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Further experiments with ERIS model prototype: sensitivity analysis for post-Kyoto

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Abstract: This paper presents the results of a sensitivity analysis with the ERIS Model Prototype in the context of a post-Kyoto analysis. The first section provides a short description of the ERIS model prototype and the definition of the two sensitivity analyses performed, regarding progress ratios and fuel prices respectively. The results obtained from these analyses are provided in sections 2 and 3. Finally, the paper concludes with the implications of considering endogenous learning for technologies generating electricity under different domains of evolution for progress ratios and fuel prices.

Keywords: Electricity generation; CO_2 emission reduction; endogenous technological learning.

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1 Introduction

ERIS (Energy Research and Investment Strategy) is a global energy model prototype specified and developed in the context of the TEEM project (funded by the European Commission, research project, 1998-1999).

The original purpose of ERIS was to capture the main mechanisms regarding the endogenous analysis of technological learning under uncertainty and to allow for a consistent cost-benefit analysis of specific policies aiming at technology prioritisation. The original prototype, specified by IIASA and coded by NTUA considered a non-linear programming (NLP) and a Mixed Complementarity (MC) formulation of experience curves. ERIS was extended by PSI to include more general constraints, a stochastic approach and a Mixed Integer Programming (MIP) formulation of learning curves. ([1-5] for technical details about model coding).

The multi-regional version of the ERIS model prototype examines electricity generation technologies in a global context with endogenous technological learning curves. Impacts of Kyoto-like CO_2 constraints are analysed considering the effects of allowing or not trade of emission permits. Complementary stochastic analyses addressing the uncertainty of emission constraints, demand and learning rates and a preliminary assessment of the effects of the geographical scale of learning are also presented. An extensive implementation of the ERIS model prototype as regards the implementation of various policies (including stochastic analysis and learning issues) in the context of a post Kyoto world can be found in [6].

The purpose of this paper is to supplement the work of [6] by providing some further experiments with the model and some new interesting results. The latest version of ERIS, which combines Linear, Non Linear and Mixed Integer Programming, as also used by S. Kypreos and L. Barreto was used in this paper.

Two sensitivity analyses were performed, which examine the model’s behaviour on changes of:

- progress ratios; and
- fuel prices.

The purpose in both cases was to evaluate the sensitivity of the benefits from learning with respect to progress ratios and fuel prices.

Progress ratios represent the learning rate of each technology and current estimations of their values are given in Table 1 in [6]. These values have been used for the central cases estimated with the model.

There are many factors, which may influence the learning rates of the technologies [7-10] for other estimations of progress ratios and further discussion about their values). Hence there is a high degree of uncertainty in the values of learning rates. Small variations in their values might have a large impact on the final technology mix and on the insights gained from the results of the model. These reasons justify performing sensitivity analysis with respect to progress ratios.

The same uncertainty governs fuel prices, especially when oil and gas is concerned. Current and future prices are likely to be over or underestimated and again a sensitivity analysis is needed in order to assess the impact that these fluctuations may have on the electricity system in the presence of a learning process.

2 Changes in progress ratios

The first sensitivity analysis is based on the Kyoto-for-Ever scenario (as defined in [6]) with endogenous learning. It examines the model's behaviour on changes of the progress ratios of 3 different technologies (Solar Photovoltaics, Wind Turbines and Gas Combined Cycle).

In the case of Wind Turbines for example the sensitivity analysis was based on progress ratios ranging from 0.84 - 0.93. The sensitivity was carried out separately for each technology, the rest of the technologies keeping their original progress ratios, which is 0.81 for Solar PV, 0.88 for Wind Turbines and 0.89 for Gas CC. The results were then compared to a basic scenario where the technology has a progress ratio of 1, i.e. the specific technology does not have any endogenous learning. Once the sensitivity analysis for a technology is done, the progress ratio is set back to its original value (for example 0.88 for Wind) and the same process is repeated for the other technologies. For Solar PV and Gas CC the sensitivity dealt with progress ratios ranging from 0.75-0.93 and 0.85-0.94 respectively.

