Modeling Experience Curves in MERGE

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Abstract: The National Centre of Competence in Research on Climate aims at exploring the predictability, variability and risk of climate change. PSI is involved in this programme, using Integrated Assessment Models (IAM) to simulate policies for climate change mitigation under uncertainty. We report here selected results of the MERGE-(ETL) model with endogenous technological learning (ETL). The study presents numerical examples concerning the timing of carbon abatement to stabilize carbon concentrations (e.g., at 550 ppmv) as well as cost/benefit analysis. The endogenous learning formulation is contrasted with the original version of the model without ETL. The improved methodology indicates a potential for significant reduction in carbon abatement cost and in economic losses. The method, which is basically in favour of late actions in abatement, assumes implicitly early R&D support and learning investments in carbon-free systems to help them following their learning curves. The endogenous treatment of learning shows significant reductions of carbon emissions already in the baseline case and indicates that low carbon concentrations and improved environmental performance can be obtained when policies are followed that compensate for externalities related to climate change.

1. Introduction

There is considerable uncertainty about the level of carbon control needed to protect mankind and ecosystems from “dangerous anthropogenic interference”. This is quite understandable if one considers the overall uncertainty that prevails in the climate change issue. Also, there are multiply alternative pathways to stabilize atmospheric concentrations of CO_2 to a given level, and considerable uncertainty exists concerning the most efficient trajectory towards the selected level. The proper timing of actions to mitigate climate change, therefore, is a highly debatable issue. The treatment of endogenous technological change in integrated assessment models is another source of uncertainty and debate. As a consequence of these uncertainties, climate policies may either take excessive or insufficient actions.

MERGE is an Integrated Assessment Model (IAM) that provides a framework for thinking about climate change management proposals, as described by Manne and Richels

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[1]. The Paul Scherrer Institute developed a special version called MERGE-ETL [2] that allows considering different ETL technologies based on fossil fuels, renewables and nuclear energy, including carbon capture and disposal options. It is therefore appropriate to highlight aspects of optimal path in carbon control. The previous version of MERGE-ETL [3, 4] was restricted to the treatment of energy and economy. Now, MERGE is applied in its full scope by including the climate and damage assessment modules, with a time horizon of 2100. Manne and Richels have reported in [5] similar efforts but with only two “learning by doing” (LBD) technologies. The extended version of MERGE reported herein was facilitated by the use of a new and efficient NLP solver based on interior point methods called NLPHOPD [6, 7].

The scenario approach followed in MERGE-ETL assumes that, for a given (in principle exogenous) socio-economic development and life-style assumptions, technological progress and international cooperation are key policy variables for sustainable development. Technological progress is assumed to be path dependent, i.e., the cost of providing energy depends on the experience gained in manufacturing and using energy technologies and favors given technology clusters. Dedicated R&D spending can also influence developments and reduce the cost of new technologies. Thus, although the price of fossil fuel resources will eventually increase with time, non-carbon emitting technologies assume a cost reduction with increasing experience. Adopting efficient policies, like global trade of carbon rights and know-how transfer allows variants of efficient international cooperation to be modelled.

Section 2 discusses the modelling framework and the assumptions describing costs, emissions and learning characteristics of technologies competing in the energy markets. As endogenous technological change is associated with increasing returns on investment, the mathematical formulation of MERGE-ETL corresponds to a non-linear and non-convex optimisation problem. Because of this non-convexity, commercial solvers traditionally used to solve MERGE do not guarantee that the global optimum will be found. To find a global optimum, we have developed a three-step iterative approach, as is explained in Section 3. As an illustration, we consider scenarios related to a stabilisation of CO_2 concentrations in the atmosphere when including (or excluding) technological learning. Section 4 reports on this numerical application and details impacts of modelling endogenous technological progress in MERGE. The last set of calculations examines the influence of endogenous learning in MERGE when the model is used in a Cost/Benefit (C/B) framework. Section 5 concludes on the importance of policies in favour of learning and describes future activities.

