Optimizing carbon tax for decentralized electricity markets using an agent-based model

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ABSTRACT

Averting the effects of anthropogenic climate change requires a transition from fossil-fuels to low-carbon technology. A way to achieve this is to decarbonise the electricity grid, however, further efforts must be made in other fields such as transport and heating for full decarbonisation. This would reduce carbon emissions due to electricity generation, and also help to decarbonise other sources such as automotive and heating by enabling a low-carbon alternative. Carbon taxes have been shown to be an efficient way to aid in this transition.

In this paper we demonstrate how to to find optimal carbon tax policies through a genetic algorithm approach, using the electricity market agent-based model ElecSim. To achieve this we use the NSGA-II genetic algorithm to minimise average electricity price and relative carbon intensity of the electricity mix. We demonstrate that it is possible to find a range of carbon taxes to suit different objectives. We minimise electricity cost to below £10/MWh and reduce carbon intensity to zero in all cases. The optimal carbon tax strategies generally increase from 2020 to 2035, and are above £81/tCO2 in all instances, with a mean of £240/tCO2.

KEYWORDS

Energy markets, policy, carbon tax, genetic algorithm, optimization, digital twin, agent-based models, electricity market model

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1 INTRODUCTION

Computer simulation allows practitioners to model real-world systems using software. These simulations allow for '*what-if*' analyses which can provide an indication as to how a system may behave under certain policies, environments and assumptions. These simulations become particularly important in systems which have high costs, impacts or risks associated with them. A 'digital twin' is a concept which has emerged in recent years. This is defined as a simulation of a specific instance of a system.

An electricity market is an example of a complex system which can be modelled using a digital twin. Disruptions to electricity supply, a substantial increase in the cost of electricity or unrestrained carbon emissions have the potential to destabilise economies [13, 19]. It is for reasons such as these that electricity market models are used to test hypotheses, develop strategies and gain an understanding of underlying dynamics to prevent undesirable consequences [12].

In this paper we use the electricity market agent-based model ElecSim to find an optimum carbon tax policy [14]. Specifically, we use a genetic algorithm to find a carbon tax policy to reduce both average electricity price and the relative carbon density by 2035 for the UK electricity market.

Carbon taxes have been shown to quickly lower emissions and lower the costs to the public [24]. Carbon taxes are able to send clear price signals, as opposed to a cap-and-trade scheme, such as the EU Emissions Trading System, which has shown to be unstable [24].

In this paper we use the reference scenario projected by the UK Government's Department for Business & Industrial Strategy (BEIS) with model parameters calibrated by Kell *et al.* [8, 15]. This reference scenario projects energy and emissions until 2035. We undertake various carbon tax policy interventions to see how we could reduce relative carbon density whilst at the same time reduce the average electricity price.

The parameter space we optimise over is the carbon tax price over a 17 year period from 2018 to 2035. The carbon price is used to influence the objectives of average electricity price and relative carbon intensity in 2035. Grid and random search are approaches which trial parameters at evenly distributed spaces and random spaces respectively. These approaches are often inefficient, however, and require an increased number of simulations due to their static nature. Genetic Algorithms in contrast use an evolutionary computing approach to find global optimal solutions faster.

In order to optimise over two potentially competing objectives, i.e. average electricity price and relative carbon intensity, we use the Non-Dominated Sorting Genetic Algorithm II (NSGA-II) [6]. The NSGA-II algorithm can approximate a Pareto frontier [22, 23]. A Pareto frontier is a curve in which there is no solution which is better than another along the curve for different sets of parameters. In this context, better means that a solution is closer to the optimal for a particular combination of objectives.

We find that the rewards of average electricity price and relative carbon intensity are not mutually exclusive. That is, it is possible to have both a lower average electricity price and a lower relative carbon price. This is due to the low short-run marginal cost of renewable technology, which has been shown to lower electricity prices [21].

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The main contribution of this paper is to explore carbon tax strategies using genetic algorithms for multi-objective optimisation.

