EMLab-Generation

An experimentation environment for electricity policy analysis

Version 1.2, August, 2015

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More information: http://emlab.tudelft.nl/generation

Please refer to this report as: De Vries, L.J., E.J.L. Chappin & J.C. Richstein, *EMLab-Generation – An experimentation environment for electricity policy analysis*, TU Delft, 2015.

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1 Introduction

Transforming the electricity sector

There is a growing consensus that Europe's electricity sector must be nearly or completely carbon-free by the middle of this century. This will need to be achieved with a combination of a substantial amount of renewable energy and perhaps nuclear power and/or the use of fossil fuels with carbon capture and sequestration. The current approach is to regulate CO_2 emissions through the EU-ETS and provide additional stimulus for renewable energy. The latter policy is implemented at the national level, as a result of which there is considerable heterogeneity in these policies (although there appears to be a tendency towards feed-in tariffs). In addition, countries have specific policies regarding the use of nuclear fuels, the combustion of coal and carbon capture and sequestration. The resulting variety of electricity market policies is further compounded by differences in basic electricity market design, for instance with respect to transmission regulation, congestion management and the balancing mechanism.

Understanding complex market behavior

The central question in this research is what the combined effect is of different policy instruments (in particular carbon policy and renewable energy policy) upon an electricity market, in isolation and in combination with neighboring electricity markets with different policies, are. What happens when two interconnected electricity markets, both participating in the EU-ETS, have different renewable energy policies? What if one of these decides to phase out nuclear power? What would be the effect of a minimum price for CO_2? What if this were implemented in only one country?

EU-ETS

While the EU-ETS is an effective instrument for allocating CO_2 emission reductions among large producers in Europe, it has failed to trigger the kinds of long-range investments that will be necessary for achieving substantial emissions reductions in the future. Two reasons can be given for this failure. The first is that the ETS does not provide a strong enough investment incentive, in part because the average CO_2 price is too low, and in part because the CO_2 price is too volatile. The second reason is that investment decisions are also affected by carbon and renewable energy policy, the design of the electricity market (especially a capacity mechanism may have a strong impact), availability of locations for new plant, permit restrictions etcetera.

Electricity prices

A second issue of concern is the phenomenon that electricity prices can be expected to become more volatile as low-carbon electricity generation technologies gain market share, because their marginal costs of generation tend to be relatively low. As a result, electricity prices can be expected to be below average cost during periods with ample generation capacity, which means that peak prices will need to be higher for power companies to recover their costs. This higher volatility is likely to discourage investment in capital-intensive technologies, slowing down the desired investment in many low-carbon technologies.

Research approach

To address these issues, a dynamic simulation model will be developed. Equilibrium models do not capture the intertemporal relations (which exist due to path dependence) that affect the long-term development of the electricity sector. This model will need to be suitable for incorporating multiple policy instruments and multiple, connected electricity markets. Finally, the model will need to include a rich representation of investment behavior and the diversity of investment strategies that may be observed in a market. For these reasons, we have chosen to use the relatively new technique of agent-based modeling. This approach has only been applied to a limited degree to European electricity markets. A great benefit of agent-based modeling is that it is not necessary to make a priori assumptions about how the system reacts to policy changes. Policies are modeled as closely to reality as possible while agent behavior is determined by the decision rules that are programmed and the results are an emergent property of the model.

Agent-based modeling

Instead of capturing aggregate behavior of market parties in formulas, in an agent-based model individual actors are modeled. In our model, we model electricity generation companies as agents who act independently from each other. Other agents may be included, such as a an agent that represents the government. The companies sell the power that they produce and make investment decisions. Therefore the model allows us to include assumptions about risk aversion and strategic behavior, for instance. The model output is not the result of equation-based calculations, but is an emergent property of the combined actions of the various agents. Thus the model resembles a virtual laboratory: given a certain context (physical constraints, technological options, energy prices, electricity demand), the agents (e.g. power companies) independently make their decisions. While the agents are confronted by the consequences of each other's decisions (such as the construction of new power stations), each agent makes its decisions independently from the others. The model can be run under a variety of scenarios in order to obtain insight in the variety of possible outcomes of a certain combination of policies and exogenous conditions.

Focus

Because the object of the model is not to make detailed analyses or forecasts, but to gain insight in the long-term dynamic behavior of European electricity markets, the model is not intended to provide a realistic representation of a specific European electricity market or of the entire EU power market. However, it is possible to upload scenarios that include the generation plant portfolios of specific countries.

Economic and social relevance

With this project, a new avenue in model-based policy support is explored. By developing an agent-based model of an energy market, it will be possible to model the 'messiness' of reality better, as the interactions and compound impacts of multiple policy instruments can be modeled. Theoretic analyses about the optimal effects of policy instruments can thus be supplemented with analyses about transition effects, interferences between instruments and other more practical issues with potentially strong economic and environmental effects. This is expected to deepen our understanding of real-world interactions between policy instruments and markets.

Base model

This report describes the base model, which enables to simulate two interconnected electricity markets in typical European countries (Chappin et al., 2012). Using and analysing this model implies the effects upon CO_2 emissions, the volume of electricity generation, the price of electricity and the generation mix, and the effect upon investment in renewables. With this basis, we will for instance be able to address the following questions:

- How would the electricity market develop, given the current ETS, reasonable reductions of the CO_2 cap, but no further policy changes?
- To what extent would an increase in renewable and nuclear energy cause electricity prices to become more volatile?
- What would be the effects of measures to reduce investment risk in the CO_2 market (e.g. a price floor for CO_2) and in the electricity market (e.g. the introduction of a capacity mechanism)?
- What are the effects upon investment of other factors such as subsidies for large energy consumers, RES-E policies, subsidies for CCS pilots and the cost of capital (which has recently risen significantly)?

In Chapter 2, the base model is described. Chapter 3 contains details regarding implementation.

2 Description of the Agent-Based Model

2.1 Overview

Object

The model is designed to analyze the aggregate effects of investment decisions of electricity generation companies under different policy scenarios and market designs in order to assess the possible effects of different policy instruments on the long-term development of European electricity markets. Because the simulations span several decades, the time step of the model is one year. The model provides insight in the types of consequences that may be expected from different policy measures and, importantly, from combinations of policy measures; it is not intended for estimating precise future values of prices, emissions or other quantities.

Drivers of change

The drivers of change in the model are changes to exogenous factors, such as fuel prices and electricity demand, and policy changes. In a static environment, a policy change such as a reduction of the CO_2 emissions cap would lead to a new equilibrium with more low-carbon generation technology. However, in an environment with continuously changing exogenous factors, the long construction time of new power plant and their long life span have as a consequence that electricity markets are not likely ever to be in an investment equilibrium. This is also the case in our model. As relative prices change, the agents' preference for generation technologies shifts. The key question is which sets of policies lead to the desired levels of CO_2 abatement and how can costs most likely be minimized, given the range of scenarios.The model provides insight in the effectiveness of policy measures in stimulating desired investment behavior under the realistic conditions of ever-changing exogenous conditions.

Agents

The main agents in the model are the electricity generation companies. In the model, they make decisions about the price at which they sell their electricity and about investment and disinvestment in generation plants. They purchase fuels at exogenously determined prices, i.e. they are price takers in these markets. The agents base their power plant dispatch on the prices of fuel, electricity and CO_2, while for their investment decisions they also consider estimates of future prices, the costs of different generation technologies and, if the modeler desires, other factors such as risk aversion or a preference for specific generation technologies such as renewable energy.

Markets

The electricity and CO_2 market are the main arenas in which the agents interact. In order to simulate the realities of European electricity markets, the model contains multiple (in first instance two) electricity markets with limited interconnector capacity between them. There is a single CO_2 market including the banking of generators. The electricity markets are modeled as power exchanges. They are cleared simultaneously, including a market splitting algorithm for the allocation of interconnector capacity. An iterative process is used to simulate arbitrage between the electricity and CO_2 markets (the current spot market and an expected future market).

Electricity generation technologies

When agents construct a new power plant, they can choose from a range of generation technologies. Innovation of these technologies is simulated as a gradual decline of costs and improvement of performance (such as fuel efficiencies). To the extent possible, these trends have been calibrated with empirical data. Established technologies, such as gas, coal and nuclear power, develop more slowly than newer technologies such as wind energy or carbon sequestration technologies.

Policies

The model has been developed to test (combinations of) carbon policies and renewable energy policies in interconnected markets, given different assumptions regarding investment behavior. The baseline carbon policy is an emissions trade scheme that is based on the EU ETS. A minimum carbon price can be included in this scheme. Instead, or in addition, a carbon tax can be implemented. Renewable energy policy instruments can be added to the model. Capacity mechanisms are another type of policy instrument that affect investment behavior and that can be included.