In order to better evaluate the benefits from endogenous learning for each technology the following method is used: For every different progress ratio of each technology, the total cost of the energy system (objective function of ERIS when using endogenous learning (with that specific progress ratio) is deducted from the total cost of the basic scenario without learning. The same procedure is followed for the CO_2 emissions. The total CO_2 emissions when using learning under the Kyoto constraint are deducted from the total CO_2 emissions of the baseline scenario. Their fraction: $\Delta(\text{Cost})/\ \Delta(CO_2)$ shows how much less (in \$) each ton of carbon avoided costs, in order to meet the CO_2 constraint. The ratio is a measurement of the effectiveness (interpreted as a benefit) of the additional learning feasibility.

In all 3 cases (see Figures 1, 2 and 3) the graphs follow an S shaped curve. As the progress ratio gets closer to 1 the learning process slows down, and the benefit, in terms of carbon emission mitigation from the specific technology, gets smaller. New investments in this technology remain relatively expensive and beyond a certain value the technology is phased out, by more attractive alternatives. On the other side of the curve as the progress ratio gets very small, the learning process is accelerated and the specific technology becomes very attractive for new investments. However along higher learning the penetration of the technology may reach a certain threshold level and from that point on there are no significant additional benefits compared to the basic scenario, even if the progress ratio becomes even smaller.

The S shaped curve shown below (Figure 1) can also be interpreted in terms of marginal benefits. These can be defined as the additional carbon cost savings per unit of improvement of the learning rate. Beyond the inflexion point of the S-curve, marginal benefits tend to decrease. An R&D planner could compare these marginal benefits with marginal costs for improving the learning ratio, so as to set up an optimal R&D strategy.

The sensitivity analysis for Solar PV in Figure 1has shown rather large sensitivity of benefits with respect to the learning ratio. For example, improving the progress ratio from 0.87 to 0.77 launches the gain from \$16 per ton of C avoided, to \$112 per ton of C avoided! According to the basic assumption adopted in this paper, the progress ratio of SPV is 0.81, which results in a gain of \$90 per ton of C avoided. This means that by trying to accelerate slightly the learning rate from 0.81 to 0.77 (if this is possible), there could be an extra gain of $22 ($112-$90) per ton of C avoided.

Accordingly, in the case of Wind the current progress ratio is 0.88, which lies in the middle of the curve (Figure 2). The slope of the curve shows for Wind technology that the sensitivity of benefits with respect to learning ratio is smaller than for the Solar PV. Hence by accelerating the learning rate by 0.3 (from 0.88 to 0.85) there is an extra gain of $15 ($60 - $45) per ton of C avoided. Finally, the current progress ratio for Gas CC is 0.89 (Figure 3), but the range of possible improvement has small effects in terms of benefits. This is also due to the small penetration of Gas CC in the total energy mix under Kyoto-for-ever constraints.

