Including renewable electricity generation and CCS into the DART model

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Abstract

This paper describes how a variety of renewable electricity generation technologies (wind, hydro, solar, and solid biomass) and advanced electricity generation from coal and gas including carbon capture and storage (CCS) is included into the multi-region, multi-sector recursive dynamic CGE-model DART. In principle, the electricity sector are split into several generation technologies to allow for renewable electricity production. CCS is introduced as latent technology and is deployed only under a sufficiently high carbon price. In all technologies, a fixed resource is used to calibrate for the path of the generation technologies.

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1 Introduction and Background

The DART model (Klepper et al. 2003)[1] is a global computable general equilibrium (CGE) model, with the aim to provide macroeconomic and welfare effects of climate policy in different scenarios. In previous versions, renewable energy was not explicitly modeled. This is problematic with regard to the analysis of long term scenarios that are likely to include strong changes in the electricity sector and prevents the analysis of renewable targets.

The DART model previously has mostly been used for a limited time horizon, e.g. until 2020 or 2030. For the near future, an implicit inclusion of renewable energy in electricity generation was a sufficient representation of the energy sector, as over the relatively short period of time there would only be limited change in the energy mix. Furthermore, in the base year, renewable energy production was already included implicitly in the calibration for the traditional electricity sector. The CES-production technology allowed for some substitution in the production structure away from fossil fuels towards capital and labor as inputs. This could be interpreted as a shift towards more capital intensive renewable or nuclear energy generation, however the technologies are not explicitly modeled as there was only a single electricity sector.

Similarly, the missing option to include carbon capture and storage (CCS) into the DART model was negligible, as widespread use will be unlikely to happen in the near future for technological reasons.

For longer term projections[2], however, inclusion of renewable energy generation and CCS provide a better picture of mitigation scenarios. First of all, including more detailed technologies options provides more information on abatement strategies in different regions. Secondly, the inclusion of additional abatement options lowers the cost of mitigation scenarios relative to a scenario where the options are excluded from. Hourcade et al. (2006)

[1]See also `http://www.ifw-kiel.de/academy/data-bases/dart_e/dart-en` for a model description and applications.

[2]Within the POEM project (Policy Options to engage Emerging Asian economies in a post-Kyoto regime) however, DART will need to analyze scenarios until 2050. For more information on the POEM project, see http://www.chalmers.se/ee/poem-en.

argue that in conventional top-down models substitution would be relatively costly and limited by historically-based elasticities. In the classical constant elasticity of substitution (CES) functions for production, a complete phase out of CO_2would lead an infinite carbon price. Solutions far away from the (observed) equilibrium in the base year could hence lead to an overestimation of abatement costs. Inclusion of these energy generating options therefore flattens the marginal abatement curve. Without these modifications, relatively high carbon prices are necessary to reach a stringent target as abatement is carried out only through substitution of fuels, substitution to more capital and labor intensive production relative to energy intensive production, and a reduction of energy demand or a shift towards less energy intensive products.

The inclusion of more detailed energy generation technologies into top-down models has been carried out by several models (see e.g. Böhringer (1998) or McFarland et al. (2004) and Hourcade et al. (2006) for a recent overview). Böhringer and Rutherford (2008) distingish between linking independent bottom-up and top-down models, implementing features of one type into the other type of models, and integrated hybrid modelling, i.e. directly combining bottom-up and top-down information. Boeters and Koornneef (2010) model supply curves for different renewable technologies and integrate them into a CGE model.

The short note is structured as followed: The next section briefly decribes the DART model, the sections thereafter provide more detailed information on how renewable energy and CCS were integrated into the DART model, and the last section presents some illustrative runs.

2 The DART model

The DART (Dynamic Applied Regional Trade) Model is a multi-region, multi-sector recursive dynamic CGE-model of the world economy. The economy in each region is modeled as a competitive economy with flexible prices and market clearing. There exist three types of agents: a representative consumer, a representative producer in each sector, and regional governments. All regions are connected through bilateral trade flows. The DART-model has a recursive-dynamic structure solving for a sequence of static one-period equilibria. The major exogenous drivers are the rate of productivity growth, the savings rate, the rate of change of the population, and the change in human capital. The model horizon goes until the year 2050. The model is calibrated to the GTAP7 database that represents production and trade data for 2004. The elasticities of substitution for the energy goods coal, gas, and crude oil are calibrated in such a way as to reproduce the emission projections of the the International Energy Agency (2009, 2010). For a more detailed description of the DART model, see Klepper et al. (2003)[3].

