ElecSIM: Stochastic Agent-Based Model to Inform Policy for Long-Term Electricity Planning

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ABSTRACT

Due to the threat of climate change, a shift from a fossil-fuel based system to one based on renewable energy is required. However, this is not as simple as instantaneously closing down all fossil fuel energy generation and replacing them with renewable sources – careful decisions need to be taken. To aid decision makers, we present a new tool, ElecSIM, an agent-based modelling framework used to examine the effect of policy on long term investment decisions. We review different techniques currently used to model long term energy decisions, and motivate why agent-based models will become an important strategic tool for policy makers.

We show how modelling stochasticity improves model reliability and motivate why an open-source toolkit is required and demonstrate how ElecSIM meets the requirements of the electricity market. The model runs in yearly time steps, making assumptions based on empirical data on the impact of intermittent renewable energy. We present the dynamics of the system through scenario testing and provide validation. ElecSIM allows non-experts to rapidly prototype new ideas, and is developed around a modular framework – which allows technical experts to add and remove features at will.

This bit seems to be saying "and our work is not complete yet" – better to say something about the results here (when we have them) and leave the text below for the conclusions.

Future work includes integrating different types of agent based learning for the bidding and investment process, utilising multi-agent reinforcement algorithms that can deal with a non stationary environment. We will use the yearly time-step as a baseline model for integration of a higher temporal and spatial resolution.

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1 INTRODUCTION

The world faces significant challenges from climate change and global warming [33]. A rise in carbon emissions increases the risk of severe impacts on the world such as rising sea levels, species extinction, heat waves and tropical cyclones [24]. The scientific literature concurs that the recent change in climate is anthropogenic, with 97% of peer reviewed articles of this view [12].

To achieve carbon neutrality, the energy mix must shift from a largely fossil fuel based system, to one based on renewable energy. In essence, using solar, wind and tidal power to generate electricity and power homes, industry and transport [22]. Electricity is a significant proportion of our energy consumption – consuming 22% of energy usage per year [29]. Although other forms of energy consumption are important we focus here only on the production and consumption of electricity. I'm wondering if some sort of graph / table of different electricity generation techniques, how common they are and how carbon neutral they are would go well in here?

For this to occur, a transition in electricity infrastructure is required. Moving from a centralised and homogenous fossil fuel-based system to a distributed system based on renewable energy and batteries. However, such a transition needs to be performed in a safe and non-disruptive manner – it may be possible to close down all fossil fuel plants in the next year, though if this leads to electricity shortages and power cuts then this is likely to cause significant problems both for companies and homes. Therefore a stepped approach which allows seamless transfer is desirable. This may seem a simple process to achieve – slowly phase out existing fossil fuel generators and replace by renewable sources – however, there are many risks and uncertainties in this process. Existing power plants have an expected lifetime and their owners wish to maximise this and the profits which can be made from them, renewable sources are still developing meaning that their efficiency and reliability will change in years to come, along with the fact that most renewable sources are effected by conditions outside the control of the owners (e.g. time or day or wind speed) thus leading to a need for electricity storage. I'm sure there are better / more.

To better understand the risks and uncertainties surrounding this transition, and to model the potential actions that can be taken by policy makers, this paper presents ElecSIM, an open source agent-based modelling toolkit, written in Python, which allows for the evaluation of alternative scenarios prior to implementation of policy. Through simulation we can evaluate many strategies in order to identify those most likely to achieve our requirements of rapid but non-disruptive migration from fossil to renewable.

This tool can be used by:

- **Policy experts** to test policy outcomes under different scenarios and provide quantitative advice to policy makers. They can provide a simple script defining the policies they wish to use along with the parameters for these polices.
- **Energy market developers** who can use the extensible framework to add such things as new energy sources, policy types, consumer profiles and storage types. Thus allowing ElecSIM to adapt to a changing ecosystem.

International agreements such as the Paris climate agreement [3], where nation states agreed on the goal of limiting the rise in global average temperature to well below 2°C above pre-industrial levels, mean that an open-source, reproducible and transparent model that can be utilised by experts and understood by non-experts is of importance. This allows for the development of policies based on known assumptions, thorough testing and validation.

Mathematical optimisation is often used to determine the least-cost energy infrastructure to attain specified goals [35]. For example, calculating the optimum mix of power plant types to attain the cheapest electricity supply. Optimisation models, therefore, provide information for governments to make investment decisions in power generators over a long-term time scale.

