SAPIENT

Systems Analysis for Progress and Innovation in Energy Technologies

SYSTEMS ANALYSIS FOR PROGRESS AND INNOVATION IN ENERGY TECHNOLOGIES

Research Project DG RES, 5th Framework Programme

Contract N° ENG2-CT1999-00003

Partners: ICCS.NTUA, CNRS.IEPE, ECN, IPTS, KUL, PSI, IER, IIASA

PART 2

–DETAILED FINAL REPORT–

Athens, February 2005

FINAL TECHNICAL REPORT

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ACRONYM: SAPIENT

TITLE: SYSTEM ANALYSIS FOR PROGRESS AND INNOVATION IN ENERGY TECHNOLOGIES

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PART I: TECHNOLOGY IMPROVEMENT DYNAMICS AND 2FLC's.

1. Technology Improvement Dynamics Database for power generation technologies
(by P. Criqui, IEPE-CNRS)

The aim of the TID database is to provide a set of consistent data in order to assess the role of the key drivers and inducement factors in the dynamics of energy technologies. Based on initial work performed in the TEEM project of the EU DG Research, this effort now develops in the SAPIENT project under the 5th RTD Framework Program.

One key finding of the TEEM project had been that a prerequisite for the endogenisation of technical change in large energy sector models was the capability of simulating the combined impacts of the experience processes and of the R&D efforts on the technologies' costs and/or performances. In order to combine the "learning by doing" and "learning by searching" effects, the concept of "Two Factor Learning Curves" (TFLC) had been developed and used in simulations with the POLES model (see corresponding Chapters in the special issue of the International Journal of Global Energy Issues V14, N°1-4, 2000).

As a reminder, the basic equation used for the Two Factor Learning Curve in the POLES model and SAPIENT project modelling exercises is of the following form:

$$\mathbf{COST_i = k \times (CUMGERD_i + CUMBERD_i)^{a} \times (CUMCAP_i)^{b}}$$

where:	**$COST_i$**	the cost of technology i in constant money,
	$CUMGERD_i$	the cumulative Government Energy R&D (exog.),
	$CUMBERD_i$	the cumulative Business Energy R&D (endog.),
	a	the "learning-by-research elasticity",
	$CUMCAP_i$	the cumulative installed capacity (endog.),
	b	the "learning-by-doing elasticity".

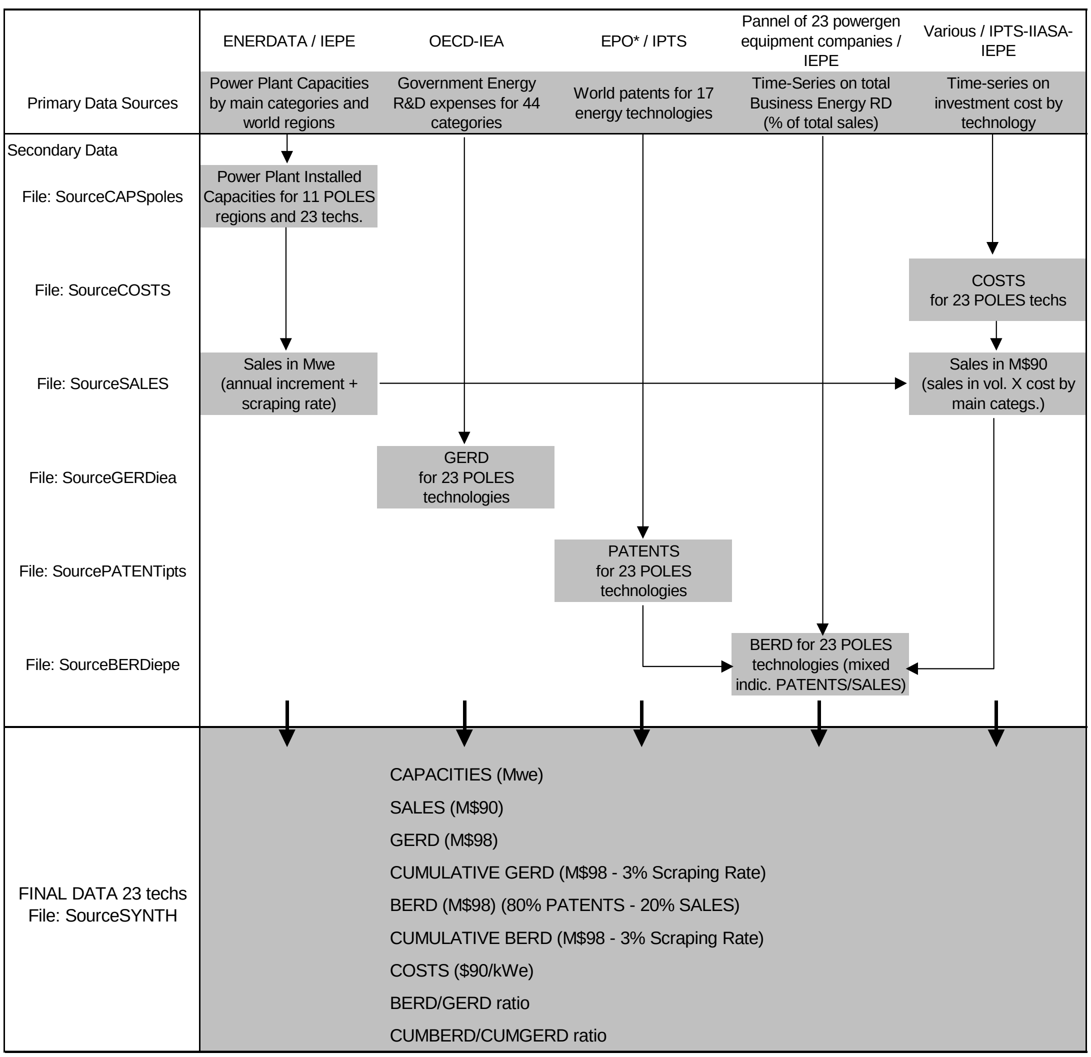
In order to improve the approach and further increase the reliability of the estimates of the TFLC it has been decided to develop in the SAPIENT project a database gathering data on the cost of the key power generation technologies (the 23 considered in the POLES model) and to the key explanatory variables considered in the TFLC i.e.: cumulative capacities, cumulative government energy R&D (GERD) and cumulative Business energy R&D (BERD).

Table 1-1 describes the set of power generation technologies and provides the corresponding acronyms used in the different files. Table 1-2 below describes the key sets of data, the way they are produced and combined and the corresponding spreadsheet for data collection and treatment. The following Sections describe the content of the data base, the hypotheses adopted for data processing and some key insights that can be extracted from the data sets in themselves.

Table 1-1: Acronyms for the 23 POLES power generation technologies

HYD	Large Hydro
NUC	Nuclear LWR
NND	New Nuclear Design (Evolutionary type)
LCT	Lignite Conventional Technology
CCT	Coal Conventional Technology
PFC	Pulverised Fuel Supercritical Coal
ICG	Integrated Coal Gasification
ATC	Advanced Thermodynamic Cycle
OCT	Oil Conventional Technology
OGC	Oil in GTCC
GCT	Gas Conventional Technology
GGC	Gas in GTCC
CHP	Combined Heat and Power
SHY	Small Hydro
WND	Wind
SPP	Solar Thermal Power Plant
DPV	Decentralised PV (building integrated)
RPV	Rural PV (electrification in LDCs)
BF2	Electricity production from waste
BGT	Biomass Gasification + GTCC
FCV	Fuel Cell Vehicle (PEMFC)
SFC	Solid Oxyde Fuel Cells
MFC	Molten Carbonate Fuel Cells

Table 1-2: Data organisation and treatment in TIDdb



EPO* = European Patent Office

1.1. World and regional power generation capacities (File SourceSALES)

The tables above extract direct information from the POLES model data-base on power generation capacities installed in the main regions of the world for each of the 23 POLES standard technologies.

Primary data come from the UN - ENERDATA database on capacities installed in each country-region. The "translation" from the UN to the POLES power-plant categories has been managed by using complementary information from national energy balances.

While some individual time-series may pose problems particularly for years remote in the past (some series had to be extrapolated as no information was available) the advantage of this data set is that it provides technology by technology information, which is consistent with aggregated world power generation capacities.

In the SourceCAPSpoles spreadsheet, primary data from POLES are organised in 23 sheets for each technology with time series for eleven POLES regions. For purposes of transfer and analysis, the detailed power generation capacities are also provided for the world and four main world regions: OECD, EIT, Asia and RoW.

1.1.1. World Level Analysis

The analysis of world power generation capacities shows a linear-type growth in the past 20 twenty years, with a marked slowdown in the last years of the period considered. The yearly average growth rate indeed goes from 6 %pa in the early seventies to 2 %pa or less in the late nineties. This is largely due to much contrasted regional dynamics examined below in Figure 1-4 to Figure 1-11.

Figure 1-1: World power generation capacities in MWe

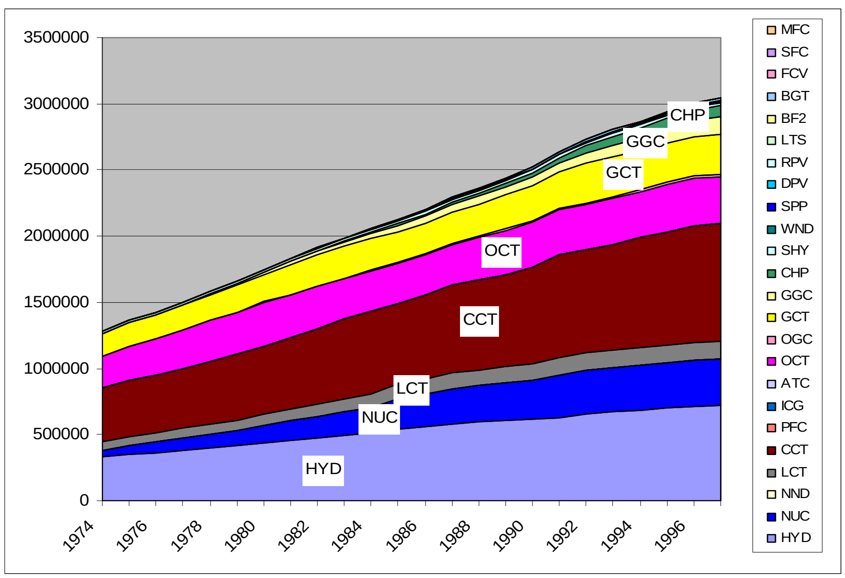


Figure 1-2: World power generation capacities, annual growth rate

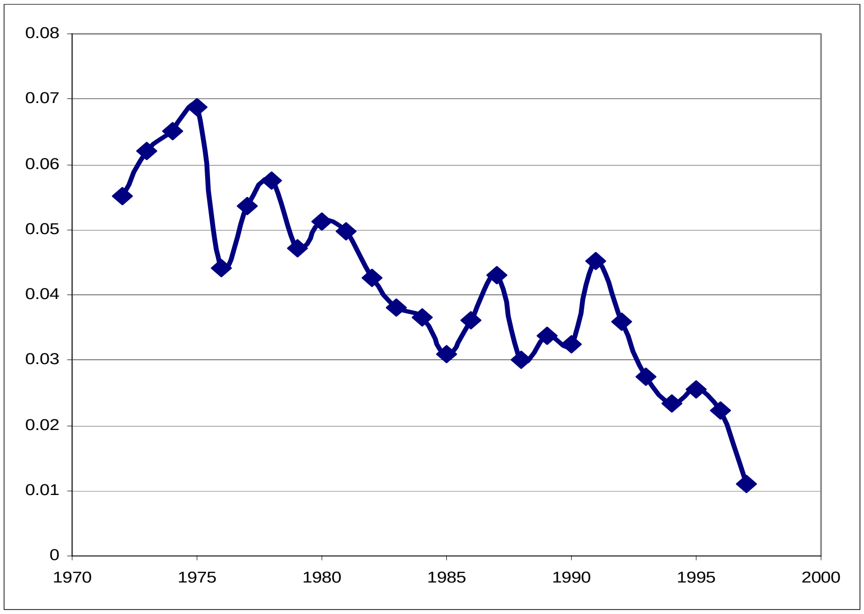
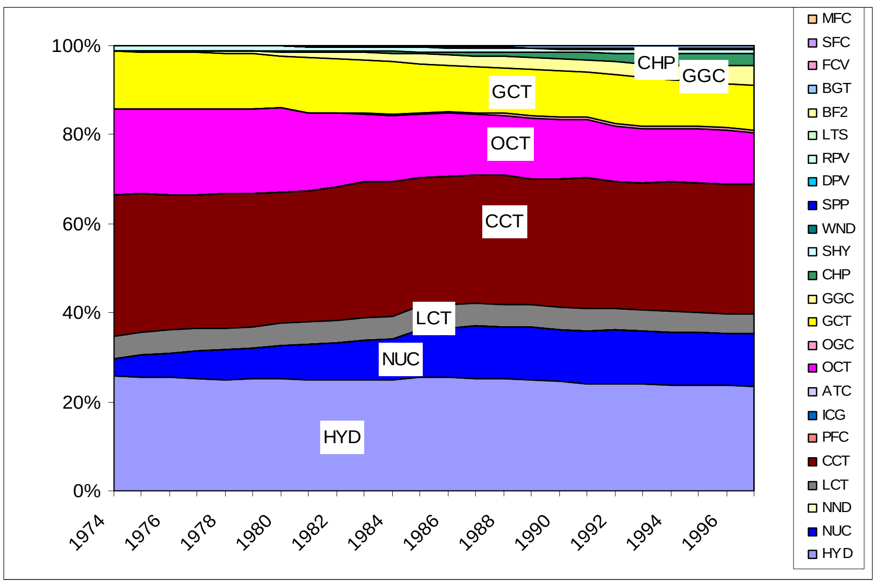


Figure 1-3: World power generation capacities, market shares



The technology-mix at world level shows important but progressive changes along the period considered with the following elements to be underlined:

- the decline in the share of oil-based power generation capacities during the whole period, but particularly pronounced in the late seventies, i.e. after the two oil shocks;
- the marked increase in nuclear share in the late seventies and until the mid-eighties, corresponding to the implementation of the large nuclear power programs immediately after the first oil shock;
- the relative stability of coal and lignite power plants;
- the increase in gas-based power plants, with the decline in conventional gas largely compensated in the nineties by the rapid progress of CHP and GTCC plants.

1.1.2. OECD countries

The slowdown in the expansion of power plant capacities is continuous along the period and the growth in the OECD region is not linear. Nuclear and gas-based solutions (conventional, gas turbines in CC and CHP) are the two categories showing the largest increases, while the shares of hydro, coal and particularly oil power plants are decreasing.

Figure 1-4: OECD power generation capacities, in Mwe

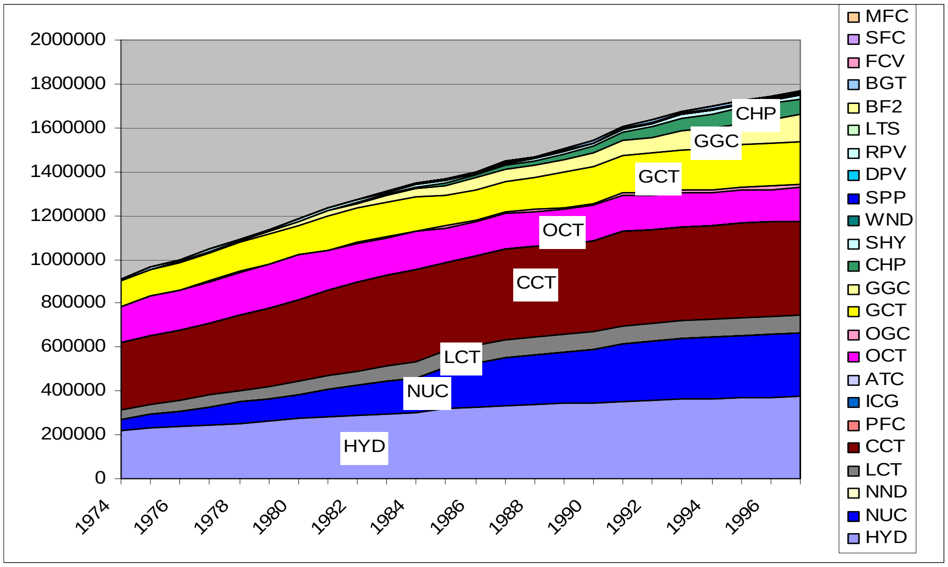
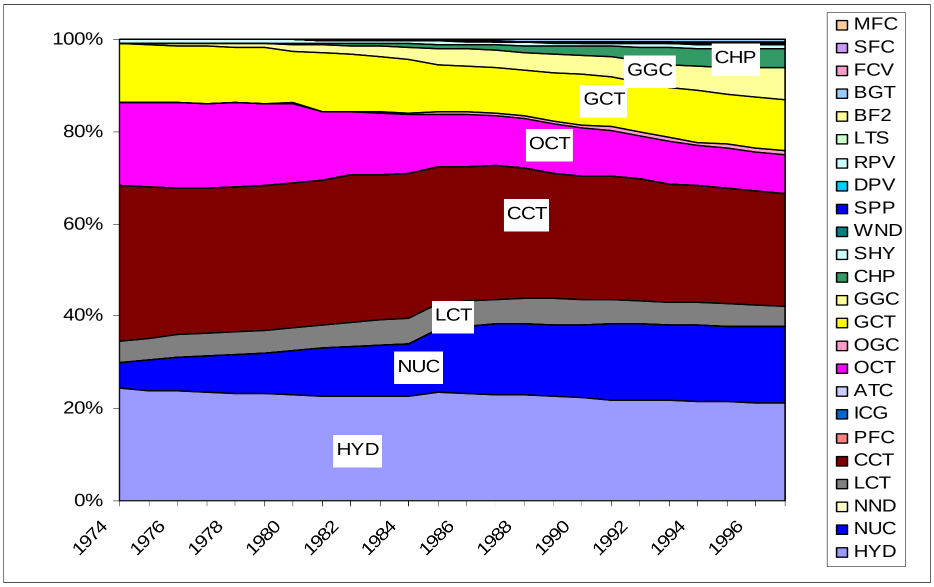


Figure 1-5: OECD power generation capacities, market shares



1.1.3. Economies in Transition

Data gathered for EIT are to be considered with cautious, as they probably reflect important statistical problems, particularly as concerns the total installed capacities. These show indeed an increase in the early nineties that can be hardly explained in the context of the triggering of the transition process. The structure of the installed capacities shows a more regular process, with an increase of nuclear in the eighties and the decline in oil-based capacities by the end of the period, compensated by coal and, to a lesser extent, gas-based power plants.

Figure 1-6: EIT power generation capacities in Mwe

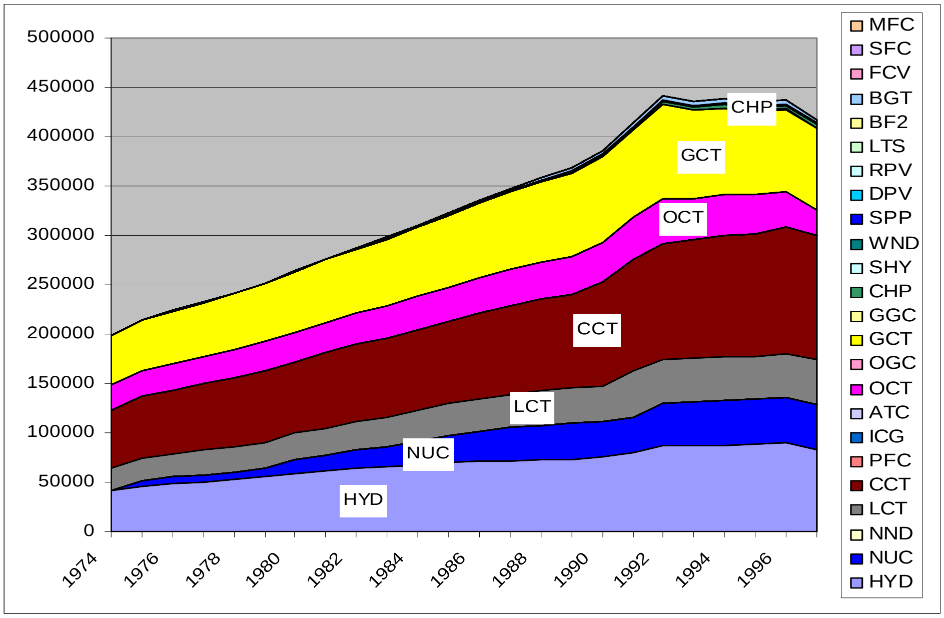
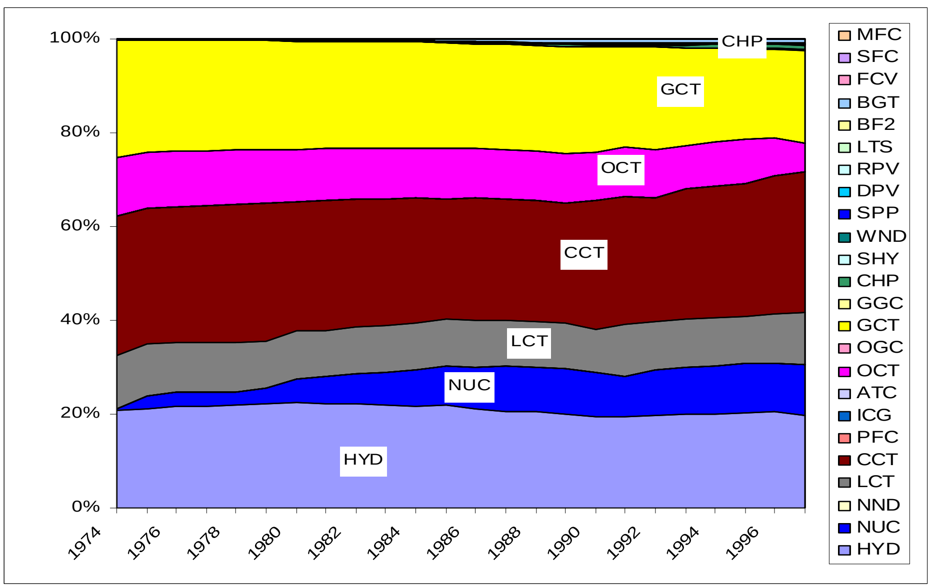


Figure 1-7: EIT power generation capacities, market shares



1.1.4. Asian Countries

The rate of growth in power generation capacities of the Asia region is the fastest of all the regions as it amounts to 8 %pa between 1971 and 1997. Coal-based power plants are largely dominating the market with a 50 % or more market share since the mid-eighties, while oil-based capacities strongly decrease after the second oil shock. Although it remains important the share of hydro is also decreasing and this decrease is not fully compensated by the surge in nuclear capacities.

Figure 1-8: Asia power generation capacities, in Mwe

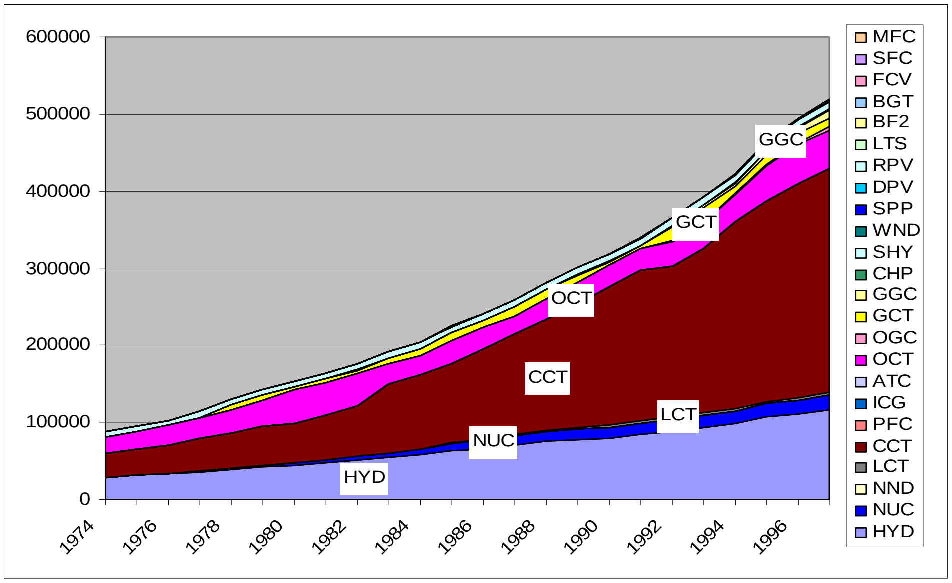
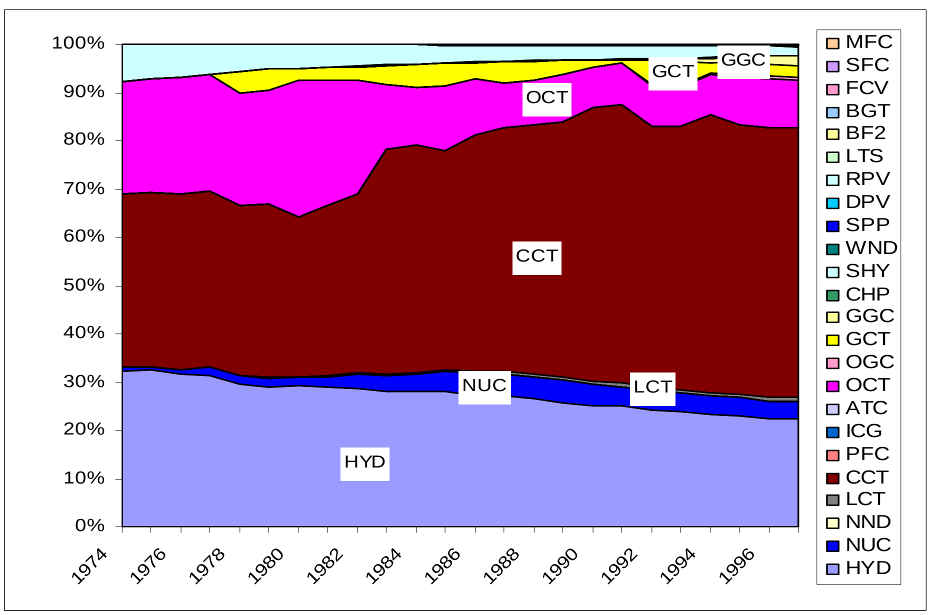


Figure 1-9: ASIA power generation capacities, market shares



1.1.5. Rest of the World

In the Rest of the World regions, the increase in generation capacities slows down significantly between the beginning and the end of the period, with average growth rates of 10 %pa in the seventies but only 4 % on average in the nineties. Large hydro and oil based capacities dominate the market with 40 % of total installed capacities each. The technology mix appears indeed very stable, with the exception of the development of gas-based capacities in the nineties.

Figure 1-10: RoW power generation capacities, in Mwe

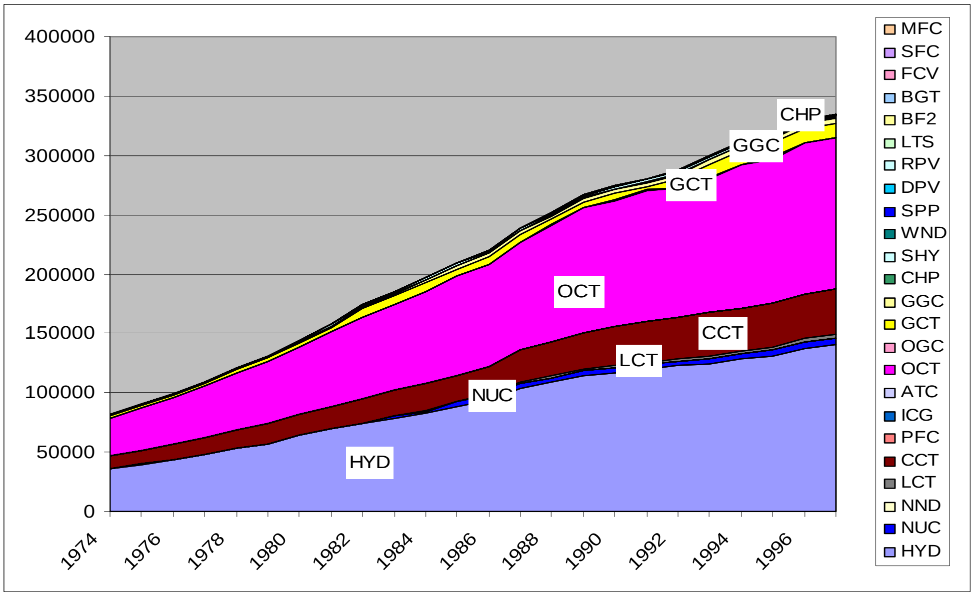
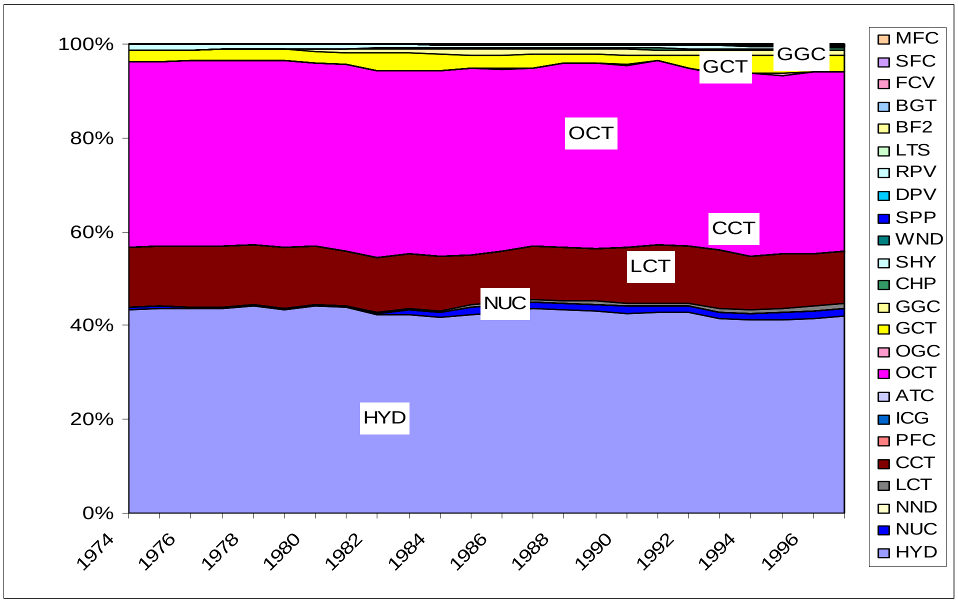


Figure 1-11: RoW power generation capacities, market shares

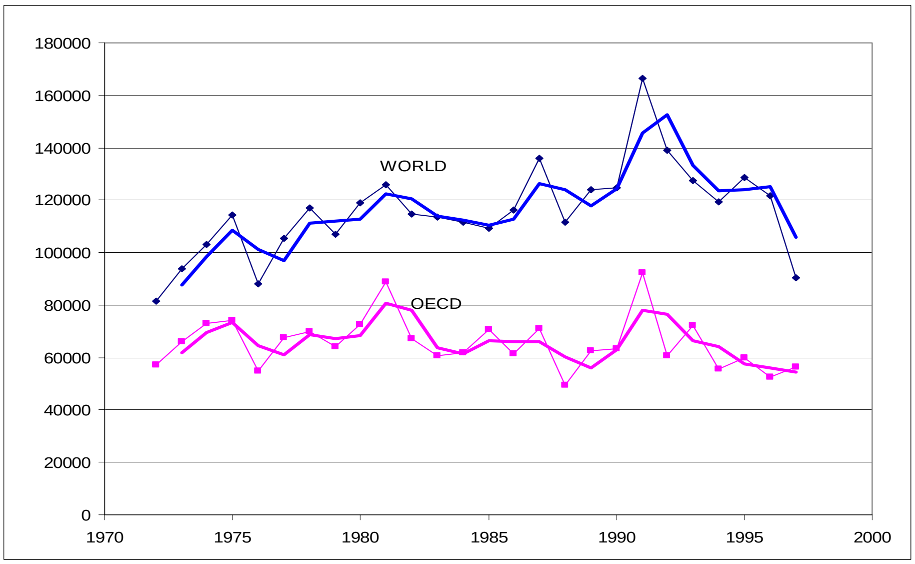


1.2. World and regional sales of power plants (File SourceCAPSpoles)

The SourceSALES file provides estimates for the sales of power generation capacities by main world region, deriving information from the files on installed capacities and costs by POLES technologies. For the estimates of sales in volumes, the use of differentiated scraping rates which take into account the characteristics of the technology (lifetime and age of existing equipment) allows to derive annual sales in MWe from the variation in installed capacities.

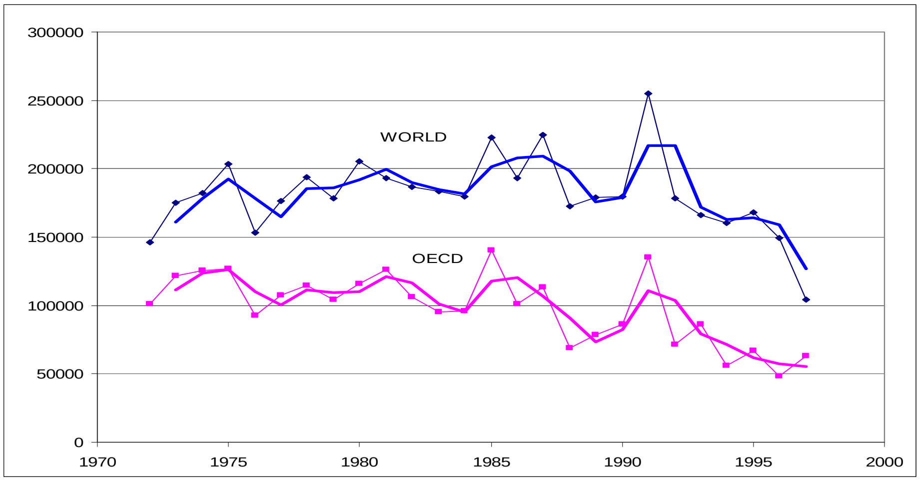
The sales expressed in $90, are then calculated using the costs that appear in file Source COST.xls. In some cases the reference costs had to be taken from other similar technologies, by lack of full cost information for all technologies. This doesn't however bias considerably the estimates as in those cases the quantities sold (in MWe) are negligible or very small.

Figure 1-12: World power generation capacities sales, in MWe



The total world power generation sales in Mwe are increasing moderately during the period considered, from 80 Gwe/yr in the early seventies to 120 Gwe/yr in the late nineties, the slow-down by the end of the period being partly due to evolutions in the EIT. While the OECD region represents three-fourths of the market in the beginning, their share is reduced to about one half of the market since the mid-eighties. Sales in this region are relatively stable, between 60 and 80 GWe/yr.

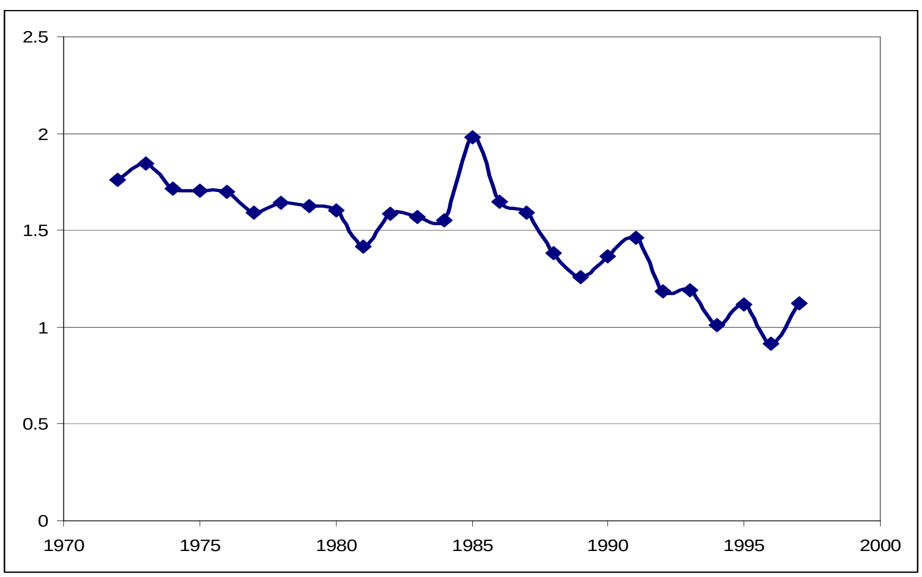
Figure 1-13: World power generation capacities sales, in 103 $90



The total power plant sales in dollars, as estimated from the sales in volume and the costs of the technologies, are relatively stable and amount to about 200 G$90 for most of the period considered, except in the very last years. The share of OECD is decreasing from two-third to one third of the total sales.

The evolution of the total sales indeed results from the combined effect of the variations in sales in volume and of the price/cost of the technologies. The latter in turn depends on the cost dynamics proper to each technology and on a technology-mix effect (some technologies presenting structurally higher costs such as hydro or nuclear). This is illustrated in the average Mwe cost which shows only a slight decline until the mid-eighties, with the development of nuclear power plants, but a marked decline later on, from an average 1 500 to 1 000 $/kWe. This corresponds to the phase of development of the new gas-based capacities, which are both investment-saving and subject to rapid technological progress.

Figure 1-14: Average capacity cost, in 103 $90/kWe

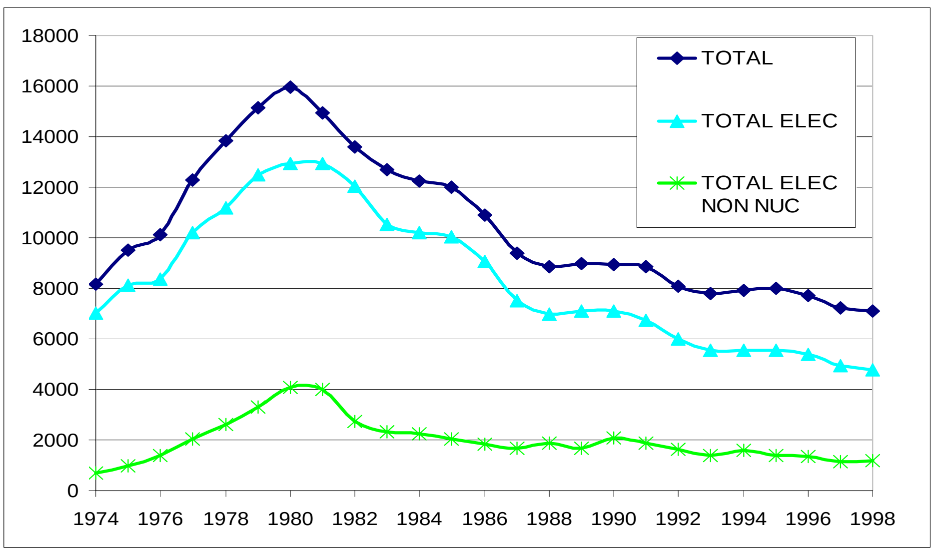


1.3. IEA countries Government Energy R&D (File SourceGERDiea)

The IEA provides statistical data for the Government Energy R&D of most of its member countries in 44 expense categories, including energy efficiency, fossil fuel production and conversion, support activities. The SourceGERDiea file corresponds to the treatment of these IEA Government Energy R&D data, according to the POLES technology framework. Basic information is taken from IEA R&D statistics in national currency, then converted into 1998 constant money and into 1998 US$ (MER). 17 national tables are available and some tables with missing years have been corrected in order not to introduce artificial breaking in the aggregate time-series. The data in M US$ 1998 from these national tables are then all summed-up.

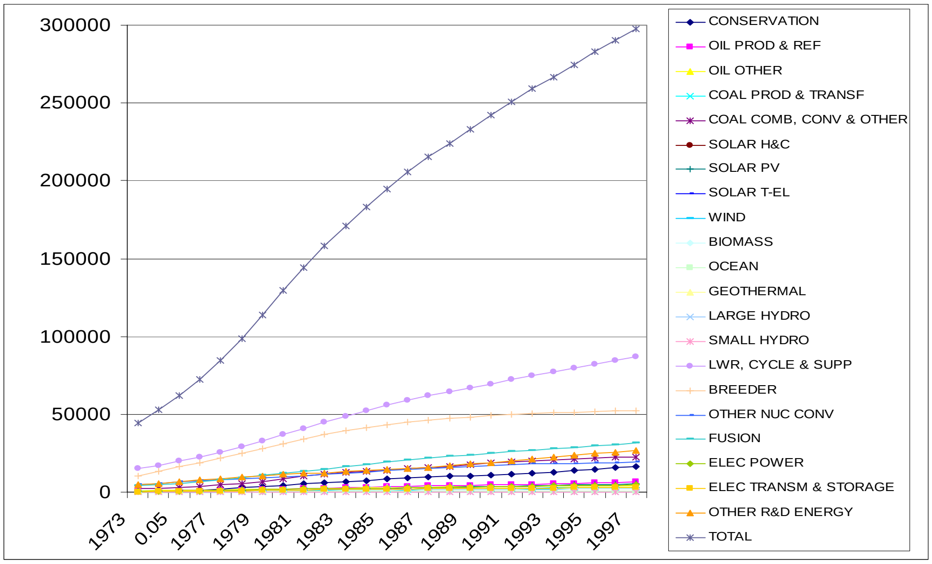
During the period considered, there has been drastic change in the total volume of GERD that first rockets from 8 G$ in 1974 to 16 G$ in 1980 during the second oil shock and then decreases following a profile which is very near to the one of the oil price – down to again 8 G$ during most of the nineties. Power generation technologies are thus only a part of this total R&D, representing approximately three-fourths of the total. Among them, nuclear technologies represent the lion's share, also three-fourths of the power technologies.

Figure 1-15: IEA countries GERD, in M$98



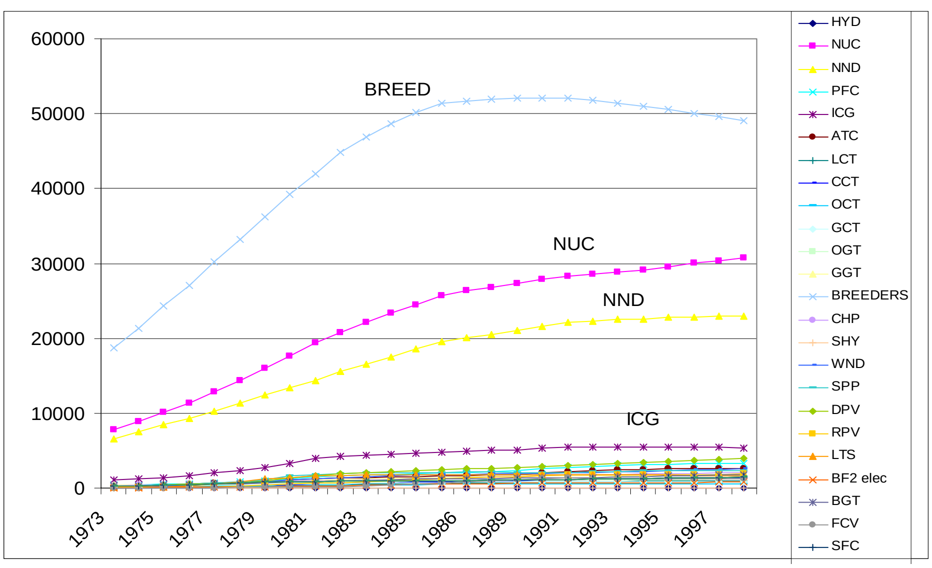
From sheet *GERD-IEAcateg*, the total cumulative GERD spending of IEA countries can be estimated to about 300 G$, of which 200 G$ have been dedicated to nuclear technologies as a whole and 50 G$ to other power generation technologies.

Figure 1-16: Cumulative GERD spending, IEA categories in M$98



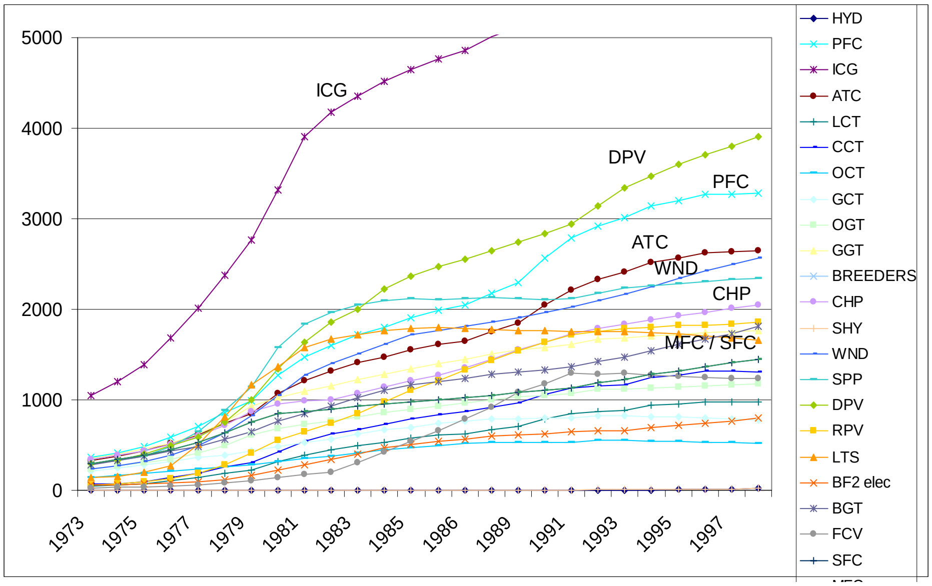
Finally, sheet GERD-POLtechs corresponds to the disaggregation of the IEA data into the 12 conventional and 11 new and renewable POLES technologies. This is done by using a decomposition matrix revisited from the TEEM study (primary source SENSER). GERD time-series are produced for each technology. Cumulative research by technology is then calculated from yearly spending, by using a 3%/yr "R&D scraping rate" for the stock of knowledge and, as far as the initial stock is concerned, by using an hypothesis of linearly increasing effort from a starting date (generally 1960 for conventional technologies and 1970 for new technologies). This revised cumulative R&D time-series thus correspond to the "net" stock of knowledge (i.e. after scraping), not to the cumulative spending for each technology.

Figure 1-17: Net cumulative GERD, all technologies, in M$98



The full disaggregation of net cumulative GERD among the POLES technologies of course confirms the predominance of nuclear technologies, although the slowdown of the nuclear programs in the nineties results in a very low increase of the net stock of R&D and even to a decrease for the breeders. However, all other technologies appear with a net cumulative R&D, inferior to 5 G$, i.e. at least one order of magnitude below nuclear technologies.

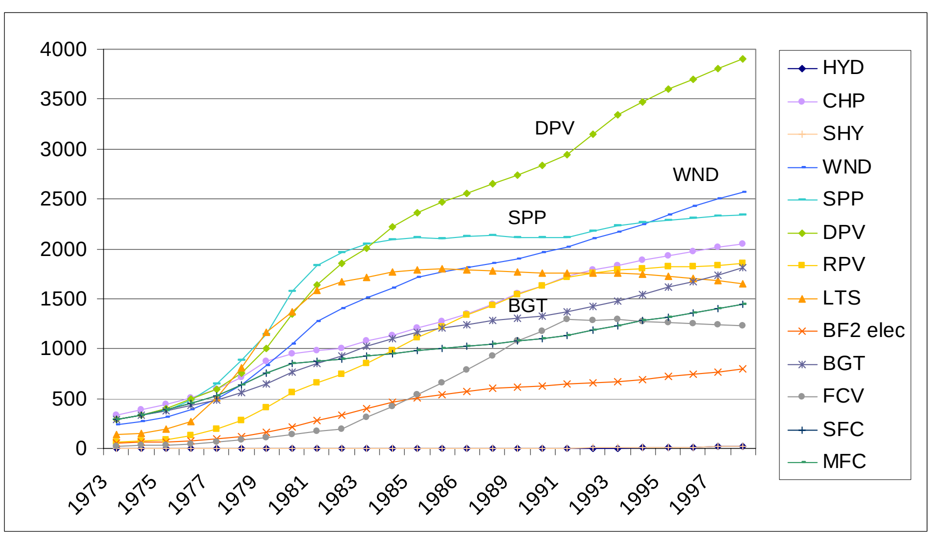
Figure 1-18: Net cumulative GERD, non nuclear technologies, in M$98



As far as renewable technologies are concerned, PV technologies clearly benefit of the highest level of net R&D stock, followed by wind, in the very last years of the period. Some technologies show a marked slowdown since the mid-eighties, particularly the solar thermal power plant technology, while the stabilisation of the R&D stock from government for fuel-cell vehicle may be explained by the fact that, since the mid nineties, large programs have been launched by the industry.

This case however poses the more general problem of the "technological clusters" in which R&D followed by progress in one technology may benefit to other technologies through direct improvements in common components and methods or through technological "spillovers". This problem has not been addressed at this stage but may be further examined in following work.

Figure 1-19: Net cumulative GERD, renewable technologies, in M$98



1.4. Patents for power generation technologies (File SourcePATENTipts)

Research and data collection undertaken at IPTS in SAPIENT has allowed gathering a complete database on the patents submitted since 1970 in the OECD countries for the key power plant technologies. Table 1-3 below provides an example of the process used in order to transform the primary data in the European Patent Office coding system into the POLES technology categories. The corresponding data appear in sheet Data by Technology.

Table 1-3: Example of treatment from EPO primary patent data to POLES categories

6. Oil-powered Conventional Thermal
F01K: Steam engine plants, steam accumulators, engine plants not otherwise provided for.
F23C: Combustion apparatus using fluent fuel
F23D5: Burners in which liquid fuel evaporates in the combustion space
F23D7: Burners in which drops of liquid fuel impinge on a surface
F23D9: Burners in which a stream of liquid fuel impinges intermittently on a hot surface
F23D11: Burners using a direct spraying action of liquid droplets or vaporised liquid
into the combustion space

7. Gas-powered Conventional Thermal
F23D14: Burners for combustion of a gas
F23C: Combustion apparatus using fluent fuel
F01K: Steam engine plants, steam accumulators, engine plants not otherwise provided for.
F02C: Gas-turbine plants

8. Gas Turbine in Combined Cycle
F02C: Gas-turbine plants
F01K23/06: Plants characterised by more than one engine delivering power,
(...) combustion heat from one cycle heating the fluid in another cycle
F23R: Generating combustion products of high pressure or high velocity, e.g. gas turbine
combustion chambers.

9. Combined Heat and Power, small to medium-size cogeneration
F01K17/02: Using steam or condensate extracted or exhausted from steam engine plant,
(...) for heating purposes

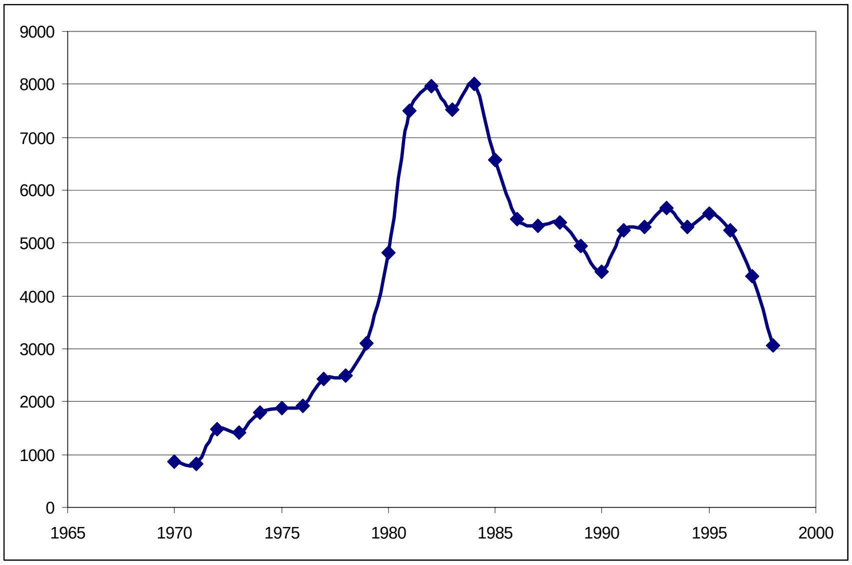
10. Wind power plants for network electricity production
F03D: Wind motors exclu dentist

11. Solar Power Plants (thermal technologies)
F24J2/07: Receivers working at high temperature, e.g. for solar power plants
F03G6: Devices for producing mechanical power from solar energy

12. Photovoltaic systems
H01L: Semiconductor devices
H01G: Capacitors, rectifiers, detectors,switching devices or light sensitive devices,
of the electrolytic type

As illustrated in Figure 1-20 below the total number of patents varies significantly during the period considered, beginning with a low level of 2 000 patents per year between 1970 and 1975 and a peak of 8 000 between 1980 and 1985. Since that time, the annual number is stable at 5 000 patents per year, except in the two last years of observation, during which it drops again.

Figure 1-20: Total number of patents for power generation technologies



As for the number of patents by technology, Figure 1-21 and Figure 1-22 clearly illustrate the dominance of nuclear technologies in the seventies, followed by photovoltaics in the early eighties, while gas powered technologies present the highest share of total patents in the nineties.

Figure 1-21: Total number of patents, 17 technologies

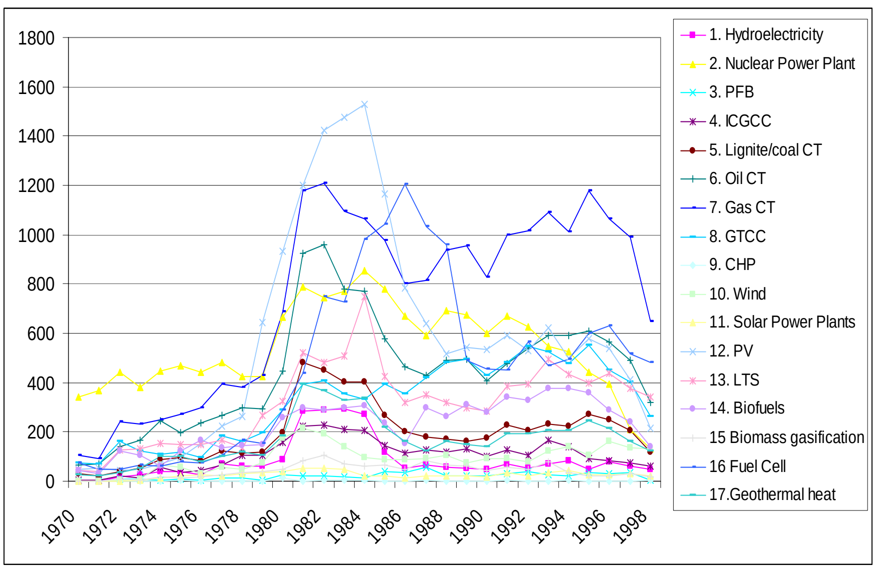
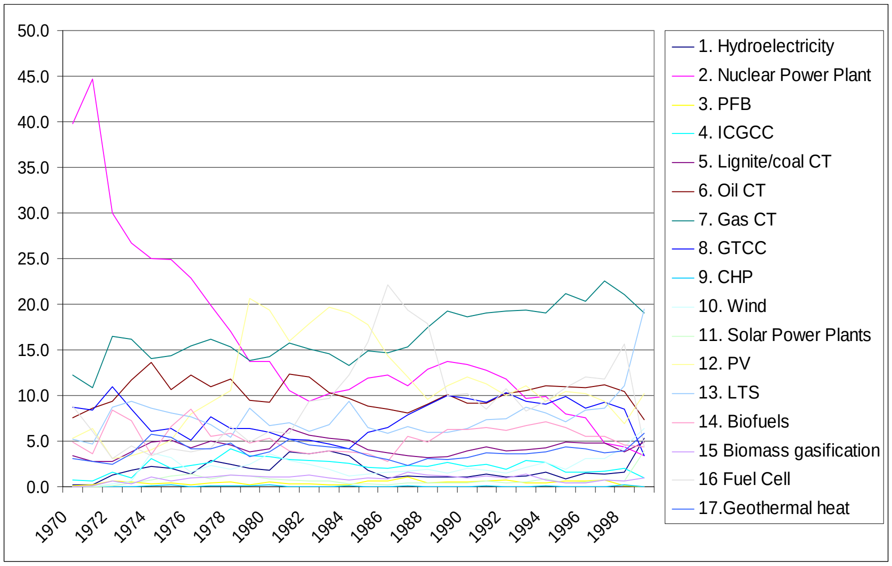


Figure 1-22: Share of total number of patents, 17 technologies



1.5. Business Energy R&D (File SourceBERDiepe)

This file aims at assessing the amount of total Business Energy R&D in the form of a time-series. Due to the difficulties in obtaining reliable results from international data on R&D by SIC categories (which appeared to be highly erratic and didn't correspond with the relevant industry categories) it has been decided to use information on sales and R&D from an international database on business companies developed in the context of another research program of IEPE. This has been made possible by the fact that this database now provides indications on the main segments of activities for each company and thus allows to isolate the power generation equipment production activity.

While sheet BERD-0 incorporates all the available information, sheet BERD-1 manages the relevant information for the project, i.e.:

- Total sales
- Power Generation Equipment Sales (PGES)
- Ratio of total R&D / total sales

While the initial panel regroups 44 companies this information has been processed only for a subset of 14 companies identified as the "key players" in the industry and listed in Table 1-4 below:

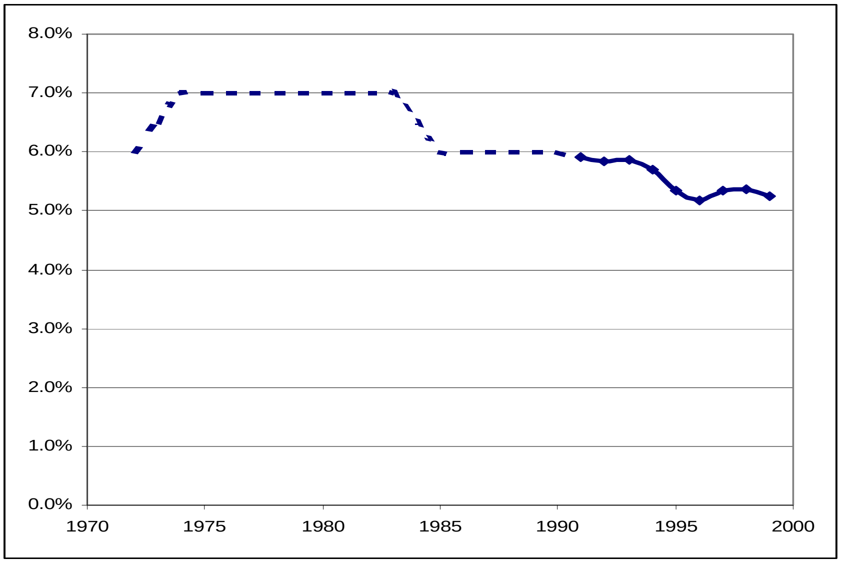
Table 1-4: Key players in the Energy Industry

SIEMENS AG
GENERAL ELECTRIC COMPANY
ABB LTD
ALSTOM SA
HITACHI, LTD.
MITSUBISHI ELECTRIC CORPORATION
TOSHIBA
CORPORATION
FUJI ELECTRIC
CO., LTD.
FOSTER WHEELER CORPORATION
FRAMATOME
GROUP
ROLLS-ROYCE PLC
MAN AG
MITSUBISHI HEAVY INDUSTRIES, LTD.
FUJI HEAVY INDUSTRIES, LTD.

The panel represents total PGES of 90 G$90 in 1995, to be compared with an estimated world PGES of 170 G$90 (53 %) for the world industry from POLES capacities and plant costs (see file SourceSALES.xls). This share is continuously increasing between 1990 and 1997 probably reflecting the increasing concentration of the sector.

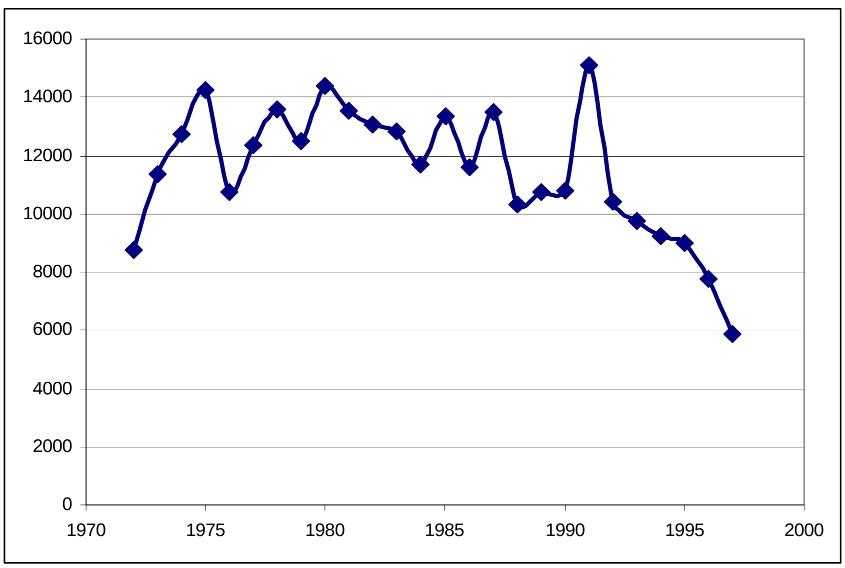
The ratio of BERD/PGES is supposed to be identical to the total R&D/Sales ratio for each company, energy equipment sales are calculated for each company in common units, and then the panel's BERD/PGES is calculated as the average BERD/PGES weighted by the PGES of each company. For the years available in the company database (1991-1999), the outcome is a relatively stable global BERD/PGES ratio, declining however from 5.9 % in 91 to 5.3 % in 1999. In order to allow an estimate of BERD for years prior to 1991, a higher "research intensity", of 7 %, has been supposed for the 1974-1985 period.

Figure 1-23: Ratio of BERD to PGES, 14 companies panel



The resulting picture of the industry total research effort inFigure ***1-24*** shows first a marked increase from the intital 8 G$90 (1 $90 = 1.2 $98) to 12 - 14 G$90 between 1974 and 1987, followed by a decrease to 8 - 10 G$ in the nineties.

