EMLab-Generation

An experimentation environment for electricity policy analysis

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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

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. Object

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. Drivers of change

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. Agents

The electricity and CO_2 markets 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. The electricity markets are modeled as power exchanges. They are cleared simultaneously, including a market coupling algorithm for the allocation of interconnector capacity. An iterative process is used to simulate arbitrage between the electricity and CO_2 markets. Markets

When agents construct a new power plant, they can choose from a range of generation Electricity generation technologies

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.

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 (random functions of) 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. 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. In addition, aggregate electricity consumption is represented by a single agent. 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:

- 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.

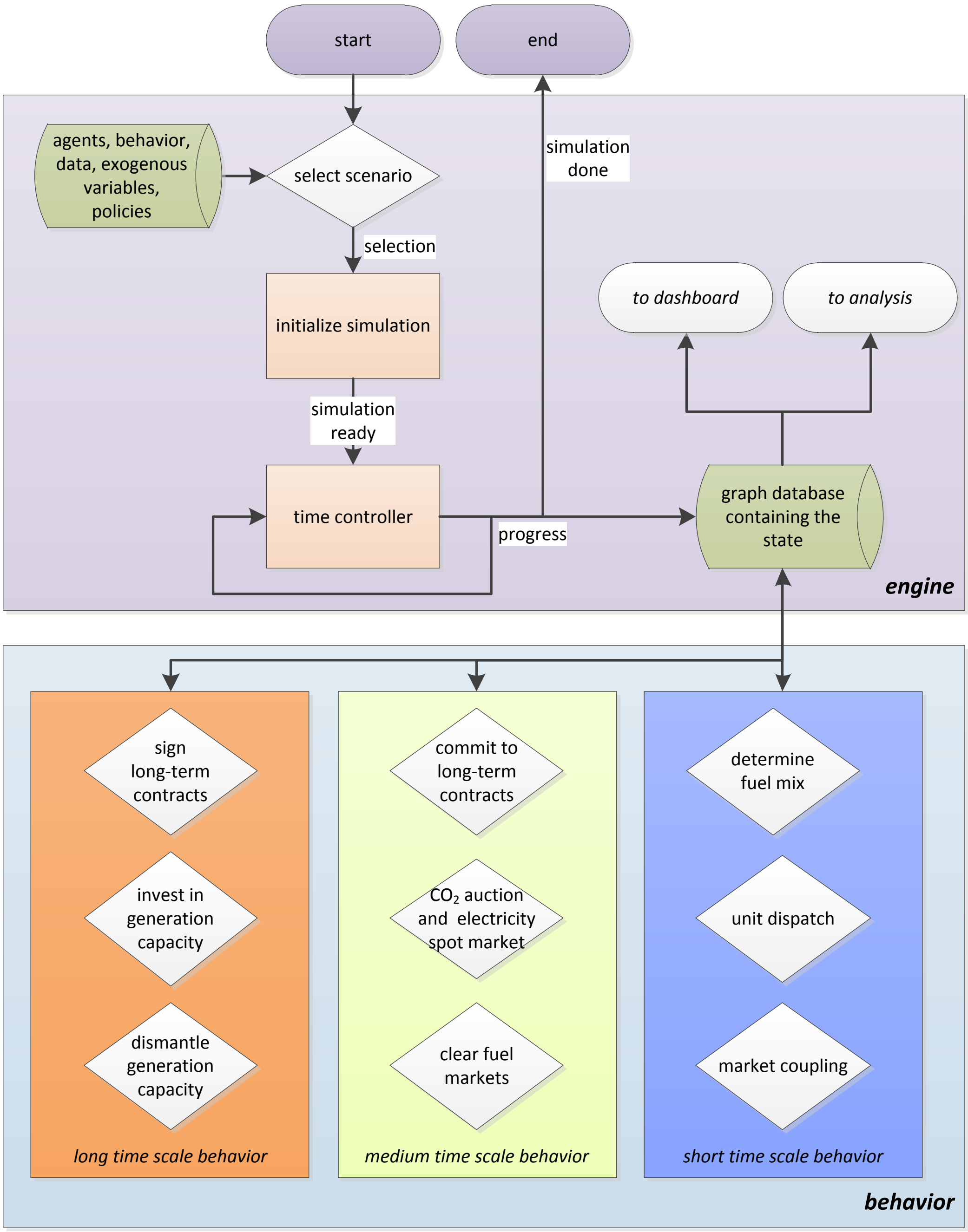

Figure 2.1 – Structure of the model

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 graduall 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

