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International Institute for Applied Systems Analysis • Schlossplatz 1 • A-2361 Laxenburg • Austria
Tel: (+43 2236) 807 • Fax: (+43 2236) 71313 • E-mail: publications@iiasa.ac.at • Web: www.iiasa.ac.at

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Emissions trading and technology deployment in an energy-systems "bottom-up" model with technology learning

Leonardo Barreto [a,*], Socrates Kypreos [b]

[a] *International Institute for Applied Systems Analysis, Schlossplatz 1, A-2361 Laxenburg, Austria*
[b] *Energy Modelling Group, Paul Scherrer Institute, CH-5232 Villigen, Switzerland*

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Abstract

An important criterion in the analysis of climate policy instruments is their ability to stimulate the technological change necessary to enable the long-term shift towards a low-carbon global energy system. In this paper, some effects of emissions trading on technology deployment when technology learning is endogenized are examined with a multi-regional "bottom-up" energy-systems optimization MARKAL model of the global energy system. In this framework, due to the action of spillovers of learning, imposing emission constraints on a given region may affect the technology choice and emissions profiles of other (unconstrained) regions. The effects depend on the geographical scale of the learning process but also on the presence of emissions trading, the regions that join the trade system and their timing for doing so. Incorporating endogenous technology learning and allowing for spillovers across regions appears as an important mechanism for capturing the possibility of induced technological change due to environmental constraints in "bottom-up" models.

Keywords: Environment; Technology learning; Emissions trading; Spillovers; Energy systems

1. Introduction

One of the central factors shaping the future path of the global energy system is technology dynamics. Cumulative learning processes constitute an important mechanism of technological change in energy systems. As a network phenomenon (Wright, 1997), technology learning takes place through interactions at local, regional and global levels. Learning networks are created around a given technology or technology cluster. The (changing) geographical configuration of those learning networks plays a significant role in the diffusion of technologies.

Emission trading has been proposed as one of the "geographical-flexibility" mechanisms to comply with greenhouse gases (GHG) emissions reductions. It gives parties with expensive in-house mitigation options the possibility of profiting from cheaper alternatives available somewhere else by buying emission permits. Many analyses have

* Corresponding author. Tel.: +43-2236-807-578; fax: +43-2236-807-488.
E-mail address: barreto@iiasa.ac.at (L. Barreto).

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shown that implementing trade could help to achieve mitigation goals at lower costs (see e.g. Weyant, 1999).

In the same way as the learning process, emissions trading can also be seen as a time-evolving network of interactions between regions. The spatial configuration of the trade network would change as parties join (or leave) the permits market. Both technology learning and trade networks could play a significant role in shaping the technology choices in a CO_2-constrained global energy system. Emissions trading may have an effect on policies for promoting technology development and diffusion. Also, the stimulation (or discouragement) of the learning processes of emerging low-carbon and more efficient technologies would affect their deployment in a region and, therefore, its ability to participate in an emissions trading system, particularly in the long-term.

The effects of emissions trading on energy technology innovation and deployment are complex and many different factors intervene. Nonetheless, our understanding of the forces involved must be improved. In this paper, using a five-region "bottom-up", energy-systems optimisation MARKAL model (Fishbone and Abilock, 1981) of the global energy system that endogenizes technology learning, some insights are gained into the influence of emissions trading on the diffusion of emerging technologies. For such purpose, the deployment of energy technologies, whose investment costs follow learning curves, is analyzed under different CO_2 constraints and emissions trading modalities.

We highlight the role of spillovers of learning across regions as an important mechanism to be considered when modeling the interaction between climate policies and technological change. Including the spatial spillovers of learning in our "bottom-up" framework allows capturing the possibility that the imposition of emission constraints in a given region may induce technological change in other regions, even when they do not face emission constraints and, therefore, it alters the effects of emissions trading on technology deployment in the "bottom-up" context.

It must be noticed that we do not attempt here a comprehensive modeling of all the very complex aspects of technological change and, specifically, we do not address it outside the context of the energy system. Neither we do address energy–economy–environment interactions that are relevant when examining the role of climate policy mechanisms in inducing technological change. Although we recognize that such treatment would be desirable and necessary to fully evaluate the interaction between emissions trading and technological change, it lies outside of the scope of this paper. We concentrate and restrain ourselves solely to the possibilities of the "bottom-up" framework outlined here. Moreover, endogenous learning curves are considered only for one specific performance indicator of technologies, namely their investment costs, and only in the electricity generation sector. Thus, results only intend to illustrate the dynamics of the intervening mechanisms.

2. Description of the modeling approach

For this analysis, a compact multi-regional MARKAL model of the global energy system has been developed (Barreto, 2001). MARKAL is a dynamic process-oriented, linear programming model of the energy system, which allows a detailed representation of supply and demand energy technologies (Fishbone and Abilock, 1981). In the global model built for this analysis, five regions are considered. Two regions represent industrialised countries: North America (NAM) and the rest of the OECD (OOECD). One region brings together economies-in-transition in the Former Soviet Union and Eastern Europe (EEFSU). Two additional regions portray the developing world: One of them groups the developing countries in Asia (ASIA) and the other comprises Latin America, Africa and the Middle East (LAFM). The number of regions chosen was influenced by the size of model that could be solved in a computationally efficient way. Such aggregate regionalisation does not allow differentiating the behavior of some regions that are important players in climate issues (such as Europe and Japan), but it is considered sufficient for the illustrative purpose of the exercise discussed here.

The results correspond to a scenario of gradual developments in population, economic growth and energy requirements. To build such a scenario, assumptions on end-use demands as well as potentials for fossil (Rogner, 1997) and renewable resources were made consistent with the B2 scenario quantification carried out with the MESSAGE model (Riahi and Roehrl, 2000) for SRES (2000). It must be noticed, however, that no attempt is made here to reproduce or emulate the B2 developments.

Energy needs for industrial, residential, commercial and transportation sectors are considered. Industrial, residential and commercial energy demands are considered at the useful-energy level. A simplified transportation sector aggregates both freight and passengers transport demands (at the final-energy level). Additional categories represent non-commercial uses of biomass and non-energy feedstocks. Demands are exogenously given but their projection takes into account some stylized facts concerning structural changes in the economy of the different regions.

Fig. 1 presents the standard reference energy system (RES) applied in all regions. Although not shown in the RES, in all demand categories generic end-use devices are considered. The time horizon is 1990–2050 with 10-year time steps. A discount rate of 5% is applied in all the calculations. A more detailed description of the model can be found in Barreto (2001).

Addressing the question of the interaction between emissions trading and energy technology innovation requires an adequate treatment of technology dynamics in energy-systems models. Here, the attention focuses on a particular aspect, namely technological learning. Learning is a key driving force of technological change and plays an important role in cost/performance improvement of technologies, stimulating the competition and continuous substitution between them in the marketplace.