2. *Modelling* framework

2.1. *MERGE*

MERGE is a Model for Evaluating the Regional and Global Effects of GHG reduction policies. In MERGE, the world is divided into nine geopolitical regions: Canada, Australia and New Zealand (CANZ); China; Eastern Europe and the former Soviet Union (EEFSU); India; Japan; Mexico and OPEC (MOPEC); OECD Europe (OECD); the USA; and the rest of the world (ROW).

An ETA-MACRO model describes each of these regions. This latter model is itself a link of two sub-models, ETA and MACRO. ETA is a 'bottom-up' engineering model. It describes the energy supply sector of a given region, in particular the production of non-electric energy (fossil fuels, synthetic fuels and renewables) and the generation of electricity. The ETA-MACRO model captures price-dependent substitutions of energy forms (e.g., switching to low-carbon fossil fuels) and energy technologies (e.g., use of renewable-energy power plants instead of fossil fuel systems) to comply with CO_2 reduction targets.

MACRO is a 'top-down' macro-economic growth model. It balances the rest of the economy of a given region using a nested constant elasticity of substitution production function. It also captures autonomous, (e.g., price independent) effects and macro-economic feedbacks between the energy system and the rest of the economy, like the impacts of higher energy prices (e.g., resulting from CO_2 control) on economic activities. Finally, inclusion of the climate and the damage subroutines make MERGE an Integrated Assessment (IA) Model. MERGE accounts for market damages (through production losses) and non-market damages (through losses in global welfare).

The mathematical formulation of the regional ETA-MACRO sub-models is a convex non-linear optimisation problem, where the economic equilibrium is determined by a single optimisation. More precisely, the model maximises a welfare function defined as the net present value of the logarithm of regional consumption, adjusted for the non-market damages. Notice that the wealth of each region includes its initial endowments in fossil fuels, renewables and CO_2 emission permits.

MERGE links these regional ETA-MACRO sub-models. It aggregates the regional welfare functions adjusted for the non-market damages, into a global welfare function using appropriate Negishi weights [8]. The regional sub-models are further linked by international trade of oil, gas, synthetic fuels, industrial energy intensive products, CO_2 permits and an aggregate good expressed in monetary units ('numéraire' good) that represents all other (non-energy) traded goods. A global constraint ensures then that international trade of these commodities is balanced.

Technological learning with global spillovers, the climate change impacts and the associated market and non-market damages further enhance the regional links and interactions. A fixed set of Negishi weights defines a so-called Negishi welfare problem, whose solving corresponds to the maximising of the global welfare function. MERGE updates iteratively the Negishi weights in solving sequentially the corresponding Negishi welfare problems. The steps to update the Negishi weights are performed until a Paretooptimal equilibrium solution is found.

2.2. *MERGE-ETL*

Following the pioneering work of Messner [9] for the MESSAGE model and Mattsson and Wene [10] for the GENIE model, Barreto and Kypreos [11] incorporated experience curves in the MARKAL model using Mixed Integer Programming (MIP) techniques. A detailed description of the approach can be found in Barreto [12]. Kypreos [2] incorporated the MIP approach in MERGE as one factor learning formula, while Bahn [4], following Barreto [13], introduced an R&D budget optimisation approach via a two-factor learning formula.

Technological learning describes how the specific (investment) cost of a given technology is reduced through the accumulation of knowledge. Recall that the latter may come from the technology's manufacturing ('learning-by-doing') or research-and-development expenditures ('learning-by-searching'). A learning curve relates then for a given technology its specific cost to one or more factors describing the accumulation of knowledge. These factors are the cumulative installed capacity in the one-factor learning curve, as well as the cumulative R&D expenditures in the two-factor learning curve.

Fig. 1. Learning curves assumed for electricity generation technologies. Markers are used only to distinguish different curves. Progress ratio (PR) gives the reduction in specific investment cost when cumulative installations double. Figure taken from [15].