Figure 1 Sensitivity analysis for changes of progress ratios for SPV

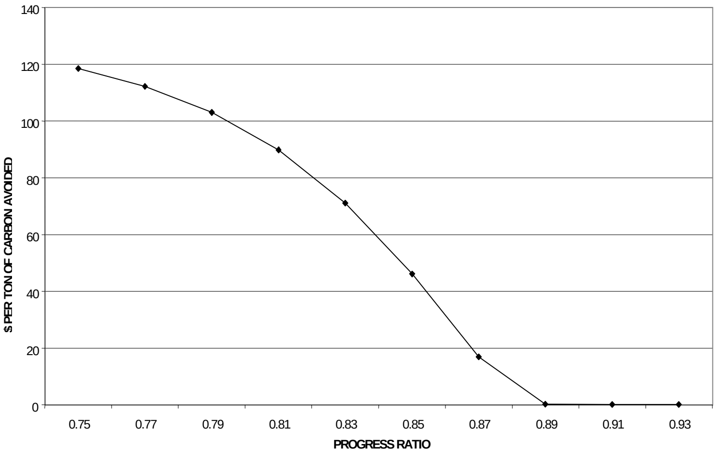


Figure 2 Sensitivity analysis for changes of progress ratios for WND

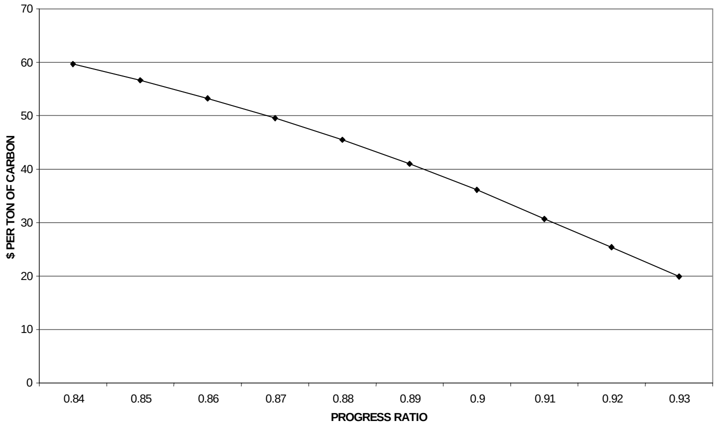
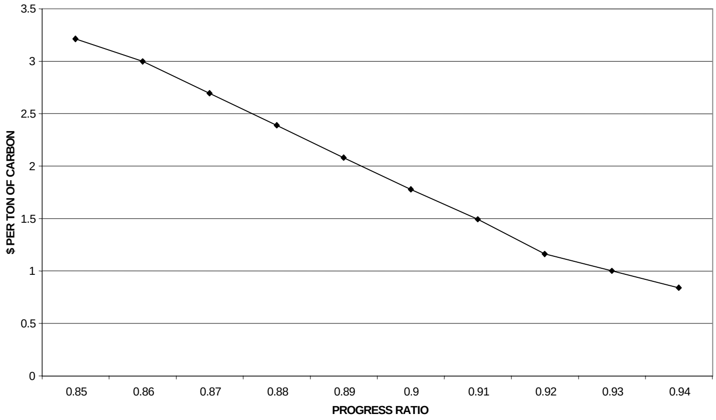
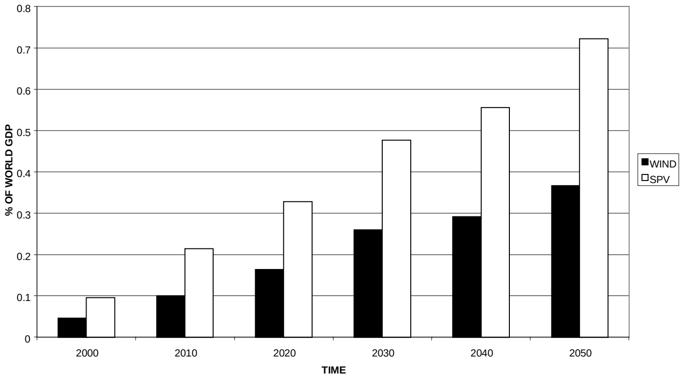


Figure 3 Sensitivity analysis for changes of progress ratios for GCC



Finally looking at the chart below (Figure 4) some interesting results arise, which might stimulate efforts in the R&D areas for Solar Photovoltaics and Wind Turbines. For each decade the extra gains from using small progress ratios, 0.75 and 0.84 respectively (as compared to the scenario without endogenous learning) are divided by the world GDP for that decade and are then presented as a percentage of it. For example for the year 2050 the benefits from using SPV are 0.7% and from Wind Turbines 0.32% of the World GDP. These significant benefits show that substantial savings can be made when technologies with endogenous learning are being used extensively.

Figure 4 Benefits from SPV and WND as a percentage of world GDP



3 Price fluctuations of oil and gas

Fuel prices were assumed for the different regions throughout the time period (1990 – 2050), using the POLES model [11] as the main source of data. The price data provided by POLES were extended by two decades in order to complete the data set. The prices can be seen in Table 1.

Table 1 Fuel prices (in $98 per kWyr)

FUEL	**REGION**	**1990**	**2000**	**2010**	**2020**	**2030**	**2040**	**2050**
OIL		168	77	120	142	162	185	211
GAS	USA+CANZ	76	79	102	111	114	117	121
	OECDE	107	88	113	139	159	175	192
	JAPAN+ROW	145	123	155	164	177	187	195
	EEFSU	71	59	75	93	106	117	129
	CHINA+INDIA	126	105	134	152	168	181	193
	MOPEC	53	55	71	78	80	82	85
CARBON		70	61	63	64	66	67	69
URANIUM		20	20	20	20	20	20	20
RENEWABLE		0	0	0	0	0	0	0

As expected these estimates have a high degree of uncertainty and even predictions for the near future are likely to be wrong. Also variations of up to 35% can be found when comparing price estimations of POLES with other scenarios. Therefore it is worth performing a sensitivity analysis for price fluctuations of Oil and Gas.