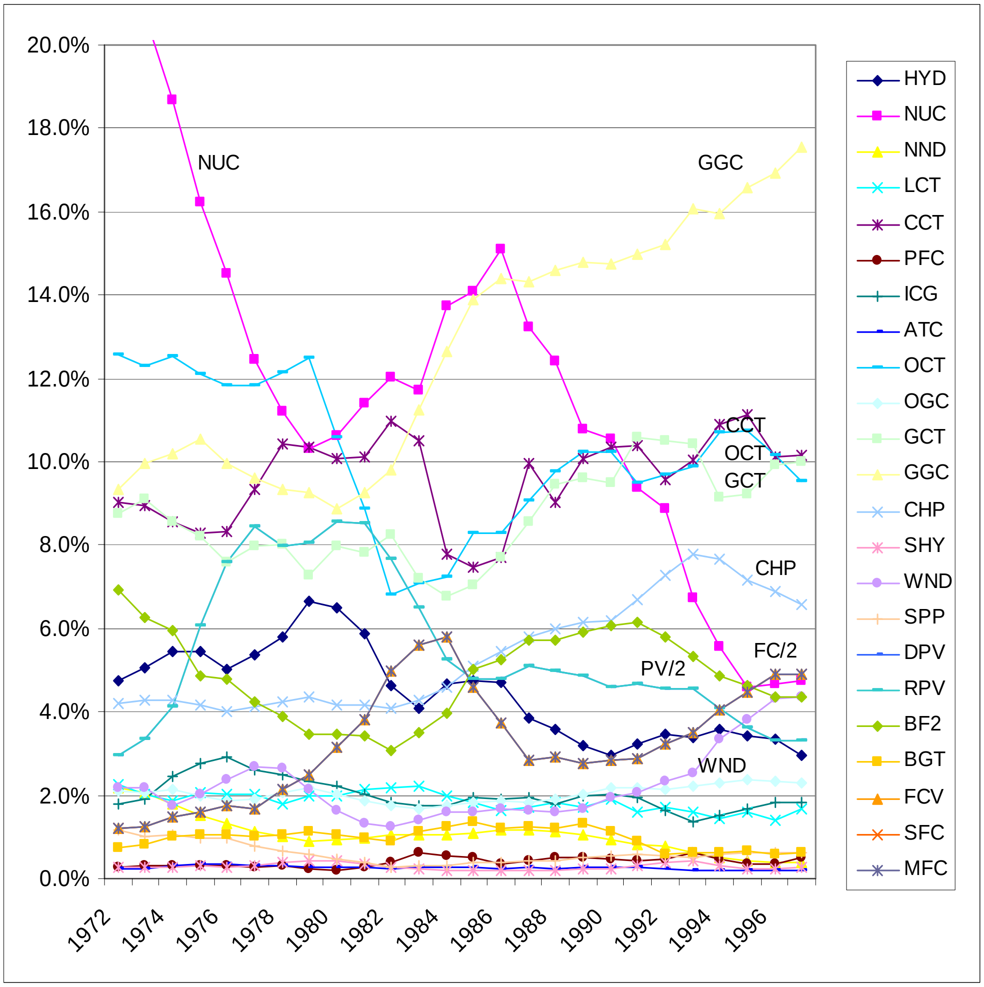
Figure 1-24: Power generation equipment manufacturer's R&D (BERD), in M$90



Finally, sheet BERD-23techs provides an estimate of BERD disaggregated by POLES technology, while using a "mixed indicator", that is a weighted average of the share of a technology in total patents and of the technology sales (respectively 80%-20%). This allows to take into account the patents as main indicators of the relative research intensity for each technology, not ignoring however the sales, as reflecting the weight of the different technologies in the activity of the firms. This aims at encompassing on-going R&D for mature technologies that in many cases do not translate into patenting.

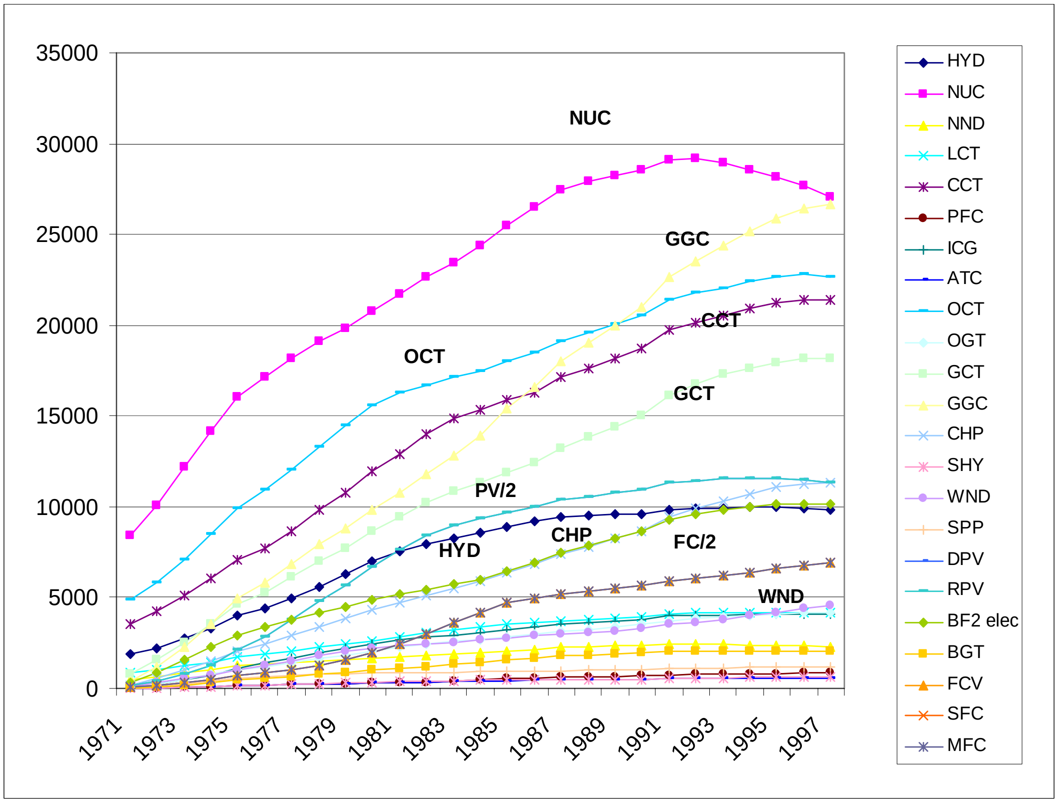
The resulting picture in Figure 1-25 is to some extent different than the one obtained with the pure patent indicator. Indeed Nuclear is now still dominant until the mid-eighties, but later on Gas turbines in Combined Cycle appear as the leading technology with a share of 18 % of total BERD by the end of the period, while nuclear decreases to about 5 %. Conventional technologies whether coal, oil or gas-fuelled represent each 10 % of BERD. CHP amounts to 7 % in 1997, Fuel Cell to 5+5 % (MFC+SFC) and Photovoltaics to 3.5+3.5 % (DPV+RPV). Wind, which represented almost 2% until 1990, is up to 4.5 % in 1997.

Figure 1-25: Shares of BERD by technology



From the new estimates of the technologies' share in total BERD, it is then possible to assess, also in sheet BERD-23techs, the annual R&D spending of industry for each POLES technology and the accumulated stock of knowledge (while using as for the cumulative GERD a 3 % "knowledge scraping rate"). Not surprisingly, the results on "net cumulative BERD" (i.e. after scraping) shown in Figure 1-26 are significantly different from those in Figure 1-17 to Figure 1-18 above for net cumulative GERD. The gap between nuclear and the other technologies is now much narrower and GTCC even gain as much accumulated knowledge by the end of the period than nuclear. Then come the conventional technologies and the new technologies as CHP, photovoltaics, fuel-cells (the three of them with comparable net cumulative GERD) and wind.

Figure 1-26: BERD by technology, in M$90

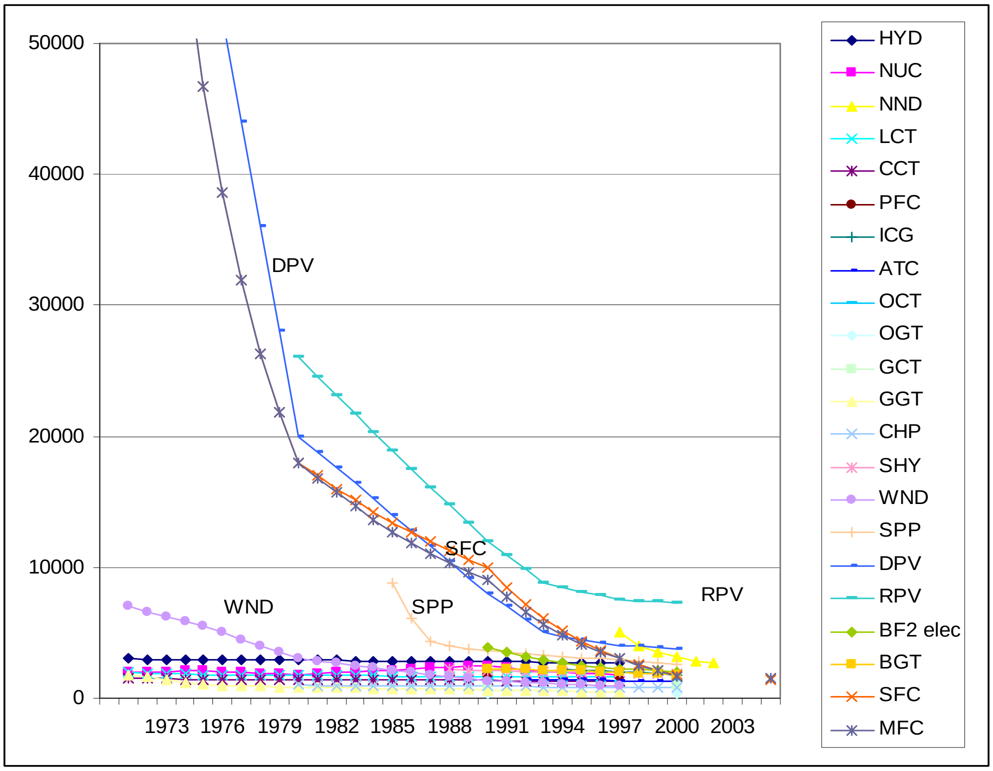


1.6. Technology costs (File SourceCOSTdiv)

For the TFLC studies, only "overnight equipment costs" are considered. Although these data represent key inputs for any analysis of technical change in the power generation technologies, it has been extremely difficult to collect and prepare consistent time-series for most technologies. Some key renewable technologies may constitute an exception, although even in that case the different primary data may also show lack of consistency. The available data, as prepared by different partners in the project (IPTS, IIASA, IEPE) have been gathered in file SourceCOSTdiv.

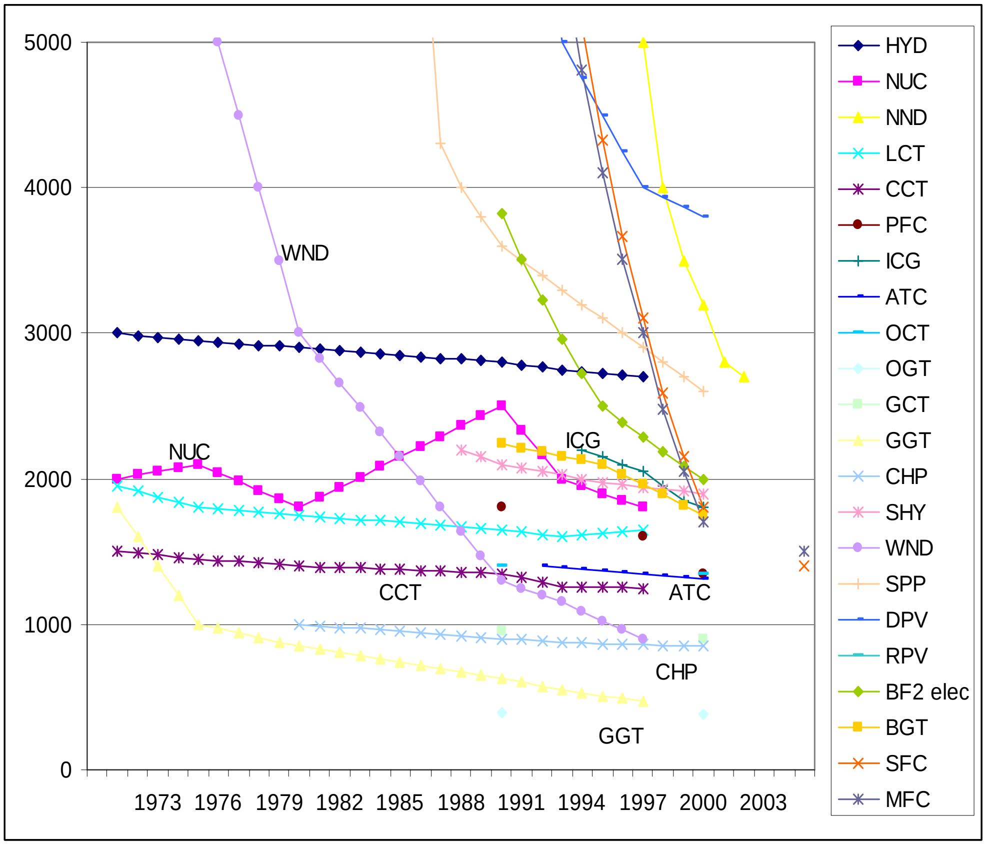
Figure 1-27 shows the results for all technologies and clearly indicate two categories one of very high but steeply decreasing cost (Photovoltaic and Fuel-Cells) and one of medium to low and more gently decreasing cost per installed kWe. Wind and Solar Thermal Power Plants are to some extent an exception as they start with intermediate costs but end, in the case of wind with very low cost level (in these two cases of course, as in the one of photovoltaics the comparison has to take into account the low load factor that characterises "flow renewable technologies").

Figure 1-27: Technology costs, all technologies, in $90/kWe



With regard to the medium to low cost technologies, one has to note the particular profile of nuclear, with a strong increase during the eighties. This can be largely explained by the increase in safety requirements and by the corresponding longer lead-time during this period. Among the other technologies, GTCC clearly presents the lowest costs since 1975 and ends up at a level that is less than half of the one of a conventional coal powerplant.

Figure 1-28: Technology costs, low cost technologies, in $90/kWe



1.7. Synthesis (File SourceSYNTH)

All the corresponding data that are relevant for the study and econometric estimate of the Two Factor Learning Curves are finally organised in the SourceSYNTH file. This file presents the 23 technologies as columns and a series of 7 tables providing all available data for:

Capacities	in MWe
Sales	in M$90
Government Energy R&D	in M$98
Cumulative Government Energy R&D	in M$98, 3% scraping rate
Business Energy R&D	in M$98
Cumulative Business Energy R&D	in M$98, 3% scraping rate
Technology cost	in $90/kWe

This set of data represents the state of the art of the TIDdb and is subsequently used for the estimation of the TFLC for some key technologies. Ultimately, it provides materials for all analyses of the impacts of R&D policies and emission constraints through simulations with the POLES model in the second phase of the SAPIENT project.

Power Generation Capacities as from the POLES model data bases

CAPS	TOT	yagr	HYD	NUC	NND	LCT	CCT	PFC	ICG	ATC	OCT	OGC	GCT
Mwe			Large Hydr	Nuclear LW	New Nucle	Lignite Con	Coal Conve	Pulverised	Integrated	Advanced	Oil Conven	Oil in GTC	Gas Conve
1971	1 071 140		280 596	20 192	0	53 128	364 501	0	0	0	205 117	0	130 617
1972	1 130 067	5.5%	290 393	30 008	0	57 564	377 267	0	0	0	216 904	0	140 639
1973	1 200 135	6.2%	310 468	37 381	0	62 084	391 565	0	0	0	229 466	0	151 573
1974	1 278 063	6.5%	327 853	51 545	0	63 798	406 573	0	0	0	242 859	0	167 522
1975	1 365 684	6.9%	346 850	70 736	0	68 417	423 267	0	0	0	261 295	493	171 961
1976	1 425 841	4.4%	363 098	78 082	0	74 823	432 317	0	0	0	274 078	616	178 728
1977	1 502 221	5.4%	378 880	91 677	0	76 852	450 836	0	0	0	289 401	770	187 986
1978	1 588 589	5.7%	397 706	104 668	0	78 757	476 193	0	0	0	303 882	962	197 173
1979	1 663 348	4.7%	417 498	113 006	0	81 150	499 108	0	0	0	314 946	1 202	204 333
1980	1 748 558	5.1%	440 565	129 162	0	85 923	513 178	0	0	0	333 725	2 115	201 011
1981	1 835 484	5.0%	459 422	147 126	0	88 969	540 116	0	0	0	319 471	2 644	228 860
1982	1 913 683	4.3%	478 240	158 159	0	96 190	571 325	0	0	0	315 968	3 305	234 179
1983	1 986 303	3.8%	493 031	176 211	0	102 744	603 306	0	0	0	303 440	4 131	237 897
1984	2 058 906	3.7%	510 804	188 135	0	107 081	622 530	0	120	0	307 419	5 164	240 463
1985	2 122 609	3.1%	541 951	228 003	0	110 471	608 121	0	120	0	305 957	7 092	227 821
1986	2 199 048	3.6%	558 077	245 935	0	114 094	636 557	0	120	0	308 352	7 734	227 439
1987	2 293 772	4.3%	579 836	268 317	0	115 407	664 641	0	280	0	309 695	8 494	237 473
1988	2 362 885	3.0%	595 378	275 914	0	118 491	682 410	0	280	0	320 127	9 399	240 819
1989	2 442 738	3.4%	607 564	287 416	0	123 564	691 009	0	280	0	334 041	10 487	255 877
1990	2 521 898	3.2%	619 494	294 731	0	121 702	731 733	135	280	0	335 379	11 802	263 899
1991	2 635 909	4.5%	629 947	319 412	0	132 868	773 417	215	280	0	342 079	13 668	268 526
1992	2 730 308	3.6%	655 568	329 973	0	131 413	778 287	215	280	0	338 978	14 124	302 503
1993	2 805 120	2.7%	670 394	338 678	0	130 238	799 408	215	533	0	341 923	12 214	305 874
1994	2 870 588	2.3%	681 542	343 186	0	134 290	827 433	1 394	533	0	346 811	15 060	295 568
1995	2 943 806	2.6%	699 362	348 393	0	131 206	848 873	1 394	795	0	358 980	16 962	298 342
1996	3 009 378	2.2%	710 305	353 810	0	133 143	873 283	1 479	1 365	0	361 755	17 786	299 679
1997	3 042 566	1.1%	716 469	359 583	0	133 157	875 227	5 269	1 872	0	356 018	19 332	301 794
1998								8 294	1 872				
1999								10 318	1 932				
2000								13 878	3 502				

Power Generation Capacities as from the POLES model data bases

CAPS	GGC	CHP	SHY	WND	SPP	DPV	RPV	BF2	BGT	FCV	SFC	MFC
Mwe	Gas in GT(	Combined	Small Hydr	Wind	Solar Therı	Decentralis	Rural PV (l	Electricity p	Biomass G	Fuel Cell V	Solid Oxyd	Molten Carl
1971	0	0	15 019	0	0	0	0	0	0	0	0	0
1972	0	0	15 319	0	0	0	0	0	0	0	0	0
1973	0	0	15 625	0	0	0	0	0	0	0	0	0
1974	0	0	15 938	0	0	0	0	0	0	0	0	0
1975	4 433	0	16 257	0	0	0	0	0	0	0	0	0
1976	5 541	0	16 582	0	0	0	0	0	0	0	0	0
1977	6 926	0	16 914	0	0	1	1	0	0	0	0	0
1978	8 658	1 356	17 252	0	0	2	2	0	0	0	0	0
1979	10 822	1 695	17 597	5	0	3	3	0	0	0	0	0
1980	16 711	3 842	17 949	10	0	6	5	0	2 377	0	0	0
1981	20 888	4 802	18 308	25	0	10	10	0	2 852	0	0	0
1982	26 111	6 003	18 674	90	0	18	17	0	3 422	0	0	0
1983	32 638	7 503	19 047	210	0	27	25	0	4 107	0	0	0
1984	40 798	9 379	19 428	600	0	37	34	0	4 928	0	0	0
1985	50 997	11 724	19 817	1 020	0	48	45	1 523	5 914	0	0.008	0.007
1986	53 573	14 655	20 213	1 270	0	61	57	1 827	7 097	0	0.016	0.014
1987	56 397	18 319	20 617	1 450	0	78	72	2 193	8 516	0	0.019	0.028
1988	59 533	22 898	21 030	1 580	0	97	90	2 632	10 219	0	0.021	0.032
1989	63 057	28 623	21 450	1 730	0	119	111	3 158	12 263	0	0.024	0.036
1990	67 068	32 603	21 896	1 930	298	131	147	3 427	13 252	0	0.028	0.041
1991	71 379	39 223	22 564	2 170	344	151	181	3 613	13 881	0	0.032	0.091
1992	77 940	52 304	25 088	2 510	329	176	212	3 831	14 584	0	0.036	0.156
1993	88 727	64 949	26 817	2 990	388	210	239	4 013	15 317	0	0.040	0.176
1994	98 020	71 680	27 999	3 680	357	254	265	4 349	16 169	0	0.044	0.196
1995	105 804	78 590	27 448	4 820	356	273	330	4 627	15 255	0	0.124	0.796
1996	123 380	77 280	26 897	6 115	385	298	402	4 903	15 115	0	0.214	1.496
1997	136 308	78 268	27 668	7 630	379	402	539	5 016	15 635	0	0.304	2.196
1998											0.394	2.676
1999												
2000												

Cumulative Government energy R&D, as from IEA statistics and hypotheses on initial stock and scraping rate (3%/yr)

CGERD	TOT	yagr	HYD	NUC	NND	LCT	CCT	PFC	ICG	ATC	OCT	OGT	GCT
M$98 3%SR													
1971													
1972													
1973													
1974	24 017		0	8 834	7 512	58	76	413	1 202	371	163	270	244
1975	27 096	12.8%	0	10 122	8 414	75	100	482	1 394	432	186	306	279
1976	30 455	12.4%	0	11 282	9 321	100	137	585	1 677	521	214	346	321
1977	34 577	13.5%	0	12 794	10 270	139	192	702	2 009	616	240	418	360
1978	39 226	13.4%	0	14 348	11 286	184	254	855	2 379	740	261	498	392
1979	44 407	13.2%	0	15 929	12 421	226	311	994	2 762	853	286	617	430
1980	50 172	13.0%	0	17 598	13 402	313	426	1 269	3 323	1 069	321	680	482
1981	55 295	10.2%	0	19 361	14 315	393	538	1 466	3 901	1 217	353	729	529
1982	59 596	7.8%	0	20 841	15 520	450	618	1 606	4 173	1 323	380	768	570
1983	63 398	6.4%	0	22 145	16 482	492	676	1 715	4 355	1 407	414	817	620
1984	67 027	5.7%	0	23 344	17 469	528	727	1 806	4 514	1 475	443	859	665
1985	70 730	5.5%	0	24 528	18 654	571	785	1 910	4 650	1 554	466	895	699
1986	73 775	4.3%	0	25 652	19 520	607	835	1 993	4 768	1 615	493	934	739
1987	76 048	3.1%	0	26 364	20 137	629	867	2 044	4 860	1 653	512	967	768
1988	78 055	2.6%	0	26 779	20 521	670	919	2 172	5 012	1 750	524	1 004	786
1989	80 331	2.9%	0	27 392	21 100	709	965	2 295	5 112	1 843	529	1 036	794
1990	82 662	2.9%	0	27 824	21 617	786	1 053	2 568	5 313	2 049	531	1 052	796
1991	84 874	2.7%	0	28 278	22 086	848	1 126	2 784	5 431	2 215	531	1 074	797
1992	86 545	2.0%	2	28 574	22 339	871	1 150	2 916	5 495	2 325	550	1 114	824
1993	87 786	1.4%	4	28 854	22 496	887	1 168	3 013	5 526	2 406	548	1 120	822
1994	89 058	1.4%	6	29 144	22 615	941	1 251	3 147	5 506	2 515	543	1 135	814
1995	90 253	1.3%	11	29 581	22 757	956	1 276	3 197	5 487	2 561	538	1 147	807
1996	91 403	1.3%	15	30 018	22 864	981	1 316	3 267	5 459	2 621	533	1 159	800
1997	92 226	0.9%	17	30 388	22 927	976	1 313	3 275	5 411	2 636	526	1 170	790
1998	92 923	0.8%	18	30 715	22 902	971	1 308	3 282	5 362	2 648	520	1 177	780

Cumulative Government energy R&D, as from IEA statistics and hypotheses on initial stock and scraping rate (3%/yr)

CGERD	GGT	CHP	SHY	WND	SPP	DPV	RPV	BF2 elec	BGT	FCV	SFC	MFC
M$98 3%SR												
1971												
1972												
1973												
1974	405	387	1	272	332	334	72	61	329	31	337	337
1975	458	438	1	316	382	394	91	69	374	37	385	385
1976	519	503	2	391	487	492	126	79	433	47	448	448
1977	626	598	2	499	648	594	192	95	486	64	529	529
1978	747	716	2	637	883	749	284	122	560	85	632	632
1979	925	869	2	828	1 138	1 000	406	166	650	111	753	753
1980	1 020	952	2	1 046	1 573	1 347	556	218	762	140	847	847
1981	1 094	983	2	1 271	1 831	1 639	653	282	848	172	869	869
1982	1 152	1 001	2	1 405	1 961	1 855	741	338	925	196	894	894
1983	1 226	1 073	2	1 506	2 045	2 002	853	404	1 019	311	925	925
1984	1 288	1 136	2	1 606	2 089	2 223	980	465	1 105	420	950	950
1985	1 343	1 208	3	1 719	2 112	2 365	1 106	511	1 166	543	978	978
1986	1 400	1 271	3	1 769	2 107	2 466	1 216	542	1 205	656	999	999
1987	1 451	1 348	3	1 810	2 120	2 553	1 332	570	1 240	789	1 021	1 021
1988	1 506	1 445	3	1 854	2 131	2 650	1 435	599	1 283	923	1 050	1 050
1989	1 553	1 557	3	1 900	2 113	2 739	1 546	616	1 308	1 077	1 077	1 077
1990	1 578	1 631	3	1 960	2 110	2 834	1 632	626	1 329	1 179	1 101	1 101
1991	1 612	1 729	4	2 019	2 113	2 944	1 720	645	1 368	1 299	1 132	1 132
1992	1 671	1 791	11	2 098	2 178	3 146	1 752	657	1 427	1 287	1 188	1 188
1993	1 679	1 837	12	2 169	2 233	3 341	1 792	664	1 473	1 291	1 229	1 229
1994	1 702	1 885	13	2 245	2 260	3 470	1 805	692	1 544	1 275	1 278	1 278
1995	1 720	1 926	14	2 338	2 287	3 597	1 818	720	1 614	1 263	1 320	1 320
1996	1 738	1 969	16	2 428	2 308	3 703	1 825	742	1 675	1 249	1 362	1 362
1997	1 755	2 014	18	2 498	2 328	3 803	1 838	762	1 734	1 239	1 406	1 406
1998	1 765	2 052	19	2 567	2 337	3 905	1 854	799	1 812	1 234	1 448	1 448

Business Energy R&D, as from company R&D data and disaggregation using a mixed indicator (here 20%/SALES - 80%/PATENTS)

BERD	TOT	yagr	HYD	NUC	NND	LCT	CCT	PFC	ICG	ATC	OCT	OGT	GCT
M$98	1$90=1.2$98												
1971													
1972	10 532		430	2 437	243	254	1 005	33	173	23	1 288	206	919
1973	13 654	29.6%	739	2 764	283	287	1 166	29	260	32	1 762	302	1 204
1974	15 308	12.1%	868	2 881	273	244	1 347	56	331	43	1 806	301	1 500
1975	17 079	11.6%	907	2 904	259	335	1 423	66	569	71	2 209	375	1 214
1976	12 879	-24.6%	685	1 661	161	337	996	17	356	41	1 485	225	996
1977	14 817	15.0%	658	2 025	183	229	1 320	62	393	51	1 640	250	1 167
1978	16 280	9.9%	1 032	1 765	156	307	1 843	43	399	49	2 106	371	1 347
1979	14 980	-8.0%	991	1 360	125	285	1 649	33	346	42	1 855	330	1 179
1980	17 256	15.2%	1 213	1 900	159	375	1 507	33	391	47	2 107	349	988
1981	16 229	-6.0%	946	1 907	160	297	1 697	25	344	41	1 158	305	1 669
1982	15 688	-3.3%	742	1 793	166	384	1 750	78	273	39	1 145	265	1 163
1983	15 388	-1.9%	515	1 976	165	356	1 734	78	251	37	916	254	1 083
1984	14 045	-8.7%	581	1 529	137	271	1 275	117	266	42	1 124	228	1 000
1985	16 037	14.2%	1 043	2 797	181	283	483	49	283	37	1 252	317	981
1986	13 925	-13.2%	500	1 936	167	247	1 442	54	297	39	1 262	267	1 099
1987	16 178	16.2%	657	2 265	193	224	1 570	66	290	39	1 297	285	1 465
1988	12 404	-23.3%	481	1 455	143	242	1 223	61	243	34	1 253	230	1 083
1989	12 867	3.7%	360	1 473	137	270	968	77	203	31	1 432	264	1 354
1990	12 924	0.4%	377	1 179	114	135	1 659	54	310	40	1 226	281	1 237
1991	18 095	40.0%	570	2 000	163	461	1 940	66	387	50	1 827	414	1 528
1992	12 472	-31.1%	458	996	90	155	943	68	166	26	1 117	263	1 710
1993	11 695	-6.2%	415	886	81	152	1 221	59	161	24	1 165	231	1 096
1994	11 062	-5.4%	331	518	48	243	1 346	93	152	25	1 184	285	913
1995	10 769	-2.6%	447	482	44	94	1 090	9	191	22	1 226	251	1 050
1996	9 334	-13.3%	297	426	38	158	1 038	9	171	19	942	204	899
1997	7 022	-24.8%	193	347	29	114	642	65	130	14	632	170	730

Business Energy R&D, as from company R&D data and disaggregation using a mixed indicator (here 20%/SALES - 80%/PATENTS)

BERD M$98	GGT	CHP	SHY	WND	SPP	DPV	RPV	BF2 elec	BGT	FCV	SFC	MFC
1971												
1972	1 037	441	31	306	109	246	246	643	62	133	133	133
1973	1 202	579	31	199	173	492	492	1 060	122	158	158	158
1974	1 722	680	53	328	119	634	634	758	141	196	196	196
1975	1 803	711	52	292	194	799	799	887	201	336	336	336
1976	1 271	493	38	286	132	1 208	1 208	565	143	192	192	192
1977	1 406	601	38	476	107	1 284	1 284	709	135	267	267	267
1978	1 534	740	71	425	105	1 186	1 186	586	164	288	288	288
1979	1 363	626	63	322	89	1 200	1 200	485	177	420	420	420
1980	1 590	750	76	290	97	1 528	1 528	616	210	501	501	501
1981	1 341	637	65	182	45	1 433	1 433	574	127	614	614	614
1982	1 613	663	40	191	51	1 233	1 233	503	152	737	737	737
1983	1 672	639	28	221	27	969	969	378	138	994	994	994
1984	1 767	631	29	223	53	741	741	687	214	797	797	797
1985	2 330	818	31	285	63	677	677	733	203	838	838	838
1986	2 033	787	27	195	52	675	675	776	178	406	406	406
1987	2 283	899	30	297	58	859	859	904	177	488	488	488
1988	1 773	761	29	201	74	630	630	738	165	318	318	318
1989	1 973	803	25	176	44	580	580	727	150	413	413	413
1990	1 907	784	28	257	75	652	652	791	188	326	326	326
1991	2 562	1 125	45	439	134	773	774	1 172	131	511	511	511
1992	1 995	977	59	217	51	586	586	731	58	407	407	407
1993	1 815	915	52	335	54	548	548	593	61	427	427	427
1994	1 842	848	41	325	72	474	474	564	93	397	397	397
1995	1 689	810	16	459	66	353	354	471	59	528	528	528
1996	1 627	586	14	401	58	306	307	408	52	458	458	458
1997	1 243	480	27	311	43	232	232	306	49	344	344	344

Cumulative Business Energy R&D, using the same hypotheses than for CGERD

CBERD	M$98	HYD	NUC	NND	LCT	CCT	PFC	ICG	ATC	OCT	OGT	GCT
1971	22 506	1 850	8 450	448	879	3 522	11	75	10	4 896	89	812
1972	30 607	2 211	10 101	627	1 051	4 210	34	229	29	5 852	269	1 558
1973	41 067	2 720	12 157	842	1 251	5 103	66	438	56	7 077	494	2 548
1974	52 592	3 336	14 177	1 045	1 454	6 042	105	740	94	8 465	750	3 566
1975	65 247	4 009	16 063	1 229	1 703	7 040	144	1 109	139	9 931	1 008	4 628
1976	74 022	4 428	17 139	1 336	1 872	7 722	173	1 389	174	10 904	1 178	5 302
1977	84 149	4 957	18 165	1 437	2 064	8 642	201	1 671	208	12 040	1 378	6 126
1978	95 191	5 595	19 139	1 531	2 244	9 795	236	1 956	244	13 324	1 616	7 029
1979	104 819	6 259	19 852	1 598	2 424	10 793	257	2 190	272	14 486	1 838	7 728
1980	116 055	7 005	20 782	1 681	2 635	11 917	277	2 445	302	15 572	2 075	8 641
1981	126 098	7 588	21 700	1 765	2 846	12 927	307	2 648	328	16 306	2 265	9 438
1982	135 388	7 966	22 619	1 848	3 048	13 972	348	2 808	351	16 705	2 425	10 232
1983	144 150	8 249	23 443	1 925	3 243	14 899	416	2 948	374	17 113	2 564	10 847
1984	151 529	8 547	24 346	1 991	3 380	15 363	468	3 066	393	17 448	2 692	11 313
1985	160 348	8 925	25 497	2 078	3 522	15 902	522	3 232	417	18 032	2 857	11 915
1986	167 142	9 204	26 486	2 152	3 607	16 318	549	3 355	433	18 454	2 990	12 449
1987	175 609	9 446	27 473	2 247	3 728	17 173	590	3 518	456	19 122	3 148	13 230
1988	180 678	9 532	27 930	2 297	3 804	17 591	624	3 596	468	19 556	3 249	13 809
1989	185 980	9 589	28 247	2 339	3 872	18 144	659	3 701	484	20 067	3 369	14 425
1990	191 171	9 620	28 535	2 371	3 960	18 715	689	3 809	499	20 567	3 502	15 016
1991	200 515	9 820	29 095	2 425	4 084	19 718	735	3 990	524	21 384	3 727	16 161
1992	204 893	9 885	29 144	2 433	4 138	20 122	761	4 038	532	21 748	3 836	16 768
1993	208 492	9 920	28 928	2 420	4 168	20 498	800	4 050	537	22 058	3 937	17 283
1994	211 456	9 951	28 574	2 394	4 178	20 889	819	4 067	540	22 381	4 031	17 606
1995	214 086	9 962	28 127	2 360	4 195	21 262	825	4 094	543	22 672	4 122	17 905
1996	215 442	9 924	27 646	2 321	4 178	21 412	829	4 113	542	22 783	4 179	18 140
1997	214 830	9 800	27 095	2 275	4 149	21 363	834	4 097	538	22 658	4 188	18 182

Cumulative Business Energy R&D, using the same hypotheses than for CGERD

CBERD	GGC	CHP	SHY	WND	SPP	DPV	RPV	BF2 elec	BGT	FCV	SFC	MFC
1971	397	179	11	93	49	126	126	295	32	52	52	52
1972	1 203	544	34	282	149	383	383	895	96	156	156	156
1973	2 301	1 015	66	520	261	754	754	1 582	184	292	292	292
1974	3 534	1 531	101	730	389	1 259	1 259	2 296	306	471	471	471
1975	4 930	2 075	143	996	516	2 085	2 085	2 917	449	682	682	682
1976	5 853	2 444	169	1 222	604	2 836	2 836	3 343	550	850	850	850
1977	6 862	2 882	204	1 516	684	3 794	3 794	3 769	658	1 032	1 032	1 032
1978	7 923	3 373	248	1 831	753	4 763	4 763	4 181	778	1 290	1 290	1 290
1979	8 839	3 816	294	2 044	805	5 626	5 626	4 489	897	1 562	1 562	1 562
1980	9 848	4 298	346	2 220	850	6 689	6 689	4 850	1 022	1 970	1 970	1 970
1981	10 804	4 732	385	2 335	877	7 639	7 639	5 169	1 125	2 425	2 425	2 425
1982	11 761	5 126	410	2 429	884	8 412	8 412	5 415	1 207	3 003	3 003	3 003
1983	12 850	5 523	425	2 537	896	8 991	8 991	5 704	1 316	3 632	3 632	3 632
1984	13 946	5 893	435	2 648	906	9 337	9 337	5 998	1 420	4 201	4 201	4 201
1985	15 386	6 396	449	2 781	929	9 696	9 696	6 488	1 559	4 690	4 690	4 690
1986	16 597	6 835	458	2 891	945	9 962	9 962	6 902	1 653	4 981	4 981	4 981
1987	18 031	7 409	471	3 022	976	10 348	10 347	7 463	1 770	5 213	5 213	5 213
1988	18 997	7 804	478	3 098	992	10 550	10 550	7 831	1 840	5 360	5 360	5 360
1989	20 013	8 229	487	3 183	1 016	10 757	10 757	8 230	1 926	5 496	5 496	5 496
1990	21 001	8 648	496	3 295	1 046	10 930	10 931	8 638	1 988	5 638	5 638	5 638
1991	22 629	9 400	528	3 506	1 101	11 307	11 307	9 307	2 062	5 902	5 902	5 902
1992	23 532	9 876	553	3 645	1 124	11 441	11 441	9 631	2 059	6 062	6 062	6 062
1993	24 391	10 337	578	3 781	1 140	11 542	11 542	9 863	2 056	6 222	6 222	6 222
1994	25 129	10 734	591	3 977	1 158	11 572	11 572	10 013	2 053	6 408	6 408	6 408
1995	25 864	11 054	593	4 201	1 180	11 549	11 550	10 127	2 050	6 617	6 617	6 617
1996	26 406	11 258	593	4 412	1 192	11 459	11 460	10 163	2 035	6 800	6 800	6 800
1997	26 641	11 304	591	4 534	1 192	11 308	11 309	10 113	2 011	6 883	6 883	6 883

Cost data from different sources (IEPE-IPTS-IIASA-DOE)

COSTdiv	TOT	HYD	NUC	NND	LCT	CCT	PFC	ICG	ATC	OCT	OGT	GCT
$90/kW												
1971		3 000	2 000		1 950	1 500						
1972		2 988	2 025		1 913	1 488						
1973		2 975	2 050		1 875	1 475						
1974		2 963	2 075		1 838	1 463						
1975		2 950	2 100		1 800	1 450						
1976		2 940	2 040		1 790	1 440						
1977		2 930	1 980		1 780	1 430						
1978		2 920	1 920		1 770	1 420						
1979		2 910	1 860		1 760	1 410						
1980		2 900	1 800		1 750	1 400						
1981		2 890	1 870		1 740	1 395						
1982		2 880	1 940		1 730	1 390						
1983		2 870	2 010		1 720	1 385						
1984		2 860	2 080		1 710	1 380						
1985		2 850	2 150		1 700	1 375						
1986		2 840	2 220		1 690	1 370						
1987		2 830	2 290		1 680	1 365						
1988		2 820	2 360		1 670	1 360						
1989		2 810	2 430		1 660	1 355						
1990		2 800	2 500		1 650	1 350	1 800			1 400	390	950
1991		2 783	2 333		1 633	1 320						
1992		2 767	2 167		1 617	1 290			1 400			
1993		2 750	2 000		1 600	1 261			1 390			
1994		2 738	1 950		1 613	1 258		2 200	1 380			
1995		2 725	1 900		1 625	1 256		2 150	1 370			
1996		2 713	1 850		1 638	1 253		2 100	1 355			
1997		2 700	1 800	5 000	1 650	1 250	1 600	2 050	1 345			
1998				4 000				1 950	1 330			
1999				3 500				1 850	1 320			
2000				3 200			1 350	1 800	1 310	1 350	380	900
2001				2 800								
2002				2 700								
2003												
2004												
2005												

Cost data from different sources (IEPE-IPTS-IIASA-DOE)

COSTdiv	GGT	CHP	SHY	WND	SPP	DPV	RPV	BF2 elec	BGT	FCV	SFC	MFC
$90/kW										15 kW vcle		
1971	1 800			7 000		150 000					100 000	100 000
1972	1 600			6 625		127 500					82 652	82 652
1973	1 400			6 250		105 000					68 313	68 313
1974	1 200			5 875		82 500					56 462	56 462
1975	1 000			5 500		60 000					46 667	46 667
1976	970			5 000		52 000					38 571	38 571
1977	940			4 500		44 000					31 880	31 880
1978	910			4 000		36 000					26 349	26 349
1979	880			3 500		28 000					21 778	21 778
1980	850	1 000		3 000		20 000	26 000				18 000	18 000
1981	828	990		2 830		18 800	24 562				16 972	16 795
1982	806	980		2 660		17 600	23 133				16 004	15 670
1983	784	970		2 490		16 400	21 713				15 090	14 621
1984	762	960		2 320		15 200	20 302				14 229	13 641
1985	740	950		2 150	8 800	14 000	18 899				13 416	12 728
1986	718	940		1 980	6 151	12 800	17 504				12 651	11 876
1987	696	930		1 810	4 300	11 600	16 117				11 928	11 080
1988	674	920	2 200	1 640	4 000	10 400	14 738				11 247	10 338
1989	652	910	2 150	1 470	3 800	9 200	13 366				10 605	9 646
1990	630	900	2 100	1 300	3 600	8 000	12 000	3 819	2 240	215 000	10 000	9 000
1991	603	893	2 074	1 250	3 500	7 000	10 924	3 509	2 212	188 031	8 459	7 693
1992	577	886	2 049	1 200	3 400	6 000	9 850	3 224	2 184	164 445	7 156	6 575
1993	550	879	2 024	1 150	3 300	5 000	8 778	2 962	2 156	143 817	6 054	5 620
1994	530	872	1 999	1 088	3 200	4 750	8 456	2 721	2 128	125 777	5 121	4 804
1995	510	865	1 975	1 025	3 100	4 500	8 136	2 500	2 100	110 000	4 332	4 106
1996	490	862	1 960	963	3 000	4 250	7 817	2 390	2 030	93 952	3 665	3 510
1997	470	859	1 945	900	2 900	4 000	7 500	2 285	1 960	80 246	3 100	3 000
1998		856	1 930		2 800	3 932	7 432	2 184	1 890	68 539	2 586	2 483
1999		853	1 915		2 700	3 866	7 366	2 088	1 820	58 540	2 158	2 054
2000		850	1 900		2 600	3 800	7 300	1 996	1 750	50 000	1 800	1 700
2001												
2002												
2003										22 000		
2004												
2005										15 000	1 400	1 500

Government energy R&D, as from IEA statistics

GERD	TOT	yagr	HYD	NUC	NND	LCT	CCT	PFC	ICG	ATC	OCT	OGT	GCT
M$98													
1971													
1972													
1973													
1974	5 310		0	1 337	1 137	9	11	62	182	56	25	41	37
1975	5 715	7.6%	0	1 553	1 127	18	26	82	228	72	28	43	42
1976	6 087	6.5%	0	1 464	1 159	28	40	117	325	101	34	50	51
1977	6 952	14.2%	0	1 850	1 229	42	60	134	382	111	32	82	48
1978	7 604	9.4%	0	1 938	1 324	49	68	174	430	143	29	93	43
1979	8 276	8.8%	0	2 011	1 473	48	65	165	455	135	33	133	50
1980	9 017	8.9%	0	2 148	1 353	93	124	304	644	242	44	82	65
1981	8 549	-5.2%	0	2 291	1 315	90	124	235	678	180	41	70	61
1982	7 881	-7.8%	0	2 060	1 635	69	96	184	388	142	38	61	57
1983	7 513	-4.7%	0	1 929	1 427	55	76	158	308	123	45	72	68
1984	7 455	-0.8%	0	1 864	1 481	51	71	142	289	111	42	66	63
1985	7 638	2.5%	0	1 884	1 710	58	81	159	272	123	36	63	54
1986	7 092	-7.1%	0	1 860	1 426	53	74	140	258	108	41	65	61
1987	6 412	-9.6%	0	1 481	1 202	40	56	111	235	86	34	62	52
1988	6 216	-3.1%	0	1 206	988	60	78	190	297	147	27	66	41
1989	6 547	5.3%	0	1 416	1 195	58	74	188	251	145	21	62	31
1990	6 670	1.9%	0	1 254	1 150	98	117	342	354	262	17	47	26
1991	6 623	-0.7%	0	1 289	1 117	85	105	293	278	227	16	54	25
1992	6 148	-7.2%	2	1 144	916	49	58	216	227	177	35	72	52
1993	5 769	-6.2%	2	1 137	827	43	52	184	196	151	15	39	22
1994	5 839	1.2%	2	1 156	793	81	119	224	146	181	11	49	17
1995	5 801	-0.6%	6	1 311	821	43	62	145	146	121	12	46	18
1996	5 793	-0.1%	4	1 325	789	54	79	165	136	137	11	46	16
1997	5 501	-5.0%	2	1 270	749	25	36	107	116	93	9	46	14
1998	5 401	-1.8%	2	1 238	663	24	35	105	113	92	9	42	14

Government energy R&D, as from IEA statistics

GERD	GGT	CHP	SHY	WND	SPP	DPV	RPV	BF2 elec	BGT	FCV	SFC	MFC
M$98												
1971												
1972												
1973												
1974	61	59	0	41	50	51	11	9	50	5	51	51
1975	65	63	0	52	60	70	21	10	55	7	58	58
1976	75	78	0	84	116	110	38	12	70	11	74	74
1977	123	110	0	120	176	117	69	18	65	19	94	94
1978	140	136	0	153	255	173	97	30	89	23	119	119
1979	200	175	0	209	282	273	131	47	106	28	139	139
1980	122	109	0	243	470	377	162	57	131	32	117	117
1981	105	59	0	257	304	332	113	70	109	37	48	48
1982	91	48	0	172	186	266	108	65	103	29	51	51
1983	108	103	0	143	142	203	134	76	122	121	58	58
1984	99	94	0	146	105	280	153	74	116	119	53	53
1985	94	107	0	160	86	209	155	59	95	135	57	57
1986	97	99	0	102	58	172	143	47	74	129	50	50
1987	93	115	0	94	76	161	153	44	71	153	52	52
1988	99	138	0	98	75	173	143	46	80	157	59	59
1989	92	155	0	102	46	169	153	34	64	182	59	59
1990	71	122	0	117	60	177	132	29	60	134	56	56
1991	81	146	1	118	66	195	137	38	79	155	64	64
1992	108	114	7	139	128	291	84	31	100	28	90	90
1993	59	100	1	134	121	289	92	27	89	42	76	76
1994	73	103	1	141	94	229	67	47	116	23	86	86
1995	69	98	2	161	95	231	67	49	116	26	81	81
1996	69	100	2	160	90	214	61	43	109	24	81	81
1997	69	104	2	143	89	211	67	43	110	27	86	86
1998	63	99	2	144	79	216	72	59	130	33	84	84

Power Generation Sales as from capacities, annual sales and costs

SALES	TOT	yagr	HYD	NUC	NND	LCT	CCT	PFC	ICG	ATC	OCT	OGC	GCT
M$90													
1971													
1972	148 244		29 269	19 877	0	11 532	35 256	0	0	0	26 686	0	22 306
1973	177 025	19.4%	59 723	15 115	0	11 713	37 783	0	0	0	28 126	0	21 214
1974	184 214	4.1%	51 503	29 390	0	6 573	39 130	0	0	0	29 656	0	24 595
1975	205 298	11.4%	56 041	40 301	0	11 759	41 893	0	0	0	37 296	714	9 465
1976	155 302	-24.4%	47 769	14 986	0	15 140	31 314	0	0	0	29 693	199	11 568
1977	178 372	14.9%	46 241	26 918	0	7 607	45 023	0	0	0	33 665	246	13 743
1978	195 787	9.8%	54 972	24 943	0	7 453	55 203	0	0	0	32 887	306	13 492
1979	180 313	-7.9%	57 595	15 509	0	8 369	52 449	0	0	0	28 451	380	11 506
1980	207 412	15.0%	66 894	29 081	0	12 613	40 660	0	0	0	39 518	1 328	2 387
1981	195 188	-5.9%	54 497	33 593	0	9 784	59 052	0	0	0	0	826	28 052
1982	188 746	-3.3%	54 196	21 404	0	17 111	65 896	0	0	0	8 453	1 029	9 821
1983	185 170	-1.9%	42 450	36 285	0	16 237	68 024	0	0	0	0	1 281	8 423
1984	182 048	-1.7%	50 831	24 802	0	12 687	51 497	0	331	0	18 051	1 596	7 394
1985	224 727	23.4%	88 769	85 716	0	11 223	5 866	0	0	0	10 668	2 863	0
1986	195 396	-13.1%	45 798	39 809	0	11 725	63 941	0	0	0	15 854	1 172	4 632
1987	226 682	16.0%	61 578	51 255	0	7 955	64 394	0	437	0	14 458	1 353	11 733
1988	174 267	-23.1%	43 829	17 929	0	10 933	51 278	0	0	0	26 819	1 577	7 057
1989	180 691	3.7%	34 243	27 950	0	14 321	39 389	0	0	0	31 865	1 856	14 529
1990	181 496	0.4%	33 404	18 288	0	3 044	82 964	365	0	0	15 335	2 201	9 890
1991	257 100	41.7%	42 977	57 589	0	24 202	83 979	211	0	0	22 120	2 929	7 568
1992	180 272	-29.9%	57 085	22 882	0	4 093	36 216	0	0	0	9 238	1 118	24 239
1993	168 164	-6.7%	40 772	17 410	0	4 427	56 081	0	638	0	16 539	0	6 845
1994	163 923	-2.5%	30 518	8 791	0	12 834	65 443	2 967	0	0	19 058	4 042	0
1995	170 190	3.8%	48 560	9 893	0	1 535	58 085	0	658	0	28 341	2 955	5 937
1996	152 221	-10.6%	29 683	10 021	0	9 618	62 484	213	1 428	0	16 969	1 670	5 040
1997	111 745	-26.6%	16 643	10 391	0	6 614	35 179	9 475	1 268	0	6 395	2 600	5 220

Power Generation Sales as from capacities, annual sales and costs

SALES	GGC	CHP	SHY	WND	SPP	DPV	RPV	BF2	BGT	FCV	SFC	MFC
M$90												
1971												
1972	0	0	1 346	0	0	0	0	0	0	0	0	0
1973	0	0	1 367	0	0	5	5	0	0	0	0	0
1974	0	0	1 389	0	0	2	2	0	0	0	0	0
1975	4 433	0	1 411	0	0	5	5	0	0	0	0	0
1976	1 204	0	1 434	0	0	10	10	0	0	0	0	0
1977	1 458	0	1 458	0	0	18	17	0	0	0	0	0
1978	1 765	1 234	1 482	0	0	38	35	0	0	0	0	0
1979	2 133	334	1 506	18	0	44	41	0	0	0	0	0
1980	5 281	1 868	1 531	15	0	49	46	0	4 159	0	0	0
1981	3 874	891	1 556	43	0	89	82	0	868	0	0	0
1982	4 714	1 084	1 582	174	0	138	128	0	1 036	0	0	0
1983	5 732	1 318	1 608	301	0	152	141	0	1 236	0	0	0
1984	6 964	1 601	1 634	910	0	152	140	0	1 475	0	0	0
1985	8 453	1 943	1 661	916	0	163	151	2 589	1 759	0	0.107	0.089
1986	2 948	2 357	1 688	515	0	172	159	540	2 099	0	0.101	0.083
1987	3 084	2 856	1 716	349	0	197	182	645	2 504	0	0.030	0.155
1988	3 254	3 457	1 744	237	0	213	197	769	2 987	0	0.028	0.041
1989	3 462	4 180	1 773	244	0	213	197	917	3 562	1	0.032	0.039
1990	3 718	3 048	1 849	282	2 385	105	296	496	1 835	0	0.040	0.045
1991	3 815	4 584	2 467	324	341	150	249	360	1 244	0	0.034	0.385
1992	5 018	8 222	7 609	434	0	155	199	411	1 360	0	0.029	0.427
1993	7 219	7 817	5 444	581	315	179	145	353	1 407	0	0.024	0.112
1994	6 337	4 600	3 970	783	0	222	137	605	1 622	0	0.020	0.096
1995	5 469	4 621	0	1 206	8	97	305	523	0	0	0.347	2.464
1996	10 168	514	0	1 293	140	115	317	529	21	0	0.330	2.457
1997	7 815	1 554	2 807	1 419	0	428	566	266	1 107	0	0.279	2.100

2. Comparison of Model Data (By G.J. Schaefer, ECN)

2.1. Background to and purpose of this chapter

Good modelling requires at least two things. A good model structure and a reliable model data set. Both items have received considerable attention during the Sapient project. With regard to data the Sapient team has spent considerable time to get a reliable set of historical data on investment costs developments and R&D-expenditures. This was done primarily to estimate reliably learning-by-doing and learning-by-searching elasticities for investment costs (the two-factor learning curve). However, large-scale models do still not always work in the ETL (Endogenous Technology Learning) mode and apart from this also other important data, apart from investment costs, do characterise a technology in the model databases.

There are many different possible causes if differences in outcomes between models occur. Perhaps two different classes of these causes can be distinguished. Either the model structure and assumptions are different, or the model data differ. The former cause is often subject to discussion. However, the latter cause might be as important. To get some feeling for how small or large differences in data currently are, the Sapient team decided to make a comparison of a small part of technology characterisation data that the models used in Sapient have in common.

How is this chapter structured? In section 2.2 an explanation is given on how the comparison is made. This includes a description of what kind of data is compared and also an explanation on some specifics of data in each model. In section 2.3 the comparison is made. For three technologies (wind, hydro and PV) we look at investment costs, O&M costs (fixed and variable), estimated lifetime and estimated availability of the technologies considered. In section 2.4 we will recapitulate the main conclusions and put forward some recommendations for future research activities. The main recommendation is that in the near future much more time should be spent on data acquisition, validation and convergence between the different models.

2.2. How the comparison has been made

Input data of six different models have been compared. These models are PRIMES, POLES, MARKAL, MESSAGE, ERIS, and MERGE-ETL. Since the databases of most of these models are huge, we restricted our analysis to technology characterisation data that influence costs of three different technologies. These technologies are wind turbines (on shore and off shore), hydro plants (varying from pumped storage hydro in one model to small run-of-the-river hydro power plants in another) and grid-connected PV-systems.

The time span of the different models varies substantially. POLES, PRIMES, MERGE-ETL and ERIS provide data up to 2030. MARKAL includes data up to 2050. Message data continue until 2100. Another difference between the models is that ERIS and MERGE-ETL are purely ETL models. This means that these models only include investment cost data for the first model year exogenously. The investment costs for the other years are calculated within the model. These outcome data are not presented here. They would obviously differ per scenario. Therefore the input data for the ETL models ERIS and MERGE-ETL are presented as being constant over time. The other models can also run in the ETL-mode, but are still often used as non-ETL models. So, for POLES, PRIMES, MESSAGE and MARKAL the input data from the non-ETL variants have been used to compare the data that are the result of different expert opinions on future cost trends.

The data from MARKAL are the data used in the Western Europe (i.e. EU plus Norway and Switzerland) database of this model. MESSAGE data represent estimated global averages. PRIMES covers data on all the EU Member States. POLES, ERIS and MERGE-ETL are global models with regions (EU is one of these).

Data on renewable technologies in PRIMES recently have undergone a large revision. Data have been differentiated per EU Member State. In the comparison the simple average of these data has been used as a proxy for the PRIMES-data.

All data have been converted into US$ of the year 2000. This has been done in the case of non-US currencies (ECU, Euro) of other years by first converting into US$ in that year and then converting to US$ of the year 2000, using the US Consumer Price Index.

2.3. Comparison of model data

2.3.1. Investment costs

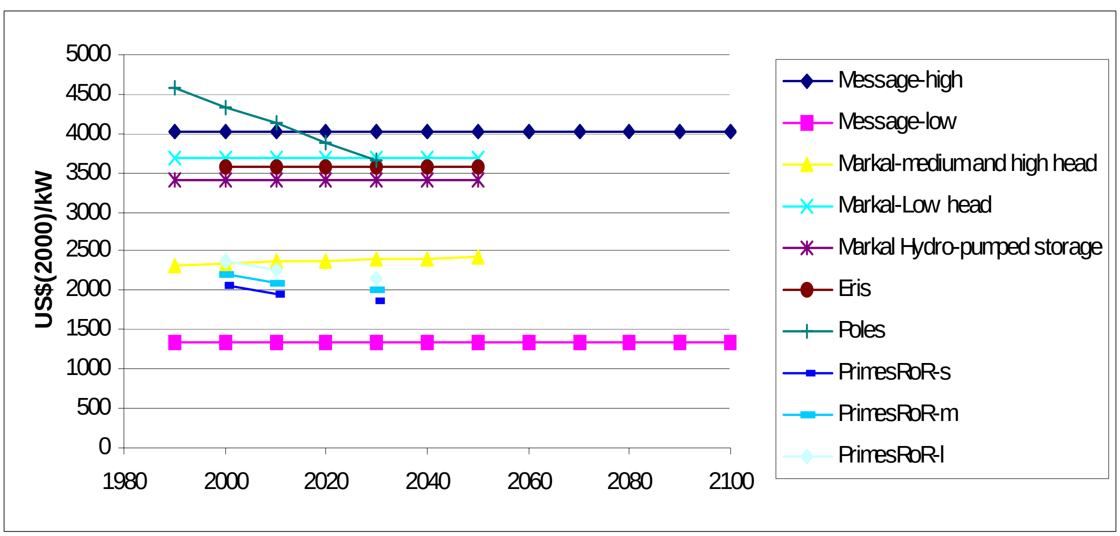
i. Hydropower

Table 2-1 gives an overview of the different investment costs assumptions in the different models with regard to hydro power options. Figure 2-1 below gives the same figures, but presented graphically.

Table 2-1: Overview of investment costs for hydro power technologies in the different models

		1990	2000	2010	2020	2030	2040	2050	2060	2070	2080	2090	2100
Message	high	4018	4018	4018	4018	4018	4018	4018	4018	4018	4018	4018	4018
	low	1339	1339	1339	1339	1339	1339	1339	1339	1339	1339	1339	1339
MARKAL	medium and high head	2328	2346	2362	2380	2397	2415	2431					
	low head	3696	3696	3696	3696	3696	3696	3696					
	pumped storage	3403	3403	3403	3403	3403	3403	3403					
ERIS		3562	3562	3562	3563	3562	3562	3562					
Poles		4580	4336	4123	3876	3665							
Primes (Run of river)	small		2055	1958		1860							
	medium		2209	2104		1999							
	large		2362	2250		2137							

Figure 2-1: Overview of investment costs for hydro power technologies in the different models



Analysing Table 2-1 and Figure 2-1 several specific observations with regard to investment costs for hydropower can be made:

- The estimation of investment costs for hydropower technologies range from less than 1500 $/kW to over 4000$/kW.
- These differences are partly due to different circumstances in which hydro power stations can be built. Most of the models make this explicit by defining a set of different hydro technologies:

high head or low head (Markal), high costs or low costs (Message) or small, medium and large Run of the River-systems Primes.

- Poles and Eris only have one hydro technology defined. Both these models have estimations that are on the high side of the range. Apparently these models refer to low-head, small-scale hydro technologies only.
- The Poles and the Primes model are the only models that assume that cost reductions for hydro technologies will be realised in the future. The other models assume constant investment costs for hydro technologies, apparently considering hydro as a technology with no learning potential anymore.
- In the case of medium and high-head hydropower the Markal model assumes a slight increase of costs (this might reflect the expectation that stricter environmental rules will apply to large-scale hydropower stations in the future which will lead to some extra required investments). This is a similar trend to what has happened in the nuclear sector).
- Since Run-of-River systems often are low-head options, these figures from Primes can be best compared to the low-head or large-scale options in the other models. This shows that the Primes figures are substantially lower than the figures in the other models.

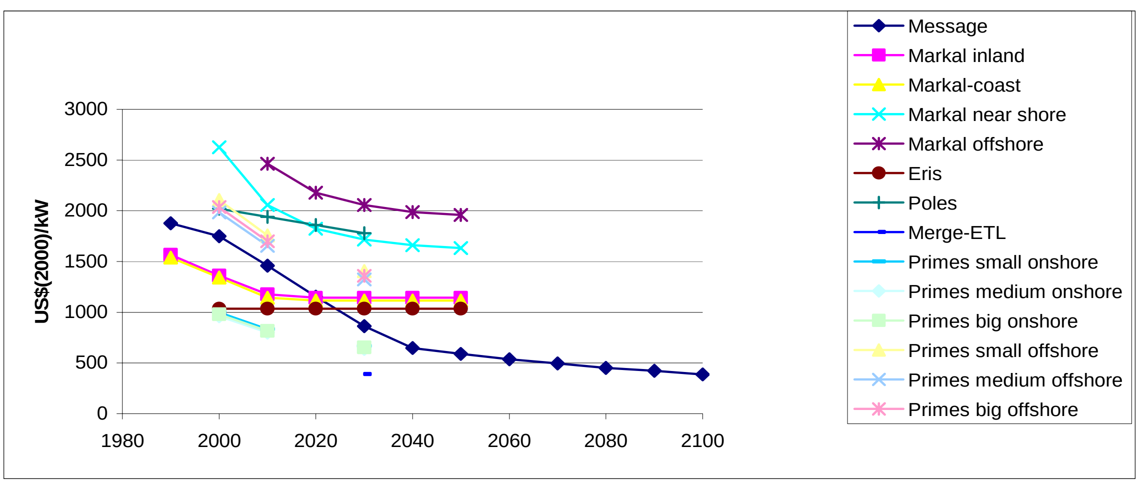
ii. Wind power

Table 2-2 gives an overview of the different investment costs assumptions in the different models with regard to wind power options. Figure 2-2 gives the same figures presented graphically.