Earlier versions of the MERGE model, (up to version 4.5) do not consider endogenous technological learning. Energy technologies have instead exogenous characteristics imposed over time. In particular in this version, generation cost assumes declining rates over time (0.5%/a) as result of autonomous technological progress. Furthermore, some of the energy technologies considered are generic. There are for instance high-cost (ADV-HC) and low-cost (ADV-LC) carbon-free power plants, or plants producing low-cost non-electric energy from renewables (RNEW). In MERGE-ETL, endogenous technological learning is applied to eight electric and non-electric energy technologies. For some specific intermittent technologies like wind and solar photovoltaic systems a constraint is applied allowing satisfying up to a maximum fraction of electricity demand. Maximum market allocation constraints are applied also for gas, coal, nuclear and synthetic fuels. Special emphasis is given to CO_2 sequestration systems: First, three reference technologies are defined based upon a MIT report [14] and include an IGCC plant, a pulverized coal (COAL-N) station and a combined gas and steam turbine (GAS-N) power generation system without sequestration options. Then, another three power stations that correspond to the reference systems but sequester CO_2 emissions are included as options to provide "clean" electricity from fossil fuels and are referred as IGCCR, COAL-A and GAS-A. Table 1 lists all technologies included in the model and Table 2 describes the technical data of these systems, while Figure 1 illustrates an example of the implied cost reductions resulting from ETL for selected technologies. Centralized and distributed power generation systems using hydrogen fuel cells are yet to be modelled.

Table 1: Technologies used in MERGE-ETL and naming conventions

Notice that in Table 1, six learning technologies correspond to power plants and two are non-electric energy technologies. The interested reader could find a detailed description of the MIP approach in [12], which explains how the linearising the non-convex problem is obtained and solved.

We use learning ratios taken from the literature. For solar photovoltaic we apply a progress ratio of 80 % based on Harmon [16], while analyses for the Danish wind industry [17] give a range of values for the progress ratio. We have adopted a progress rate of 90% for the specific investment costs.

Fuel cells are technologies still in the R&D phase and little information about learning curves is available but they have a significant potential for cost reductions in the future. For stationary fuel cell power plants a progress ratio of 82% has been used.

For generic advanced coal technology we adopt a conservative value for progress ratio of 95%, e.g., similar to the cost reduction per capacity doubling used in [9] while a 96% rate applies for new nuclear designs based on expectations of the DOE/EIA [18].

Gas turbines have experienced significant cost reduction and although a cost trend is difficult to establish from price trends, Claeson and Cornland [19] estimate that a future learning ratio for investment costs could be around 10% once the market stabilises. The value considered here for the combined-cycle gas turbine was 11%.

Although it is generally acceptable that LBD is a common experience in industrial dynamics, estimates of progress rates are uncertain and difficult to obtain based on econometric analyses while the extrapolation of the estimated values into the future is an even more difficult undertaking. We have introduced a barrier in the maximum reduction of generating cost by defining the so-called floor cost, which can be estimated, based on assessments studies concerning technological developments of the different sub-systems of the technology in evaluation.

Table 2: Technical data for systems used in MERGE-ETL

2.2.1. One-factor learning curve

The section describes the inclusion of endogenous technological learning in MERGE, using the learning-by-doing formula. In the one-factor learning curve, the cumulative (installed) capacity is used as a proxy for the accumulation of knowledge that affects the specific investment cost of a given technology. Learning is applied to a fraction of the systems cost associated to the specific investments and fixed operation and maintenance cost. As MERGE considers only annual energy and electricity flows we have had to introduce new variables and constraints to represent the cumulative capacity installations. This is obtained in a more complex MERGE-ETL model formulation which introduces annual investments in new capacity as variables, together with some new constraints on capacity build-up, as described below. Let $\mathrm{CC}_{k,t}$ be the cumulative capacity per period t of a technology k for which endogenous learning is assumed. $\mathrm{CC}_{k,t}$ is computed using the annual investments in new capacity in region r and time t, $\mathrm{INV}_{k,r,t}$:

$$CC_{k,t} = CC_{k,t-1} + \sum_{r} nyper \cdot INV_{k,r,t} \qquad (1)$$

where *nyper* is the number of years per period. Beforehand, $INV_{k,r,t}$ is computed using two alternative expressions of the installed capacity $CAP_{k,r,t}$ at time t in region r. For a power plant k, capacities expressed in GW can first be computed based on the electricity production and the plant load factor as follows:

$$CAP_{k,r,t} = \frac{PE_{k,r,t}}{\left(lf_k \cdot 0.00876\right)}, \qquad (2)$$

where $\mathrm{PE}_{k,r,t}$ is the annual generation of electricity (in kTWh) in region r, lf_k the plant's load factor and 8760 are the number of hours per year. Also, $\mathrm{CAP}_{k,r,t}$ is defined as the sum of the annual investments $\mathrm{INV}_{k,r,\tau}$ in new capacity in region r and time τ, plus the residual capacity $\mathrm{RES}_{k,r,t}$ (i.e., the existing installations at the beginning of the time horizon still in operation at t):

$$CAP_{k,r,t} = RES_{k,r,t} + \sum_{t-life_k \le \tau \le t} nyper \cdot INV_{k,r,\tau} \qquad (3)$$

where $life_k$ is the plant's life time.

The learning curve for the specific cost $SC_{k,t}$ (in $ per kW or EJ/yr) of a technology *k* is then defined as:

$$SC_{k,t} = a \cdot CC_{k,t}^{-b} \tag{4}$$

where a is a parameter that can be calibrated by applying in equation (4) the initial point ($SC_{k,0}, CC_{k,0}$) of the learning curve, and b a learning index. The latter defines the speed of learning and is derived from the learning ratio. The learning ratio lr is the rate at which the specific cost declines each time the cumulative capacity doubles. The relation between b, *lr* and *pr* can be expressed as:

$$\mathrm{pr} = 1 - \mathrm{lr} = 2^{-b} \tag{5}$$

The functional form of the learning curve given in (3) is not used directly in MERGE-ETL. A total cumulative cost (TC) curve is used instead. The latter is expressed as the integral of the specific investment cost curve:

$$TC_{k,t} = \int_0^{cc} SC_{k,t} \cdot dCC = \frac{a}{1-b} \cdot CC_{k,t}^{1-b} \tag{6}$$

Notice that the non-electric technologies are described using energy flows while the learning equation above can be also expressed assuming the accumulation of electricity generation $CG_{k,t}$ to serve as a measure of experience. In such a case the learning curve for the specific generating cost $GC_{k,t}$ (in $/GJ) of a technology k could be defined as: $GC_{k,t} = \alpha \cdot CG_{k,t}^{-\beta}$ with α being a parameter that can be calibrated for the initial point ($GC_{k,0}, CG_{k,0}$) of the learning curve. Again the learning index β defines the speed of learning. "Experience" is defined based on the annual production of electricity by technology as $CG_{k,t} = CG_{k,0} + \sum_{0 \le \tau \le t} \mathrm{nyper} \cdot GE_{k,r,\tau}$ while the generating cost is approximated by: $TC_{k,t} = \int_0^{cc} GC_{k,t} \cdot dCG = \frac{\alpha}{1-\beta} \cdot CG_{k,t}^{1-\beta}$

3. *Solving* techniques

Technological learning is associated with increasing returns on investment. Indeed, the more experience is accumulated in a given technology, the more its specific cost is reduced and the more likely its further adoption occurs. Due to such increasing returns mechanism, the indigenisation of technological learning in MERGE yields a non-linear non-convex optimisation problem.

Because of this non-convexity, the commercial solver MINOS, Murtagh et al., [20] traditionally used to solve MERGE does not guarantee that the global optimum will be found in MERGE-ETL, but only a local one. To find a global optimum, we use a heuristic iterative approach in three steps, which is explained below. The rationale of this approach is to transfer the non-convex problem to a convex one. The error introduced from the linearisation of the investment cost integral remains as a problem, but these errors could be reduced when increasing the number of segments.

In this first step, the original MERGE model (i.e., without learning), is solved to define an initial vector of equilibrium demands for electric and non-electric energy. These fixed energy demands are input into a regional energy model (ETA) with endogenous technological learning. This new model, called ETA-ETL, corresponds to the bottom-up part of MERGE. ETA-ETL is linearized by defining a piece-wise linear approximation of the total cumulative cost curve where integer variables define the sequence of linear segments. This model is then solved using Mixed Integer Programming (MIP) techniques ILOG, [21].