Table 1: Regions and sectors of DART

Countries and regions			
WEU	Western Europe	CPA	China, Hong-Kong
EEU	Eastern Europe	IND	India
USA	United States of America	LAM	Latin America
JPN	Japan	PAS	Pacific Asia
CAN	Canada	MEA	Middle East and Norther Africa
ANZ	Australia, New Zealand	AFR	Sub-Saharan Africa
FSU	Former Soviet Union		
Production Sectors/Commodities			
Energy Sectors		**Non-Energy Sectors**	
COL	Coal	AGR	Agricultural Production
CRU	Crude Oil	ETS	Energy Intensive Production
GAS	Natural Gas	OTH	Other Manufactures & Services
OIL	Refined Oil Products	CRP	Chemical Products
ELY	Electricity	MOB	Mobility
		OLI	Other light Industries
		OHI	Other Heavy Industries
		SVCS	Services
Renewable and advanced electricity technologies			
WIN	Wind	SOL	Solar
HYD	Hydro	SBIO	Solid Biomass
GASCCS	Advanced Gas with CCS	COLCCS	Advanced Coal with CCS

[3]The only real change to the model described in Klepper et al. (2003) is that we introduced an LES consumption function, replacing the former Cobb-Douglas consumption function.

For the simulation of Post-Kyoto emission reduction scenarios in POEM, DART is calibrated to an aggregation of 13 regions and 12 sectors, which are shown in Table 1. The electricity sector is split into several sub-sectors, which produce electricity at perfect substitutability. Besides the traditional electricity sector which includes fossil fuel (and nuclear) generation, there are four renewable energy sectors (wind, solar, hydro, and solid biomass) as well as advanced generation from gas and coal with CCS.

3 Modeling of renewable energies in the DART model

In the current set-up of DART several renewable electricity technologies are explicitly modeled: Wind, solar, hydro, and solid biomass. These technologies provide electricity that is a perfect substitute to (traditional) fossil fuel electricity, albeit at a higher cost.[4]

For this version, the elasticity between capital and labor has been reduced to 0.7, and the elasticity of the KL bundle with energy to form the KLE bundle has been increased to 0.7 except in the electricity sector, where it has been decreased to 0.25. Modeling the electricity sector with a CES production function with high substitution possibilities could result in thermodynamically infeasible input combinations (McFarland et al. 2004).[5] The adjusted values better reflect estimations of electricity use in the future compared to projections of the World Energy Outlook or the TIMER model. Furthermore, the parameters also are better matched with empirical evidence (van der Werf 2008).

The basic modeling approach is to split the electricity sector into renewable electricity sub-sectors and a remaining traditional electricity sector.

To achieve some market penetration as well as to avoid "flip-flop" adjustments due to the fact that electricity from different generation sectors is a perfect substitute, a fixed

[4]This does not regard a limitation for intermittent electricity from solar and wind, another modeling approach would hence be to consider intermittent electricity as imperfect substitute (Paltsev et al. 2005); such an approach prevents a very high share of intermittent energy. Yet another approach is to explicitly include backup capacities to allow for intermittent energy to become better substitute for conventional electricity (Morris et al. 2010). There is also no distinction in load characteristics of the different generation technologies as in McFarland et al. (2009).

[5]If the electricity sector is understood as a broad combination of generation technologies, this might be less important, as a substitution away from fossil fuel input could be interpreted as a switch to more capital and labor intensive renewable technologies. If the electricity sector is however reduced to traditional thermal generation from fossil fuel this assumption might be less reasonable.

factor is introduced. An intuition behind such a factor can both be seen in a capacity constrained in actual resources (e.g. suitable land) or knowledge needed as input. The modeling approach does herein follow the EPPA model (Paltsev et al. 2005). This is also familiar to the production of fossil fuels in DART where a fixed resource enters the production function. In any given year, there are hence decreasing returns to scale in the renewable energy sectors as the fixed factor is becoming scarcer and substitution away from the fixed factor requires additional other inputs. For a graphical representation of the production function, see figure 1.