Analysis of model results

Because the future prices of fuels and the growth of electricity demand are uncertain, the model is run a number of times for different scenarios. Within each scenario, these input parameters are varied stochastically based on a number of exogenous scenarios. The results therefore need to be analyzed statistically.

The following assumptions underlie the model:

1. Fuel is always available. There is an unlimited supply of biomass and natural gas.
2. Fuel prices are exogenous and reflect the relative scarcity of fuels. The modeled system is too small to impact world fuel prices.
3. Biomass is assumed to be 100% carbon-neutral. In our model, biomass represents the general characteristics of renewable energy: carbon-free, but more expensive.
4. The main characteristics of Phase 3 of the EU ETS (2013 and beyond) are included: 100% of CO_2 emission rights are auctioned and the cap will decrease over time.
5. The effect of inter-sector emissions trading is assumed to be negligible compared to intra-sector trade.
6. Innovation is limited to learning; available technologies gradually improve in terms of cost and performance, entirely new technologies do not become available in the model.
7. All costs and prices are in constant 2011 Euros. Electricity prices are wholesale prices; taxes and network fees are not included.

Figure 2.1 provides an overview of the model. Before the start of the simulation, a scenario file is uploaded which specifies the time series data (such as fuel prices), demand functions, generation technologies, generation portfolio's and the parameters of policy instruments such as the CO_2 cap or tax level. Within each time step (which is one year), the electricity markets are cleared for each section of the load-duration function. If a CO_2 market is implemented, the CO_2 price is determined in an iterative process with electricity market clearing: the price is adjusted until the emissions just match the cap (and the expectations regarding future emissions). Each time step, agents also decide whether to invest in new plant and whether to dismantle old plant and they buy CO_2 credits, if applicable.

2.2 Agents

Strategic decisions of producers

The main agents in the model are the electricity generation companies (**`domain.agent.EnergyProducer`**). Other agents and their complexity level are given in Table 2.1. Besides the ElectricitySpotMarket and the EnergyProducer they have rather simple behaviour or exist mainly for accounting reasons.

The number of power generation companies can be chosen by the modeler, as well as the size and consistency of their power plant portfolios at the start of the simulation. The generation companies need to make the following types of strategic decisions:

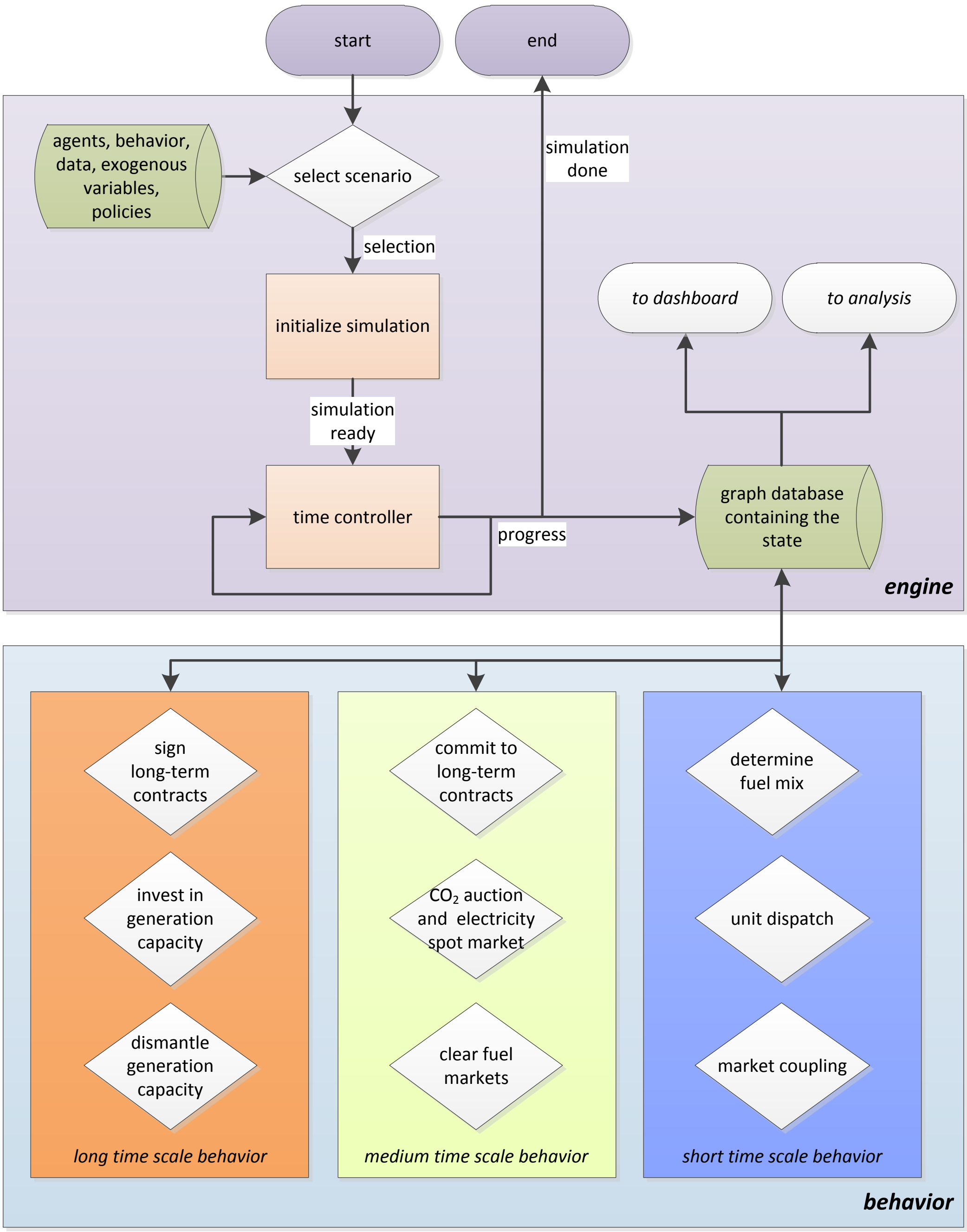

Figure 2.1 – Structure of the model

Agent Names	Complexity	Class
Energy Producer	High	`domain.agent.EnergyProducer`
TargetInvestor	Simple Rules	`domain.agent.TargetInvestor`
PowerPlantManufacturer	Accounting	`domain.agent.PowerPlantManufacturer`
PowerPlantMaintainer	Accounting	`domain.agent.PowerPlantMaintainer`
BigBank	Accounting	`domain.agent.BigBank`
CommoditySupplier	Accounting	`domain.agent.CommoditySupplier`
EnergyConsumer	Accounting	`domain.agent.EnergyConsumer`
Government	Simple Rules	`domain.agent.Government`
NationalGovernment	Simple Rules	`domain.agent.NationalGovernment`
ElectricitySpotMarket	High	`domain.market.electricity.ElectricitySpotMarket`
CommodityMarkets	Simple Rules	`domain.market.electricity.CommodityMarket`

Table 2.1 – Agents in EMLab-Generation and their complexity level. Adapted from Richstein et al. (2015b).

- Investment. The agents decide whether investing in a new power generation facility is sufficiently attractive to them. Agents invest when a new power plant appears attractive enough; see Section 2.7 for a description of the investment algorithm.
- Technology type. If agents decide to invest, they need to choose a type of electricity generation technology.

Generators' operational decisions

Apart from strategic management, power generators make the following operational decisions:

- Sell electricity. Generation companies offer their electricity to the power exchange at marginal cost plus a price markup, which is assumed to exist due to market power. The marginal cost of generation is derived from fuel and CO_2 prices.
- Purchase fuel. Based on actual electricity production, the required fuel is determined and acquired. In case of multi-fuel power plants, agents optimise their fuel consumption based on expected fuel prices.
- Acquire CO_2 emission rights. The volume of CO_2 emission rights that generation companies purchase is determined in an iterative process in which the arbitrage between the electricity and CO_2 markets is optimized. See Section 2.6 for a description. The assumption is that the short-term electricity and CO_2 markets work optimally and that arbitrage between them also is optimal.

Consumer agent

A single consumer agent represents the aggregate demand of all domestic consumers for electricity. The yearly demand depends on the scenario (see below).

2.3 Generation technologies

Available technologies

There is no restriction on the number of electricity generation technologies that can be used in this model. For simplicity's sake, however, we start the model with the following technologies.

- Coal (with optional biomass co-firing) with and without CCS
  - Pulverised Super Critical (PSC)
  - Integrated Gasification Combined Cycle (IGCC)
- Biomass
- Gas
  - Open Cycle Gas Turbine (OCGT)
  - Combined Cycle Gas Turbine, with and without CCS (CCGT)

- Nuclear Power
- Wind
  - Onshore
  - Offshore
- Photovoltaic

The main attributes of power plants that are modeled are fuel efficiency, investment cost, operating and maintenance (O&M) cost, maximum load, lifetime and construction time.