Table 2-2: Overview of investment costs for wind power technologies in the different models in US$(2000)/kW

		1990	2000	2010	2020	2030	2040	2050	2060	2070	2080	2090	2100
Message		1875	1748	1458	1153	864	648	589	536	496	450	423	387
Markal	inland	1566	1361	1178	1144	1144	1144	1144					
	coast	1538	1341	1144	1116	1116	1116	1116					
	near-shore		2627	2056	1824	1715	1661	1634					
	offshore			2464	2178	2056	1988	1960					
Eris			1035	1035	1035	1035	1035	1035					
Poles			2021	1940	1860	1779							
Merge-ETL			986	986	986	389	389	389					
Primes Onshore	small		999	833		666							
	medium		959	799		639							
	large		979	816		653							
Offshore	small		2107	1756		1405							
	medium		1985	1654		1323							
	large		2038	1698		1358							

Figure 2-2: Overview of investment costs for wind power technologies in the different models



Analysing the Table 2-2 and Figure 2-2 several specific observations with regard to investment costs for wind power can be made:

- There are large differences between the estimated costs for wind power. Onshore wind power investment costs for the year 2000 for instance vary from 959 $/kW (Primes-medium) to 1748 $/kW (Message) and even 2021 $/kW (Poles). However most models assume investments costs of around 1000 $/kW in 2000.
- The Poles figures for wind power investment costs correspond to the estimated costs of wind offshore technologies in the other models. These cost estimations for the year 2000 range from 1985 $/kW (PRIMES-medium) to 2627 $/kW (Markal near-shore). This is still a difference of more than 30%.
- All models assume that investment costs for wind will decline in the future. Markal assumes this learning effect will stop after 2020. Other models assume continuous cost reductions, until a level of around 400 $/kW for onshore wind (in 2100).
- The differences between the different options for Primes (small, medium and large) are not substantial. It seems as if the model could be simplified by only defining one on-shore and one off-shore technology.

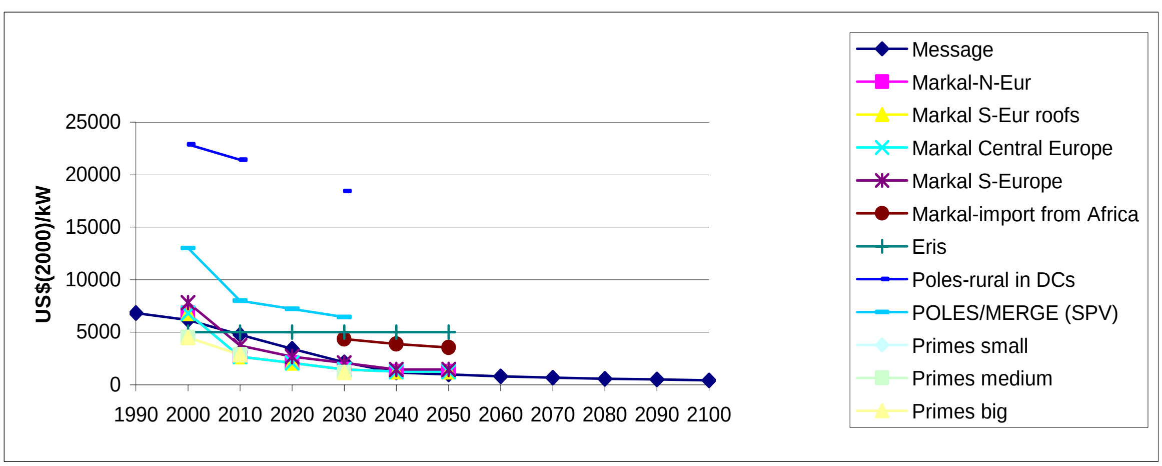
iii. Solar PV

Table 2-3 gives an overview of the different investment costs assumptions in the different models with regard to solar PV. Figure 2-3 below gives the same figures presented graphically.

Table 2-3: Overview of investment costs for solar PV technologies in the different models in US$(2000)/kW

		1990	2000	2010	2020	2030	2040	2050	2060	2070	2080	2090	2100
Message		6830	6190	4780	3419	2158	1157	970	813	695	581	505	426
Markal	North-Eur.		6807	2695	2076	1457	1266	1266					
	South-Eur.		6807	2695	2076	1457	1266	1266					
	Central Eur.		6807	2695	2076	1457	1266	1266					
	Import from Africa		7828	3744	2695	2076	1457	1457					
Eris			5000	5000	5000	5000	5000	5000					
Poles	Rural in DC		22896	21409		18436							
	Roof with grid		13016	7999	7228	6457							
Primes	small		4500	2850		1150							
	medium		4500	2850		1150							
	large		4500	2850		1150							

Figure 2-3: Overview of investment costs for solar PV technologies in the different models



Analysing the Table 2-3 and Figure 2-3 several specific observations with regard to investment costs for solar PV technologies can be made:

- Most models converge with regard to investment costs estimations for the year 2000 around 5000 $/kW.Primes has an estimate just below that, Message and Markal just above this level.
- Poles figures are substantially higher than those of the other models. One technology option in Poles (PV for rural areas in developing countries) can be regarded as another technology (solar home systems). For the other Poles options the reasons of this difference is not clear.
- Markal, Poles and Primes assume a very substantial cost reduction in the first decade of the 21st century. After that the speed of cost reductions slows down in this model.
- Expected prices in 2030 for models other than Poles vary between 1150 $/kW (Primes) and 2158 $/kW (Message). Message estimates for 2040 converge to the 1200 $/kW figures of the other models.
- Message expects continuing declining costs at least until the year 2100 (426 $/kW).

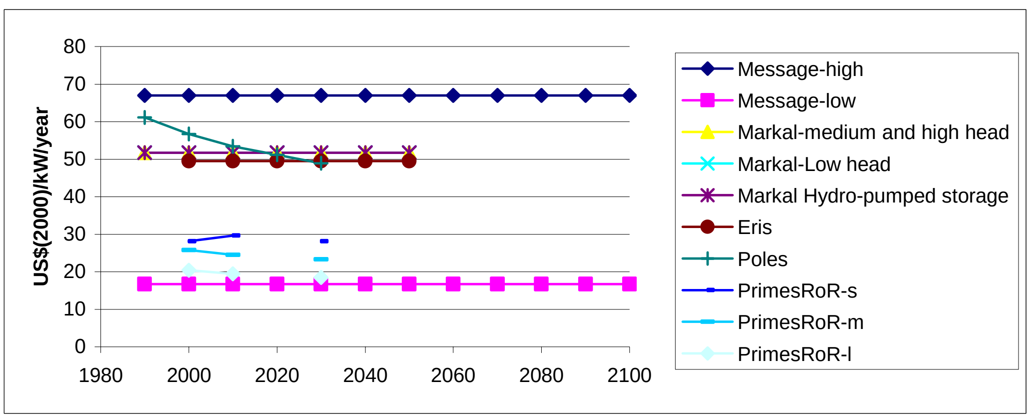
iv. Investment Costs – Conclusions

A detailed analysis of the investment costs of just three technologies shows that large differences (up to 100%) in investment cost estimations exist between the different models. Sometimes this can be explained by differences in assumptions about a certain variant of the technology (e.g. high-head or low-head hydropower, wind onshore or wind offshore). However, this is not always the case. Since investment costs are one of the major determinants of electricity production costs in the case of renewable technologies, these differences in assumptions lead without any doubt to differences in model outcomes.

2.3.2. Fixed Operation and Maintenance (O&M) costs

The next three figures give a summary of O&M costs estimates for the same three renewable technologies in the different models:

Figure 2-4: Overview of fixed O&M costs for hydropower technologies in the different models

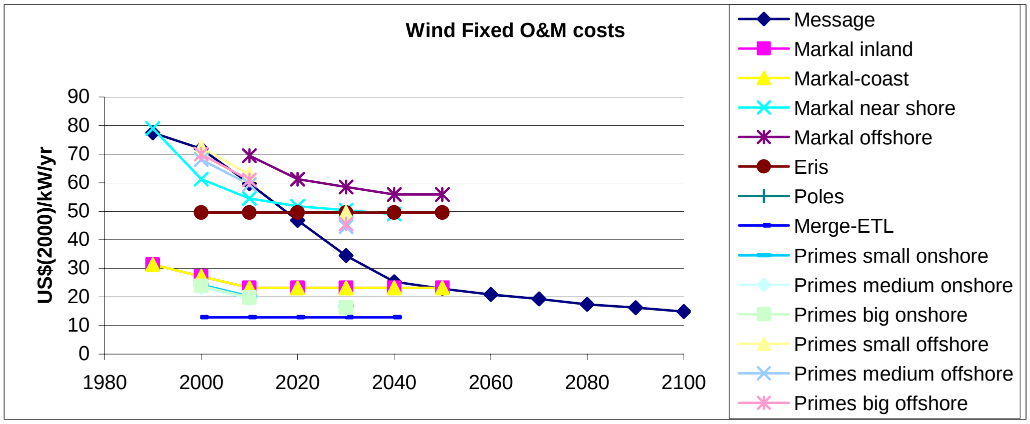


Looking at Figure 2-4 the following observations can be made:

- All estimates are between the Message-high and Message-low estimates.
- Except for Poles none of the models assume cost reductions for fixed O&M-costs for hydro power.
- Markal, Poles and Eris assume fixed O&M costs for hydro of about 50 $/kW/year
- Primes figures are about 50% lower than the estimates ofMarkal, Poles and Eris.

Fixed O&M-costs for hydro contribute to about 10% of the hydro electricity production costs. A difference of 50% in fixed O&M-costs leads to a difference of about 5% in calculated production costs. Clearly the importance of fixed O&M-cost is not as important as investment costs assumptions in the case of hydro technologies.

Figure 2-5: Overview of fixed O&M costs for wind power technologies in the different models

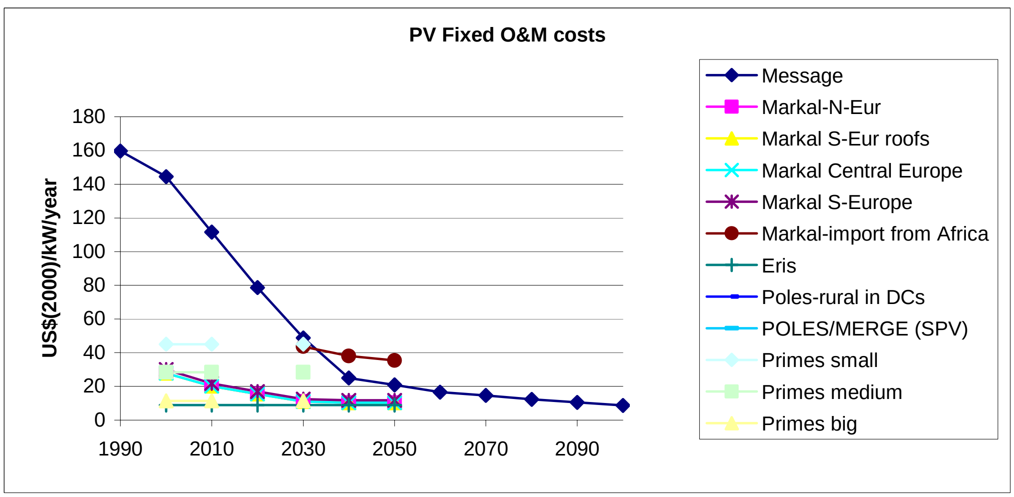


Looking at Figure 2-5 the following observations can be made:

- All models assume future costs reductions for fixed O&M-costs in the case of wind energy, except for Eris and Merge-ETL.
- Message is rather pessimistic compared to the other models. Current cost levels will only be reached at the end of the 21st century in the Message model.
- Eris is also rather pessimistic compared to the other models.
- Primes, Markal and Poles' estimations for fixed O&M costs for wind come pretty close to each other:
  - They all assume current fixed O&M-costs for wind offshore options of about 60-70 $/kW/year. Over time this will be reduced to about 50 $/kW/year.
  - They all assume current fixed O&M costs for wind onshore options of about 30 $/kW/year, which will be reduced to 15-20 $/kW/year in the future.

Fixed O&M-costs contribute to about 15-20% to electricity production costs in the case of wind energy. With the small differences in input costs data for Primes, and Poles, will not have a big impact on model outcomes. The difference with the models Eris and especially Message however might lead to a difference in outcome of about 5-10%.

Figure 2-6: Overview of fixed O&M costs for solar PV technologies in the different models



Looking at Figure 2-6 the following observations can be made:

- Also for solar PV, Message has by far the highest fixed O&M costs assumptions (more than 140$/kW/year in the year 2000).
- The differences in the other models are also quite substantial. From 10 $/kW/year to about 45 $/kW/year. For Primes this is related to the size of the units. Smaller units have higher fixed O&M-costs than larger units.
- Primes and Eris do not assume any cost reductions over time.

With fixed O&M-costs of about 30 $/kW/year the contribution to electricity production costs is somewhere between 5% and 10%. Except for the Message figures, this means that the differences in outcomes for electricity production costs will not be substantial.

Fixed O&M costs - Conclusions

In the case of hydro power substantial differences exists between the estimation of fixed O&M-costs. For wind and solar technology these differences are lower, at least for most models. Since for renewable energy technologies fixed O&M-costs do not constitute a substantial part of electricity production costs, these differences are not that important. However, added up to other differences (in investment costs or other cost-influencing variables), it contributes to differences in outcomes. Another important observation is that, whereas investment costs are often assumed to decline over time, this is not always the case for fixed O&M-costs. Whether this is due to expert opinions that do not expect any decline in these costs over time, or whether it is due to a lack of study and understanding of O&M-cost processes and developments within these processes, is something to be made clearer in the future.

2.3.3. Variable Operation and Maintenance (O&M) costs

The three figures below give an overview of the differences in variable O&M-costs for the three renewable technologies.

Figure 2-7: Overview of variable O&M costs for hydropower in the different models

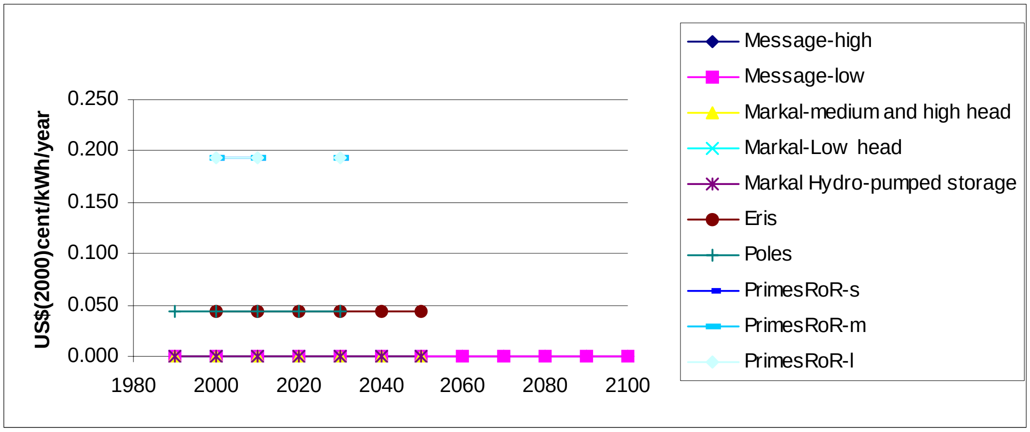


Figure 2-8: Overview of variable O&M costs for wind power in the different models

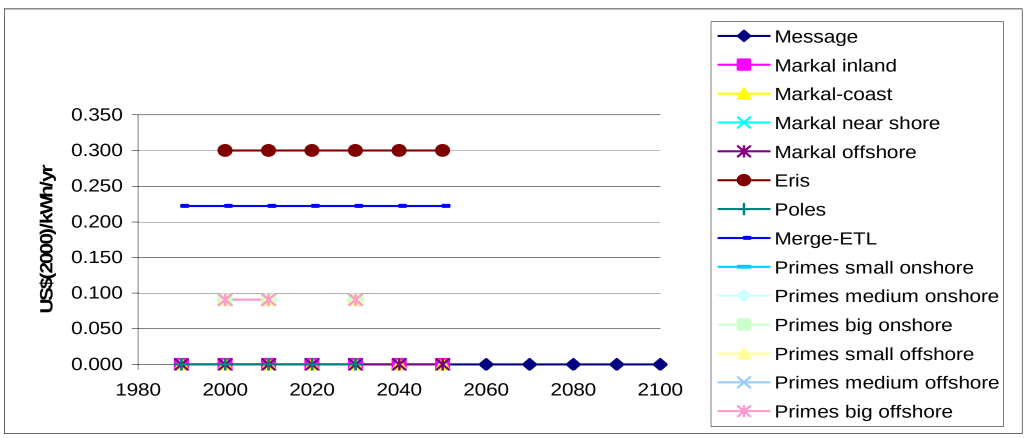
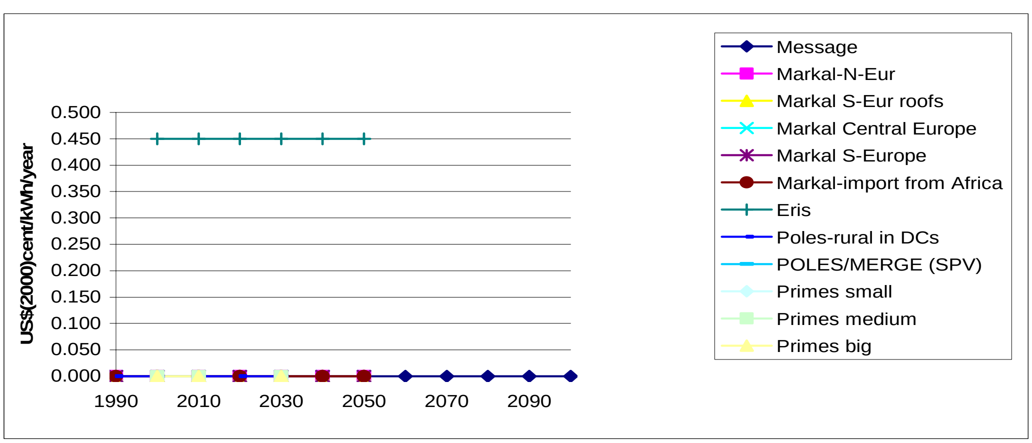


Figure 2-9: Overview of variable O&M costs for solar PV technologies in the different models



As is apparent in Figure 2-7 to Figure 2-9 the estimates for variable O&M costs are apparently an under-studied item. There is only one model (Poles) that has estimated any values for variable O&M-costs for all three technologies. The other models either operate without variable O&M-costs or have estimated it to be too unimportant to put any effort in establishing good figures for this. What is striking is that none of the models assumes any variable O&M cost reductions over time. This seems highly unlikely in case of new technologies for which much learning still can be expected (wind and solar). That variable O&M-costs are important can be seen when comparing the costs that are assumed (if they are assumed) with electricity market prices: 0.3 $cents/kWh is in the neighbourhood of 10% of electricity market prices, which is not negligible.

2.3.4. Lifetime

The next three figures give an overview of another factor that determines electricity production costs in the different models, namely the lifetime of the technology.

Figure 2-10: Estimates for lifetime of hydropower options in the different models

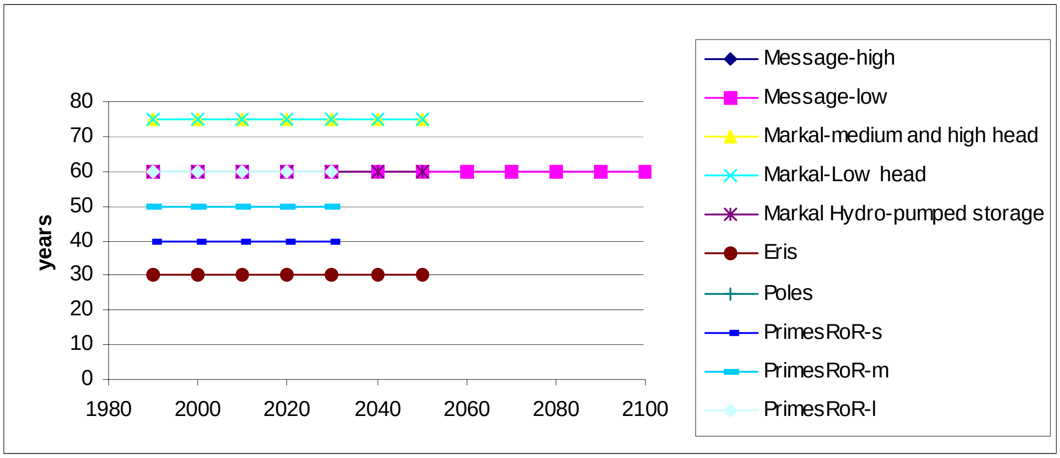


Figure 2-11: Estimates for lifetime of wind power options in the different models

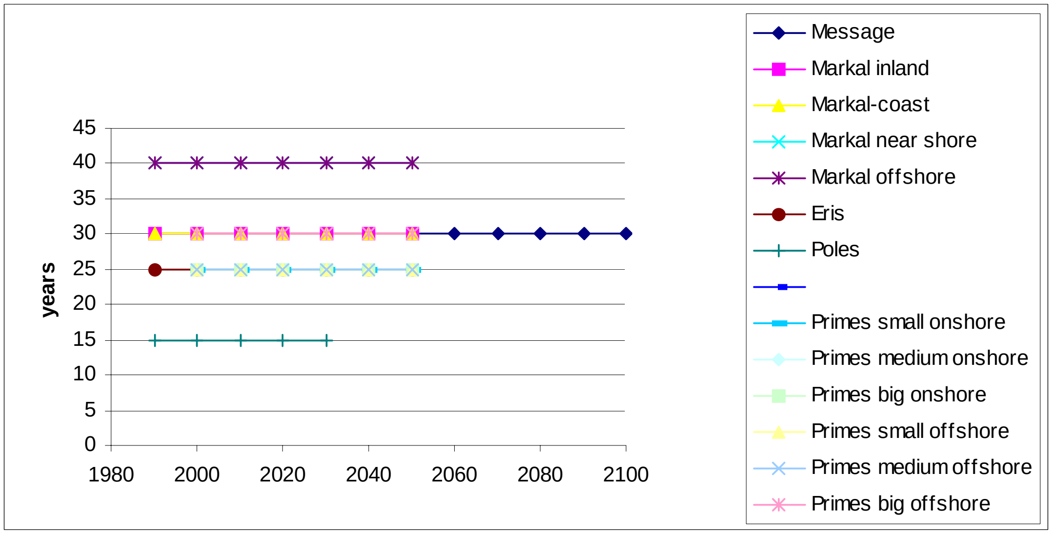
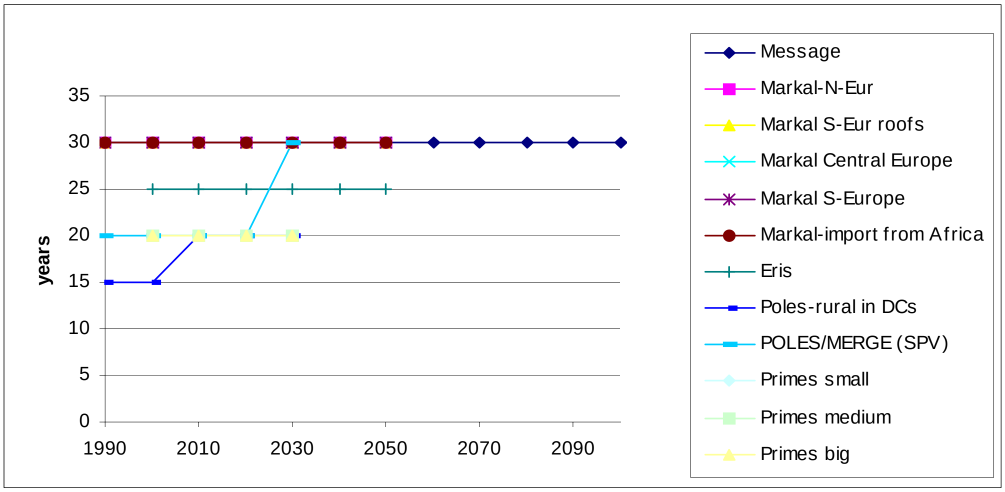


Figure 2-12: Estimates for life time of solar PV technologies in the different models



The following observations can be made:

- For hydro power plants values vary from 30 years lifetime to 75 years lifetime.
- Primes data for hydro lifetime vary from 40 to 60 years, depending on the scale
- For wind lifetime expectations vary also. 30-40 years for wind onshore and 15-30 years for wind offshore.
- For solar PV lifetime expectations vary from 15 to 30 years.
- Poles is the only model that assumes improvements in lifetime figures for one technology: solar PV. In all other cases and in all other models no improvement in lifetime is expected (no learning here).

Lifetime has a substantial impact on electricity production costs. Since differences are large in the models (in the order of 100%), electricity production costs outcomes will probably also be very different. Longer lifetimes will in general favour capital-intensive technologies such as renewable technologies.

2.3.5. Availability

A last input data set that cannot be neglected is the number of hours per year a technology is assumed to be able to produce at full capacity: the availability of the technology. The availability of capital-intensive technologies is, apart from variable O&M-costs, inversely linear with the electricity production costs. In the next three figures the input model data on this aspect for the different models is presented.

Figure 2-13: Estimates for availability of hydropower options in the different models

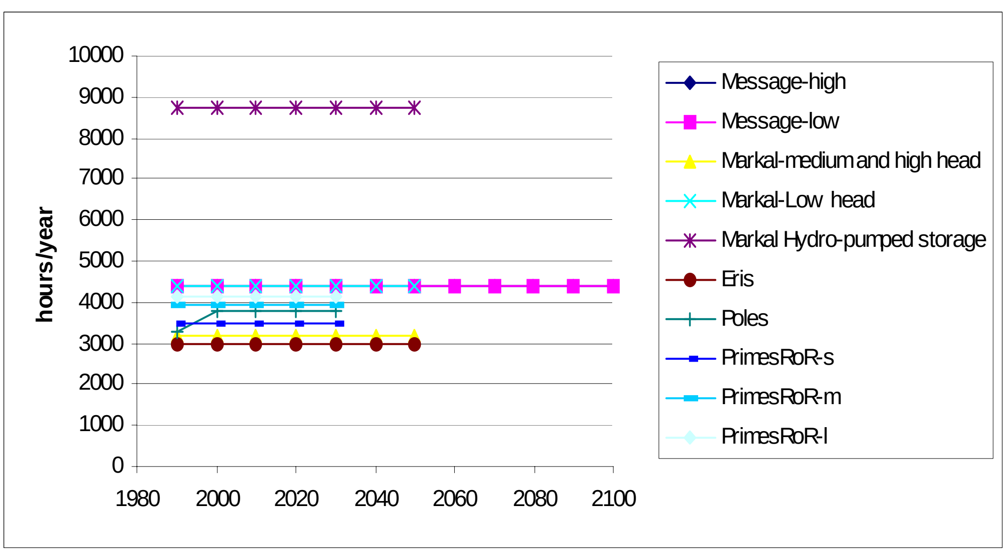


Figure 2-14: Estimates for the availability of wind power options in the different models

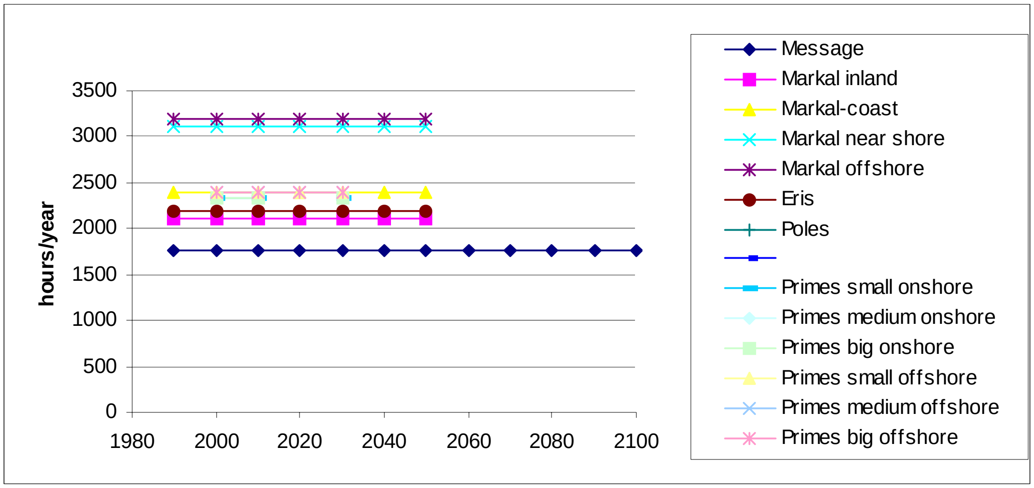
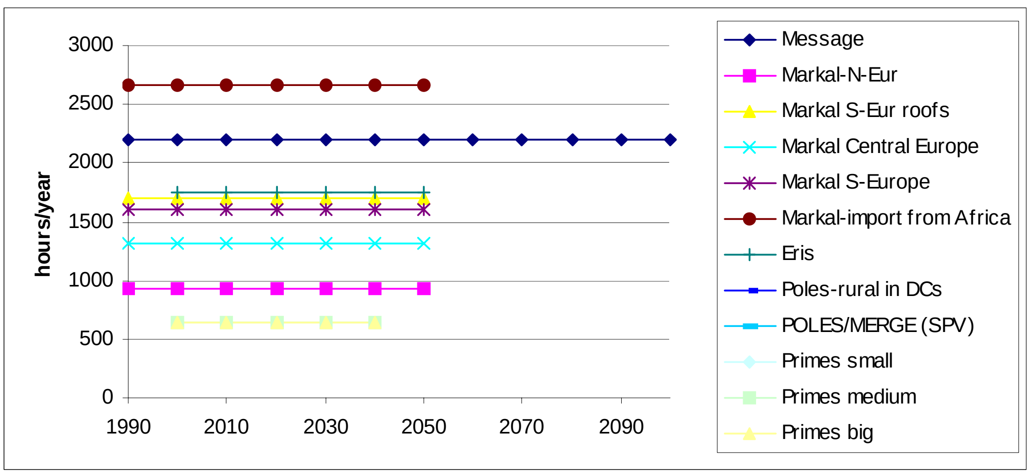


Figure 2-15: Estimated for availability of solar PV technologies in the different models



The following observations can be made:

- For hydro the Eris assumptions seem to be on the low side comparing it to the other models. The Markal-hydro pump storage figures compares to 100% availability, which might be possible in the case of pumped storage facilities.
- In general hydro figures for availability vary from 3500 to 4500 hours/year. This is still a difference of a little bit less than 30%.
- For wind offshore the figures vary from 2400 hours/year (Primes) to 3200 hours/year (Markal). This is a difference of 33%.
- For wind onshore the figures vary from 1600 hours/year to 2200 hours/year. This is a relative difference of 35%-40%.
- The PV availability varies very much with a reason. It is the way to distinguish PV-technology applications in different areas of the world. Still the Message figure of 2200 hours as a world average seems very high, whereas the Primes average of 600 hours for Europe might be on the low side. Compared to Markal Northern-Europe figures (900 hours) this is a relative difference of 30%.
- In none of the models for none of the technologies availability is expected to increase. Apparently the modellers estimate that no efficiency gains can be expected anymore with regard to the current state-of-the-art in hydro, wind and solar power technology.

In general one can observe that availability figures differ substantially from each other, whereas availability is one of the most important factors in calculating electricity production costs.

2.4. Conclusions and recommendations

The following conclusions can be drawn:

- **i.** Most attention and efforts have been spent to investigating the development of investment costs. There is a lack of knowledge on the development of the other four factors that determine electricity production costs: Fixed O&M-costs, variable O&M-costs, lifetime and availability.
- **ii.** Recent insights in developments in investment costs (Technology Improvement Database) have not always been implemented in the models. Investment costs figures have only be used to estimate learning curve factors, not to harmonise year 2000 investment costs assumptions.
- **iii.** There is a need for a better investigation of the other factors influencing electricity production costs.
- **iv.** Especially (developments in) availability and lifetime deserve attention and harmonisation.
- **v.** Although O&M-costs are somewhat less important for capital-intensive technologies such as renewables, differences can still be substantial. More knowledge and discussion is needed on these items.
- **vi.** In general it can be concluded that more time and attention for model data in future work will enhance the quality of models and the comparability of their outcomes.

3. Problems in the Quantification of Two-Factor Learning Curves

Two-factor learning curves (TFLCs) are in the core of the SAPIENT project. Their specification for energy technologies requires the quantification of the parameters defining each 2FLC, in particular the estimation of the two learning elasticities. As it turned out, estimating these elasticities met with many problems. In this chapter, these problems are documented and discussed from three different perspectives.

Before going into detail, we feel that it is important to say that despite the problems encountered, we are nowhere near abandoning the 2FLC concept, mainly for two reasons. The first is that more general and aggregate research has found R&D expenditures highly profitable (see, e.g., Griliches, 1998 or Watanabe 1999). The second reason is that we have gained insights into the dynamics of R&D effectiveness that appear independent of the specific analytical tool. These insights may well remain intact even if and when more appropriate concepts of R&D effectiveness and new tools will have been developed.

3.1. Econometric estimation with large model calibration testing [Juan Carlos Ciscar Martinez (IPTS), Nikos Kouvaritakis, (ICCS-NTUA)]

Three main criteria have been used to estimate elasticities:

- **i.** Economic sense of the elasticities. The sign and order of magnitude of the estimates is coherent with the economic and empirical literature.
- **ii.** Statistical fitness. The statistical characteristics of the estimated equations are sound.
- **iii.** Simulation properties in the POLES model. Since the main goal of the whole exercise is to make simulations with the estimates, the simulation properties of the estimated equations have to be checked, so that reasonable results are obtained. Several tests have been implemented. One test has been to assume a 50% rise in the R&D expenditure in the year 2000, being the R&D expenditure constant till 2030.

3.1.1. Estimation of two-factor learning curves

In the TEEM project the learning-by-doing and learning-by-searching elasticities were estimated following a two-stage procedure[1]. In the first stage the value of the elasticity of the learning by searching factor was fixed and, in a second stage, the elasticity of the learning by doing factor was econometrically estimated. Yet this procedure is not valid for the SAPIENT project because the covariance matrix of the estimators is necessary. This section presents the main results of this applied econometrics exercise.

The twenty-three technologies considered in the estimation are summarized in Table 3-1: Technologies.

[1] See Kouvaritakis N., Soria A. and S. Isoard. “Modelling energy technology dynamics: methodology for adaptive expectations models with learning by doing and learning by searching. Int. J. Global Energy Issues. Vol. 14. Nos. 1-2.2000.

Table 3-1: Technologies

Technologies	POLES Abbreviation
Conventional Large Hydro	HYD
Conventional Nuclear	NUC
New Nuclear Design	NND
Super-Critical Coal	PFC
Integrated Coal Gasification with Combined Cycle	ICG
Advanced Coal Cycle	ATC
Conventional Lignite	LCT
Conventional Coal	CCT
Conventional Oil	OCT
Conventional Gas	GCT
Oil-fired Gas Turbine in Combined Cycle	OGC
Gas-fired Turbine in Combined Cycle	GGC
Combined Heat and Power	CHP
Small Hydro	SHY
Wind	WND
Solar Power Plants	SPP
Decentral Photovoltaics to Grid in Buildings	DPV
Rural Photovoltaics in Developing Countries	RPV
Biomass Gasification for Gas Turbines	BGT
Biofuels	BF2
Solid Oxide Fuel Cell	SFC
Molten Carbonate Fuel Cell	MFC
Fuel Cell Vehicle	FCV

i. The constant-elasticity approach

Assuming that the elasticities are constant during time, the following equation was estimated:

$$C_t = A \cdot RD_t^{\varepsilon 1} \cdot CA_t^{\varepsilon 2} \qquad (1)$$

with:

C_t the cost of the technology,

RD_t the R&D cumulative expenditure,

CA_t the installed capacity,

A, *ε1*, *ε2* elasticity parameters, to be estimated.

Mostly due to the multicollinearity (see also the illustration in Figure 3-4) between the exogenous variables, the statistical results of estimating this function are very poor. One way to deal with this problem is to differentiate equation (1):

$$(C_t / C_{t-1}) = (RD_t / RD_{t-1})^{\varepsilon 1} \cdot (CA_t / CA_{t-1})^{\varepsilon 2} \qquad (2)$$

The results for some of the technologies with good statistical results appear in Table 3-2:

Table 3-2: Two-factor learning curves.

Technology	Data temporal range	Constant Elasticity				Variable Elasticity					
		Level		*Differences*		*Exponential Approach*		*Hybrid*	*Exp. Differ. Approach*		
		Er&d	Eca	Er&d	Eca	Er&d (97)	Eca	R&D shock (%)	Er&d(97)	Eca	R&D shock (%)
HYD	71-97	<	<	<	<	-0.035	-0.15	1.5	<	<	na
NUC	71-97	<	<	<	<	<	<	na	<	<	na
LCT	71-97	<	<	<	<	-0.06 / -0.32	-0.11 / -0.13	13 / 2.8	-0.027 *	-0.06 *	0.9
CCT	71-97	-0.13	-0.06	-0.02	-0.1	<	<	na	-0.027 *	-0.1 *	1.2
GGT	71-98	<	<	-0.16	-0.08	-0.48	-0.47	23.8	-0.18	-0.08	6.5
CHP	80-97	-0.028	-0.066	-0.09	-0.017	-0.09 */ (0.88)	-0.037	1.4	-0.09	-0.017	1.5
WND	71-97	<	<	<	<	-1.77	-0.93	77	-0.07	-0.05	9.2
SPP	90-97	<	<	<	<	-0.71	-0.85	75	<	<	na
DPV	71-97	<	<	-0.18	-0.23	-0.37	-0.44	18.4	-0.14	-0.24	7.4
SHY	88-97	<	<	<	<	-0.61 / -0.62	-0.35 / -1.46	26 / 61	<	<	na
RPV	80-97	<	<	<	<	-0.11	-0.97	12	<	<	na
BF2	90-97	-0.53	-1.1	-0.45	-1.1	-0.58	-1.12	20.3	-0.44*	-1.1	75
BGT	90-97	<	<	<	<	-1.27 / -0.44	-0.4 / -1	48 / 66	<	<	na

<	very poor statistical results (low significance level) and/or wrong sign of elasticities
na	non available result
*	weak statistical significance (0.5 to 1.8 t value). T-value between brackets
Er&d	=elasticity of R&D. Er&d(97) refers to the value in the year 1997
Eca	=elasticity of Capacity
R&D shock	= % drop in cost due to a 50% rise in R&D in 1998 (kept constant to 2030). A -0.5 capacity elasticity is assumed.

Hybrid Approach: Simulations results of the Exp. Diff. Approach using the estimated elasticities from the Exp. Approach

i. The variable-elasticity approach

Given that the statistical results implementing the previous approach were only satisfactory for five, out of thirteen, technologies, other approaches have been applied. One possibility is to introduce exogenous information into the equation to be estimated (intervention analysis). In this case, it could be argued that the explanatory power of the R&D factor diminishes along time. At the same time, the importance of the Capacity factor may grow as time passes. This idea can be captured by defining variable elasticities. The general model in which both elasticities are time-dependant did not produce good statistical results. The model with only the R&D elasticity being variable yielded reasonable results. The model estimated has been the following:

$$C_t = A \cdot RD_t^{\varepsilon 1(t)} \cdot CA_t^{\varepsilon 2} \qquad (3)$$

Where $\varepsilon 1(t) = a \cdot e^{b \cdot Z_t}$

Z_t is exogenous, with b a parameter.

When a and b are negative and Z_t positive and non-increasing, the R&D elasticity is negative, and decreases over time in absolute terms. The results of using this approach for the estimations appear in Table 3-2:, under the columns called *Exponential Approach*. For eleven technologies the results are relatively satisfactory. However, the properties of the resulting learning curve were not good in every case because the variable elasticity can lead to rising cost in some periods.

One way to overcome this difficulty is to apply the variable-elasticity approach to the equation in differences:

$$(C_t / C_{t-1}) = (RD_t / RD_{t-1})^{\varepsilon 1(t)} \cdot (CA_t / CA_{t-1})^{\varepsilon 2} \qquad (4)$$

The results of these estimations appear in the last columns of Table 3-2:, in the columns under *Exp. Dif. Approach*. It can be noted that the estimated elasticities are similar to those of the constant-elasticity approach in differences. In addition, the simulation properties of this equation appear in the last column, being at a first glance of 'reasonable' values.

Nevertheless, there are only results for seven technologies, of them being only two renewable and new ones. This problem led to the formulation of the called 'Hybrid Approach'. This approach combines the variable-elasticity approach and the differences approach. This approach uses estimates from the exponential approach (which have good statistical properties), and for the simulation exercises uses the differences approach. On the positive side this combines the main advantages of the other two approaches, but the main disadvantage is that it lacks econometric rigor. This approach is a kind of compromise. The simulation results appear in Table 3-2: under the column called *Hybrid*.

3.2. Impacts of R&D intensity on learning rates in MARKAL (ECN)

This section describes an indirect approach to analyse two-factor learning curves (2FLC's) with the MARKAL application for Western Europe.

There were several reasons to refrain from introducing 2FLC directly in MARKAL:

i. TEEM (TEEM, 1999) has shown that a 2FLC does not always result in a better fit to the data than a single-factor learning curve (1FLC: learning by doing and learning by searching incorporated in one factor). So, a fundamental data problem existed to provide statistical support for such a two-factor approach. These empirical flaws are not surprising, because a firm theoretical basis to support the relationship with two factors does not yet exist.

ii. Adding a 'learning by searching' factor to the current 'learning by doing' learning curve leads to a non-linear programming (NLP) optimisation model that cannot be approximated by a mixed-integer programming (MIP) model.

iii. Given the complexity of the Western European MARKAL application, in terms of number of technologies (hundreds), and the need to further expand on the concept of clusters of technologies (Seebregts et al, 2000), an NLP formulation would further hamper such expansion: the model would become too complex to be solved.

iv. The uncertainty introduced by the use of either a 1FLC or 2FLC may be smaller than the uncertainty caused by the value of the 1FLC progress ratio. As illustrated in e.g (Kram et al, 2000; Table 2), (McDonald and Schrattenholzer, 2001), and (Junginger, 2000), progress ratios for one particular technology exhibit a large uncertainty range, e.g. see the Tables for solar PV modules and wind turbines progress ratios in Part II Stochastic Models – MARKAL Section 6.3.3.

v. So, methodological uncertainty may be overshadowed by pure data uncertainty. In Part II, Section 6.3 Stochastic models – MARKAL, this is illustrated to some extent for wind turbines).

Therefore, the MARKAL model with endogenous learning was not extended with two-factor learning curves (2FLC's).

As an alternative, ECN proposed to treat the impact of public energy R&D indirectly, that is, external to the MARKAL model, and to estimate the impact on the progress ratio of the 1FLC.

To start with, the basic assumptions behind the approach are:

i. Public R&D expenditure is a good indicator for overall R&D expenditures.

ii. An additional R&D budget (an 'R&D shock') will lead to an increase in the so-called R&D intensity of the technology. R&D intensity is defined as the following relationship between public R&D expenditures over a period and the turnover of that technology: R&D intensity = (amount of R&D)/(amount of R&D + turnover)

iii. The higher the R&D intensity, the lower (i.e., better) the progress ratio.

iv. This relationship between a change in R&D-intensity and the change in progress ratio is the same for each technology.

v. R&D budget for each technology is applied with the same level of efficiency.

vi. The progress ratio will not change after the period of additional R&D shock.

The approach is then as follows:

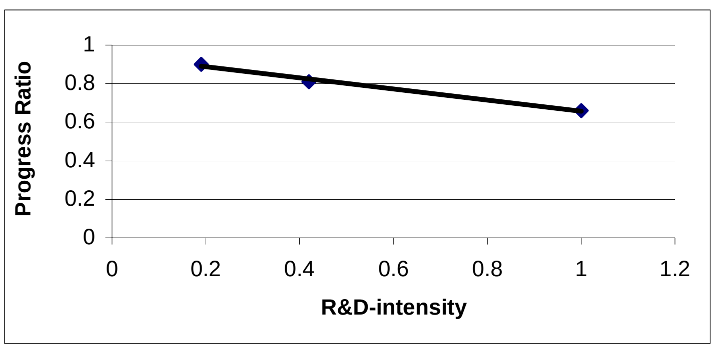
i. MARKAL uses the 'overall' progress ratio, which includes all factors of learning, including effects of R&D.
ii. Additional R&D budget (an 'R&D shock') will lead to an increase in the R&D intensity of the technology.
iii. An increased R&D intensity will lead to a lower (i. e., better) progress ratio.
iv. This updated progress ratio is used in the MARKAL model to study the overall impact of R&D.

The quantitative relationship between R&D intensity and the change in progress ratio has been based on available statistical data for three technologies. The progress ratios in the following table (Table 3-3) are judged to be more or less realistic, and the R&D intensities have been based on SAPIENT data collected by IEPE (Criqui, 2001).

Table 3-3: Relationship between progress ratio and R&D intensity for 3 emerging technologies.

Technology	Progress ratio Source: Kram et al. (2000), Table 2, MARKAL-Europe	Public R&D intensity 1985–1995 Based on Criqui (2001)
Fuel Cell	0.66	100%
Solar PV	0.82	42%
Wind Turbine	0.9	19%

Figure 3-1: Fitted relationship progress ratio vs. R&D intensity for 3 emerging technologies.



PR = -0.29*R&D-intensity + 0.9451 (R^2 = 0.9898)

Figure 3-1: Fitted relationship progress ratio vs. R&D intensity for 3 emerging technologies. indicates that an increase in R&D intensity by 1% lowers the progress ratio by 0.29%. It also indicates that if no public R&D would be spent on a new energy technology, there is still a progress ratio of about 94.5%. This progress ratio is then interpreted as solely due to non-R&D-factors (i.e. 'learning-by-doing'). At the other extreme – the theoretical maximum of R&D intensity at 100% – the progress ratio gets as low as 65.5%.

The relationship and the resulting coefficients could be further underpinned or estimated on available R&D statistics and progress ratios of more than these 3 technologies.

Based on the relationships outlined above, the procedure to implement tie impacts of R&D intensity on learning rates in MARKAL is as follows:

1. Estimate the current progress ratio (PRC1) of technology T1 without extra R&D over a given historical period P1.
2. Estimate the R&D-intensity of this technology T1 over the same historical period P1
3. Calculate what would be the amount of R&D to be spent in a reference scenario, assuming that the R&D-intensity stays constant over time.
4. Calculate what an extra R&D budget of x billion Euro means for the change in R&D-intensity (ΔRDI).

5. Multiply ΔRDI by 0.29: This gives the change in PR, ΔPR.
6. Add ΔPR to PRC1, resulting in PRenh-R&D-1, the new PR, enhanced by additional R&D.

During this procedure several estimates had to be made based on historical data for the key technologies in MARKAL. These include:

- Estimate of the historical progress ratio of the key technology. This includes an estimate of the sales volume and cost reductions of the key technologies over time.
- Estimate of the historical R&D-intensity of the key technology.
- Estimate of future R&D-spending in a reference scenario. This includes an estimate of future sales in the reference scenario.

For these estimates the Technology Improvement Database as developed within the SAPIENT project has been used. Since this database is based on the POLES categorisation of technologies, it had to be related to MARKAL key technologies by 'allocation' factors. These factors can be seen in Table 3-4 (for R&D) and Table 3-5 (for sales).

Table 3-4: Translation from POLES R&D-expenditure figures to MARKAL key technology R&D-expenditure figures.

	Key technologies in MARKAL											
POLES Techn.	NUK	HYK	GTK	FCK	EWK	ESK	BOK	GFK	COK	CCK	STK	
HYD		1										1
NUC	1											1
NND	1											1
LCT							0.5				0.5	1
CCT							0.5				0.5	1
ICG			0.2					0.6		0.1	0.1	1
OCT							0.4				0.6	1
OGT			0.3					0.5		0.1	0.1	1
GCT			1									1
GGC			0.8							0.1	0.1	1
CHP			0.7								0.3	1
SHY		1										1
WND					1							1
DPV						1						1
BGT			0.2					0.6		0.1	0.1	1
RPV						1						1
BF2								0.4			0.6	1
FCV				1								1
SFC				1								1
MFC				1								1

Table 3-5: Translation from POLES sales figures to MARKAL key technology sales figures.

	Key technologies in MARKAL											
POLES Techn.	NUK	HYK	GTK	FCK	EWK	ESK	BOK	GFK	COK	CCK	STK	
HYD		1										1
NUC	1											1
NND	1											1
LCT							0.60				0.4	1
CCT							0.60				0.4	1
ICG			0.1					0.5		0.3	0.1	1
OCT							0.4				0.6	1
OGT			0.2					0.5		0.1	0.2	1
GCT			1								0	1
GGC			0.6							0.1	0.3	1
CHP			0.6								0.4	1
SHY		1										1
WND					1							1
DPV						1						1
BGT			0.1					0.5		0.3	0.1	1
RPV						1						1
BF2								0.7			0.3	1
FCV				1								1
SFC				1								1
MFC				1								1

3.3. Data preparation for IIASA-ECS runs

Throughout the work within the SAPIENT project, data and statistical problems were manifested during the estimation of the parameters of Two-factor Learning Curves. In this subsection, we add to the documentation of these problems by reporting the results of some sensitivity analysis of parameters that have to be specified for doing the estimations. The bad news here is that sensitivities arose where they were not necessarily expected, but the good news is that the two learning elasticities (the learning-by-doing elasticity and the learning-by-searching elasticity) were the least sensitive of a set of four variables.

The sensitivity analysis reported here was motivated by early SAPIENT work, which had raised the hope that replacing “cumulative R&D expenditures” by the more general concept of “knowledge” would bypass some of the initial statistical difficulties. This hope was not really fulfilled, but even to fully analyze the statistical advantages of such a modification would require a better data situation than the one we have now.

Anyway the following formulation of “knowledge” was applied (instead of ‘cumulative R&D expenditures’) which introduces knowledge depreciation and a time lag between R&D expenditure and its effectiveness.

Kouvaritakis et al. (2000) have used cumulative R&D expenditures as the representative variable, where past R&D expenditures are added up in a similar way as past cumulative installed capacity. However, a more general representation of the knowledge accumulated through R&D efforts can be formulated using a knowledge stock function, as proposed in the literature (Griliches, 1995, Watanabe, 1999). The more general concept of knowledge stock allows taking into account several aspects of the R&D process. First, the fact that it takes time to conduct R&D projects as well as to apply the results to the production process can be reflected by the specification of a lag parameter. This parameter describes the time lag between actually spending R&D money and the corresponding effects on productivity. Second, past R&D investments depreciate and become obsolete (Griliches, 1995). This observation can be reflected in the knowledge stock function by specifying a depreciation rate for knowledge.

For the use in ERIS, the recursive expression for knowledge stock proposed by Watanabe (1999) is implemented. This formulation assumes that knowledge depreciates in time at a constant rate and that only the R&D expenditures performed at least rdlag years before contribute to the current knowledge stock. That is, a constant lag is assumed between the time at which R&D spending takes place and the time at which its results materialise and become part of the knowledge stock. The original expression is given on a year-by-year basis. The knowledge stock in the year y (KSy) is expressed as the sum of the (depreciated) stock of the previous year (KSy-1) and the lagged R&D expenditures (ARDy-rdlag):

$$KS_y = (1-\delta) * KS_{y-1} + ARD_{y-rdlag}$$

Where:

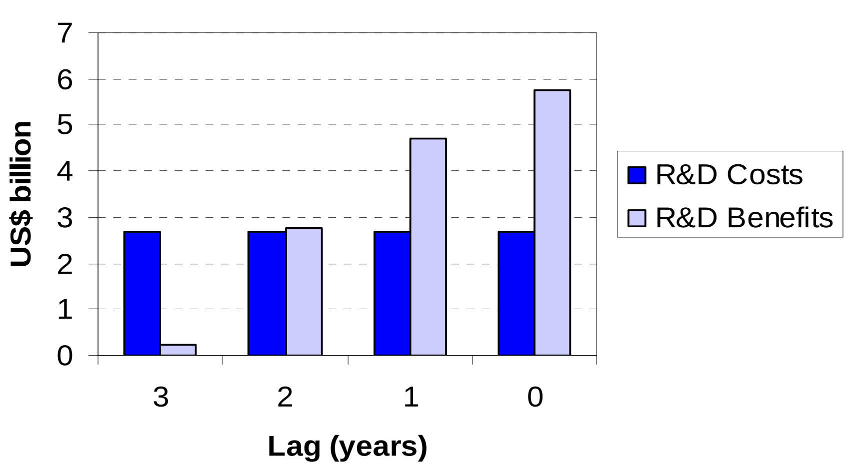
KS_y:	Knowledge stock in year y
KS_{y-1}:	Knowledge stock in year y-1
δ:	Annual depreciation rate
$ARD_{y-rdlag}$:	Lagged annual R&D expenditures per technology
rdlag:	Lag in years between R&D expenditures and knowledge stock.

As the knowledge stock is a more general formulation than cumulative R&D expenditures, it is the more suitable form of measuring the R&D contribution to technological progress. Tests performed with time series from energy technologies indicate that the application of the knowledge stock appears to improve the statistical estimates of the two-factor learning curves as compared to the case where cumulative R&D expenditures are specified beyond what could be expected from simply increasing the number of "free" parameters of any function (Criqui et al., 2000)xx. However, it also introduces the problem of obtaining sensible assumptions or estimations of the relevant lag structure and the depreciation rate. Although some case studies are available (Watanabe, 1999), estimates of such parameters in the case of energy technologies must still be developed. In the meantime, sensitivity analyses can be used to assess their effect. For such task, ERIS with 2FLC constitutes a valuable tool.

i. Sensitivity with respect to the lag parameter

As a first illustration of the sensitivity of the estimation procedure, we used different values (between 0 and 3 years inclusively) for the lag parameter in the definition of the knowledge variable. With each of these values we estimated the parameters of the 2FLC for lignite-fuelled power plants and calculated (approximations of) R&D costs and benefits. The result of this exercise is illustrated in

Figure 3-2: R&D costs and benefits, lignite-fuelled power plants.



The figure suggests that the choice of *lag* can make a difference of several billion US dollars and the difference between net gain and net loss. Two observations (caveats) are in order, however. The first is that the calculation of costs and benefits was done in a rather rough way, e. g., ignoring boundary effects. The second observation is that the more favourable results – those with shorter time lags – are likely to be unrealistic. In a study of the Japanese manufacturing industry, Watanabe (1999) has estimated a time lag of 1.8 years to lie between energy R&D expenditures and their impacts.

ii. Sensitivity with respect to the initial knowledge stock

Next the sensitivity of the 2FLC parameters was analysed and quantities were derived by varying the initial knowledge in a 2FLC of solar PV. The longer the time lag, the more past values of R&D expenditures must be known – in addition to the initial knowledge stock – to formulate the knowledge function for the entire time period of interest. For testing the sensitivity of the function with respect to initial knowledge and past R&D expenditures it therefore appears reasonable to assume a fixed growth rate (of past R&D expenditures) as a single parameter to generate different values of initial knowledge stock. The result of this piece of analysis is shown in Figure 3-3.

Figure 3-3: Dependence of 2FLC parameters and indicators on initial knowledge[2].

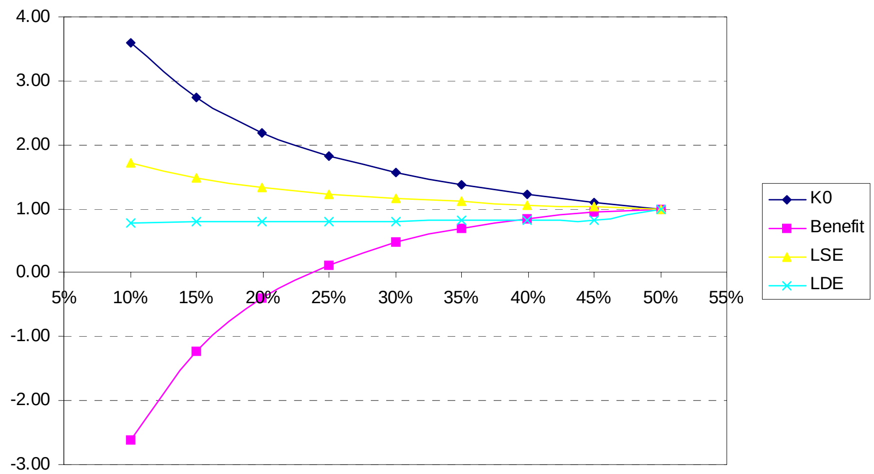


Figure 3-3 shows the dependence of four quantities – (i) initial knowledge, (ii) approximate R&D net benefits, (iii) learning-by-searching elasticity (LSE), and (iv) learning-by-doing elasticity (LSE) – on the assumed value of this parameter. To ensure comparability of the cases, other parameters such as knowledge depreciation (here set to 5% per year) and time lag (here set to zero) were kept constant, of course.

The key to understanding the results is the observation that low growth rates of past R&D expenditures lead to a bigger initial knowledge stock. The bigger the initial knowledge stock, the more expensive is its doubling and therefore the more difficult it is to spend R&D money beneficially. The net benefit of R&D – and even its sign – thus depends in a very sensitive way on the values chosen for past R&D expenditures.

A positive result in our opinion is that the two parameters (learning elasticities) of the 2FLC change much less drastically than the net benefits. LSR varies by a factor of 1.7 and LDR by a factor of less than 1.3.

3.4. Numerical Values Chosen for the Analysis with ERIS at IIASA-ECS

Without going into great numerical detail, we report that an unmodified ("blind") estimation of the 2FLC parameters would lead to implausible parameter values, that is, 2FLCs that could not be reasonably analysed with the ERIS model. This observation is clearly shared by the other members of the SAPIENT Consortium IPTS, IEPE, and PSI.

In the light of this unfortunate data situation it appeared to be useful to analyse the sensitivity of model results that are based on 2FLCs. At IIASA-ECS, ERIS was used for this purpose. To keep the sensitivity analysis understandable and within manageable limits, we limited the number of "learning" technologies

[2] (K0=initial knowledge, LSE=learning-by-searching elasticity, LDE=learning-by-doing elasticity.)

to two, wind and solar PV. Another simplification was that for the estimation of the reference learning rates we used cumulative R&D expenditures instead of the more elaborate "knowledge stock" presented above. (For the analysis with ERIS, we again used "knowledge stock".) In our opinion, this simplification was justified by the results of the above sensitivity analysis (in Subsection 3.3), from which we concluded that trying to apply best judgment on initial knowledge stock and depreciation rate was not promising anyway, in particular from the perspective of varying the two learning elasticities within wide ranges later.

The task of estimating the "best" parameters of 2FLCs for these two technologies was therefore reduced to finding plausible starting values, which would provide an appropriate basis for a systematic sensitivity analysis. Our way to calculate these was inspired by estimation methods reported by the POLES team in the late phases of TEEM, i. e., we fixed a learning-by searching rate (LSR) and estimated the corresponding learning-by-doing rate (LDR).

The estimates that satisfied our aspirations are reported in Table 3-6 below.

Table 3-6: Estimating learning-by-doing rates (LDRs) while keeping learning-by-searching rates (LSRs) fixed.

	LSR (fixed)	LDR (estimated) *t-statistics*	R^2
Solar PV	10.00%	17.46% *-18.20*	0.94
Wind	10.00%	9.73% *-7.93*	0.80

As a statistical check, we tried to estimate the learning rates in the opposite way, i. e., fixing the learning-by-doing rate and estimate the learning-by-searching rate. The statistical results were clearly inferior. To illustrate, we present, in Table 3-7, the results of estimation that we considered inadequate.

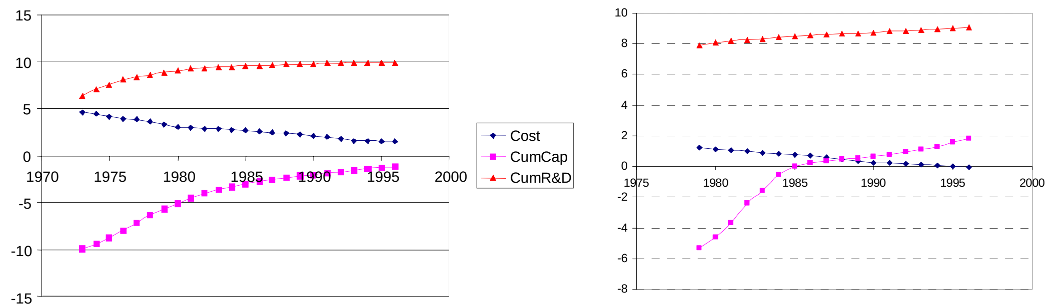
Table 3-7: Estimating learning-by-searching rates (LSRs) while keeping learning-by-doing rates (LDRs) fixed.

	LDR (fixed)	LSR (estimated) *t-statistics*	R^2
Solar PV	17.50%	9.74% *-3.30*	0.33
Wind	10.00%	15.47% *-2.26*	0.24

Although for Solar PV, the resulting learning rates are similar to the preferred estimation, this is not so for wind. Moreover, t-statistics and correlation coefficients (R^2s) have unsatisfactorily low values.

In addition to the somewhat abstract numerical results, we want to illustrate the more geometric properties of the time series involved in the estimation. Figure 3-4 shows the time series of variables used in the estimation. The variables are plotted in the logarithmic form in which they are used by the statistical software.

Figure 3-4: Input data used for the parameter estimations of Solar PV (left) and wind (right) technologies. The variables specific cost, cumulative installed capacity, and cumulative R&D expenditures are plotted on a logarithmic scale.



The data for Solar PV on the right side of the figure show that the two independent (explanatory) variables ‘cumulative installed capacity’ and ‘cumulative R&D expenditures’ have quite similar shapes. In statistical terms, this is called “multi-collinearity”. Without going into greater detail it is noted that for this reason, it is difficult to decide which of the two variables has the greater explanatory power. Numerically, this is reflected in some appropriate statistics. In practice, it is reflected in instabilities during the estimation procedure.