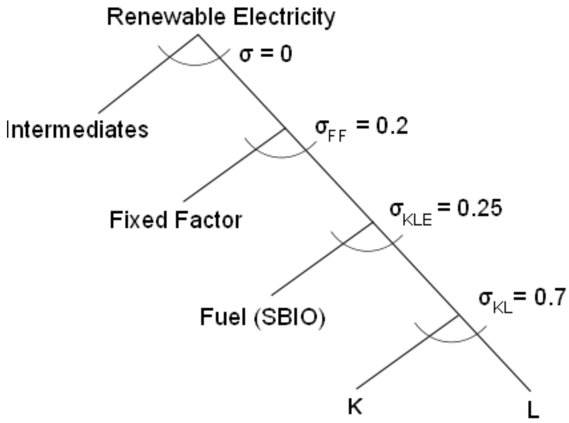

Figure 1: Production structure of renewable electricity.

In the short run, subsidies are needed to have some renewable energy generation, in the absence of such a support, the renewable energy sectors would not be active because there exists a cheaper way to produce electricity. The subsidy rates are calculated such that the share of renewable energy production in the base year is reached. While the tax or subsidy rate for the conventional electricity sector is fixed, the subsidy rates to achieve a given level of renewable energy production are calculated endogenously such as to reach a given level of renewable electricity generation (see section 3.2). The taxation rate τ of the conventional electricity sector in region $r$is calculated such that the value of the output matches the value of the output of the sector, i.e. the value of the sum of all input costs faced by the producer match the electricity generation valued at the average cost of electrictity:

$$\tau_r = 1 - \frac{Input_r^{non-renewable}}{(1 - Share_r^{non-renewable}) * Y_r}$$

Here Y_r refers to the output value of the complete electricity sector.[6]

In the long run, renewable energy technology improves its relative position to traditional energy via cost reduction through learning, a rising availability of the fixed factor, and increasing fossil fuel prices.[7] In the baseline scenario, wind energy becomes competitive and does not need the subsidy thereafter, however, solar energy remains to be subsidized throughout the whole modelling period.

3.1 Translating the bottom-up information into DART

Data for cost shares, penetration levels and price mark-ups is taken from the global energy model TIMER (de Vries et al. 2001).[8] The bottom-up model TIMER uses cost data for various generation technologies in different world regions. With an underlying learning assumption, cost parameters change over time and react to installed capacities (learning-by-doing) and carbon prices. Specifically we use information of the "Electric Power Generation" sub-model of TIMER that simulates investment decisions based on electricity demand and relative generation costs which are mainly driven by fuel and carbon prices.

The approach to match the bottom-up data with the data from GTAP is broadly following Sue Wing (2008), using O&M as labor cost and capital cost as capital input. All cost inputs (labor, capital and fuel) are broken down per unit of electricity generated.

In the approach chosen here, output and inputs of various factors were calculated independently. The output of the complete electricity sector in GTAP was split according to the shares of generation of the respective technologies taken from the TIMER model for the year 2004.[9] For the factor input of capital and labor, the total input of these factors

[6]This sets the tax rate to achieve zero-profits, as manipulating yields $(1-\tau_r)*(1-Share_r^{non-renewable})*Y_r = Input_r^{non-renewable}$. The output value for non-renewable electricity corrected by the tax hence equals the the value of the inputs.

[7]Fossil fuel prices are rising over time in the DART model with increasing demand. In scenarios with climate policy, the fuel price faced by the producer in the electricity sector is even higher due to the carbon tax.

[8]See also `http://www.pbl.nl/en/themasites/image/model_details/energy_supply_demand/index.html`, and `http://www.pbl.nl/en/themasites/image/model_details/energy_supply_demand/Mainassumptions.html` for updates and additional data sources.

[9]The baseline share in of wind energy in Africa and the former Soviet Union as well as the share

in the GTAP data was divided into the different generation technologies. The parameter of the allocation share was calculated from data taken from the TIMER model: Capital or labor input to each generation technology was divided by the total capital or labor input of all generation technologies. Fossil fuel input was completely allocated to generation of the conventional sector. Renewable electricity therefore has no direct carbon emissions, however, some of the intermediate inputs cause carbon emissions.