Innovation

We use typical cost and technology characteristics of existing generation plants (or, in case of coal with CCS, a plausible estimate). The specific assumptions are described in Appendix A. In the model, the efficiency of new power plants improves gradually over time (resulting in lower fuel consumption and CO_2 output per MWh_e produced). For new technologies such as wind and CCS, these learning rates develop more quickly than for existing ones. Capital and operating costs of new plants also decline, but during the course of a plant's lifetime, its fixed operating and maintenance costs increase, first gradual and then more strongly after its nominal life span has elapsed.

2.4 Intermittent energy sources

Short-term effects in a long-term model

Intermittent energy sources such as wind and solar energy present a challenge to a long-term model. In order to represent prices and the need for capacity realistically, the intermittancy of wind needs to be represented in the model. This is a short-term effect, but in order to reduce run-time and complexity, the model abstracts from the details of short-term power system operation and price formation. However, the effects of intermittent sources on prices and the load factor of thermal plant cannot be ignored. As the availability of these resources cannot be controlled, their contribution to meeting peak generation capacity needs is limited. Instead, we model the impact that intermittent resources have on each step of the load-duration function.

Approximation of intermittency

In our model, we approximate this effect by letting intermittent resources contribute different ratios of their nameplate capacity for different segments of the load-duration curve. To take onshore wind as an example, it only contributes 5% of its capacity during peak hours, but up to 40% of their nameplate capacity during the lowest segment of the load-duration function. In the load-duration segments in between, the contribution of intermittent resources is scaled linearly, and calibrated in such a way, that full load hours during one year correspond to empirical values. In this way, When there is much investment in intermittent resources, the model will reflect the limited contribution to peak generation capacity, while the load factor of fossil plants will decrease.

2.5 Power plant operation and spot market bidding

The algorithms described in the section can be found in the classes **`role.operating-.DetermineFuelMixRole`** and **`role.market.SubmitOffersToElectricity-SpotMarketRole`**.

Dispatch and fuel mix

Generation companies dispatch their power stations in strict merit order . Outages, start-up costs and ramp rates are not considered. They base their bids in the market on the available capacity and the variable costs (including the price of CO_2) of their plants. Some types of power plant can run on multiple fuels. A common example is coal with biomass, but more innovative technologies such as multi-fuel natural gas/coal gasification/biomass gasification plants can be added. The fuel dispatch of these plants is optimized for fuel and CO_2 prices and the energy densities of the fuels.

The fuel mix of multi-fuel power plants is determined in iteration with the market clearing algorithm. This is to ensure that the fuel mix decision of multi-fuel power plants are in equilibrium with market results (especially with the CO_2 price) and reflects the ability of power plant generators in reality to adjust the fuel mix during the year according to CO_2 and fuel prices.

The fuel mix is determined with a linear program that uses current fuel prices (which are known), the current CO_2 price (see the next section), power plant efficiencies and the fuel mix constraints given in Table **??**. The resulting variable fuel costs $vc_{g,t}$ per MWh_{el} for power plant g in time step t are then determined as the product of the volumes of the fuels (f) in fuel mix $s_{g,f,t}$ and the fuel prices $p_{f,t}$:

$$vc_{g,t} = \sum_{f} \frac{p_{f,t} \cdot s_{g,f,t}}{\eta_g} \tag{2.1}$$

Bidding

Assuming that variable power plant costs are solely determined by their fuel costs, and that all generators can exercise market power, the bidding strategy (cf. equation 2.3) for all agents is defined as:

$$p_{z,s,g,t} = vc_g \cdot (1 + m) \tag{2.2}$$

We assume the price mark-up to be 10% for all generators, following the example of Eager et al. (2012). To start of the market clearing algorithm in the first iteration last years CO_2 price is used.

2.6 The electricity and CO_2 market algorithms

The algorithm described in the section can be found in the class **`role.market-.ClearIterativeCO2AndElectricitySpotMarketTwoCountryRole`** in the method *`clearIterativeCO2ElectricitySpotMarketAndFutureMarket-TwoCountryForTimestepAndFuelPrices`* . The text was updated by including verbatim model descriptions by Richstein et al. (2014) that introduce banking.

Overview of Iterative Process

In this section we will describe how the electricity and CO_2 markets are cleared. The time step of the model is one year. There are two interconnected electricity markets with a number of generators (chosen by the modeller, and dependent on the scenario), distributed over these markets. Electricity demand is represented by a step-wise load-duration function which is different per modeled price zone. Electricity prices may thus vary between markets if the interconnector is congested. The number of steps can be varied in the model; the higher the number, the more refined the representation of demand, but the slower the model. The supply function is constructed by placing the generator bids in merit order. Generators base their bids on the price of CO_2 (in the first iteration, this is the previous year's CO_2 price) and the exogenously determined fuel prices. CO_2 emissions are constrained by the annual emissions cap, . As perfect trade in CO_2 is assumed between these markets, so that the CO_2 price is the same in all markets in the model. It is assumed that the 'consumption' of CO_2 credits can be arbitraged perfectly between the different hours of a year; therefore, there is only one CO_2 price in each year. An iterative process is used to find the market prices of electricity and CO_2. Given a certain starting value of the CO_2 price, the markets are cleared. When the emissions are higher than the cap, the CO_2 price is increased and vice versa. The electricity markets are cleared again, with the different CO_2 price leading to an adjustment in emissions. This process is repeated until the CO_2 emissions are equal to the emissions cap. The different steps are described in more detail below.

Electricity Market Bidding

Each generation company submits its electricity bids, one price-volume pair per power plant g for each segment s of the load-duration function according to Section **??**. This also includes updating the fuel mix according to the CO_2 price of the current iteration. They only bid into the electricity market in which their power plant is located (zone z). The bidding strategy is described in Section 2.5.

$$b_{z,s,g,t} = (p_{z,s,g,t}, V_{z,s,g,t}) \tag{2.3}$$

CO_2 Price adjustment

The bids of the power generators are than universally adjusted for a given, identical CO_2 price $p_{CO_2,t}$ and the complimentary CO_2 tax $T_{CO_2,z,t}$, as well as the the emission intensity $e_{g,t}$ of the power plant, so that the costs of CO_2 emission are accounted for in the bid. In the first iteration round, the CO_2 price of the last year is taken.

$$b^{CO_2}_{z,s,g,t} = (p_{z,s,g,t} + (p_{CO_2,t} + T_{CO_2,z,t}) \cdot e_{g,t}, V_{z,s,g,t}) \tag{2.4}$$

If a complimentary tax is implemented, it is set to create a CO_2 price floor $F_{CO_2,z}$ in zone z:

$$T_{CO_2,c} = \max(0, F_{CO_2,z,t} - p_{CO_2,t}) \tag{2.5}$$

Electricity market clearing

In principle, the electricity markets in the model are than cleared the same way as real power exchanges. For each segment in the load-duration function, price and volume are determined by the intersection of supply and demand. The generator bid pairs including the CO_2 costs are sorted from low to high price and the intersect of the resulting supply function with demand (which is presumed inelastic) determines the price and volume of electricity sold. The markets are cleared independently for every step of the load-duration functions, yielding a step-wise price-duration function with the same number of steps as the load-duration function. In each segment the highest accepted bid (that is needed to satisfy demand) $b^{CO_2,*}_{z,s,g,t} = (p^{CO_2,*}_{z,s,g,t}, V^*_{z,s,g,t})$ sets the market clearing prices $p^*_{s,t}$for segment s. In case demand $D_{s,t}$ in segment s cannot be satisfied, the clearing price is set to the value of lost load.

Congestion management

The market clearing algorithm, as described above, is first run for all zones in the model together. This implies the assumption that there is no congestion between the zones and results in a single electricity price for all zones together. If the resulting flows over the interconnectors exceed available capacity, the congestion is managed by means of market splitting. (In the simplified environment of this model, the outcome is the same as if market coupling were applied.) We will now describe the congestion management algorithm for the case of two zones. In case of congestion, the markets are cleared separately for each zone. In the exporting (low price) zone, the demand is increased until the interconnector is fully utilized. This additional demand is subtracted from the demand in the importing (high priced) zone. The market clearing price $p^*_{z,s,t}$ is thus the highest accepted bid $b^{CO_2,*}_{z,s,g,t} = (p^{CO_2,*}_{z,s,g,t}, V^*_{z,s,g,t})$ for Zone z and segment s that is needed to fulfil the adjusted demands $D^*_{z,s,t}$ in segment s in zone z. This causes the market prices to move closer together and reduces the average cost of generation.