Dispatch

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 at the beginning of each year, implicitly assuming that this is the time that fuel supply contracts are concluded. As a consequence of this assumption the CO_2 price is not known, and the agents take the previous year's CO_2 price as a best estimate to calculate their optimal fuel mix. This is done via a linear program taking into consideration current fuel prices (which are known), last year's CO_2 price, the power plant efficiency and the fuel mix constraints given in Table A.2. The resulting variable fuel costs per MWh_{el} for power plant p are then determined as the weighted average of the fuel prices:

$$c_{p,fuel} = \sum_{f} \frac{p_f \cdot s_{p,f}}{\eta_{p,e}} \tag{2.1}$$

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:

$$p_{c,s,p,t} = c_{p,fuel} \cdot (1 + m_g) \tag{2.2}$$

We assume the price mark-up to be 10% for all generators, following the example of **?**.

2.6 The electricity and CO_2 market algorithms

Overview of Iterative Process

In this section we will describe how the electricity and CO_2 markets are cleared. The

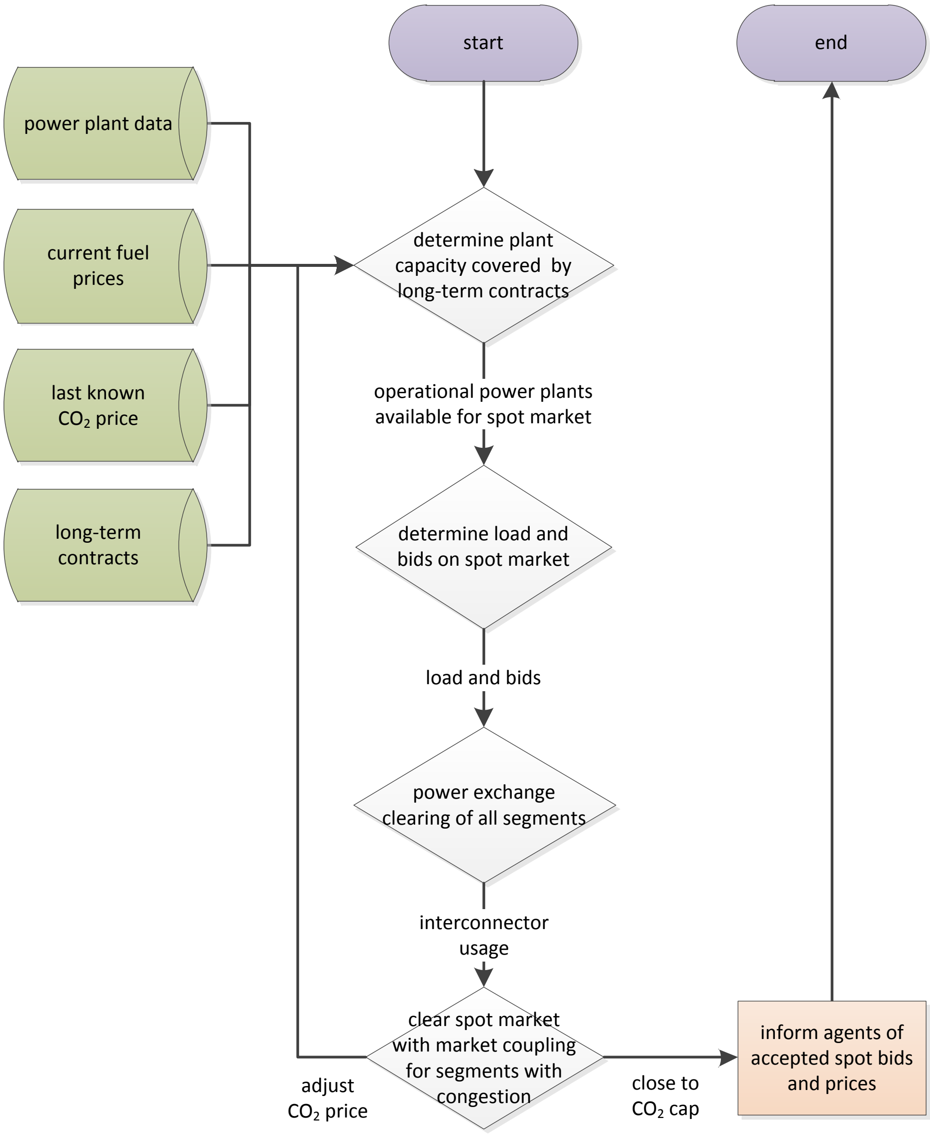

Figure 2.2 – Structure of the market clearing algorithm

time step of the model is one year. There are 2 interconnected electricity markets with 5 generators, 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. Figure 2.2 on page 8 provides an overview of the electricity and CO_2 market clearing algorithm, and the different steps are described in more detail below.

Electricity Market Bidding

The generators bid into each of the segments, using one price-volume pair per segment and power plant. The electricity market they bid into is determined by the location (country c) of the power plant p. The bidding strategy is described in Section 2.5.

$$b_{c,s,p,t} = (p_{c,s,p,t}, V_{c,s,p,t}) \tag{2.3}$$

CO_2 Price adjustment

