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 [17]. 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. We have used the United Kingdom as an exemplar, however any country can be used through parametrisation. We vary carbon tax to observe the effects on investment up until 2050. We find that a carbon tax of £70 ($90) 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 ($26) would lead to a 50% low-carbon, 50% traditional generation energy mix.

1 INTRODUCTION

Governmental policy is a tool that can be used to aid in 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 vary carbon taxes to assess the long-term impacts on investment in the electricity market. We used a general agent-based model simulation made for wholesale electricity markets, created by us.

Simulation is a technique to create a physical system in a virtual world. In this context a model is defined as a set of mathematical formulas and algorithms which are designed to mimic real life [10]. 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 [18]. 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 [4, 5, 23]. ABMs have been utilised in this field to address phenomena such as market power [21].

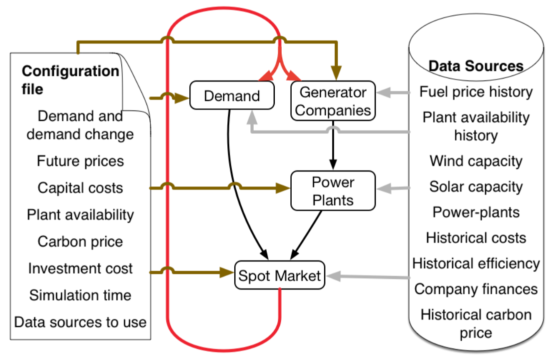


Figure 1: System overview of agent-based market model.

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. Whilst we have modelled the United Kingdom, it would be possible to model for any country with different parameters. 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 and different carbon scenarios. Section 2 details the model, assumptions made and parameters. Section 3 presents our results. We conclude our work in Section 4 and explore possible routes forward .

2 MODEL ARCHITECTURE

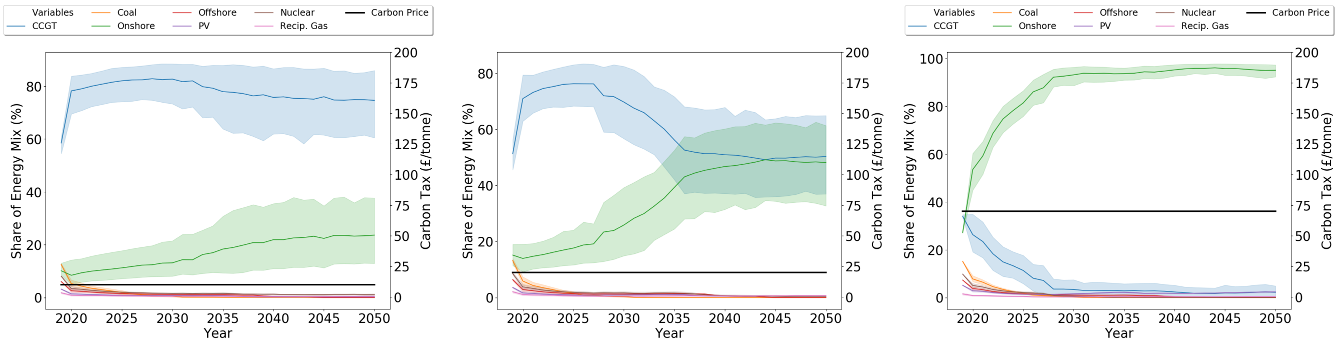
The agent-based model is made up of five significant parts: the agents which are made up of the generation companies (GenCos) and demand agents; power plants and a market operator which controls the spot market. How these parts interact are displayed in Figure 1. The relevant data sources are also provided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

We initialise the United Kingdom with our model with exemplar data from the UK. We model every single power plant in operation in the year 2018, which are owned by their respective generation companies. Individual historical power plant costs are estimated from levelized cost of electricity (LCOE) [7, 12, 13], whereas future and present power plant costs are taken from the department of business and industrial strategy [8]. The variable operation and maintenance cost was defined stochastically to model the varying 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 yearly load duration curve (LDC),

e-Energy '19, June 25–28, 2019, Phoenix, AZ, USA

ACM ISBN 978-1-4503-6671-7/19/06.
https://doi.org/10.1145/3307772.3330175



(a) £10 carbon tax. **(b) £20 carbon tax.** **(c) £70 carbon tax.**

Figure 2: Scenarios from 2020 to 2050 with varying carbon tax.

enabling us to increase speed of computation whilst maintaining accuracy. An LDC is defined as load sorted in order of magnitude.

We model the influence of outages using availability data for gas, coal, photovoltaic, and wind power generators [3, 11, 16]. Historical availabilities are modelled for old gas, coal and hydro power plants [1]. Capacity factors per geographical location were taken as an average of the UK for solar and wind [20, 22]. Where a capacity factor 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 per load segment.

GenCos have the ability to invest every year in new power plants based on the expected net present value (NPV) of each type of power plant. 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 average rate that a company is expected to for its stock and debt. This is used as the discount rate in the NPV calculation [14]. The WACC is modelled as a stochastic variable, with a Gaussian distribution, with a ±3% standard deviation, with values of 5.9% for non-nuclear power plants, and 10% for nuclear power plants [15, 19].

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 [9] was fit to historic coal and natural gas prices.

3 RESULTS

We experimented with the following levels of carbon tax: £10 ($13), £20 ($26) and £70 ($90) with demand decreasing 1% per year. This was chosen due to the increasing efficiency of homes, industry and technology, and due to the recent trend in the UK. We run each scenario 8 times to capture the stochastic nature of the process. Via the observation of the emergent investment behaviour until 2050, an understanding of how real life investors may behave emerges.

Figure 2a shows that with a carbon tax of £10, whilst renewable technology does grow, gas power plants provide the majority of supply in each year. However, at a level of £20 the increase in wind turbines is enough to match gas turbines. A carbon tax of £70, however, shows a near 100% uptake of wind turbines.

It is infeasible for the power supply to be provided solely by wind turbines today. This overestimation, however, is due to the low time granularity of the model [6]. This scenario therefore assumes perfect storage capabilities.

4 CONCLUSIONS

Agent-based models provide a method of simulating investor behaviour in an electricity market. We observed that an increase in carbon tax had a significant impact on investment. These findings enable policy makers to better understand the impact that their decisions may have. For a high uptake of renewable energy technology, rapid results can be seen after 10 years with a carbon tax of £70 ($90).

Agent-based models open up the possibility of testing differing investor behaviours through techniques such as reinforcement learning. This can be extended to incorporate collusion which can have an impact in liberalized electricity markets [2].

ACKNOWLEDGMENTS

This work was supported by the Engineering and Physical Sciences Research Council, Centre for Doctoral Training in Cloud Computing for Big Data [grant number EP/L015358/1].

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