Expected electricity market clearing

In case that the CO_2 market is active in the model the steps described above are carried out for an electricity market forecast in three years (taking into account power plants under construction and dismantlement), except that the CO_2 price, used to clear the market, is compounded to $\hat{p}_{CO_2,t+3} = p_{CO_2,t} \cdot (1 + i_B)^3$. The discount rate i_B is set to 5%, which lies in the reported range of interviews done by Neuhoff et al. (2012). As input data for the electricity market forecast, fuel price and demand trend forecasts for three years ahead are calculated. The applied regression methodology is described in Section **??**. The past 5 years are used as input data for the regression.

CO_2 emissions in one iteration

The market results lead to a certain (optimal) generation unit commitment of power plants ($V^{\dagger}_{z,s,g,t}$ denotes the production of a power plant), from which the resulting CO_2 emissions of the current market and the market forecast are determined.

$$\begin{aligned} E_t &= \sum_{z,s,g} V^{\dagger}_{z,s,g,t} \cdot e_{g,t} \\ \hat{E}_{t+3} &= \sum_{z,s,g} \hat{V}^{\dagger}{}_{z,s,g,t+3} \cdot e_{g,t+3} \end{aligned} \tag{2.6}$$

CO_2 market clearing iteration algorithm

The clearing emission cap is given by the sum of the emission cap $C_{CO_2,t}$ of the current year, by the emission cap in three years time $C_{CO_2,t+3}$ and the difference to the banking target divided by a revision speed factor $\Delta T_{B,t}/r$. The banking target is determined by assuming that producers aim to hedge 80% of expected emissions in the coming, 50% in two and 20% in three years time. The expected emissions of E_{t+1} and E_{t+2} are determined by linear interpolation between E_t and E_{t+3}. This banking rule is based on a study done by **?** and an interview series by Neuhoff et al. (2012). To allow some flexibility in returning to the banking target a revision speed factor r of $r = 3$ is used.

$$C_{CO_2,t} + C_{CO_2,t+3} + \Delta T_{B,t}/r = E_t(p_{t,CO2}) + \hat{E}_{t+3}(p_{t,CO2} * (1 + i_B)^3) \tag{2.7}$$

If the CO_2 emissions exceed the clearing emissions cap, the CO_2 price $p_{CO_2,t}$ is raised, and vice versa if the emissions are below the cap, and steps 2) through 5) are repeated. The iteration stops and the market is considered to be cleared when the emissions are approximately equal to the CO_2 cap, when a price minimum (0 or global price floor) or price ceiling $C_{CO_2,t}$ is reached. In scenarios without a price ceiling, a constant maximum price of €500/ton is assumed[1]. Alternatively if the maximum number of iterations is reached, the last value of p_{CO_2} is used. We apply a tolerance band of $\pm 3\%$ in order to finish the iteration in a timely fashion.

Determination of banked CO_2 permits

Depending on whether the clearing emission cap is approximately reached, or if the lower of the national (or a common) price floor is sufficient to lead to emissions below the cap, the banked allowances are adjusted. In case the cap is approximately reached, the sum of banked allowances by all agents is adjusted by the difference between the emission cap of the current year and the emissions in the current year ($\Delta B_t = C_{CO2,t} - E_t$). In case that the lower of the two emission floors is sufficient to lead to sub-cap emissions, the difference to the overall banked emissions is given by the difference to the banking target divided by the revision speed factor $\Delta T_{B,t}/r$. Thus, the lower of the price floors (or a common price floor) is simulated as a reserve price at which agents buy or sell[2] their credits to reach their hedging target. If more permits would be consumed than are banked, the target search algorithm is run for only the current period. The banked permits are assigned to agents according to their share in overall emissions. The difference to the previous years banked credits affects their cash position at the current year's permit prices. The agents start the simulation with 500 million CO_2 certificates already banked, which is at the upper limit of the estimation by Neuhoff et al. (2012).

[1] At that point the last fuel switching alternatives under most price scenarios are exhausted.

[2] Assuming that the reduction in banked allowances is not so large that it will depress secondary market prices below the reserve price.

Variable	Unit/Content	Description
t	a	Time step, in years
z	{CWE,GB}	Zone index
$S_{s,z}$	(D_s, l_s)	Segment is a tuple of demand and length
$D_{s,z}$	MW	Demand in Segment S
l_s	h	Length of Segment S (identical for both countries)
s	$\{1, \ldots, 20\}$	Segment index
$LDC_{z,t}$	$\{S_{z,1}, \ldots, S_{z,20}\}$	Load Duration Curve with 20 segments
$b_{z,s,g,t}$	$(p_{z,s,g,t}, V_{z,s,g,t})$	Bid into zone z, segment s, year t for power plant g, excluding CO2 cost
$p_{z,s,g,t}$	$€/MWh_{el}$	Bidded price
$V_{z,s,g,t}$	MWh	Bidded energy
$V^{\dagger}_{z,s,g,t}$	MWh	Energy produced (of an accepted bid)
$p^{*}_{z,s,t}$	$€/MWh_{el}$	Segment clearing price
$b^{CO_2}_{z,s,g,t}$	$(p^{CO_2}_{z,s,g,t}, V_{z,s,g,t})$	Bid adjusted by the iterative CO_2 target search.
g	$\{1, \ldots, G\}$	Power plant index
$e_{g,t}$	t_{CO_2}/MWh	Emission intensity of power plant g in time step t
$p_{CO_2,t}$	$€/ton$	CO_2 Market Price
$F_{CO_2,z,t}$	$€/ton$	CO_2 Price Floor in zone z
$T_{CO_2,z,t}$	$€/ton$	Complementary CO_2 tax in zone z
$C_{CO_2,t}$	$€/ton$	Common price ceiling
$B_t, \Delta B_t$	ton	Banked emission permits, difference in banked emission permits
i_B		Interest rate for compounding the CO_2 price
$T_{B,t}, \Delta T_{B,t}$	ton	CO_2 permit banking target, and difference to it
r		Revision speed factor towards the banking target
$vc_{g,t}$	$€/MWh_{el}$	Variable fuel costs of power plant g in t
$fc_{g,t}$	€	Fixed costs of power plant g in t
$p_{f,t}$	$€/MWh_{th}$	Price of fuel f in time step t
$s_{g,f,t}$	MWh_{th}	Amount of fuel f in fuel mix in time step t
η_g		Efficiency of power plant g
$a_{s,g}$		Segment dependent availability of power plant g
m		Price mark-up of generators
$\hat{r}_{g,s,t}$	h	Expected running hours of power plan g, in segment s, in year t
I_g	€	Investment cost of power plant g in t
$WACC$	€	Weighted average cost of capital

Table 2.2 – Notation

2.7 Investment algorithm

The outer algorithm that leads to several rounds of investment is contained in the class **`role.market.DecarbonizationModelRole`**.

This calls per energy producer an agent-specific investment algorithm (defined in the property `investmentRole`), which must be of the type **`role.investment.GenericInvestmentRole`**.

The specific investment behaviour discussed in this section is only one realisation of possible investment behaviours and implemented in the class **`role.investment.InvestInPowerGenerationTechnologiesStandard`**.

Overview

In order to come to an investment process, where decisions by generator agents are influenced by other agents' actions, the investment are made sequentially in several rounds. The investment process is stopped as soon as no agent is willing to invest any more, i.e. further investments seem unattractive due to already announced power plants. To prevent a continuous bias towards agents induced by the investment rounds, the order in which agents invest is determined randomly in each year. Agents are assumed to finance a part of their investment cost of a power plant from their cash flow, expecting a specific return on equity $k_{e,i}$, and finance the remaining investment cost from debt, at an interest rate $k_{d,i}$ given by the bank. The loan is assumed to be payed back in equal annuities during the depreciation period of the power plant.

Principle: NPV for reference year

The investment algorithm is based on the assumption that investors would like to invest to the point that their investment just makes a profit, but that they do not have perfect information. In every time step, and each iteration of the investment rounds, each agent considers the potential profitability of each type of generation technology. For each type of generation technology, a simple approximation of a net present value (NPV) calculation is made for a reference year which lies t years ahead of the year that the decision is made, taking into account the required return on equity, the interest rate on loans, as well as the debt ratio. In the intervening time, all generation technologies can be built, so all plants that are under construction at the time of the investment decision are assumed to be completed in the reference year. The agents add the power plants that are under construction to the existing generator set and subtract plants that will reach the end of their expected lives. They also forecast demand, fuel prices and carbon prices for the reference year. From these data, an expected price duration curve is made for each price zone, from which the expected electricity and CO_2 prices are calculated. From these prices and the expected fuel costs, the expected operating profit of the proposed plant is calculated. In the following the steps taken by the agents in each round of the investment cycle are described:

Estimating the generator set in the reference year

An agent who is considering an investment makes a small model of future supply and demand for the national market of the planned power plant. He estimates the future supply function by adding the capacity of new power stations that are announced or already under construction to the existing supply function and subtracting the capacity of the plants that will probably have reached their technical end of life in the intervening time. The agent makes the estimate only for his own country and ignores import and export possibilities.