The bids of the power generators are than universally adjusted for a given, identical CO_2 price p_{CO_2} and the complimentary CO_2 tax $T_{CO_2,C}$, as well as the the emission intensity e_p 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.

$$b^{CO_2}_{c,s,p,t} = (p_{c,s,p,t} + (p_{CO_2} + T_{CO_2,c,t}) \cdot e_p, V_{c,s,p,t}) \tag{2.4}$$

The complimentary tax is set such that the minimum CO_2 price floor $F_{CO_2,c}$ in Country c is guaranteed:

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

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) $b^{CO_2,*}_{s,p,t} = (p_{s,p,t}, V^*_{s,p,t})$ sets the market clearing price $\rho_{s,t}$ 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

Variable	Unit/Content	Description
t	a	Time step, in years
i		Generator agent index
c	{A,B}	Country index
$S_{s,c}$	(D_s, l_s)	Segment is a tuple of demand and length
$D_{s,c}$	MW	Demand in Segment S
l_s	h	Length of Segment S (identical for both countries)
s	$\{1, \ldots, 20\}$	Segment index
$LDC_{c,t}$	$\{S_{c,1}, \ldots, S_{c,20}\}$	Load Duration Curve with 20 segments
$b_{c,s,p,t}$	$(p_{c,s,p,t}, V_{c,s,p,t})$	Bid into country c, segment s, year t for power plant p, excluding CO2 cost
$p_{c,s,p,t}$	$€/MWh_{el}$	Bidded price
$V_{c,s,p,t}$	MW	Bidded capacity
$\rho_{c,s,t}$	$€/MWh_{el}$	Segment clearing price
p	$\{1, \ldots, P\}$	Power plant index
e_p	t_{CO_2}/MWh	Emission intensity of power plant p
p_{CO_2}	$€/ton$	CO_2 Market Price
$F_{CO_2,c,t}$	$€/ton$	CO_2 Price Floor in country C
$T_{CO_2,c,t}$	$€/ton$	Complimentary CO_2 tax in country C
$c_{p,fuel}$	$€/MWh_{el}$	Variable fuel costs of power plant p
p_f	$€/MWh_{th}$	Price of fuel f
$s_{p,f}$	MWh_{th}	Amount of fuel in fuel mix
$\eta_{p,e}$		Efficiency of power plant p
$a_{s,p}$		Segment dependent availability of power plant p
m_g		Price mark-up of generator g
$\hat{r}_{p,s,t}$	h	Expected running hours of power plan p, in segment s, in year t
I_p	€	Investment cost of power plant p
$k_{e,i}$		Interest rate for equity
$k_{d,i}$		Interest rate for debt