Intermediate inputs to the electricity sector are taken to be the same for all generation technologies and are hence distributed according to the generation share. These inputs could be thought of as inputs to transmission and distribution (T&D) and would hence be equal across all generation technologies per unit of electricity generated.[10] Intermediate inputs also include electrictity, this could be thought of as transmission losses which are proportional to the unit of electricity generated.

For solid biomass, the amount of fuel (i.e. agricultural) input in region r was calculated given the capital and labor inputs:

$$Input^r_{AGR,SBIO} = (Input^r_{CAP,SBIO} + Input^r_{LAB,SBIO}) * \frac{Share^r_{FUEL,SBIO}}{Share^r_{LAB,SBIO} - Share^r_{CAP,SBIO}}$$

where $Input$ refers to the total dollar value of the respective factor input and $Share$ to the share in levelized cost of electricity from TIMER (without transmission and distribution). The amount of agricultural input assigned to solid biomass exceeds the total agricultural input into energy generation reported of the GTAP data in many regions. Hence, in this case, the initial production is not in an equilibrium and needs to be solved for.

This approach of calculating the input shares and relating them to the output of each sector already includes a region and technology specific mark-up. This markup differs from the mark-up that would be calculated purely from the TIMER model because the ratio of the factor inputs into the electricity sector in GTAP differs from the ratios in the TIMER model, and there are intermediate inputs that are equal for all generation

for solar energy in Africa was revised upwards from the original TIMER data. Otherwise increases of predicted generation would be very large and cause problems with convergence in the DART model.

[10]This is similar to Sue Wing (2008) where each input was in part allocated to generation, overhead and T&D.

technologies. Nonetheless, the differences in the levelized cost of electricity of the TIMER model are well reflected in the DART model.

As there were substantial reductions in the levelized cost of renewable energy to be observed in the previous decades, learning-by-doing has been implemented in the development of inputs relative to outputs. This was done by multiplying the inputs of renewable inputs by a learning factor $\gamma < 1$, thus reducing the cost relative to conventional generation technologies.[11] The parameter reflects the learning rate, i.e. the cost adjustment resulting from a duplication of deployment of the technology (Yelle 1979).

$$\gamma^t = \left(\frac{\sum_r Y_r^t}{\sum_r Y_r^{2005}} \right)^{\frac{log(Learning\ rate)}{log(2)}}$$

The values for the learning rate comparable to the TIMER and have been set to 0.925 for wind, 0.825 for solar, and 0.95 for solid biomass.

3.2 Fixed resource and calibration

A fixed resource is included in the production of renewable energy. This prevents flip-flop changes in the generation structure as the different generation technologies are modeled as perfect substitutes and capital is perfectly mobile. Furthermore, the calibration prevents shares from intermittend renewable energy that are not possible to sustain without additional backup or storage capacities. Alternatively higher costs for additional deployment could be viewed as measures, e.g. to increase the grid or have backup capacities, although this is not explicitly modelled.

A support policy (i.e. subsidies) ensures that there is a minimum level of each renewable activity, even if it would not be cost efficient to run. The subsidy rates are calculated endogenously as to meet a given level of renewable energy generation.[12] First, the level

[11] Learning does not apply for intermediate inputs as these are thought to the constant per unit of electricity generated as described above.

[12] This is not a renewable energy target in the sense of the European directive on renewable energy, since the level of renwable energy is not a percentage share and not dependent on total generation but rather dependent on the generation in the base year and the price development of electricity.

of the activity is not allowed to fall short of unity, i.e. there is at least the level of production that was present in the base year. Furthermore, the level of renewable energy of a given technology Y_{tech} is increasing with an increase in the electricity price P^r_{ELY}, but inversely to the price mark-up relative to the average cost of generation:[13]

$$Y^{r,t}_{tech} = 1 + \frac{P^{r,t}_{ELY} - P^{r,2005}_{ELY}}{1 + mark\ up_{tech}}$$

The subsidy rates decline over time depending on the competitiveness of the various technologies which is governed by the price of elasticity and the cost of generation which is subject to learning-by-doing.