Visual inspection of the wind data (the right graphics of Figure 3-4) shows that it is difficult to imagine one single mechanism at work through the whole time horizon. The reason is that around the year 1985, the curve for ‘cumulative installed capacity’ exhibits a break in trend that is not visible in the dependent variable. This too leaves its tracks in bad statistical indicators.

In the version of ERIS used for the presentation of the IIASA-ECS sensitivity analysis, ‘knowledge’ is used instead of ‘cumulative R&D expenditures’. This requires the specification of three more parameters, ‘initial knowledge stock’, ‘annual knowledge depreciation’, and ‘time lag for knowledge effectiveness’. The first two were chosen in accordance with IEPE’s data compilation for the SAPIENT project, and the ‘time lag’ parameter has been chosen based on Watanabe (1999), who has estimated a time lag of 1.8 years to lie between energy R&D expenditures and their impacts.

The complete set of input parameters used for the specification of the two-factor learning curves is given in Table 3-8.

Table 3-8: Parameters determining 2FLCs for solar PV and wind power and their numerical values used in the analysis.

	Solar PV	Wind
Initial (1990) knowledge stock, US $ billion	14.9	5.2
Annual knowledge depreciation, % per year	3.0	3.0
Time lag for knowledge effectiveness, years	2	2
Learning-by-doing rate (LDR), %	17.5%	10%
Learning-by-searching rate (LSR), %	10%	10%

There may be some remaining wishes with respect to data quality or, more generally, with respect to the robustness of the statistical estimates, but we think that this set of input parameters serves the purpose of testing the sensitivity of two-factor learning curves in the environment of an energy optimization model well. Fuelled by the more general findings on R&D effectiveness, we hope that our analysis using the ERIS model will retain its basic value even when one day a better model of R&D effectiveness will have been found.

***References*:**

Criqui, P. (2001): Technology Improvement Dynamics database (TIDdb), developed by IEPE under the EU-DG Research SAPIENT project, IEPE-report, Grenoble, France, July 2001.

Griliches, Z., 1998, *R&D and Productivity – The Econometric Evidence*, The University of Chicago Press, Chicago, USA.

Junginger, M. (2001): see part II. 4-MARKAL

Kram, T., A.J. Seebregts, G.J. Schaeffer, A.J.M. Bos, S. Kypreos, L. Barreto, S. Messner, L. Schrattenholzer (2000): Technology dynamics in energy systems models with perfect foresight, , Int. J. Global Energy Issues, Vol. 14, Nos. 1-4, pp. 48-64, 2000.

Lange, de T.J., L. Crommentuijn (2000): Fotovoltaische zonne-energie – Achtergrondnotitite behorend bij de rapportage: Klimaat en verzuring in 2030: Oplossingsrichtingen voor energie en mobiliteit, ECN/RIVM-N-2000-6, Petten, Bilthoven, the Netherlands (in Dutch).

McDonald, A., L. Schrattenholzer (2001): Learning rates for energy technologies. Energy policy 29 (2001) 255-261.

Seebregts, A.J., T. Kram, G.J. Schaeffer, A.J.M. Bos (2000): Endogenous learning of technology clusters in a MARKAL model of the Western European energy system, Int. J. Global Energy Issues, Vol. 14, No.1-4, pp. 289-319.

Watanabe, C., 1999, Systems option for sustainable development – effect and limit of the Ministry of International Trade and Industry's efforts to substitute technology for energy, *Research Policy* 28, 719–749.

PART II: Implementing 2FLC's in Large Scale Models

4. Comparison of assumptions and results across models (by IIASA, IEPE, PSI)

The key to a better understanding of results from multi-model analyses is the systematic comparison of scenario indicators developed with different models. This is particularly important for the SAPIENT baseline scenarios, which have served as the basis for the sensitivity analysis to estimate the various indicators related to the effectiveness of R&D presented in the proceeding sections. In summary, this section will review scenario assumptions and results for the baselines developed by the IEPE, IIASA, and the PSI modeling groups.

For the quantification of the baseline scenarios, each of the three modeling groups use energy models that include a sufficiently high degree of technological detail for the estimation of R&D effectiveness of specific technologies. Besides some dissimilarity of the models with respect to e.g., the regional specification, treatment of renewable and fossil resource availability, all of them encompass all relevant stages of energy conversion, transformation and transport, all the way from energy resources to provision of energy services. The three models that were adopted by the modeling groups are:

1. *IEPE: POLES* model

2. *IIASA: MESSAGE* model (Model of Energy Supply Strategy Alternatives and their General Environmental impact; Messner and Strubegger, 1995)

3. *PSI: MERGE-ETL* model (Kypreos and Bahn, 2002)

Just comparing alternative emissions across different scenarios would not be sufficient to analyze the differences and commonalities of the assumptions behind the scenarios. The analysis of the underlying driving forces is thus also an important part of the evaluation. This section gives an analysis of the main variables characterizing the scenarios. They are population growth, economic growth, energy consumption and energy and carbon intensities. Some of these driving forces are model inputs, and some are derived from model outputs, so an attempt was made to determine the assumed relationships among the main driving forces. The relationship is given by the so-called Kaya identity (Kaya, 1990; Yamaji et al., 1991). This identity explains total CO_2 (or GHG) emissions as the result of multiplying determining factors (the so-called driving forces). More precisely, it establishes a relationship between population growth, per-capita value added (i.e., average global world product, GWP, per capita), energy consumption per unit value added, and emissions per unit energy (Yamaji et al., 1991)[3]

In the sequel, trajectories for each of the SAPIENT baseline scenarios are presented for each of the four factors in the Kaya identity. In addition, the SAPIENT baseline trajectories are compared to the ranges of scenarios summarized in the SRES database (Morita and Lee, 1998). This is a database of greenhouse gas emission scenarios, which was developed as part of the process of compiling the IPCC (Intergovernmental Panel on Climate Change) Special Report on Emissions Scenarios (SRES, 2000). Presently, it includes more than 400 scenarios from 171 published literature sources and other scenario evaluation activities (Weyant, 1993 and Manne and Schrattenholzer, 1996, 1997).

The SAPIENT baselines differ with respect to the analyzed time horizon. The POLES scenario covers a time frame up to the year 2030, the MERGE-ETL up to 2050, and MESSAGE presents results for the whole century (up to 2100). Table 4-1 gives an overview of the main indicators of the SAPIENT baseline scenarios for the year 2030, the last year, for which results are available for all three models.

[3] CO_2 = (CO2/E) x (E/GWP) x (GWP/P) x P, where E represents energy consumption, GWP the gross world product (or global value added) and P population. Changes in CO2 emissions can be described by changes in these four factors or driving forces.

Table 4-1: Overview of scenario drivers and results.

	Estimates for the year 1990 [c]	Sceanrio Projections		
		MERGE-ETL	*MESSAGE*	*POLES*
Population (billion)	5300	8645	8182	8164
Gross World Product (trillion US$1990) [a]	21	56	85	63
Per Capita Income (US$1990)	3940	6533	10407	7773
Primary Energy Use (EJ)	352[b]	712	901	706
Energy Intensity of GWP (MJ/US$1990)	16.8	12.6	10.6	11.1
Carcon Intensity of Energy (kgC/MJ)	17	15.2	14.0	16.9
Carbon Dioxide Emissions (GtC)	5.9	10.8	12.6	11.9

[a] *The scenario's GWP for the year 2000 was standardized to 30.3 1997US$ (EIA, 2001). GWP trajectories were calculated from the GWP growth rates of the respective scenario based on the standardized values for 2000.*
[b] *Calculated with the direct equivalent accounting convention (including use of non-commercial energy)*
[c] *1990 estimates: SRES, 2000.*

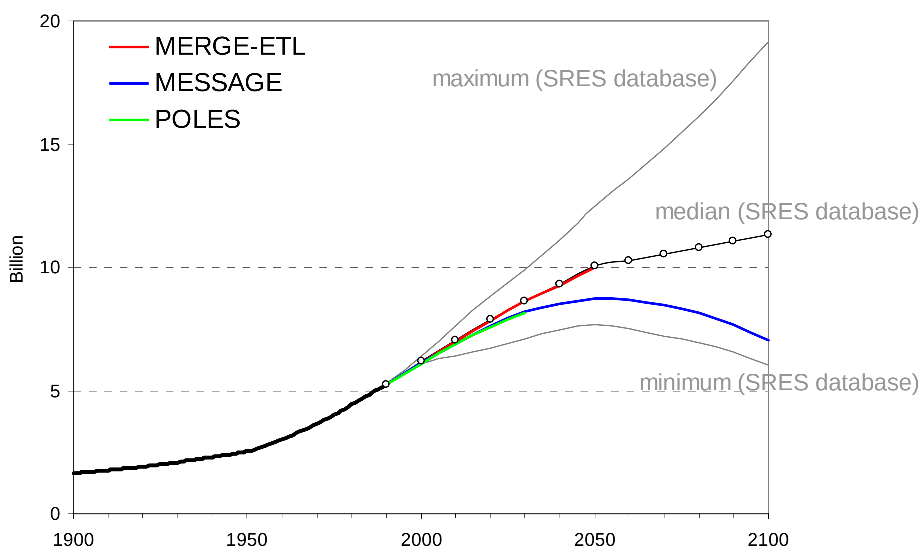
We shall now proceed to discuss the variables of Table 4-1, one by one.

i. Population

Population is one of the fundamental driving forces of future emissions. Most of the population projections that are used for the development of emissions scenarios are taken from the literature[4], and are exogenous inputs in the majority of the energy models.

Figure 4-1 shows the global population range of the SRES database scenarios and the three SAPIENT baseline scenarios. The range for all scenarios is from more than six to about 19 billion people in 2100 with the central or median estimates in the range of about eleven billion.

Figure 4-1: Global population in the SAPIENT baseline scenarios compared to the scenario range from the SRES database[5].



The long-term average historical population growth rate was about one percent per year during the last two centuries and about 1.3 percent per year since 1900. Currently, the world's population is increasing at a rate of about two percent per year. The scenarios and other global population projections envision a slowing population growth in the future. The most recent doubling of the world population took approximately 40 years. Even the highest population projections in Figure 4-1 require 70 years or more for the next doubling while roughly half of the scenarios do not double population during the 21st century.

[4] Today there are three main research groups that project global population – United Nations (UN, 1998), World Bank (Bos and Vu, 1994) and IIASA (Lutz *et al*., 1997).

[5] .Source of historical data: Durand, 1967; Demeny, 1990; UN, 1996; Database: Morita and Lee, 1998.

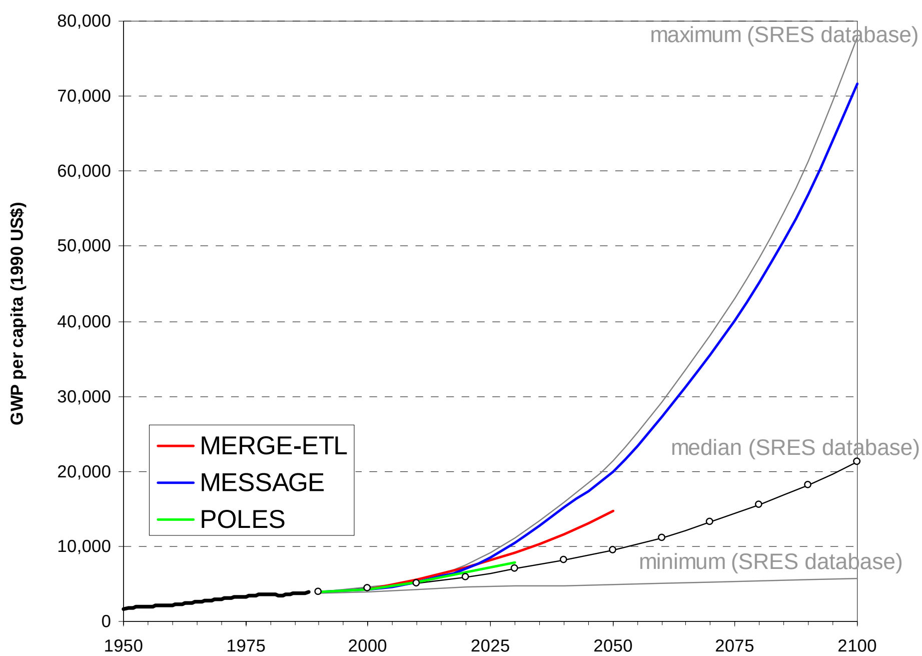
The lowest average population growth across all projections is 0.1 percent per year, the highest is 1.2 percent per year, and median is about 0.7 percent per year.

The SAPIENT baseline scenarios show similar trends up to the year 2030, the timeframe relevant for the R&D calculations presented later in this report. Thereafter, global population in the MERGE-ETL scenario increases continuously in line with the median development of the SRES database. In contrast, in the MESSAGE scenario population growth slows down leading to a peak of total population at about 9 billion in 2050 and to about 7 billion until 2100.

ii. Gross World Product (GWP)

Economic development is a fundamental prerequisite for the eradication of poverty in the world. Figure 4-2 shows the future increase in GWP and GWP per capita compared with the actual development since 1950.

Figure 4-2: Global world product (GWP) per capita, trajectories in the SAPIENT scenarios and ranges from the SRES database. Also shown is the historical development from 1950 to 1990. (The insert shows Global world product (GWP) development from 1950 to 1990 and in the scenarios from 1990 to 2030. Historical data: UN, 1996; Database: Morita and Lee, 1998).



Since 1950, GWP per capita has grown at an average annual growth rate (AAGR) of about 2 percent; in the database scenarios the AAGRs between 1990 and 2100 range from 0.4 percent per year to 2.2 percent, with a median value of 1.6 percent.

Relative to 1990, GWP per capita in 2030 increases by factors of between 1.1 to more than 2.7 for the database scenarios. These figures should be compared to a GWP per capita increase of 1.8 to 2.5 times for the SAPIENT baseline scenarios, which corresponds to GWP per capita growth rates ranging from 2 percent to 3 percent per year.

The insert in Figure 4-2 shows the GWP projections of the SAPIENT scenarios compared with the historical developments since 1950. Global GWP has grown at about 4 percent per year since 1950; in the SRES database scenarios the average annual growth rates between 1990 and 2030 range from 1.5 percent to 4.5 percent , with the median value of 2.9 percent. The corresponding range of GWP is from about 40 to more than 96 trillion US dollars by 2030 (with the median GWP of US$62) compared to a range of US$56 to US$85 trillion for the SAPIENT baseline scenarios.

Up to the year 2030, the range for GWP in the SAPIENT baseline scenarios is relatively small compared to the range of SRES database scenarios. GWP grows fastest in the MESSAGE scenario, followed by the MERGE-ETL and POLES. After 2030 the global economy in the MESSAGE scenario continues to grow at a relatively high pace. Hence, the deviation between the MERGE-ETL and MESSAGE baseline scenarios become more pronounced in 2050.

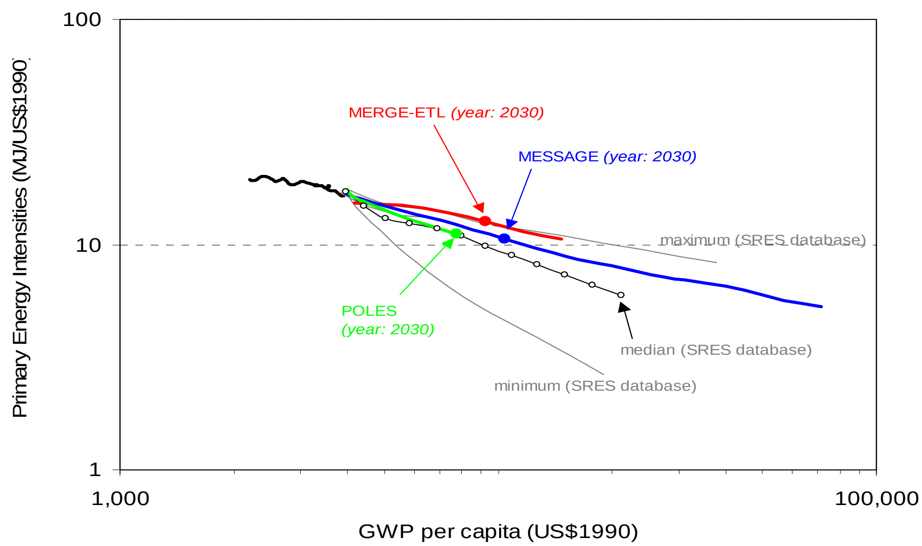
iii. Primary-Energy Intensity of GWP

Of the scenario driving forces considered here, primary-energy intensity of GWP is the most descriptive of technological progress in the energy system. In all three SAPIENT scenarios, economic growth outpaces the increase in energy consumption, leading to substantial reductions in the ratio of primary energy consumption of GWP. Typically, higher GWP growth rates correspond to faster decline rates of energy intensity because in a situation of faster economic growth, inefficient technologies are retired faster in favour of more efficient ones. Also, the structure of the energy system and patterns of energy services change faster with the same effect on the primary-energy intensity.

Therefore, a meaningful comparison of primary energy intensities across scenarios should depict the relationship between energy intensity and economic development. This is shown in Figure 3, which illustrates the relationship between energy intensity and GWP per capita in the scenarios and the actual development between 1960 and 1990 on double-logarithmic axes. As can be seen, economic growth during that time was associated with a reduction in energy intensity on the global level. Energy intensities develop along straight lines on the double-log scale, which illustrates the relatively faster improvement of energy intensities at early stages of economic development, where highly inefficient technologies are replaced by more advanced ones. The further energy intensities improve the harder it becomes, and the longer it takes, to achieve additional efficiency improvements.

The lowest energy intensity improvement rate of the database scenarios is 0.6 percent per year and the highest is 1.8 percent per year between 1990 and 2100. The median improvement rate in the SRES database is about one percent per year, corresponding to the long-term historical trend. The energy intensity reduction until 2030 decreases relatively fast (at a rate of 1.3 percent per year) in the POLES and MESSAGE scenarios. This corresponds to an average energy intensity of about 11 MJ/$ in 2030, compared to 12.6 MJ/$ in the MERGE-ETL baseline scenario in the same year. Still, the projections of energy intensity in the SAPIENT baseline scenarios cluster at a comparatively narrow range in 2030, when compared to the database scenarios where they range from 6 to 17 MJ/$.

Figure 4-3: Global primary-energy intensity as a function of GWP per capita on logarithmic scales, trajectories in the SAPIENT scenarios and ranges from the SRES database. (Also shown is the historical development from 1960 to 1990. Historical data: IEA (1993), World Development Report (1993); Database: Morita and Lee (1998)).



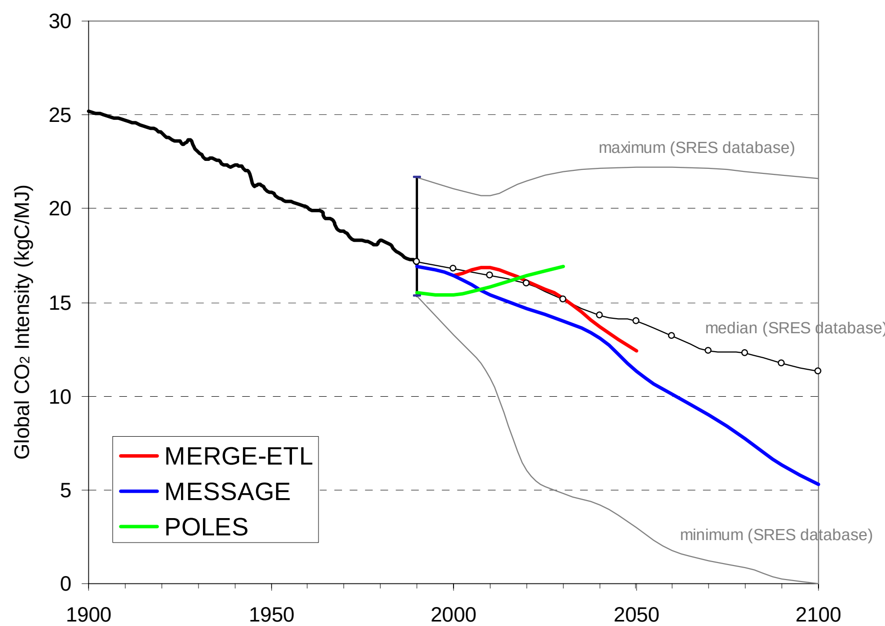
iv. Carbon Intensity of Energy

Declining carbon intensity[6] of primary energy has been termed decarbonisation (Kanoh, 1992). Although the average decarbonisation of the world's energy system shown in

Figure 4-3 was not more than 0.3 percent per, this trend has persisted throughout the last two centuries (Nakićenović, 1996). The overall tendency toward lower carbon intensities is due to the continuous substitution of fuels with high carbon content such as the coal by fuels with lower carbon content such as natural gas and non-fossil energy sources[7].

Figure 4-4 shows the carbon intensities of the SAPIENT scenarios, the ranges from the SRES database, and the actual development since 1900. The highest rates of decarbonisation in the SRES database are about 3.3 percent per year between 1990 and 2100, which corresponds to a reduction of energy-related carbon emissions per unit of energy by a factor of 40 in this time horizon. The median trajectory of the SRES database corresponds quite closely to the historical rate of decarbonisation with 0.3 percent per year.

Figure 4-4: Global decarbonisation (carbon intensity) of primary energy, trajectories in the SAPIENT scenarios and ranges from the SRES database. (Also shown is the historical development from 1900 to 1990. Historical data: IEA (1993), World Development Report (1993); Database: Morita and Lee (1998)).



No decarbonisation is projected for the most fossil-intensive scenarios in the SRES database. In some of these scenarios, carbon intensities of primary energy even increase at annual rates of up to 0.2 percent. This is also the case in the POLES baseline scenario, where global carbon intensity increases by a factor of 1.1 until 2030. Consequently, the POLES scenario shows the highest carbon intensity across the SAPIENT baseline scenarios. In contrast, the MERGE-ETL and the MESSAGE scenarios include some decarbonisation. Their carbon intensity in 2030 is about 15.2 kgC/MJ and 14 kgC/MJ respectively, which corresponds to a relatively moderate decarbonisation rate between 0.2 to 0.3 percent per year.

Note also the wide range of the carbon intensities across the SRES database scenarios for the base year (1990). There are many possible reasons for this discrepancy. The reasons include genuine differences across the scenarios such as sources of data, inclusion or exclusion of different sources of carbon emissions, and early base years that included 1990 emissions as an estimate. Also the SAPIENT baseline

[6] Note that the scenarios' carbon emissions, which were used to calculate the carbon intensities, do not include emissions from biofuels.

[7] However, it should be noted that carbon intensities are increasing in some developing regions. This is especially if emissions from non-commercial energy consumption are not accounted for. In this case, the substitution of non-commercial energy by other (commercial) fossil fuels result in significant emissions increases, which is rather a consequence of the accounting convention than the real change of the countries' carbon intensity.

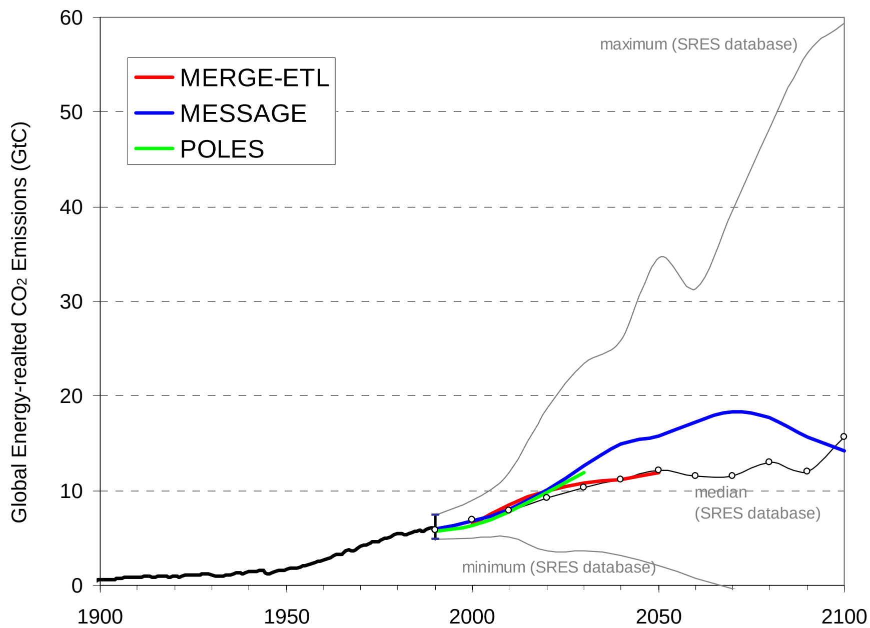
scenarios show considerable differences in the 1990 base year. The main reason for this deviation is that only the MESSAGE scenario includes non-commercial energy (i.e., non-commercial biomass use in the today's developing world) accounting for roughly 10 percent of the total primary energy use.

v. Carbon Dioxide Emissions

The range of CO2 emissions across all scenarios in the SRES database is large indeed, ranging, in 2100, from ten times the current emissions all the way to negative net emissions (i.e., a preponderance of carbon sinks, which was assumed in some scenarios). There are many possible interpretations of this wide range and many good reasons why it should be so wide. As has been shown above, common to most of the SRES scenarios is the high uncertainty about how the development of the main driving forces – population growth, economic development and energy use – during the next century.

Figure 4-5 shows the global CO2 emission paths for the SAPIENT, scenarios, the ranges of the SRES database, and the actual emissions from 1900 to 1990. The large differences in the base year data from the database (ranging from to 4.8 to 7.4 GtC) are visible again. The SAPIENT scenarios use values between 5.7 (POLES) and 5.9 (MESSAGE) GtC of carbon emissions from fossil fuel consumption in 1990.

Figure 4-5: Global carbon dioxide emissions, trajectories in the SAPIENT scenarios and ranges from the SRES database. (Also shown is the historical development from 1900 to 1990. Historical data: Marland, 1994; Database: Morita and Lee, 1998).



Global CO2 emissions have increased at an average annual rate of about 1.7 percent since 1900. If this trend continues, global emissions will have doubled by the year 2030. Many scenarios in the database in fact describe such a development. However, already by 2030, the range of projections by SRES scenarios is very large around this value of double global emissions. The highest projections by SRES database scenarios have emissions four times the 1990 level by 2030 while the lowest are barely above half the current emissions. This divergence continues, the highest projected emissions including a ten-fold increase by 2100.

All three SAPIENT baseline scenarios feature increasing global carbon emissions. Up to the year 2030, the SAPIENT projections are almost identical, clustering in 2030 between 10.8 and 12.6 GtC. This increase corresponds to roughly a doubling of today's emissions. In the longer run (until 2050), emissions increase relatively faster in the MESSAGE scenario compared to MERGE-ETL. Later in the century (in 2060), emissions peak in the MESSAGE scenario around 20 GtC and decrease later to reach about 14 GtC in 2100.

vi. Conclusions

This section reviewed scenario assumptions and results for the SAPIENT baselines developed by the IEPE, IIASA, and the PSI modeling groups. Our analysis focused on the GHG emissions driving forces population and economic growth, energy intensity, and carbon intensity, and on the scenario results for carbon emissions. Moreover, we have compared the scenario indicators from the SAPIENT scenarios with ranges from the SRES database, which includes more than 400 scenarios from 171 published literature sources.

For all analyzed scenario indicators, the SAPIENT scenarios show comparatively narrow ranges. Relative to the median development of the SRES database the SAPIENT scenarios show the following characteristics:

- Population grows at median SRES rates.
- Economic growth is at or slightly above the SRES median.
- Energy intensity improves at or slightly below SRES median rates.
- Carbon intensity of the MERGE-ETL and MESSAGE scenario improves at SRES median rates, whereas in the POLES scenario, carbon intensity increases over time.
- Carbon emissions rise slightly faster than the SRES median.

From this it can be concluded that despite minor differences with respect to some of the driving forces, the SAPIENT baseline scenarios show particularly consistent developments of the resulting carbon emissions. They therefore serve particularly well as the basis for the sensitivity analysis to estimate the various indicators related to the effectiveness of R&D.

References

Bos, E., and Vu, M.T., 1994: World Population Projections: Estimates and Projections with Related Demographic Statistics 1994-1995 Edition, The World Bank, Washington, DC, USA.

Demeny, P., 1990: 'Population', in B.L.Turner II, *et al*. (ed.), *The Earth As Transformed by Human Action*, Cambridge, Cambridge University Press.

Dowlatabadi, H. *et al*. 1995: 'Key Uncertainties in Climate Change Policy: Results from ICAM-2', *Proceedings of the Global Warming Conference*, San Francisco.

Durand, J.D. 1967: 'The modern expansion of world population', *Proceedings of the American Philosophical Society*, 111(3):136–159.

EIA (Energy Information Administration), 2001: International Energy Outlook 2001, US Department of Energy, Washington, DC, USA. <http://www.eia.doe.gov/oiaf/ieo/index.html>.

IEA (International Energy Agency) 1993: *Energy Statistic and Balances for OECD and non-OECD countries 1971–1991*, OECD, Paris, France.

Kanoh, T., 1992: 'Toward Dematerialization and Decarbonization', in *Science and Sustainability*, *Selected Papers on IIASA's 20th anniversary*, IIASA, Laxenburg, Austria.

Kaya, Y., 1990: *Impact of Carbon Dioxide Emission Control on GNP Growth: Interpretation of Proposed Scenarios*. Paper presented to the IPCC Energy and Industry Subgroup, Response Strategies Working Group, Paris, (mimeo).

Lutz, W., Sanderson, W., and Scherbov, S., 1997: Doubling of World Population Unlikely, *Nature*, 387(6635):803-805.

Manne, A., and Schrattenholzer, L., 1996: *International Energy Workshop January 1996 Poll Edition,* IIASA, Laxenburg, Austria.

Manne, A., and Schrattenholzer, L., 1997: *International Energy Workshop, Part I: Overview of Poll Responses, Part Infrequency Distributions, Part III: Individual Poll Responses,* February 1997, IIASA, Laxenburg, Austria.

Marland, G., R.J. Andres, and T.A. Boden, 1994: Global, regional, and national CO_2 emissions. pp.505-584. In *Trends '93: A Compendium of Data on Global Change,* ORNL/CDIAC-65. T.A. Boden, D.P. Kaiser, R.J. Sepanski, and F.W. Stoss (eds).,Carbon Dioxide Information Analysis Center, Oak Ridge National Laboratory, Oak Ridge, TN, pp. 505-584.

Messner, S., and M. Strubegger, 1995: *User's Guide for MESSAGE III*. WP-95-69, International Institute for Applied Systems Analysis, Laxenburg, Austria, 155 pp.

Morita, T., and Lee, H.-C., 1998: *IPCC SRES Database, Version 0.1, Emission Scenario Database prepared for IPCC Special Report on Emission Scenarios*, http://www-cger.nies.go.jp/cger-e/db/ipcc.html.

Nakićenović, N., 1996: Freeing Energy from Carbon*, Daedalus*, 125(3):95–112.

Peck, S.C., and Teisberg, T.J., 1995: 'International CO_2 Emissions Control-An Analysis using CETA', *Energy Policy*, 23(4), 297-308.

S. Kypreos and O. Bahn (2002). 'A MERGE model with endogenous technological progress", Paul Scherrer Institute, Switzerland, submitted to Environmental Modelling and Assessment.

SRES (Special Report on Emissions Scenarios): 2000, *Special Report on Emissions Scenarios (SRES) for the Intergovernmental Panel on Climate Change*. Nakićenović *et al*., Cambridge University Press, Cambridge, UK.

UN (United Nations), 1996: *Annual Populations 1950–2050: The 1996 Revision.* UN Population Division, United Nations, New York, NY. (Data on diskettes).

UN (United Nations), 1998: *World Population Projections to 2150*, UN Department of Economic and Social Affairs, Population Division, New York, United Nations.

Weyant, J.P., 1993: Costs of reducing global carbon emissions, *Journal of Economic Perspectives,* 7(4):7–46.

World Development Report, 1993: *World Bank,* Oxford University Press, New York, USA.

Yamaji, K., Matsuhashi, R., Nagata, Y., and Kaya, Y., 1991: An Integarated Systems for CO_2 /Energy/GNP Analysis: Case Studies on Economic Measures for CO_2 Reduction in Japan, *Workshop on CO_2 Reduction and Removal: Measures for the Next Century, 19–21 March 1991*, IIASA, Laxenburg, Austria.

5. Endogenous versus Exogenous Technical Change Scenarios with the POLES model (by P. Criqui and S. Mima, IEPE-CNRS)

Forecasting technology development is a highly speculative activity, especially for a long-term time horizon. However, considerable efforts have been recently made to improve the modelling of technology development in energy models. The usual and simplest approach consists in introducing exogenous forecasts on technology development and economic performances that are based on expert judgement. This type of exercise has been performed at the beginning of the project with the updated databases and scenario hypotheses in the SAPEX (Sapient exogenous) scenario. This preliminary scenario has then be used as a benchmark for the assessment of the SAPEN (Sapient endogenous) scenario. In the latter case exogenous hypotheses have been replaced by a description of technology cost dynamics which endogenises, at least partially, technological change in the new and renewable technologies and in the electricity modules of the POLES model.

As any model POLES is a simplified representation of reality. This means that important factors, which may have a decisive impact on the future development of the world energy system, are either ignored or at least not explicitly dealt with in the model. Among these factors, one has to mention the geopolitical drivers and constraints, which have already played a major role on the energy scene, in the past decades. Also the consequences of the major changes in the industries' regulation and organisation schemes that occurred in the past twenty years are not taken directly into account in the modelling system used for this study. However, recent developments in the POLES model allowed to introduce a set of features that were ignored before, i.e. the basic elements of endogenous technical change in the energy sector, through learning effects and R&D induced improvements.

The exogenous technology base case for the SAPIENT project (SAPEX) is presented in Section 5.1. Section 5.2 describes the methodology used to endogenise technical change and then provides the comparison of the SAPEX and SAPEN results with a focus on the key variables, i.e. investment costs and installed capacities for the set of 23 technologies considered in the exercise.

5.1. Global energy and technology trends to 2030: The SAPEX case

The SAPEX scenario provides an image of how the world energy system may develop in the next decades in a "business and technical change as usual" context and with exogenous technology performance and costs. In other terms, it is supposed that this development is mostly driven by changes in the fundamental variables that reflect rational economic behaviours and not, as mentioned above, by major political, economic or technological disruptions. The main hypothesis of SAPEX scenario are:

1. The main drivers in the future development of the world energy system will remain the population and economic growth. As the on-going trends for these two sets of variables are differentiated across the main world regions, their continuation results in significant changes in the regional structure of population, GDP, energy demand and associated emissions.
2. Technical change has been a continuous phenomenon throughout history, although this process may be submitted to slowdowns or accelerations. Thus, any projection of the economic system has to take into account the consequences of the continuous improvement in the technologies' economic and technical performances. As far as energy technologies are concerned, the hypotheses that are taken into account in the SAPEX indeed take into account technological progress, at least along the lines of past improvements. This approach relies exclusively on exogenous forecasts based on expert judgement concerning technology development and economic performance.
3. The availability of energy resources is clearly a potential constraint for the development of fossil fuel use in the long term, or at least it is a factor that can drive their price up and limit the demand. Coal resources are known to be overabundant, at least for the next century. But huge uncertainties surround any assessment of the recoverable oil and gas resources at the world and regional level. The SAPEX scenario uses median estimates for resources that are identified at the regional level, with values that are globally well accepted by the experts.

4. As far as energy or environmental policies are concerned, the SAPEX scenario only includes the consequences of the policies and measures that have already been decided up to now. It is even considered by judgement that these policies and measures may not benefit of a full implementation over the projection period. Thus the SAPEX does not include a full compliance to the policy decisions or announcements made by governments, including the European Commission, or industries. The carbon constrained case, defined in the project as the SAPIENT-Reference (SREF), is presented below in Chapter 1.1.1.

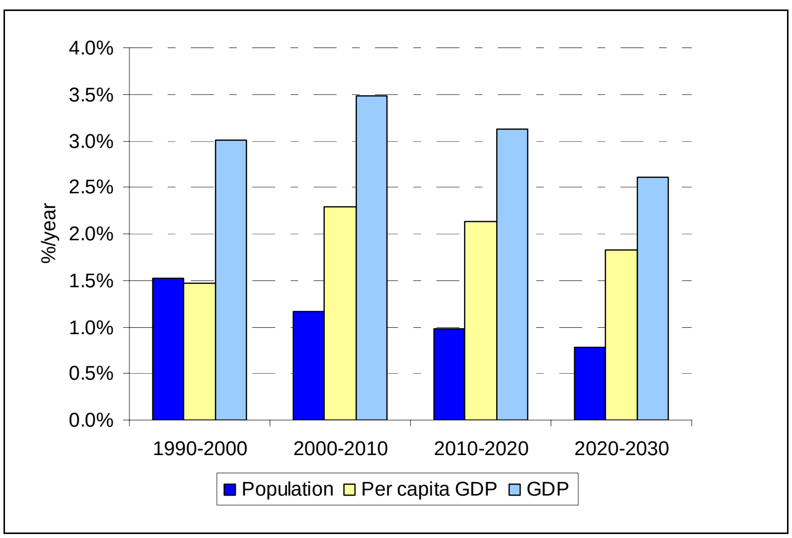
5.1.1. The dynamics in world population and economic growth

The combined growth in the world population and economy will remain key driving forces in the development of the energy sector over the next decades. The population outlook used in this study is based on the UN population prospects (United Nations, 2000). The economic outlook has been prepared by the CEPII (IEPE, CEPII, 2002) and is based on a simple growth model that takes into account the accumulation of physical and human capital in the different regions considered.

The resulting picture of the world population and GDP[8] to 2030 reflects a combination of continuing trends and of important structural changes. The key features of these dynamics can be summarised as follows:

- World population growth rate will continue to decrease over the projection period from 1.5 %/year in the past decade to 1 %/year over the 2000 to 2030 period. This results in a total population of 8.2 billions in 2030, from 6.1 billions in 2000.
- On average, world economic growth will be slightly above 3 %/yr for the next thirty years, a level that is comparable with the one of the past thirty years (3.3 %/yr from 1970 to 2000 and 3.0 %/yr from 1990 to 2000, due in particular to the transition process in the CEEC - Central and Eastern European Countries - and CIS region during the past decade).
- This is made possible by the acceleration in the world average per capita GDP growth that is marked in the 2000-2010 decade, and is largely due to the projected economic recovery in the CEEC and CIS region.
- The combination of the continuous slowdown in the population growth rates and per capita GDP results, after the initial upsurge, in an economic growth rate that is weakening over time, from 3.5 %/year in the first decade, to 3.1 %/year in the following decade and finally 2.6 %/year between 2020 and 2030 (Figure 5-1).

Figure 5-1: World population, per capita GDP and GDP growth



[8] All GDP figures in this study are calculated using a constant 1995 Purchasing Power Parity system

5.1.2. GDP growth projections and changes in relative per capita GDP

The simple growth model that has been used to project GDP for the different world regions is based on the hypothesis of a convergence in GDP growth rates, subject to conditional hypotheses on investment rates in physical and human capital. The hypotheses used for the GDP projections intend to reflect the particular conditions of each country or region.

Box: GDP forecasts by CEPII

The GDP projections used in the POLES model scenarios are provided by the CEPII (Centre d'Etudes Prospectives et d'Informations Internationales), a research centre of the French Government specialised in international economic analysis, modelling and forecasting.

GDP forecast by world region is based on a neo-classical growth model with exogenous technological progress but also with an explicit consideration of the role of human capital.

The main assumption of the model is the convergence in labour productivity towards a long-term equilibrium in a closed economy. The active population being exogenous (from UN projections) the forecast depends on three key factors: physical capital, human capital and technology level incorporated in labour. The physical capital is a function of the investment rate. The human capital is a function of the school enrolment, linked to per capita GDP. The convergence in the labour productivity variation is due to an assumption of a decreasing marginal output of the physical and the human accumulated capital.

$$GDP = K^{a} \times H^{b} \times (A \times L)^{(1-a-b)}$$

with: **K:** *physical capital, function of investment rate*

H: *human capital, function of school enrolment (*linked to GDP per cap*)*

L: *active population (*exogenous from UN projections*)*

A: *technology level incorporated in labour*

Investment rates and school enrolment are differentiated among countries and the growth of the technology level incorporated to labour is higher for developed countries.

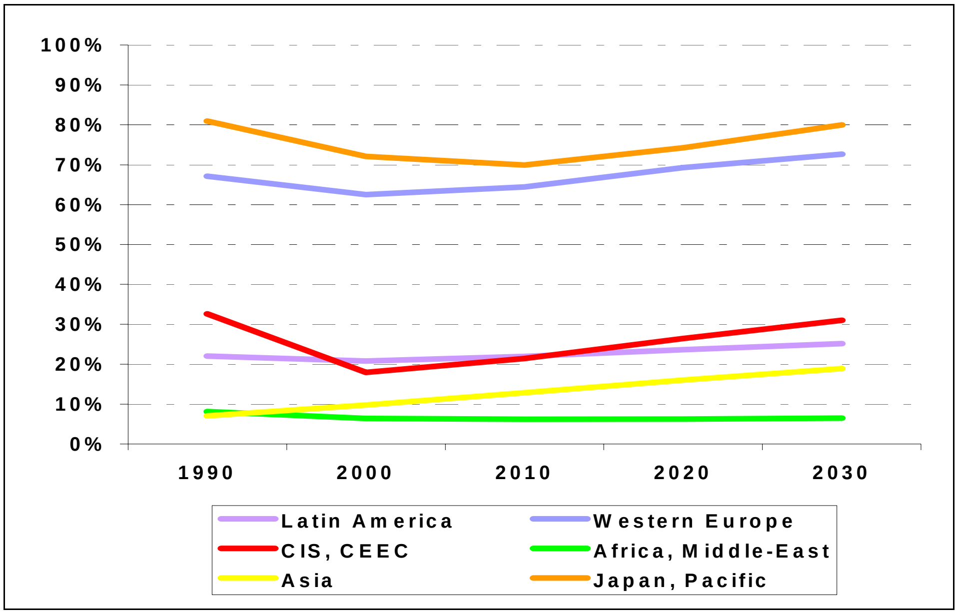
When translated into per capita GDP levels, the projections show some convergence across the different world regions. This convergence can be analysed by calculating the ratio of each region's per capita GDP on that of the higher income region, i.e. North America (Figure 5-2).

After the 1990-2000 decade during which Western Europe and the Japan and Pacific regions lost some ground comparatively to North America, the projection results in some catch-up of these two regions in the following decades. The Japan and Pacific region recovers its 1990 position in 2030 (80 % of the North American level) while Western Europe slightly improves it (from 68 to 72 %).

As far as the economies in transition are concerned, the per capita GDP ratio relatively to North America follows a much more uneven trajectory, with a huge drop from 1990 to 2010 (from 32 to 18 % of the North American level). A sustained recovery follows, without however allowing a full recovery of the 1990 level at the end of the projection (31 % in 2030).

The trajectories of the developing regions are contrasted. While Asia sees a significant improvement in its per capita GDP ratio (from 8 to 19 % of the North American level between 1990 and 2030), the convergence process of Latin America is much more limited (from 20 to 25 %). The Africa and Middle-East region does not experiment any convergence, as its per capita GDP represents a stable 7.5% of the North American level over the period.

Figure 5-2: Per capita GDP by region as a percentage of North America



5.1.3. Exogenous assumptions on energy technology development

The assumptions on the development of energy technologies play a crucial role in the analysis of future energy systems. The ability to reduce greenhouse gas emissions and especially the cost of the corresponding policies will indeed largely depend on the availability, costs and performances of the different energy technologies, and particularly of the power generation technologies. This section provides a closer look on specific investment cost and installed capacities as exogenously introduced in the SAPEX case, before the analysis in Section 5.2 of the changes introduced by the endogenisation of technology dynamics in the SAPIENT endogenous case.

Table 5-1: Exogenous investment costs (full costs, with interests during construction and decommissioning)

€99/kWe	HYD	NUC	NND	LCT	CCT	PFC	ICG	ATC	OCT	OGC	GCT	GGC
1971	4 220	3 309		2 499	1 873							2 243
1980	4 080	2 978		2 242	1 748							1 059
1990	3 939	4 137		2 114	1 686	2 233			1 794	472	1 178	866
2000	3 678	3 111	4 567	2 088	1 535	1 861	2 306	2 109	1 730	459	1 116	815
2010	3 305	3 000	2 940	2 003	1 452	1 545	1 926	1 900	1 568	377	1 064	790
2020	3 270	2 989	2 826	1 994	1 444	1 516	1 892	1 880	1 553	370	1 059	787
2030	3 235	2 978	2 712	1 986	1 436	1 489	1 858	1 861	1 538	363	1 054	785

€99/kWe	CHP	SHY	WND	SPP	DPV	RPV	BF2	BGT	FCV	SFC	MFC
1971			8 289		287 977					122 785	122 785
1980	1 214		3 552		37 784	47 545				22 101	22 101
1990	1 093	2 698	1 539	4 626	14 854	24 063	4 671	2 789	267 726	12 279	11 051
2000	1 032	2 441	1 013	3 341	6 938	12 700	2 441	2 179	62 262	2 210	2 087
2010	961	2 334	857	2 459	6 374	7 397	2 031	1 916	15 927	1 447	1 579
2020	954	2 323	843	2 385	6 232	6 924	1 993	1 892	15 427	1 398	1 526
2030	947	2 313	829	2 313	6 097	6 742	1 957	1 868	14 943	1 351	1 473

Figure 5-3: POLES projection to 2030 with exogenous costs, ex-post Learning Curves

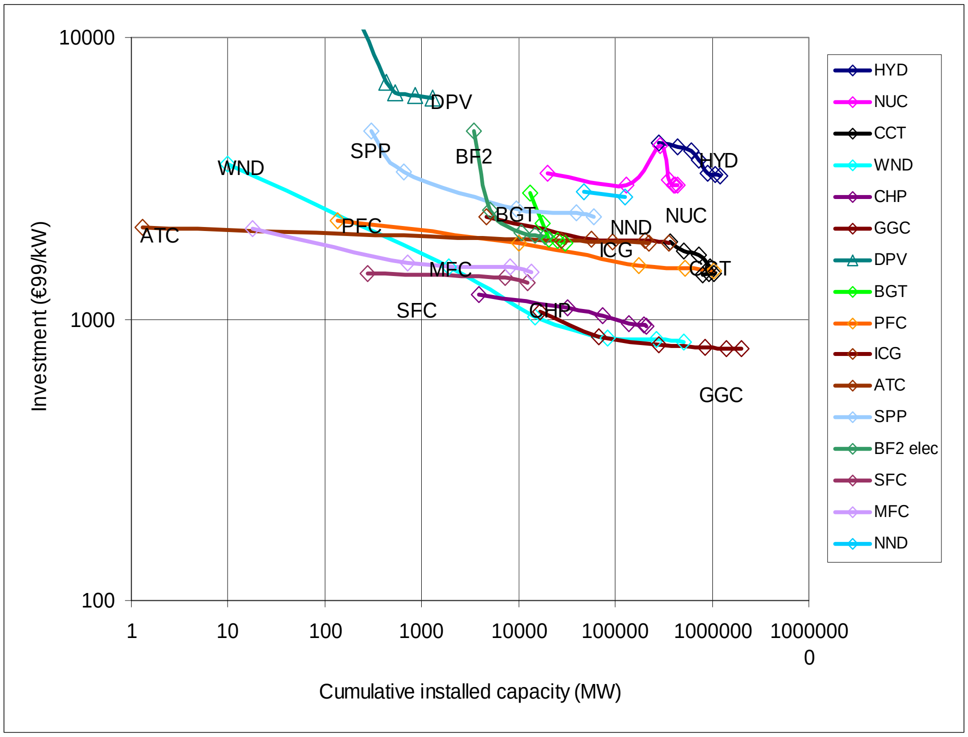


Figure 5-3 provides an outlook on technology diffusion and improvement in the SAPEX case while using the Learning Curve approach as a filter that is applied ex-post to the model's result. As it can be seen from the figure, some technologies indeed show trajectories that are consistent with a regular learning-by doing effect. This is however not the case for all of them and in general expert judgements on technology improvement seem to reflect a relatively pessimistic or conservative view.

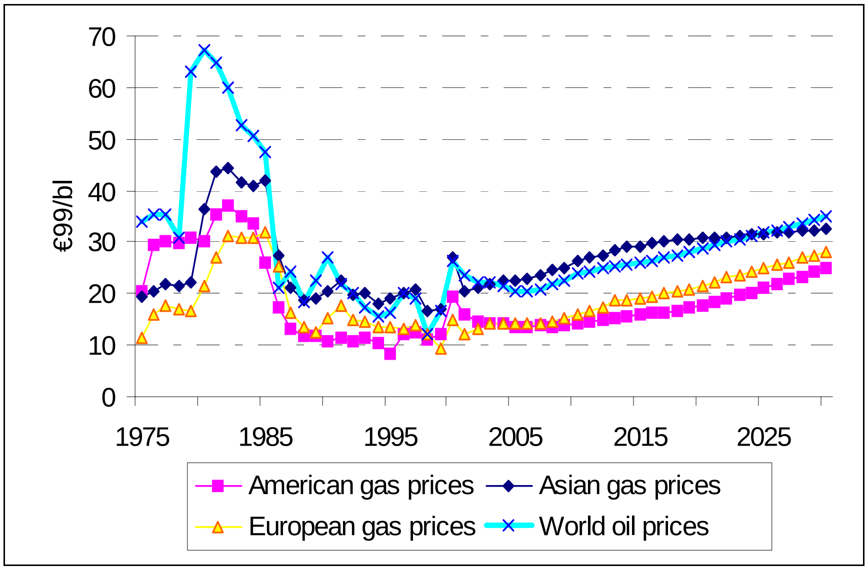
5.1.4. International energy prices

The long-run evolution of the international oil and gas prices is endogenously simulated in the POLES model, reflecting the dynamics and lagged adjustments of world demand and supply.

The global picture for oil and gas prices[9] in the SAPEX is illustrated in Figure 5-4 that shows relatively low oil prices until the middle of the current decade, due to a moderate oil demand. Later on, the oil price increases relatively sharply to 24 €/bl in 2010 before a phase of more moderate but steady increase until 2030. It reaches 29 €/bl and 35 €/bl in 2020 and 2030 respectively. In fact, before 2010 a new period begins for the oil market, in which the oil production of the Gulf countries has to grow beyond its maximum historical level of about 23 Mbl/d. Consequently, the Gulf oil producers need by that time to continuously develop new production capacities, while the reduction in Reserve on Production ratios at world level exerts an upward pressure on oil price. However, the price-path obtained from the model only indicates a trend that is consistent with the relative dynamics of world supply and demand and do not pretend to provide a precise oil price forecast. In particular, the projection do not account for possible geopolitical events that many times in the past proved to affect the price level.

[9] All prices are in € of 1999 (equivalent to US$ of 1995).

Figure 5-4: Oil and gas prices

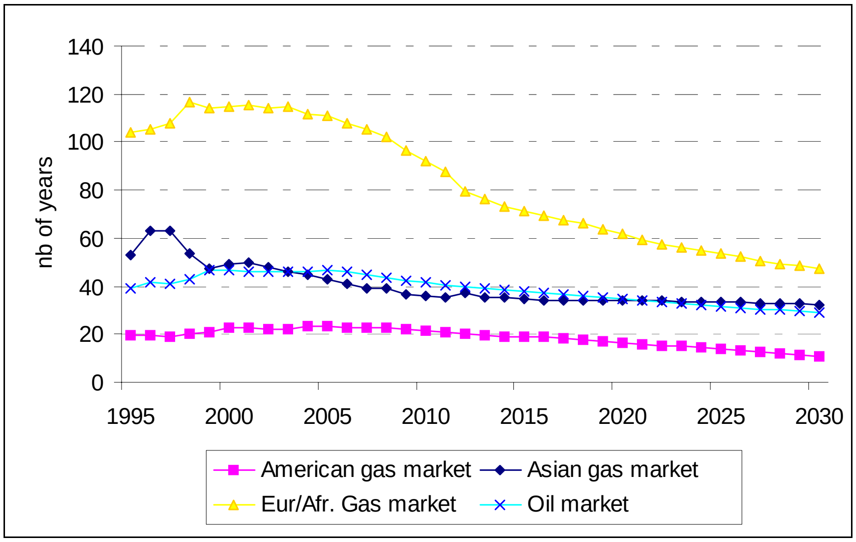


For gas, three continental markets are considered, namely America, Europe/Africa and Asia. They continue to be characterised by price levels that are structurally different. This reflects differences in the development of transport infrastructures and conditions in supply, particularly the mix between pipeline gas and Liquefied Natural Gas (LNG). For instance, the Asian gas market is significantly dependent on LNG imports; consequently, current gas prices on this market are higher than those of Europe and America. However, regional price differentials are expected to diminish significantly over the next 30 years, reflecting more comparable gas supply mixes by 2030:

- On the Euro-African market, notwithstanding a period of relative stabilisation in the middle of the current decade, the gas price is projected to increase regularly to reach 28 €/boe in 2030.
- On the American market, the gas price declines first significantly from the high level of 2000, down to 14 €/boe before 2010 and then it increases again steadily, although more slowly than on the European market, to reach 25 €/boe in 2030.
- Contrary to gas prices on the American and European markets, which follow comparable trends, the gas price on the Asian market increases constantly throughout the projection period, although at a slower pace after 2015, from 20 €/boe in 2001 to 33 €/boe in 2030.

According to the mechanism of oil and gas prices formation, the price movements mainly depend on the variation of the Reserve on Production (R/P) ratio, which constitutes a long-term indicator of the balance between demand and supply. Nevertheless, the Gulf production capacities are also taken into account for the projection of oil price, as well as a partial oil-indexation term for the calculation of gas prices. The latter parameter is however assumed to be of decreasing importance throughout the projection period. Figure 5-5 shows the evolution of the R/P ratios on the different markets: the international market for oil and the three regional markets for gas.

Figure 5-5: Oil and Gas Reserve on Production ratios



Coal price is independent of oil price and is assumed to remain so. Moreover, and contrary to oil and gas, coal supply will not be subject to resource constraints over the projection period. Therefore, in the POLES model, the evolution of coal price is derived from the development of production costs of the key producing countries. The SAPEX scenario ultimately projects stable and then slowly increasing coal prices to reach levels of about 10 €/ton in 2030. This is due to the availability of a large number of low cost coal production sites worldwide.

5.1.5. Global outlook for energy consumption

In the SAPEX case, the world energy scene in 2030 mainly reflects an expanded vision of the current system. However, some significant changes occur, particularly in the relative shares of the main world regions and of the primary energy sources. These changes are associated, respectively, to different population and economic growth dynamics, higher energy prices and more efficient technologies. The world energy consumption is projected to increase by some 70% over the 2000-2030 period (Figure 5-6).

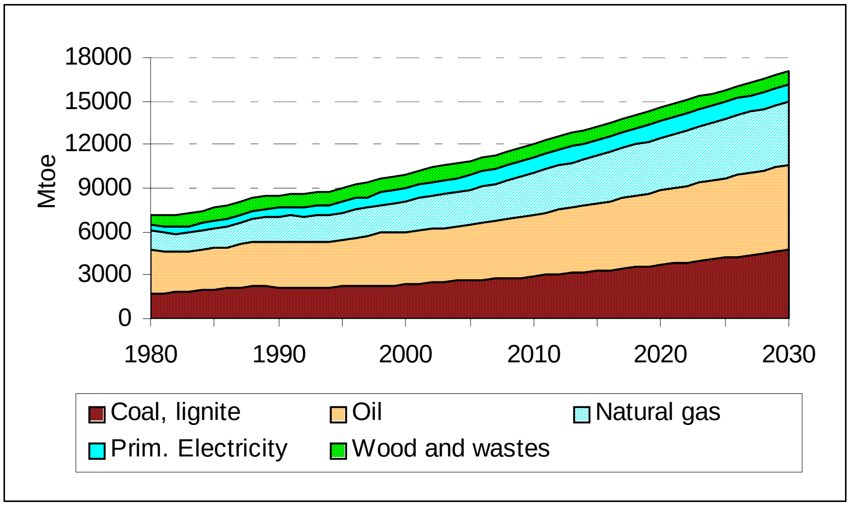
The gross inland consumption is the sum of the final energy demand and the energy demand for electricity production and other energy transformations. In the POLES model, the final demand is modelled at the level of various sectors. In each sector, energy demand is driven by economic activity variables and price changes and trends. The energy demand for electricity production results from the simulation of power generation technologies. The dynamics of the GIC can be analysed through the evolution of three factors: population (POP), Gross Domestic Product/capita (GDP/POP) and the energy intensity (GIC/GDP). Under this decomposition, the Gross Inland Consumption is described as: POP x GDP/POP x GIC/GDP.

In the SAPEX case, the gross consumption increases at 1.8%/year between 2000 and 2030, while population grows at a rate of 1%/year and the per capita GDP at 2.1%/year, while the energy intensity of GDP decreases by - 1.2%/year. The projections show that at the world level and in most regions, the GDP/capita is the main factor in energy consumption growth. Nevertheless, in Africa, Latin America and Asia, the growth in total population is also a key factor in the energy demand growth.

In 2030, fossil fuels (coal, lignite, oil and natural gas) are projected to represent 88% of world energy consumption. This percentage is greater than the 81% share observed in 2000. Despite a rapid growth of coal and gas utilisation, oil still represents the largest share (34%) of world gross inland consumption (GIC) in 2030:

- ➢ Oil demand increases at a rate that is similar to the one observed during the 1990-2000 decade (i.e. 1.6%/yr) and demand reaches 5.9 Gtoe in 2030.
- ➢ Natural gas demand increases by 3%/year on average between 2000 and 2010 and by 2.1%/year afterwards. The share of natural gas in total consumption extends to 25% in 2030 from 21% in 2000.
- ➢ Coal demand is also projected to grow rapidly over the next thirty years. Between 1990 and 2000 the growth of coal consumption has been 0.9%/yr but after 2000 it goes up to 2.1%/year until 2010 and then to 2.5%/year between 2010 and 2030 as coal gains competitiveness relatively to other fuels.

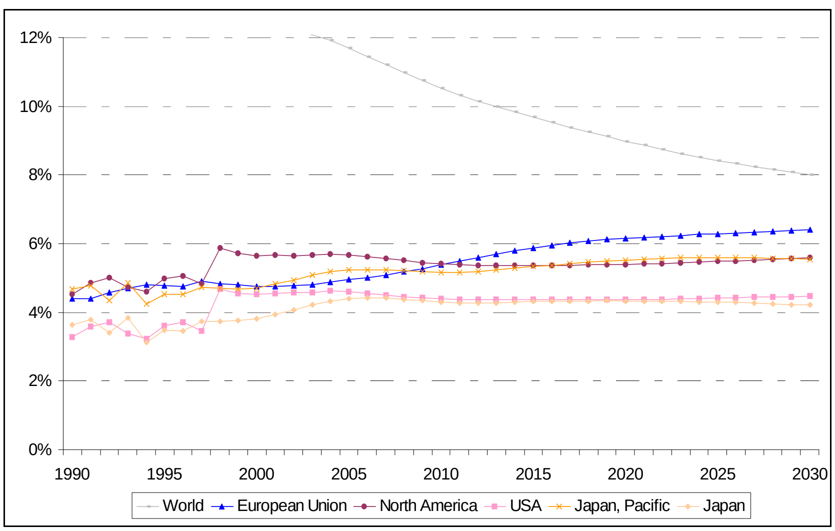
Figure 5-6: World energy consumption



Over the entire projection period, nuclear energy increases only slightly in absolute terms. During the 1990-2000 decade the growth of nuclear has been of 2.7%/year, but this rate weakens to 0.9%/year in the next thirty years. In 2030, nuclear represents 5% of the world GIC, compared to 7% in 2000.

The share of large hydropower and geothermal energy stabilises at 2% of world GIC. Wind, solar and small hydropower altogether grow at 7%/yr between 2000 and 2010 and then at about 5%/yr until 2030. In spite of the marked acceleration in the diffusion process of these renewable sources and because of their limited initial penetration, their market share represents less than 1% of world GIC in 2030. Conversely, wood and wastes consumption decreases steadily during the projection period, but its share in world GIC (5% in 2030, to be compared with 9% today) remains higher than the share of the new renewable sources.

Figure 5-7: Share of total renewable in total energy consumption



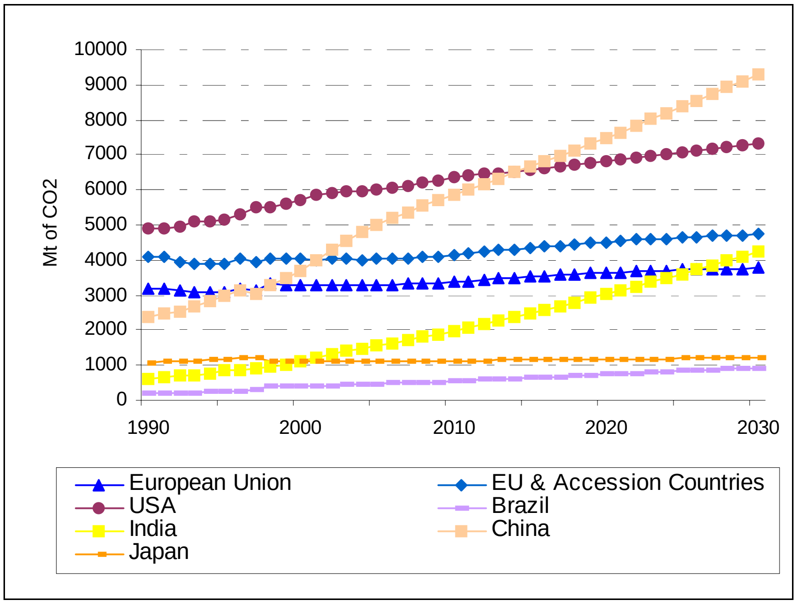
Globally, energy from renewable sources is projected to cover 8% of world energy requirements in 2030 (Figure 5-7). This is less than the 13% share observed in 2000 and is essentially due to the continuous decline of traditional biomass consumption in Asia and Africa, due to increased urbanisation, deforestation and substitution to modern energies in rural areas. Actually, the evolution of the share of renewable in total energy consumption shows contrasted patterns across regions, while the European Union with a regular increase achieves the highest share among industrialised regions (6% of total consumption in

2030)[10]. These changes in the primary fuel-mix impact considerably on the carbon intensity of the world energy system and on the associated CO2 emissions, as discussed below.