However, in many Western democracies, the government has liberalised energy markets, with control given to heterogeneous, private investor companies. Agent-based modelling offers a way to model these heterogeneous investor agents, and observe changes in investment decisions based on policies such as carbon tax or subsidies.

Due to the long construction times, long operating periods and high costs of power plants, investment decisions can impact electricity supply over a long time scale [9]. Governments, and society, therefore have a role in ensuring that the negative externalities of pollution and carbon emission are priced into electricity generation, so that optimal decisions are made. Due to the absence of central control in electricity generation investment, other methods must be used to influence the independent players of the electricity market. Methods such as carbon taxes, policy and regulation can aid in the goals of reducing carbon emissions to limit global warming, as agreed in the Paris agreement [3].

Think this is quite crucial – though needs drawing out more clearly – there is no overseer in the energy industry and each player can act independently. Hence we can influence the different players but not force them to do something. A diagram showing the different players, who can influence them and how?

This paper details our model, ElecSIM. Section 2 is a literature review of the models currently used in practice. Section 3 details the model and assumptions made, and section 4 details how we validated our model, and displays performance metrics. Section 5 details our results, and explores ways in which ElecSIM can be used. We conclude the work in section 6

- We have developed a framework for evaluating alternative scenarios, prior to implementation of policy.
- Used by experts working in collaboration with policy makers.
- Importance of a transition in electricity infrastructure (Paris agreement, UK Climate change act)
- Importance of understanding effect of decisions made today on the future (limit of 1.5C by 2050)
- Introduce ElecSIM as a toolkit to inform long-term domestic policy questions in the electricity market.
- Ability to model the effects of carbon taxation, and the effect of different scenarios
- Talk about the need to model a non-stationary, dynamic system, with multiple interacting agents with imperfect information
- Requirement for an Open-Source, free Toolkit written in python. Low barrier of entry, and integration with existing python data analytics and machine learning techniques. Transparent, reproducible, and data made available. This allows for results to be open to greater criticism and better inform policy decisions.
- Simple model which matches real life behaviour for low complexity and therefore increases transparency.

2 LITERATURE REVIEW

Live experimentation of physical processes is often not practical. The costs of real life experimentation can be prohibitively high, and it normally requires significant time in order to fully ascertain the long-term trends. There is also a risk that changes can have detrimental impacts [17]. These factors are particularly true for an electricity market, where decisions made can have long term impacts on energy mix, carbon emissions and agent behaviour. A solution to this is simulation, which can be used for rapid testing and prototyping of ideas. Simulation is the substitution of a physical process with a computer model. The computer model is parametrised by real world data and phenomena. The user is then able to experiment using this model, and assess the likelihoods of outcomes under certain scenarios and input variables [30].

Energy policy modelling is an example where simulation can be used. Real-life experimentation of energy policy is not always feasible, and as discussed, decisions can have long-term impacts. 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 macro-economic models or bottom-up techno-economic models [6]. Top-down models generally focus on behavioural realism with a focus on macro-economic metrics. They are useful for studying economy-wide responses to policies. [19], for example MARKAL-MACRO [16] and LEAP [21]. Bottom-up models represent the energy sector in detail, and are written as mathematical programming problems [18]. They detail technology explicitly, and can include cost and emissions implications [19].

It is possible to further categorise bottom-up models into optimisation and simulation models. Optimisation energy models minimise costs or maximise welfare from the perspective of a central planner, for instance a government [25]. A use-case would be a government that wants cheap, reliable and low-carbon electricity supply by a future date. An optimisation model would find the optimal mix of generators to meet this whilst taking into account the constraints. Examples of optimisation models are MARKAL/TIMES [16]

Tool name	Open Source	Long-Term Investment	Market	Stochastic Inputs	Country Generalisability
SEPIA	✓	x	✓	Demand	✓
EMCAS	x	✓	✓	Outages	✓
NEMSIM	Unknown	✓	✓	x	x
AMES	✓	x	Day-ahead	x	x
PowerACE	x	✓	✓	Outages/Demand	✓
MACSEM	Unknown	x	✓	x	✓
GAPEX	Unknown	x	Day-ahead	x	✓
EMLab	✓	✓	Futures	x	✓
ElecSIM	✓	✓	Futures	✓	✓

Table 1: Features of electricity market agent based model tools.

and MESSAGE [41]. MARKAL is possibly the most widely used general purpose energy systems model [37].