In this second step of our solving approach, NLPHOPDM solves the MERGE-ETL model as a non-linear but convex model. The solving of MERGE-ETL is done using a unit generating cost per technology and time that corresponds to the cumulative installations, estimated in the ETA-ETL solution by applying equation (4). In that way the non-convexity is bypassed and MERGE is solved as a plane non-linear problem.

A third step is necessary to ensure that demands for energy and electricity are consistent between the initial ETA and MERGE estimates. Also, the cumulative installed capacities $CC_{k,T}$, where T corresponds to the end of the time horizon, should differ by a given margin between iterations. These capacity adjustments are done simultaneously with the Negishi iterations on trade. Notice that market penetration constraints bound the production of competitive systems and stabilize their penetration. Thus, in order to look for the global optimum of MERGE-ETL, one may repeat the solving of ETA-ETL and MERGE-ETL until demands and cumulative capacities found by the two models are equal (within a given margin).

4. Case studies

As an illustration, we present several scenarios related to CO_2 emission control. Apart of the business as usual cases (BaU) where CO_2 emissions are not limited, we have in particular considered implications of stabilizing atmospheric carbon concentrations to 550 and 500 ppmv. All cases are considered with and without ETL options. BaUN denotes the baseline case where technological change is exogenously assumed, whereas BaUL denotes the baseline case where “learning-by-doing” (LBD) applies. The database for the baseline cases reflects partially the original data of the MERGE 4.5 while for sequestration technologies the MIT study [14] applies. Together with the carbon stabilization constraint, another constraint is applied, on the rate of temperature change, as research indicates that this rate, if low enough, could help to prevent catastrophic effects.

All cases assume world population levels of 10 billion inhabitants by 2100. Most of the world population growth occurs in the (current) developing countries, while by 2100, the (current) industrialized countries make up less that 14 percent of the world population.

Differentiated growth by region is assumed such that the income per capita over time converges to the same long-term level, e.g., late after 2100.

4.1 The BaU cases

In the BaUN case, the world GDP between 2000 and 2100, grows above 9.3 times (up to 284 trillion USD 1997) as shown in Figure 2, primary energy supply increases by 5.8 times (up to 2211 EJ/yr) and energy related carbon emissions grow by 4.9 times (up to 31.7 Gt C) . Figure 3 describes the energy and economic indices for the baseline case.

Fig. 2. Regional GDP in the BaUN case; the current developing countries will produce more than 66% of the global economic output late in the century while OECD contributes by only 30%.

Fig. 3. Energy and Economic Indices for the baseline BaUN case

Global CO_2 concentrations increase to 756 ppmv while the global average temperature rise is 2.3 degree centigrade. Notice that most of the economic growth occurs in (current) economies in transition and developing countries, and that regional differences in income, primary energy intensity and in carbon intensity of GDP are decreasing overtime. The current less-developed countries assume a high economic growth such that they will produce 66% of the global GDP in the year 2100 versus 30% for OECD regions. Notice also that the potential socio-economic growth underlying this scenario is exogenous. The average annual economic growth is 2.3 %; the income elasticity for primary energy is 0.79, while the production of electricity corresponds to an income elasticity of 1.08. This indicates substitution for non-electric energy based on electricity. Also, the income elasticity for CO_2 production is slightly lower than the energy elasticity i.e., 0.71 which indicates a continuation of the de-carbonization trend.

Fig. 4. Electricity Generation in the BauL case

The changes in the baseline case under policies that favour “learning by doing” are dramatic. Energy efficiency and decarbonisation continues to contribute to a set of better energy, economic and environmental indices. Policies in favour of learning result to a strong contribution of renewables in the non-electric sector demands. This shift enhances the use of non-electric backstop technologies for which an optimistic learning rate of 20% per doubling of production has been assumed. Therefore renewables in the BaUL case contribute 45%, coal 30%, nuclear 17% of the energy mix with oil and gas contributing the remaining 8%, versus a 53% distribution of coal (including synthetic fuels) in the BaUN case, without LBD.