5.1.6. Global CO2 emissions more than double between 1990 and 2030

This section examines the dynamics of the energy-related CO_2 emissions, which reflect the changes in fossil fuel combustion described above. On a world scale, CO_2 emissions more than double over the 1990-2030 period, from 21 to 45 Gt of CO_2. The regional shares also change significantly: in 1990, the emissions from the industrialised regions represented 70% of CO2 emissions; this share decreases to only 42 % by 2030. By then China is the largest world CO_2 emitter in absolute terms, while it has overcome US emissions by 2015. This of course doesn't hold for per capita emissions.

Figure 5-8: Energy-related CO2 emissions in selected regions or countries



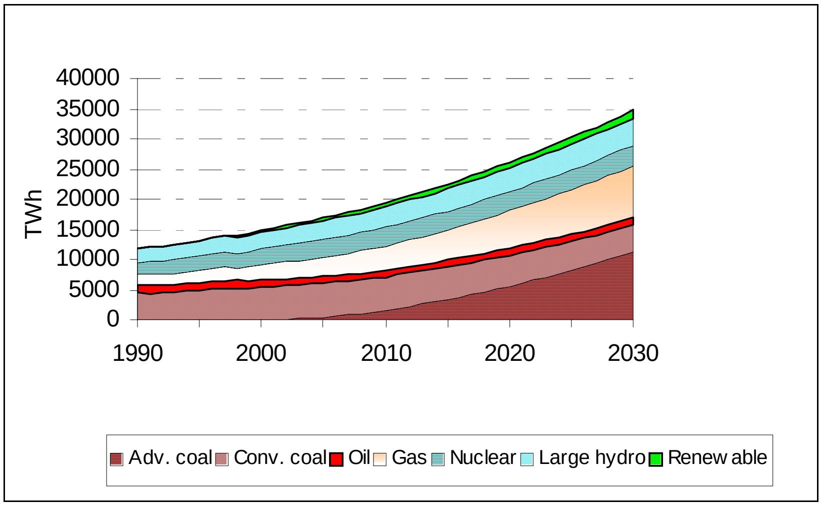
Emissions growth is expected to be extremely rapid in developing countries, whereas developed and industrialised regions undergo a more moderate growth or even a decline. For instance, India experiences a six-fold increase (5%/yr). The emissions in the other developing regions increase in a range of 200-350%. CO_2 emissions of the CIS and CEEC decreased spectacularly during the economic recession of the nineties, with a drop in emissions of 41% and 22% respectively in the 1990-2000 period. Only in 2030 do their CO_2 emissions reach the 1990 level again. The European Union, the Japan and Pacific region and North America experience a more moderate but still substantial growth of their emissions with increases of 18%, 32% and 50% respectively.

[10] Nevertheless, it is worth underlining that the Reference outlook does not include the EU global indicative target of 12% of GIC for renewable electricity in 2010, as outlined in the EC White Paper on Renewable Energy Sources (OJ C, 6.7.1998).

5.1.7. Power generation and renewable technologies

In the SAPEX case, the world electricity demand and production rises steadily at an average rate of 3%/yr over the projection period, to a level 2.3 times higher in 2030 than in 2000. The level of detail in the POLES model allows the detailed analysis of the evolution of the power generation technology mix.

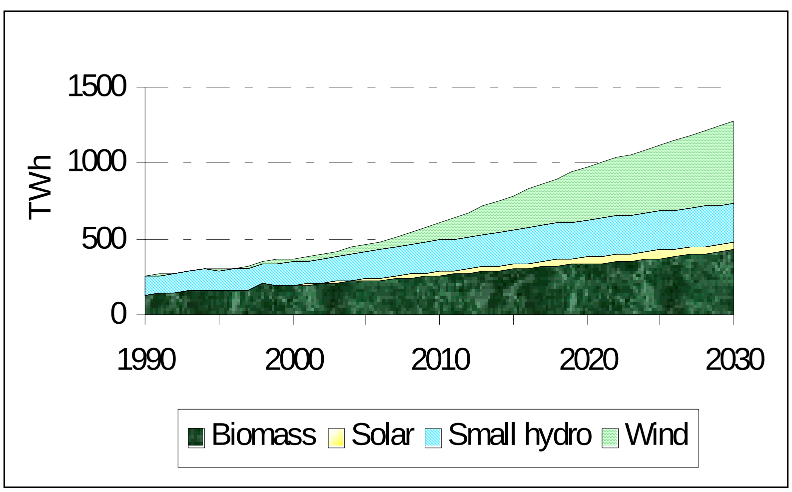
Figure 5-9: Fuel mix in world power generation



More than half the total electricity production in 2030 is provided by technologies that emerged in the nineties and afterwards, like gas combined cycle turbines, advanced coal technologies and renewable. These two fossil fuel-based technologies are expected to largely replace conventional thermal power plants by the end of the projection period. The share of conventional coal is expected to decrease from 36 % in 2000 to 12 % in 2030, while the share of gas increases from 16 % to 25 % and advanced coal takes a share of 33 % in 2030.

In spite of a continuous expansion, the development of nuclear power does not keep pace with total electricity production: nuclear world market share comes down to 10 % of total electricity production in 2030, from 18 % in 2000. The same applies, although to a lesser extent, to large hydropower, whose market share decreases from 19 % to 13 %. On the contrary, the share of other renewable technologies is expected to increase from 2 % to 4 % despite the rapid increase in solar and wind power of about 11%/yr at world level.

Figure 5-10: World electricity production from renewable sources



At world level, the growth of electricity production from biomass, solar, wind and small hydro is remarkable (more than 4 %/year on average) although no policy targets for renewable sources (as for instance the EU Directive 2001/77/EC) have been taken into account in the SAPEX. The growth is the most pronounced for solar and wind, the production of which is expected to increase at an average rate of about 11 %/year over the 2000-2030 period (Figure 5-9). In spite of this quick development and because of very low initial levels, electricity from renewable sources is not expected to exceed 3 % of world total electricity production in 2030 (16 % when large hydro and geothermal are included).

Figure 5-10 displays the outlook for electricity production from renewable sources (excluding large hydro and geothermal) in the EU. The development of wind is the most significant although expanding at a slower rate than for the world, i.e. an increase of about 7 %/year, whereas the contribution of solar photovoltaic is negligible. Power generation from small hydro and biomass increases steadily covering together half the electricity produced from renewable sources in 2030, the other half being covered by wind power production.

5.2. Endogenisation of Technical Change: the SAPEN case

5.2.1. The endogenous technology module

Learning curves taking into account both 'learning by doing" and "learning by research" effects are the key elements for the endogenisation of technical change in the POLES model and for the introduction of a causality link between R&D variables and technology performances. In order to develop these equations, considerable problems of data had to be overcome˜ as explained in Chapter 1 describing Technology Improvement Dynamics Database for power generation technologies the TID database in particular for the disaggregation of public and private sector R&D for the set of technologies considered in this study.

Based on modelling efforts developed in preceding research projects (in particular Climate Technology Strategies), the module for the endogenisation of technical change connected to the POLES main model can be described as following (Figure 5-11):

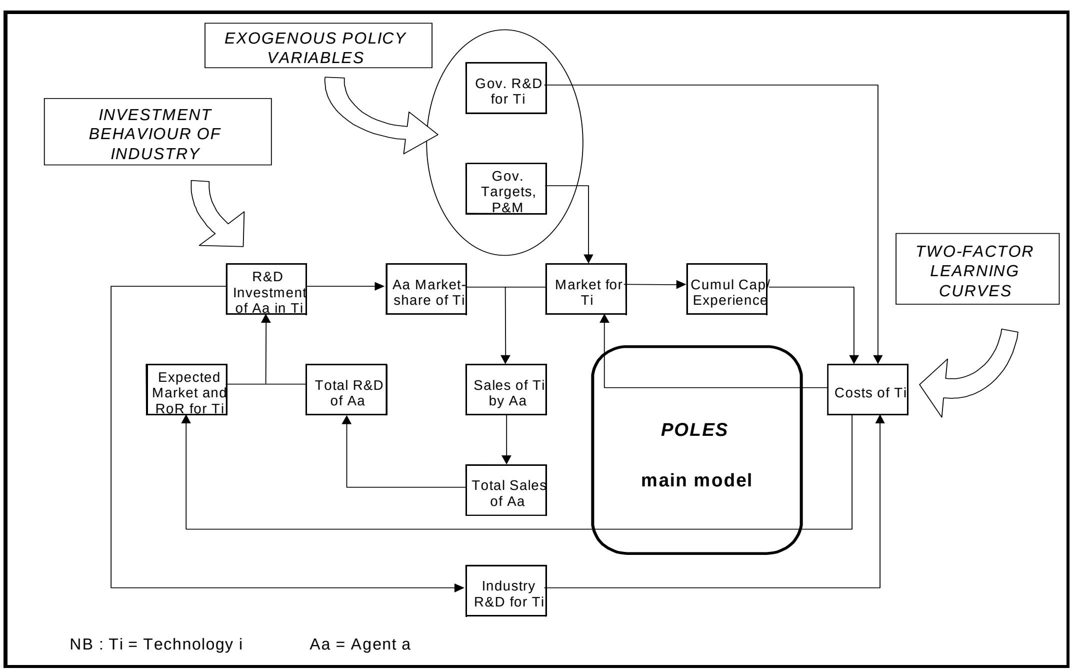
i. exogenous public policies provide both the environmental constraint (either in the form of quantitative targets or of a GHG emission penalty) and the impulse or "technology push" through public R&D spending;

ii. the endogenous industry R&D investment module allows to simulate the private sector investment behaviour through the interplay of a limited number of more or less risk averse "representative agents" with investment capabilities limited by their sales and that take into account in their decisions the attributes of each technology in terms of cost, performance and associated uncertainty;

iii. the "two factor learning curves" provide the dynamics for technology improvement depending on the cumulative capacities for the "learning by doing" part and on the cumulative knowledge stock (R&D) for the "learning by searching" part;

iv. the main POLES model provides the inter-technology competition and diffusion framework while taking into account all relevant key variables in the energy sector (prices, demand capacities etc.).

Figure 5-11: The endogenisation of Technical Change in the POLES model



The "two factor learning curves" (TFLC) that are the key elements in the SAPIENT are used for all technologies in the "new and renewable energy" and in the "large scale power generation" modules of POLES model endogenous technology cases. They are expressed as follows:

$$INV_{i,tech+otech} = (1+res) * INV_{i,tech+otech,t-1} * CIP_{i,tech+otech} * \left(\frac{TOTRD_{i,tech+otech,t-1}}{TOTRD_{i,tech+otech,t-2}}\right)^{rdb_{i,tech+otech}}$$

where :

- *INV* is the investment cost of the considered technology,
- *res* is a residual variable,
- *tech* is the index for new power generating technologies
  (NND, PFC, ICG, ATC, OGC, GGC, BGT, CHP, DPV, MFC, SFC, SHY, SPP, WND)
- *otech,* is the index for conventional power generating technologies
  (HYD, NUC, LCT, CCT, OCT, GCT, BF2, RPV)
- *CIP* is the variation in cumulative installed capacity:

$$\begin{aligned} CIP_{i,tech+otech} = {} & IF\ CAPINS_{i,tech+otech} < 20 \\ & THEN\ \ 1 \\ & ELSE\ \ IF\ \ \frac{CAPINS_{i,tech+otech,t-1}}{CAPINS_{i,tech+otech,t-2}} > MAXG_{tech+otech} \\ & \qquad THEN\ \ MAXG_{tech+otech}^{rda_{tech+otech}} \\ & \qquad ELSE\ \ \left(\frac{CAPINS_{i,tech+otech,t-1}}{CAPINS_{i,tech+otech,t-2}}\right)^{rda_{tech+otech}} \end{aligned}$$

(MAXG is a technology dependent parameter which is currently set to 2 as a cap on the learning that can be achieved in one given year and introduced to avoid excessive cost reductions due to big movements in near zero capacities)

- *TOTRD* is the total (public plus private) cumulative R&D for the technology considered
- *rda* is the "learning by doing" elasticity

$$\begin{aligned} rda_{i,tech+otec} = {} & IF\ \ abs\left(\frac{floor_{i,tech+otech}}{floor_{i,tech+otech} - INV_{i,tech+otech}}\right) < 20 \\ & THEN\ \ rda0_{i,tech+otec}{}^{\frac{floor_{i,tech+otech}}{floor_{i,tech+otech} - INV_{i,tech+otech}}} \\ & ELSE\ \ 0 \end{aligned}$$

(rda0 is the learning by doing elasticity parameter calibrated for 1995)

- *rdb* is the "learning by searching" elasticity

$$\begin{aligned} rdb_{i,tech+otec} = {} & IF\ \ abs\left(\frac{floor_{i,tech+otech}}{floor_{i,tech+otech} - INV_{i,tech+otech}}\right) < 20 \\ & THEN\ \ rdb0_{i,tech+otec}{}^{\frac{floor_{i,tech+otech}}{floor_{i,tech+otech} - INV_{i,tech+otech}}} \\ & ELSE\ \ 0 \end{aligned}$$

(rdb0 is the learning by searching elasticity parameter calibrated for 1995)

This set of equations is more complicated than a simple TFLC formulation. This has been deemed necessary in order to simulate the "technology improvement dynamics" in the model, while avoiding the instability in the results for technologies at their very early stage of development as well as too strong "snowballing" effects for more mature technologies that would otherwise see in some cases their diffusion explode and their cost go to near to zero levels.

5.2.2. Endogenous technology dynamics in the SAPEN case

The exogenous hypotheses of the SAPEX case have been replaced in the SAPEN case by the "technology endogenisation" module described above. The methodology applied in the endogenous technology case takes into account the "learning by doing" effect and the "learning by searching" effect, i.e. the impact of R&D on technology improvement.

With harmonized hypotheses on the learning parameters i.e. the CRDA0 and CRDB0 parameters (see Table 5-3 the SAPEN case yields projections of technology development that are more consistent, both with historic trends and in an inter-technology comparison perspective, than in SAPEX case. The SAPEN case thus provides a set of consistent trends as regards energy technology development.

Table 5-2: Investment cost floors (€/kW).

ATC	550
BF2	685
BGT	685
CCT	500
CHP	450
DPV	2000
FCV	0
GCT	250
GGC	250
HYD	1300
ICG	700
LCT	600

MFC	500
NND	950
NUC	1150
OCT	500
OGC	180
PFC	600
RPV	3600
SFC	650
SHY	635
SPP	600
WND	350

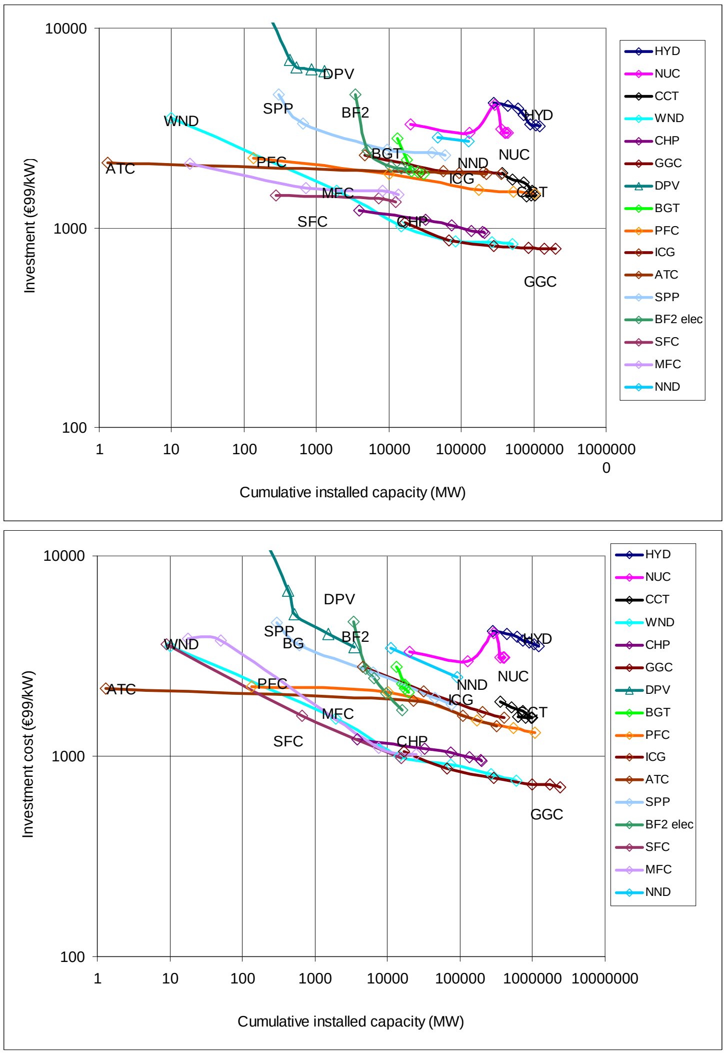
Table 5-3: CRDA0 and CRDB0 coefficients for large power generation and New and Renewable technologies

	CRDA0	CRDB0
ATC	-0.20	-0.15
PFC	-0.30	-0.15
ICG	-0.30	-0.15
CCT	-0.05	-0.15
LCT	-0.10	-0.15
HYD	-0.25	-0.20
NUC	-0.25	-0.20
NND	-0.25	-0.20
GCT	-0.20	-0.10
GGC	-0.30	-0.05
OCT	-0.20	-0.10
OGC	-0.25	-0.05

	CRDA0	CRDB0
BF2	-0.70	-0.05
BGT	-0.50	-0.10
CHP	-0.05	-0.05
DPV	-0.50	-0.30
FCV	-1.00	-0.20
MFC	-0.40	-0.20
SFC	-0.40	-0.20
RPV	-0.50	-0.40
SPP	-0.25	-0.10
SHY	-0.50	-0.13
WND	-0.30	-0.14

Figure 5-12 provides a comparison of the SAPEX and SAPEN case results, while using the "ex-post learning curves" as ways of characterising the technology improvement dynamics in both cases. It indicates that the behaviour of the model is more satisfactory and the results more consistent in the endogenous technology case than in the exogenous case.

Figure 5-12: POLES SAPEX (above) and SAPEN (below) in the ex-post learning curve perspective



The new trends in technology development, as simulated in the SAPEN case, lead to significant changes in the structure of electricity production. As shown in the tables below, clean coal technologies and electricity from wastes benefit of significantly increased capacities in the endogenous technology SAPEN case: respectively of 70% (ATC), 22% (PFC), 30% (ICG), 76% (BF2) compared with the SAPEX case. Other new and renewable technologies (DPV, MFC, RPV, SHY) also show capacity increases in relative terms, but given their modest installed capacities in SAPEX their role in SAPEN the absolute figures remain low. Conversely, conventional technologies as OGC, LCT, CCT, GCT, OCT show reduced capacities of respectively -31%, -27%, -22%, -21% and -6%.

As a consequence, the investment cost of advanced coal technologies and of renewable technologies are lower in the SAPEN, respectively of about 30% and of 20-50%, while most conventional technologies show higher investment costs.

Table 5-4: POLES SAPEN/SAPEX changes in the structure of electricity capacities

	CAP-SAPEX in GW	CAP-SAPEN	% SAPEN/SAPEX	INV-SAPEX in €99/kW	INV-SAPEN	% SAPEN/SAPEX
ATC	214	365	70%	1861	1222	-34%
PFC	1028	1258	22%	1489	1106	-26%
ICG	351	457	30%	1858	1340	-28%
CCT	792	617	-22%	1436	1470	2%
LCT	113	83	-27%	1986	2031	2%
HYD	1230	1221	-1%	3235	3351	4%
NUC	396	377	-5%	2978	2931	-2%
NND	88	58	-34%	2712	2529	-7%
GCT	325	256	-21%	1054	1077	2%
GGC	2122	2471	16%	785	536	-32%
OCT	160	150	-6%	1538	1849	20%
OGC	396	273	-31%	363	359	-1%
	CAP-SAPEX in GW	CAP-SAPEN	% SAPEN/SAPEX	INV-SAPEX in €99/kW	INV-SAPEN	% SAPEN/SAPEX
BF2	18	31	76%	1957	1354	-31%
BGT	33	22	-32%	1868	2163	16%
CHP	247	199	-19%	947	945	0%
DPV	1	4	304%	6097	3145	-48%
FCV	0	0	-	14943	102169	584%
MFC	15	23	60%	1473	767	-48%
SFC	13	15	14%	1351	994	-26%
RPV	6	10	62%	6742	6162	-9%
SPP	12	13	10%	2313	1888	-18%
SHY	41	52	27%	2313	1876	-19%
WND	384	282	-27%	829	822	-1%

5.3. The impact of Carbon Constraints on Technical Change

5.3.1. The SAPIENT carbon constrained reference case (SREF)

The SAPIENT carbon constrained reference case has been developed to simulate and assess the impact of global constraints at world level and for the 2030 horizon. Its aim is to describe a reasonable hypothesis for the development of CO2 emissions, while taking into account the different regions' willingness to commit themselves in medium-term reductions as well as the expected reinforcement of climate change policies beyond the year 2010.

The SREF case is designed through the introduction of a penalty for CO2 emissions within the POLES model, a method that impacts, in theory, identically as the introduction of regional taxes on CO2 emissions or as CO2 emissions constraints within a world emission trading system. The SREF case is defined so as to reach a level of CO2 emissions in 2030 that is comparable to the emissions projected in the "B1" scenario of the IPCC projections (IPCC, 2001). The IPCC integrated assessment analysis indicates that this type of trend assumes the implementation of sustainable development policies in a large amount of sectors of the economy. Such an emission path lies at the upper end of an emission control strategy that would remain compatible with an objective of stabilisation of greenhouse gas concentration around 500 to 550 ppmv (twice the pre-industrial concentration) by the end of this century and a global temperature rise of no more than 2°C relative to the year 1850.

In order to take into account the commitments of the industrialised countries for the Kyoto period, the carbon penalty is differentiated by main regions up to 2010. For European Union a penalty of 55 €/tC is chosen, a lower penalty being applied to the other countries that accepted a commitment. No carbon penalty applies to the CIS - that remains below its target without the implementation of any carbon constraint - and to countries without commitment until 2010. Consequently, these latter countries follow the CO2 emissions trends projected in the SAPEX until 2010. Between 2010 and 2030 and in order to meet an emission path that remains compatible with the concentration target, a 121 €/tC2 carbon penalty is then implemented.

Table 5-5: The Carbon Values introduced in SREF (€99/tC):

Carbon Values in SREF	2003-2010	2010-2030
EU	55	121
Rest of Ann B (except CIS)	22	121
Rest of the World	0	121

As described below, the key outcome of the SREF case is that about half of the reduction comes from reductions in total energy demand while the other half comes from changes in the world primary energy-mix.

5.3.2. World energy demand and CO2 emissions

The major changes in world energy-related CO2 emissions, total energy consumption and fuel switching as resulting from the above-defined carbon constrained case are illustrated in Table 5-6 below.

Table 5-6: World energy demand and CO2 emissions

	SAPEN 2030	SREF 2030	% Change
CO_2 emissions (GtC)	12.1	9.6	-21%
Total consumption (Gtoe)	17.1	15.2	-11%
Coal, lignite (Gtoe)	4.7	2.7	-43%
Oil (Gtoe)	5.9	5.4	-8%
Natural gas (Gtoe)	4.3	4.3	0%
Nuclear (Gtoe)	0.9	1.2	36%
Renewables (Gtoe)	1.3	1.6	25%

The carbon penalty introduced in the SREF case leads to a reduction of nearly 2.5 GtC compared to the SAPEN case, i.e. a decrease of 21 %. Nevertheless, world CO2 emissions in 2030 still increase compared to the 1990, up to 9.6 GtC. The average growth between 1990 and 2030 is projected to be 1.3 %/year in the SREF case, compared to 1.9 %/year in the SAPEN. The carbon penalty in SREF leads allows a slowdown in the growth of CO2 emissions but does not yet trigger a strong trend towards the progressive “decarbonisation” of the world economy.

The results of the SREF case show that the projected reduction by 21 % of world CO2 emissions compared to the SAPEN case comes in equal parts, on the one hand from the reduction in energy demand and on the other hand from the decrease in the carbon intensity of the total consumption – which clearly indicates drastic changes in the primary fuel mix. The total energy demand decreases from 17.1 Gtoe to 15.2 Gtoe. This reduction needs to be examined in the light of the projected increase of the total consumption from about 8.7 Gtoe in 1990. It also shows that both actions on the energy system, i.e. the slowdown in the growth of energy demand and changes in the mix of primary fuels are necessary to achieve significant reductions CO2 emissions.

The 10 % reduction in the carbon intensity of the world total consumption in the SREF case reflects the opportunities for fuel substitution in the energy system. As expected, the carbon penalty affects primarily the fuels with the highest carbon content, namely coal (-43 %) and oil (-8%), while in this latter case however substitutions are limited by the transport-fuel market constraints. Natural gas is not affected as the impact of reduced global demand is compensated by significant substitutions from gas to coal. The market shares lost by coal and oil are balanced by substantial increases in nuclear and renewable energies[11], of respectively 36 and 25% in 2030, compared to the SAPEN case. Within the renewable sources a 20-fold increase is expected for wind, solar and small hydro.

5.3.3. The carbon constraint impact on power generation and new and renewable technologies

In a context where electricity demand grows at an annual rate that is twice the growth of final energy consumption, the carbon penalty also results in significant substitutions of technology in power generation. Table 5-7 and Table 5-8 show the effect of the carbon penalty on electricity generation, respectively for large scale and for new and renewable technologies, at world level.

Table 5-7: SREF impacts on Powergen Technologies

SREF/SAPEN-1	CAP	INV
ATC	-53%	12.4%
PFC	-61%	6.5%
ICG	-49%	5.2%
CCT	-9%	0.2%
LCT	-35%	2.4%
HYD	3%	-0.3%
NUC	27%	-2.4%
NND	119%	-1.6%
GCT	-6%	0.8%
GGC	-2%	0.2%
OCT	-1%	0.1%
OGC	-46%	0.2%

Table 5-8: SREF impacts on New and Renewable Technologies

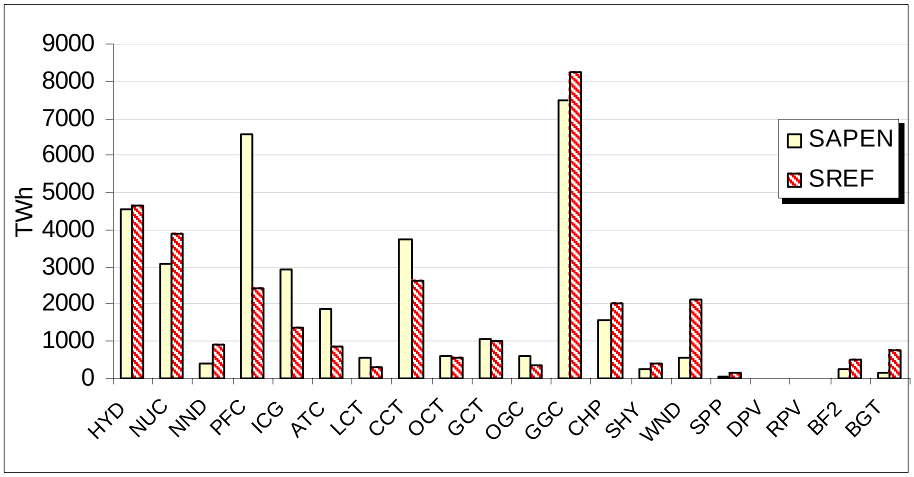
SREF/SAPEN-1	CAP	INV
BF2	101%	-5.8%
BGT	331%	-28.3%
CHP	30%	-1.8%
DPV	-5%	11.5%
FCV	0%	0.0%
MFC	21%	11.4%
SFC	33%	10.1%
RPV	46%	-2.2%
SPP	286%	-16.2%
SHY	63%	-11.4%
WND	295%	-11.8%

Figure 5-13: Technology mix in world electricity generation in 2030 illustrates the changes in the technology mix for electricity generation. In relative terms, the greatest changes occur for electricity

[11] Biomass, wind, solar, small hydro, large hydro, geothermal and wastes.

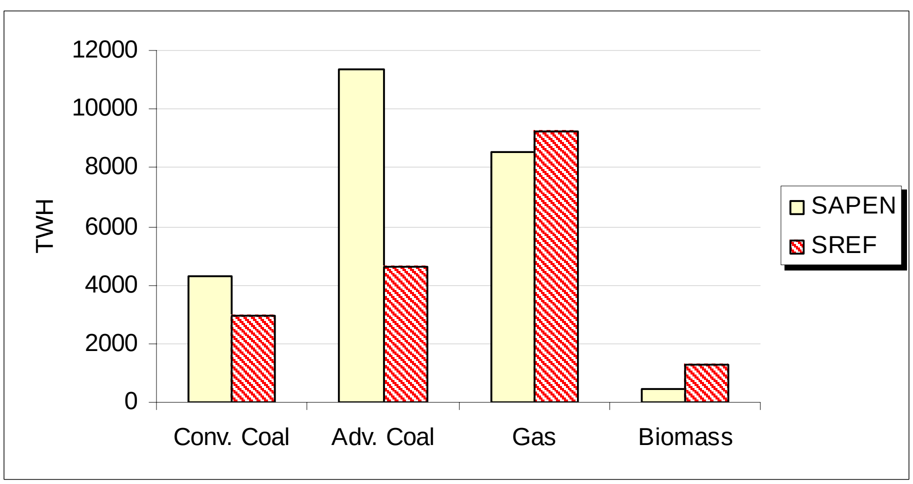
generation from renewable sources as wind, solar and biomass gasification (a threefold increase), and small hydro (+63 %) but in absolute terms of installed generation capacity the most significant changes occur for thermal, nuclear and combined heat and power (CHP).

Figure 5-13: Technology mix in world electricity generation in 2030



Among the thermal power plant category, the carbon constraint significantly reduces the development of coal and advanced coal power plants, initially projected in the SAPEN case (Figure 5-14). While, the advanced coal technologies lead to substantial improvements in terms of conversion efficiency comparatively to conventional coal, in terms of CO2 emissions reduction their performance remain weak when compared to technologies based on less carbon intensive fuels. Thus, the share of advanced coal drops from about 46 % of thermal power production in 2030 in the SAPEN to 26% in the SREF case. On the contrary, gas and biomass power plants increase their share in thermal generation power with respectively 51 % and 7 % in 2030.

Figure 5-14: Fuel mix in world thermal power generation in 2030



6. Perfect Foresight Models

6.1. ERIS

This section presents the implementation of two-factor learning curves (thereon referred to as 2FLC) in the energy-systems optimisation ERIS (Energy Research and Investment Strategies) model and associated analyses.

ERIS was developed as a joint effort between several partners (IIASA-ECS, PSI, NTUA) during the EC-TEEM project as a tool to examine different approaches for the endogenous representation of technological change and has found further application in SAPIENT. The 2FLC formulation applied in ERIS allows endogenising two basic learning channels, i.e. accumulation of capacity and R&D expenditures, within this perfect-foresight framework. Specifically, the optimal allocation of R&D expenditures between competing learning technologies occurs endogenously, guided by the two-factor learning curve and being influenced by specific parameters and variables of the model. The implementation of the 2FLC in ERIS was carried out as a joint effort between the Paul Scherrer Institute (PSI) and IIASA-ECS, where both partners benefited from each other's insights and experience.

Two sets of analyses performed independently are described below. Both sets of exercises provide interesting methodological and policy insights and open promising ways for further exploration. Section (Barreto and Kypreos) describe the implementation of 2FLC in ERIS in detail introducing the notion of knowledge stock, which allows considering depreciation of knowledge and time lags in the R&D process. The dynamics of allocation of a given R&D budget to competing learning technologies is illustrated. In addition, some of the parameters that influence the allocation are examined. In particular, the influence of the rate of depreciation of the knowledge stock (i.e. the action of the "forgetting-by-not-doing" feature that it introduces) on the model results is analysed.

Sections 6.1.2 (Miketa and Schrattenholzer) advance in the understanding of the basic dynamics of the model with the knowledge stock formulation. A more stylised version of the model that includes two learning technologies for which empirical learning parameters were estimated using time series data is applied. Using this version of ERIS, the dependence of optimised R&D expenditures for a given technology on its own learning-by-doing and learning-by-searching elasticities and on those of a competing technology is analysed. The point of that analysis, which uses absolute units for R&D expenditures, is to test the sensitivity of the optimised R&D expenditures with respect to the two learning rates. In addition, the "on/off" properties of the learning mechanism and the "hand-in-hand" behaviour of the two learning channels in the model are illustrated.

6.1.1. R&D and market experience: Two-factor learning curves in ERIS [Leonardo Barreto (IIASA-ECS), Socrates Kypreos (PSI)]

R&D is one of the basic driving forces of technological progress, contributing to productivity increases and economic growth. It has been recognised that, although difficult to measure, the payoffs produced by R&D expenditures are high, both at the public and private levels (Griliches, 1995). In the case of energy systems, R&D constitutes a fundamental factor for the successful introduction of new, more efficient and clean supply and end-use technologies. R&D is also one of the variables that government policies may affect, as private companies are likely to not invest enough in R&D from a public interest perspective.

Therefore, it is important to study the main mechanisms by which R&D investments contribute to cost and performance improvements of individual technologies and productivity increases of the energy system as a whole. By the same token, it is also interesting to gain insights about the optimal allocation of scarce R&D resources, taking into account that such allocation is influenced by expectations of market opportunities. Thus, it becomes necessary to incorporate those mechanisms into the energy policy decision-support frameworks, e.g. in energy systems optimisation models.

However, assessing and quantifying the effects of R&D efforts in energy technology innovation is particularly difficult because of a number of reasons, the broad range of R&D activities relevant to energy issues, the variety of institutions carrying R&D, the difficulties in assessing the (central) role played by industrial R&D and the lack of underlying data, among others (Sagar and Holdren, 2002). Moreover, the role of R&D must be examined within the context of an assessment of the whole energy innovation system, of which R&D activities are but only a part. Demonstration and deployment of energy technologies in the marketplace also play a very important role in their improvement, in particular regarding cost reductions. Thus, if possible, analyses and methodologies should try to incorporate the different mechanisms that intervene in the ERD3[12] process (PCAST, 1999).

Technological learning processes play an important role in technological change. They are typically represented through learning, or experience, curves. The standard learning curve considers the specific investment cost of a given technology as a function of cumulative capacity, which is used as an approximation for the experience accumulated when the technology is deployed. The formulation reflects the fact that some technologies experience declining costs as a result of their increasing adoption (Argote and Epple, 1990). As such, it takes into account the effects of experience due to actual deployment of technologies but does not provide a mechanism to capture explicitly the effects of public and private R&D efforts, which constitute an essential basis for cost reductions and performance improvements, particularly in the early stages of development of a technology.

R&D and market experience can be thought of as two learning mechanisms that act as complementary channels for knowledge accumulation (Goulder and Mathai, 2000). Different approaches to model the R&D factor as an endogenous driving force of technological change have been reported in the literature (see e.g., Grübler and Gritsevskyi, 1997, Kouvaritakis et al., 2000, Buonanno et al. 2000, Goulder and Mathai, 2000). Kouvaritakis et al. (2000) have applied the so-called two-factor learning curve (hereon referred to as 2FLC) concept in POLES, a system dynamic, behavioural oriented model where technological learning is driven by adaptive expectations (without perfect foresight). In such 2FLC formulation, the specific cost of a given technology is a function of cumulative capacity and cumulative R&D expenditures.

Here, a modified version of the two-factor learning curve, which incorporates the concept of knowledge stock instead of cumulative R&D expenditures, is implemented in ERIS, a perfect-foresight optimisation model. The ERIS (Energy Research and Investment Strategy) model was developed as a joint effort between several partners within the EC-TEEM project. The model provides a stylised representation of the global electricity generation system and endogenizes learning, or experience, curves. A detailed description of the model may be found in Kypreos et al. (2000). Analyses using ERIS have been reported in Barreto and Kypreos (2000).

In implementing the 2FLC, we recognize the limitations posed by the formulation and the unsolved estimation and data issues associated with it (see chapter I.2 of this report), but emphasize the fact that it constitutes an important step towards the understanding of the role of R&D in energy innovation and its conceptual treatment in energy systems models. Analyses with the formulation of ERIS with 2FLC developed here have also been reported by Miketa and Schrattenholzer (2001). Their results are described in section 6.1.2 below.

The remainder of this section is structured as follows. First, the concept of knowledge stock is introduced in section 6.1.1.1 below. Subsequently, the implementation of the two-factor learning curve in ERIS is presented in section. The salient features of our test case are briefly described in section 6.1.1.3. Section 6.1.1.4 presents and discusses some illustrative results. In section 6.1.1.5 the sensitivity of the model results to the rate of knowledge depreciation is analysed. Some concluding observations are outlined in section 6.1.1.6.

6.1.1.1. The knowledge stock function

As mentioned above, Kouvaritakis et al. (2000) have used cumulative R&D expenditures as the representative variable for the knowledge accumulated through R&D efforts. Here, the recursive expression for knowledge stock proposed by Watanabe (1999) and described above in chapter I.2 is implemented, allowing depreciation of knowledge (i.e. "forgetting-by-not-doing") and time lags in the R&D process to be taken into account.

Originally, the knowledge stock is given as an annual expression but in ERIS values are assigned to variables on a period-by-period basis and the length of the period is normally bigger than one year. Therefore, in order to be consistent, it is necessary to compute the knowledge stock for each period in the model, taking into account the year-by-year formulation above.

[12] ERD3 stands for Energy Research, Development, Demonstration and Deployment. The term was introduced in PCAST (1999) to refer to the whole energy innovation process. It emphasizes the need of recognizing the importance of the combined effects of "technology push" and "demand pull" mechanisms in the diffusion of emerging energy technologies.

For such purpose, it is assumed that annual R&D expenditures per technology are constant along the period, as it is the case with the other variables in the model. The value of the knowledge stock for a given period (computed at the end of the period) is obtained using the corresponding ARD series for the current and the previous periods as:

$$KS_{te,t} = KS_{te,t-1} * (1-\delta_{te})^{\Delta_t} + ARD_{te,t} * \sum_{\tau=0}^{\Delta_t - rdlag - 1} (1-\delta_{te})^{\tau} + (1-\delta_{te})^{\Delta_t - rdlag} * ARD_{te,t-1} * \sum_{\tau=0}^{rdlag-1} (1-\delta_{te})^{\tau}$$

Where:

$KS_{te,t}$	Knowledge stock for technology te in period t
$ARD_{te,t}$:	Annual R&D expenditures in technology te in period t
δ:	Annual depreciation rate
Δ_t :	Length of the period
rdlag	Lag in years between R&D expenditures and knowledge stock.

This expression provides a period-by-period computation of the knowledge stock that is consistent with the above year-by-year formulation, under the assumption that the R&D expenditures series remains constant along each period.

For the first period the computation must include the lagged historical annual R&D expenditures values (ardpastτ) and, thus, it becomes:

$$KS_{te,t} = dknow_{te} * (1-\delta_{te})^{\Delta_t} + ARD_{te,t} * \sum_{\tau=0}^{\Delta_t - rdlag - 1} (1-\delta_{te})^{\tau} + (1-\delta_{te})^{\Delta_t - rdlag} * \left[\sum_{\tau=0}^{rdlag-1} (1-\delta_{te})^{\tau} * ardpast_{te,\tau} \right]$$

Where the $ardpast_{\tau}$ values are given backwards with respect to the specification of the initial knowledge stock (*dknow*$_{te}$). That is, $ardpast_0$ corresponds to the R&D expenditures in the same year for which *dknow*$_{te}$ is given, $ardpast_1$ are those of the previous year etc. The equations above assume that *rdlag* < period length (Δ_t).

The computation is performed at the end of each period because the cumulative capacity for a given period is computed as the one in the previous period plus the investments taking place in the current one and both values should be consistent in order to be introduced into the learning curve[13].

In view of the uncertainty associated to empirical estimates of the learning-by-doing, learning-by-searching, depreciation and time lags for energy technologies, sensitivity analyses are necessary to establish to which of them is the model more responsive. Those analyses may be also useful to examine the effects of different assumptions on the relative competitiveness of the different technologies.

6.1.1.2. The two-factor learning curve formation in ERIS

Applying the definition of knowledge stock described above, the two-factor learning curve for the specific investment costs of a given technology is expressed as:

$$SC_{te,t} = a * CC_{te,t}^{-b} * KS_{te,t}^{-c}$$

Where:

$CC_{te,t}$:	Cumulative capacity for technology te in period t
$KS_{te,t}$	Knowledge stock technology te in period t
b:	Learning-by-doing elasticity
c:	Learning-by-searching elasticity
a:	Specific cost at unit cumulative capacity and unit knowledge stock

Using the initial values of specific costs (SC_0) cumulative capacity ($dcap_{te,t}$) and the initial value of the knowledge stock per technology (*dknow*$_{te}$), the coefficient a can be expressed as:

$$a = SC_{0,te} \Big/ \left[(dcap_{te})^{-b} * (dknow_{te})^{-c} \right] = i_{te,rg} * (dcap_{te})^{b} * (dknow_{te})^{c}$$

Instead of the learning-by-doing and learning-by-searching elasticities, corresponding learning-by-doing (LDR) and learning-by-searching (LSR) rates can be defined as follows:

[13] In ERIS, it is assumed that the period named as "2000" comprises the years from 2001 to 2010, the period "2010" goes from 2011-2020 etc. Thus, for the purposes of knowledge stock calculation the variable ARD (2000) will be the annual R&D expenditures for 2001-2010 and the variable KNOW(2000) is the corresponding knowledge stock at the end of the period.

$$LDR = 1 - 2^{-b}$$
$$LSR = 1 - 2^{-c}$$

It must be noticed that the inclusion of the knowledge stock in the learning curve provides the model with a mechanism of "forgetting-by-not-doing" for the R&D learning channel. That is, leaving aside the effects of cumulative capacity, if no R&D expenditures are made in a given technology, the knowledge stock will depreciate. Consequently, the specific costs of the technology will increase.

The expression for the specific costs above is not applied directly in the model formulation, but the cumulative cost curve is used instead. Thus, the changes are applied to the latter one. The cumulative cost ($TC_{te,t}$) can be expressed as the integral of the specific cost curve with respect to $CC_{te,t}$.

$$TC_{te,t} = \int_0^{CC} SC(CC, KS) * dCC = \frac{a}{1-b} CC_{te,t}{}^{1-b_{te}} * KS_{te,t}{}^{-c_{te}}$$

Then:

$$TC_{te,t} = \frac{i_{te,rg} * dcap_{te} * (dknow_{te})^{c}}{1-b_{te}} * (G_{te,t})^{1-b_{te}} * (KS_{te,t})^{-c_{te}}$$

Thus, the undiscounted investment cost ($ICOST_{te,t}$), computed as the difference between two consecutive cumulative cost values, becomes:

$$ICOST_{te,t} = \frac{i_{te,rg}}{1-b_{te}} * dcap_{te} * (dknow_{te})^{c} * \left[(G_{te,t})^{1-b_{te}} * (KS_{te,t})^{-c_{te}} - (G_{te,t-1})^{1-b_{te}} * (KS_{te,t-1})^{-c_{te}}\right]$$

The annual R&D expenditures per technology and time period (ARDte,t) can be given exogenously or can be determined endogenously by the model. Here the endogenous case is examined. That is, ARDte,t and KSte,t are declared as variables. Letting the model choose which fraction of a given R&D budget should each of the competing learning technologies become, it can act as a decision-support tool regarding the adequate allocation of R&D funds across a portfolio of competing technologies.

An annual R&D budget is specified (GRD_t), which can be allocated among the different learning technologies. The R&D budget constraint is formulated as an inequality. With such specification, the model can decide whether the assigned R&D budget should be spent or not, that is:

$$GRD_t \geq \sum_{te \in TEG} ARD_{te,t}$$

TEG: Set of learning technologies

For a multi-regional model GRD_t can be expressed as the summation of regional budgets:

$$GRD_t = \sum_{rg} GRD_{rg,t}$$

ERIS minimizes total discounted system costs, including investment costs, O&M and fuels costs. The objective function is modified in order to include the R&D investments. The new objective function becomes:

$$z' = \sum_{t=1}^{T} \sum_{te} \left[ICOST_{te,t} + \left[O\&M_{te,t} + Fuel_{te,t} \right] * \Delta_t \right] * (1+d)^{-\Delta_t * t} + \sum_{t=1}^{T} \sum_{te \in TEG} ARD_{te,t} * (1+d)^{-\Delta_t * t} * \Delta_t$$

With:

z':	Total discounted system costs including discounted R&D expenditures
$ICOST_{te,t}$	Investment costs per technology te and time period t
$O\&M_{te,t}$	Annual fixed and variable O&M costs per technology te and period t
$Fuel_{te,t}$	Annual fuel costs per technology te and time period t
d:	Discount rate

If required, additional maximum and minimum growth constraints can be specified for the $ARD_{te,t}$ as follows:

$$ARD_{te,t} \leq ARD_{te,t-1} * (1 + grrd)^{\Delta_t}$$
$$ARD_{te,t} \geq ARD_{te,t-1} * (1 - derd)^{\Delta_t}$$

Where:

grrd:	Maximum annual growth rate for R&D expenditures
derd:	Maximum annual decline rate for R&D expenditures

This formulation with endogenous R&D expenditures was applied only to the NLP version of the model. Due to the non-linear, non-convex nature of the problem, solving the NLP version with conventional solvers such as MINOS5, the one used here, enables only the identification of a locally optimal solution. In fact, even if the solution found with the standard NLP algorithm corresponds to the global optimum, it cannot be identified as such. However, previous experiments (Kypreos *et al*. 2000) with the single-factor formulation of the learning curve have shown that if the solution of the linearised.

Mixed Integer Programming (MIP) approximation is used as a starting point for the NLP problem, in some cases it is possible to identify a better local optimum. A similar procedure is followed here for the 2FLC NLP problem. The solution of the single-factor MIP problem is used as the starting point of the two-factor NLP problem with endogenous R&D expenditures. Such solution to the re-started NLP problem is the one reported here.

The caveat should be made that there is no guarantee that such procedure is the most adequate for the two-factor NLP problem. It is possible that using the single-factor MIP solution as starting point the model will find a two-factor NLP solution in the "vicinity" of the single-factor learning curve MIP solution, which is not necessarily the best possible alternative. The reader should be aware that, since only a conventional NLP solver is used here, we do not claim that the procedure applied allows the identification of the global optimum for the 2FLC problem. Therefore, we limit ourselves to examine the behaviour of the model for the local optimum identified with MINOS5. The issue should be explored more carefully in the future and alternatives such as the application of global optimisation algorithms (see e.g. Manne and Barreto, 2001) should be considered.

6.1.1.3. Description of the test case

In this section some results applying the 2FLC formulation described above are presented. As a test case, the multi-regional ERIS model of global electricity generation applied in Barreto and Kypreos (2000) is considered here. The model divides the world into nine geopolitical regions (USA, OECDE, CANZ, JAPAN, EEFSU, CHINA, INDIA, MOPEC, ROW). For convenience results are presented here only at the global aggregate level.

As an illustrative example we have chosen a case where the global electricity system must fulfil a Kyoto-for-ever constraint. That is, Annex B regions must achieve their Kyoto targets by 2010 and keep such level of CO_2 emissions constant along the rest of the time horizon. Emission trading between Annex B regions is allowed from 2010. After 2030 non-Annex B regions join the CO_2 emissions trading system. A 5% discount rate is used in all calculations. The time horizon of this exercise is 2000-2050.

Technology representation is relatively detailed. Thirteen different electricity generation technologies are considered in the model (see Table 6-1). Their characteristics are assumed equal across regions. Six technologies are considered to exhibit learning effects. The corresponding learning-by-doing (LDR) and learning-by-searching (LSR) learning rates considered here are presented in Table 6-1. The learning process is assumed to occur at the global scale. That is, cumulative capacities are added up across all world regions and R&D expenditures occur at the global scale. Thus, both factors contribute to a unique global cost reduction that is common to all regions. For the non-learning technologies investment costs are assumed constant along the time horizon (i.e. they are considered with effective LDRs and LSRs of 0%).

Due to the lack of available estimates of two-factor learning curves using knowledge stock for the learning technologies applied here, additional assumptions were necessary here. The LDR and LSR are assumed to be the same as the ones estimated with the cumulative R&D expenditures formulation. Those coefficients have been taken from the statistical estimation performed by Kouvaritakis et al. (2000) using cumulative capacity and cumulative R&D expenditures as explicative variables. Also, as a simplification, the initial knowledge stock (dknowte) for each technology is considered equal to the initial cumulative R&D expenditures (see Table 6-2 below). In addition, no R&D lag was assumed and the same depreciation rate is applied to all learning technologies. Thus, the results presented here only intend to illustrate the response of the model with the new relationship.

Table 6-1: Main characteristics of electricity generation technologies considered here.

Technology	Abbrev.	Inv. Cost (US$/kW)	Fixed O&M (US$/kW/year)	Var. O&M (US$/kWyr)	LDR	LSR
Conventional Coal	HCC	1357	69	22.7	1	1
Advanced Coal	HCA	1584	67.5	23.6	0.11	0.05
Gas Steam	GSC	987	50.6	17.7	1	1
Gas CC	GCC	600	36.6	19.7	0.24	0.02
Gas Turbine	GTC	350	58.5	16.03	1	1
Gas Fuel Cell	GFC	2463	43.5	80.	0.19	0.11
Oil Steam	OLC	1575	63.6	18.13	1	1
Nuclear	NUC	3075	114	5.91	1	1
New Nuclear	NNU	3400	114	5.91	0.04	0.02
Hydro	HYD	3562	49.5	3.9	1	1
Solar PV	SPV	5000	9.	39.4	0.25	0.10
Wind	WND	1035	13.5	26.3	0.16	0.07
Geothermal	GEO	3075	7.8	92	1	1

As for the R&D expenditures, the figures applied are based on the estimates available from IEPE (2000). The numbers correspond mainly to the aggregation of expenditures in OECD countries, where the bulk of research activities take place. Those figures, however, cannot be considered definitive and they are used here only with illustrative purposes. There exist significant difficulties in gathering R&D related information. This is particularly so for business R&D because private manufacturers may not be willing to make their figures publicly available.

The initial cumulative R&D expenditures for each technology corresponds to the summation of the estimates of cumulative governmental and business R&D in 1997, the last year available in the database (see Table 6-2, figures are in US1998$ millions). In addition, in order to set an initial condition, it is assumed that the annual R&D expenditures (ARDte,t) for the first period modelled are also those of 1997. The illustrative scenario presented here assumes that the available R&D budget increases in the future for this set of technologies. The R&D budget is assumed to increase at 1.5% per year along the time horizon, from a starting value computed as the summation of the expenditures in the six learning technologies for the first period. In addition, a maximum growth rate of 10% per annum and a maximum decline rate of 15% per annum have been specified for all the ARDte,t variables.

Table 6-2: Annual and cumulative R&D expenditures for 1997 used as the base for the model assumptions. (Figures in US1998$ millions. Source: IEPE(2000)).

Technology	Annual Gov. R&D	Annual Business R&D	Annual Total R&D	Cum. Gov. R&D	Cum. Business R&D	Cum. Total R&D
NNU	749	24	773	22927	2244	25171
HCA	116	104	220	5411	3983	9394
GCC	69	1062	1131	1755	25771	27526
WND	143	266	409	2489	4361	6850
GFC	86	294	380	1406	6669	8075
SPV	211	198	409	3803	11091	14894
Total	1374	1948	3322			

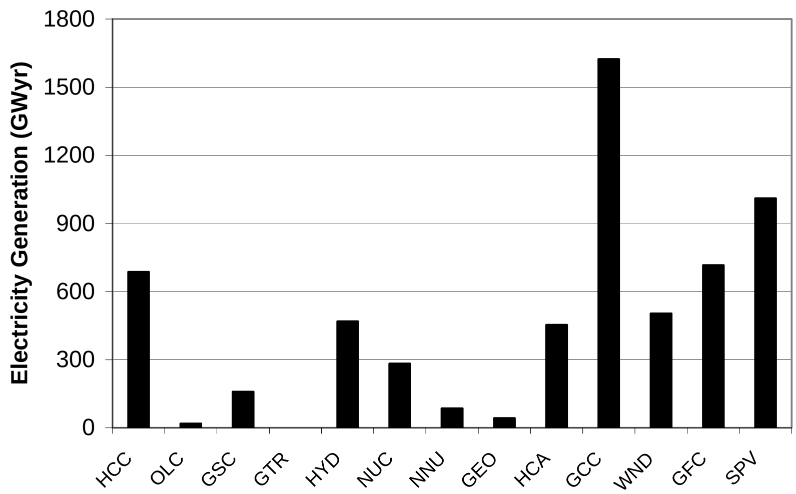
6.1.1.4. Some results

In this section, we present some illustrative results obtained with our test case applying the 2FLC formulation described above. We will describe first a situation without depreciation or R&D lags, i.e. using cumulative R&D expenditures. In section 6.1.1.5, the sensitivity to the depreciation rate is examined. When describing the results, we will concentrate mainly on the allocation of the R&D expenditures.

Before describing the results, it is important to notice the way the endogenised learning mechanism acts in the model. Due to the underlying increasing returns mechanism, if a given technology has enough "learning potential" (which depends on progress ratio, starting point of the learning curve, maximum growth rates allowed, upper bounds imposed etc), the model will try to install it at the maximum rate possible as to exhaust the potential. If not, it will very likely leave it "locked-out". This behaviour will be better illustrated by the examples below.

Figure 6-1 presents the global electricity generation for the year 2050 for our test case. With a carbon constraint imposed on the Annex B regions, a significant decarbonisation takes place in the global electricity generation system. Coal-fired power plants (HCC, HCA) still hold an important share of the generation mix, with a significant fraction of the coal-fired generation supplied by advanced clean coal technologies. However, the generation mix is dominated by less-carbon-intensive technologies. Gas combined-cycle turbines (GCC) provide the largest contribution. Other technologies, such as solar photovoltaic (SPV), wind turbines (WND) and gas fuel cells (GFC) also have a sizeable share of the market.

Figure 6-1: Global electricity generation mix in 2050 for our test case.



The budget is not fully allocated along the time horizon (see Figure 6-4 below). In the first period, the full R&D budget is allocated because of the initial condition imposed, as mentioned above. The amount of spent R&D funds decays in the second period, declining to the minimum bound imposed by the minimum growth constraints of the R&D expenditures per technology, which do not allow R&D investments for a particular technology in a given period to reduce below 20% of the R&D expenditures of the previous period. Then, total R&D expenditures show an upward trend. In the final period total R&D expenditures decay again, mainly due to end effects of the model, as no "salvage costs" for R&D investments have been considered here.

Thus, the model finds it effective to spend in R&D only once sizeable spending in cumulating capacity takes place. In reality, however, R&D expenditures are in many cases a precursor of the accumulation of experience through capacity deployment. Specifically, they can be essential in the first stages of development of the technology, before it goes to the marketplace. Therefore, this behaviour of the model must be taken carefully. Moreover, this points out that, although the specification of the 2FLC applied here constitutes an important first step in incorporating R&D into the model, the model causality still has to be improved in order to adequately represent the R&D mechanism. Also, this drives to the more general question of the role of both learning channels in different stages of the life cycle of a given technology. Figure 6-2 presents the absolute values of R&D expenditures in each learning technology and Figure 6-3 shows the relative share of each technology of the fraction of the R&D budget actually spent.

Figure 6-2: Annual R&D expenditures per technology in our test case.

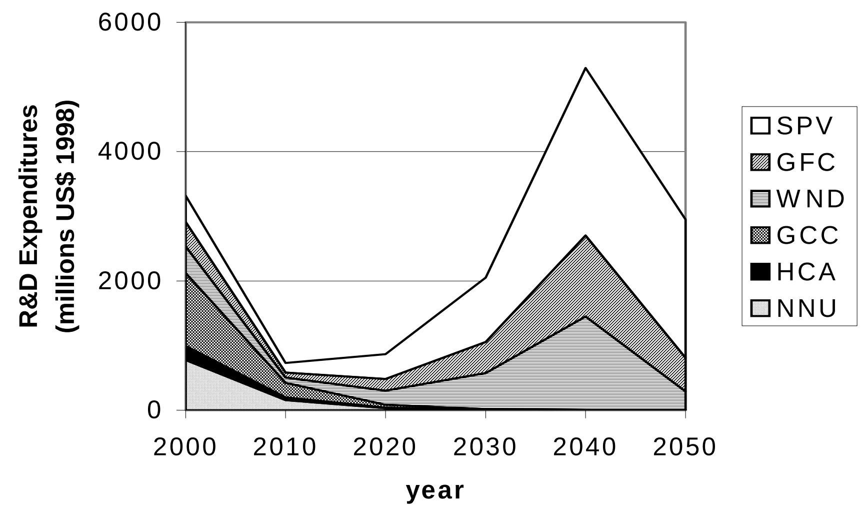
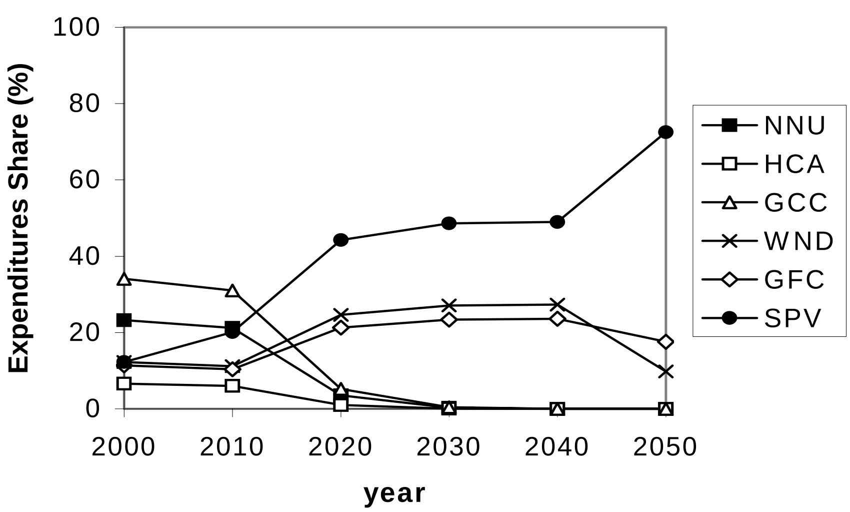


Figure 6-3: Share of the total annual R&D expenditures allocated to each learning technology in our test case.



Solar photovoltaic, the technology with the highest LDR and LSR, dominates the allocation of R&D resources[14]. The gas fuel cell and the wind turbine also receive significant fractions of the R&D funds. R&D investments in the gas combined cycle turbine, which received the highest amount of resources in the first period, decline and disappear. The same happens to the clean coal technology, having a very low LSR but a relatively attractive LDR, and the new nuclear power plant, with the lowest LDR and LSR. They result unattractive and R&D investments on them decay along the minimum growth constraint and disappear.

As expected, technologies with higher LSRs appear to be more attractive for expending R&D resources. However, other factors such as the LDR, the maximum growth rates allowed and the presence or absence of a constraint on emissions, which may force low-carbon technologies into the solution, play also an important role.

[14] This could be regarded as an example of the possibility of having a sort of "lock-in" of the R&D spending in the model. The model may try to continue to assign R&D money to a technology because it makes its cost cheaper and cheaper.

The allocation of R&D resources occurs endogenously, guided by the two-factor learning curve and being influenced by the specific set-up of the model and the particular developments in a given scenario. The coupling of the R&D expenditures both with the learning-by-doing mechanism and the other variables in the model, made possible here by its specification as an endogenous contributing factor to the cost reduction, is important because it helps to reflect in the model the fact that market investments and expectations play an important role in whether or not R&D money would be expended on a given technology.

6.1.1.5. Sensitivity to the depreciation rate

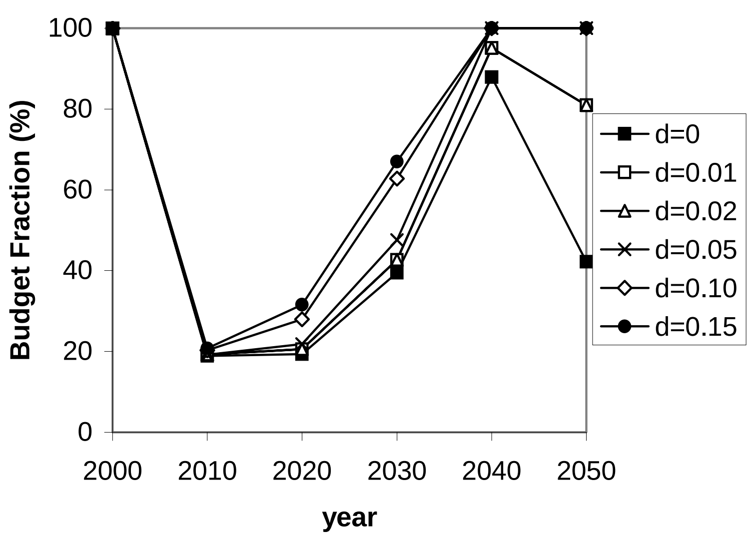
The introduction of depreciation of the knowledge stock reduces the effectiveness of R&D as a cost reduction factor as compared to the case where R&D expenditures are simply accumulated. Consequently, it alters the dynamics of allocation of R&D funds in the model. The specific costs of the different learning technologies can be affected by the "forgetting" mechanism. When depreciation is possible the specific costs can increase if not enough R&D is spent in a technology as to keep the knowledge stock at least at previously reached levels. In contrast, the cumulative R&D expenditures variable is non-decreasing and in such case specific costs will only remain at the same level or decline.

The degree to which the cost trends of a given technology are affected by a higher depreciation rate depends on how strong the R&D factor contributes to its cost reduction[15], how attractive are its LDR and LSR as compared to other technologies, which is the size of the R&D budget and how cost-competitive is the technology already.