However, electricity market liberalisation in many Western democracies has changed the framework conditions. Centralised, monopolistic, decision making entities has given way to multiple heterogeneous agents acting in their own best interest [34]. Therefore, certain policy options which encourage changes must be used by a central planner to attain a desired outcome, for example carbon taxes or subsidies. It is therefore proposed that these complex agents are modelled using agent-based modelling.

As a result of this, agent-based simulation has received increasing attention in recent years, and a number of simulation tools have emerged, for example SEPIA [20] EMCAS [11], NEMSIM [5], AMES [43], PowerACE [40], [39], GAPEX [10] and EMLab [9]. However, none of which suit the needs of an open source, long-term market model which has a stochastic representation of input variables.

SEPIA [20] is a discrete event agent based model which utilises Q-learning for agent behaviour. SEPIA models plants as being always on, and does not have an independent system operator (ISO), which in an electricity market, is an independent non-profit organization for coordinating and controlling of regular operations of the electric power system and market [44]. SEPIA does not model a spot market, instead focusing on bilateral contracts. As opposed to this, ElecSIM has been designed with a merit-order, spot market in mind and renewable energy supply running intermittently.

MACSEM [39] simulates a bilateral and pool market. It has been used to probe the effects of market rules and conditions by simulating and testing different bidding strategies. However, MACSEM does not model long term investment decisions.

EMCAS [11] is a closed source agent-based framework which investigates the interactions between physical infrastructures and economic behaviour of market participants. ElecSIM, however, focuses on purely the dynamics on the market, with an aim of providing a simplified, transparent, open source model of market operation, whilst maintaining robustness.

PowerACE [40] is also a closed source agent-based simulation of electricity markets that integrates short-term perspectives of daily electricity trading and long-term investment decisions. Similarly to ElecSIM, PowerACE initialises agents with all power plants in their respective country. However, unlike ElecSIM, PowerACE does not take into account stochasticity of price risks in electricity markets which is of crucial importance to real markets [34].

EMLab [9] is also an agent-based modelling toolkit for the electricity market. EMLab models an endogenous European emissions trading scheme with a yearly time-step. However, like PowerACE, EMLab differs from ElecSIM by not taking into account stochasticity in the electricity markets, such as outages, differing fuel prices within a year period and stochasticity in power plant operating costs. However, after correspondence with the authors, we were unable to run EMLab.

AMES [43] is an agent-based model specific to the US Wholesale Power Market Platform. GAPEX [10] is an agent-based framework for modelling and simulating power exchanges in MATLAB . GAPEX utilises an enhanced version of the reinforcement technique Roth-Erev to consider the presence of affine total cost functions. However, neither of these model the long-term dynamics that ElecSIM is designed for.

Table 1 shows the features of each of the tools reviewed in this section. We propose ElecSIM to fill the gaps that are not currently covered, which includes an open source long-term stochastic investment model.

- Agent Based Models - eg. EMCAS, PowerACE, EMLab: Leaves a requirement for an open source toolkit written in python. Many one-off models available, however difficult to apply to different scenarios. (SEPIA [6], EMCAS [7], NEMSIM [8], AMES [9], PowerACE [10], MASCEM [11, 12], and GAPEX [13] [31])
- Bottom-up optimization models to find minimum cost of electricity system. [37]. eg. MARKAL/TIMES, MESSAGE. (These do not provide information on how to achieve a certain goal, particularly in a liberalized energy market. Or scenarios as to why a goal may not be achieved as the goal is assumed to be achieved.)
- Computational general equilibrium (CGE) models - Top-down macroeconomic models partial equilibrium model (energy supply, demand, cross-border trade, emissions)- Can be highly complex and difficult to understand. eg. NEMS, PRIMES.

3 ELECSIM ARCHITECTURE

ElecSIM has been designed for ease of use to enable non-experts to rapidly test different policies and the outcome of various scenarios such as demand growth. The user is able to input exogenous variables such as fuel cost, carbon taxes, power plants, power plant costs, electricity demand and availability factors. This allows for the initialisation of different countries and scenarios to be tested.

3.1 High-Level Overview

A schematic of ElecSIM is displayed in Figure 1. We have provided data sources to calibrate the model, for instance, historical fuel prices, historical plant availability, wind and solar capacity, power plant costs, historical costs, historical efficiency, company finances and historical carbon price. Unless otherwise stated, these data have been calibrated to the UK or Europe.