The following sections are set out as follows. Section 2 covers examples of optimisations using genetic algorithms and different carbon strategies. Section 3 details the optimization techniques applied. Section 4 explores the electricity market model used. We present our results in Section 5, and conclude in Section 6.

2 LITERATURE REVIEW

Multi-objective optimisation problems are commonplace. In this section we review multiple applications that have used multi-objective optimisation, as well as explore the literature which focus on finding optimal carbon tax strategies.

2.1 Examples of Optimization

Similar to our work, Ascione *et al.* use the NSGA-II algorithm to generate a Pareto front to optimise for two objectives: operating cost for space conditioning and thermal comfort [2]. The aim of their paper is to optimise the hourly set point temperatures with a day-ahead planning horizon. A Pareto front is generated which allows a user to select a solution according to their comfort needs and economic constraints. This work showed a reduction in operating costs by up to 56% as well as improved thermal comfort.

Gorzałczany *et al.* also apply the NSGA-II algorithm, however, they apply it to the credit classification problem [10]. The objectives optimised over were accuracy and interpretability when making financial decisions such as credit scoring and bankruptcy prediction. This technique was able to significantly outperform the alternative methods in terms of interpretability while remaining competitive or superior in terms of the accuracy and speed of decision making in comparison with the existing classification methods.

2.2 Carbon Tax Strategies

In this section we explore different strategies employed in the literature to analyse the benefits and consequences of a carbon tax. To the best of our knowledge, we are the first to employ a multi-objective optimisation algorithm to minimise average electricity price and relative carbon density.

Levin *et al.* use an optimisation model to analyse market and investment impacts of several incentive mechanisms to support investment in renewable energy and carbon emission reductions [17]. Carbon tax was found to be the most cost-efficient method of reducing emissions.

Zhou *et al.* construct a social welfare model based on a Stackelberg game [25]. The differences and similarities between a flat carbon tax and an increasing block tariff carbon tax are analysed using a numerical simulation. This work shows that an increasing block tariff carbon tax policy can significantly reduce tax burdens for manufacturers and encourage low-carbon production. In contrast to Zhou *et al.* we trial multiple different carbon tax strategies using a machine learning approach.

Li *et al.* use a hierarchical carbon market scheduling model to reduce carbon emissions [18]. Multi-objective optimisation was applied to discover optimal behaviours for policy makers, customers and generators to minimise the costs incurred by these actors. Our work, however, focuses on the different strategies of carbon tax as opposed to optimal actor behaviour.

Algorithm 1 Genetic algorithm [3]

```
t = 0
initialize P_t
evaluate structures in P_t
while termination condition not satisfied do
    t = t + 1
    select reproduction C_t from P_{t-1}
    recombine and mutate structures in C_t
      forming C'_t
    evaluate structures in C'_t
    select each individual for P_t from C'_t
      or P_{t-1}
end while
```

3 OPTIMIZATION METHODS

Multi-objective optimisation allows practitioners to overcome the problems with optimising multiple objectives with classical optimisation techniques. Multi-objective optimisation algorithms are able to generate Pareto-optimal solutions as opposed to converting the multiple objectives into a single-objective problem. A single-objective problem assumes that there is only a single optimum, and that other combinations are inferior. This may not be the case, as different solutions are superior for a different set of circumstances. A Pareto frontier is made up of many Pareto-optimal solutions which can be displayed graphically. A user is then able to choose between various solutions and trade-offs according to their wishes.

The NSGA-II algorithm, a multi-objective genetic optimisation algorithm, is able to generate a Pareto frontier in a single optimisation run.

In the following sub-sections we detail the standard genetic algorithm followed by the NSGA-II algorithm.

3.1 Genetic Algorithms

Genetic Algorithms (GAs) [11] are a class of evolutionary algorithm which can be used for optimisation.