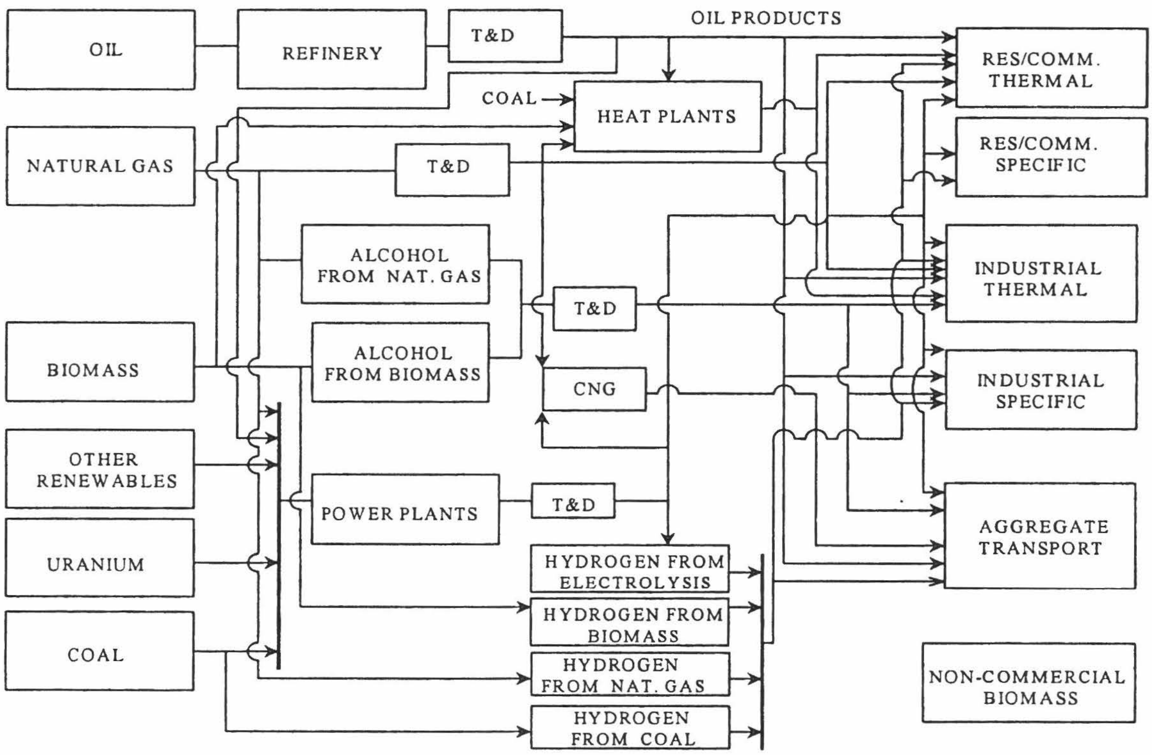

Fig. 1. Reference energy system applied in our multi-regional global MARKAL model.

A typical learning curve describes the specific cost of a given technology as a function of the cumulative capacity, a proxy for the accumulated experience (Argote and Epple, 1990). It reflects the fact that some technologies may experience declining costs as a result of their increasing adoption, due to the accumulation of knowledge through, among others, learning-by-doing processes. The specific investment cost (SC) is formulated as

$$\mathrm{SC}(\mathrm{CC}) = a * \mathrm{CC}^{-b},$$

where CC is the cumulative capacity, b the learning index, a the specific cost at unit CC.

Usually, instead of the learning index b the progress ratio (PR), i.e. the rate at which the cost declines each time the cumulative production doubles, is specified. The progress ratio can be expressed as

$$\mathrm{PR} = 2^{-b}.$$

Endogenizing technology learning represents an advance towards a more comprehensive treatment of technological change in energy optimization models, capturing the early investments (i.e. early accumulation of experience) required for a technology to progress and achieve long-term cost competitiveness. More importantly, it also provides a mechanism that makes an important aspect of technological change (i.e. cost development) dependent upon parameters and variables in the model (e.g. on the imposition of emissions constraints).

However, when the original formulation of the learning curves is included in standard linear programming models, the result is a non-linear and non-convex optimisation problem. Such kind of problems possesses several local optima, and a global optimal solution cannot be guaranteed with the normal non-linear optimisation solvers.

The existence of local optima is of interest to the policy analyst, as it illustrates how, under the presence of increasing returns, a system may evolve in significantly different directions. Analyses by Mattsson and Wene (1997), with the non-linear, non-convex version of the GENIE model, illustrate that different local optimal solutions can exhibit very different technology dynamics but very similar system costs. Such local minima represent situations where the system has followed a trajectory that drives to its "lock-in" to a certain technology or group of technologies and highlight the fact that diverging technological configurations of the energy system and associated environmental impacts can be reached depending on the (path-dependent) direction that technological change follows. Here, however, we do not examine or compare those different local optimal solutions.

It is possible to identify a globally optimal solution for this non-linear, non-convex program through the application of global optimization algorithms (see e.g. Manne and Barreto, 2001 [1]) or by resorting to heuristics, for instance using different conventional nonlinear programming algorithms and several different starting points for each of them and/or imposing alternative terminal conditions for the problem (for an application of the latter option see e.g. Manne and Richels, 2002). Heuristics, however, cannot fully guarantee that a global optimum has been reached.

Making use of these techniques, however, becomes more difficult for large-scale models or when the number of learning technologies increases. Thus, here we do not solve the original non-linear, non-convex optimization program, but resort to a linearisation of the problem applying Mixed Integer Programming (MIP) techniques. The MIP approach provides such linearisation by a piecewise interpolation of the cost curve. Binary variables are used to control the sequence of segments along the curve. Although more computational intensive, an optimal solution can be identified for this linear approximation.

Following the pioneering work of Messner (1997) for the MESSAGE model and Mattsson and Wene (1997) for the GENIE model, [2] Barreto and Kypreos (1999) incorporated experience curves in the MARKAL model using MIP techniques. A summary of the MIP approach used in MARKAL is presented in Box 1. A detailed de-

[1] Manne and Barreto (2001) have applied the global optimisation BARON algorithm (Sahinidis, 2000) to a similar small-scale problem.

[2] See also Mattsson (1997).

scription can be found in Barreto (2001). For other analysis using MARKAL with experience curves see Seebregts et al. (2000).

Box 1. Description of the Mixed Integer Programming approach

- The cumulative capacity of a given technology k in the period t is defined as

$$\mathrm{CC}_{k,t} = \mathrm{CC}_{k,0} + \sum_{\tau=1}^{t} \mathrm{INV}_{k,\tau},$$
$$k \in \{1,\ldots,K\}, \quad t \in \{1,\ldots,T\}.$$

The parameter $C_{k,0}$ is the initial cumulative capacity (the corresponding cumulative cost $\mathrm{TC}_{k,0}$ is also defined). The variable $\mathrm{INV}_{k,t}$ represents the investments made on this technology in a particular period t.

- The cumulative capacity is expressed as a summation of continuous lambda variables:

$$\mathrm{CC}_{k,t} = \sum_{i=1}^{N} \lambda_{k,i,t}.$$

- The cumulative cost is expressed as a linear combination of segments expressed in terms of the continuous lambda and binary delta variables:

$$\mathrm{TC}_{k,t} = \sum_{i=1}^{N} \alpha_{i,k} * \delta_{k,i,t} + \beta_{i,k} * \lambda_{k,i,t},$$
$$\delta_{k,i,t} \in \{0,1\}$$

with: $\beta_{i,k} = (\mathrm{TC}_{i,k} - \mathrm{TC}_{i-1,k})/(\mathrm{CC}_{i,k} - \mathrm{CC}_{i-1,k})$ and $\alpha_{i,k} = \mathrm{TC}_{i-1,k} - \beta_{i,k}\mathrm{CC}_{i-1,k}$.

- The logical conditions to control the active segment of the cumulative curve are:

$$\lambda_{k,i,t} \geqslant \mathrm{CC}_{i,k} * \delta_{k,i,t}, \quad \lambda_{k,i,t} \leqslant \mathrm{CC}_{i+1,k} * \delta_{k,i,t}.$$

- The sum of delta binary variables is forced to one:

$$\sum_{i=1}^{N} \delta_{k,i,t} = 1.$$

- Using the fact that experience must grow or at least remain at the same level, additional constraints are added to the basic formulation, helping to reduce the solution time. For $t = 1,\ldots,T$, $k = 1,\ldots,K$, $i = 1,\ldots,N$,

$$\sum_{P=1}^{i} \delta_{k,P,t} \geqslant \sum_{P=1}^{i} \delta_{k,P,t+1}, \quad \sum_{P=i}^{N} \delta_{k,P,t} \leqslant \sum_{P=i}^{N} \delta_{k,P,t+1}.$$

- The investment cost $\mathrm{IC}_{k,t}$ associated to the investments in learning technologies is computed as

$$\mathrm{IC}_{k,t} = \mathrm{TC}_{k,t} - \mathrm{TC}_{k,t-1}.$$

The discounted investment cost is included in the objective function.