The configuration file give the ability to the user to rapidly change scenarios, and points to the various previously mentioned data sources. This data is then used to calibrate the GenCos and demand agent. GenCos then invest in power plants based on the highest positive net present value (NPV). Bids are made for each power plant based on the power plants short run marginal cost. A power exchange operator matches these bids with demand in merit order.

This is then repeated for each year of the simulation.

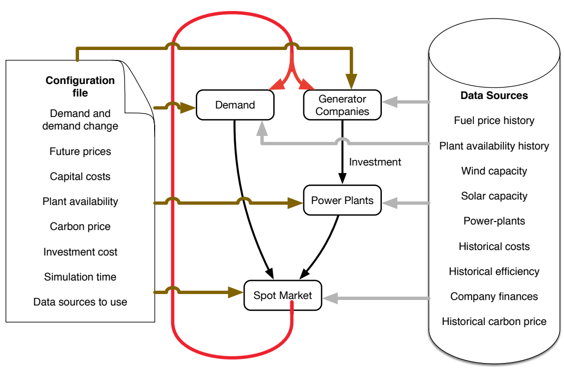

Figure 1: ElecSIM simulation overview

3.2 Detailed Overview

ElecSIM is made up of two different agent types, GenCos (Generation Companies) and a Demand agent. GenCos can be initialised by the user. For example, to a desired country, or a toy-example. Each of the GenCos are initialised with their respective power plants. GenCos are given a randomized discount rate, which can be set by the user, around a mean of 10% for nuclear power plants [36] and 5.9% for all other generators [27].

3.2.1 Data Initialisation. ElecSIM's power generation costs is initialised using the UK government Department for Business, Energy and Industrial Strategy (BEIS) power plant generation report [14]. This contains information such as capital costs and operation and maintenance costs, including details such as insurance and connection costs. Where there are power plants of a size not included in this report, the parameters are linearly interpolated. Where the capacity of a power plant is larger or smaller than the data points in the report, the parameters are extrapolated by using the last known data point.

For historical power plants, we used historical costs of Levelised Cost of Energy (LCOE) [13]. Each parameter was scaled linearly from the modern LCOE calculated from the BEIS report, to attain the relevant historical LCOE. This was achieved by using linear optimisation, and therefore each parameter can be changed based on an individual user's country and dataset by modifying these constraints. As well as historical LCOE, historical plant efficiency was taken into account for gas and coal power plants [15].

When initialised, the variable operation and maintenance costs are selected from a uniform distribution, with the ability for the user to set maximum and minimum percentage increase from the BEIS report. This enables variance in costs between individual power plants for processes such as preventative and corrective maintenance, labour costs and skill, health and safety and chance.

As per [9], we created a load duration curve of the electricity demand for one year with 20 segments. 20 segments enabled us to capture the varying demand of electricity throughout a year to a high enough degree of accuracy, but also reduce computational complexity. To model the Intermittency of wind and solar power we allow them to contribute only a certain percentage of total capacity for each load segment based on empirical wind and solar capacity factors, relating demand to average capacity [9, 38, 42]. The requirement of storage to provide constant electricity from intermittent resources is an important issue. However, due to our model taking yearly time steps, we are unable to model short term variability in electricity demand. We also, do not model long-term storage due to its currently limited liability.

However, we do not model curtailment of renewables, or storage capabilities.

Whilst fuel price is controlled by the user, there is inherent volatility in fuel price in a single year. To take into account this variability, an ARIMA model was fit to historical gas and coal price data [1, 2]. The standard deviation of the residuals was used to model the price of fuel that a generation company will buy fuel at in a given year. This takes into account differences in hedging strategies and chance between generation companies.

Outages are modelled by using availability data of gas, coal, photovoltaic, offshore and onshore power generators [7, 23, 32]. Plants bid a reduced percentage of their nameplate capacity based on their respective availability. Historical availabilities are modelled for older gas, coal and hydro power plants [4].

With historical power plants which have been refurbished, we sample their initialisation randomly between 15 years prior to initialisation year and the initialisation year.

Power plants are taken out of service if they have not sold any electricity in the past 7 years. We decided upon this due to the fact that power generators have high, sunk capital costs, which often have high demolition costs. We assume, therefore, that generator companies are willing to wait circa $\frac{1}{4}$ of their lives to see if a pay-out occurs due to the breakdown of competing power plants, increasing demand, or governmental support in the form of a carbon tax increase or reduction.