As shown by Algorithm 1, initially, a population of parameters P_0 are generated to be trialled in the simulation. P_0 is then evaluated for fitness, by running an instance of the simulation with the respective parameters as inputs. Where fitness in this case is the reward that is to be optimised. Next, a subset of individuals from P_0 are chosen for mating, $C_{t+1} \subset P_t$. This subset of individuals are selected proportional to their fitness. For mating with the subset C_{t+1}, the 'fitter' individuals have a higher chance of reproducing to create the offspring group C'_{t+1}. The individuals of C'_{t+1} have characteristics dependent on the genetic operators, crossover and mutation [20]. These genetic operators are an implementation decision [3]. The new population P_{t+1} is then created by merging individuals from C'_{t+1} and P_t. See Algorithm 1 for detailed pseudocode.

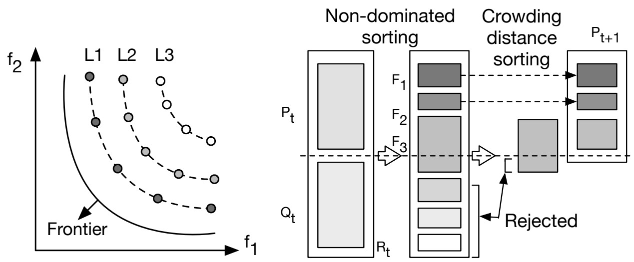


Figure 1: a) Schematic of non-dominated sorting with solution layering b) Schematic of the NSGA-II procedure

3.2 NSGA-II

NSGA-II is efficient for multi-objective optimization on a number of benchmark problems and finds a better spread of solutions than Pareto Archived Evolution Strategy (PAES) [16] and Strength Pareto EA (SPEA) [26] when approximating the true Pareto-optimal front [6].

The majority of multi-objective optimisation algorithms use the concept of *domination* during population selection [5]. A non-dominated algorithm, however, seeks to achieve the Pareto-optimal solution. This is where no single solution should dominate another. An individual solution $\mathbf{x}^1$ is said to dominate another $\mathbf{x}^2$, if and only if there is no objective of $\mathbf{x}^1$ that is worse than objective of $\mathbf{x}^2$ and at least one objective of $\mathbf{x}^1$ is better than the same objective of $\mathbf{x}^2$ [4].

Non-domination sorting is the process of finding a set of solutions which do not dominate each other and make up the Pareto front. See Figure 1a for a visual representation, where f_1 and f_2 are two objectives to minimise and L1, L2 and L3 are dominated layers.

In this section we define the processes used by the NSGA-II algorithm to determine which solutions to keep:

3.2.1 Non-dominated sorting. We assume that there are M objective functions to minimise, and that $\mathbf{x^1} = \{x_j^1\}$ and $\mathbf{x^2}$ are two solutions. $x_j^1 < x_j^2$ implies solution $\mathbf{x}^1$ is better than solution $\mathbf{x}^2$ on objective j. A solution $\mathbf{x}^1$ is said to dominate the solution $\mathbf{x}^2$ if the following conditions are true:

(1) The solution $\mathbf{x}^1$ is no worse than $\mathbf{x}^2$ in every objective. I.e. $x_j^1 \leq x_j^2 \;\; \forall j \in \{1, 2, \ldots, M\}$.
(2) The solution $\mathbf{x}^1$ is better than $\mathbf{x}^2$ in at least one objective. I.e. $\exists\, j \in \{1, 2, \ldots, M\} \;\; s.t. \;\; x_j^1 < x_j^2$.

Next, each of the solutions are ranked according to their level of non-domination. An example of this ranking is shown in Figure 1a. Here, f_1 and f_2 are the objectives to be minimised. The Pareto front is the first front. All of the solutions in the Pareto front are not dominated by any other solution. The solutions in layer 1, L1, are dominated only by those in the Pareto front, and are non-dominated by those in L2 and L3.

The solutions are then ranked according to their layer. For example, the solutions in the Pareto front are given a fitness rank (i_{rank}) of 1, solutions in L1 have an i_{rank} of 2.