In the MARKAL model with multi-regional learning, the cumulative capacities of the regional technologies are added up to obtain the cumulative capacity of an aggregate "dummy" learning technology, which is used for the computation of the corresponding investment costs. The approach implicitly assumes that the investment costs of a given learning technology are the same for all the regions that conform a given spatial learning domain. As cumulative capacities are added up across regions in order to compute the investment costs, installations of a given technology in one region will affect the uniquely defined investment cost and can make the technology cost-effective in another region(s) that belong(s) to the same spatial learning domain (Barreto and Kypreos, 2002).

We now turn to discuss the assumptions on the learning technologies. Within the electricity generation sector of the model 13 technologies are considered. Learning curves are specified for their investment costs. Six of them are assumed to exhibit progress ratios lower than one (see Fig. 2). The deployment of the learning technologies is examined under different CO_2 constraints, different modalities of emissions trading and different configurations of learning spillover. The role of these technologies is analyzed within the context of the evolution of the full energy system, represented in our MARKAL model. However, the treatment of investment costs through learning curves is limited only to the electricity generation sector. For the rest of the energy supply and demand technologies considered investment costs are treated exogenously. Thus, no attempt is made here to

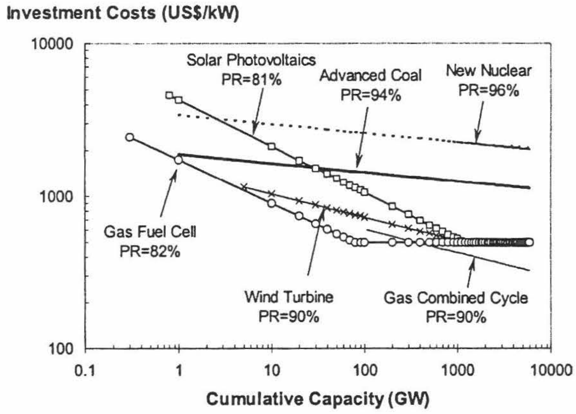

Fig. 2. Learning curves assumed for electricity generation technologies. Markers are used only to distinguish different curves. No allusion to historical trends is intended.

provide a comprehensive modeling of endogenous technological change neither inside nor outside the energy system. Therefore, results are only illustrative but they allow us to examine some effects of emissions trading on technology deployment in our multi-regional "bottom-up" context when endogenous learning is considered.

We do not offer a full justification of the progress ratios assumed here, but they lie within the ranges reported in the literature. For solar photovoltaics the value applied here is based on Harmon (2000), who assembled data for the world market between 1968 and 1998, finding a progress ratio of 80%.

For wind turbines, which have also experienced significant cost reductions in the past, our value is based on Neij (1999), who presents a detailed analysis of learning within the Danish wind industry, reporting a progress ratio of 92% for all Danish wind turbines in the period 1982–1997.

As for the fuel cell, although a significant potential for cost reductions exist, there is uncertainty about future cost levels. Being the technology still in the R&D phase, little information about learning curves is available. Thomas et al. (1998) conducted analyses for penetration of fuel cell vehicles using an estimated PR of 82%, which is also the value assumed here.

Some evidence of learning has been found for the construction costs of conventional coal power plants, when leaving aside the costs incurred as response to environmental regulations (Joskow and Rose, 1985). However, besides the analysis of MacGregor et al. (1991), which found a progress ratio of 83.6% for the early phase of development of the Integrated Gasification Combined Cycle power plant, no additional learning curve analyses appear to be available for clean coal technologies in the literature. This may be due, among other factors, to the uncertainty in installed capacities as the technologies are still in an early stage of deployment. However, analyses have been reported with a moderate PR of 94% for a generic advanced coal technology (Messner, 1997). Such value is adopted here.

Although there is evidence of cost reductions due to learning effects in the very early stages of introduction of nuclear power units (Zimmermann, 1982), conventional nuclear power plants have not shown capital cost reductions as a result of cumulative experience, among other factors due to ever-increasing safety regulations. Learning effects may have manifested in other performance indicators such as increased safety and reliability of operation. Nonetheless, new technologies could exhibit a different dynamics. First-of-a-kind units of the newly designed plants would certainly be expensive, but there are expectations that experience with them may lower construction and operation costs (EIA, 1998). Here, a conservative progress ratio of 96% is considered for a generic advanced nuclear power plant.

Gas turbines have experienced significant cost reductions along their history. MacGregor et al. (1991) presented a learning curve of simple cycle gas turbines using data for the period 1958–1980. The technology exhibited a rapid learning (PR = 80%) in the R&D and demonstration phase (1958–1963), but learning slowed down (PR = 90%) once it went into the commercialisation phase (1963–1980). Claeson and Cornland (2002) carried out another analysis. The learning curve of the combined cycle gas turbine was examined using investment prices (not costs) from 1983 to 1997. According to such analysis, the technology actually experienced price increases with accumulation of experience (i.e. PR > 100%) during the period 1983–1990 and experienced again decreases in the period 1991–1997 (PR = 75%), probably due to increasing competition among manufacturers to gain market share in that period (market "shake-out" phase). Although a cost trend is difficult to establish out of price trends, Claeson and Cornland (2002) estimate that a likely future progress ratio for investment costs could be around 90% once the market stabilises. This is the value considered here for the combined cycle gas turbine.

It must be recognized, however, that progress ratios are highly uncertain and, even if estimated accurately from the historical data, it is difficult to extrapolate those values into the future.

Regarding CO_2 emissions, two scenarios have been considered. The first is an unconstrained reference scenario. In the second, labeled Kyoto-trend scenario, Annex I regions (i.e. NAM, OOECD, EEFSU) are compelled to reach their Kyoto targets by 2010 and to follow, from this target, a linear reduction of 5% per decade until the end of the horizon. The CO_2 constraint considered here, however, is only illustrative.

In the Kyoto-trend scenario three variants of emissions trading are contemplated. In the first case, no trade is allowed. In the second, trade is allowed only between Annex I regions, starting in the year 2010. In the third case, non-Annex I regions join the trade of permits from the outset in 2010.

In the constrained scenario non-Annex I regions are bounded to their baseline emissions. That is, they are endowed to their reference emissions and, when allowed, they can trade any emission reductions below them. The emission trading mechanism considered here refers to all trade of emission permits generally and does not distinguish particularities of the Emissions Trading, Joint Implementation and Clean Development Mechanism considered under the Kyoto protocol.

The multi-regional MARKAL model takes emissions trading between regions into account by the following constraints:

$$\mathrm{EMCO2}_{\mathrm{rg},t} + \mathrm{NTXCO2}_{\mathrm{rg},t} \leqslant \mathrm{IECO2}_{\mathrm{rg},t},$$

$$\sum_{\mathrm{rg}} \mathrm{NTXCO2}_{\mathrm{rg},t} = 0,$$

where $\mathrm{EMCO2}_{\mathrm{rg},t}$ is the CO_2 emissions in the region rg for the time period t (a variable). $\mathrm{NTXCO2}_{\mathrm{rg},t}$ the net export of CO_2 emissions from the region rg in the time period t (a variable). $\mathrm{IECO2}_{\mathrm{rg},t}$ the initial endowments of CO_2 emissions for the region rg in the time period t (a parameter).