Table 2.1 – Notation - The accent ˆ symbolises expectations of agents

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 $\rho_{c,s,t}$ is thus the highest accepted bid $b^{CO_2,*}_{c,s,p,t} = (p_{c,s,p,t}, V^*_{c,s,p,t})$ for country c and segment s that is needed to fulfil the adjusted demands $D^*_{c,s,t}$ in segment s in country c. This causes the market prices to move closer together and reduces the average cost of generation.

CO_2 market clearing

When this process has been completed for every step of the load-duration function, the resulting CO_2 emissions are calculated.

$$E_t = \sum_p V_{c,s,p,t} \cdot e_{p,t} \tag{2.6}$$

If the emissions are higher than the cap, the CO_2 price is increased and the markets are cleared again. The higher the CO_2 price, the lower in the merit order the CO_2 intensive technologies will be. Eventually, their output will be reduced to the point that the CO_2 cap is met. If, on the other hand, the emissions are below the cap, the CO_2 price is reduced, yielding the opposite effect. This process is reiterated until the CO_2 emissions are (nearly) equal to the emissions cap (within a bandwidth of 5%). This process is visualized in Figure 2.2. If the cap cannot be met with the portfolio of power plants, the CO_2 price is capped to a high value. Otherwise there would not be a solution. A very low CO_2 price (or close to the minimum CO_2 price) is rounded down when the CO_2 cap is not met, in order to come to a solution in the iterative clearing process.

2.7 Investment algorithm

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 multiplying the height of each step with the expected growth rate of demand, which is estimated by averaging the demand growth rates of the past five years. For each segment of the load duration function:

$$\hat{D}_{s,c,t+n} = D_{s,c,t} \cdot (1+h)^t \tag{2.7}$$

in which:

$\hat{D}_{s,c,t+n}$ = is the estimated demand in year $t+n$

$D_{s,c,t}$ = demand in year t, segment s and country c

h = estimated demand growth rate (percent), average of the past five years' growth rates

The expected prices of coal, gas, uranium and CO_2 are estimated in the same way as the future demand. For each section of the load-duration function the corresponding price is