The list of future generators thus contains the current generators, including plants under construction that will be completed in year $t+n$, minus plants that reach their life end before year $t+n$, in which t is the current year and n the reference year time horizon.

Estimating future demand, fuel prices and CO_2 prices

Future demand is estimated by taking the current load-duration function and on a per segment basis forecast future demand by performing a linear regression. The expected prices of coal, gas, and uranium are estimated in the same way as the future demand. CO_2 prices are estimated using the same regression forecast, but than taking the average of this

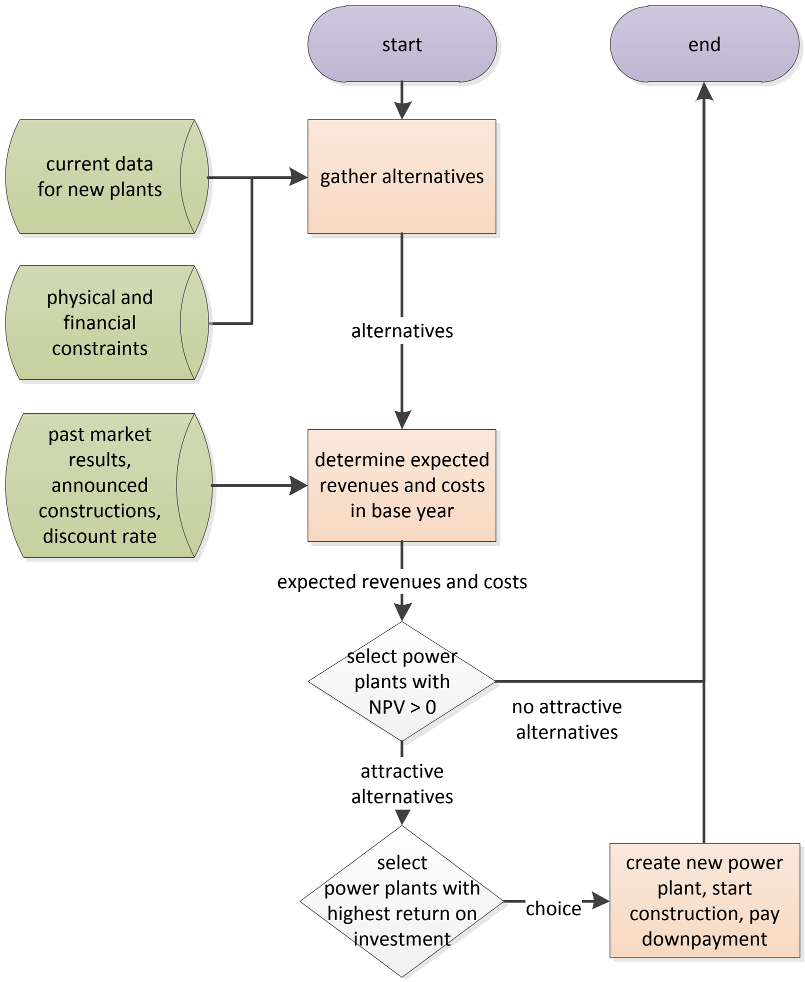

Figure 2.2 – Structure of the investment algorithm

forecast and an average of past prices, to come to an final forecasting value.

For each section of the load-duration function the corresponding price is than estimated as the variable cost of the marginal plant. Thus a price-duration function is determined that has the same number of steps as the load-duration function ($\hat{p^*}_{z,s,t+n}, \forall s$).

First criterion: financial status of company

The first question is whether an agent invests at all. Before considering the question of which technology might be profitable, an agent (or his financiers) decide whether he is capable of paying the downpayment (typically 30% of the total capital cost).

Expected running hours

The expected running hours in each segment $\hat{r}_{s,g,t+n}$ are determined from the estimated future energy prices $\hat{p^*}_{z,s,t}$ the variable costs $\hat{vc}_{g,t+n}$ of the power plant and the segment dependent availability rate a_s, which lowers running hours for intermittent renewable technologies. If the plant is expected to be in the merit order, i.e. variable costs are smaller than expected prices, the running hours are the product of the segment length l_s and segment dependent availability a_s.

$$\hat{r}_{s,p,t} = \begin{cases} l_s \cdot a_s & , \hat{p^*}_{z,s,t+n} \geq \hat{vc}_{g,t+n} \\ 0 & , \text{else} \end{cases} \tag{2.8}$$

The sum of running hours is than compared to the minimum running hours of the generation technology, and the investment decision only proceeds if this requirement has been fulfilled.

Cash Flow Estimation

The agent estimates a plant's expected cash flow by subtracting the plant's variable costs $\hat{c}_{v,p,t}$ (based on the estimates of fuel and CO_2 costs) from the estimated market price $\hat{p^*}_{z,s,t}$ for each segment s of the load-duration curve. Where the result is negative, the plant does not run and operating profits are zero, due to the multiplication with zero running hours $\hat{r}_{s,p,t+n}$ (cp. Equation 2.8). This yields the expected operating cash flow $CF_{Op,g}$ in the reference year $t+n$. For the final cash flow estimation the fixed cost of the power plant are subtracted.

$$CF_{Op,g} = CF_{g,t+n} = \sum_s \left((\hat{p^*}_{z,s,t+n} - \hat{vc}_{g,t+n}) \cdot \hat{r}_{s,g,t+n} \cdot a_{g,s} \right) - fc_{g,t+n} \tag{2.9}$$

Discounted Cash Flow

In order compare power plants of different capacities κ_p with each other, the specific project net present value (NPV) of the considered power plant is calculated using the weighted average cost of capital (WACC) as the interest rate. It is assumed that the total investment costs are spread linearly over the building time $(0, \ldots, t_b)$, and that the cash flow CF is representative for the life time of the power plant $(t_b + 1, \ldots, t_b + t_D)$.

$$\text{NPV}_g = \Big(\sum_{t=0\ldots t_b} \frac{-I_g}{(1+\text{WACC})^t} + \sum_{t=t_b+1\ldots t_b+t_D} \frac{CF_{Op,g}}{(1+\text{WACC})^t} \Big) / \kappa_g \tag{2.10}$$

If positive NPVs exist,the power plant p with the highest specific NPV_p per megawatt is chosen for investment.

This investment algorithm is only a first approximation of investment behavior. A number of possible extensions present themselves.

An obvious extension is to calculate the NPV calculated for each year within (a certain time horizon), as the expected cash flows may vary significantly. The price is that the run time of the model will increase proportionally.

For better accuracy, cross-border flows should be taken into account in the NPV. This is complicated, however, as it would require the agents to make forecasts of the results of the congestion management in order to estimate their revenues.

The investment decision process itself is more complex than a simple NPV calculation. Subjective factors such as risk aversion and technology preferences could be included in the future.

2.8 Exogenous scenarios

The electricity producers operate in a dynamic world which is represented by several exogenously determined trends: time series of fuel prices, electricity demand and carbon policy parameters (emission caps or tax levels). We assume that the electricity producers are price takers in these markets and therefore do not influence prices, nor can they influence electricity demand or policy decisions. In order to simulate the unpredictable nature of fuel prices and demand growth we always perform Monte-Carlo analysis of at least 120 scenarios. These scenarios can either be generated within the simulation using triangular distributions or supplied via CSV-files to the simulation. The second option has the advantage that result are more reproducible. An R script has been developed which can generate stochastic time series, that are mean reverting to a trend line and can be correlated with each other.

Modeling exogenous trends

2.9 Optional modules

2.9.1 Backloading and the market stability reserve

The algorithms described in the section can be found in the classes **`role.market-.ClearIterativeCO2AndElectricitySpotMarketTwoCountryRole`** and **`role.-co2policy.MarketStabilityReserveRole`**.

The text below is only slightly adjusted from Richstein (2015) and Richstein et al. (2015b).

Backloading can be modelled by changing the volume of auctioned EUAs in the model. To avoid model artificats that occur due to reliance on two reference (t and $t+3$) years, the action of backloading is smoothed over three years.