It should be clarified how the emissions trading mechanism operates in this "bottom-up" context. Emissions trading basically allows the reallocation of the carbon reduction targets and, therefore, of the incentives to deploy low-carbon technologies among the regions participating in the trade system. Carbon emissions reductions are distributed across regions such that their marginal reduction costs are equalized and the most cost-effective emission reduction options are selected. Also, since buying expenses and sales revenues of emission permits are not endogenous to the model but can only be computed ex-post, our approach cannot measure the benefits of trading, which can be particularly significant for the selling regions.

The spatial scale of the learning process has a significant influence on the outcome. In this analysis it is assumed that all technologies exhibit the same spatial scale of learning, and that such scale remains unchanged along the time horizon. The attention has primarily been concentrated in a global learning scenario. That is, when a single learning curve is specified at the global level. Capacities deployed across all regions are added up to obtain the global cumulative capacity, which is used for the computation of the corresponding investment costs. Assuming global learning has an important implication for the diffusion of the learning technologies. With all regions contributing to the cost reduction, deploying the technology in one of them traduces in a reduction of the specific cost common to all of them. Thus, installations in a given region will contribute to render a learning technology more cost-effective also in other regions.

The scale of the learning process, however, depends on the degree of technology spillover between different regions. A global learning scenario, of the kind applied here, implies the existence of full spillover of learning at the global level. That is, different regions are able to fully profit from cost reductions induced by capacity installed somewhere else. Although this portrays a situation consistent with global manufacturing and energy services companies operating in a borderless world, global learning should not be taken for granted for all technologies, particularly when taking into account the spatial dynamics of the process of diffusion of innovations and the fact that local science and technology capacity building is necessary for the successful penetration of a technology into the marketplace.

As a complement to the global learning case, an example in Section 6 illustrates the response of the model under three additional scales of learning. Compared to the global learning scenario, they represent a geographical fragmentation of the process into Annex I/non-Annex I, IND/EIT/DEV (industrialised, economies-in-transition and developing groups) and single-region learning domains, respectively.

3. Reference case

In order to provide an appropriated context, the structure of primary energy consumption and electricity generation in the unconstrained baseline case (labeled as reference) is briefly described at first. It should be borne in mind here that a scenario does not constitute a projection of the future of the energy system, which is highly uncertain, but only a picture of the possible development under a particular combination of driving forces (for a definition see e.g. SRES, 2000). Therefore, no attempt is made here to present our figures as projections or predictions of the future trajectory of the global energy system, which is highly uncertain and no model or modeler is in a position to predict.

Under this scenario, global primary energy consumption, as computed by the model, experiences a significant increase, growing at an average rate of 1.5% per year. It is still largely dominated by fossil fuels (see Fig. 3).

Both coal and natural gas experience a substantial growth, with gas becoming the predominant source by the end of the horizon. Growth of oil remains modest, but it still continues to hold a significant contribution. Non-fossil resources slowly gain market share. According to our assumptions in this scenario, demands for energy

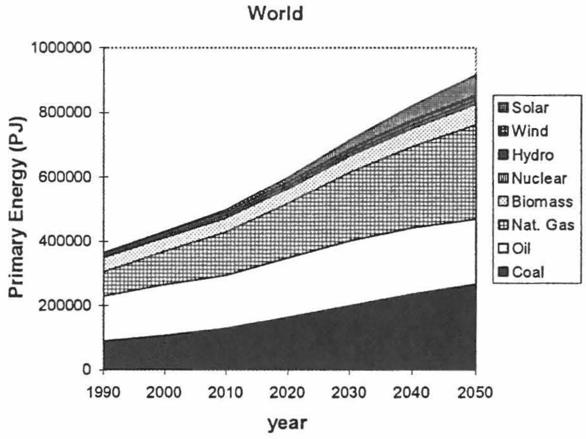

Fig. 3. Global primary energy consumption per energy carrier (reference scenario).

services grow substantially more in developing regions than in developed regions. This seems, from our perspective, a plausible assumption, which is consistent with recent historic trends and other scenarios of the future global energy system (IEA, 2002) which depict developing regions steadily approaching industrialized regions as the largest energy consumers.

Fig. 4 presents the corresponding CO_2 emissions per region. Global emissions grow at an average rate of 1.5% per annum for the period 1990–2050, reaching 2.5 times their value in 1990 at the end of

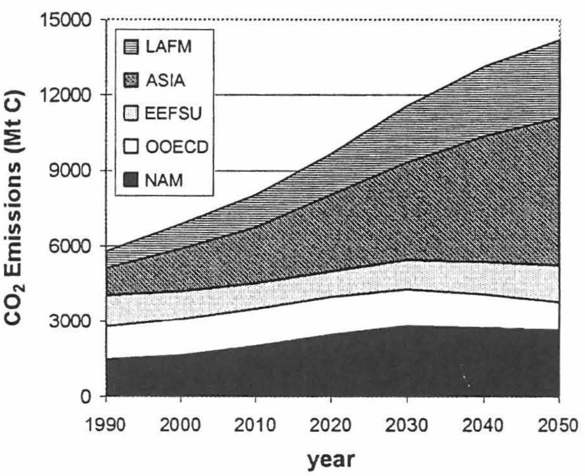

Fig. 4. Global energy-related CO_2 emissions per region in the reference scenario.

the horizon. As the center of gravity of energy consumption is displaced toward developing regions, their weight in global CO_2 emissions augments substantially along the time horizon. Specifically, developing ASIA becomes the most important emitter in the very long run. On the other hand, emissions in the Annex I group follow a moderate growth until 2030, stagnating in the subsequent period.

At the global level, electricity generation experiences a vigorous growth, with an average rate of 2.8% per annum for the period 1990–2050. The technology mix of the global electricity generation system in the reference scenario is shown in Fig. 5.

Coal continues to be the main primary fuel for electricity production, but it is the clean coal technology that becomes predominant at the end of the time horizon. The gas combined cycle and wind turbines experience a vigorous growth. The gas fuel cell also penetrates. Co-generation becomes an attractive option. Nuclear power essentially does not grow, but a substitution of conventional plants by new designs takes place. The amount of hydroelectric production grows only slightly. Solar photovoltaics penetrates only very marginally, remaining in essence "locked-out".

4. Imposing a Kyoto-trend constraint

Imposing a Kyoto-trend CO_2 constraint on the Annex I regions does not imply radical changes in the structure of the global energy system. Still, the system weans away from a carbon-intensive energy production. But, although industrialized and economies-in-transition regions reduce their emissions, global emissions continue to grow considerably driven by the dynamic growth of developing regions. Fig. 6 depicts the emissions in each region for the year 2050. At the global level the Kyoto-trend target entails a reduction of approximately 15% from the reference emissions in 2050. With Annex I trade, NAM and OOECD regions increase their emissions, as they buy permits from the EEFSU, which in its turn reduces further the level of emissions in order to sell. The allowance of full trade enables Annex I regions to emit more, as the developing ones assume part of their mitigation targets.

A comparison of the electricity generation mix in 2050 for the different variants of the Kyoto-trend scenario is shown in Fig. 7. The reference scenario is also shown.