3.2.2 Density Estimation. ($i_{distance}$) is calculated for each solution. This is the average distance between the two closest points to the solution in question.

3.2.3 Crowded comparison operator. ($\prec_n$) is used to ensure that the final frontier is an evenly spread out Pareto-optimal front. This is achieved by using the two attributes: (i_{rank}) and($i_{distance}$). The partial order is then defined as:
$i \prec_n j$ if ($i_{rank} < j_{rank}$) or (($i_{rank} = j_{rank}$) and ($i_{distance} > j_{distance}$)) [6].

This order prefers solutions with a lower rank i_{rank}. For solutions with the same rank, the solution in the less dense area is preferred.

3.2.4 Main loop. Similarly to the standard GA, a population P_0 is created with random parameters. The solutions of P_0 are then sorted according to non-domination. The child population C_1' of size N is then created by binary tournament selection, recombination and mutation operators. In this case, tournament selection is the process of evaluating and comparing the fitnesses of various individuals within a population. In binary tournament selection, two individuals are chosen at random, the fitnesses are evaluated and the individual with the better solution is selected [1].

Next, a new combined population is formed $R_t = P_t \cup C_t'$. R_t has a size of $2N$. R_t is then sorted according to non-domination. A new population is then formed P_{t+1}. Solutions are added from the sorted R_t in order of non-domination. Solutions are added until the size of P_{t+1} exceeds N. The solutions from the last layer are prioritised based on having the largest crowding distance [6].

This process is shown in Figure 1b, which is repeated until the termination condition is met. A termination condition could be: no significant improvement over X iterations or a specified number of iterations have been performed. The full procedure is detailed formally by Algorithm 2.

4 EXPERIMENTAL SETUP

4.1 Simulation Environment

In order to evaluate the different carbon strategies we used the model developed by Kell *et al.*, ElecSim [14, 15]. ElecSim is an agent-based model which mimics the behaviour of decentralised

Algorithm 2 NSGA-II main loop [6]

$R_t = P_t \cup C_t'$ combine parent and child population
$\mathcal{F}$ = fast-non-dominated-sort (R_t)
  where $\mathcal{F} = (\mathcal{F}_1, \mathcal{F}_2, \ldots)$
$P_{t+1} = \emptyset$
while do $|P_{t+1} < N|$
  Calculate the crowding distance of ($\mathcal{F}_i$))
  $P_{t+1} = P_{t+1} \cup \mathcal{F}_i$
end while
Sort($P_{t+1}, \prec_n$) sort in descending order using $\prec_n$
$P_{t+1} = P_{t+1}[0 : N]$ select the first N elements of P_{t+1}
Q_{t+1} = make-new-population(P_{t+1}) using
  selection, crossover and mutation to create
  the new population Q_{t+1}
$t = t + 1$

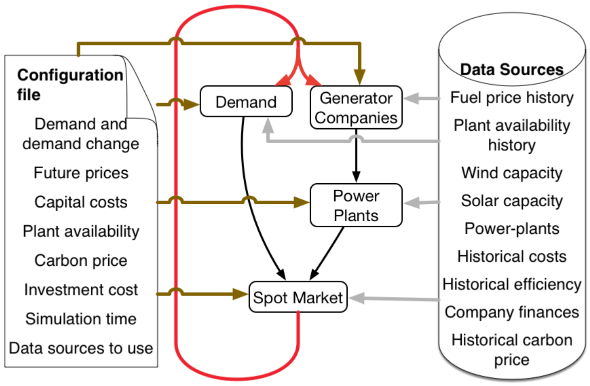


Figure 2: System overview of ElecSim [14].

electricity markets. For this paper, we have parametrised the model to data for the UK in 2018 to act as a digital twin of the UK electricity market. This includes the power plants in operation in 2018, and the funds available to their respective companies [7, 9].