In this section, we examine the effects of different values of the rate of depreciation of the knowledge stock (from 0 to 15% per annum) in the allocation of R&D funds for the test case presented above. As mentioned before, as a simplification the depreciation rate is considered equal for all the learning technologies. Also, it is assumed that the lbd and lbs progress ratios remain the same as those applied above. In addition, the effects of R&D lags are ignored.

Figure 6-4 presents the total amount of R&D expenditures, expressed as a fraction of the budget available in each period, for different values of the depreciation rate.

Figure 6-4: Expended fraction of the total R&D budget. Different depreciation rates.



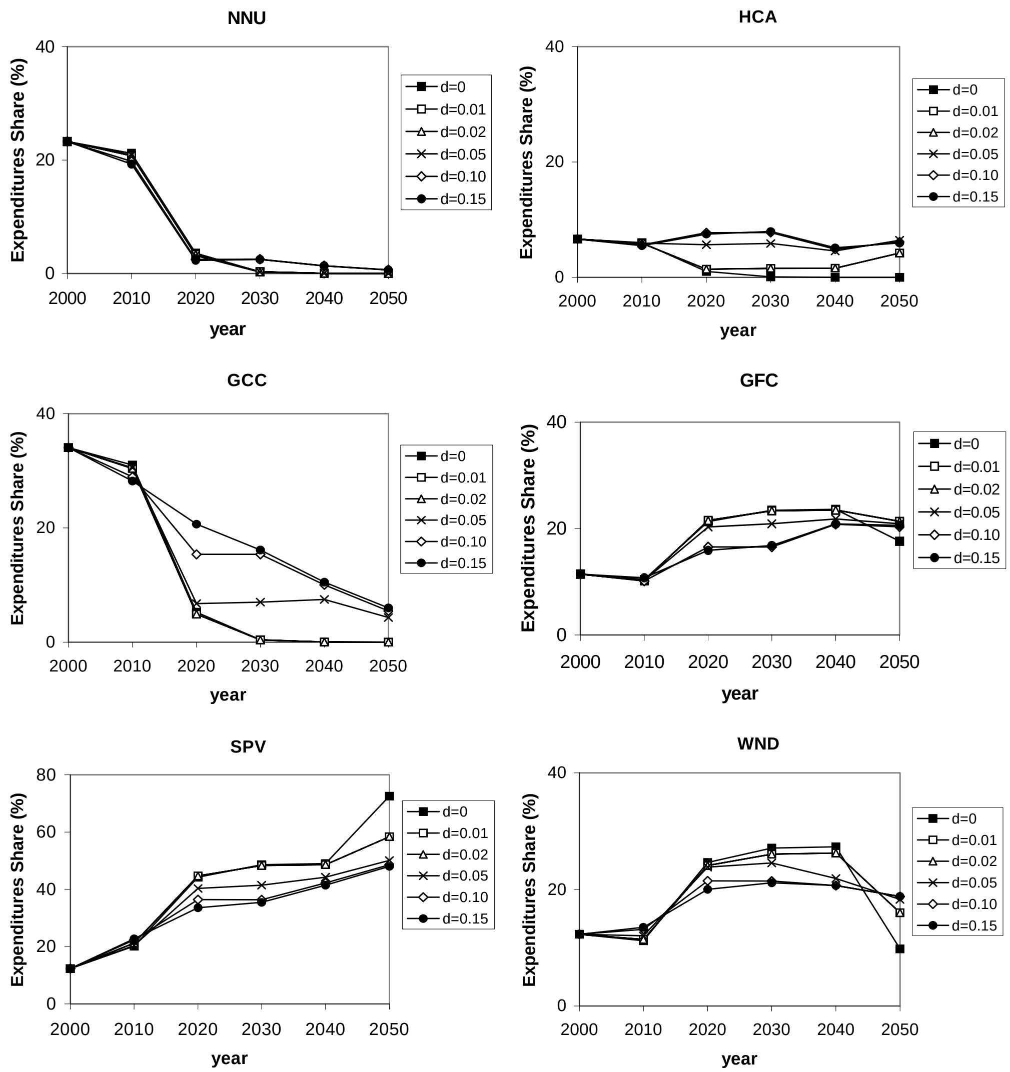
Although the budget is still not fully allocated, with an increasing depreciation rate there is a tendency to augment the fraction of the R&D budget that is spent. At a higher depreciation rate, more funds are necessary to produce the same results in terms of cost reductions and the model decides to invest more in order to counteract the "forgetting-by-not-doing" effect introduced by the depreciation in competitive technologies.

[15] This depends on the relative weight of the learning-by-searching elasticity respect to the learning-by-doing one, but also on other factors such as the size of the R&D budget and the maximum growth rates of both capacity and R&D expenditures.

This is an interesting behaviour because, in principle, a higher depreciation rate would reduce the attractiveness of investing in R&D. For high depreciation rates, the model could consider more beneficial either to invest more in capacity, given that such factor does not suffer depreciation, or simply not to invest in R&D. However, an additional counterbalancing factor intervenes here. No R&D investment would mean "forgetting" and this would translate into increasing investment costs for the different technologies. Thus, there is an incentive to invest in R&D to counteract the "forgetting" effect. Although a definite interpretation of this fact is not possible here, one could probably expect the increasing tendency on the expenditures to last only as long as the model considers the technology attractive enough. These interactions, however, deserve further investigation.

Figure 6-5 presents the changes of the share of each technology as the depreciation rate is modified. Solar PV continues to be the most attractive technology across the range of depreciation rates evaluated. However, its share of the R&D budget decreases as the depreciation rate is increased. Investments on the gas fuel cell and the wind turbine also decrease. On the other hand, R&D investments in the gas combined-cycle experience a much slower decline. The new nuclear and advanced coal power plants still result unattractive, but the amount of R&D expenditures tends to increase.

Figure 6-5: Share of total R&D expenditures per learning technology. Different depreciation rates.

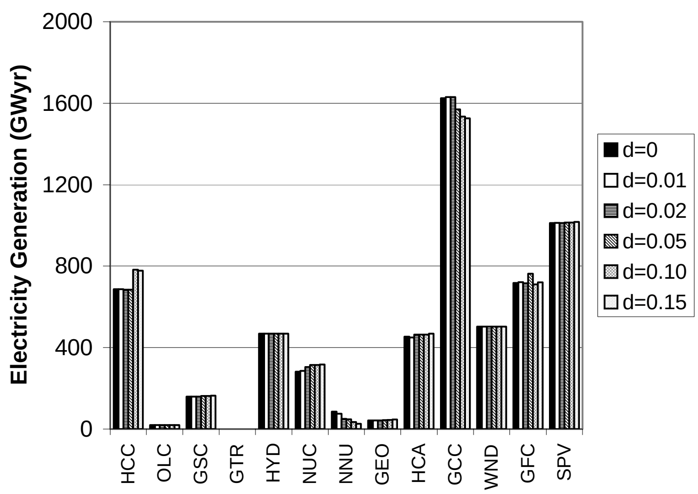


In the particular case illustrated here, as the depreciation rate was increased, the model shifted towards investing more R&D money to counteract the effect of higher depreciation in the investment cost of the gas combined-cycle, already a very competitive technology that holds the highest share of the generation mix (see Figure 6-6 below). Gas combined-cycle has a very attractive LDR and R&D investments are allocated to it despite the fact that its LSR is very low.

In consequence, given that a limited R&D budget is available, the support to more expensive but promising technologies such as solar PV or the gas fuel cell is diminished, despite the fact that they posses a more attractive learning-by-searching elasticity. This is an interesting insight of how the model may respond in the presence of a forgetting factor. Still, a more profound examination of the implications of this formulation is necessary.

Finally, Figure 6-6 presents the electricity generation mix in the year 2050 under the different depreciation rates. In this CO2 constrained scenario and taking into account that the cumulative capacity mechanism plays the predominant role in the learning of the technologies considered here, the variations in the generation mix when the knowledge depreciation rate is modified are not large. Still, some technologies alter their outputs. In particular, the gas combined-cycle (GCC) diminishes its electricity generation as the depreciation rate is increased. Despite the injection of R&D funds, the depreciation makes it slightly less competitive. The increasing depreciation rate also affects the new nuclear power plant (NNU), whose output declines substantially. Correspondingly, other technologies are able to increment their share of the market. In particular, the advanced (HCA) and conventional coal plants (HCC) and the conventional nuclear plant (NUC) increase their output.

Figure 6-6: Electricity generation mix in 2050. Different depreciation rates.



As mentioned before, in order to develop the exercises presented here, we have made a number of assumptions concerning the knowledge stock and LDR and LSR of the different technologies. However, we do not want to give the reader the impression that those assumptions do not affect the results and we are aware that a number of open issues remain. One particular point that may affect the conclusions derived here is our consideration that LDRs and LSRs do not change when the depreciation rate is changed. Actually, choosing a different depreciation rate implies that a new statistical estimation of LDR and LSR must be carried out. In that sense, those parameters are not independent from each other. Thus, in order to be meaningful, sensitivity analyses with ERIS must be linked to an assessment of the 2FLC parameters for the technologies involved.

6.1.1.6. Concluding Observations

A two-factor learning curve formulation is implemented in the energy systems optimisation ERIS model and some illustrative modelling results are presented. The 2FLC formulation allows considering the effects of R&D expenditures together with those of cumulative capacity in the cost reduction of learning technologies. With R&D expenditures specified as an endogenous variable, the optimal allocation of R&D funds across a set of competing learning technologies can be obtained using the 2FLC as the guiding allocation rule.

The incorporation of R&D in ERIS and other energy systems models is important for the examination of energy technology policies. Model analyses may produce insights into how to invest scarce R&D resources more effectively and, thus, they could contribute to more systematic efforts in conforming robust and flexible portfolios of promising new energy supply and demand technologies whose development should be supported.

However, the approach followed here depends critically on obtaining a statistically meaningful estimation of separate learning-by-doing and learning-by-searching indexes and associated parameters. Problems regarding the quality of the underlying data and the estimation itself remain to be solved. Nonetheless, the 2FLC constitutes a first step towards the incorporation of mechanisms that capture the effects of R&D efforts in the technological progress of energy technologies in the ERIS model.

Including R&D expenditures in the learning curve and formulating it endogenously in the model provide more “degrees of freedom” as to the way its impact and related policy questions may be addressed. But, increased “degrees of freedom” will very likely imply increased data requirements and, in the absence of reliable data, they will drive to a mounting number of assumptions. Although this certainly will pose difficulties, the 2FLC concept points out the need of evaluating the effects of energy R&D investments within the context of technological learning and highlights the need to collect the corresponding data and conduct the case studies necessary to evaluate the missing variables.

Possible drawbacks of this implementation should be analysed more carefully and alternative approaches should be explored. Also, further work should be devoted to a more elaborated representation of the process of allocation of R&D resources. If possible, the contributions of public and private actors should be differentiated. Also, the possibility of introducing stylised considerations concerning the influence of the technology's life cycle in the relative contributions of market deployment and R&D efforts should be explored. In addition, although the formulation applied here treats both contributing factors as substitutes, some degree of complementarity between them could very likely exist. The examination of their substitutability and/or complementarity characteristics and how they can alter the basic formulation given here is an aspect that deserves a more profound analysis.

It is still early to establish whether the two-factor learning curve will prove a convenient and sound aggregate model adequately supported by the empirical evidence. But, even so, it must be understood as a helpful step towards the development of a more consistent representation of the technological learning process, where both market deployment and R&D efforts contribute to the progress of technologies and interact with each other and other model parameters and variables in a common framework.

References:

Argote L., Epple D. (1990). Learning Curves in Manufacturing. *Science* ; **247**, 920-924.

Barreto L., Kypreos S. (2000). A Post-Kyoto Analysis with the ERIS Model Prototype. *Int. J. of Global Energy Issues*; **14** (1/2/3/4), 262-280.

Buonanno P., Carraro C., Galeotti M. (2000). Endogenous Induced Technical Change and the Costs of Kyoto. *Proceedings of the Workshop on Economic Modelling of Environmental Policy and Endogenous Technological Change*. Amsterdam, The Netherlands. November 16-17, 2000.

Criqui P., Klaassen G., Schrattenholzer L. (2000). The Efficiency of Energy R&D Expenditures. *Proceedings of the Workshop on Economic Modelling of Environmental Policy and Endogenous Technological Change*. November 16-17, 2000. Amsterdam, The Netherlands.

Goulder L.H., Mathai K. (2000). Optimal CO_2 Abatement in the Presence of Induced Technological Change. *Journal of Environmental Economics and Management* **39**, 1-38.

Griliches Z. (1995). R&D and Productivity: Econometric Results and Measurement Issues. In Paul Stoneman (Editor), *Handbook of the Economics of Innovation and Technological Change*. Blackwell Handbooks in Economics.

Grübler A., Gritsevskyi A. (1997). *A Model of Endogenous Technological Change Through Uncertain Returns on Learning (R&D and Investments).* Paper presented at the International Workshop on induced Technical Change and the Environment. 26-27, June. International Institute for Applied Systems Analysis. Laxenburg, Austria.

IEPE (2000). *Database for the Two-Factor Learning Curve*. Institut d'Économie et de Politique de l'Énergie. Contribution to the Technical Meeting of the SAPIENT Project. September 28-29, 2000. Athens, Greece.

Kouvaritakis N., Soria A., Isoard S. (2000). Modelling Energy Technology Dynamics: Methodology for Adaptive Expectations Models with Learning by Doing and Learning by Searching. *Int. J. of Global Energy Issues* ; **14** (1/2/3/4), 104-115.

Kypreos S., Barreto L., Capros P., Messner S. (2000). ERIS: A Model Prototype with Endogenous Technological Change. *Int. J. of Global Energy Issues*; **14** (1/2/3/4), 374-397.

Manne A., Barreto L. (2001). *Learn-by-doing and Carbon Dioxide Abatement*. IR-01-57-1. International Institute for Applied Systems Analysis. Laxenburg, Austria.

Messner S., (1998). *IIASA Maquette Model Prototype on Endogenized Technological Learning*. TEEM Project of Joule-III. International Institute for Applied Systems Analysis. Laxenburg, Austria.

Miketa A., Schrattenholzer L. (2001). Assessing Alternative Technology Accelerating Options. Paper submitted to *Energy*.

PCAST (1999). *Powerful Partnerships: The Federal Role in International Co-operation on Energy Innovation*. President's Committee of Advisors on Science and Technology. Panel on International Co-operation in Energy Research, Development, Demonstration and Deployment. Washington, USA.

Sagar A.D., Holdren J.P. (2002). Assessing the Global Energy Innovation System: Some Key Issues. *Energy Policy*. In press.

TEEM (1999). *Energy Technology Dynamics and Advanced Energy System Modelling. Final Technical Report*. Contract JOS3 CT97 0013. Non-Nuclear Energy Programme JOULE III. European Commission.

Watanabe C. (1999). Industrial Dynamism and the Creation of a Virtuous Cycle between R&D, Market Growth and Price Reduction. The Case of Photovoltaic Power Generation (PV) Development in Japan. In Wene C.O., Voss A., Fried T. eds, *Experience Curves for Policy Making - The Case of Energy Technologies*. Proceedings IEA Workshop May 10-11, 1999, Stuttgart, Germany.

6.1.2. Assessing alternative technology accelerating options: Optimizing R&D expenditures on energy technologies with ERIS [Asami Miketa and Leo Schrattenholzer (IIASA)]

As has been described in several places of this SAPIENT Final Report, the data on which the estimations of two-factor learning curves are based is not really satisfactory. As a consequence for the analysis, the values of the two learning rates, LDR (learning-by-doing rate) and LSR (learning-by searching rate) are surrounded by considerable uncertainty. This situation calls for a sensitivity analysis that tests the consequences, on optimised R&D expenditures, of assuming the "wrong" learning rates. This subsection reports on the results of this sensitivity analysis.

In order to focus on testing the dynamics of ERIS in response to changing the parameters of two-factor learning curves, the model was used in an aggregate ("stylised") fashion. Our analysis started with calculating optimised R&D support for two technologies, one at a time, using empirically estimated learning parameters (Subsection 6.1.2.2.) We used solar photovoltaic and wind electricity generation to paraphrase a situation in which one technology has a long way to go before it reaches competitiveness but has a high potential for technological progress, and the other technology being closer to competitiveness, but learns at a slower pace. The next step was to test the sensitivity of the results with respect to the learning parameters in regard to the ranges around some reference values.

After this, we assessed the model with 2FLC applied to both technologies at the same time. We did this to study how the optimised R&D support of one technology is influenced by the presence of a competitor (Subsection 6.1.2.3). One consequence of using a stylised approach was that model runs were made with unrealistically low specific investment cost assumptions set for the initial period. We did this to test the model with input parameters that generated the largest variety of the results – at the expense of thus being unable to formulate detailed quantitative recommendations at this stage. Assuming more realistic (i.e., higher) technology cost, might have suggested that these technologies will not enter the energy supply market if cost minimization is the only goal. We therefore concluded our report with a case with CO2 constraints and with more realistic investment cost assumptions. Formulating that case, we intended to reflect the insights we gained through the analysis and, at the same time, to move into the direction of policy relevance.

6.1.2.1. Some methodological remarks

In mathematical terms, the (numerically negative) feedback of cumulative installation and knowledge stock on the costs is referred to as "increasing returns". It leads to the well-known consequence of having a non-convex objective function in optimisation models. This, in general, leads to the existence of more than one local minimum (maximum) point of the objective function. Moreover, the local minimum points are not necessarily of equal size and, more importantly, not necessarily close to each other in the feasible regions as defined by the model constraints.

For solving ERIS, we used a solver with non-linear programming (NLP) capabilities. With this solver, the main task in finding the global optimum is to find a starting point for the NLP that leads to it. In the comparatively simple cases reported here this did not present a problem because we never included more than two learning technologies in any model run. However, with an increasing number of technologies, this can become quite a task because we can expect two local minimum points per learning technology (one with and one without that technology). Ten technologies would then have 1024 (210) local minimum points.

We have chosen wind electricity generation and solar photovoltaic (PV) for our analysis of the model dynamics introduced by 2FLC. The learning parameters for these technologies were estimated using time series data of global quantities, and were used as reference values in the ERIS runs. Three kinds of time-series data were taken from Criqui (2000): investment costs, cumulative installed capacity, as well as public and private R&D expenditures. Most of the time series covered 26 years (1971-1997).

The numerical values of learning parameters estimated statistically are presented in Table 6-3 together with the parameters defining the knowledge stock from R&D expenditures. Other input parameters such as electricity demand development and the maximum annual production limits were taken from the B2 scenario contributed to the IPCC Special Report on Emission Scenarios (SRES, Nakićenović et al. 2000). The discount rate was 5%.

Table 6-3: Parameters determining 2FLCs for solar PV and wind power and the numerical values used in the analysis.

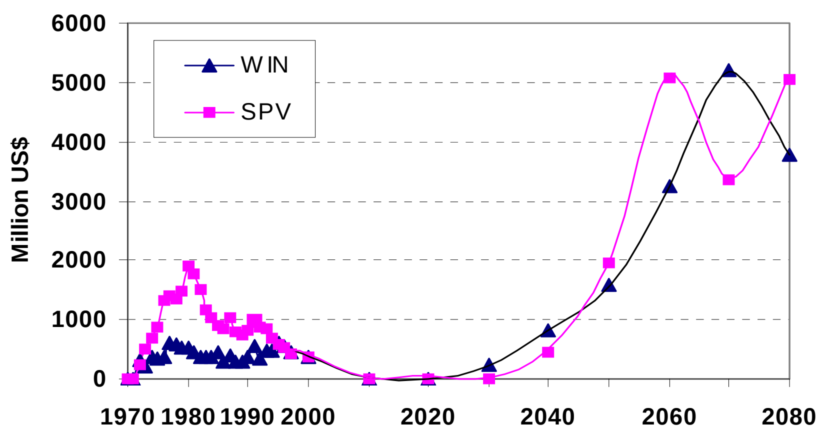
	Solar PV	Wind
Initial knowledge stock, billion US$(98)	14.9	5.2
Annual knowledge depreciation, % per year	3.0	3.0
Time lag for knowledge effectiveness, years	2	2
Learning-by-doing rate (LDR), %	17.5	10
Learning-by-searching rate (LSR), %	10	10

6.1.2.2. Results for single "learning" technologies

In this section, the results of the ERIS model are presented for a situation where only a single technology is learning. We begin with presenting the "reference case" where learning parameters are set to those estimated. The sensitivity analysis concerns optimised R&D expenditure and capacity installation in dependence on variations of the two learning parameters.

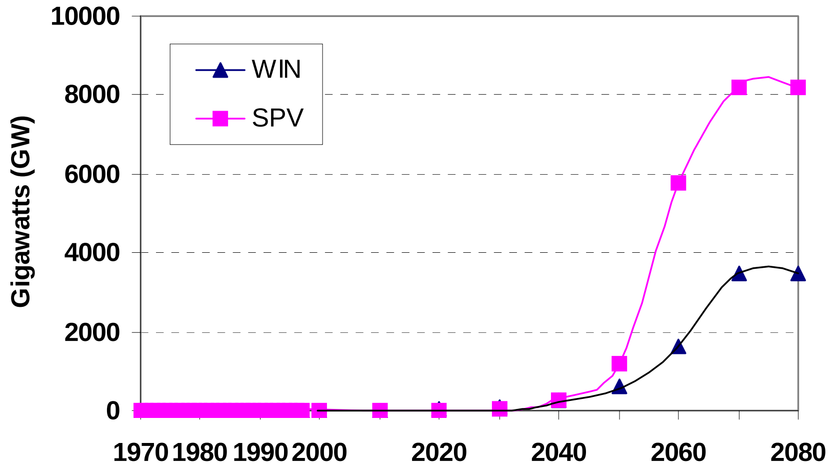
Our first question to ERIS concerned the levels of optimised R&D expenditures in a hypothetical situation of an unlimited R&D budget. Figure 6-7 shows the optimised level of the R&D expenditures calculated separately for wind and solar up to 2080, together with their actual development between 1971 and 1997. The figure shows that ERIS finds optimised levels of R&D support that begin to exceed today's levels after the year 2050. For both technologies considered here, there was a "hole" of optimised R&D support in the near future. Under reference conditions, the model tells us that the time for intensive R&D support is still to come for wind and solar PV. Put differently, the amount of the installed capacity until 2040 may be too small for the R&D money to be worth spending.

Figure 6-7: R&D expenditures for wind and solar PV power generation (Reference Case), optimised separately by ERIS, and actual past R&D expenditures.



Higher R&D spending after 2050 is accompanied by optimised paths of installed capacities of the two technologies that are also higher than in past periods. This is illustrated in Figure 6-8 which shows actual past and optimised future installed capacities. Installed capacities for both technologies remain at an insignificant level until 2030. However, after 2040, they are installed rapidly and in 2070, the share of installed capacity for wind reaches nearly 20% of the total electricity generating capacity and that of solar PV reaches 35%. These shares may appear unrealistically high, but upper limits were chosen very high just so that the model dynamics could be studied more readily.

Figure 6-8: Installed capacities for wind and solar PV power generation, optimised by ERIS, and actual past cumulative capacities.



Under the plausible assumption that higher capacities warrant higher R&D expenditures, we note that the optimised future levels of R&D are very much in the range of past R&D expenditures, which were, quite likely, constrained by R&D budgets, whereas optimised R&D was calculated without R&D budget constraint. This means that the optimisation rule alone prevents R&D expenditures from reaching unrealistically high levels and that therefore no further constraints need to be included in the model to keep optimised R&D expenditure within plausible limits.

Analysing the trajectories of R&D support and newly installed capacities, we find that the build-up of new capacities is limited by factors other than those included in the 2FLC. In our case, these other factors include the so-called market penetration constraints (limiting the speed of introducing new technologies) and absolute limits set on the annual electricity production of a technology. We have experimented with different market penetration constraints, and have found that the optimised R&D expenditures would become higher if market penetration constraints would allow for faster introduction.

We test the sensitivity mainly of optimised R&D expenditures of the model results with respect to the two learning indices of the 2FLCs. The model results we analyse first concern optimised R&D levels and, second, the installed capacity of the learning technology as a function of the two learning parameters.

First, we look at the optimised levels of R&D when we keep the learning-by-doing rate (LDR) fixed at our reference value and vary the learning-by-searching rate (LSR) from 1% to 30%. The development of the optimised R&D support between 2000 and 2080 is presented in Figure 6-9 for wind. The figure points out that higher LSRs correspond to larger levels of R&D support, indicating that if a technology is more "responsive" to R&D (expressed by higher LSRs), then more R&D support is found optimal. This pattern is further illustrated in Figure 6-10, showing this dependence for the year 2050 only. Here we can see that there seems to be an upper limit to this effect. If the LSR is higher than a certain value, in this case 25%, this effect saturates.

Figure 6-9: Development of optimised R&D expenditures of wind, LDR fixed at 10%. The reference case (LDR=10 and LSR=10) is represented by a bold line.

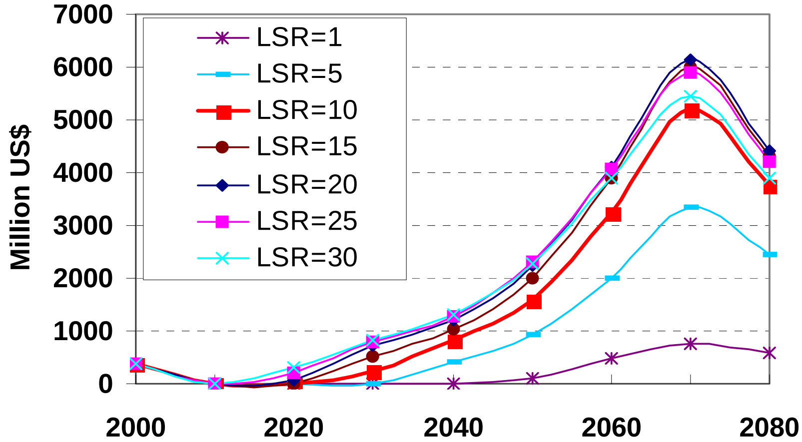
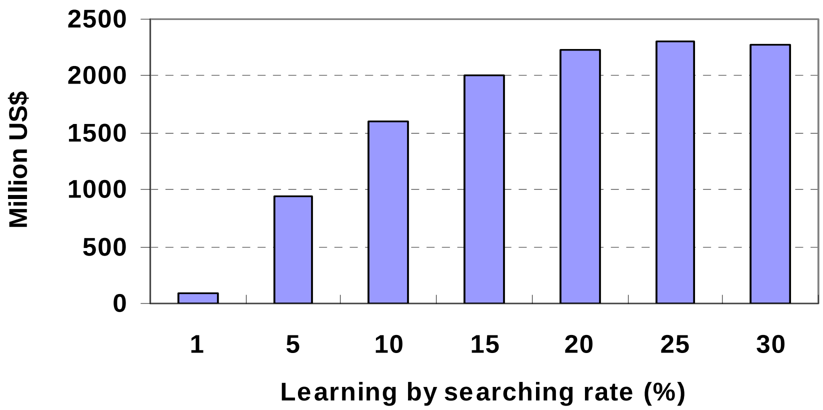


Figure 6-10: Optimised R&D expenditures for wind in 2050, LDR fixed at 10%.



We have also calculated the optimised R&D support with fixed LSRs but varying LDRs. The results of these calculations for wind power are presented in Figure 6-11 and Figure 6-12, showing the development of the optimised R&D expenditure over time and, separately, in 2050.

Figure 6-11: Development of optimised R&D expenditures of wind, LSR fixed at 10%. The reference case (LDR=10 and LSR=10) is represented by a bold line.

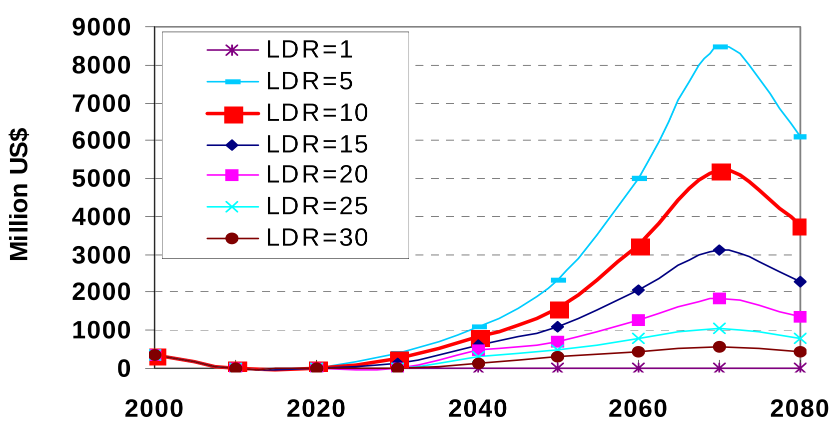


Figure 6-12: Optimised R&D expenditures of wind in 2050, LSR fixed at 10%.

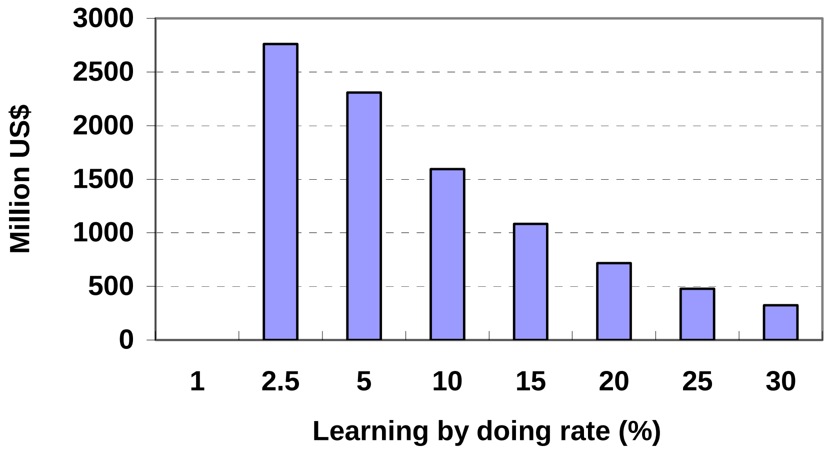


Figure 6-11 demonstrates that, generally, higher LDRs correspond to smaller levels of R&D support, indicating that if a technology is more prone to progress as a result of learning-by-doing, then less R&D support is needed to reach the optimised cost reductions of the technologies. For the same reason, smaller LDRs suggest that additional R&D expenditures can compensate for a lack of responsiveness of the technology to experience (cumulative capacity) of wind energy.

Figure 6 12 confirms the general observation of a negative correlation between optimised levels of R&D support with respect to the LDR, but shows one exception on the low end of the spectrum of LDRs considered here. When an LDR is equal to only 1%, wind technology does not enter the market, and the LSR at 10% (reference value) will not be high enough to prevent this from happening.

Next, we look at the trajectories of installed capacity for each of the cases considered. The figure below shows that there are only two distinct trajectories of wind capacity in all cases! As surprising as this result may appear at first, reflection on the model formulation leads to the plausible explanation that build-up constraints limit the speed of introduction of wind technology. Once the model finds that this technology is worthwhile to introduce, it introduces it to the limit specified elsewhere in the model.

Figure 6-13: Installed capacity of wind for different pairs of parameters of the 2FLC (The zero-capacity case corresponds to LDR=1, LSR=10).

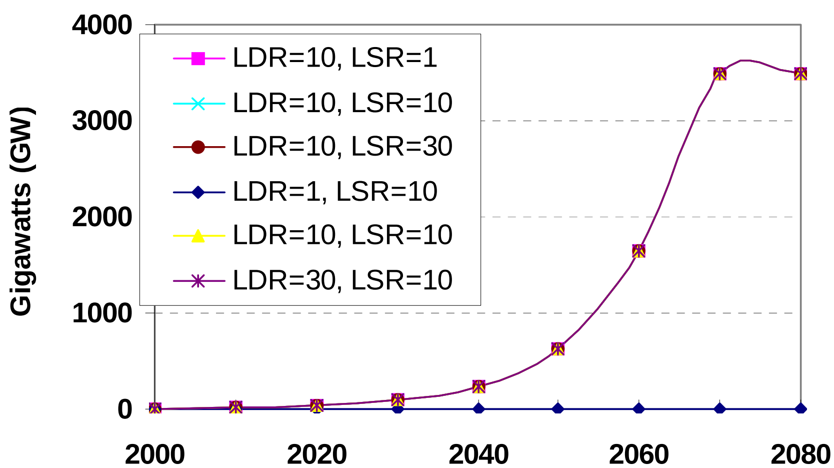
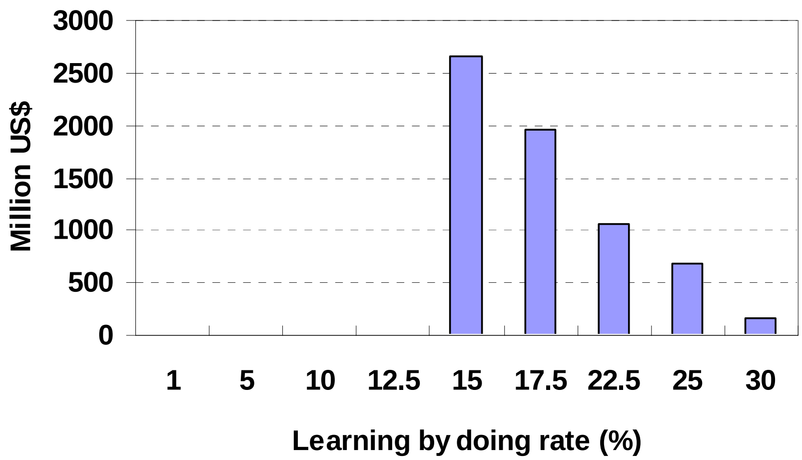


Figure 6-14: Optimised R&D expenditures of solar PV in 2050, LSR fixed at 10%.



Optimised R&D expenditures for solar PV show a similar pattern as that obtained for wind (Figure 6-14). As the investment costs of solar PV are higher than wind, it would take a higher "threshold" LDR (of 15%) to bring the technology into the market. Likewise, the trajectory of the installed capacity for solar PV showed the same "two-trajectory" situation (with LDR=1, LSR=10 as the zero-capacity case). One trajectory reaches its maximum of electricity production of solar PV in 2070 and the other stays at the insignificant level of installed capacity.

To summarize, the learning rates affect the optimised R&D level in opposite ways. Higher learning-by-searching rates (LSR) result in a steeper cost reduction, implying that more R&D investment pays off. In contrast, a higher learning-by-doing rate (LDR) leads to lower optimised R&D expenditures. This result is in some analogy to the concept of optimal value shares in Cobb-Douglas functions. There, higher exponents of one production factor lead to higher optimal value shares. Similarly, a relatively more effective learning by doing (higher LDR) lead to a relatively lower "value share" of knowledge, that is, lower R&D expenditures and *vice versa*.

As for the optimal development of the cumulative capacity, results for both wind and solar is a kind of "all-or-nothing" solution: Once the model finds that it is optimal to introduce a technology, this technology is introduced up to the assumed limits. Whether this happens or not is determined by the comparison of the benefit of the R&D investment (investment cost reduction) and the cost of the investment (R&D expenditure). Once this cost-benefit comparison is resolved in favour of the "learning" technology (wind or solar respectively), it is optimal to install this successful technology as fast as other model constraints (in particular, market penetration constraint) permit. Otherwise, it is optimal not to install wind or solar PV power. Only these two choices exist for each combination of values for both learning rates. A single trajectory of capacity expansion therefore corresponds to different levels of R&D, and a zero trajectory of capacity expansion always corresponds to the zero R&D expenditure. In other words, different R&D does not change the capacity path, and with no cumulative capacity, it is not worth spending R&D at all.

6.1.2.3. Technologies competing for R&D support

So far, we have reported ERIS runs in which only one technology was learning at a time. We now proceed by putting wind power and solar PV into ERIS at the same time. Our purpose was to determine whether supporting one technology can be so profitable that it will be the only one to receive R&D support, i.e., "crowds out" the other.

For this phase of analysis, we used the learning rates summarized in Table 6-3 for solar PV and wind energy as a reference case, and then moved on to a sensitivity analysis with respect to different learning indices. Figure 6-15 shows the optimised R&D expenditures that ERIS calculated for the reference case where wind and solar PV learn at the same time.

Figure 6-15: Time evolution of R&D expenditures for wind (WIN) and solar PV (SPV) energy technology.

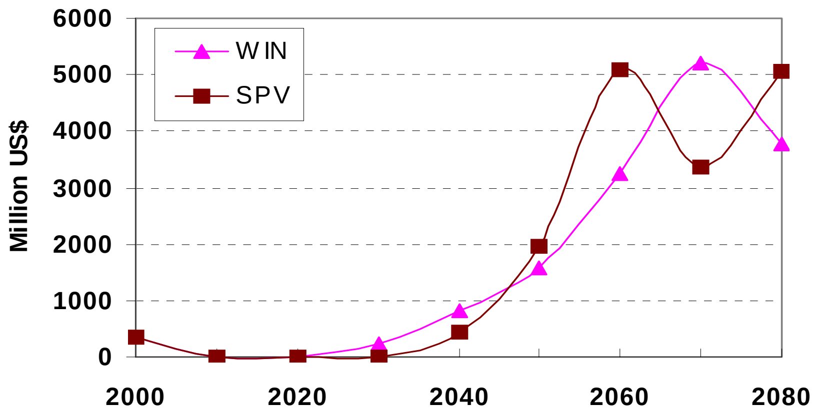


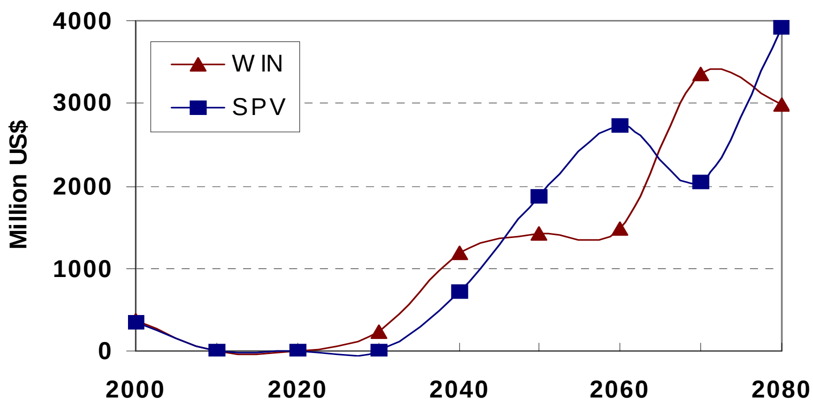
Figure 6-15 shows that the optimised R&D expenditures for one technology are independent of the presence of the other technology. The two trajectories are identical to those we found when we let the technologies learn separately (Figure 6-15). We have also made a run with the carbon emission constraints and found that it does not change the optimised R&D expenditure as to what the two technologies would get without the constraints.

Regarding the optimised installed-capacity path, without presenting the graphical evidence here, we report that the optimised cumulative capacity in the two-technology-learning-together case was also identical to the single-technology-learning case (Figure 6-8). In other words, optimised R&D expenditures in our case are a function of the learning characteristics of the two technologies and not the result of competition between them!

This result was not quite expected, so we repeated the experiment, this time in the presence of a budget constraint[16]. Figure 6-16 illustrates the optimised R&D expenditures for the two technologies under the assumed R&D budget constraint.

The comparison with Figure 6-15 where no R&D limitation was set reveals that the evolution over time for the two cases is quite similar, but that the absolute levels are reduced. One thing worth mentioning is that even in the presence of the R&D constraint, each technology continues to receive R&D support and stays in the market.

Figure 6-16: Time evolution of R&D expenditures for wind (WIN) and solar PV (SPV) energy technology assuming a limit on R&D budget.



This result suggests that for decisions on optimal R&D support it is primarily important to estimate (with the help of 2FLCs, for example) the responsiveness of a technology to R&D. In the single-technology

[16] The assumed budget constraint limits the available total R&D budget for the two technologies to approximately 15% of the government R&D budget for IEA countries in 1997 (IEA,2000) but takes into account that the level grows with GDP growth (based on the MESSAGE B2 scenario from SRES (Nakićenović et al.2000). 15% is an arbitrary number but it is the level that limits the R&D spending to 50% of what has been calculated as the optimal level in the non-limited case for 2060.

case, where there was no competition, this point was perhaps more obvious, but here the model results say that looking at other technologies which might compete with a given technology for R&D seems to be only of secondary importance for the determination of optimised R&D support of a given technology.

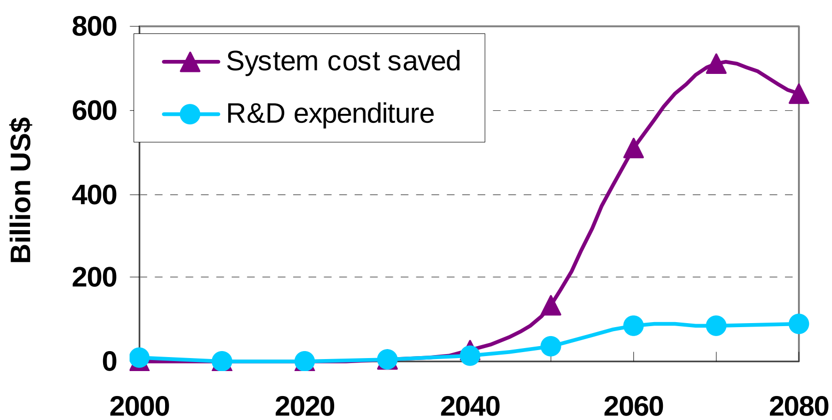
Our total system cost consists of investment cost, operation and maintenance cost, fuel cost and R&D expenditures. Numerical results of systems cost items for the reference case are presented in the first column in Table 6-4. In order to determine cost savings as a result of R&D spending, we also made a model run with an R&D budget restriction that sets R&D at zero (second column in Table 6-4). We defined the difference in the total system costs of the zero-R&D run and the reference run as the cost reduction effect due to the R&D spending. It came out to be 54.7 billion US$. If this value is compared with the level of R&D expenditure, which is 14.9 billion US$, the benefit of the R&D is 3.7 times as large as R&D expenditures.

Table 6-4: Comparison of total discounted cost and R&D expenditure.

	Reference case	No R&D case	Difference of the two
Total discounted system cost, billion US$(98)	14,318.6	14,373.3	54.7[a]
Total discounted R&D expenditure, billion US$(98)	14.9	-	14.9[b]
Net R&D benefit ([a]-[b])	-	-	39.8

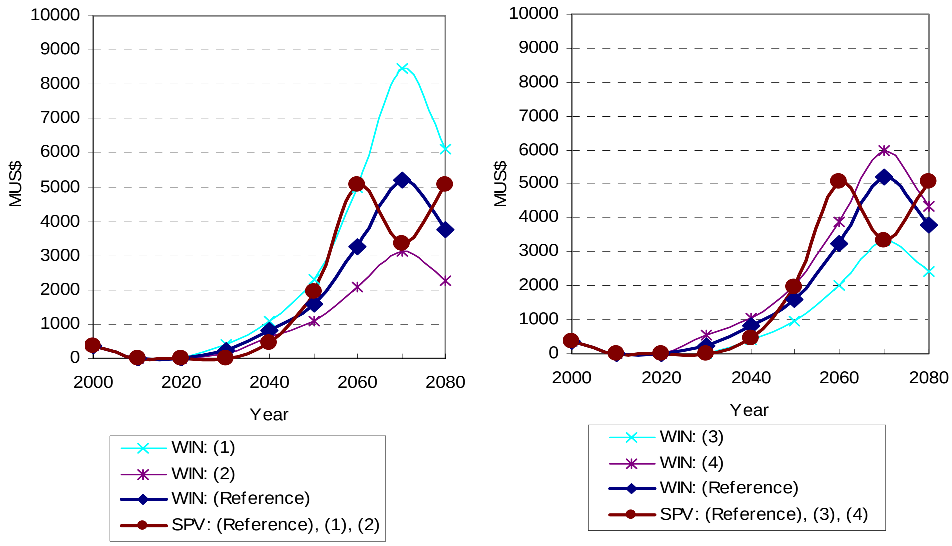
Looking at undiscounted costs, we arrive at what is shown in Figure 6-17. The figure confirms the generally high profitability of R&D expenditures.

Figure 6-17: Development of non-discounted system cost saved due to R&D (gross R&D benefit) and non-discounted R&D expenditure.



Now we present the results of a sensitivity analysis of the optimised R&D expenditures for the two technologies with respect to their learning parameters. We investigated whether optimised R&D support of one technology remains unaffected by the presence of the other technology when the learning parameters are varied, as was the result in the reference case. In all investigated cases of two technologies learning together we could have obtained the same result on optimised R&D and on capacity expansion of the renewable-energy technologies if we had combined the corresponding cases in which only one technology was learning at a time.Figure 6-18 presents selected graphical results obtained from our sensitivity analysis. It illustrates the optimised R&D allocation between the two renewable technologies according to the different learning parameters of the wind technologies. The learning parameters for solar PV are fixed. The reference case is presented as a bold line. The left-hand side of the figure is the case where the LDR for wind is changed whereas the right-hand side is the case where the LSR for wind is changed.

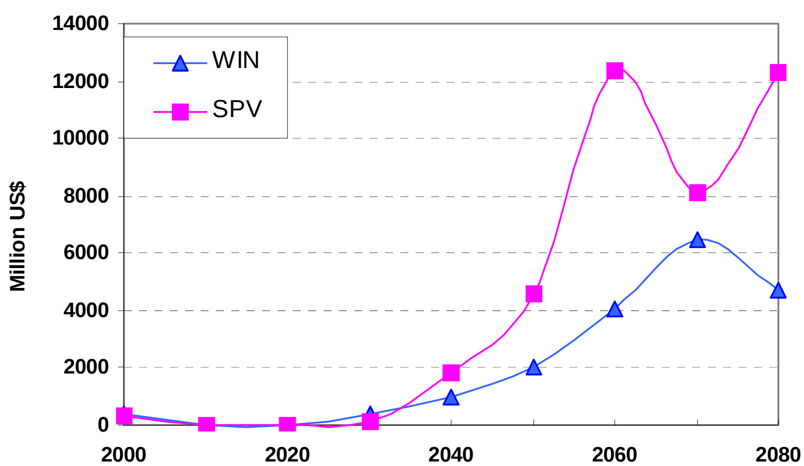
Figure 6-18: Time evolution of optimised R&D expenditures for wind (WND) and solar photovoltaic (SPV) energy technology when learning parameters for SPV are fixed for all cases[17].



Throughout most of our analysis, we have emphasized the methodological aspect of running ERIS. We have therefore chosen some of the model's input parameters in a way that generated particularly dynamic model outputs rather than the most realistic values we could find. At the same time, our eventual goal is to use ERIS results to generate policy-relevant insights. As a first step into that direction, we ran one case with more realistic numbers, but still close to the other cases reported here to maintain comparability.

For this case, we use a run with a CO2 emission constraint as a basis. Solely for illustrative purposes, we constrained CO2 emissions from global electricity production to stay below the 2020 level of the non-constrained case. Instead of the unrealistically low cost figures (800 US$/kW for wind and 1800 US$/kW for solar in the year 1990), we used 1035 US$/kW for wind and 5000 US$/kW for solar. Figure 6-19 illustrates the optimised level of the R&D expenditures. This figure can be compared with Figure 6-15. The biggest differences between the two cases are that the more realistic case shows higher levels of optimised R&D (plus 25% for wind and plus 140% and higher for solar PV) than the earlier case. Figure 6-20 shows that the optimised installed capacity for both technologies remain the same in comparison with the previous runs. This means that the higher R&D expenditures are only due to the higher specific investment costs. We therefore conclude that the higher the initial specific investment cost is for each technology, the more R&D investment is optimal.

Figure 6-19: Optimised R&D expenditures for wind and solar PV power generation, optimised separately by ERIS.



[17] LSR fixed for WIN at 10% (LDR=5% for case 1, LDR=15% for case 2, and LDR=10% for reference case) [left] and LDR fixed for WIN at 10% (LSR=5% for case 3, LSR=15% for case 4, and LDR=10% for reference case) [right].

Figure 6-20: Installed capacities for wind and solar PV power generation, optimised by ERIS.

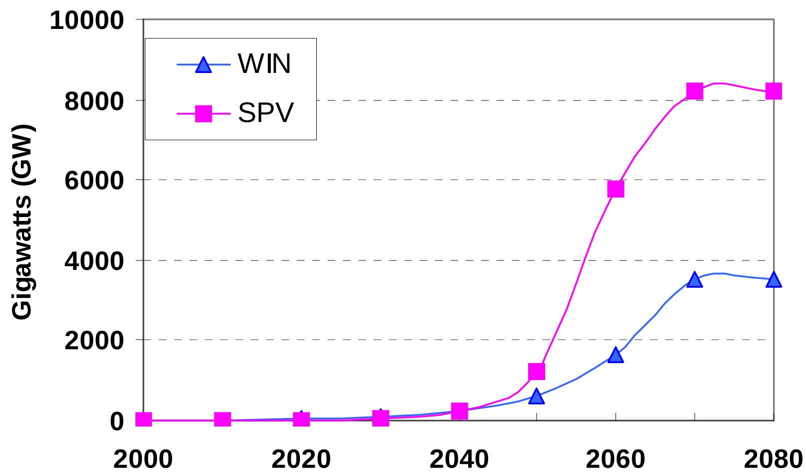


Figure 6-21 shows the development of the specific investment costs. The specific investment cost for wind gradually drops to 194 US$/kW and for solar it will drop as low as 132 US$/kW. This is the combined effect of the two factors learning by doing (cumulative capacity) and learning by searching (knowledge stock). Figure 6-22 and Figure 6-23 show the percentage change (compared with the previous decade) of the specific investment cost for wind and solar respectively, decomposed into the effect of learning by doing and learning by searching. One common phenomenon for both technologies is that during the earlier periods of our time horizon, a decreasing knowledge stock (caused by zero or low R&D expenditures) increases the specific investment cost. In other words, ERIS finds it optimal to "forget" some of the knowledge accumulated in the periods prior to the model's time horizon. After 2040 in the case of solar – and after 2030 in the case of wind – new capacities of the two technologies are again being built, accompanied by further R&D expenditures.

Figure 6-21: Specific investment cost development for wind and solar PV power generation.

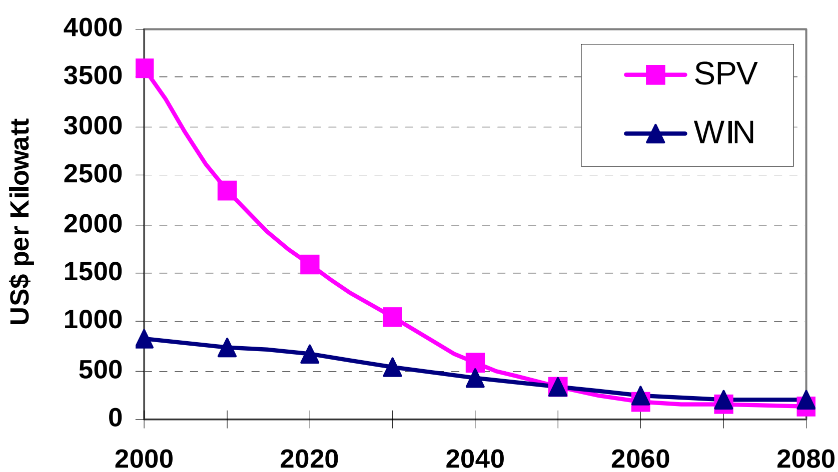


Figure 6-22: Decomposition of the cost-reduction factors for wind.

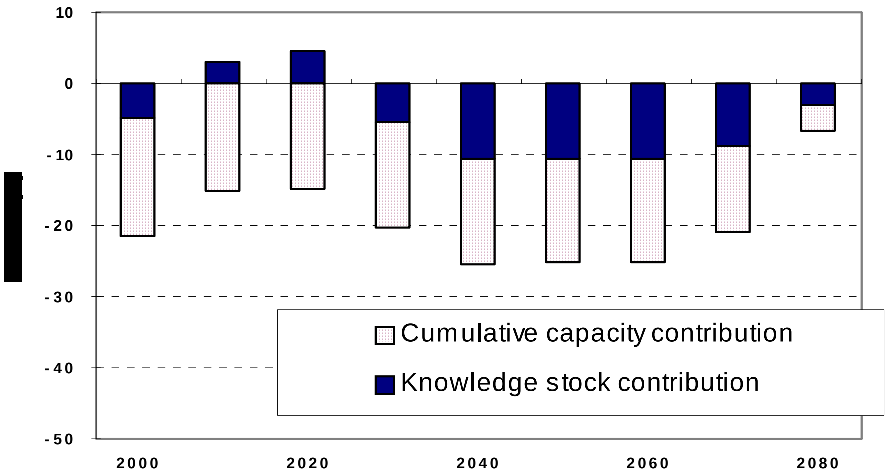
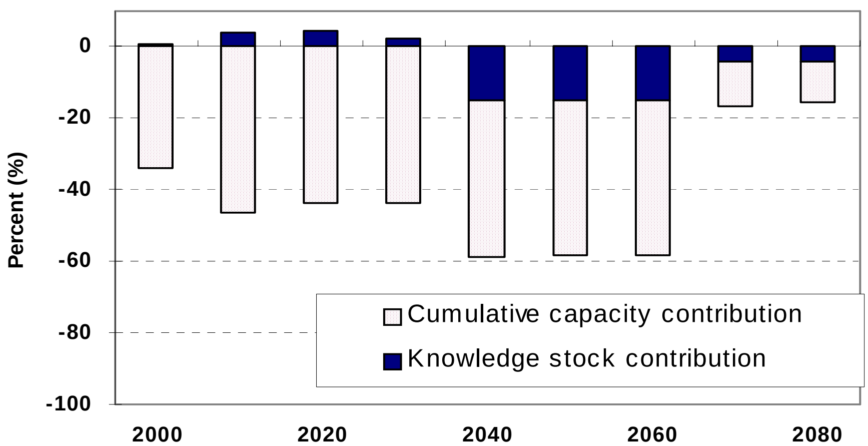


Figure 6-23: Decomposition of the cost reduction factors for solar PV.



6.1.2.4. Summary and conclusions

The results of the ERIS runs shown in this section provide the basis for the understanding of the model and provide several qualitative and quantitative results. The entire exercise was stylised in the sense that we emphasized model dynamics rather than realistic input data, but we think that we have provided a solid point of departure from which important quantitative policy implications could be derived during further work.

We first analysed the optimised R&D levels and installed capacity for the reference case for each technology in turn. Although the orders of magnitude of actual past R&D support and optimised R&D expenditures in the future are the same, there is a break in the trend. After a decline during the initial periods, the present level of R&D spending is reached again only in 2040. The amount of installed capacity until 2040 may be too small for the R&D money to be worth spending.

From the sensitivity analysis of the parameters of the 2FLC, we can identify some of the robust results concerning the optimal R&D allocation. A robust result is that as soon as a technology is found to respond profitably to R&D support, the optimised levels of R&D move continuously, i.e., without jumping as a consequence of one of the learning rates changing just a bit. In general, the optimised levels of R&D are sensitive to both learning parameters, but in different directions. Higher LDRs correspond to lower levels of optimised R&D support, but higher LSRs correspond to the higher levels of optimised R&D spending.

The transitions between no R&D support at all and high levels are the only major jump we observed. The expression "bang-bang" (also "all-or-nothing"), often used to characterize solutions of LP models, applies here in the sense that either a technology never enters the market or quickly proceeds to enter the electricity market up to the constraints defined elsewhere in the ERIS model, most notably the market penetration constraints. This phenomenon also explains why there is not much to analyse in terms of optimal combination of the two factors of the 2FLC from a policy point of view, i.e., the combination of procurement (capacity expansion) and R&D support. However, we note that if sufficient capacity cannot be installed, there is no use of spending R&D. A technology must promise to pay back the investment made in it.

Then we analysed cases where two technologies are learning at the same time. We found that the level of optimised R&D allocation to one technology is independent of the presence of the other technology. The competition both in terms of R&D support and market shares between the technologies turns out to be of secondary importance and what matters for both is the combination of a technology's own learning parameters that warrant its profitable deployment. It is also independent of the learning parameters of the other technology. In this sense, we have failed to observe the often-quoted phenomena of "lock-in" (the dominance of one learning technology as a consequence of increasing returns to scale) and "crowding-out" (a limited R&D budget leaving room for supporting only one technology). Of course, the absence of these two phenomena is also a consequence of the limited availability of the two technologies. In a hypothetical case of many technologies learning as described by two-factor learning curves, some of this would surely be observed, in particular if the capacities of those technologies are not tightly constrained.

References:

Barreto, L., Kypreos, S., Some tests with the Two-Factor Learning Curve. Unpublished document. Paul Scherrer Institute. Villigen, Switzerland, 2000.

Dutton, J.M., Thomas, A. Treating progress functions as a managerial opportunity. *Academy of Management Review* 1984;**9**(2):235–247.

Griliches, Z., *R&D and productivity.* University of Chicago Press, Chicago/London, 1998.

Griliches, Z., Returns to Research and Development Expenditures in the Private Sector. In Kendrick, J.W., Vaccara, B.N. eds. *New Developments in Productivity Measurement and Analysis*, University of Chicago Press, Chicago, IL, USA, pp.419-461 (ISBN 0-226-43080-4), 1975.

Gritsevskyi, A., Ermoliev, Y., An energy model incorporating technological uncertainty, increasing returns, and economic and environmental risks. In IAEE, ed. Technological *Progress and the Energy Challenges, Concurrent Sessions Proceedings of 1999 European Energy Conference*. 30 September – 1 October 1999, Paris, France, pp.192-201, 1999.

IEA (International Energy Agency), IEA Technology R&D Statistics, November 9, 2000, http://www.iea.org/stats/files/R&D.htm.

Kouvaritakis, N., Soria, A., Isoard, S., Modelling energy technology dynamics: methodology for adaptive expectations models with learning by doing and learning by searching. *International Journal of Global Energy Issues* 2000;**14**(1–4):104–115.

McDonald, A., Schrattenholzer, L., Learning rates for energy technologies. *Energy Policy* 2001; **29**(4):255-261.

Nakićenović, N., Alcamo, J., Davis, G., de Vries, B., Fenhann, J., *et al.*, *Special Report on Emissions Scenarios (SRES.* A Special Report of Working Group III of the Intergovernmental Panel on Climate Change, Cambridge University Press, Cambridge, UK, 2000.

Nordhaus, W., Modeling induced innovation in climate-change policy. Paper presented at the International Workshop on Induced Technological Change and the Environment Workshop, 21-22 June 1999, IIASA, Laxenburg, Austria.

Watanabe, C., Industrial Dynamism and the Creation of a 'Virtuous Cycle' between R&D, Market Growth and Price Reduction-The Case of Photovoltaic Power Generation (PV) Development in Japan. In Wene, C.O., Voss, A., Fried, T., eds. *Experience Curves for Policy Making: The Case of Energy Technologies,* Proceedings IEA Workshop 10-11 May 1999, Stuttgart, Germany, 2000.

Wright, T.P. Factors affecting the cost of airplanes. *Journal of the Aeronautical Science* 1936; **3**:122-128.

Zhu, B., *Theoretical analysis and empirical demonstration of optimal R&D investment trajectory control*. Ph.D. thesis done at the Tokyo Institute of Technology, 2000

Criqui, P., Data for the two-factor learning curve, 15 December, IEPE, Grenoble, France, 2000.

6.2. MERGE-Modelling framework [by S. Kypreos, O. Bahn (PSI)]

In the following, first the basic characteristics of the model MERGE and its sub-models ETA and MACRO are presented followed by the discussion of required extensions for implementing endogenous technological learning (ETL) options.

The MERGE model is a well-established tool for assessing economical and technological options to deal with the global climate change issue. 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 (OECDE); 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. It captures substitutions of energy forms (e.g., switching to low-carbon fossil fuels) and energy technologies (e.g., use of renewable power plants instead of fossil ones) to comply with CO2 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 captures macro-economic feedbacks between the energy system and the rest of the economy, for instance impacts of higher energy prices (due to CO2 control) on economic activities.

The mathematical formulation of ETA-MACRO can be cast as 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 regional consumption. Notice that the wealth of each region includes its initial endowments in fossil fuels, nuclear resources, renewables and CO2 emission permits.

MERGE links these regional ETA-MACRO sub-models. It aggregates the regional welfare functions into a global welfare function, using appropriate Negishi weights (Negishi, 1972). The regional sub-models are further linked by international trade of oil, gas, synthetic fuels, CO2 permits and an aggregate good in monetary unit ('numéraire' good) that represents all other (non-energy) traded goods. A global constraint ensures then that international trade of these commodities is balanced.

A fixed set of Negishi weights defines a so-called Negishi welfare problem, whose solving corresponds to the maximising of the global welfare function. The solving of MERGE is done by updating iteratively the Negishi weights and by solving the corresponding Negishi welfare problems. The steps to update the Negishi weights are performed until a Pareto optimal equilibrium solution is found.

6.2.1. MERGE-ETL

Technological learning describes how the specific (investment) cost of a given technology is reduced through the accumulation of knowledge. The latter may have different sources, such as the technology's manufacturing ('learning-by-doing') or research-and-development expenditures ('learning-by-searching'); see for instance Grübler (1998). A learning curve relates then for a given technology its specific cost to one or more factors describing the accumulation of knowledge. Empirical evidences of such learning curves for energy technologies are given in the literature; see for instance Christiansson (1995) or again Grübler (1998).

In the original MERGE model, technological learning is not considered. Energy technologies have instead fixed characteristics over time. In particular, a fixed production cost is assumed over time. Furthermore, some of these energy technologies 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, which are all specific ones. Table 6-5 lists these learning technologies, and gives their corresponding name in the original MERGE model.

Table 6-5: Learning technologies in MERGE-ETL.

Technology name in MERGE	Technology name in MERGE-ETL	Technology identification in MERGE-ETL
ADV-HC	SPV	Solar photovoltaic
ADV-LC	WND	Wind turbine
ADV-LC	NNU	New nuclear designs
COAL-A	IGCC	Integrated coal gasification with CC
GAS-A	GFC	Gas fuel cell
GAS-N	GCC	Gas turbine CC (combined cycle)
NE-BAK	NE-BAK	H2 from solar photovoltaic
RNEW	RNEW	H2 from biomass

Notice that in Table 6-5, the first six technologies correspond to power plants, the last two to non-electric energy technologies. The next two sections describe the inclusion of endogenous technological learning in MERGE, using a one-factor (learning-by-doing) and two-factor (learning-by-doing and by-searching) learning curve formulations.