The effect of ETL is substantial in the BaUL case and becomes apparent in the second half of the 21st century. In this scenario, a carbon constraint although is not imposed, only 16.3 Gt C are emitted by the year 2100, resulting in a CO_2 atmospheric concentration of 680 ppmv and a maximum temperature change of around 2.3 degree centigrade. This corresponds to a 47% reduction relative to the BaUN case.

Figure 4 shows the production of electricity by technology and time in the BaUL case. In the absence of a carbon constraint, advanced coal power generation and new nuclear systems dominate the market. Note that the GCC systems increase market shares up to the year 2050 and then start to decline because of the increased gas prices. In the second part of the century a massive introduction of pulverized coal takes place followed by IGCC systems.

4.2 Stabilising Carbon Concentrations

Economic considerations and the perfect foresight of economic agents as simulated in the model govern the transition to a low-carbon economy. More precisely, exhaustion of oil and gas resources and significant cost reduction in carbon-free energy technologies, when learning by doing is applied, explain this significant reduction in carbon use relative to the BaUN case (Fig. 5).

Fig. 5. Carbon emission paths for the reference and the stabilisation cases analysed

When considering endogenous technological change, the specific (investment) cost of a given technology decreases with the accumulation of knowledge that occurs through the increase of the cumulative capacity. Figure 6 illustrates the resulting decrease of the specific cost of some power plants in the learning cases.

Fig. 6: Electricity generating cost in the 550L case. Here the autonomous cost reduction is not shown; ADV-HC, ADV-LC, IGCCR, NEB-LC, NEB-HC and NNU assume cost reduction due to LBD.

The 550-ppmv-carbon concentration cases (denoted 550) assume that efficient strategies will be adopted worldwide and a full scope know-how transfer will take place. Under these circumstances the following conclusions can be made:

Fig. 7. Cumulative and undiscounted GDP losses for the atmospheric carbon stabilisation cases, relative to the GDP of BaUN, in percent. The cumulative and undiscounted GDP losses are significantly reduced by LBD; thus, in the 550-ppmv-stabilisation case the cumulative losses (0.52%) are reduced to 0.1 % while in the 500-ppmv case losses are reduced from 1.42% to 0.22%.

First, the cumulative GDP losses due to the introduction of carbon stabilisation constraint at 550 ppmv, in relation to the cumulative baseline-GDP production, are very low e.g., below 0.52%. LBD supporting policies for technologies that have zero emissions or sequester CO_2 further reduce the GDP losses (Fig. 7).
Second, the marginal costs related to carbon stabilisation are also reduced to a fraction of the marginal cost without learning (Fig. 8).

Fig. 8. The marginal costs in the case of LBD are reduced well below $100 per ton of Carbon by the year 2090 in the 550-ppmv cases due to the introduction of fossil fuel sequestration options and the penetration of renewables in the non-electric markets. The shape of the marginal costs reflects the price of a resource with limited cumulative availability. Only in the last period an extra constraint that is forcing a maximum production of emissions to 3 Gt of carbon, is changing the shape of the marginal cost function. The 500-ppmv stabilisation cases imply higher marginal costs.

Another possibility to express the importance of “learning-by-doing” is to graph the reduction of GDP losses by time and scenario, when LBD is introduced, given relatively to the same constrained cases but without LBD, as shown in Fig. 9. Notice that the importance of LBD increases with the severity of the constraint imposed.

Fig. 9. “GDP gains” from “learning-by-doing” expressed as percentage change relative to the baseline case without LBD, (e.g., 100 (BaUL-BaUN)/BaUN); gains increase at lower CO_2 stabilisation targets.

“Learning-by-doing” has the effect of postponing strong actions in carbon abatement by a few decades, as indicated in Fig. 10. Notice that early policies in form of RD&D support for the new and carbon-free technologies are implicitly assumed in the approach. Notice also the strong emissions reduction needed in the second part of the 21st century in order to obtain the same concentration of carbon dioxide in the atmosphere as in the case that excludes learning. Temperature change remains well below 2 degree centigrade. Also, imposing constraints in the rate of temperature change per decade (i.e., 0.21 degree per decade for the scenario 550DT) favours again early actions in carbon abatement, which are even stronger than the Kyoto protocol in its original formulation.