The MSR is closely modelled after the actual, proposed design, as described by Richstein et al. (2015b). Before the electricity and CO_2 markets are cleared, the MSR adjusts the EU ETS cap for the current year t based on the volume of EUA allowances that were banked two years ago. If the volume of banked EUAs is within a certain target corridor, the MSR does not change the cap; otherwise, the cap is adjusted. In our model, we scaled the target corridor linearly to the scope of the model (the electricity sectors of CWE and GB). If the banked allowances in $t-2$ are above the upper trigger, 12% of these allowances are deducted from the EU ETS cap in the current year. If the banked allowances in $t-2$ are below the lower trigger, the MSR releases a fixed volume of EUAs.

The model's CO_2 market algorithm should be adjusted in two ways. First, it should take into account the emergency price trigger by Richstein et al. (2015b). Second, the MSR should be factored into the current emission cap and its effects should be included in agent expectations for the future. This will influence the market equilibrium and therefore also the current CO_2 price.

If for more than six consecutive months the EUA price is above the average price of the past two years, the MSR emergency price trigger releases a fixed volume of EUAs. Since our model does not simulate events within one year, there are two possibilities for implementing this rule. One is that a high price in the current year triggers a release of credits in the following year. Alternatively, when the EUA price is above the trigger, the EUA price finding algorithm is rerun with the release of EUAs for the current year. If the released quantity is large enough to offset the shortage, this could cause the EUA price to return to its normal level. We implemented the second option because its effect is more direct; the potential avoidance of high prices is justified by the downward pressure on prices that would be caused by the expectation of an emergency release.

To implement the MSR, the emission-clearing cap must be adjusted. When active, the MSR changes the volume of auctioned EUAs, so equation 2.7 should reflect this change for the current year as well as the expected change in the volume of auctioned EUAs in the future. The original cap $C_{CO_2,t}$ in the model is substituted by the sum of the original cap and the action of the MSR in t (MSR_t), which depends on the volume of banked EUAs two years ago (B_{t-2}). The expected action of the MSR in three years time ($\hat{MSR}_{t+3}$) depends on the expected banked EUAs in the next year B_{t+1} (due to the two-year delay). B_{t+1} is linearly interpolated between the banked emissions of the current year B_t and the projected banked emissions B_{t+3} in three years time. Both B_t and B_{t+3} are intermediate results available during the iterative clearing of the CO_2 and electricity markets. Thus the emission-clearing cap from Section 2.6 is adjusted according to equation 2.11 to take the action of the MSR into account:

$$\begin{aligned} &C_{CO_2,t} + MSR_t(B_{t-2}) + C_{CO_2,t+3} + MSR_{t+3}(\hat{B}_{t+1}) + \Delta T_{B,t} / = \\ &E_t(p_{t,CO2}) + \hat{E}_{t+3}(p_{t,CO2} * (1+i_B)^3) \end{aligned} \tag{2.11}$$

2.9.2 Adaptive CO_2 cap to renewable policy

The algorithms described in the section can be found in the classes **`role.market-.ClearIterativeCO2AndElectricitySpotMarketTwoCountryRole`** and **`role.-co2policy.RenewableAdaptiveCO2CapRole`**.

The text below is only slightly adjusted from Richstein (2015) and **?**.

As discussed by Richstein et al. (2015a), two different rule-based cap adjustment mechanisms based on the volume of subsidised renewable energy production that exceeds the policy targets were implemented in EMLab-Generation. In the first, the SRES excess is set in proportion to the total electricity production (TBA). In the second, it is only set in proportion to unsubsidised electricity production only (RBA). We assume that implementation is based on observed data, which is available with a delay. Therefore, indicators of the previous year's data (electricity production, emissions and SRES) are used to calculate the current year's cap reduction. If the regulator would wish to adjust the cap in real time, he would need to rely on forecasts and estimations.

The adjustment of the cap needs to be implemented in two parts of the electricity & carbon market clearing. Firstly in the current cap $C_{CO_2,t,TBA}$ or $C_{CO_2,t,RBA}$, which replaces $C_{CO_2,t}$ in Equation (2.7). This is a certain adjustment, because it occurs in the current year. Secondly, in the future the expected cap $\hat{C}_{CO_2,t+3,RBA}$ or $\hat{C}_{CO_2,t+3,TBA}$, depending on the, replaces $C_{CO_2,t+3}$ in Equation (2.7). The expected cap adjustments needs to be estimated from expected generation of renewables. The formulas that are used to implement the TBA and RBA policy options in the current market are introduced in Section **??**, by Equations (**??**) and (**??**). The expected cap in $t+3$ is calculated with the same equations but with forecasts[3]:

$$\hat{C}_{CO_2,t+3,TBA} = (1 - \frac{max(\hat{G}_{SRES,t+2} - G_{SRES,Announced,t+2}, 0)}{\hat{G}_{t+2}}) \cdot C_{CO_2,t+3,original} \tag{2.12}$$

$$\hat{C}_{CO_2,t+3,RBA} = (1 - \frac{max(\hat{G}_{SRES,t+2} - G_{SRES,Announced,t+2}, 0)}{\hat{G}_{t+2} - \hat{G}_{SRES,Announced,t+2}}) \cdot C_{CO_2,t+3,original} \tag{2.13}$$

[3] Denoted by a hat above the forecasted variables

Since the renewable and overall generation in $t+2$ needs to be estimated, the values for $\hat{G}_{t+2}$, $\hat{G}_{t+2}$ and $\hat{G}_{SRES,t+2}$ are linearly interpolated between the generation results current market clearing (in time step t) and the future generation results of the market clearing in time step $t+3$ (which is a direct result of the market clearing algorithm). Since the RES investment targets are given in the model as absolute capacity, not as relative production targets, $G_{SREG,Announced,t-1}$ and $G_{SREG,Announced,t+2}$ need to be calculated as a counter-factual scenario. This is done by scaling the production according to the ratio of the planned capacity to the actual installed capacity.

2.9.3 Risk averse investment based on historical profits

The outer algorithm that leads to several rounds of investment is contained in the class **`role.market.DecarbonizationModelRole`**.

This calls per energy producer an agent-specific investment algorithm (defined in the property `investmentRole`), which must be of the type **`role.investment.-GenericInvestmentRole`**.

The specific investment behaviour discussed in this section is only one realisation of possible investment behaviours and implemented in the class **`role.investment.-InvestInPowerGenerationTechnologiesStandard`**.

The text below is only slightly adjusted from Richstein (2015).

In order to incoorperate an experience-based risk based adjustment of investment decisions in EMLab-Generation, we implement a new objective function in the investment algorithm. Instead of choosing the technology with the highest non-negative specific NPV, as described in Section 2.7, Equation (2.10), the agents choose the technology which has the highest risk adjusted value. Following the example of **?** and **?** the risk adjusted objective function is the sum of the risk-neutral NPV and the (historical) Conditional value at risk (CVar), which is also called the mean excess shortfall. The CVar is defined as the expected value of the α-tail of a profit distribution, i.e. the average of all the NPV with a value that is lower than the α-quantile of the NPV distribution. For our simulation we only take negative CVar values into account.

$$NPV_{RiskAdj,g} = NPV_g - \beta \cdot min(CVar_{Hist,g,\alpha}, 0) \tag{2.14}$$

The risk-aversion factor β defines the level of risk aversion of investors. A β of zero corresponds to risk-neutral investors, whereas a very high β corresponds to an investor who solely minimises the CVar value. We assume a mixed β distribution between the agents. In each country there are four agents with β-values of 0.85, 0.95, 1.05 and 1.15.

The agents calculate the $CVar_{Hist,g,\alpha}$ from the historical distribution in the last years (1 to 4 years, varying between the agents) of the gross marginal profits of the power plants of technology g that the investing agent owns. The gross marginal profit (GMP is defined here as the revenue of the power plant on the electricity market minus the incurred variable costs (fuel and carbon cost). Of these historical GMPs the average of the worst α are taken. In case fewer than 20 historical observations of GMP exist, the worst GMP is taken. This may lead to both over- or underestimation of the associated risks. The result is denoted $GMP_{CVar,\alpha}$. Following Equations (2.9) and (2.10) the CVar is then calculated as follows:

$$\mathrm{CVar}_{Hist,g} = \Big(\sum_{t=0\ldots t_b} \frac{-I_g}{(1+\mathrm{WACC})^t} + \sum_{t=t_b+1\ldots t_b+t_D} \frac{GMP_{CVar} - fc_{g,t+n}}{(1+\mathrm{WACC})^t} \Big) / \kappa_g \tag{2.15}$$

In order to include risk considerations for new technologies which the agents do not own, one dummy power plant per technology that the agent doesn't own is introduced to the simulation via the investment algorithm. These power plants are set at a very small capacity (0.001 MW), as to not influence market clearing and the finances of the agents. Every year the dummy power plants are updated to reflect technological progress in the new technologies. When the agents decide to build a new technology, the dummy power plant is removed and the agents rely on "real" power plants for their investment decision.