6.2.1.1. One-factor learning curve

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. Let CCk,t be the cumulative capacity per period t of a technology k for which endogenous learning is assumed. For a power plant k, this variable is expressed in GW and computed based on the electricity production as follows:

$$CC_{k,t} = CC_{k,0} + \frac{\sum_{regions,\tau}^{\tau\in[1,t]} 10 \cdot PE_{k,r,\tau}}{life_k \cdot lf_k \cdot 0.00876} \tag{1}$$

where CCk,0 is the cumulative capacity at the beginning of the time horizon, PEk,r,τ the yearly generation of electricity (in TkWh) in region r, lifek the plant's life time (in years), lfk its load factor, and 8760 are the number of hours per year. A similar relation is introduced for non-electric energy production technology k. The corresponding cumulative capacity is then expressed in EJ per annum and computed as:

$$CC_{k,t} = CC_{k,0} + \frac{\sum_{regions,\tau}^{\tau\in[1,t]} 10 \cdot PN_{k,r,\tau}}{life_k} \tag{2}$$

where PNk,r,τ is the yearly production of non-electricity energy (in EJ) in region r. The learning curve for the specific cost SCk,t of a technology k is then defined as:

$$SC_{k,t} = a \cdot CC_{k,t}^{-b} \tag{3}$$

where a is a parameter given by the initial point (SCk,0, CCk,0) of the learning curve, and where b is a learning index. The latter defines the speed of learning and is derived from the progress ratio. The progress ratio pr is such that 1-pr is the rate at which the specific cost declines each time the cumulative capacity doubles. The relation between b and pr can be expressed as:

$$pr = 2^{-b} \tag{4}$$

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 cost curve, as follows:

$$TC_{k,t} = \int_0^{cc} SC_{k,t} \cdot dCC = \frac{a}{1-b} \cdot CC_{k,t}^{1-b} \tag{5}$$

The latter expression is then used to compute the investment cost IC per period t, as the difference of two consecutive values of TC:

$$IC_{k,t} = TC_{k,t} - TC_{k,t-1} = \frac{a}{1-b} \cdot \left(CC_{k,t}^{1-b} - CC_{k,t-1}^{1-b} \right) \tag{6}$$

However, instead of the investment cost, the MERGE model deals with the full cost of generating electricity or with the one of producing non-electric energy, cost which includes the investment cost; see also the relation COSTNRG in the annex, below. One has then to assume that technological learning (cost reduction) applies only to a fraction fr of the energy production cost PC corresponding to the investment cost. The remaining of the production cost, not included in the endogenous cost reduction process, is related to (a fraction of) operation and maintenance cost as well as fuel cost. Notice that in energy systems not only the capital cost but also the efficiency and the load factor can be improved over time to reduce the generating cost. These effects are taken into account in the database. For each technology k for which endogenous learning is assumed, the energy production cost can then be cast as:

$$PC_{k,t} = IC_{k,t} + \left(1 - fr_k\right) \cdot PC_{k,1} \tag{7}$$

6.2.1.2. Two-factor learning curve

The one-factor learning curve used in the previous section does not take into account public and private research and development (R&D) expenditures. However the latter may be an important factor, especially for the development of new, cleaner and more efficient energy technologies. To consider also this factor, we use as well a two-factor learning curve, where the specific cost is reduced both as a function of the cumulative capacity and of the cumulative R&D expenditures. More precisely, the specific cost SCk,t of a technology k is here defined as:

$$SC_{k,t} = a \cdot CC_{k,t}^{-b} \cdot CRD_{k,t}^{-c} \tag{8}$$

where CRDk,t are the cumulative R&D expenditures per period t, a is a parameter given at the origin (SCk,0, CCk,0, CRDk,0) of the learning curve, b a learning-by-doing index, and c a learning-by-searching index. The cumulative R&D expenditures could be endogenously estimated as in the ERIS model (Barreto, 2001). For simplicity, we shall consider only the case where they are exogenously estimated. Cumulative R&D expenditures per technology k and period t can then be computed as:

$$CRD_{k,t} = CRD_{k,0} + \sum_{\tau=1}^{t} \left(\Delta_\tau \cdot ARD_{k,\tau}\right) \tag{9}$$

where Δt is the number of years per period and ARDk,t are the exogenously specified R&D expenditures per year. As in the case of the one-factor learning curve, MERGE-ETL uses a total cumulative cost curve. The latter is again expressed as the integral of the specific cost curve, as follows:

$$TC_{k,t} = \int_0^{cc} SC_{k,t}\left(CC, CRD\right) \cdot dCC = \frac{a}{1-b} \cdot CC_{k,t}^{1-b} \cdot CRD_{k,t}^{-c} \tag{10}$$

The latter expression is again used to compute the investment cost IC per period t, as the difference of two consecutive values of TC:

$$IC_{k,t} = TC_{k,t} - TC_{k,t-1} = \frac{a}{1-b} \cdot \left(CC_{k,t}^{1-b} \cdot CRD_{k,t}^{-c} - CC_{k,t-1}^{1-b} \cdot CRD_{k,t-1}^{-c}\right) \tag{11}$$

Finally, the investment cost is used as in (7) to compute the energy production cost PC. For both the one-factor and two-factor formulas, the market penetration constraints of the original MERGE model have also been updated as follows, for each technology k for which endogenous learning is assumed:

$$EP_{k,r,t} \le sf \cdot ED_{r,t} + exr_k^{10} \cdot EP_{k,r,t-1} + gdf_k \cdot \sum_{s \in regions} exr_k^{10} \cdot EP_{k,s,t-1} \tag{12}$$

where EPk,r,t is the yearly energy production in region r (namely the generation of electricity PE or the production of non-electricity energy PN), sf a low seed value parameter, EDr,t the yearly energy demand of region r, exrk the annual expansion rate and gdfk a global diffusion factor reflecting regional spill-over effects.

6.2.1.3. Carbon capture and disposal

Besides endogenous technological learning, another modification done in the original MERGE database is the modelling of CO2 capture and disposal into depleted oil and gas reservoirs. For this purpose, two new power plants are introduced: an integrated gasification combined cycle coal power plant —IGCC— with CO2 capture —using Selexol®— and carbon disposal (COAL-D); and a gas turbine combined cycle —GCC— with CO2 capture —using monoethanolamine, MEA— and disposal (GAS-D). These technologies have the following specifications.

Table 6-6: Characteristics of two power plants with CO2 capture and disposal

	COAL-D (IGCC with CO2 capture using Selexol® & disposal)	GAS-D (GCC with CO2 capture using MEA & disposal)
Efficiency	38% (instead of 48%)	50% (instead of 56%)
Emissions (gCO2/kWh)	170 (instead of 800)	76 (instead of 406)
Production cost (mills/kWh)	64.5	38.2

These characteristics have been adapted from Freund (1998). Notice that the production cost has been computed from the corresponding IGCC and GCC production cost, adding the cost of CO2 capture (based on the efficiency loss) and the one of CO2 disposal (assumed to be 10 USD/tC). It is assumed furthermore that there is a maximum storage capacity of 50 GtC in depleted oil and gas reservoirs between 2000 and 2050.

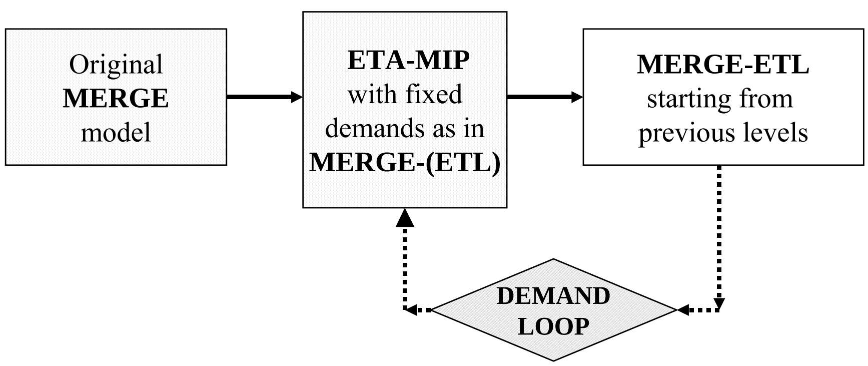
An important caveat is that both COAL-D and GAS-D are not yet subject to endogenous technological learning, although they should. Indeed the integrated gasification combined cycle part of COAL-D is subject to learning within the IGCC technology. Similarly, the gas turbine combined cycle part of GAS-D is learning within the GCC technology. One should thus envision a cluster of learning technologies. One such cluster could be for instance gas turbine combined cycle. Through endogenous technological learning in the latter technology, the corresponding production cost of GCC and GAS-D would then be reduced.

6.2.1.4. Solving techniques

Technological learning is associated with increasing returns. 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 endogenisation 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., 1995) traditionally used to solve MERGE does not guaranty to find the global optimum of MERGE-ETL, but only a local optimum. In order to find a global optimum, we use a heuristic iterative approach in three steps, which are described in Figure 6-24 below.

Figure 6-24: An iterative procedure to solve MERGE-ETL



i. Pre-solving

In this first step, the original MERGE model is solved to define equilibrium demands for electric and non-electric energy. These fixed energy demands are input into a regional ETA model with endogenous technological learning, model that corresponds to the bottom-up part of MERGE-ETL.

This model is again non-linear and non-convex. But following Barreto and Kypreos (1999), it may be 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, hence the name ETA-MIP given to it. Let us now detail the approximation procedure of the total cumulative cost curve for a technology k for which endogenous learning is assumed.

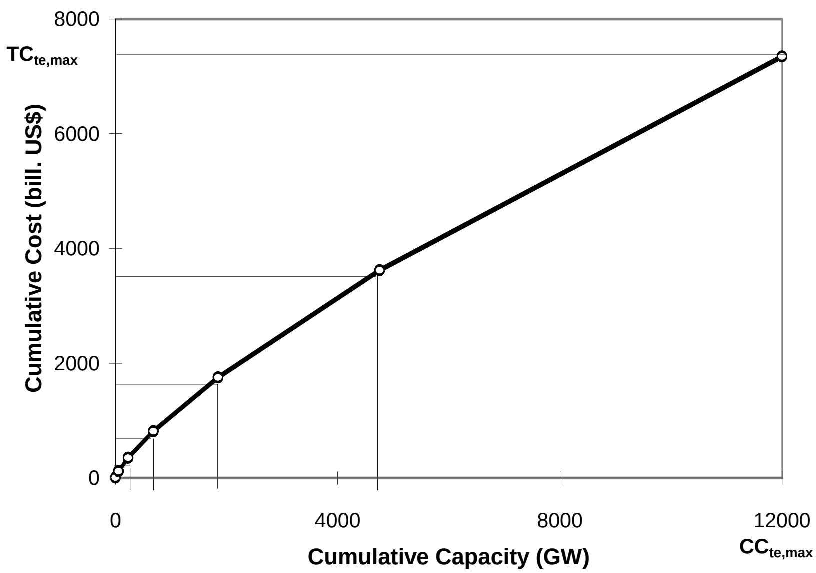
One first needs an initial cumulative capacity CCk,0 and the corresponding initial cumulative cost TCk,0. One needs then to define the number of segments N for the segmentation of the cumulative cost curve. Notice that N controls the number of integer variables to be used per period (and per technology).

Consequently, the higher N one chooses, the better the approximation one defines, but the longer the time to solve ETA-MIP one can expect. One must define also a maximum cumulative capacity CCmax,k and compute the corresponding maximum cumulative cost TCmax,k. CCmax,k may be estimated from the technology potential according to technical, economic and environmental criteria. But below this upper bound, a convenient value has to be chosen, given that a lower value for CCmax,k may provide a better approximation. One can then compute the kink points for the cumulative capacity and the cumulative cost using the initial and final points of the curve and according to number of segments previously defined. In order to obtain a better representation for the first part of the curve, where rapid cost changes occur, a segmentation procedure with variable length segments (shorter ones at beginning and then increasingly longer segments) is used as follows for i=1..N-1:

$$TC_{i,k} = TC_{k,0} + \frac{2^{i-N-1} \cdot \left(TC_{\max,k} - TC_{k,0}\right)}{\sum_{j=0}^{N-1} 2^{j-N}}, \quad CC_{i,k} = \left(\frac{1-b}{a} \cdot TC_{i,k}\right)^{b-1} \tag{13}$$

The segmentation procedure is illustrated in Figure 6-25 below for a technology k = te.

Figure 6-25: Piece-wise approximation of the cumulative cost curve



The cumulative cost is thus expressed as a linear combination of segments as follows:

$$TC_{k,t} = \sum_{i=1}^{N} \left(\alpha_{i,k} \cdot \delta_{k,i,t} + \beta_{i,k} \cdot \lambda_{k,i,t}\right) \tag{14}$$

The coefficient αi,k is the TC-axis intercept of the linear segment i. It is computed as follows:

$$CC_{k,t} = \sum_{i=1}^{N} \lambda_{k,i,t} \tag{15}$$

The variable λk,i,t is continuous (real). It is such that:

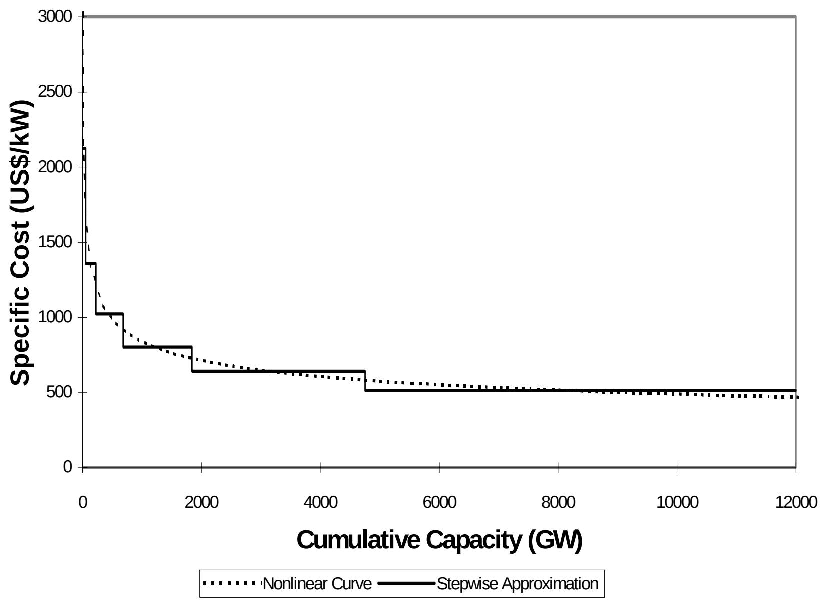
$$CC_{k,t} = \sum_{i=1}^{N} \lambda_{k,i,t} \tag{16}$$

The coefficient βi,k represents the slope of the linear segment i. It is computed as follows:

$$\beta_{i,k} = \frac{TC_{i,k} - TC_{i-1,k}}{CC_{i,k} - CC_{i-1,k}} \tag{17}$$

Notice that βi,k corresponds also to the specific cost of each linear segment i as illustrated in Figure 6-26 below.

Figure 6-26: Stepwise specific cost curve (with variable length segments)



Finally δk,i,t is a binary variable, namely it can take either the value 0 or 1. Notice that only one such variable is non-zero at any given time t, to indicate the active linear segment. To ensure this, their sum is forced to one as follows:

$$\sum_{i=1}^{N} \delta_{k,i,t} = 1 \tag{18}$$

To control the active segment, some additional constraints are required, which relate a continuous variable λk,i,t to a corresponding binary variable δk,i,t, ensuring that λk,i,t remains between the two corresponding successive cumulative capacity breakpoints (CCi,k and CCi+1,k). These logical conditions are as follows:

$$\lambda_{k,i,t} \geq CC_{i,k} \cdot \delta_{k,i,t} \ , \quad \lambda_{k,i,t} \leq CC_{i+1,k} \cdot \delta_{k,i,t} \tag{19}$$

Finally, given that experience must grow or at least remain at the same level, the following additional constraints are added in order to reduce the solving time of ETA-MIP:

$$\sum_{j=1}^{i} \delta_{k,j,t} \geq \sum_{j=1}^{i} \delta_{k,j,t+1} \ , \quad \sum_{j=i}^{N} \delta_{k,j,t} \leq \sum_{j=i}^{N} \delta_{k,j,t+1} \tag{20}$$

The model (ETA-MIP) uses the energy production cost, computed following (7) using in particular the investment cost per period. In the one-factor formula, the latter is computed as the difference of two consecutive values of TC given by (14):

$$IC_{k,t} = \sum_{i=1}^{N} \left(\alpha_{i,k} \cdot \left(\delta_{k,i,t} - \delta_{k,i,t-1} \right) + \beta_{i,k} \cdot \left(\lambda_{k,i,t} - \lambda_{k,i,t-1} \right) \right) \tag{21}$$

In the two-factor formula, one has to take also into account the cumulative (exogenous) R&D expenditures. The above formula becomes (22):

$$IC_{k,t} = \sum_{i=1}^{N} \begin{pmatrix} \alpha_{i,k} \cdot \left(\delta_{k,i,t} \cdot CRD_{k,t}^{-c} - \delta_{k,i,t-1} \cdot CRD_{k,t-1}^{-c} \right) \\ + \beta_{i,k} \cdot \left(\lambda_{k,i,t} \cdot CRD_{k,t}^{-c} - \lambda_{k,i,t-1} \cdot CRD_{k,t-1}^{-c} \right) \end{pmatrix}$$

ii. Solving

In this second step of our solving approach, the MERGE-ETL model is solved as a non-linear and non-convex model by MINOS. Let us recall that, besides the objective function, the non-linearities come from the computation of the investment cost IC following (6) in the one-factor learning case, or (11) in the two factor learning case.

The solving of MERGE-ETL by MINOS is done using as starting points, for the energy sector, the optimum values found by ETA-MIP, and the ones found by MERGE for the rest of the economy. This usually provides a reasonable approximation for the localisation of the global optimum of MERGE-ETL, since ETA-MIP, an approximation of the ETA model with endogenous technological learning, is solved until (global) optimality.

An important factor for a successful solving of MERGE-ETL is the 'quality' of the starting point provided by ETA-MIP. This depends on the quality of the approximation procedure of the total cumulative cost curve. This in turn depends in particular on the number of segments N and on the maximum cumulative capacities CCmax,k. If occasionally MINOS does not succeed in solving MERGE-ETL, one needs then to adjust CCmax,k closer to the optimal value of CCk,T found in ETA-MIP for the end of the time horizon T, and to increase the number of segments N, so as to perform a better approximation of the total cumulative cost curve.

iii. Post-Solving

A third step in our solving approach may be necessary if the cumulative installed capacities CCk,T differ (beyond a given margin) between ETA-MIP and MERGE-ETL. In that case, in order to look for the global optimum of MERGE-ETL, one may repeat the solving of ETA-MIP and MERGE-ETL until the cumulative capacities found by the two models are equals (again, within a given margin).

The post-solving phase, after the first solving of ETA-MIP and MERGE-ETL (M-ETL), is performed as follows:

$$\Delta = 1 - \frac{\sum_k CC_{k,T}^{ETA-MIP}}{\sum_k CC_{k,T}^{M-ETL}}$$

While

$\Delta > \varepsilon$ do

Solve ETA-MIP fixing energy demands to the values found by M-ETL

Solve M-ETL, using as starting points the values found by ETA-MIP

Compute again

$$\Delta = 1 - \frac{\sum_k CC_{k,T}^{ETA-MIP}}{\sum_k CC_{k,T}^{M-ETL}}$$

Endo

where ε is a tolerance parameter.

Notice that at the end of the algorithm, one may test the 'quality' of the solution by running the MERGE model with fixed technological progress as determined by MERGE-ETL. The former model being convex, one may thus check that the solution obtained by the latter model corresponds indeed to a global optimum.

6.2.1.5. Case studies

As an illustration, we have considered several scenarios related to CO2 emission control and the introduction of endogenous technological learning. We have in particular considered implications of satisfying the Kyoto Protocol emission limits; see for instance Kypreos (2000) or Kypreos and Bahn (2001). We report here on new scenarios related to the Marrakech Agreements. These scenarios and their characteristics are detailed below.

The database for the baseline (BAU) case where CO2 emissions are not limited and endogenous technological change is not considered reflects the original data of the MERGE version 3 model with some modifications related to the newly introduced technologies described in Table 6-5. We have in particular adopted more conservative values for the annual expansion rate of these technologies. The BAU case assumes a world population level of 10 billion by 2050 as in the IPCC B2 scenario. Most of the world population growth occurs in the (current) developing countries, and by 2050, the (current) industrialised countries have less that 10 percent of the world population. Between 2000 and 2050, world GDP grows 3.5 times (up to 93 trillion USD 1990), whereas primary energy supply increases 2.4 times (up to 948 EJ) and energy related carbon emissions also 2.4 times to a level (15.6 Gt C) that is within the range of the IPCC B2 scenario. Notice that most of the economic growth occurs in (current) economies in transition and developing countries, and that regional differences in primary energy intensity and in carbon intensity of GDP are decreasing overtime. Notice furthermore that after 2040, Non-Annex I regions of the Kyoto Protocol emits more than 50% of the world CO2 emissions. Regional GDPs are displayed in

and regional CO2 emissions in Figure 7 28 below. There are then two baseline scenarios (namely, without CO2 emissions limits) where endogenous technological progress is considered: a one-factor learning curve in the B1F case and a two-factor learning curve in the B2F case.

There are finally three scenarios (SFL, S1F and S2F) related to carbon control. The latter corresponds to a 'soft landing' of world energy related CO2 emissions to a level of 10 Gt C by 2050. Emission limits (between 2010 and 2050) are displayed in Figure 7 29 below that recalls also the 2000 emission levels. Notice that the 2010 emission limits for CANZ, EEFSU, Japan and OECDE correspond to their Kyoto reduction commitments, whereas the emissions of the other regions (including USA) are simply bounded by their baseline (BAU) levels. This is done to avoid carbon leakages among the regions, since full regional trade of CO2 emission permits is allowed in all carbon control scenarios.

Figure 6-27: Regional GDPs in the BAU case

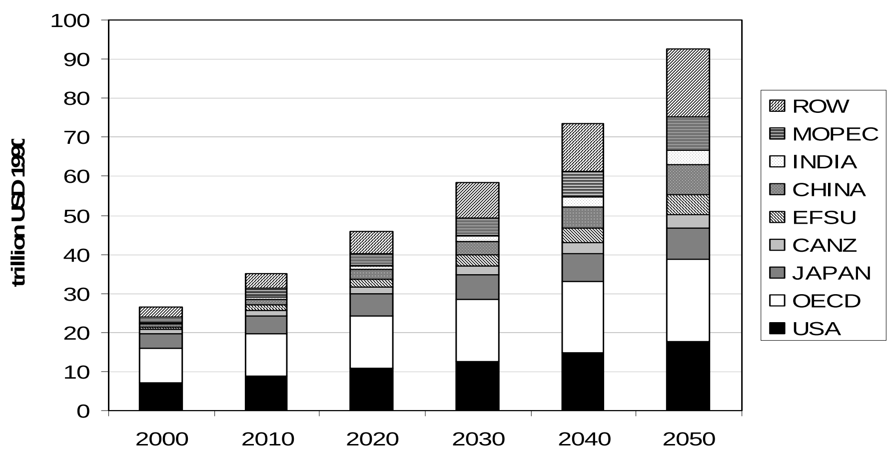


Figure 6-28: Regional CO2 emission limits in the BAU case

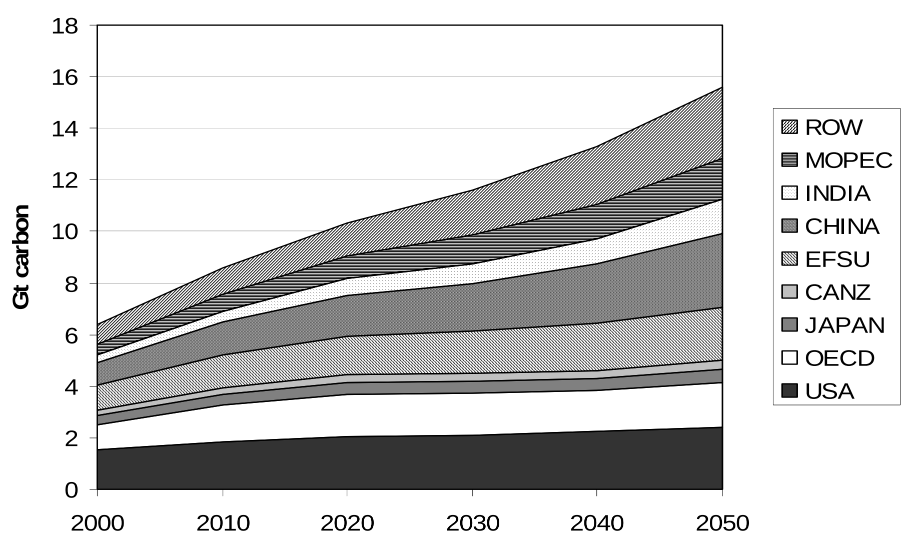


Figure 6-29: Regional CO2 emission limits in the BAU case

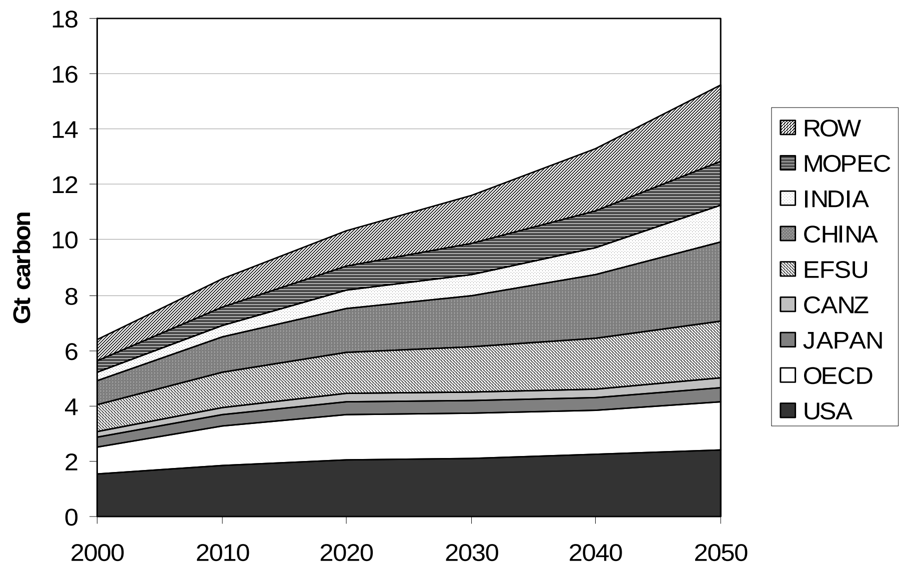
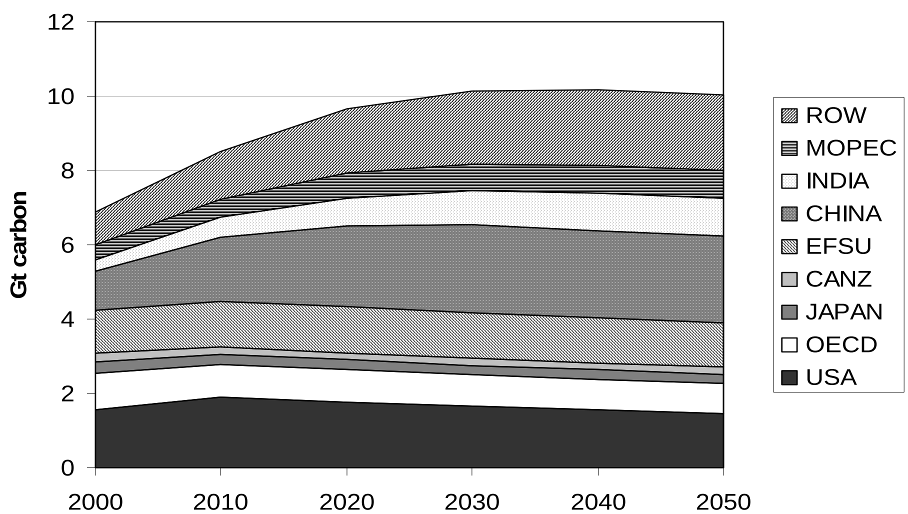


Figure 6-30: Regional CO2 emission limits for the carbon control cases



Notice that in the SFL case, endogenous technological change is not considered, whereas it is in the other two control cases: a one-factor learning curve in the S1F case and a two-factor learning curve in the S2F case.

Let us finally recall that in the two-factor learning curve cases (B2F and S2F) R&D spending is exogenously specified, see Annex A below.

i. Impacts of modelling ETL on energy systems

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, in the one-factor learning curve, and through as well the increase of the cumulative R&D spending, in the two-factor learning curve. As an illustration, Table 6-7 reports on the resulting decrease of the specific cost of some power plants in the learning cases.

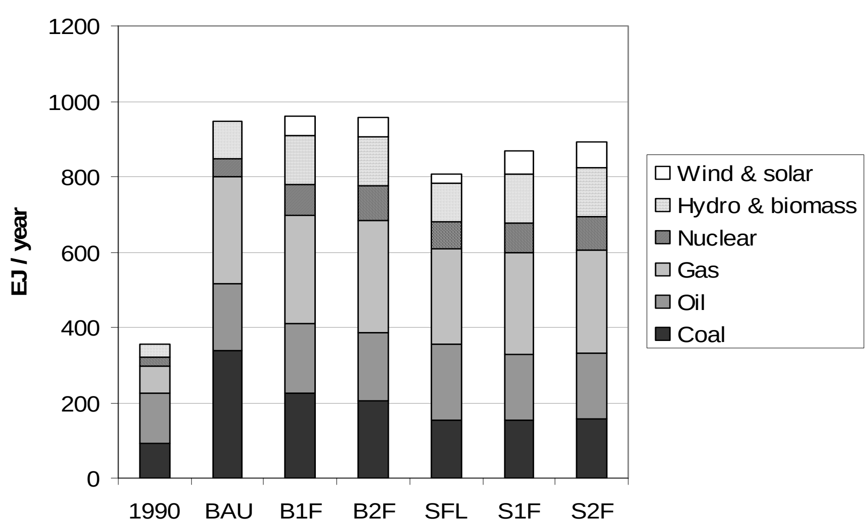
Table 6-7: Specific costs (USD/kW) in 2000 and in 2050 by cases

	2000	B1F	B2F	S1F	S2F
IGCC	2020	1355	1254	1349	1252
GCC	713	513	503	514	505
GFC	5096	884	826	856	819
NNU	3999	2454	2366	2460	2371
WND	887	564	525	562	520
SPV	6075	6075	5022	1775	5022

Notice that SPV specific investment cost is higher in S2F than in S1F, despite knowledge accumulated through R&D spending. Indeed, SPV cumulative capacity is much higher in S1F (82 GW) than in S2F (less than 1 GW), and this triggers a stronger cost reduction. And recall that SPV cumulative installation results in both cases from SPV competitiveness relative to other learning technologies. This means in particular that in the S2F case, the other power plants profit more from R&D spending than SPV.

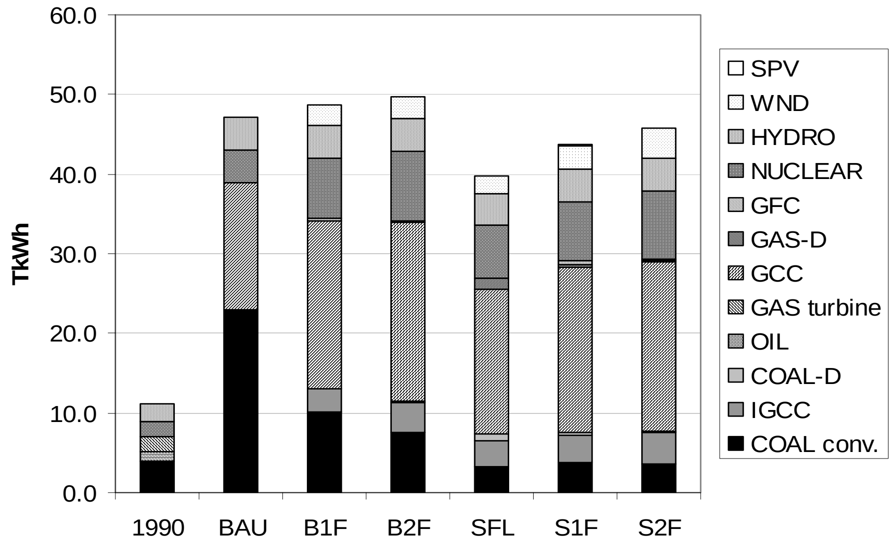
As illustrated in Table 6-7, taking into account endogenous technological progress yields a decrease of energy production costs over-time, as knowledge in the different learning technologies builds up. In other words, the production factor energy becomes less expensive over-time. It can thus substitute partly for the two other production factors capital and labour. Consequently, as illustrated in Figure 6-30, primary energy use is higher in the B. (resp. S.) learning cases compared to the BAU (resp. SFL) case. Comparing now the .1F and .2F cases, primary energy use is lower in B2F compared to B1F, whereas the opposite takes place in the carbon control cases. This is due to opposite variations in overall GDP; see Figure 6-33 below. Furthermore, the reduction of primary energy use due to carbon control (that increases energy costs) is lower when considering endogenous technological change: 15% reduction in the SFL case compared to BAU, 9% in S1F case compared to B1F and only 7% in S2F compared to B2F. Endogenous technological change affects also the primary energy mix. First, the share of fossil fuels decreases, especially coal in the baseline cases and oil in the carbon control cases (where coal use is already significantly reduced compared to the baseline). Second, the share of nuclear increases, especially in the baseline cases. And third, the share of renewables increases, especially biomass and wind, to reach 22% by 2050 in the S2F case. Notice finally that these trends are stronger when considering also knowledge accumulated through R&D spending (.2F cases).

Figure 6-31: World primary energy use in 1990 and in 2050 by cases



The overall effect of endogenous technological progress is similar on electricity generation that is higher in the B. (resp. S.) learning cases compared to the BAU (resp. SFL) case. Electricity generation is also always higher in .2F cases compared to the .1F cases. This means in particular that in the B2F case, where primary energy use is slightly lower than in B1F, electricity substitutes partly for non-electric energy following relative price changes in energy markets. Furthermore, similarly to primary energy use, the reduction of electricity generation due to carbon control is lower when considering endogenous technological change. Indeed, electricity generation costs decrease over-time for learning technologies, as are non-electric energy production costs. Electricity (and non-electric energy) can thus substitute partly for capital and labour as production factors. Notice also that endogenous technological progress favours the advanced learning power plants: integrated coal gasification with combined cycle (IGCC), gas combined cycle (GCC), new nuclear (NND) and wind turbine (WND) in the baseline cases; GCC, gas combined cycle, new nuclear and wind turbine in the carbon control cases. Notice finally that the two power plants with carbon capture and disposal (COAL-D and GAS-D) are used in the SFL case (our carbon control scenario without endogenous technological learning). However, these two power plants, which are not subject to endogenous technological progress, are not used in the S1F and S2F cases, where in particular nuclear power plants and wind turbine are used instead. This fact points once more to the necessity to consider COAL-D and GAS-D within clusters of learning technologies. Figure 6-32 reports on world electricity generation.

Figure 6-32: World electricity generation in 1990 and in 2050 by cases



ii. Economic impacts of modelling ETL

Table 6-8 reports first on marginal abatement costs in the carbon control scenarios. As these scenarios assume full trading possibilities of CO_2 emission permits among the nine regions, these marginal costs correspond also to the market equilibrium prices of the CO_2 emission permits. Table 6-8 shows the economic benefits of endogenous technological progress, as marginal abatement costs in the S2F case are always lower than in the S1F case, with the latter costs being always lower than in the SFL case.

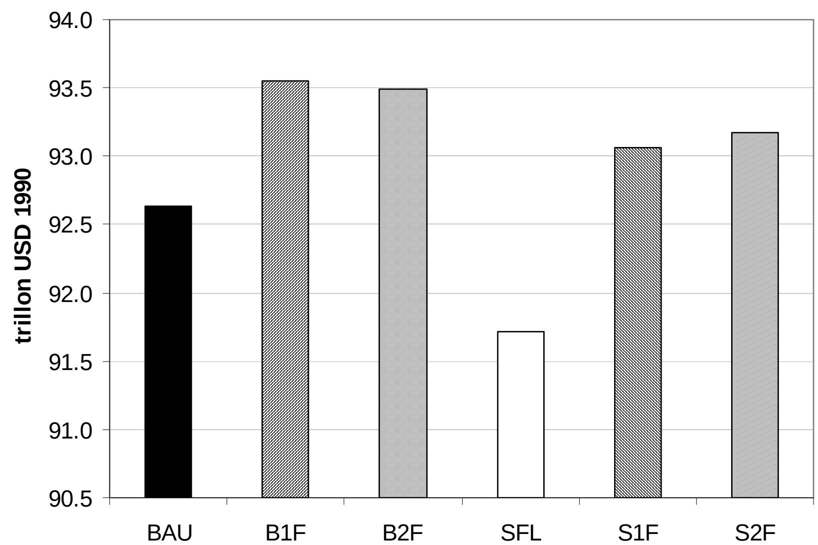
Table 6-8: Marginal abatement costs (USD/tC) in the carbon control cases

	2010	2020	2030	2040	2050
SFL	16	26	44	74	122
S1F	13	21	36	59	99
S2F	11	19	31	52	87

Figure 6-33 gives finally the implication of considering endogenous technological change on world GDP. It shows that technological learning yields GDP growth in the B. cases (compared to BAU) and reduces

GDP losses in the S. cases (compared to SFL). Indeed, through the learning mechanism, the production of energy becomes cheaper and absorbs thus less economic resources. Comparing now the .1F and .2F cases, world GDP is slightly lower in B2F compared to B1F, whereas the opposite takes place in the carbon control cases. This means that the exogenously determined R&D spending on energy technologies is not efficient in B2F, where it would be better to improve the productivity of the other two production factors (capital and labour). However, with the necessity to curb carbon emissions, R&D spending on energy technologies becomes economically efficient in S2F.

Figure 6-33: World GDP per case in 2050



6.2.2. Conclusions

Technological progress plays a fundamental role in the evolution of energy systems. It shall in particular favour 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 done so in the MERGE model. More precisely, we have introduced in the ETA part of MERGE a one-factor and two-factor learning curves for a set of electric and non-electric energy technologies. Such learning curves describes how the specific investment cost of a given technology is reduced as function of the knowledge (approximated by the cumulative installed capacity) accumulated during the manufacturing and use of such a technology in the one-factor case, as well as function of public and private R&D (cumulative) expenditures in the two-factor case.

The difficulty with incorporating endogenous technological progress in MERGE comes from the resulting formulation of the MERGE-ETL model. Indeed, as technological learning is associated with increasing returns, the mathematical formulation of MERGE-ETL corresponds then to a (non-linear and) non-convex optimisation problem. To solve MERGE-ETL, we have devised a heuristic approach, where we search for the global optimum in an iterative way.

To study the impacts of modelling endogenous technological change in MERGE, we have considered several scenarios related to CO2 emissions and technological learning. Our numerical application shows that technological learning favours new advanced systems such as gas turbines with combined cycle, advanced nuclear plants and wind turbines. It shows also the importance of technological progress for carbon control, as this brings low-cost reduction options and hence reduces GDP losses for CO2 emission reduction.

Our numerical application reveals also that, when a learning technology is already competitive in the one-factor learning case, it does not profit much from R&D spending (in the two-factor learning case), as its growth is then bounded by its market penetration constraint. This calls for a model improvement linking the market penetration constraint of a given learning technology with competitive gains due to R&D spending.

References:

Barreto, L. (2001). Technological Learning in Energy Optimisation Models and Deployment of Emerging Technologies, PhD Dissertation No 14151. Swiss Federal Institute of Technology, Zurich.

Barreto, L. and Kypreos, S. (1999). Technological Learning in Energy Models: Experience and Scenario Analysis with MARKAL and the ERIS Model Prototype, PSI Report No 99-08, Paul Scherrer Institute, Villigen.

Freund, P. (1998). Abatement and Mitigation of Carbon Dioxide Emissions from Power Generation, Proceedings Power-Generation 1998 Conference, Milan, Italy.

Grübler, A. (1998). Technology and Global Change, Cambridge University Press, Cambridge.

Kypreos, S. (2000). The MERGE Model with Endogenous Technological Change, Proceedings of the Economic Modelling of Environmental Policy and Endogenous Technological Change Workshop, Amsterdam, The Netherlands, November 16-17.

Kypreos, S. and Bahn, O. (2001). Endogenous Technological Learning: Insights from the MERGE-ETL Model, Joint EMF/IEA/IEW Meeting, Vienna, Austria, June 19-21.

Manne, A.S. and Richels, R.G. (1997). "On stabilizing CO2 concentrations? Cost-effective emission reduction strategies", Environmental Modeling and Assessment, Vol. 2, pp. 251-265.

Manne, A.S. and Richels, R.G. (1992). Buying Greenhouse Insurance: The Economic Costs of CO2 Emission Limits, The MIT Press, Cambridge, MA.

Murtagh, B.A. and Saunders, M.A. (1995). MINOS 5.4 User's Guide, SOL 83-20R, Stanford University, California.

Negishi, T. (1972). General Equilibrium Theory and International Trade, North-Holland Publishing Company, Amsterdam.

Annex A : Merge-ETL Sets, Variables and Equations

SETS:

dle	electric technologies that decline
dln	non-electric technologies that decline
et	electric technologies
etl	electric technologies with learning
netl	electric technologies without learning
nntl	non-electric technologies without learning
nt	non-electric technologies
ntl	non-electric technologies with learning
r	world regions
t	time periods
trd	traded goods such as numéraire (nmr)
x	fossil fuels
xle	electric technologies that expand
xln	non-electric technologies that expand

VARIABLES:

Cr,t	consumption (1012 USD)
CLEVr,t	carbon emission level (109 tons)
CRLXr,t	carbon limit relaxation (109 tons)
DCr,t	delay carbon utilisation – banking (109 tons)
ECr,t	energy cost (1012 USD)
Er,t	demand for electric energy (TkWh)
ENr,t	new vintage demand for electric energy (TkWh)
GASNONr,t	gas consumed to meet non-electric demands (EJ)
GCAPt,etl	cumulative (electric) installations relative to CCet,0
GCAPNt,ntl	cumulative (non-electric) installations relative to CCnt,0
Ir,t	investment (1012 USD)
IMPr,t,trd	imports of traded goods
Kr,t	capital stock (1012 USD)
KNr,t	new vintage capital (1012 USD)
Nr,t	demand for non-electric energy (EJ)
NNr,t	new vintage demand for non-electric energy (EJ)
NTXr,t,trd	net exports of traded goods
OILNONr,t	oil consumed to meet non-electric demands (EJ)
PEr,t,et	production of electric energy (TkWh)
PNr,t,nt	production of non-electric energy (EJ)
RAr,t,x	reserve additions (EJ)
RSCr,t,x	undiscovered resources (EJ)

RSVr,t,x proven reserves (EJ)

Yr,t production, excluding energy sectors (1012 USD)

YNr,t new vintage production, excluding energy sectors (USD)

EQUATIONS:

The following two sections describe the equations of MERGE-ETL that have been adapted from the MERGE model. For more details on the standard MERGE equations, the reader is kindly referred to Manne and Richels (1992).

MACRO equations

The Negishi welfare function NWEL, whose maximising for a fixed set of Negishi weights nw corresponds to the Negishi welfare problem, is defined as follows:

NWELDF: $$NWEL = \sum_r \left(nw_r \cdot \sum_t \left(udf_{r,t} \cdot \log C_{r,t} \right) \right)$$

where a r,t and b r,t are calibration parameters, LN r,t is the exogenously specified labour force available for the new vintage production, α the optimal value share of capital in the value added aggregate, β the optimal value share of electricity in the energy aggregate and ρ is defined through ESUB (the elasticity of substitution between the value added and the energy aggregates) by $\rho = 1 - ESUB^{-1}$.

The total production corresponds to:

TOTALPRODr,t: $$Y_{r,t+1} = YN_{r,t+1} + speed_{r,t} \cdot Y_{r,t}\,.$$

Trade among regions are subject to the following trade balances:

TRDBALt,trd: $$\sum_r NTX_{r,t,trd} = 0\,.$$

Finally, the following terminal condition is applied:

TCr,T: $$I_{r,T} \geq K_{r,T} \cdot (grow_r + depr_r)$$

where *grow r* is the potential economic growth rate.

ETA equations

The first constraint is a supply-demand balance for electric energy:

SUPELECr,t: $$\sum_{et} PE_{r,t,et} \geq E_{r,t}\,.$$

The next constraint is a supply-demand balance for non-electric energy, where oil and gas non-electric uses, coal direct use (CLDU), synthetic fuel (SYNF), renewables (RNEW) and non-electric backstop fuels (NE-BACK) are perfect substitutes to cover non-electric demands:

SUPLNONr,t:

$$OILNON_{r,t} + GASNON_{r,t} + PN_{r,t,CLDU} + PN_{r,t,SYNF} - NTX_{r,t,SYNF} +$$
$$PN_{r,t,RNEW} + PN_{r,t,NE-BACK} \geq N_{r,t}$$

There is then a supply-demand balance for coal.

SUPCOALr,t: $$PN_{r,t,coal} \geq PN_{r,t,CLDU} + \sigma \cdot PN_{r,t,SYNF} + \sum_{e\_coal} hr_{e\_coal} \cdot PE_{r,t,e\_coal}$$

where the demand for coal comes from its direct use, the production of synthetic fuel and consumption (computed through heat rate coefficients, hr) in coal power plants.

The following constraint is a supply-demand balance for oil.

SUPOILr,t: $$\sum_{oilc} PN_{r,t,oilc} \geq OILNON_{r,t} + NTX_{r,t,oil} + \sum_{e\_oil} hr_{e\_oil} \cdot PE_{r,t,e\_oil}$$

where oilc are cost categories for oil production and e_oil the set of oil power plants.

There is similarly a supply-demand balance for natural gas.

SUPGASr,t:
$$\sum_{gasc} PN_{r,t,gasc} \geq GASNON_{r,t} + NTX_{r,t,gas} + \sum_{e\_gas} hr_{e\_gas} \cdot PE_{r,t,e\_gas}$$

where gasc are cost categories for gas production and e_gas the set of gas power plants.

Natural gas is then limited to supply only a fraction (gasfr) of non-electric energy markets.

GFRACr,t:
$$GASNON_{r,t} \leq gasfr \cdot N_{r,t} \ .$$

Similarly, natural gas is also limited to supply only a fraction (gasfre) of the electric energy market.

GFRACEt:
$$\sum_{r} \sum_{e\_gas} PE_{r,t,e\_gas} \leq gasfre \cdot \sum_{r} E_{r,t} \ .$$

The next constraint prevents synthetic fuel exports to exceed domestic production.

SYNTHr,t:
$$NTX_{r,t,SYNF} \leq PN_{r,t,SYNF} \ .$$

The next two constraints define the cumulative capacity (relative to CC0) for technologies for which endogenous learning is assumed. The first one concerns electric technologies and follows equation (1):

GROWTHEt,etl:
$$GCAP_{t,etl} = \frac{\sum_{r,\tau}^{\tau \in [1,t]} nyper_t \cdot PE_{r,\tau,etl}}{CC_{0,etl} \cdot life_{etl} \cdot lf_{etl} \cdot 0.00876} + 1 \ .$$

Similarly, the next constraint concerns non-electric energy technologies and follows equation (2):

GROWTHNt,ntl:
$$GCAPN_{t,ntl} = \frac{\sum_{r,\tau}^{\tau \in [1,t]} nyper_t \cdot PN_{r,\tau,ntl}}{CC_{0,ntl} \cdot life_{ntl}} + 1.$$

There are then some constraints controlling the decline and expansion of the energy technologies. The first one controls the decline rate of electric technologies.

DECEr,t,dle:
$$PE_{r,t+1,dle} \geq PE_{r,t,dle} \cdot decf_r^{nyper_t}$$

where decfr is a maximum decline rate.

A similar constraint controls the decline rate of non-electric technologies.

DECNr,t,dln:
$$PN_{r,t+1,d\ln} \geq PN_{r,t,d\ln} \cdot decf_r^{nyper_t} \ .$$

The following constraint limits then the expansion rate of electric technologies.

EXPPr,t, xle:
$$PE_{r,t+1,xle} \leq nsf_r \cdot E_{r,t+1} + PE_{r,t,xle} \cdot exf_{r,xle}^{nyper_t} + gdf_{r,t} \cdot \sum_{r} \left(PE_{r,t,xle} \cdot exf_{r,xle}^{nyper_t} \right)$$

where nsfr is a low seed value parameter, exfr,xle an annual expansion rate and gdfr,t a global diffusion factor reflecting regional spill-over effects.

A similar constraint limits also the expansion rate of non-electric technologies.

NXPPr,t,xln:
$$PN_{r,t+1,x\ln} \leq nsf_r \cdot N_{r,t+1} + PN_{r,t,x\ln} \cdot nxf_r^{nyper_t}$$

where nxfr,xln is also an annual expansion rate.

There are then several constraints describing the production of exhaustible resources. The first constraint determines the production of these resources as a fraction of proven reserves:

PRVLIMr,t,x: $$PN_{r,x,t} = pfr_{r,x} \cdot RSV_{r,t,x}$$

where pfrr,x is a fixed ratio of current production to proven reserves.

Proven reserves are then defined by a distributed lag function of reserve additions less production:

RSVAVr,t+1,x:

$$RSV_{r,t+1,x} = RSV_{r,t,x} + 5(RA_{r,t,x} - PN_{r,t,x}) + 5(RA_{r,t+1,x} - PN_{r,t+1,x})$$

Undiscovered resources are next defined as a distributed lag-function of reserve additions:

RSCAV r,t+1,x: $$RSC_{r,t+1,x} = RSC_{r,t,x} - 5(RA_{r,t,x} + RA_{r,t+1,x}) \, .$$

Reserve additions cannot finally exceed a fixed fraction of undiscovered resources:

RDFLIM r,t,x: $$RA_{r,t,x} \le rdf_{r,x} \cdot RSC_{r,t,x}$$

where rdfr,x is a resource depletion factor.

The next constraint computes net regional carbon emission level using electric and non-electric energy production times carbon coefficients (ce), trade of fuels, non-energy use (nenc), and a carbon relaxation value (charged at high cost):

CARLEVr,t:

$$CLEV_{r,t} + CRLX_{r,t} = \sum_{et} PE_{r,t,e} \cdot ce_{r,e} + \sum_{nt} PN_{r,t,nt} \cdot ce_{r,nt} - NTX_{r,t,x} \cdot ce_{r,x} - nenc_r$$

Annual carbon emission limits (carlimr,t) can then be imposed as follows:

ANCr,t:

$$CLEV_{r,t} + NTX_{r,t,crt} \le car\lim_{r,t} + DC_{r,t-1} - DC_{r,t} + CRLX_{r,t}$$

where the index crt denotes tradable emission permits.

Finally, the following equation computes the energy cost, assuming a two-factor learning curve:

COSTNRGr,t:

$$EC_{r,t+1} = \sum_{etl} \left(\frac{SC_{0,etl} \cdot CC_{0,etl} \cdot CRD_{0,etl}^{c}}{1-b} \cdot \left(GCAP_{t+1,etl}^{1-b} \cdot CRD_{t+1,etl}^{-c} - GCAP_{t,etl}^{1-b} \cdot CRD_{t,etl}^{-c} \right) \right)$$

$$\sum_{ntl} \left(\frac{SC_{0,ntl} \cdot CC_{0,ntl} \cdot CRD_{0,ntl}^{c}}{1-b} \cdot \left(GCAP_{t+1,ntl}^{1-b} \cdot CRD_{t+1,ntl}^{-c} - GCAP_{t,ntl}^{1-b} \cdot CRD_{t,ntl}^{-c} \right) \right) +$$

$$\sum_{etl} (1 - fr_{etl}) \cdot PE_{r,t+1,etl} \cdot ecst_{r,1,etl} + \sum_{ntl} (1 - fr_{ntl}) \cdot PN_{r,t+1,ntl} \cdot ncst_{r,1,ntl} +$$

$$\sum_{netl} PE_{r,t+1,netl} \cdot ecst_{r,t+1,netl} + \sum_{nntl} PN_{r,t+1,nntl} \cdot ncst_{r,t+1,nntl}$$

where b, c, CRD, fr and SC are notations that have previously been introduced, ecst is a cost of generating electricity and ncst a cost of producing non-electric energy. Notice that the energy cost includes also an allowance for oil-gas price differential, taxes on electricity, non-electric energy and carbon emission, the cost of relaxing carbon limit, a lump-sum rebate of tax revenues and the transportation cost for interregional trade.

Annex B: MERGE-ETL Database

The MERGE-ETL database is based on the one of MERGE version 3, which has been adapted for the purpose of the SAPIENT project. This annex gives some details on modifications that have been done to the original MERGE database.

In MERGE-ETL, endogenous learning is applied to eight electric and non-electric energy technologies. The data for the six electric technologies with learning has been adapted from the POLES database. Table 6-9 gives the correspondence between the MERGE-ETL (M-ETL) and the POLES nomenclature.

Table 6-9: Learning electric technologies with POLES nomenclature

Name in M-ETL	Name in POLES	Technology identification in POLES
GCC	GGC	Gas turbine CC (combined cycle)
GFC	SFC	Solid oxide fuel cell
IGCC	ICG	Integrated coal gasification with CC
NNU	NND	New nuclear design (evolutionary)
SPV	DPV	Decentralised photovoltaic
WND	WND	Wind turbine

Table 6-10: Characteristics of learning electric technologies

	CC0 (GW)	lf	fr	ecst0 (m/kWh)	fcst (m/kWh)	hr	life (yr)	prld	prls
GCC	292.52	0.70	0.42	18.56	10.70	6.48	15	0.89	0.99
GFC	0.01	0.65	0.72	104.05	28.82	5.49	15	0.81	0.89
IGCC	0.48	0.70	0.33	57.26	38.19	7.57	20	0.94	0.96
NNU	0.01	0.75	0.57	63.81	27.66	10.00	25	0.96	0.98
SPV	0.17	0.20	0.82	342.10	63.01	16.36	15	0.81	0.90
WND	14.80	0.20	0.51	57.83	28.28	10.91	15	0.88	0.94

Notice that in Table 6-10 CC0 is the cumulative installed capacity in 2000, and recall that lf is the plant load factor, fr the fraction of the production cost to which technological learning (cost reduction) applies, ecst0 the 2000 cost of generating electricity (in 10-3 USD1990 per kWh), fcst the floor cost in 2050 for generating electricity (in the same unit as ecst) defined by $fcst = (1 - fr) \cdot ecst_0$ hr the heat rate defined by $hr = (\text{plant's efficiency})^{-1} \cdot 3.6$, life the plant's life time, prld the progress ratio for learning-by-doing (used to define the learning-by-doing index b) and prls the progress ratio for learning-by-searching (used to define the learning-by-searching index c). Notice furthermore that the last two parameters do not come from the POLES database. More precisely, values for prld are from Barreto and Kypreos (1999), the ones for prls have been adapted from Barreto (2001).

Endogenous technological learning applies also to two non-electric energy technologies, cf. Table 6-5. Table 6-11 gives the techno-economic characteristics for these two technologies.

Table 6-11: Characteristics of learning non-electric energy technologies

	CC0 (EJ)	lf	fr	ecst0 (90$/GJ)	fcst (90$/GJ)	life (years)	prld	prls
NE-BAK	1	1	0.80	13.30	2.66	25	0.85	0.92
RNEW	1	1	0.75	6.00	1.5	25	0.90	0.95

6.3. MARKAL [by M. Feber, A. Seebregts, K.L. Smekens and G.J. Schaefer (ECN)]

ECN did not implement 2FLC's in MARKAL directly, but developed and used an indirect approach. In this chapter, the focus is therefore on the changes to the MARKAL model (i.e. source code level and controlling level) in order to accommodate the following SAPIENT-specific requirements:

1. the use of the 'cluster of technologies' concept in conjunction with the Windows-based MARKAL user-interface (ANSWER);
2. the ability to perform multiple runs easily: this has been used to perform the MARKAL R&D shocks and the MARKAL Monte Carlo runs;
3. changes to the MARKAL ETL output module in order to provide the relevant information for the ISPA objectives.

6.3.1. Clusters of technologies

A 'cluster of technology' is defined as a group of technologies which share a common essential component. This component, which can be a technology in itself, is called the 'key technology' and is selected as the learning component in each of the technologies in the cluster. Examples of key technologies and, correspondingly, clusters of technologies are gas turbines, fuel cells, photo-voltaic (PV) modules, wind turbines, steam turbines, boilers. The existing technologies need to be grouped into clusters of technologies which are similar with respect to their learning behaviour i.e. the development of these technologies is in some way linked to each other. One technology can appear in more than one cluster, e.g. an integrated coal gasification power plant is composed of, among other things, a gas turbine, a steam turbine, a gasifier and a boiler (Seebregts et al., 2000).

During the TEEM project, this concept was implemented rather 'ad hoc' and relatively cumbersome. For each cluster, the analyst had to add a user-defined constraint (or in MARKAL terminology: an ADRATIO). To be more flexible and to incorporate it in the most recent, Windows based user-interface, the MARKAL model was extended with the following equation (see Box 6-1 MARKAL for GAMS source code):

$\forall key\ \forall tp \geq start\ key: INV(key, tp) = \Sigma(tch \text{ in cluster of } key)\ INV(tch, tp)*\ coupling\_factor(key, tch)$

Thus in words: For all key technologies, and for all time periods (tp) including and exceeding the start year of the key technologies, the investment in the key technologies is the weighted sum of all technologies within the corresponding cluster. The weight is the so-called coupling factor of the key technology with the underlying technology.

The corresponding data that need to be entered/added, either in ANSWER or separate as '@INCLUDE' in the MARKAL GAMS data file, is the assignment of the coupling factors via the table CLUSTER(TEG, TCH), where TEG is the set of key learning technologies (with associated learning parameters). Set TEG defines the set of key technologies and is the label of the corresponding clusters. Set TCH defines the set of all technologies in the MARKAL model (TEG is a subset of TCH).

By default, CLUSTER(TEG, TCH) = 0. If CLUSTER(TEG, TCH) = cf $\neq$ 0 for a certain combination of two technologies A $\in$ set TEG, and B $\in$ TCH, say CLUSTER(A,B) = cf, then cf is the corresponding coupling factor.

For SAPIENT, ECN has made 10 clusters of technologies comprising 60 technologies (mainly supply side but also a few demand side technologies i.e. fuel cell vehicles).

Box 6-1: GAMS source code equation that couples investments on (learning) key technology level to investments of technologies in the corresponding cluster.

```
*mmequac.ml to be included at end of mmequa.inc/ms/reg
*    %1 - equation name prefix 'EQ' or 'MS' or 'MR'
*    %2 - SOW indicator => '' or 'SOW,' or ''
*    %3 - coef qualifier => '' or '' or '_R'
*    %4 - variable/coef prefix => '' or 'S_' or 'R_'
*    %5 - REGional indicator => '' or '' or 'REG,'
*    %6 - regional scaling => '' or '' or '(REG)'
*    %7 - loop control set => 'TPTCH(TP,TEG)' or 'TPNTCH(TP,SOW,TEG)'
or 'TPTCH_R(REG,TP,TEG)'
*
*AS, 28/01/00 coupling equation for key in TEG to cluster TCH's
*only if TCH in cluster TEG and TEG NE TCH
%1_CLU(%7)$((ORD(TP) GE
TCH_STRT%3(%5TEG))*NTCHTEG%3(%5TEG))..%4INV(%5TP,%2TEG) =E=
  SUM(TCH%3$(CLUSTER%3(%5TEG,TCH%3)*(ORD(TP) GE TCH_STRT%3(%5TCH))),
      CLUSTER%3(%5TEG,TCH) * %4INV(%5TP,%2TCH)
     );
```

Multiple runs feature

Specifically meant for SAPIENT purposes, ECN modified the controlling MARKAL BATch file ‘ANS_RUN.BAT’. This file was changed in two ways:

- to enable a consecutive execution of either Reference run plus the 10 corresponding R&D shock runs, or the Soft Landing run plus the 10 corresponding R&D shock runs
- to enable the Monte Carlo experiments with MARKAL with the number of runs set to 100, and with appropriate pre- and post-processing.

Modification to MARKAL-ETL output module

The MARKAL ETL output module has been modified in two ways:

1. to accommodate the new way of modelling clusters of technologies, and
2. to provide specific output needed for computation of some of the ISPA objectives.

The table below presents a total overview of the MARKAL files affected and modified.

Table 6-12: Changed MARKAL controlling and source code files

File type	Specific Files modified
Controlling BAT files	ANS_GAMS.BAT (Changed version number and indicated files affected compared to previous version) ANS_RUN.BAT (changed in order to perform multiple runs, can be tailor made for specific R&D shock runs, or Monte Carlo runs)
Standard MARKAL source code	MMINCLUD.INC, MMINIT.INC, MMEQUA.INC, MODEL.MRK
Specific ETL MARKAL source code	Coefficients and equations files: MMCOEF.ML MMEQUAC.ML ETL Output module files: ATLEARN.ML ATLEARN1.ML ATSC.ML (includes specific ISPA objectives output: sales and investments learning technologies, CO2 emissions and energy system costs) ATLEARN8.ML ATLEARN9.ML

6.3.2. MARKAL Monte Carlo experiments

This section describes the use of Monte Carlo analysis methods with the MARKAL model. Monte Carlo analysis (MCA) is a method to analyse and propagate data uncertainties in models.

MCA is a relatively time-consuming (i.e. computationally) method. However, with the current speed and memory capabilities of PC's, Monte Carlo analysis with complex MARKAL models e.g. ECN's MARKAL model for Western Europe now becomes feasible. Monte Carlo analysis can be used complementary to conventional MARKAL practices as (in decreasing order of frequency of use):

- Scenario analysis
- Sensitivity analysis
- Stochastic programming and
- Cost-benefit analysis.