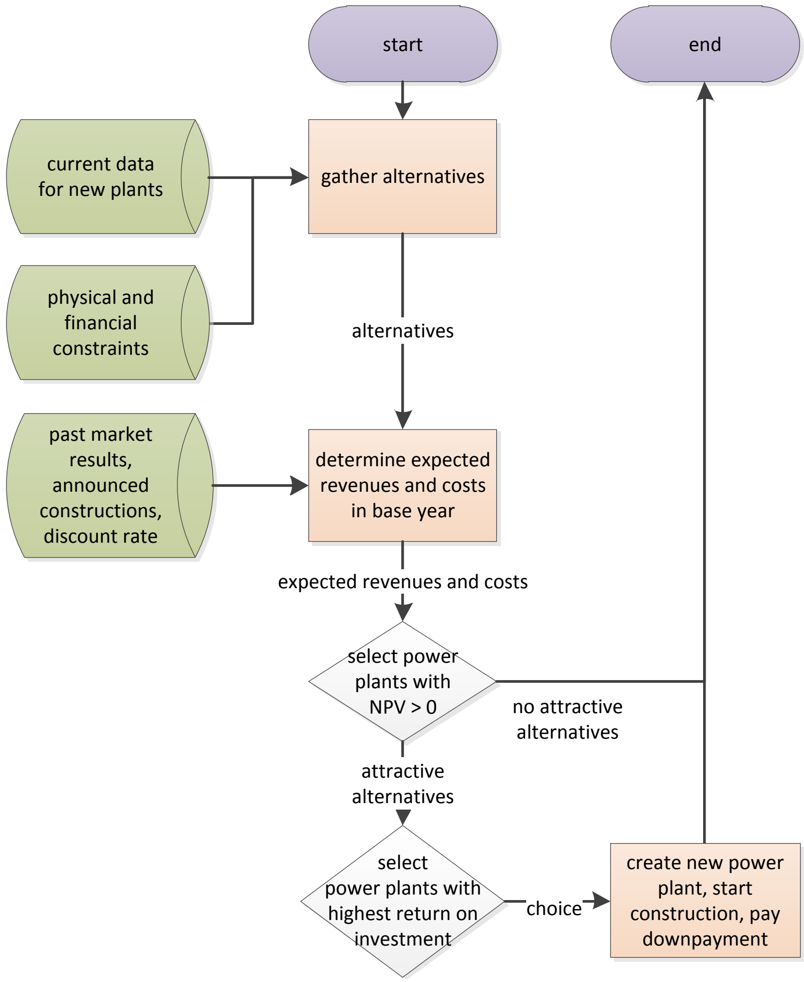

Figure 2.3 – Structure of the investment algorithm

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 ($\hat{\rho}_{c,s,t+n}, \forall s$).

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 $\hat{r}_{s,p,t+n}$ are determined from the estimated future energy prices $\hat{\rho}_{c,s,t+n}$ the variable costs $\hat{c}_{v,p,t+n}$ 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.

$$\hat{r}_{s,p,t} = \begin{cases} l_s \cdot a_s & , \hat{\rho}_{c,s,t+n} \geq \hat{c}_{v,p,t+n} \\ 0 & , \text{else} \end{cases} \tag{2.8}$$

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 $\hat{\rho}_{c,s,t}$ 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 in the reference year $t+n$. For the final cash flow estimation the fixed cost of the power plant are subtracted.

$$\hat{CF}_{p,t+n} = \sum_s \left((\hat{\rho}_{c,s,t+n} - \hat{c}_{v,p,t+n}) \cdot \hat{r}_{s,p,t+n} \right) - c_{f,p,t} \tag{2.9}$$

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 $(t_b + 1, \ldots, t_b + t_D)$.

$$\text{NPV}_p = \Big(\sum_{t=0\ldots t_b} \frac{-I_p/(t_b+1)}{(1+\text{WACC})^t} + \sum_{t=t_b+1\ldots t_b+t_D} \frac{\hat{CF}_{p,t+n}}{(1+\text{WACC})^t} \Big) / \kappa_p \tag{2.10}$$

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.

Table 2.2 – Fuel price scenario

Parameters	Initial value	Min	Avg	Max
Natural gas price	0.23 €/Nm^3	+x%/year	+2%/year	+x%/year
Coal price	100 €/ton	+x%/year	+1%/year	+x%/year
Uranium price	1400 €/kg	+x%/year	+0%/year	+x%/year
Bio-fuel price	120 €/ton	+x%/year	+1.5%/year	+x%/year

2.8 Exogenous scenarios

Modeling exogenous trends

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, they are randomly generated, so each simulation run has a unique scenario. Fuel prices and demand growth are represented with triangular probability distributions. These are mean-reverting distributions, which means that on average, they are equal to the peaks of their distribution functions. This type of probability distribution was chosen because it makes it possible to determine which trend is simulated, even when the year-to-year realization is probabilistic, and because these distribution functions have the property that when their realization is above average in one year, it likely is above average again the next year. As a consequence, the trendlines show multi-year swings which resemble the cycles in real markets. Table 2.2 lists the settings for these trendlines in the base scenario.

Underpinning of scenario assumptions

The rationale for these choices is as follows. Natural gas is relatively cheap since the economic crisis, but due to limited availability in Europe and its attractiveness we assume that its price will grow the fastest. Coal has a much lower price per energy unit than natural gas, because it pollutes and can only be used in large power plants or gasification units at relatively high investment costs, while the conversion efficiency is relatively low (40–45%). World coal resources suffice for many years at the present rate of consumption, but production may lag behind the growing demand in especially China. Therefore the price of coal will increase gradually. Biomass for use in power generation is expected to be traded at a somewhat higher price than coal, because its CO_2 emissions are not counted. On the other hand, biomass demand is negatively affected by higher handling costs, more expensive installations and the lower conversion efficiency (35–40%). We assume that the growing demand for biomass will gradually push up its price. Uranium costs per GJ are assumed to remain near their current low levels, as a result of the limited interest in new nuclear plants and the phasing out of existing plants.