2.9.4 Improved implementation of intermittent renewables

3 Implementation in AgentSpring

The consequence of policy intervention typically materialize by changing the behavior of actors regarding their options, assets and decisions. That is a core reason in favour of ABM, but it also highlights that the scope of models for policy decisions is relatively large. The models need to be rich enough in order to properly represent the social, the technical and socio-technical components and their interactions (Chappin, 2011). For policy support, elaborate and diverse behavior of agents has to be possible. Models are data driven and have to incorporate extensive behavior algorithms (Chmieliauskas et al., 2012). Policy support

The desire to open up models to a community of researchers, public and private problem owners, and the general public is an important approach to ventilate research results to the public. It changes the role of models and simulations in the debate, and allows the end user to explore, validate and experiment with the tools that researchers develop. In addition, extendability and reusability of code is important, because it allows developed models to become a basis around years of policy-supporting modelling research. Open access models

3.1 AgentSpring framework

There are many ABM frameworks in existence, some more popular than others. Although it may have been possible to use and modify existing frameworks, we have taken up the opportunity to build the AgentSpring framework that would leverage off the new and powerful open source libraries and changing software development paradigms. AgentSpring is developed as an *open-source* tool. This implies that anyone can use and contribute to the platform. AgentSpring is available online[1]. AgentSpring is based on Java technologies and runs on all popular operating systems (Linux, Windows, and Mac). AgentSpring gets its name from and makes use of Spring Framework – a popular software development framework, that promotes the use of object oriented software patterns (Johnson et al., 2009). One such pattern calls for separation of data, logic and user interface (Krasner and Pope, 1988). Although the latter is an old concept, most modeling frameworks mix the three. This may be reasonable for creating smaller models, but for a base electricity and CO_2 model (see the application section) it will be ineffective in the long run. Developing and using AgentSpring enabled us to build a model that is better maintainable and expandable. Modelling frameworks

3.2 User interface

AgentSpring is characterized by a web-based user interface. See figure 3.1 for a snapshot of a running model. As a developer, AgentSpring runs as a local webserver (typically located Web-based user interface

[1] AgentSpring can be found at https://github.com/alfredas/AgentSpring. At the time of writing, the current version AgentSpring is 1.0.

Figure 3.1 – Snapshot of the user interface of AgentSpring with the model running

at http://localhost:8080/agentspring-face/). This setup also allows AgentSpring to be ran on a dedicated server that is securely opened up for external visits.

The interface allows to start, pause and stop the model, to change and create graphs by writing queries and to observe a textual log. Additionally, the interface can be used to select various predefined scenarios and to change key parameters in the model. A model in AgentSpring can also be controlled from command line, with or without running the AgentSpring user interface.

3.3 The system captured in a database

AgentSpring makes use of special way to contain the state of the modelled system. The modelled system is captured in a so-called *graph database*, which is a database that uses a graph structure of nodes, edges, and properties to represent and store information (Eifrem, 2009).

Graph database

The complete state of the system at any point in time is considered a graph of objects and their relationships. AgentSpring allows the graph to scale to hundreds of agents, millions of things and relations between them. The application of a database in ABM is promising as it allows for a different representation of the system modeled: the structure of the system – the objects and their interactions/relations – emerges and evolves. Capturing the data and perserving it in a database, makes it flexible to save and search. It enables efficient selection and finding by performing appropriate queries.

Queries

An example of a query could be to find all electricity spot markets for which the property *valueOfLostLoad* is higher than 500 €/MWh load lost and on which the *loadDurationCurve* contains at lest 15 segments (see figure 3.2 for the relational diagram for this

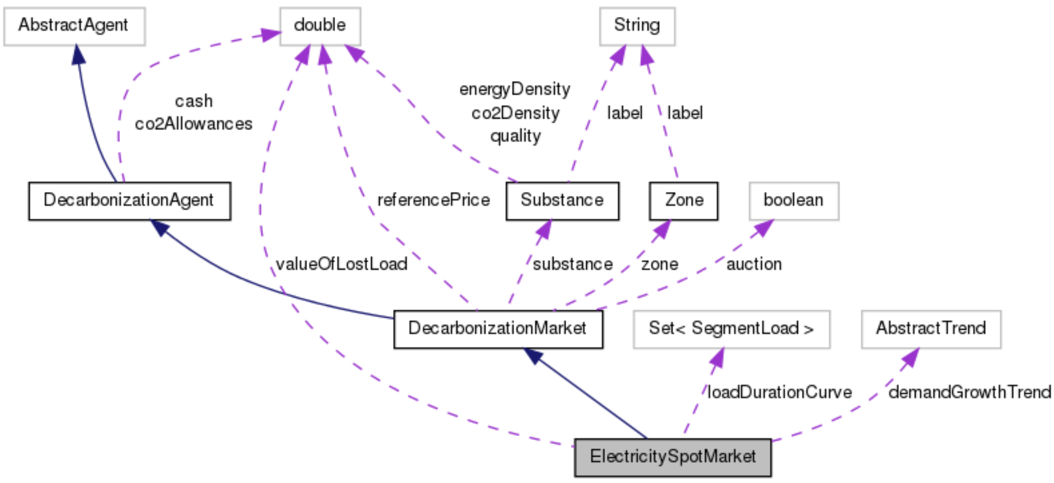

Figure 3.2 – The graph of possible relations for an electricity spot market, a relatively small example. The grey box is the starting point. Solid arrows refer to an 'is a' relationship. Dashed arrows are either property or a relation to another object. In this example an *ElectricitySpotMarket* is a *Decarbonization-Market*, which is a *DecarbonizationAgent*. An *ElectricitySpotMarket* has (or can have) a property called *valueOfLostLoad*, which is a *double* precision number. It also has the property *loadDurationCurve*, which is a set of *SegmentLoad* objects. Graphs like these are part of the documentation (see below)

example, which is part of the documentation). Traditionally, this would be solved maintaining a list of all spot markets in the model, looping over them and checking piece by piece for both conditions. A query, however, will be easier to compose, shorter in code, and it will be much faster. These advantages become even more relevant when queries span various types of objects. It also allows for thinking differently about extracting information, both for analysis of a running model as well as for the behavior of agents themeselves. An example of a more complicated query would be one that calculates the average efficiency of all *PowerPlants* that have a *PowerGeneratingTechnology* that uses fuels emitting CO_2, of which the *EnergyProducer* agent – the owner – has a positive cash balance.

3.4 Types of classes and other files

AgentSpring uses various types of Java classes and other files.

Domain classes are the definitions of things and their properties. For instance it contains the classes *Agent* and *PowerPlant*. Domain classes

Role classes capture pieces of behavior, such as *InvestInPowerPlantRole*, that can be executed by specific types (or classes) of Agents (which are in the domain, *EnergyProducer* in this case). Behavior typically results in new or changed information or objects that are persisted in the database with the help of repositories. Role classes

Repository classes contain functions that deal with the interaction of typical model code and the database. For instance, *findAllOperationalPowerPlants* is a function in the *Power-PlantRepository*, that executes a query to the database for all power plants, checks which ones are operational (and are not unavailable, under construction or decommissioned), and returns the result. Repositories also assist in updating current information or storing new information. Repository classes

Scenario xml files contain all data to define and initiate a simulation run. A scenario contains data, but also relations between objects. An example of data is parameters of power plants, and a price trend for coal. An example of a relation that is captured in the scenario is the fact that on a market for trading a specific substance a relation is made to the substance coal that can be traded on this particular market. Furthermore, a coal supplying Scenario files agent is connected to the market.

3.5 Modelling agents and their behavior

Modular behavior

AgentSpring makes use of the concepts of *roles* to encode agent behavior in a modular way. Agents play their roles in the simulation by executing their in modules coded behavior. Models are made by linking agents to such roles and composing a script that together define the set of behaviors in the context of social situations. This makes AgentSpring particularly suited to modeling complex socio-technical systems. AgentSpring decouples agents, their behaviors and their environments. That enables to reuse the pieces, to compose consistent new pieces. Experience has shown that only modular and reusable models can accommodate changing scope and new research questions.

Properties of roles

The roles that make up the behavior of agents have the following properties:

- A role is enacted by a specific class of agents.
- A role encodes a piece of behavior.
- Input for roles are the properties of the agent enacting the role, but also other parts of the system. Queries are used to access the graph database and retrieve the information needed for the behavior to be executed.
- The outcome of the behavior that is captured in a role implies a change in something in the state of the system. This is then stored in the graph database.
- A role can initiate other roles, i.e. a hierarchy of roles can be developed.
- Roles do not interact with each other directly (apart from iniating other roles, see the previous bullet).