The contribution of the electricity system to the emissions reduction is achieved mainly through fuel switching from coal to natural gas, the less

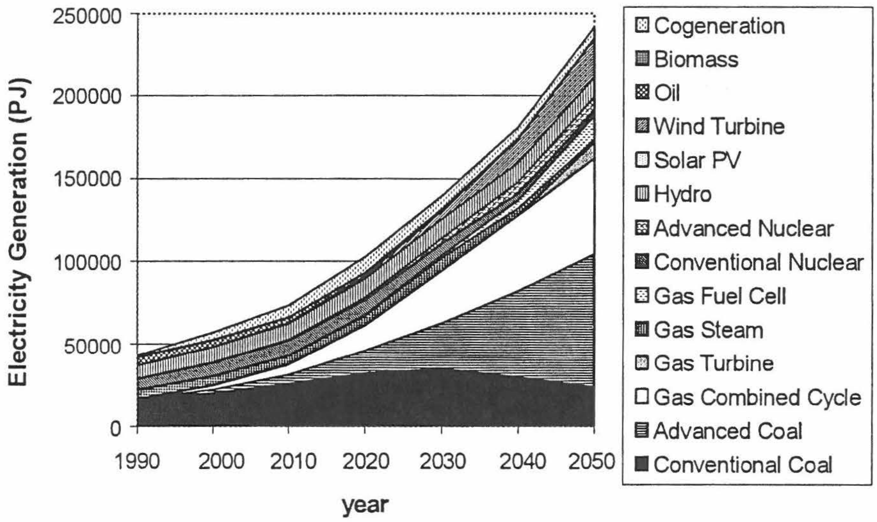

Fig. 5. Global electricity generation in the reference scenario under a global learning scale.

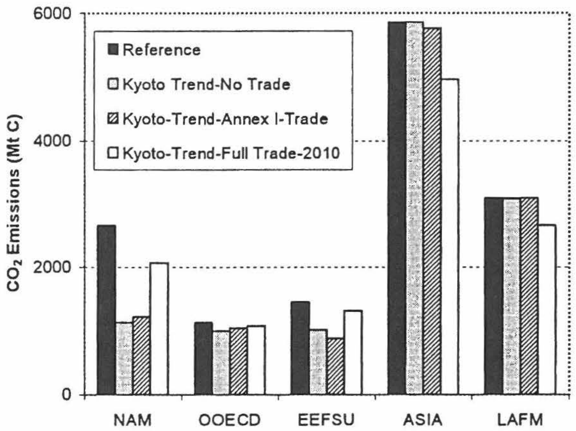

Fig. 6. Comparison of CO_2 emissions per region in the reference and Kyoto-trend scenarios for the year 2050.

carbon-intensive fossil fuel, and higher penetration of zero-carbon alternatives. Thus, coal plays a more reduced role as primary fuel for electricity generation than in the baseline situation, particularly in the no-trade and Annex I-trade cases. Advanced coal technologies dominate the fraction of coal-fired generation remaining at the end of the horizon. The gas combined cycle, hydro and nuclear (both conventional and advanced) power plants increase their output. Wind turbines continue to grow at the maximum allowed rates, cogeneration continues to be an attractive option and solar PV begins to make a dent. The gas fuel cell, on the other hand, reduces its role in the cases where trade is permitted.

4.1. Mitigation costs

In a "bottom-up" framework, the mitigation costs for a given region have two components. The first is the difference between the total discounted regional system cost in each of the Kyoto-trend cases and the corresponding baseline cost. This corresponds to the cost of the changes effected in each regional energy system in order to fulfill the emissions reduction target, i.e. the domestic mitigation cost. The second component is the money transferred due to permit sales/purchases to/from other regions. The MARKAL model, however, only allows computing the second component ex-post, since sales/revenues of emissions trading are not endogenous. Therefore, only the domestic abatement costs are examined here.

Fig. 8 presents the difference between the total discounted system costs in each of the Kyoto-trend cases and the corresponding baseline cost for each region. The global difference, which corresponds to the global abatement cost, [3] is also shown. There are significant disparities in the costs of implementation of the Kyoto-trend target in the different variants. If each Annex I region has to achieve its target on an isolated basis the abatement costs are high. The allowance of emission trade, either between Annex I regions or at the global level, substantially improves the cost effectiveness of the abatement efforts.

The assumption of global learning spillover affects the discounted system costs in the different cases, in particular, in the no-trade and Annex I-trade situations, where only the learning mechanism accounts for interactions between the Annex I and non-Annex I groups, the energy system costs in ASIA decrease, while those of LAFM increase (although the latter only very slightly).

The reason is that, in the Annex I group, as part of the mitigation measures, the gas combined cycle substitutes for coal-fired power plants. This stimulates the combined cycle's cost reduction and, under full global learning spillover, renders it more attractive also in the ASIA region driving to substitution of conventional coal-fired by gas-fired generation also there. This results in a decrease of the region's total discounted system cost. In the no-trade case lower emissions due to this effect are not observed because the model compensates emitting more somewhere else in the energy system. But, in the Annex I-trade case, the higher penetration of the combined cycle drives to an effective reduction of emissions below the baseline (see Fig. 6 above).

The case of LAFM is somewhat more complex. As the gas combined cycle is already penetrating at

[3] At the global level the difference between the discounted system cost in the reference scenario and the constrained one corresponds to the mitigation cost because the net transfers of money due to sales/purchases of emission permits across regions are zero. This is also the case at the regional level when no emissions trade is considered.

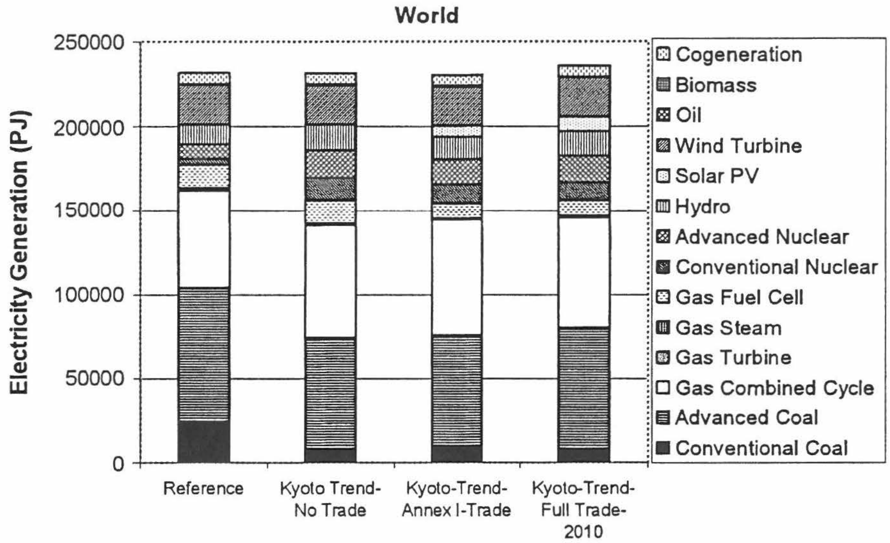

Fig. 7. Global electricity generation in 2050 (reference and Kyoto-trend scenarios, global learning).

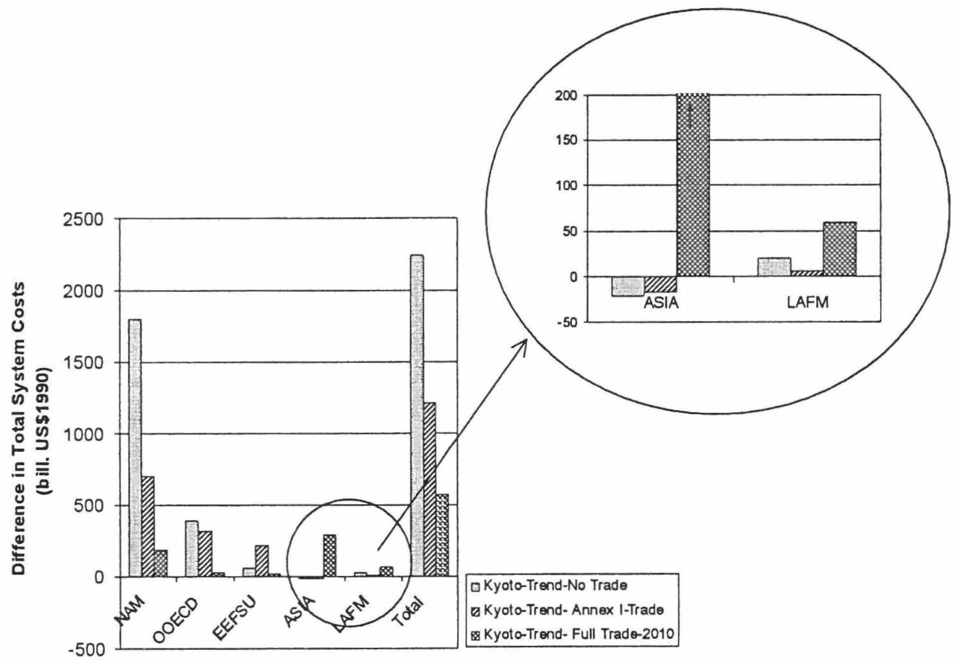

Fig. 8. Difference in the total discounted system costs from the baseline in each region (Kyoto-trend scenario). Positive values imply additional costs.