All these results demonstrate how difficult it would be to reach a consensus in policy against global warming as we are not able to value the importance of the rate of temperature change and emphasize the need to reduce the scientific uncertainty and to apply flexible strategies against the climate risk.

Fig. 10*:* LBD (second column) is postponing actions to reduce carbon emissions by a few decades while annual emissions remain almost as in the BaUL case. Results are quite different if another constraint is imposed concerning the rate of temperature change (e.g., by applying a maximum temperature increase of 0.21 degree Celsius per decade) as shown for the 550DT case.

4.3 Cost/Benefit Analysis with MERGE-ETL

Usually, integrated assessment models define optimal paths of carbon reductions over time that would maximize the present value of avoided damages less mitigation costs. In MERGE the global welfare function is maximized after adjusting for non-market damages. Also, the competing claims on overall economic output account for market damages together with consumption, investment, the energy costs and the net exports of the numéraire good. Energy costs include the cost of providing energy together with the cost of mitigation. Adaptation claims to the economy are not included in the analyses. Thus, market damages reduce in MERGE the available capital for investments and consumption and as a consequence, also the global welfare, which is defined as the logarithm of consumption.

The damage cost estimations in MERGE are simple functions that include market and non-market damages. The cost of market damages as a linear function of the actual temperature change (ATC) and it is calibrated such that when ATC equals 2.5 degree Celsius, damages amount to 0.25%-0.5 % of the global GDP. The willingness to pay (WTP) to avoid ecological non-market damages that include biodiversity, environmental quality and human health is proportional to the per-capita income and the square of temperature change modified such as to represent the “hockey-stick” shape of the temperature profile. The WTP is an S-shaped function that starts from a threshold income to attain 2.0% of the income for avoiding a temperature change of 2.5 degree Celsius and

8% of income to avoid a temperature change of 5 degree Celsius. This functional form representation of damages needs a revision and must be further elaborated in order to represent more recent work and if possible, to include adaptation functions.

Discounting damages that take place decades in the future reduces the present value of these costs today. On the contrary, mitigation measures have to be introduced early enough to control sufficiently carbon emissions as energy infrastructures have a long lifetime and changes in the energy production and end-use systems need time. This time difference between mitigation actions and impacts and the discounting of costs to present day monetary equivalents postpones the timing of optimal mitigation paths. Thus, the higher the discount rates the later mitigation actions will occur. The benefit of reducing GHG emissions in the near term is estimated in many studies to be on the order of $5–25 per ton of avoided carbon (Tol 1999). MERGE produces similar results but indicates higher carbon values at the end of the century. Critics expect that the results will change if IA models address properly issues like uncertainty, irreversibility, risk of catastrophes and intergenerational equity. In the following, we illustrate with a numerical example that significant mitigation can be obtained even in the neo-classical framework of MERGE when ETL is properly simulated. Based on the model formulation as in version 4.5 we have introduced ETL options to perform C/B optimisations with and without ETL options. This C/B analysis corresponds to a climate sensitivity of 3 degree Celsius and the damage costs functions described above.

Comparing the end-time emissions in the year 2100 and the cases analysed we conclude that ETL reduces carbon emissions to 16.3 Gt of carbon in the baseline case. All the runs that stabilize carbon concentrations to 550 ppmv have been forced to emit 3 Gt C in 2100. Finally, in the C/B analyses following ETL policy options, carbon emissions are almost similar to the stabilisation case with the exception of the last decade. These carbon emission trajectories accumulate emissions into the atmosphere to reach a CO_2 concentration below 600 ppmv, at a maximum carbon value around $ 60 per ton. The winners in the power generation markets are the IGCC systems with sequestration options together with advanced low cost systems (i.e., wind). In the non-electric markets NEB-LC systems based on carbon-free hydrogen are introduced. Finally a good way to illustrate the contribution of "learning-by-doing" is to compare the emission profile for the C/B and the stabilisation case, as shown in Figure 11.