The fixed resource in the production function is dependent on the current deployment of the technology and calibrated to match the projections in 2050 of the TIMER model for the various technologies. The functional form for the development of the fixed factor FF is similar to McFarland et al. (2004):

$$FF = 0.1 * {Y_{tech}}^{\lambda} K$$

where Y is the output level (output relative to the base year output), λ is a parameter smaller than unity and K is the capital to be used as input in the renewable technology in the reference year. Hence in the base year, when Y is equal to unity, 10% of the capital are a technology specific factor.[14] This means the fixed resource grows with the capacity in the region ("local learning") but as a rate slower than the capacity. λ is calibrated such that the level of the respective renewable activities are matching the level in the TIMER model.[15]

As in the TIMER model, the development for hydro energy is taken to be exogenously.

[13]Expensive technologies such as solar hence react less sensitive to a change in the Armington price of electricity in comparison to wind energy which is closer to being competitive in the market.

[14]This is deducted from the capital input K in figure 1. The capital stock of the economy is reduced by the amount of the fixed resource to avoid double counting, although the impact would be negligable as the fixed resource is tiny in comparison to the capital endowment of a region.

[15]For solid biomass, the calibration does not work in all cases, as input from agriculture was too costly and hence did not become competitive in some countries in the baseline scenario. With sufficiently stringent climate policy scenarios, however, a higher level of the solid biomass activity can be observed in all regions.

It could be argued that deployment of (large scale) hydro power does not only take into account economic cost benefit analysis in the presence of climate change, but also political factors. To replicate the TIMER growth path of hydro energy in DART, the activity level to be met is implemented as an additional constraint; it is met by endogenously choosing the relevant tax or subsidy rate for hydro energy.

4 Modeling of CCS in the DART model

The inclusion of advanced coal and gas technologies with capability of capturing and storing CO_2 closely follows the approach of the EPPA model (McFarland et al. 2004; McFarland et al. 2009; Paltsev et al. 2010). The general approach is to add two additional sectors (gas and coal with CCS) into DART that are initially not active in the base year and are activeted once their ability to generate zero-profits (as opposed to negative profits) is ensured. In mixed complementary problems, as DART is formulated, this method of including additional technologies that are not present in the base year is relatively simple (see Böhringer (1998) for a more theoretical discussion).[16]

Whereas for renewable energy the electricity sector was split into subsectors, here cost shares are assigned based on data from Paltsev et al. (2010) as the technologies are not present in the base year. The cost shares are reported in table 2, the remainder to unity are intermediate inputs. The cost mark-up for the various regions is taken from the TIMER model.[17]

Input	CCSCOL	CCSGAS
CAP	0.610	0.318
LAB	0.095	0.052
FUEL	0.105	0.432

Table 2: Input shares for CCS electricity.

The production function of the CCS sectors is modeled as shown in figure 2. As for

[16] Additionally, CCS technologies are constrained to become active only for a carbon price above US$$_{2004}$ 30 and only after the year 2020.

[17] The mark-up levels for coal are: CAN 1.53, USA 1.68, LAM 1.53, MEA 1.40, AFR 1.92, WEU 1.45, EEU 1.56, FSU 1.63, IND 1.97, CPA 1.95, PAS 1.58, JPN 1.30, ANZ 1.78. For advanced gas with CCS the mark-up was taken from Paltsev et al. (2010) and set to 1.57 for all regions.

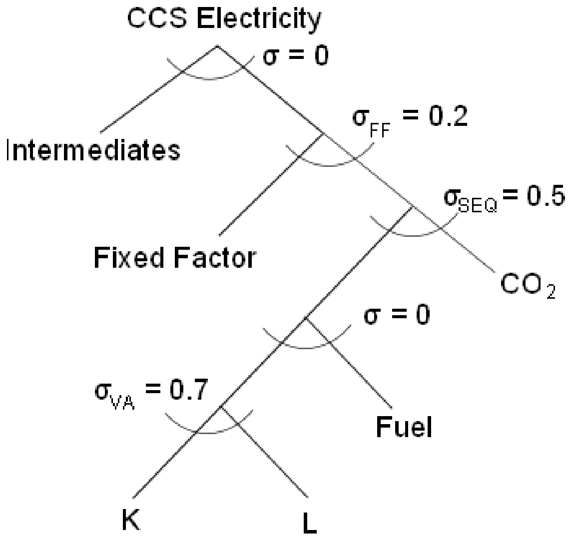

Figure 2: Production structure of renewable electricity.