3.6 Development and documentation

Software practices

Typical software development practices enable version control of model through github (https://github.com/emlab/emlab-generation for the model described). This is connected to a wiki-enabled interface to communicate between developers. Another practice in Java coding is on writing documentation. Online documentation is generated based on the structure of the code and the documentation written as part of the code. See figure 3.3 for a snapshot of the online documentation. The documentation is intuitive enough to find your way and grasp both the structure and details of model in multiple ways. Links between classes are visualized and linked and for each function a graph is made what other functions it uses and it is used by. The documentation supports modellers and the community around models to understand and explore the structure of the model. It also enables a platform to think about changes and different scenarios.

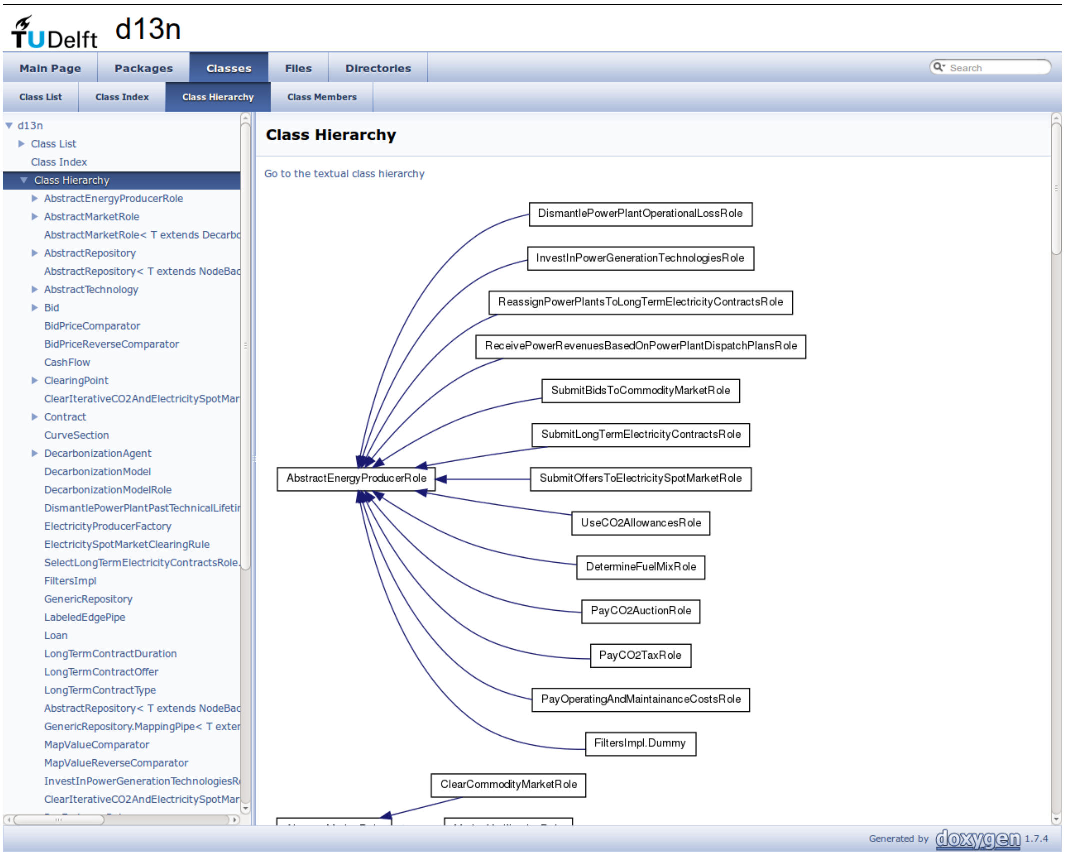

Figure 3.3 – Snapshot of the documentation of the model as a website

Appendices

A Power plant and fuel data

A.1 Energy densities of fuels

We have used the following conversion factors in the power generation model (see Table A.1).

Table A.1 – Conversion factors for power plants

Fuel	Energy density
Biomass	15 GJ/ton
Coal	25 GJ/ton
Natural gas	0.0383 GJ/m^3
Uranium	1,865,150 GJ/ton

A.2 Power plant data

See table A.2 for the data on power plants.

Table A.2 – Power plant data

Technology	Minimal running hours	Lifetime	Efficiency modifier	Down payment	Annuitized investment cost	Depre- ciation time	Maximum installed capacity fraction	Total investment cost	Capacity	Efficiency	Leadtime	Fixed operating cost
Biomass	0	30	0.00500	375,000,000	115,040,000	15	1	268,402,500	500	0.35	3	93,99,750
CCGT	0	30	0.00108	121,707,000	37,336,000	15	1	527,292,000	776	0.56	2	13,475,240
Coal CSS	5000	40	0.00188	537,561,000	147,331,000	20	1	1,745,499,600	676	0.35	7	52,569,140
Coal	5000	40	0.00400	343,000,000	94,120,000	20	1	1,087,351,000	758	0.44	4	32,620,530
IGCC	0	40	0.00261	343,000,000	94,120,000	20	1	1,373,496,000	758	0.48	4	48,072,360
IGCC CCS	0	40	0.00622	537,561,000	147,331,000	20	1	1,776,122,400	676	0.35	7	62,266,360
Nuclear	5000	40	0	900,000,000	231,000,000	25	1	3,020,000,000	1000	0.3	7	75,500,000
OCGT	0	30	0.00165	121707000	37,336,000	15	1	56,625,000	150	0.38	2	2,265,000
Wind	0	25	0	345,000,000	105,836,000	15	1	191,392,500	150	1	2	2,831,250

B Sample load-duration function

The following load-duration function is used in the examples in this report and in some of the model runs.

Table B.1 – Sample load-duration function

Segment	Demand (MW)
1	24581
2	23280
3	22432
4	21764
5	21477
6	20768
7	20241
8	19586
9	18918
10	18243
11	17637
12	17074
13	16506
14	15957
15	15385
16	14874
17	14392
18	13957
19	13459
20	12628

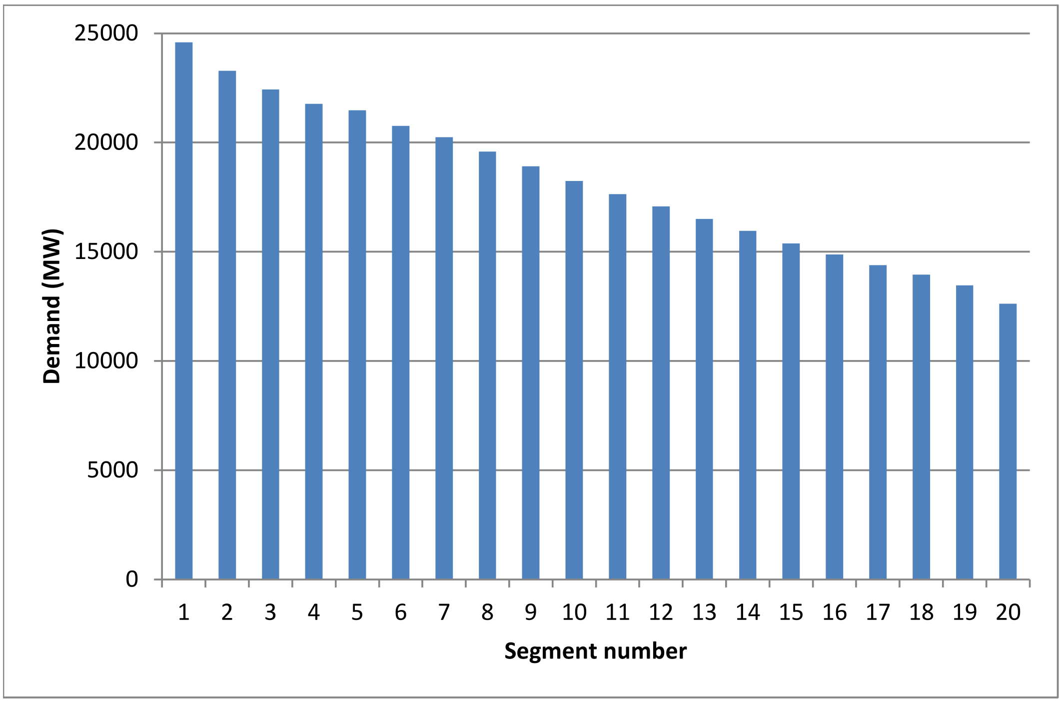

Figure B.1 – Sample load-duration curve

Acknowledgements

This work was supported by the Energy Delta Gas Research program, project A1 – Understanding gas sector intra-market and inter-market interactions and by the Knowledge for Climate program, project INCAH – Infrastructure Climate Adaptation in Hotspots.

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