its maximum rate in the baseline scenario, no additional growth can be observed. However, other effects are noticed. The de-stimulation of the learning process of the advanced coal power plant in Annex I regions, due to the need of curbing carbon emissions, also reduces the competitiveness of the technology in LAFM, driving to a slightly lower output. This is partially compensated by a slightly higher production of the conventional coal plant, but results also in an overall reduction of the electricity generation. In consequence, changes in the mix of final energy carriers are observed. Specifically, hydrogen and oil products are now favored. Emissions are also slightly reduced below the baseline bound. As a final result the system cost becomes higher.

It should be noticed that this effect would not have been observed in a model without spillovers of learning. In such a model, the discounted system costs for the non-trading regions under the Kyoto-trend constraint would have remained the same as in the baseline case, since there would have been no linkage between the cost of technologies across regions and, therefore, the deployment of a given technology in a region cannot be influenced by the deployment actions in other regions.

But, with the possibility of having spillovers of learning, abatement efforts in Annex I regions stimulate learning, rendering some less carbon-intensive technologies more cost-effective and, therefore, attractive also in other regions, driving to positive effects in their discounted system costs and emissions profiles. Although the effect is not big here, among other reasons because the action of the learning mechanism can be observed only in electricity generation technologies, it is an indication of the possible positive effects of induced technology spillovers (Grubb et al., 2002a,b).

4.2. Deployment of learning technologies

In this section, the deployment of the learning electricity generation technologies is examined. For the sake of brevity we will discuss only some of them, which allow us to illustrate the model dynamics. The deployment depends on numerous factors and singling out their influence is a difficult task. However, one can still try to provide an interpretation of the main mechanisms involved. Here, the analysis concentrates on the influence of CO_2-trade and learning spillovers. Fig. 9 presents the output of the different learning electricity generation technologies in each region for the year 2050 under the baseline conditions and the different variants of the Kyoto-trend scenario.

In order to understand the results, in particular the "abrupt" changes in the penetration of some of the technologies from one case to the other, it is important to bear in mind the way the learning mechanism operates in the model. Although other factors also intervene, the potential available for cost reductions strongly influences the outcome. Learning is an increasing returns phenomenon (i.e. the more capacity is accumulated the smaller the investment costs become). Due to the underlying increasing returns mechanism, the model tends to act in an "all-or-nothing" fashion. If enough learning potential is at hand (depending on the learning rate, the starting point of the learning curve, maximum market penetration rates, potentials etc. specified in the model), the model may choose to introduce the technology as much as possible. But, if the learning potential is not sufficient to render it cost-effective, the technology will very likely remain "locked out" or left only with a marginal contribution.

The new nuclear power plant penetrates to some extent in the reference scenario, particularly in ASIA, the OOECD and NAM. With the imposition of the Kyoto-trend target its role becomes more significant. Without trade the technology grows substantially in Annex I regions. Its share in the EEFSU electricity mix diminishes again under the Annex I-trade case, as it recedes in the competition with conventional nuclear, but increases in NAM and OOECD.

In the full-trade-2010 case, two counterbalancing factors play a role in the diffusion of this technology, namely the lack of incentives to deploy it in Annex I regions, which can now acquire permits from the developing world, and the incentive to do so in non-Annex I regions that may sell them. As a consequence of the first factor much less capacity is built in the Annex I group. Due to the second factor, an increase takes place in the LAFM region, which now sells a higher absolute volume of permits. Nonetheless, due to the global learning spillover assumption, the effects of the weaker stimulus in the Annex I group are felt across all regions.

As for the gas fuel cell, under the particular conditions assumed here, it results more attractive in the reference scenario than in the constrained

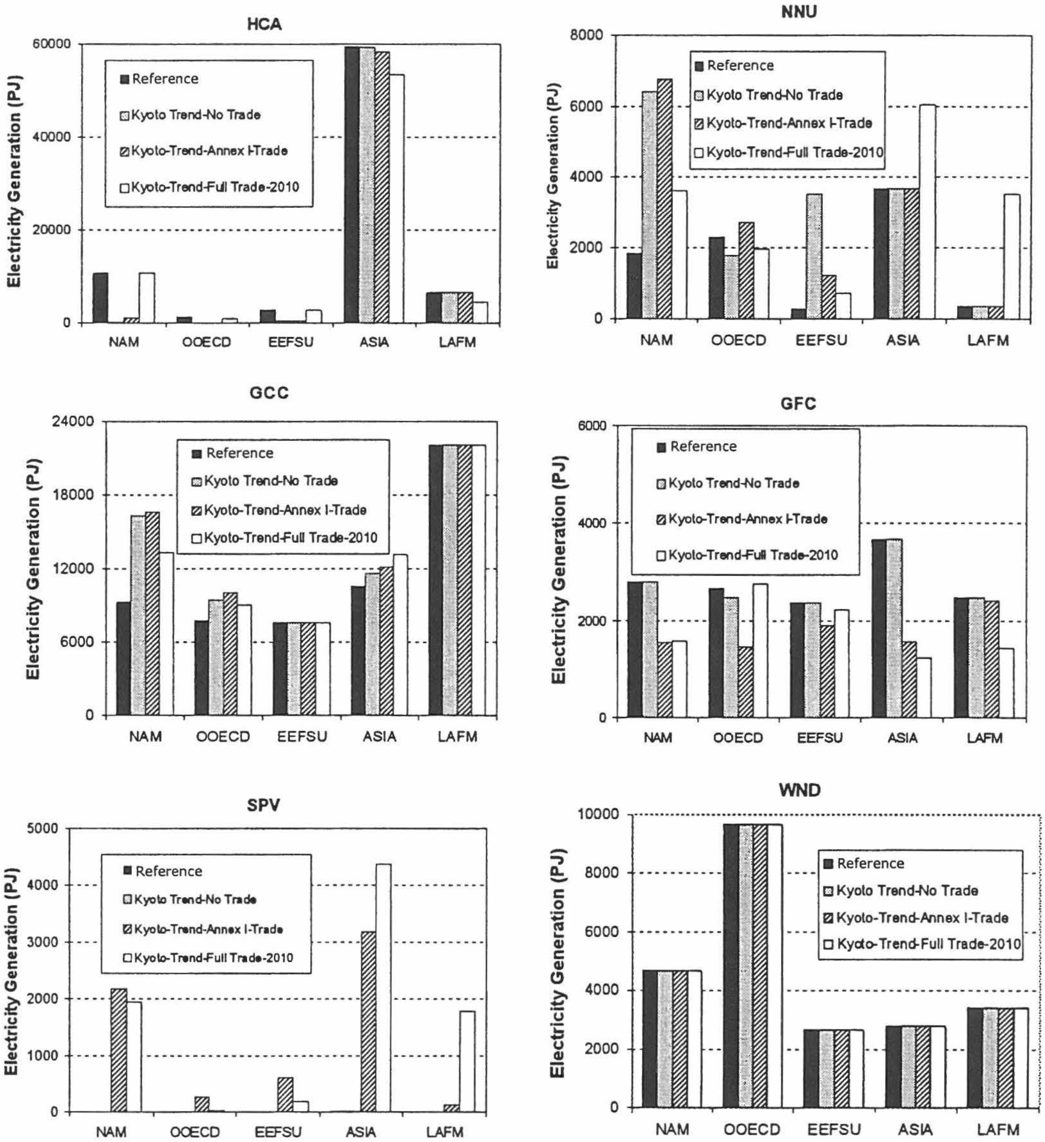

Fig. 9. Output of learning electricity generation technologies in 2050 (reference and Kyoto-trend scenarios). The abbreviations are as follows: HCA: advanced coal, NNU: new nuclear, GCC: combined cycle gas turbine. GFC: gas fuel cell. SPV: solar photovoltaics, WND: wind turbine.