Six fundamental sections make up ElecSim: 1) power plant data; 2) scenario data; 3) the time-steps of the algorithm; 4) the power exchange; 5) the investment algorithm and 6) the generation companies (GenCos) as agents. ElecSim uses a subset of representative days of electricity demand, solar irradiance and wind speed to approximate a full year. In this context, representative days are a subset of days which when scaled up can adequately represent a year. Figure 2 details how these components interact.

Specifically, the configuration file details the scenario which can be set by the user. This includes electricity demand, carbon price and fuel prices. The data sources parametrise the digital twin to a particular country, including information such as wind capacity and power plants in operation. Generation Companies own and invest in power plants. These power plants are then matched to electricity demand using a spot market.

The market runs in merit-order dispatch and bids are made by the power plant's short-run marginal cost (SRMC). Investment in power plants are based upon a net present value (NPV) calculation. NPV is able to evaluate and compare investments with cash flows spread over many years. This is shown formally in Equation 1, where t is the year of the cash flow, i is the discount rate, N is the total number of years, or lifetime of power plant, and R_t is the net cash flow of the year t:

$$NPV(t, N) = \sum_{t=0}^{N} \frac{R_t}{(1+t)^t}. \tag{1}$$

The yearly income for each power plant is estimated for each generation company by running a merit-order dispatch electricity market 10 years into the future. However, the expected cost of electricity 10 years into the future is uncertain. We therefore use the reference scenario projected by BEIS and use the predicted costs of electricity calibrated by Kell *et al* [8, 15]. The agents predict the future carbon price by using a linear regression model.

4.2 Optimization

4.2.1 Non-parametric carbon policy. The optimization approach has two stages. First, we initialize the population of the NSGA-II algorithm P_0 with 18 attributes. These correspond to a separate carbon tax for each year, shown by Equation 2:

$$P_0 = \{a_1, a_2, \ldots, a_{18}\}, 0 \le a_y \le 250, \tag{2}$$

where P_0 is the first population, a_y is the attribute or carbon price in year y and a_1 is the carbon price in year 1, a_2 the carbon price in year 2 and so forth. Each of the carbon prices are bound between the values of £0 and £250. This provides the optimization algorithm with the highest degree of freedom. The value £250 was chosen due to the relative costs of electricity, where £250 would be the upper bound for the cost of electricity. This high degree of freedom enables a high number of strategies to be trialled due its non-parametric nature. This, however, comes with a large search space requiring a large number of iterations.

4.2.2 Linear carbon policy. To reduce the search space for the carbon strategy, we also trial a linear carbon strategy, of the form:

$$p_c = a_1 y_t + a_2, -14 \le a_1 \le 14, 0 \le a_2 \le 250, \tag{3}$$

where p_c is the carbon price, y_t is the year, a_1 is the gradient or first attribute and a_2 is the intercept or second attribute. a_1 is bound by -14 and 14, and a_2 by 0 and 250. These bounds are chosen to ensure that the carbon price does not exceed ~£500 in the year 18 (2035) and is greater than about -£250, as well as ensuring that the carbon tax in the first year is greater than £0 but smaller than £250. The bounds for a_1 was chosen to make the mathematics simpler, whilst remaining in range.

5 RESULTS

In this section we explore the results of the optimisations, the optimum carbon strategies and the resultant electricity mixes.

5.1 Non-parametric carbon policy

Figure 3 displays the development of the genetic algorithm against the rewards, relative carbon density and average electricity price. Darker colours display higher generation numbers. The first generation shows a wide spread in relative carbon density and average electricity price. However, over successive generations the solutions converge to a relative carbon density of 0 and an average electricity price under £10MW/h.

Strikingly, the rewards of relative carbon density and average electricity price are not mutually destructive. This could be due to the low short-run marginal cost of renewable energy which reduces both electricity prices and carbon emissions [21].

To understand the optimum carbon strategies we visualised the parameters that produced the lowest average electricity prices in Figure 4. Specifically, we filtered for electricity prices under £5/MWh and displayed the results using a heat map. The darker colours represent a higher density of points.