3.2.2 Spot Market. The buying and selling of electricity is modelled as a spot market, where each year, electricity is bought and sold in merit order. GenCos place bids for each of their plants at their respective short run marginal cost. We assume that generator companies do not have market power, however we set the lost load to be £6000 to encourage investment as per the recommendations of the UK government [8].

3.2.3 Investment. Investments are made on a yearly basis and are made purely on net present value calculations. The order in which GenCos invest in each simulated year is randomised as to not give certain generation companies an advantage.

Agents have imperfect information, and therefore fuel and carbon prices are predicted using linear regression, with a training period sampled uniformly from 3 to 7 years back. This allows us to model heterogeneity of GenCos. Demand is modelled through the use of an exponential function, so that compounded growth can be modelled. However, if a reasonable fit for the previous data is not found, a linear regression is used.

GenCos only bid if they have 25% of the upfront capital costs, with the rest of the capital provided through equity and debt. The cost of equity and debt is modelled as a weighted average cost of capital (WACC), with values of 5.9% for non-nuclear power plants, and 10% for nuclear power plants [27, 36]. The WACC is used as the discount rate for net present value calculations [26]. Each GenCo is initialised with a slightly different discount rate based on a uniform distribution, with a ±3% standard deviation. This allows us to model the variability in discount rates that GenCos may have, based on different factors such as preference, confidence in the future and readiness for investors and lenders to supply capital.

The sale price of electricity in the future reference year is predicted by each generation company simulating the same merit-order market algorithm that is used for the spot market. They simulate the bids that they expect each of the power plants that are in operation to make, and use the demand predicted to match supply with demand. They then assess whether their investment option is likely to make a profit, ie. with a positive net present value. The power plant with the highest net present value is then invested in.

- Model can be modified through a single python scenario file which includes exogenous variables such as number of generation companies, power plants, power plant costs, tax and fuel prices, and demand.
- Architectural framework:
  - Agents are generation companies.
  - Generation companies initialized from government data. And randomized discount rate around a mean of 10% for nuclear power plants and 5.9% for other types of generators.
  - Costs of power plants taken from empirical data.
  - Historical LCOE costs taken from data, with individual costs such as fixed operation and maintenance, construction and pre-development costs scaled linearly to match LCOE value. (This can be changed by user by specifying linear optimisation constraints).
  - Historical Gas turbine and Coal plant efficiency taken from epa data.
  - Variable operation and maintenance costs are stochastic to take into account differences in design types, preventative and corrective maintenance, labour costs and skill, asset and site management, health and safety and chance.
  - Electricity demand taken from historical data and split up into 19 load segments.
  - CO2 prices, fuel Prices, demand growth are exogenous
  - Fuel is bought by power producers each year at different prices, related to the standard deviation from historical data. This simulates different hedging strategies, luck and timing of fuel purchasing.
  - Outages are modelled by assuming a 93% outage rate for fuel plants [32] and 97% outage for renewables. [7]
  - Generation companies bid their short run marginal costs.
  - Investments made on highest Net Present Value results. CO2 price, fuel price and demand are predicted 7 years ahead using linear regression.
  - Estimated sale of electricity price calculated by simulating a market 7 years into the future with expected power plants that are running and have been taken out of service.
  - Investors will only invest if they have 25% of the total upfront costs. (the rest taken on by debt and equity as assumed by WACC value.)
  - Intermittent power generators can only submit a certain percentage of their total capacity for each load segment. This percentage is matched with empirical data.
  - Bids accepted by a centralised power exchange based on merit order. Generation companies bid their short run marginal cost.
- Assumptions:
  - Yearly time step
  - Renewables contribute to load curve of each demand segment matched with empirical data of typical wind and solar availability at each demand segment
  - Different discount rates per user (randomized)
  - Country initialized with full amount of power plants and generation companies in country and total demand data considered
  - No curtailment of renewables
  - Imperfect foresight - Prediction required for demand, co2 price, fuel cost, other investments.
  - Power plant construction and pre-development periods and costs modelled from UK Government BEIS data
  - Investments based on highest NPV using a single year 7 (can be changed in scenario file) time steps into the future to predict all years of power plant.
  - Agents predict next year's fuel, carbon and demand using linear regression and randomized look back period (between 3 and 6.)
  - Plants are dismantled after their lifetime, and only enter operation after pre-development/construction.
  - Legacy power plants are reinitialized to random starting year to account for refurbishment.