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

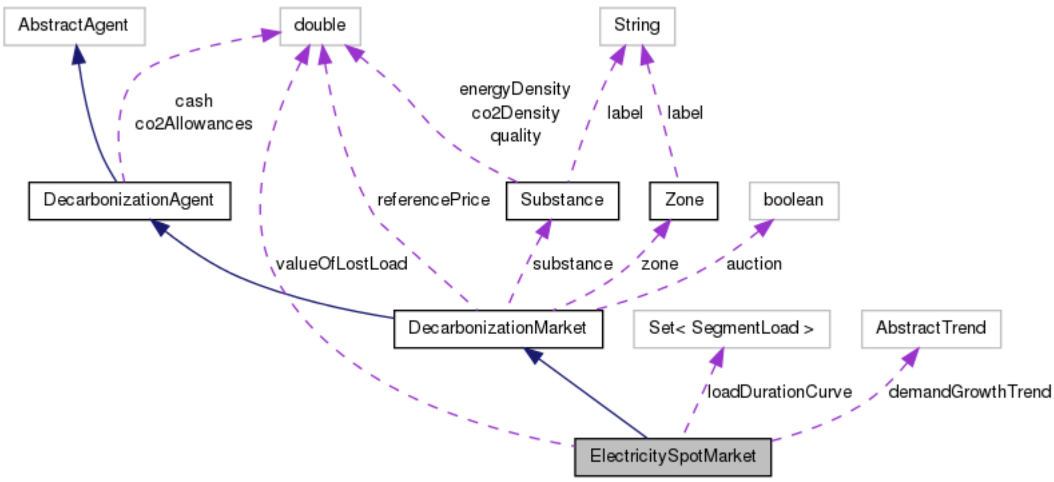

Figure 3.2 – The graph of possible relations for an electricity spot market, a relatively small example. The grey box is the starting point. Solid arrows refer to an 'is a' relationship. Dashed arrows are either property or a relation to another object. In this example an *ElectricitySpotMarket* is a *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.