one. In the latter, the technology faces competition from the gas combined cycle plant and solar photovoltaics, among others. However, in the Kyoto-trend-no-trade case it still results almost as attractive as in the baseline. But, with the introduction of trade, its role in the generation mix decreases. With Annex I-trade, a significant decrease takes place in the NAM and OOECD regions, and a lower, but still noticeable, decline in the EEFSU. As a result, and due to the presence of global spillovers of learning, its penetration in ASIA is substantially affected, although its output in LAFM remains almost unchanged (due, among other factors, to the fact that in this case solar photovoltaics penetrates only slightly in this region, see below). With the allowance of global trade in 2010 its growth recovers somewhat, led by installations in the OOECD and EEFSU.

Solar photovoltaic cells do not diffuse in the reference or Kyoto-trend-no-trade cases. Despite some investments taking place in the first periods, particularly in the OOECD region, the technology remains "locked-out". It is introduced, however, when trade takes place. With Annex I-trade, introduction occurs mainly in NAM and ASIA, and to a less extent in EEFSU and OOECD. Being EEFSU the main permit seller, an incentive for deployment exists there. The potential in that region is relatively small, but the system is allowed to benefit from global learning. Thus, early investments there trigger installations in constrained and non-constrained regions alike, in order to take full advantage of the available learning potential. As no trade linkage between Annex I and non-Annex I regions exists, the penetration in the latter regions is a result of the global spillovers of learning.

With full trade, incentives for deployment are present mainly in developing regions, the main permit providers. However, an earlier/later entry of those trading partners has effects on the levels the technology reaches. With an earlier full trade (from 2010), capacity built-up in Annex I regions is discouraged. But, the trade linkage encourages its introduction in developing regions and a higher growth takes place both in ASIA and LAFM, the main permit sellers in this situation. But, if these two regions join the trade later (i.e. in 2030), Annex I regions are compelled to stimulate the learning of this zero-carbon technology in the first periods. In addition, in this perfect foresight framework, early deployment also takes place in the developing regions, which are due to become permit sellers later on. As each region profits from the learning of the others, both processes cross-enhance each other and the technology is able to reach a sizeable expansion in all regions.

The effects of spillovers in the technology choice depend also on the stringency of the constraint and the characteristics of the region(s) where it is imposed. For instance, in this exercise, the imposition of the Kyoto-trend constraint on Annex I regions (without trade) stimulated the increase of output of gas combined cycle in ASIA, as already described above. But, despite the full global learning spillover, such constraint was not enough to produce noticeable additional deployment of the other learning technologies in the developing regions compared to the baseline situation.

A model with multi-regional learning spillovers has a fundamental, although still rudimentary and perfectible, mechanism that helps reflecting the possible response of accelerating technological progress (here represented as cost reductions) in low-carbon technologies in different regions of the world induced by stronger climate control policies in one of them. This effect cannot be taken into account in a conventional linear programming model, where the exogenous specification of cost trends for the technologies precludes such kind of interaction. In such a model, the technology mix in regions not facing a carbon constraint and not being part of the trading system is bound to be the same in both cases because no mechanism of interaction between regions is present.

Thus, considering multi-regional learning spillovers improves the modeling of technological change induced by environmental constraints. First, under the presence of the learning mechanism, the imposition of environmental constraints can induce cost reductions (increasing competitiveness and likelihood of diffusion) of environmentally compatible technologies. Second, when spillover across regions is possible, other regions can benefit from the learning stimulated by tighter environmental policies in a given region.

5. Sensitivity to the spatial learning spillover

The analysis above has assumed full spillover of learning at the global level. In this section the sensitivity of the results to different geographical configurations of learning is examined. Here, besides global learning, three additional cases are considered. In the first case, called Annex I/non-Annex I learning, two separate learning domains are specified: the Annex I group (i.e. NAM, OOECD and the EEFSU) and the non-Annex I group (ASIA and LAFM). In the second case, labeled IND/EIT/DEV learning, three learning blocks are defined: Industrialized regions (NAM and OOECD), economies-in-transition (EEFSU) and developing regions (ASIA and LAFM). Finally, a single-region learning case, with each region learning alone, is considered. For simplification it has been assumed that the same learning curves applied in the global learning situation are valid for the other learning scales. Also, all technologies are considered to have the same learning scale.

The learning configurations analyzed here consider that spillover between two given regions is either full or it does not exist. In such sense, they are arbitrary and applied only with illustrative purposes. They may not reflect the real "topology" of the learning networks of the technologies affected, particularly in an increasingly globalised world where more multi-national energy technology suppliers operate at the international level. Still, examining such hypothetical learning configurations allows insights into the consequences of co-operative/non-cooperative "learning strategies" on the diffusion of a given technology and the interaction between the multi-regional learning and emissions trading mechanisms. Further work should be devoted to establish whether an empirical estimation of spillover coefficients for specific technologies can be made and/or to develop criteria for supporting the corresponding assumptions in the models.

As an example, we illustrate here how the variation of the learning scale affects the deployment of solar photovoltaics in the different regions under the Kyoto-trend scenario. Under the particular conditions assumed in these model runs, solar photovoltaics is a marginal technology and as such is strongly affected by the variation of the learning scale.

Before discussing it, an interesting aspect of the influence of the learning scale on emissions trading should be noticed. Changes in the learning topology of the low-carbon technologies available in a given region can make it more prone to buy/sell permits (see Fig. 10 for an example with the ASIA region). Owing to the action of emissions trading, those changes become also influential in the technology choice in other regions.

Let us turn now to the diffusion of solar photovoltaics, the example chosen here. Fig. 11 presents the aggregate electricity generation of the solar photovoltaic technology for the year 2050 in

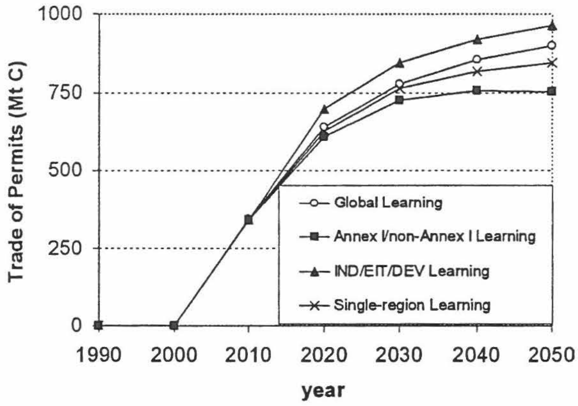

Fig. 10. Volume of CO_2 permits sold by ASIA in the Kyoto-trend scenario with full trade 2010 under different scales of learning.

the Annex I and non-Annex I groups of regions under the different sub-cases of the Kyoto-trend scenario. In order to examine the effects of a later entry of the non-Annex I regions to the trade system, a case where full trade across regions takes place after 2030 is also shown.