4 VALIDATION AND PERFORMANCE

- Validation of model
  - Compare price duration curve
  - Compare power plant costs and NPV calculations
  - Look number of steps ahead to compare electricity mix and compare to actual (cross-validation)
- Performance metrics - Comparison with EMLab, PowerACE (15 minute run time)
  - Memory, disk size, runtime
  - Increase in time complexity with additional data.

5 SCENARIO TESTING

- Effect of different carbon tax on investments made.
- Effects of different demand scenarios. (High peaks, high growth, high reduction in demand)
- Effects of high fuel prices.
- Different costs of capital (eg. Borrowing for Nuclear of interest rate to equal 2% at government bonds rate, as opposed to 10% for private companies.)
- Different learning rates for renewable costs.
- The effect of long term carbon tax policy (eg. Carbon price known for next 25 years) vs short term changes in carbon tax.

6 CONCLUSIONS

- Requirement for agent based models based on imperfect information, liberalised energy markets
- Requirement for low barriers to entry open source model.
- Discuss results
- Future work:
  - Embedding multi-agent intelligence such as Genetic Algorithms, Q-learning and dynamic reinforcement learning
  - Raise spatial and temporal resolution.

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A RESEARCH METHODS

A.1 Parameters

Type	Plant_Size	year	η	OP	P_D	C_D	P_C	C_C	I_C	F_C	V_C	In_C	Con_C
CCGT	168.0	2018, 2020, 2025	0.34	25.0	3	3	60000.0	700000.0	13600.0	28200.0	5.0	2900.0	3300.0
CCGT	1200.0	2018, 2020, 2025	0.54	25.0	3	3	10000.0	500000.0	15100.0	12200.0	3.0	2100.0	3300.0
CCGT	1471.0	2018, 2020, 2025	0.53	25.0	3	3	10000.0	500000.0	15100.0	11400.0	3.0	1900.0	3300.0
Coal	552.0	2025	0.32	25.0	6	6	40000.0	3400000.0	10000.0	68200.0	6.0	13000.0	3800.0
Coal	624.0	2025	0.32	25.0	5	5	70000.0	4200000.0	10000.0	79600.0	3.0	19300.0	3800.0
Coal	652.0	2025	0.3	25.0	5	5	60000.0	3900000.0	10000.0	65300.0	5.0	22700.0	3800.0
Coal	734.0	2025	0.38	25.0	5	5	60000.0	2600000.0	10000.0	56400.0	3.0	9600.0	3800.0
Coal	760.0	2025	0.35	25.0	5	5	40000.0	2800000.0	10000.0	52100.0	5.0	14000.0	3800.0
Hydro	0.033	2018, 2020, 2025	1.0	35.0	0	0	0.0	6300000.0	0.0	83300.0	0.0	0.0	0.0
Hydro	1.046	2018, 2020, 2025	1.0	35.0	0	0	0.0	3300000.0	400.0	18200.0	0.0	0.0	0.0
Hydro	11.0	2018, 2020, 2025	1.0	41.0	2	2	60000.0	3000000.0	0.0	45100.0	6.0	0.0	0.0
Nuclear	3300.0	2025	1.0	60.0	5	8	240000.0	4100000.0	11500.0	72900.0	5.0	10000.0	500.0
OCGT	96.0	2018, 2020, 2025	0.35	25.0	2	2	80000.0	600000.0	12600.0	9900.0	4.0	2500.0	2400.0
OCGT	299.0	2018, 2020, 2025	0.35	25.0	2	2	30000.0	400000.0	13600.0	9600.0	3.0	1600.0	2500.0
OCGT	311.0	2018, 2020, 2025	0.35	25.0	2	2	30000.0	400000.0	13600.0	9500.0	3.0	1600.0	2500.0