Fig. 11. Emissions in the C/B case with ETL are quite similar to the emission levels of the 550-ppmv case while the corresponding concentrations remain around 590-ppmv.

5. Conclusions

Technological progress plays a fundamental role in the evolution of energy systems and favours the transition towards more efficient and cleaner energy technologies. It is thus important to incorporate the dynamics of technological change in energy system models.

We have therefore introduced in MERGE the one-factor learning curves for a set of electric and non-electric energy technologies. Such learning curves describe how the specific investment cost (or the generating costs) of a given technology is reduced as function of knowledge (approximated by the cumulative installed capacity or the cumulative production of energy) accumulated during the manufacturing and operation of such technologies. A heuristic approach is applied to linearize the integral of investment costs (or energy generation cost) based on MIP techniques and avoids non-convexities in solving MERGE by iterative searching for the global optimum.

To study the impacts of modelling endogenous technological change in MERGE, we have considered several scenarios related to CO_2 emissions and technological learning. In the baseline cases, our numerical application shows that technological learning favours new advanced systems such as integrated coal gasification with combined cycle, gas combined cycle, wind turbine and new nuclear plants as well as non-electric back-stop systems. Apart from this, the new model formulation does not significantly change the conclusions of the original MERGE model for the first half of the century, as fossil fuels (mainly coal and natural gas) will continue to hold a significant share of the global electricity and energy supply markets in the next fifty years, while energy related carbon emissions will continue to grow substantially. The results differ significantly for the second half of the century, however. In the BaUN case the use of synthetic fuels dominates while in the case with endogenous learning (BaUL) the market penetration of carbon-free technologies reduces emissions to 16.3 Gt of Carbon per annum. In the 550-ppmv stabilization cases, a significant development and market penetration of low-carbon generation options is required to fulfil the imposed CO_2 reduction targets. Technological learning in this case favours new advanced systems, in particular GCC, NNU and WND and mainly IGCC systems with carbon sequestration together with non-electric renewables. Our numerical application shows finally the importance of technological progress for carbon control, since this brings in low-cost reduction options and hence reduces GDP losses and the marginal cost of carbon control. Most important, by applying the model in a cost/benefit approach we conclude that the optimal path of emissions is such that concentrations can be stabilized at 590-ppmv CO_2 at a carbon value approaching a maximum of \$60 per ton of coal. Another important conclusion concerns the impositions of constraints related to the rate of temperature change. If this constraint is imposed together with constraints that stabilize carbon concentration levels, then significant carbon reductions are justified at the early decades of the century.

Since previous model results show that in the case of global trade of emission permits with global spillovers in technological learning, promising win-win situations should be expected for all participants [15], we have thus applied MERGE under the above conditions in order to minimize the cost of mitigation. MERGE-ETL views the development of cleaner and innovative energy technologies as a long-term strategy to mitigate global climate change (i.e., a strategy that can significantly reduce the cost of carbon control). However, such a penetration of new technologies is not necessarily going to happen in the real world relying on market forces. These new technologies are still expensive and not competitive against fossil fuels or phase other barriers. The new systems identified as promising require an initial support either in form of R&D spending for their development or in form of demonstration (e.g., subsidized) projects for their implementation. Otherwise, they will be locked out of the energy markets. A portfolio of innovative policies and measures to support new technologies is needed up to the point where they will become attractive to private investors [22].

In the future we would like to elaborate, using MERGE, on fundamental issues like discounting, treatment of uncertainties and catastrophic effects. We also want to extend the technological description of the supply and end-use sectors in order to represent the hydrogen-economy in details. Solution algorithms and eventually decomposition methods are needed to be able to apply the above into a cost-benefit framework and propose hedging strategies balancing the risk of irreversible damages against the risk of premature action.

6. Acknowledgment

This research has been conducted within the Swiss NCCR-Climate (grant form the Swiss National Science Foundation). We would also like to thank A. Manne and R. Richels for making the latest version of MERGE available to PSI.

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