renwable resources, there are intermediate inputs which are constant per unit of electricty generated and a fixed factor. The elasticities of the generation and sequestration process follow Paltsev et al. (2005).[18]

In contrast to the conventional sector, there is no carbon price for the fuel input to be paid based on its carbon content. CO_2 emissions however are not completely abated with CCS, the share that is abated depends on the quantities of inputs, initially roughly 85 to 90% of CO_2 emissions are avoided (Hendriks et al. 2004). It is however allowed for the possibility to improve capture rates at the cost of a lower plant efficiency, i.e. an increase in capital, labor and fuel can improve the capture and hence reduce residual emissions. The calibration chosen for DART is such that 90% of the emissions are captured, i.e. for 10% of the fuel input, a carbon permit is needed or the carbon tax has to be paid. The CO_2 content of the respective fuel is used to calculate the carbon permits needed as input. An increase in capture rates can thus be observed when input prices are reduced relative to the carbon permit price.

Similar to the renewable energy sectors, there is also a fixed resource. The fixed resource growth initially is 2.5% annually, when CCS electricity is deployed, the fixed factor growth is dependent on the level of the activity, as in the case for renewable energy. The level of

[18]Different to the EPPA model, the generation and sequestration process have been collapsed into a single process, and the transmission and distribution part are not modelled with capital and labor but rather include other intermediate inputs.

the fixed factor however is only 5% of capital input. Hence, the fixed factor endowment can be calculated $FF = 0.05 * {Y_{tech}}^{\lambda} * K$, where K is the capital input and Y_{tech} the level of the activity. It is made sure that FF does not fall below the level of the last year in which growth was determined by the percentage growth rate. λ is calibrated such that the share of CCS electricity in total electricity in 2050 matches the results from TIMER in a scenario with a carbon tax of \$50 from 2010 onwards. The parameter values for different regions fall in the range of 0.8 to 0.9 which is used by McFarland et al. (2004). Initially the endowment in the base year is set such that it would suffice to produce 1% of electricity with CCS in the initial calibration.

5 Some illustrative runs with DART

Renewable energy technologies and CCS provide for new abatement options in the DART model. This reduces marginal abatement costs compared to the previous version, especially in the long run.

In some simple runs with the updated version of the DART model, the shift in the MAC curves can be seen in figure 3.[19] For 2020 or for relatively low carbon prices the changes are relatively small, as CCS is not an option and renewables are still relatively costly. There is hence no large difference to the implicity representation for the whole electricity sector. For higher carbon prices and for the more distant future (year 2050) however, the inclusion of CCS and renewable energy has a considerable effect by shifting the global MAC curves outward, hence reducing the carbon price necessary to reach a given percentage reduction.

Simulating a simple policy regime such as the Contraction and Convergence (C&C) regime to reach a 40% reduction of global emissions in 2050 relative to 1990 with global carbon trade, the necessary carbon price almost halves to ca. $\$US_{2004}$ 650 compared to the previous version of DART. Figure 4 shows the global electricity mix under the baseline scenario and the C&C regime. In this graph the interaction of the features of the

[19]Note that the changes are not only due to the inclusion of renewable energy and CCS, but also stem from changes parameter values for elasticities as described in the text.