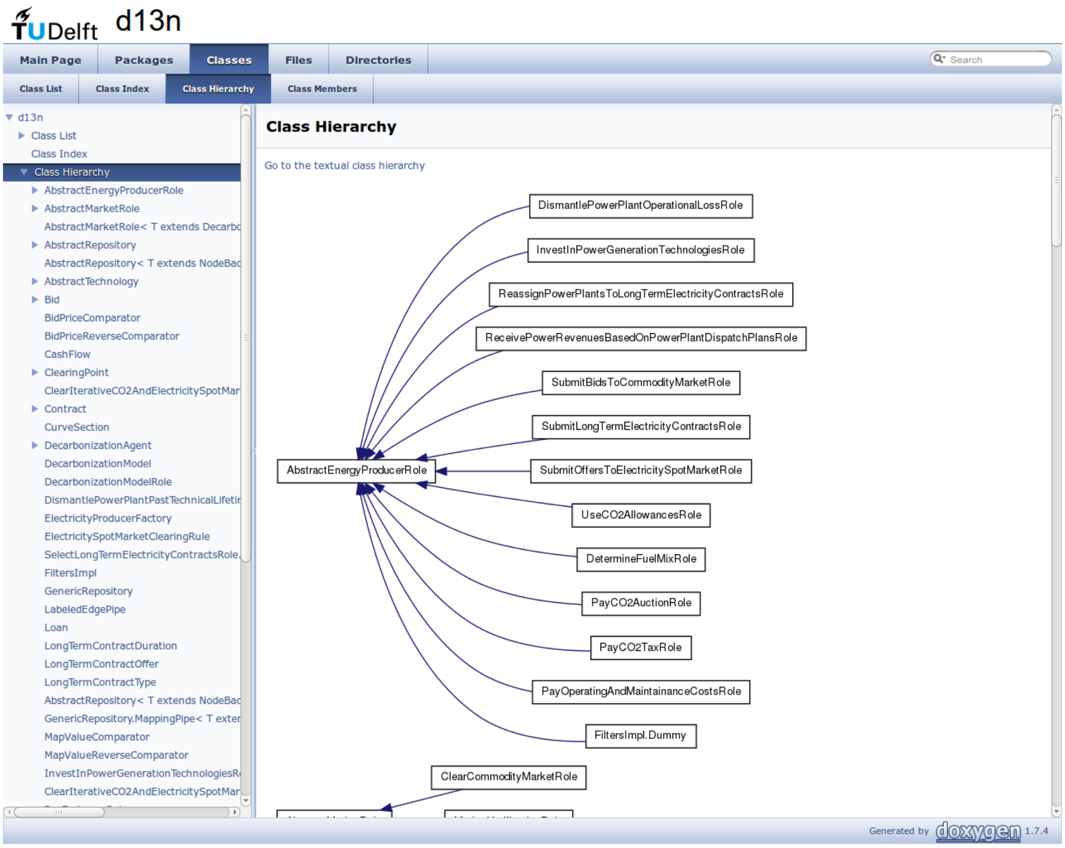

Figure 3.3 – Snapshot of the documentation of the model as a website

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

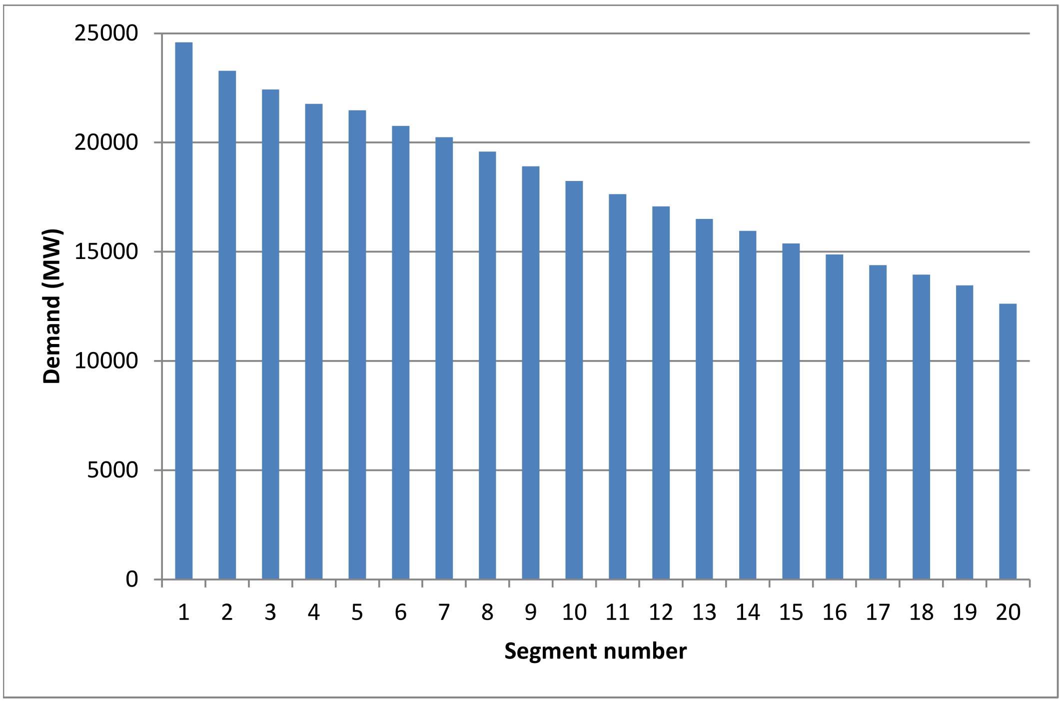

Figure B.1 – Sample load-duration curve

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