Figure 2c that a carbon tax of £10 per year does little to influence investment in low-carbon, renewable technology. With traditional, fossil fuel based generation, providing the majority of supply in each year. However, there is an increase in renewable technology over the years, starting from mean 15.85% market share in the year range 2019-2029, to 24.38% in the year range 2039-2050. A similar increase of renewable energy with a carbon tax of £0 can be seen, albeit at a lower mean by the year range 2039-2050 (22.29%).

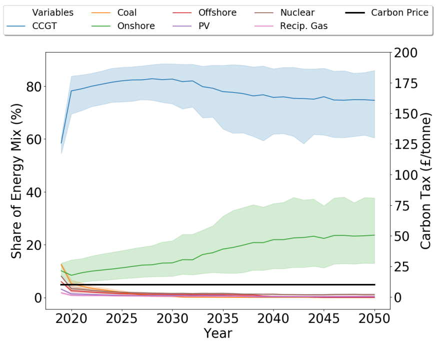
4 CONCLUSIONS

The shift in electricity markets from a centrally controlled monopoly, to a liberalised market with many heterogeneous players has increased the need for a new type of modelling. We motivate that agent-based models can be used as a solution to this, by their ability to model many actors with individual properties.

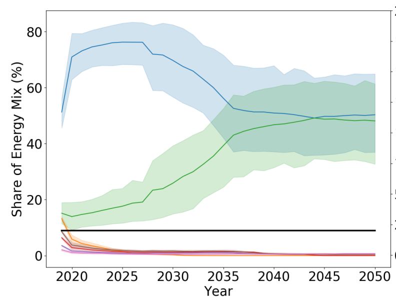
Agent-based models are able to model imperfect information as well as heterogeneous actors. ElecSIM models imperfect information through forecasting of electricity demand and future fuel and electricity prices. This leads to agents taking risk on their investments, and more realistically model market conditions.

We demonstrated that increasing carbon tax can lead to a significant increase in investment of low-carbon technologies such as onshore wind. However, an interesting result was that early decisions have a long impact on the future energy mix. The market can be significantly changed through investment decisions made many years previously.

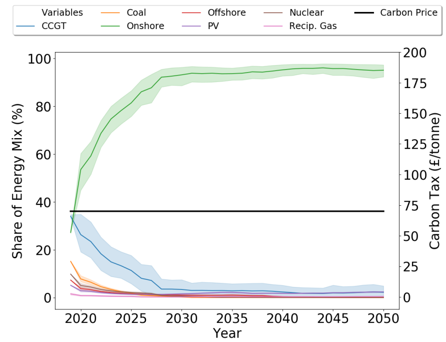
Our future work includes comparing agent-learning techniques, using multi-agent reinforcement learning algorithms and artificial intelligence to allow agents to learn in a non-static environment. We propose the integration of a higher temporal and spatial resolution to model changes in daily demand, as well as capacity factors by region, and transmission effects.



(a) £10 carbon tax.



(b) £20 carbon tax.



(c) £70 carbon tax.

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