OCGT	400.0	2018, 2020, 2025	0.34	25.0	2	2	30000.0	300000.0	15100.0	7800.0	3.0	1300.0	2500.0
OCGT	625.0	2018, 2020, 2025	0.35	25.0	2	2	20000.0	300000.0	15100.0	4600.0	3.0	1200.0	2400.0
OCGT_CCS	290.0	2025	0.24	25.0	5	5	80000.0	2300000.0	15100.0	31800.0	3.0	8500.0	2500.0
Offshore	321.0	2018	0.0	23.0	5	3	60000.0	2200000.0	69300.0	30900.0	3.0	1400.0	33500.0
Offshore	321.0	2020	0.0	23.0	5	3	60000.0	2100000.0	69300.0	30000.0	3.0	1400.0	32600.0
Offshore	321.0	2025	0.0	23.0	5	3	60000.0	1900000.0	69300.0	28600.0	3.0	1300.0	31100.0
Offshore	844.0	2018	0.0	22.0	5	3	120000.0	2400000.0	323000.0	48600.0	4.0	3300.0	50300.0
Offshore	844.0	2020	0.0	22.0	5	3	120000.0	2300000.0	323000.0	47300.0	3.0	3300.0	48900.0
Offshore	844.0	2025	0.0	22.0	5	3	120000.0	2100000.0	323000.0	45400.0	3.0	3100.0	47000.0
Onshore	0.01	2018	1.0	20.0	0	0	0.0	3700000.0	0.0	29700.0	0.0	0.0	0.0
Onshore	0.01	2020	1.0	20.0	0	0	0.0	3600000.0	0.0	29600.0	0.0	0.0	0.0
Onshore	0.01	2025	1.0	20.0	0	0	0.0	3500000.0	0.0	29600.0	0.0	0.0	0.0
Onshore	0.482	2018	1.0	20.0	0	0	0.0	2200000.0	200.0	56900.0	0.0	0.0	0.0
Onshore	0.482	2020	1.0	20.0	0	0	0.0	2100000.0	200.0	56900.0	0.0	0.0	0.0
Onshore	0.482	2025	1.0	20.0	0	0	0.0	2000000.0	200.0	56700.0	0.0	0.0	0.0
Onshore	20.0	2018	0.0	24.0	4	2	110000.0	1200000.0	3300.0	23200.0	5.0	1400.0	3100.0
Onshore	20.0	2020	0.0	24.0	4	2	110000.0	1200000.0	3300.0	23000.0	5.0	1400.0	3100.0
Onshore	20.0	2025	0.0	24.0	4	2	110000.0	1200000.0	3300.0	22400.0	5.0	1400.0	3000.0
PV	0.003	2018	1.0	30.0	0	0	0.0	1500000.0	0.0	23500.0	0.0	0.0	0.0
PV	0.003	2020	1.0	30.0	0	0	0.0	1500000.0	0.0	23400.0	0.0	0.0	0.0
PV	0.003	2025	1.0	30.0	0	0	0.0	1400000.0	0.0	23200.0	0.0	0.0	0.0
PV	0.455	2018	1.0	30.0	0	0	0.0	1000000.0	200.0	9400.0	0.0	0.0	0.0
PV	0.455	2025	1.0	30.0	0	0	0.0	900000.0	200.0	9200.0	0.0	0.0	0.0
PV	1.0	2018	0.0	25.0	1	0	20000.0	700000.0	0.0	6600.0	3.0	2600.0	1300.0
PV	1.0	2020	0.0	25.0	1	0	20000.0	700000.0	0.0	6300.0	3.0	2600.0	1300.0
PV	1.0	2025	0.0	25.0	1	0	20000.0	600000.0	0.0	5900.0	3.0	2400.0	1200.0
PV	4.0	2018	0.0	25.0	1	0	60000.0	700000.0	200.0	8300.0	0.0	1200.0	1300.0
PV	4.0	2020	0.0	25.0	1	0	60000.0	700000.0	200.0	8000.0	0.0	1100.0	1300.0
PV	4.0	2025	0.0	25.0	1	0	60000.0	600000.0	200.0	7500.0	0.0	1100.0	1200.0
PV	16.0	2018	0.0	25.0	1	0	70000.0	700000.0	400.0	5600.0	0.0	2000.0	1300.0
PV	16.0	2020	0.0	25.0	1	0	70000.0	600000.0	400.0	5400.0	0.0	1900.0	1300.0
PV	16.0	2025	0.0	25.0	1	0	70000.0	600000.0	400.0	5100.0	0.0	1800.0	1200.0
Reciprocating Engine (Diesel)	20.0	2018, 2020, 2025	0.34	15.0	2	1	10000.0	300000.0	2200.0	10000.0	2.0	1000.0	-31900.0
Reciprocating Engine (Gas)	20.0	2018, 2020, 2025	0.32	15.0	2	1	10000.0	300000.0	3400.0	10000.0	2.0	1000.0	-31900.0