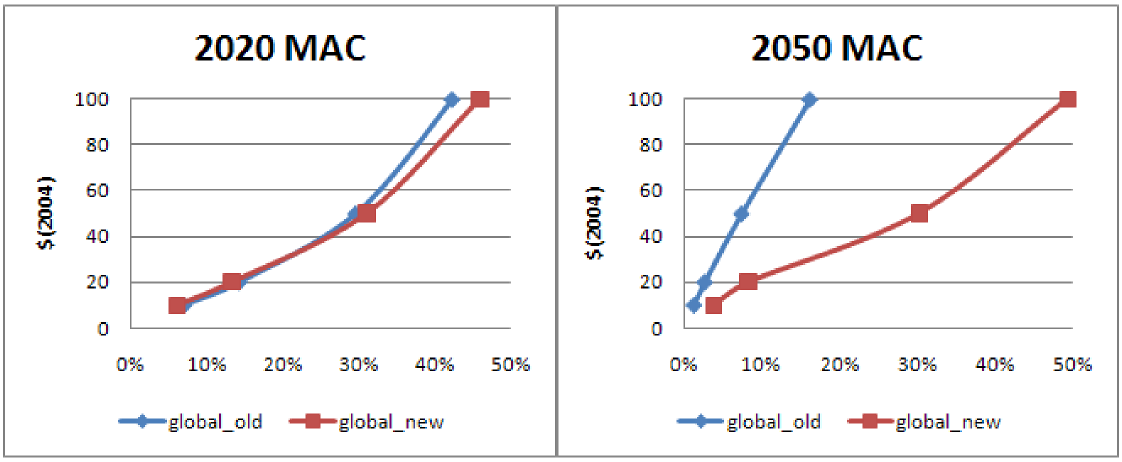

Figure 3: Marginal abatement curves.

top-down and the bottom-up are obvious: The top-down part determines the demand for electricity, which is reduced under the policy scenario, the bottom-up information provide information on the shift in generation to more renewable electricity and the deployment of CCS technology. With a carbon price of ca. $\$US_{2004}$ 650, the electricity sector becomes (almost) decarbonized by 2050, this shows that abatement in the energy sector is cheaper compared to other sectors.

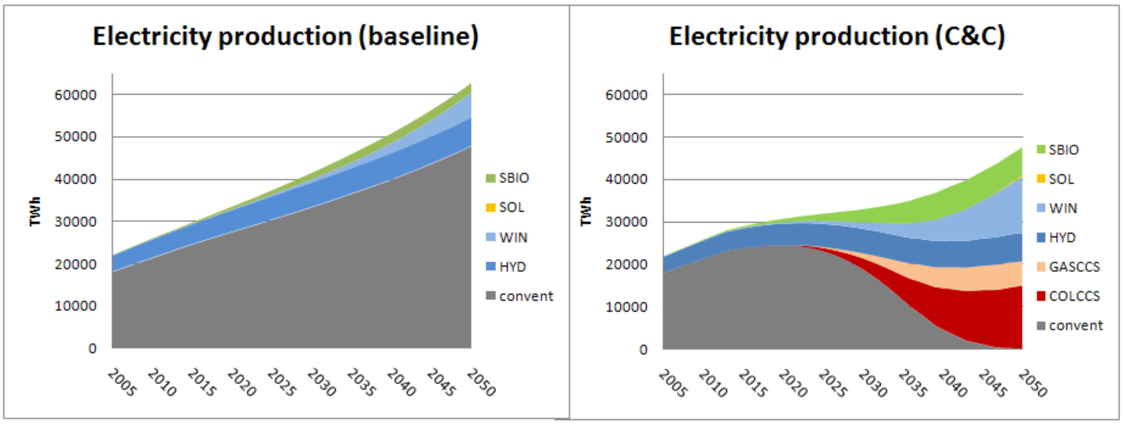

Figure 4: Electricity mix under baseline and C&C scenarios.

There remain several shortcomings and limitations in this version. In the classification of Hourcade et al. (2006), DART would remain a top-down model, but there are now some elements from bottom-up models included. In some assumptions, the current implementation of renewables and CCS remains "ad hoc", however, some additional features of the electricity sector now provide more detailed information on abatement options, albeit naturally much less than a more detailed bottom-up model. More specific low carbon technologies are only modeled in the electricity sector, but not in other sectors, such as the transport sector. A difference to bottom-up models is also the treatment of capital, which is fixed in a bottom-up model, but flexible in DART. Some CGE models have implemented capital vintages which captures some of the characteristics of less flexible capital treatment, such as lock in-effects. With the fixed factor which evolves over time based on the previous deployment of advanced generation technologies, however, some features of time dependence are now present in the current model.

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