The three Annex I regions show a similar pattern of installations. The technology is introduced in significant amounts only under the global learning situation. Otherwise, it remains practically "locked-out". Under global learning, as already discussed above, installations take place exclusively under the Kyoto-trend scenario and only when (Annex I- or full) trade is permitted. In those cases the technology is deployed in all regions. The highest penetration is achieved in the Kyoto-trend-full-trade-2030 case.

But, with the reduction of the learning scale, Annex I regions cannot benefit from the cost reductions caused by the deployment in non-Annex I regions, where higher production potential is at hand. As a result, the technology is no longer attractive in Annex I regions. Other technologies take the lead. Among others, new nuclear power plants have a higher output.

In the non-Annex I group installations also take place only when emissions trade is allowed. With global learning spillover the technology is introduced both when Annex I-trade or global trade are possible. Penetration in the Annex I-trade case is a

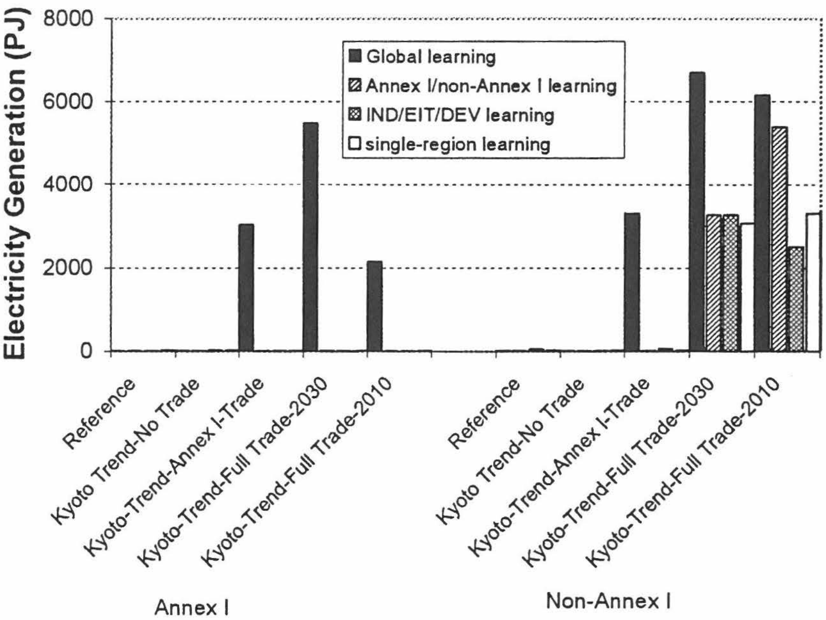

Fig. 11. Comparison of the electricity generation of solar photovoltaics in Annex I and non-annex I groups for the year 2050. Different scales of learning (reference and Kyoto-trend scenarios).

consequence of spillover effects. The introduction in the full trade case is, as mentioned before, the result of the incentive to sell permits to Annex I regions.

The technology still remains relatively attractive when the learning scale shrinks. This is basically due to installations in ASIA and, to a much lower extent, in LAFM. However, with reduced learning scales it is installed in these regions only when full trade is allowed. That is, only when an incentive to sell permits to the Annex I regions exists. Under the no trade or Annex I-trade situations none of the two mechanisms of interaction between the Annex I and non-Annex I groups considered here, namely learning spillover and trade, is acting. The two groups are "decoupled" from each other and this strongly undermines the diffusion process in all regions.

On the whole, solar photovoltaics benefits from a larger learning domain. Imposing restrictions on the scale of learning affects its diffusion substantially. This is particularly so in Annex I regions, which do not possess large solar electricity potentials, but it becomes apparent also in non-Annex I regions, despite having a larger solar resource at their disposal. The competitiveness of the photovoltaics option suffers when both groups are left only with their own learning opportunities or when a further fragmentation of the learning network occurs, leaving smaller groups or single regions learning alone. As for the influence of emissions trading, its allowance stimulates the deployment of this otherwise marginal technology, but different trading modalities combined with diverse scales of learning drive to various degrees of penetration. Specifically, Annex I-trade only drives to installations when global spillover of learning is possible. Allowing full trade provides an effective stimulus for the penetration of the technology in the non-Annex I regions, although the magnitude of such penetration is affected when the learning scale shrinks.

It is not easy to derive a straightforward conclusion about the influence of the learning scale and the trade on the final model outcome. The interactions are complex and appear case and technology dependent. But, basically, the reduction of the learning scale changes the ranking and, therefore, deployment of technologies in the different regions. As a consequence, the amount of

CO_2-permits bought/sold by them also changes. The magnitude of those changes depends on the emissions trading configuration and the stringency and location of the emission constraint.

6. Conclusions

An indicative analysis has been performed using a five-region compact "bottom-up" MARKAL model of the global energy system that considers endogenous technology learning for several electricity generation technologies. The response of the model to an illustrative Kyoto-like constraint on CO_2 emissions is analyzed. The fulfillment of the abatement targets under different configurations of emissions trading is examined. Results remain, of course, highly dependent on the assumptions but, more importantly than the numbers and assumptions here, the deployment of learning technologies in response to changes in emissions trading configurations and geographical scale of the learning process has been illustrated.

With learning, carbon abatement activities in a given region stimulate technological change, here represented as costs reductions, of low-carbon technologies. Under the presence of multi-regional learning spillovers in the model, this may foster their diffusion also in other regions, even if they do not face an emissions reduction commitment. Thus, introducing multi-regional technological learning spillovers provides a fundamental, though still perfectible, mechanism to represent environmentally induced technological change in the model. Such induced technological change may produce positive effects in terms of system costs and emission profiles in those regions.

Within the limitations of this "bottom-up" framework, some effects of emissions trading on technology deployment under the presence of technology learning have been studied here. As a rule, the cheaper mitigation options brought about by the emissions trading mechanism produce a disincentive to deploy low-carbon technologies in permit-buying regions. But, on the other hand, trade stimulates their penetration in (potentially) selling ones. This is particularly so in the case where non-Annex I regions join the trading system. The final effects on technology deployment depend, among other factors, on the configuration of the learning and trading networks, the magnitude of learning spillover between regions and the level and location of the carbon constraint imposed. But, even in the cases where the trade configuration strongly reduces the incentives for technology learning of low-carbon technologies in constrained Annex I regions (e.g. global emissions trade), the model still finds cost-effective to stimulate early deployment of some low-carbon technologies, although to a lower extent, provided global spillovers of learning are possible.

Changes in the spatial configuration of the learning and trade networks along the time horizon have also noticeable impacts. Here, as an example, a later inclusion of non-Annex I in the emissions trading system is analyzed, in order to determine how such delay affects the "triggering" of the learning mechanism of electricity generation technologies. In these experiments, within a perfect-foresight framework, delaying the availability of cheaper mitigation options in non-Annex I regions keeps learning processes going on in the constrained Annex I regions. Through spillover effects, such learning processes have an influence on the technology choice of the permit-selling non-Annex I regions as well. By contrast, an earlier global trade hinders the learning process of low-carbon technologies in constrained Annex I regions with expensive mitigation measures. However, in the long term it fosters it in the selling regions. Provided the existence of learning spillovers, the latter can drive to deployment of those low-carbon options also in the constrained (buying) regions. The final outcome depends, among other things, on the relative weight of these counteracting forces.

In addition, the "topology" of the multi-regional learning network has an influence on the competitiveness of the learning technologies. Here, such influence is illustrated with examples of hypothetical configurations of learning spillovers. The different regions are either allowed to fully benefit from the learning potential in others or completely precluded to do so. Such changes in the learning configuration, basically shrinking or expanding the spatial domain of the learning process, alter the regional ranking of technologies and, consequently, the balance between domestic mitigation measures and transactions (sales/purchases) in the permits market for the different regions. The configurations of learning and emissions trading networks appear as important determinants of the diffusion (or not) of emerging low-carbon technologies in a CO_2-constrained world.

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