Figure 4 displays a general trend, where carbon tax starts at ~£100 until the year 2030, where it increases to ~£200 by 2035. This may be due to the fact that a lower initial carbon tax of ~£100 encourages investment in low-carbon technologies before the higher rate of ~£200 comes into force. This higher rate of carbon

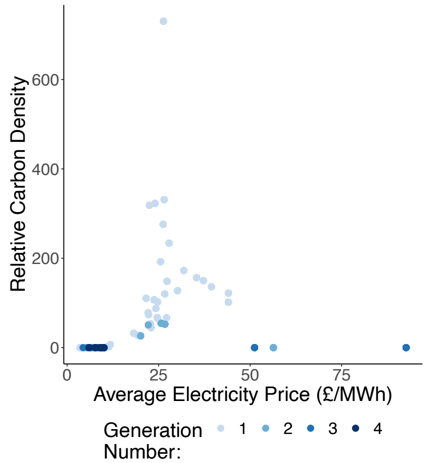


Figure 3: Development of genetic algorithm rewards for non-parametric carbon tax policy results in 2035.

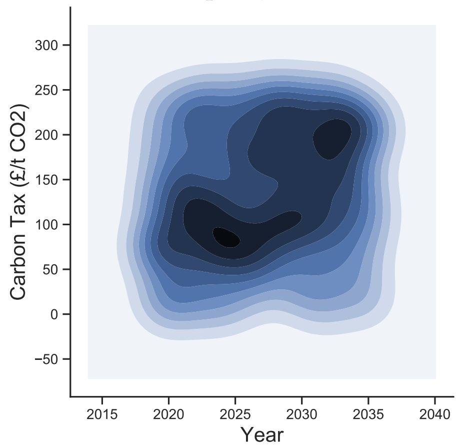


Figure 4: Density plot of points with an average electricity price <£5/MWh for non-parametric carbon tax policy results in 2035.

in Figure ??, the first generation shows a wide spread of results. However, the spread is smaller than that of the linear carbon policy. This may be due to the fact that it is easier for the GenCos to predict the carbon policy, which increases confidence in the NPV calculations. The linear carbon policy also converges to a relative carbon density of 0, and an average electricity price smaller than £10MW/h.

Figure ?? compares the distributions of average electricity price for both techniques. Both methods show improvements as the number of generations of the genetic algorithm increase. The linear policy, however, is able to more quickly converge to a low average electricity price, with a mode of ∼£5.4MW/h. The non-parametric policy has a number of poorer performing parameters, and Generation Number 4 has a bimodal distribution, with a mode of ∼£6.3MW/h.

Figure ?? displays the linear carbon policies which had an average electricity price under £4.5MW/h. There is no single 'optimum'

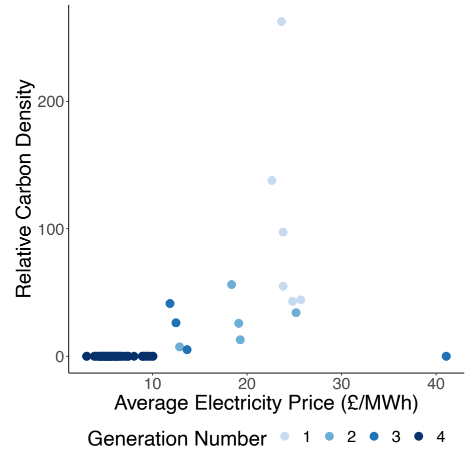


Figure 5: Development of genetic algorithm rewards in 2035 for linear carbon strategy.