The point is to evaluate the impact that these price fluctuations (ranging from –50% to +50% compared to the original prices given in Table 1) may have on the learning process and on the technology mix in general. So the model is given different oil and gas prices for two scenarios:

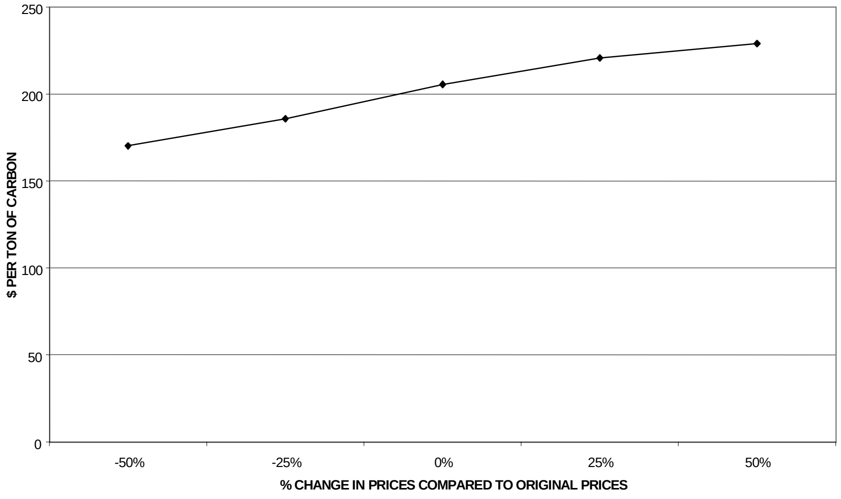
1. No learning, Kyoto for ever constraint (Scenario #1); and
2. Endogenous learning, Kyoto for ever constraint (Scenario #2).

Then the total cost of the endogenous learning scenario (#2) is deducted from the total cost of the scenario without learning (#1) for each different fuel price of Oil and Gas (-50% to 50%). Also, as in the previous sensitivity analysis, the total CO_2 emissions when using learning under the Kyoto constraint (for the whole price range) are deducted from the total CO_2 emissions of the baseline scenario. Their fraction $\Delta(\text{Cost})/\ \Delta(CO_2)$ is plotted below (Figure 5) and shows how much less each ton of carbon avoided costs in order to meet the Kyoto-for-ever constraint.

As can be seen from Figure 5 the sensitivity of the benefits from learning with respect to fuel price fluctuations is noticeable. If prices drop to –50% from today's estimations, the benefit from endogenous learning also drops to $170 per ton of carbon avoided (-17%), while if prices rise, the benefit becomes higher reaching $220 per ton of Carbon avoided (7.5% from base case).

The reason behind this is that for high fuel prices, Solar PV, Wind Turbines and New Nuclear Energy tend to penetrate the market faster than in the case of low fuel prices. Higher penetration means more investment and bigger installed capacity, further implying acceleration of the learning process and therefore lower capital costs. Also faster penetration means more use of renewable energy sources that have no fuel costs. Hence the extra benefit in the case of high fuel prices.

Figure 5 Sensitivity analysis for gas and oil price fluctuations



4 Conclusion

The latest version of the ERIS prototype was used in this paper, in order to explore the implications of considering endogenous learning for technologies generating electricity. Emphasis was given to the sensitivity analysis, which examines the model's behaviour on changes of progress ratios and fuel prices.

The first sensitivity analysis has shown that each technology has a different sensitivity of benefits with respect to the learning ratio. In the case of Solar Photovoltaics for example, additional carbon cost savings per unit of improvement of the learning rate, are very high. On the other hand for Gas Combined Cycle plants, possible improvement of the learning rate has small effects in terms of benefits. The above should be taken into account when planning for an optimal R&D strategy.

Another important result showed that acceleration of the learning process (by increased efforts in the R&D) of technologies like Solar PV and Wind Turbines, would result in great cost reductions, as high as 1% of the world GDP.

Finally, the second sensitivity analysis showed that the sensitivity of the benefits from learning with respect to fuel price fluctuations is noticeable, but not too high (100% change in prices resulted in 25% change in the benefits of learning). Hence, price fluctuations are not a source of significant error for the model.

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