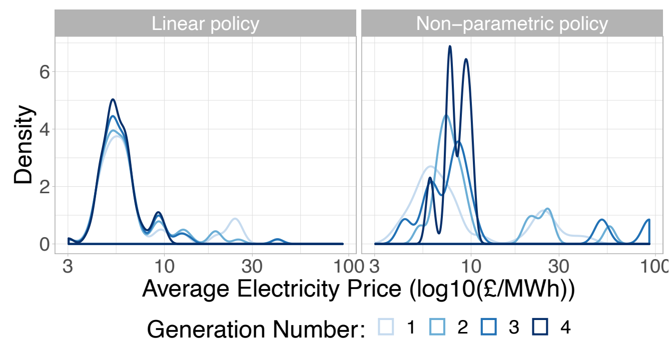
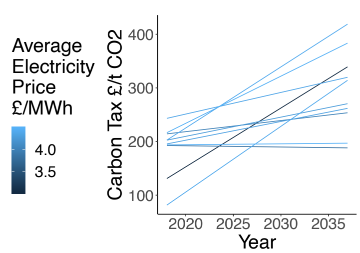
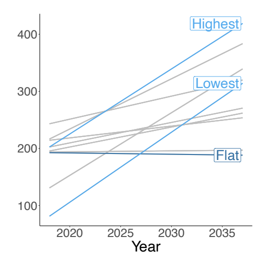


Figure 6: Density plot of average electricity price in 2035 over generation number of genetic algorithm for both linear and non-parametric policy.



(a) All carbon policies.



(b) Highlighted policies.

Figure 7: Linear carbon policies under £4.5MW/h visualised.

carbon policy; a range of policies are able to achieve low carbon and a low average electricity price.

We explore the electricity mix generated of three different strategies shown in Figure ??. We selected the highest, lowest and the lowest flat carbon strategy to show a range of possible strategies.

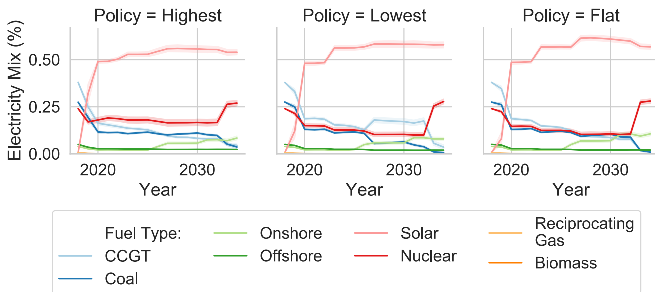


Figure 8: Electricity mixes under selected linear carbon policies.

Figure **??** displays the generated electricity mixes for each of the selected strategies. To generate these images we ran 80 scenarios to capture the variability between scenarios.

Whilst there does not seem to be a significant difference between scenarios, with solar providing ~60% of electricity mix by 2035, there is an observable difference with the other generator types.

The 'highest' carbon strategy exhibits a higher uptake in nuclear, possibly due to the fact that nuclear becomes more competitive when compared to coal or gas. The 'lowest' carbon strategy shows a higher uptake in Combined Cycle Gas Turbines (CCGT) during the years of 2026 to 2031 as it outcompetes nuclear. The 'flat' carbon policy shows a higher percentage of solar energy than any of the other scenarios, albeit with a lower percentage of nuclear. Onshore wind is shown to be consistent for these scenarios.

6 CONCLUSION

In this paper we have demonstrated that it is possible to use the genetic algorithm technique NSGA-II to optimise carbon tax policy using an electricity market agent-based model.

We trialled a non-parametric carbon policy by allowing the genetic algorithm to optimise a carbon price for each year. These results showed us that a linear carbon tax may be appropriate. We then used a linear model as a carbon tax policy to reduce the total number of parameters for the genetic algorithm to optimise.

We were able to show that a range of linear carbon taxes were able to achieve both low average electricity price and a relative carbon intensity of zero in 2035. By exploring three different carbon tax policies we saw that ~60% of electricity consumption in the UK would be provided by solar. The difference between these 'optimal' carbon tax policies was largely shown by competition between CCGT, coal and nuclear.

This was largely due to the low short-run marginal cost of solar and nuclear energy which means that they are often dispatched ahead of the fossil-fuel based generators. CCGT and coal, however, are useful for filling demand when there is low solar irradiance.

In future work we would like to try additional scenarios with varying future generation costs and calculate a sensitivity analysis to carbon taxes.

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