These approaches are described in previous literature (ETSAP, 1999), (Ybema et al, 1995) and (Ybema et al., 1998).

The MARKAL Monte Carlo experiments have been carried out as a kind of shadow calculation of the PROMETHEUS calculation. The marginal cost of CO_2 reduction, as computed by PROMETHEUS for e.g. the EU, is the basic parameter for comparison. Like PROMETHEUS, the MARKAL Monte Carlo experiments result in a probability distribution for this parameter.

i. Monte Carlo methods compared to other approaches

To our knowledge, Monte Carlo (MC) uncertainty analysis methods have hardly ever - or even never - been applied to complex energy system models like MARKAL (see also Kann & Weyent, 2000). The main reason is probably that Monte Carlo analysis methods generally require a lot of model runs in order to obtain stable and sensible results. With the current speed of PC's and even with rather complex models like the EU MARKAL model, MC analysis is now feasible in terms of computational complexity and solution times. E.g. the ECN MARKAL long term scenario study (Ybema et al., 1998) comprised about 60 models runs (2 scenarios with about 30 variants and sensitivity analyses for each scenario). From other type of MC analysis applications, it is known that even 100 runs can be sufficient to produce meaningful results if a stratified sampling method such as Latin Hypercube Sampling is applied (IAEA, 1989). From the first experiments conducted by ECN and reported here, it appears that MC analysis can be used in combination with scenario analysis, even with ECN's Western European MARKAL model (e.g. see (Lako et al., 1998)) and including technology learning (e.g. see (Seebregts et al, 2000)).

ii. What type of uncertainties can be addressed?

Monte Carlo analysis can give an indication of the parameter and data uncertainties within one particular scenario. The main results derived from a MC analysis are:

1. A probability distribution (and hence, indicators like means, variance, spread, percentile points) of the results of interest ('endpoints').
2. A ranking of the uncertain parameters based on their contribution to the uncertainty in selected endpoints.

The spread obtained this way can also show whether different scenarios can overlap in some instances. Model structure, more methodological (e.g. using ETL or not/using 1FLC or 2FLC) uncertainties and 'incompleteness' uncertainties cannot be dealt with this type of analysis. Sensitivity analyses or analyses with different model variants are better suited to address such uncertainties.

In first instance, the parameters to be addressed in such an MC analysis should be restricted to parameters not typically characterising the scenario. So, typically uncertainties associated with technology characteristics are candidate to be included in a Monte Carlo analysis: Investment costs; O&M costs; efficiencies, maximum growth rates (e.g. due to production limits), physical potentials (e.g. onshore wind turbines), progress ratios, etc.

However, parameters characterising the scenario parameters can also be included [18] .

[18] Economic and demographic (energy demands, energy prices), market and production related (market penetration constraints, growth rates), 'environmental' (resources, emissions constraints, physical potential), discount rate (coupled to investment decisions) or the social rate of time preference.

6.3.3. Example: Uncertainties in progress ratios solar PV and wind turbines:

The Monte Carlo (MC) experiments have been performed with the Soft Landing CO2 reduction limits (Blanchard et al, 2000). The focus has been on the uncertainties in progress ratios, in particular for solar PV and wind turbines. This section summarises the inputs and main results, including a comparison with PROMETHEUS results. Next, the development of investment cost and installed capacity is given as more conventional indicators of the market penetration of the two learning technologies. Finally, a comparison is made with 4 (traditional) deterministic analyses.

6.3.3.1. Ranges for progress ratios

Uncertainties in progress ratios, among others, are one of the key uncertainties associated with modelling of technological learning in energy models. E.g. from (Kram et al., 2000), (McDonald & Schrattenholzer, 2001), and (Junginger, 2000) the following ranges can be deduced for the progress ratio on specific (investment) cost.

Table 6-13: Uncertainty ranges progress ratios solar PV modules and wind turbines (learning curve for inv. cost/kW(p))

Technology	Kram et al, 2000	McDonald & Schrattenholzer, 2001	Junginger, 2000
Solar PV (modules)	0.72-0.85	0.80	-
Wind energy, wind turbines	0.85-0.90	0.83-0.92	0.85-0.96

Based on the various reported progress ratios in (Kram et al, 2000) and (Junginger, 2000), the following probability distributions have been chosen. The ranges are based on (Junginger, 2000) for wind turbines, and on the range arising from the values used in the models MESSAGE, POLES, ERIS, and MARKAL (Kram et al, 2000)). The mean values are the values as derived by ECN (Seebregts et al., 1998).

Table 6-14: Probability distributions progress ratios Solar PV and Wind turbines

Technology	Distribution	Mean value	Remarks
Solar PV (modules)	Uniform (0,76; 0,88)	0.82	-
Wind energy, wind turbines	Triangular (0.85;0.90;0.96)	0.90	0.85 and 0.96 are about 5-th and 95-th percentile point

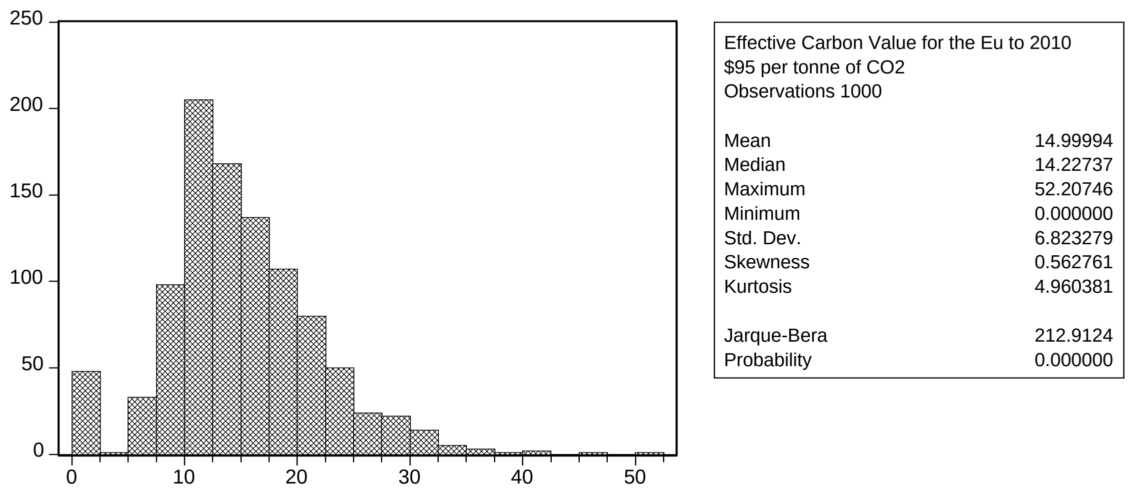
6.3.3.2. Marginal cost CO2 reduction and comparison with PROMETHEUS

The resulting marginal cost of reducing CO2 as computed from the MARKAL results is given in the next table. As can be seen, the mean values for 2010 and 2030 (128 and 63 euro) are much higher than the corresponding values from PROMETHEUS. For 2010 also the minimum and maximum differ a lot (2030 PROMETHEUS values other than the mean are not known).

Table 6-15: Marginal Cost of CO2 reduction in (euro/tCO2). (Between brackets, the corresponding PROMETHEUS values ($95))

	2010	2030	2040	2050
Maximum	145 (54 $95)	67	76	99
95-th perc. Point	141	67	75	98
Mean	128 (15 $95)	63 (33 $95)	66	94
5-th perc. Point	122	53	59	91
Minimum	122 (0 $95)	52	56	91

Figure 6-34: Distribution carbon value 2010 EU (from PROMETHEUS)



6.3.3.3. Development of investment cost and capacity

The next tables show the results for the endpoints ‘Investment cost’ and ‘Capacity’ in de model years 2030 and 2050. As can be seen with respect to the progress ratios, the means and other distribution indicators are in line with the input distributions defined. The ranges in investment cost and capacity are rather large. It is important to note that the values now depicted as e.g. 5-th percentile point are not belonging to the same model run. A rather low cost of solar PV does not match with low values for capacity. In fact, the corresponding values for investment cost should be ‘mirrored’, i.e. a minimum for cost corresponds with the maximum for capacity. So e.g. 344 €/kWp in 2030 for solar PV matches with 172 GWp capacity in 2030.

The results show that the success of the two technologies is very dependent on the value of the progress ratio. In a few cases, solar PV does not enter the market, except on a level caused by a lower bound in the model. In a few other cases, solar PV goes to its maximum (300 GWp).

Table 6-16: Investment cost and capacity installed, 2030 and 2050, from 100 MC runs

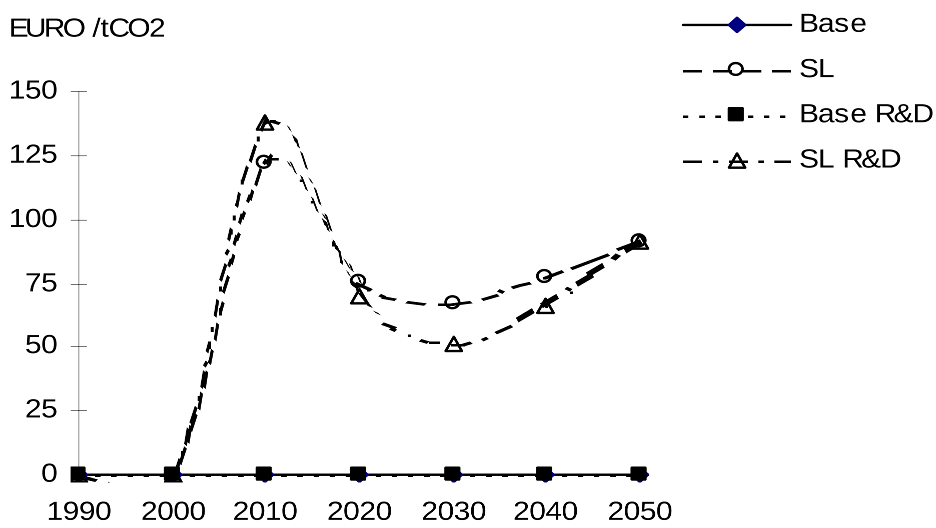
Results solar PV	pr_PV (input)	i.c. 2030 [€/kWp] (result)	i.c. 2050 [€/kWp] (result)	cap. 2030 [GWp] (result)	Cap. 2050 [GWp] (result)
Minimum	0.761	344	260	1	1
5-th perc. Point	0.765	373	282	1	1
mean (input)	(0.820)				
Mean	0.819	1833	1565	55	176
95-th perc. Point	0.872	3619	3441	165	300
Maximum	0.880	3767	3611	172	300
Maximum (input value)				(300)	(300)

Results Wind turbines	pr_wind (input)	i.c. 2030 [€/kW] (result)	i.c. 2050 [€/kW] (result)	cap. 2030 [GWp] (result)	Cap. 2050 [GWp] (result)
Minimum	0.863	322	271	42	77
5-th perc. Point	0.870	360	309	58	102
mean (input)	(0.900)				
Mean	0.904	559	500	82	155
95-th perc. Point	0.938	765	718	129	245
Maximum	0.954	934	876	134	245

6.3.3.4. Comparison with four deterministic cases

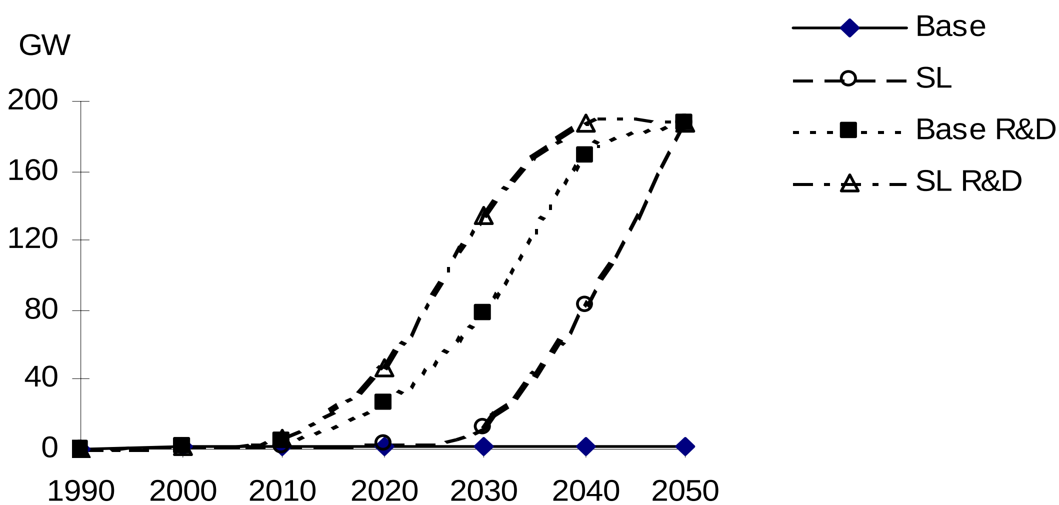
The next figures show the results in the SL scenario with the mean values of the two progress ratios. In addition, a Base scenario plus two R&D impact variants are shown. The Base scenario is the variant without CO2 emission constraints. The R&D cases are cases with better progress ratios for solar PV (from 0.82 to 0.0765, so to the lower limit of the MC distribution) and wind (from 0.90 to 0.897, so hardly any change). In this case, the 300 GWp is not reached for solar PV. For wind energy, the capacity in 2050 is about 150 GW, more or less equal to the mean of the MC analyses (compare with table above).

Figure 6-35: Marginal cost of CO2 reduction (Base=without CO2 emission constraints; R&D=with better progress ratios)



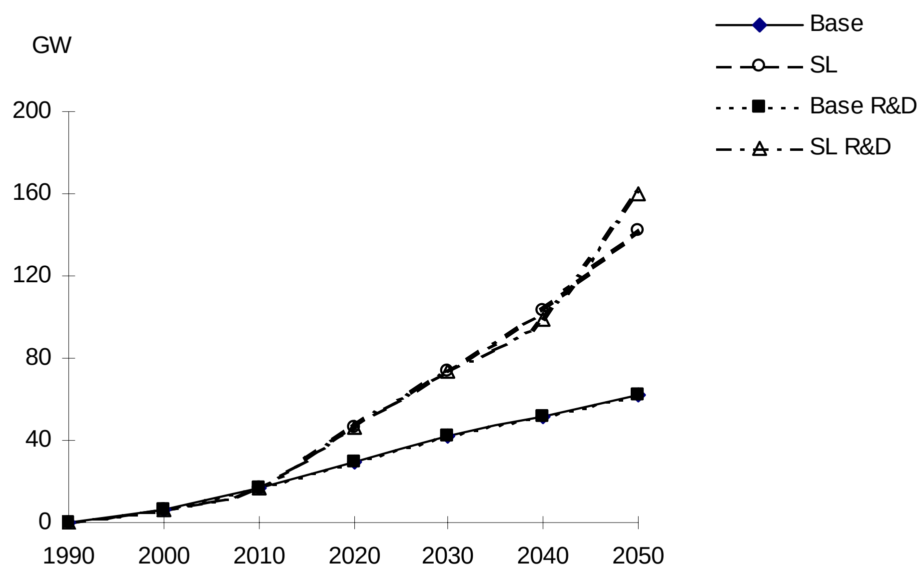
As can be seen, overall CO_2 costs are lower in the SL R&D case. Since Base is unconstrained, CO_2 cost equals zero.

Figure 6-36: Installed capacity solar PV (Base = without CO2 emission constraints; R&D = with better progress ratios)



As can be seen, R&D leads to elevated levels both in constrained (SL) and unconstrained (Base) case. In the Base case without R&D, solar PV does not become attractive.

Figure 6-37: Installed capacity Wind energy (Base = without CO2 emission constraints; R&D = with better progress ratios)



As can be seen, only in the constrained (SL) case, R&D leads to somewhat elevated levels for wind energy. Extra R&D has no or hardly any impact. Note that in the R&D case, solar PV seems to win over wind turbines from 2020 on.

It should be noted that the MC analyses and the SL/Base and R&D analyses outlined above, have been performed prior to the final MARKAL R&D shock runs, as reported in Part III. The main differences are the number of clusters (here: only 2; R&D shocks part III: 10) and different bounds on the renewable technologies.

6.3.4. Monte Carlo analysis as pre-processor of maximally realisable potentials and floor-costs

MC analysis can also be used as a step prior to executing MARKAL calculations. It is for example possible to test and check inputs of models, e.g. for technology learning parameters, it is possible to investigate the maximum potentials of learning technologies, as function of uncertain inputs. This potential can be expressed as: floor cost (i.e. the lowest investment cost that can be achieved when a technology is fully employed up to its upper limits), maximum number of doublings or maximum capacity that can be reached within the model time horizon.

Inputs needed for this are: progress ratio, initial cost, initial cumulative capacity and maximum cumulative capacity. Uncertain parameters in this example are:

Pr = progress ratio

C0 = initial cumulative capacity (at start time horizon)

Cm = maximum cumulative capacity (at end time horizon)

Here an example is presented for the floor cost of solar PV modules. The distributions of the uncertain parameters are given in Table 6-17.

Table 6-17: Example input distrubutions (EU MARKAL 1990-2050)

Parameter	Unit	Distribution
Progress ratio solar PV	-	Triangular (0,76; 0,82; 0,88)
Initial cumulative capacity solar PV	GWp	Uniform (0,05; 0,15)
Maximum cumulative capacity	GWp	Uniform (400; 800)

An example of output displayed as Tornado diagram, is given below in Figure 6-38. This figure shows a Tornado diagram for the endpoint 'floor cost'. As can be seen, the uncertainty in the progress ratio mostly determines the uncertainty in the floor cost. The higher the progress ratio (pr), the higher the floor cost (i.e. less learning potential). The higher the maximum cumulative capacity, the lower the floor cost (hence, more learning). The higher the initial cumulative capacity (C0), the higher the floor cost (i.e. less learning potential). Figure 6-39 shows the cumulative distribution function of the floor-cost of solar PV. A mean value of 560€/kWp is computed for 2050.

Figure 6-38: Example of Tornado diagram: more important uncertain input parameters are listed on top

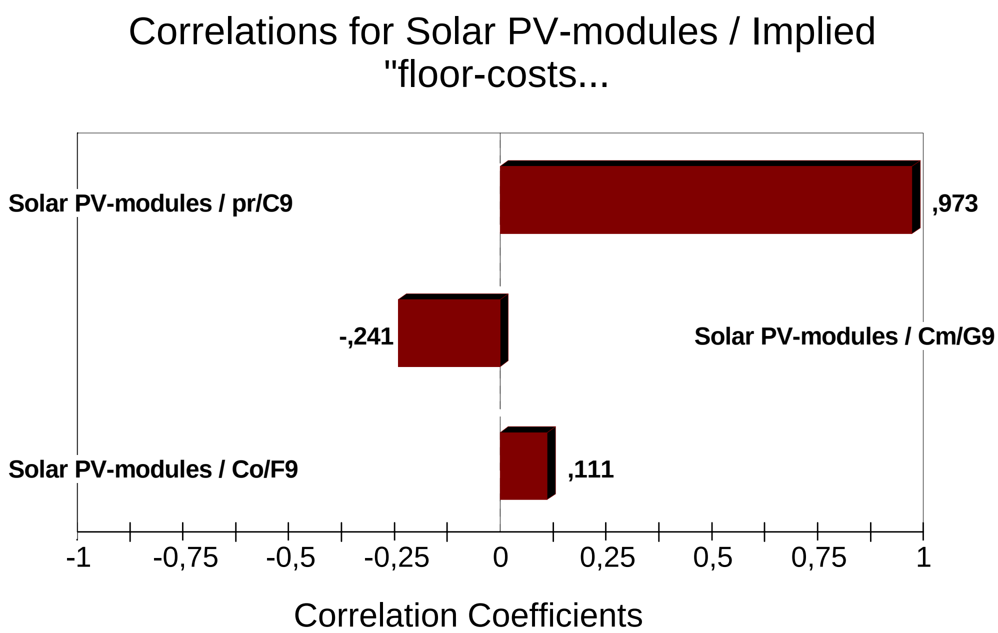
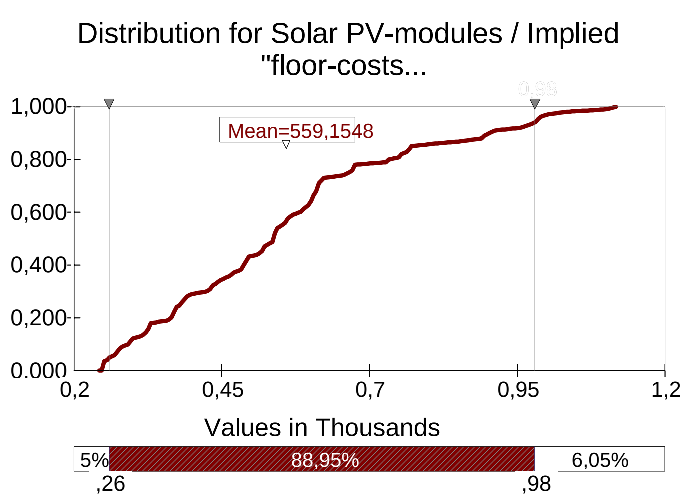


Figure 6-39: Distribution of floor cost



Possibly, the life of a technology, bounds like maximum annual growth rates, capacity upper bounds or investment upper bounds can be added to further determine the maximum potential or the uncertainty. These latter parameters may result in a better estimate of first maximum cumulative capacity (Cm) as input to the actual MARKAL run with endogenous learning. However, this has not been done in the Sapient project.

Table 6-18: Progress ratios selected for the MARKAL clusters of learning technologies

Code	Description	Progress Ratio	Max. annual growth factor	Source of information or rationale
1.	Solar PV modules	0.82	1.35 from 1990-2000 1.25 thereafter	Updated from 0.81 from (Seebregts et al, 1998,) Section 3.4.1 to 0.82. (de Lange & Crommentuijn, 2000) show that 1.25 annual growth over longer periods (2000-2050) is rather optimistic
2.	Wind turbine	0.90	1.46 from 1990-2001 1.25 thereafter	PR Value has been underpinned in (Seebregts et al, 1998) Section 3.4.2 (de Lange & Crommentuijn, 2000) show that 1.25 annual growth over longer periods (2000-2050) is rather optimistic
3.	Fuel cell	0.82	-	Value has been underpinned in (Seebregts et al, 1998) Section 3.4.3
4.	Gasifier	0.9	-	Generic value used in (Seebregts et al, 1999,) which was based on (Neij, 1997/1999?) with gasifier termed as 'advanced' technology
5.	Gas turbine	0.87	-	No recent statistics or references available, decided to use 'old' IIASA value (up to 1980) as estimate (McDonald & Schrattenholzer, 2001)
6.	Hydro turbine	0.997	-	1FLC fitted by ECN from base data derived from data supplied with (Criqui, 2001)
7.	Steam turbine	0.99	-	0.99, as generic value for a more conventional technology that hardly learns
8.	Boiler	0.99	-	0.99, as generic value for a more conventional technology that hardly learns
9.	Combined cycle boiler	0.95	-	0.95, more advanced than a conventional boiler, and therefore a better progress ratio
10.	Nuclear reactor	0.99	-	0.99, as generic value for a more conventional technology that hardly learns

6.3.4.1. Use of @Risk as pre and post-processor of MARKAL runs

The @RISK software (Winston, 1999) has been used as pre-processor and post-processor of the MARKAL runs; @RISK is an Excel add-on. The series of input samples are made using @Risk. Output of @Risk has been converted to appropriate text data ('DD' files in MARKAL terminology) files to be used in the ANS_RUN.BAT file. The uncertainty measures, i.e. correlation coefficients between inputs and results are computed afterwards. The next box provides some more details of the sequential steps.

Box 6-2: MARKAL-1. Detailed steps

1. Establish uncertain input parameters and their distributions (in the first test with a MARKAL learning model: only progress ratios for Solar PV and Wind turbines, just to illustrate the approach) -> IN @Risk
2. Generate input sample (for each of the M scenarios/variants) -> IN @Risk and Excel: inputs are also selected as output in order to obtain samples from @Risk.
Colums in @Risk Data Window are copied to a separate XLS file. This last XLS file is edited somewhat, written to a text file.
3. Convert these samples to MARKAL input files in the appropriate format
With BAT and Pascal utility program: Text file from step 2 is processed to appropriate format. For each sample a separate file is made.
4. Rrun MARKAL M x N (N=100) times
5. Derive the endpoints from these resultsi.e. CO2 emissions, capacities of (selected) technologies
6. Derive spread, distribution of these endpoints/indicators and correlations with the uncertain input parameters, or correlations between outputs.

Step 1-3 is a kind of pre-processing (outside MARKAL)

Step 4-5 is integrated into MARKAL source and batch files (only 1 GAMS source file that to filter the relevant and desired endpoints (results) in each run and 1 DOS BAT file (ANS_RUN.BAT) file.

6.3.5. Conclusions Monte Carlo experiments

Despite the limitations in the MC analyses (e.g. only 2 clusters of learning technologies, only progress ratios as uncertain parameter), we can conclude from these experiments:

1. Monte Carlo analysis can be applied for complex MARKAL models.
2. Further research is needed to conclude definitely that it is a feature to be included as ‘member’ of the official family of MARKAL models (Seebregts et al, 2001).
3. The uncertainty range in the wind turbine progress ratio (PR), as derived from literature, is much larger than the impact of R&D on the progress ratio. Therefore, given the impact from the R&D assumption on the wind turbine PR, for wind turbines no robust conclusions can be derived solely on R&D impacts. The uncertainty in the PR, which can be caused by a variety of factors, is far more important. Only applicable for wind or also for solar?
4. This finding supports the idea that it is more important to obtain good data for the one-factor learning curve parameters, than to introduce a more complex two-factor learning curve (either indirect or direct).

The uncertainty in the input data for learning can be analysed well with a combination of sensitivity analyses and Monte Carlo analyses.

PART III: Towards the definition of R&D strategies

7. The ISPA meta-model for R&D budget exploration (by N. Kouvaritakis, ICCS-NTUA)

The main aim of the ISPA meta-model is to serve as a tool for the exploration of public R&D budget allocation options in the context of:

- Multiple Objectives
- A non-Deterministic environment (presence of risks)

The main features of ISPA are:

- A single horizon i.e. budget allocation is supposed to occur at some time near the present in order to obtain desired effects on a fixed future horizon (this is an essential feature of this type of exercise where it is clearly understood that allocations in future dates can wait and can incorporate knowledge acquired in the meantime).
- The impact of allocation decisions is treated stochastically giving the possibility to make probabilistic statements.
- Statistical dependence of impacts is allowed for arising from the fact that they are affected (albeit differently) by the same variables themselves subject to risk.
- The allocation itself does not affect the stochastic characteristics of the problem - clearly a simplifying assumption necessary for a manageable specification; it can be justified in terms of a relatively limited significance of the budget allocation*
- Under certain conditions as an extension it can be envisaged to allow average impacts (as opposed to their risk characteristics) to depend on budget decisions.

In order to incorporate fully the stochastic characteristics of the problem (enable the analysis of different risk averse stances) and at the same time treat the different objectives symmetrically it is proposed to specify the ISPA meta-model as an optimization problem where:

- The probability that an objective exceeds a given threshold is maximized
- subject to the condition that the probability that the other objectives exceed given thresholds is greater than a certain level.
- Also subject to the budget and non-negativity constraints.

Alternative specifications are of course possible as for example setting the goal as the maximization of the expectation or alternatively the constraints as inequalities on the expectation of the different objectives. Such specifications would result in asymmetric treatment of the objectives rendering the discussion of the presentation of the results somewhat ambiguous. Replacing both the goal and the objective in terms of expectations would effectively destroy the stochastic character of the exercise rendering meaningful risk analysis impossible.

In algebraic terms the standard ISPA specification becomes:

$$\max \Pr\left\{\sum_j x_j r_{1j} > A_1\right\}$$

Subject to:

$$\Pr\left\{\sum_j x_j r_{ij} > A_i\right\} \geq p_i$$

$$\sum_j x_j \leq B$$

$$x_j \geq 0$$

$$\vec{r}_i \approx \tilde{N}(\vec{\rho}_i, V_i)$$

Where:

the x(j) are the budget allocations to technology j;

the r(i,j) are random variables representing the impact on objective ;

i of expenditure on technology j;

A(i) are the thresholds for each objective and p(I) the probabilities ;

associated with them B is the total R&D budget;

r(i) and V(i) the mean and variance covariance of the r(i,j).

Alternatively the distribution can be Log Normal and this is in fact what is suggested frequently by the evidence. In this case all objective functions must be expressed in terms of products with the r(i,j)s as exponents.

7.1. A more concrete specification of the ISPA meta-Model

In its simplest form the ISPA meta-model could have the following structure (bold lower case indicate vectors, bold upper case matrices and ‘ marks the transposition):

$$\max_{\mathbf{x}} \frac{\boldsymbol{\rho}_1'\mathbf{x} - A_1}{\sqrt{\mathbf{x}'\mathbf{V}_1\mathbf{x}}}$$ the main objective under consideration

Subject to:

$$\boldsymbol{\rho}_i'\mathbf{x} - F^{-1}(p_i)\sqrt{\mathbf{x}'\mathbf{V}_i\mathbf{x}} \geq A_i$$ i=2,….,m the constraints on the other objectives

$$\mathbf{u}'\mathbf{x} \leq B$$ the budget constraint

$$\mathbf{x} \geq \mathbf{0}$$ the non-negativity of budget allocation constraint

Where:

- **x** is an n by 1 vector containing the budget allocation for each of the n technological options considered
- $\boldsymbol{\rho}_i = E(\mathbf{r}_i)$ where the $\mathbf{r}_i$ are n by 1 vectors representing the random impacts of the budget contributions on objective i
- $\mathbf{V}_i = E\left[(\mathbf{r}_i - \boldsymbol{\rho}_\iota)(\mathbf{r}_i - \boldsymbol{\rho}_i)'\right]$ and are therefore n by n matrices. They are positive definite symmetric by definition and their estimation through PROMETHEUS will ensure that (preliminary experiments should take this condition into account or risk illegal arithmetic and many other problems in the optimization algorithm)
- p_i is the probability requirement concerning the ith objective and $F(p_i) = \int_{-\infty}^{p_i} 0.39894228 \cdot e^{0.5z^2}\,dz$. The latter is the cumulative standard normal distribution function the inverse of which is used as a parameter in the constraints of the model (i.e. it does not involve **x**). Consequently the integral need not be evaluated in the course of solving the ISPA model (prior evaluation is required but can be obtained using standard statistical functions or indeed any standard statistical table).
- **u** is an n by one vector of ones
- A_i represents the threshold associated with the ith objective. It is highly advisable that $A_i < \max\{\rho_{i1}........\rho_{in}\}$ **.** Failure to respect this condition would necessitate some slight changes in specification (under some conditions both the objective function and the constraints on the other objectives may have to be multiplied by –1 while the character of the problem will be somewhat modified (high risk becoming an asset and extreme solutions resulting as a consequence)

- B is a scalar representing the budget. It can be envisaged to set B equal to 1 in which case **x** becomes a vector of R&D shares

All expected values above and indeed all the parameters of the optimization problem are assumed to be non-stochastic.

The above specification is the simplest that ensures the desired properties of the ISPA meta-model. The preferred distribution for the rs would be the Log Normal but then a logarithmic transformation would produce valid normal variates that can be used in the way specified above. Both the objective function and the feasible set should be convex.

A major enhancement (and increase in the complexity of the problem) could be to consider:

$\rho_{ij} = \varphi_i(x_1,........,x_n)$ for i=1,….,m

This enhancement is a convenient and indeed a necessary means through which information from the large models can be introduced into ISPA.

A tentative specification of such a function would be:

$$\rho_{ij} = R_{ij0}\prod_{j=1}^{n}\left(x_j + 1\right)^{\alpha_{ij}} \quad \text{for i=1,……,m}$$

At any rate special care was given to eventual loss of convexity when variable expectations were introduced into ISPA. In itself it does not pose logical problems but could lead to local minima, which had to be adequately investigated and avoided.

7.2. Specification of the Objectives

The following formula was used for the measurement of impacts:

Impact on ith objective= (Change in ith objective measured in specific units)/ (Change in R&D expenditure in euro).

The change in the objective is a model result arising from introducing a once-off positive shock on R&D allocated to the *i*th technology at the beginning of the forecast period. It had been decided to try shocks equivalent to ten percent of cumulative R&D expenditure for the particular technology however alternative sizes could be used where it was found that they may give rise to more meaningful impacts. For the sake of realism such shocks should not represent absurdly high expenditures (i.e. expenditures that are way above what could be a worldwide power technology budget). Shocks were orthogonal applied at the beginning of forecast horizon (affecting one technology at a time) and some combined shocks (perhaps a uniform expansion of cumulative R&D on all technologies) were implemented to enable an eventual extension of the expected productivity of R&D functions to include interdependence. All models used IEPE's database (calibrated to the POLES reference scenario and IIASA A1B).

Objectives involving discounting used a constant 4% discount rate throughout as requested by the Commission.

7.2.1. The measure of market impact ('profitability')

In the course of experimentation with TFLCs integrated to large models (and in particular with the POLES model) a problem had been identified concerning the measurement of the market impact objective (which incidentally was supposed to be one of the most straightforward measurements). This arised from the fact that if crude sales (in constant value terms) were taken to be the indicator there was a distinct and legitimate possibility that the market impact arising from an increase in R&D funding proved to be negative. This was the case if the reduction in cost was deeper than the increase in sales often due to some saturation effect incorporated in the baseline (the problem was identified for example in the case of gas turbine combined cycle technologies which penetrate to near saturation levels already in the reference case). In fact this problem rose in all cases where the implied "elasticity" of demand for equipment was less than one. Clearly such an outcome made nonsense of R&D budgeting at least in view of this particular objective.

The main problem with the sales indicator was that it did not really constitute an R&D objective. More appropriate measures would be profitability accruing to the agent undertaking the R&D action and resulting from an optimal positioning with regard to aggressive pricing in order to gain market share and cost advantages arising from technological improvements. Furthermore such advantages in the "real world" are not eternal and are eroded with technological diffusion, the expiry of patents etc. Clearly all the above constitute mechanisms that are far too micro-economic and complex to figure in the kind of model that we use in the SAPIENT project.

Consequently the following proxy mechanism was proposed:

→ Assume that the reference case improvements are obtained under "perfect competition" conditions that represent zero profits (for the purpose of the exercise).

→ Assume that all incremental sales constitute a gain for the agent undertaking the R&D action (other agents retaining their market sales) in perpetuity.

→ Assume that the reference case cost remains the reference price of the technology in a way that all the cost reduction implied by the R&D action accrues as profit to the agent also in perpetuity.

Of course the above scheme contains too many restrictive assumptions that clearly do not hold in practice: they imply a mixture of monopoly power with an inability to expand market share beyond net market increments. In this sense it is just as inappropriate as the "sales" scheme. However it enjoys some clear advantages in the sense that it avoids the problems encountered so far, introduces some notion of appropriation, hitherto completely absent from the calculations and hopefully gives better relative measures for productivity of R&D expenditure on different technologies. The latter point is crucial because in the policy analysis we are only interested in relative impacts.

An alternative way of looking at this objective as defined above is that it represents a composite index of two desirable outcomes namely a technological cost reduction and the increase in volume sales. The indicator would then be:

Impact = discounted ((reference cost -R&D induced cost)*change in equipment sales volume)/R&D expenditure shock

This formula is the one used in PROMETHEUS.

An alternative but closely linked approach is to obtain approximate measures of additional consumer surplus arising from the R&D action. This entails the advantage of being better grounded on recognisable concepts in economic theory. Such an indicator could be:

impact=discounted (0.5*(reference cost +R&D induced cost)*change in equipment sales volume)/R&D expenditure shock

Impacts using this formula would tend to be considerably higher although the relative ranking of technologies would be little affected. Higher impacts may on the other hand be more palatable (an impact of less than one always posing some problems of relevance of R&D actions).

Clearly this second formula involves the same variables as the first one and carrying out the experiments in view of the one automatically implies the ability to calculate the other.

7.2.2. The measure of impact on the CO2 limitation objective

The maximum transparency, comparability of results as well as facility of implementation was obtained by defining measuring the impact of R&D action on cumulative emissions. In this way the formula for impact is defined as:

Impact = change in cumulative emissions/ R&D expenditure shock

The CO2 problem being global the variable of interest is cumulative world emissions. Models covering the EU only could also perform this exercise and subsequently for the sake of comparability results could be scaled up by using the inverse of the share of the EU in World emissions.

It is worth noting that no discounting is necessary or desirable with respect to this objective. On the other hand impacts were sensitive to the horizon (PROMETHEUS runs only up to 2030 and hence distributions were only available for cumulative emissions up to that year).

Expected impacts with respect to this objective can normally be either positive or negative. PROMETHEUS results suggest that for many technologies (notably the clean coal ones but also gas fired ones) the range of the distribution includes zero with non-negligible probability densities. It was therefore important to express impacts also in terms of relative reductions in cumulative CO2 emissions in order to retain the possibility to use as an alternative the Log Normal distribution in the ISPA policy tool.

7.2.3. The measures of cost reductions to the consumer

This objective is retained separately for the EU and for the developing World. The calculation is quite straightforward and the impact formula is given by:

Impact = (R&D induced total discounted cost to the consumer - reference total discounted cost to the consumer)/R&D expenditure shock

All final energy consumers (households and firms) are considered in the calculation. Attention was paid to avoid double counting (i.e. costs of inputs to power generation should not be included as they would be properly reflected in electricity prices to final consumers).

Expected impacts with respect to this objective are normally negative. However PROMETHEUS results suggest that for some rather “exotic” technologies (notably photovoltaics) the range of the distribution includes zero with non-negligible probability densities. The same applied albeit to a lesser extent at the tails of distributions for some fossil fuel technologies where their enhanced adoption arising from R&D actions combined with particularly severe resource limitations to produce small increases in overall cost due to higher fossil fuel prices affecting all consumers. It is therefore important to express impacts also in terms of relative reductions in total discounted cost to the consumer in order to retain the possibility to use as an alternative the Log Normal distribution in the ISPA policy tool.

7.2.4. A measure of the impact on security of supply

Initially the security of supply objective was measured as a deviation above a threshold (variously suggested between $35 and $50 per boe for oil and gas). On further reflection however it became clear that such an objective would be very closely related to the costs to the consumer objectives discussed in the previous section. Hence such a measure would provide few additional insights to the strategy exploration. ICCS/NTUA has therefore proceeded to define and incorporate in PROMETHEUS an impact defined as follows:

Impact = (maximum increase in oil and gas prices in any 3 year period of the horizon after the shock has been introduced - maximum increase in oil and gas prices in any 3 year period of the horizon in the reference)/ R&D expenditure shock

It was unlikely that most deterministic models, whether simulation or optimisation, could measure such an objective. PROMETHEUS incorporates a Middle East productive capacity constraint subject to fluctuations equivalent to those experienced in history as an element in price formation and is therefore capable of producing sufficiently meaningful outcomes. Furthermore it was found to be an objective displaying high differentiation from the other objectives (R&D expenditure on some technologies like clean coal and nuclear was found to be very productive in contrast to their performance in terms of other objectives) and hence susceptible of introducing interesting elements in the R&D strategy analysis to the extent that different priorities are attached to it.

8. The PROMETHEUS World Stochastic Energy Model [by N. Kouvaritakis, K. Manolitzas, V. Panos (ICCS-NTUA)]

8.1. General Features

PROMETHEUS is a self-contained energy model consisting of a set of stochastic equations. The model contains relations and/or exogenous variables for all the main quantities, which are of interest in the SAPIENT project. These include demographic and economic activity indicators, energy consumption by main fuel, fuel resources and prices, CO2 emissions, technology uptake and two factor learning curves.

All exogenous variables, parameters and error terms in the model are stochastic with explicit representation of their distribution including on many cases terms of co-variance. It follows that all endogenous variables as a result are also stochastic.

By necessity it is a very aggregate model especially in terms of regional coverage. However it must be remembered that:

- There are diminishing returns to detail in terms of error reduction
- ISPA where PROMETHEUS results will be used adequately incorporates error and can be run giving useful insights even with relatively large ones as long as they are balanced across choices.

8.2. PROMETHEUS output

The basic output of PROMETHEUS is a data set of Monte Carlo simulations containing values for all the variables in the model. This set can subsequently be used:

- To fit joint Normal or Lognormal distributions for the impact variables to be used in the ISPA policy tool. Note that the problem of estimating the covariance is satisfactorily solved by the process itself. Justifications for the co-variances can also be provided through the data set itself or through inspection of PROMETHEUS relations.
- In its own right, as strategically or analytically important information on risks and probabilities regarding the variables incorporated in it or any pre-determined function involving them. Major applications could be in security of supply assessment environmental risk assessment, investment risk analysis etc.
- It is envisaged to create a facility allowing for the results to be processed by fitting generalised distributions in order to avoid some of the vagaries often associated with crude Monte Carlo results.

8.3. PROMETHEUS Model Characteristics

Regional Coverage

- OECD Europe
- Other OECD (USA, Canada, Japan, Australia, N. Zealand)
- Rest of the World

Final Demand Categories

- Industry (non-electric uses)
- Transport
- Residential/Commercial/Other (non-electric uses)
- Industry (electric uses)
- Residential/Commercial/Other (electric uses)

Fuels/Energy forms for final demand

- Coal
- Oil
- Natural Gas
- Electricity

Prices Fuels/Energy forms for final demand

- Coal (Industry)
- Oil (HFO, LFO, Gasoline)
- Natural Gas (Industry, Residential)
- Electricity (Industry, Residential)

Fossil Fuel Supply

- Fuel "in Place"
- Gross Additions to Reserves
- Reserves
- Production

Identified at World level for Oil and regional level (Enlarged European Region, North America, Other World) for Natural Gas. Coal is assumed to be demand driven (abundant supplies). Specific relations model non-conventional oil sources (Tar sands and Extra-Heavy oil) through price dependent recovery rates. The inclusion of this source acts as a crucial "backstop" preventing frequent occurrences of very high World oil prices

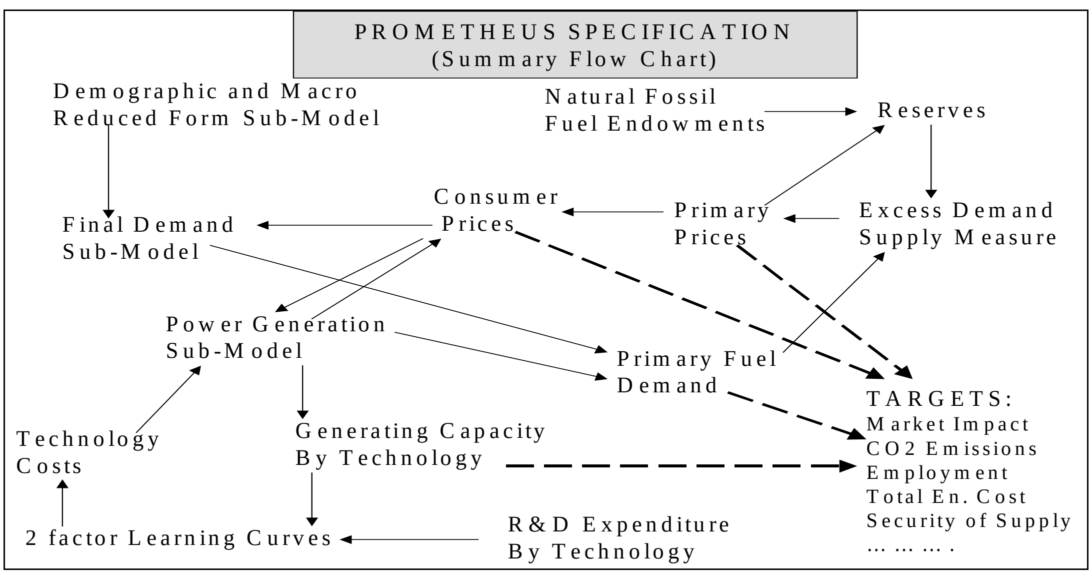
Primary Fuel Prices

- Oil (World)
- Natural Gas (Regional)
- Coal (Regional derived from simple time series analysis)

Electricity is generated by "existing" Fuel/Source (Coal, N. Gas, Oil, Nuclear, Hydro). The model provides for Generation by 'new' Source/Technology (Renewables, Advanced gas, New Nuclear, Fuel Cells). Capacity takes into account "existing" and "new" technologies. The Capital Costs are presented with respect to Technology Type. R&D expenditure is assigned to each type of technology considered in the project.

- Currently R&D expenditures are not stochastic and in this sense constitute a unique exception justified since this variable constitutes the main lever of the current PROMETHEUS utilisation

Table 8-1: Prometheus Specification



8.4. Using Econometric Estimation for obtaining Stochastic Information

In constructing PROMETHEUS extensive use of econometric techniques was made in order to obtain the detailed stochastic information required for as complete a representation of their interaction as possible.

Main Advantages

- Provides an element of objectivity
- Forces the analyst to investigate the nature and extent of stochastic elements (why past variability occurred)
- Is amenable to the analysis of co-variance both in terms of statistical dependence of the parameters and in terms of the simultaneous solution of sets of econometrically estimated equations

Main Disadvantage

- Excessive reliance on history
- However it is not clear whether this reliance leads to exaggeration or under-estimation of variability – therefore the method does not in itself produce systematic bias

The derivation of stochastic elements takes into account that:

- The variance of the regression is unknown and hence itself a random variable (in the process of implementation in PROMETHEUS this has proved to be a major source of variability especially since the samples used were relatively small and the distribution of the variance skewed)
- The parameter estimates are stochastic. As these are used in PROMETHEUS as time independent variables it was found that it was preferable to specify equations in dynamic form to avoid excessive early variability
- The parameter estimates are not statistically independent (i.e. they co-vary). This has often proved an element of stability (example: negative covariance between autonomous efficiency gains and activity elasticities). However this is not a general rule: a positive (or negative) co-variance between activity and price elasticities combined with decreasing (or increasing) prices in the course of a Monte-Carlo run will increase variability.
- The residuals of the equations vary with time but are independent and hence their cumulative effect though it increases, does so at a decreasing rate.

8.5. From Econometric Estimation to Monte-Carlo Runs in Prometheus

In practical terms following the performance of regression estimation the following steps are performed in order to obtain the appropriate parameters to be used in the operational version of PROMETHEUS.

1. Divide the variance co-variance matrix of the estimated parameters by the estimated variance.
2. Apply Cholesky decomposition to the matrix resulting in the previous step.
3. Generate a chi squared distributed random value for the variance (with the estimated mean and the sample requisite degrees of freedom).
4. Multiply the triangular matrix resulting from step 2 by the random variable generated in 3.
5. Multiply the triangular matrix resulting from step 4 by a vector of standard normal variates to obtain an experimental trial vector of equation parameters (they will have the required variance and covariance)
6. Generate residuals for all time periods as normal random variables with zero mean and the experimental variance obtained in step 3.
7. Repeat the same for all equations in the model and then solve the whole model (using also experimental values obtained with non-econometric methods

Repeat the whole process for the number of Monte Carlo runs

- A major problem encountered in the procedure described above has been the possibility of values that violate economic theory or downright common sense:
- Standard Least Squares estimation and statistical interpretation is based on the assumption of normality of error terms.

- This leads to parameter estimator distributions (Student t), which in theory imply the possibility that a parameter changes sign.
- While this may not always cause problems, in most cases economic theory (and common sense) stipulate a specific sign for key parameters.
- The problem is aggravated by the fact that many of the PROMETHEUS equations have rather poor statistics (high variances) for many estimated parameters (in itself a minor problem in the context of PROMETHEUS), which implies non-negligible probabilities for illegal values.
- Clearly such values cannot generally be tolerated and in the context of PROMETHEUS could prove particularly pernicious as in the course of Monte-Carlo runs they could be combined with extreme values for some results thus completely perverting the experiment Possible solutions to the problem presented above are:
- Assume a different distribution (log normal or some generalised form) for parameter estimators while attempting to maintain key properties (mean, variance, co-variance with other parameter estimators)
  - → Major drawback – complex specifications in order to maintain desired properties while at the same time arbitrary interventions cannot be avoided anyway
- Ignore illegal values (equivalent to scaling the distribution)
  - → Major drawback – different moments from those implied by the estimation
  - → Advantages: better respect to the initial "form" of distributions and naturally simplicity of implementation

NB Rejection of an illegal value must be accompanied by rejection of associated (and very probably legal) values for the other parameters in order to maintain the desired properties in the Monte- Carlo exercise

8.6. Example of a Prometheus Equation Estimation and Implementation: Coal Consumption in Industry OECD (other than Europe)

By way of illustration the case a step-by-step example of the procedure discussed in the previous section is presented below.

SER05=FINAL CONSUMPTION OF SOLID FUELS OF INDUSTRY (OTHER OECD)

SER01=GDP OF OTHER OECD

SER06= PRICE OF BITUMINOUS COAL

SER06/SER04=RELATIVE PRICE OF BITUMINOUS COAL / PRICE OF HEAVY FUEL OIL

PDL01= POLYNOMIAL DISTRIBUTED LAG OF (LOG PRICE FOR BITUMINOUS COAL) (Own Price)

PDL02,03= POLYNOMIAL DISTRIBUTED LAG Parameters FOR (LOG (PRICE OF COAL / PRICE OF HEAVY FUEL))

DUM1= DUMMY VARIABLE (for discontinuity in data)

Table 8-2: The econometric estimation using least squares

Dependent Variable: LOG (SER05)					
Sample (adjusted): 1985 1998					
Included observations: 14 after adjusting endpoints					
Variable	**Coefficient**		**Std. Error**	**t-Statistic**	**Prob.**
C	-0.113		0.035	-3.179	0.0130
LOG(SER01)	3.386		1.296	2.612	0.0310
DUM1	0.127		0.027	4.670	0.0016
PDL01	-0.128		0.289	-0.442	0.6697
PDL02	-0.051		0.033	-1.542	0.1616
PDL03	0.009		0.010	0.907	0.3908
R-squared	0.785		**Mean dependent var**		-0.011
Adjusted R-Squared	0.652		**S.D. dependent var**		0.059
S.E. of regression	0.034		**Akaike info criterion**		-3.577
Sum squared resid	0.009		**Schwarz criterion**		-3.303
Log likelihood	31.03		**F-statistic**		5.873
Durbin-Watson stat	2.339		**Prob(F-statistic)**		0.014

Lag Distribution of LOG(SER06)		**i**	**Coefficient**	**Std. Error**	**T-Statistic**
* .|		0	-0.096	0.217	-0.442
* .|		1	-0.128	0.289	-0.442
* .|		2	-0.096	0.217	-0.442
	Sum of Lags		***-0.320***	***0.724***	***-0.442***
Lag Distribution of LOG(SER06/SER04)		**i**	**Coefficient**	**Std. Error**	**T-Statistic**
* .|		0	-0.080	0.054	-1.495
* .|		1	-0.071	0.045	-1.556
* .|		2	-0.061	0.038	-1.591
* .|		3	-0.051	0.033	-1.542
* .|		4	-0.041	0.031	-1.331
* .|		5	-0.031	0.032	-0.969
* .|		6	-0.021	0.037	-0.584
	Sum of Lags		***-0.360***	***0.233***	***-1.542***

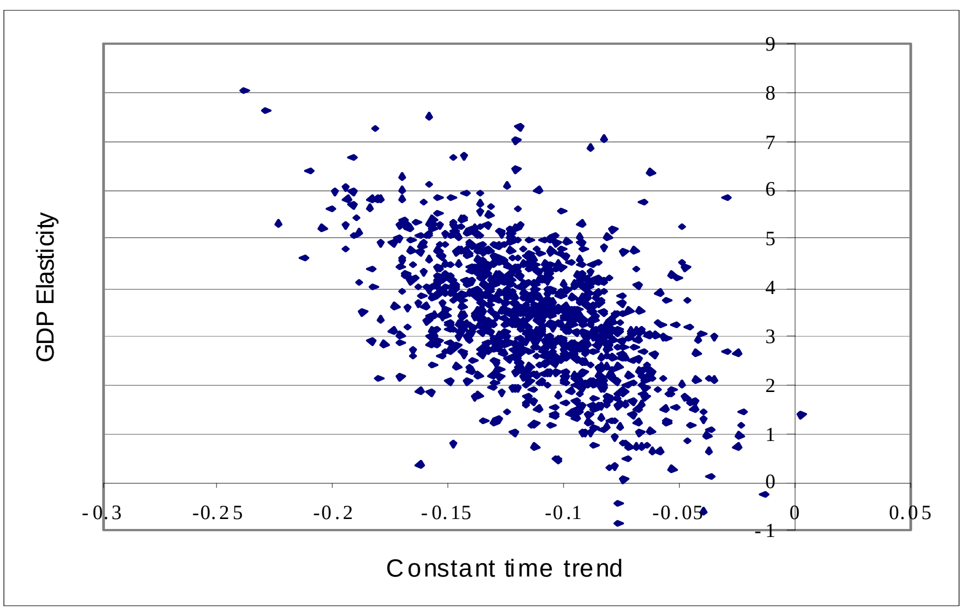
Table 8-3: Variance covariance matrix for parameter estimates occurring from the above estimation

	C	*LOG(SER01)*	*DUM1*	*PDL01*	*PDL02*	*PDL03*
C	0.0012	-0.0251	-0.0002	0.0043	9.9e-05	-0.0001
LOG(SER01)	-0.0251	1.6809	0.0148	0.1855	0.0174	-9.9e-05
DUM1	-0.0002	0.0148	0.0007	0.0011	7.9e-05	3.04e-05
PDL01	0.0043	0.1855	0.0011	0.0840	0.0057	-0.0015
PDL02	9.9e-05	0.0174	7.9e-05	0.0057	0.0011	-0.0001
PDL03	-0.0001	-9.9e-05	3.04e-05	-0.0015	-0.0001	0.00011

Table 8-4: Cholesky decomposition of the variance co-variance matrix

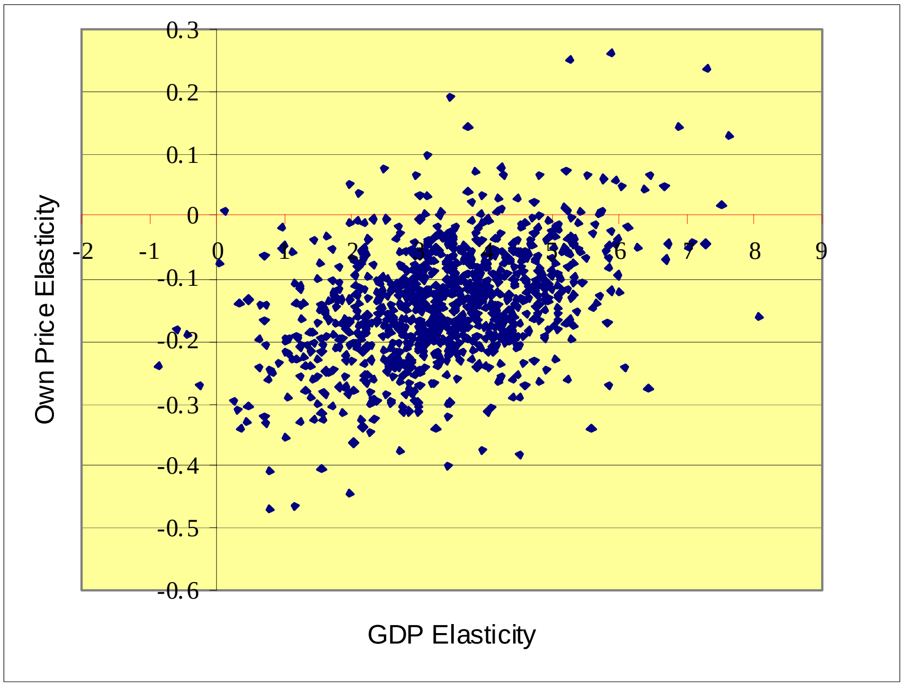
	C	*LOG(SER01)*	*DUM1*	*PDL01*	*PDL02*	*PDL03*
C	0.0356	0	0	0	0	0
LOG(SER01)	-0.7044	1.0884	0	0	0	0
DUM1	-0.0074	0.0088	0.0248	0	0	0
PDL01	0.1223	0.2496	-0.0042	0.0823	0	0
PDL02	0.0027	0.0177	-0.0022	0.0121	0.0252	0
PDL03	-0.0044	-0.0029	0.0009	-0.0031	-0.0008	0.008

Figure 8-1: Values of two of the parameters as they occur from the preliminary Monte-Carlo runs



In what concerns these two parameters most pairs of values are acceptable. However the four (out of a thousand) that lie below the horizontal axis must be rejected since their inclusion could lead to perverse model behaviour.

Figure 8-2: Values of two of the parameters as they occur from the preliminary Monte-Carlo runs



Concerning these two parameters apart from the four pairs rejected in the test presented above, all pairs of values lying above the horizontal axis must be rejected as they imply a positive price elasticity. They are clearly much more numerous and lead to a considerable number of additional Monte-Carlo experiments until all values are "acceptable".

8.7. PROMETHEUS Results

Having estimated and constructed PROMETHEUS, the model was run for one thousand times and preliminary results obtained. The results data set has proved to be of considerable interest with a large potential for analytical applications. Such work as is required for realizing this potential is only beginning and the results presented in this section are either indicative or constitute selected preliminary general remarks.

The table in the next page provides some summary statistics for a small selection of key variables at World level for the year 2030.

Table 8-5: Summary statistics for a small selection of key variables at World level for the year 2030.

KEY PROMETHEUS VARIABLES(WORLD 2030)	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Prob. Test for Normality	Prob. Test for Log Normality
Population th.	8112245.0	8114811.0	8359936.0	7765037.0	95308.7	-0.01	2.76	0.29	0.28
GDP million 95$	88538878.0	88400186.0	121000000.0	65340228.0	7365036.0	0.18	3.15	0.04	0.56
GDP per capita th. 95$	10.9	10.9	14.6	8.2	0.9	0.17	3.09	0.08	0.58
CO2 Emissions mil. tonnes	45650.5	44916.5	77663.8	26005.6	7603.9	0.58	3.56	0.00	0.59
Effective Carbon Value $95/t.Co2	34.6	30.3	211.7	0.0	20.7	1.71	9.56	0.00	0.13
Yet to be discovered conv. oil (Bil. Bl)	960.81	898.82	3243.57	248.20	369.96	1.30	6.36	0.00	0.69
Yet to be discovered gas (Trillion m3)	172.23	150.51	1044.61	30.56	100.43	2.62	15.66	0.00	0.00
World Oil price $95/bl	37.2	35.1	133.5	9.3	13.8	1.74	9.46	0.00	0.00
Gas Price $95/toe	223.7	209.5	679.7	61.9	88.1	1.08	4.84	0.00	0.14
Coal Price $95/tce	32.2	29.4	132.0	7.5	13.6	1.78	9.48	0.00	0.01
Middle East oil prod. Th.bl	29702078.0	29029130.0	53589551.0	9541125.0	5476927.0	0.82	4.64	0.00	0.00
Non-Conventional oil prod. Th.bl	4385976.0	3964064.0	13002069.0	322841.9	2434419.0	0.79	3.21	0.00	0.00
Non-Middle East Conv. oil prod. Th.bl	13451766.0	12713661.0	40240184.0	4830011.0	4435692.0	1.10	5.61	0.00	0.79
World oil prod. Th.bl	47539820.0	46702017.0	77454204.0	28651117.0	7542013.0	0.78	3.86	0.00	0.00
Oil Demand MTOE	6468.0	6354.0	10538.0	3898.1	1026.1	0.78	3.86	0.00	0.00
Nat. Gas Demand MTOE	3855.7	3794.9	5992.6	2283.6	570.0	0.62	3.48	0.00	0.06
Coal Demand MTOE	4261.2	4082.8	9479.0	1575.2	1339.1	0.80	3.81	0.00	0.43
Electricity Prod. TWH	37124.3	36628.0	58143.3	22859.0	5457.6	0.56	3.45	0.00	0.30
Final Cons. of Elec. Industry MTOE	1065.6	1045.0	2043.1	546.2	208.2	0.78	4.24	0.00	0.13
Final Cons. of Elec. Resid/Com MTOE	1445.9	1411.4	2780.5	847.1	261.6	0.73	3.82	0.00	0.02
Oil fired Power Prod. TWH	1286.3	1192.3	5202.1	481.4	465.7	2.10	12.40	0.00	0.00
Gas fired Power Prod. TWH	10107.0	9758.1	21241.1	4739.4	2545.6	0.73	3.76	0.00	0.60
Coal fired Power Prod. TWH	12512.5	12066.1	31200.1	3940.6	4166.3	0.76	4.04	0.00	0.01
Nuclear Power Prod. TWH	4017.1	3740.1	13344.2	2793.2	991.2	2.76	17.07	0.00	0.00
Large Hydro Power Prod. TWH	4954.7	4956.5	5575.6	4360.6	202.0	0.02	2.94	0.89	0.40
Power Prod. From NREN sources TWH	4246.8	3125.5	19270.3	101.4	3466.5	1.28	4.45	0.00	0.00

A cursory look at Table 8-5: Summary statistics for a small selection of key variables at World level for the year 2030. indicates that some variables like population, Large Hydro production but also GDP display relatively low variability. The broad energy aggregates such as demand for the main fuels and electricity as well as CO2 emissions display somewhat higher variability though of a similar relative order among them with the exception of coal which due to the uncertainties surrounding eventual measures to tackle the Climate Change issue, is characterized by higher variability. Primary fuel prices are apparently much more volatile in line with considerable uncertainties surrounding undiscovered resources of fossil fuels. Finally very high variability is displayed by non-conventional oil production (due mainly to variability in world oil prices), the effective carbon value and the contribution of new and renewable power generating options (due to an accumulation of uncertainties surrounding the two factor learning curves and hence their cost performance as well as carbon abatement policy in the context of an otherwise quite volatile energy environment).

With the exception of Hydro production and World population the probability that the Monte-Carlo samples come from normal distributions are negligible. On the other hand a much larger number of variables could be said to be possibly Log-Normally distributed. In fact skewness is reduced in almost all cases when passing to the logarithms of variables as is shown in the graph that follows.

Figure 8-3: Changes in skewness due to logarithmic transformation

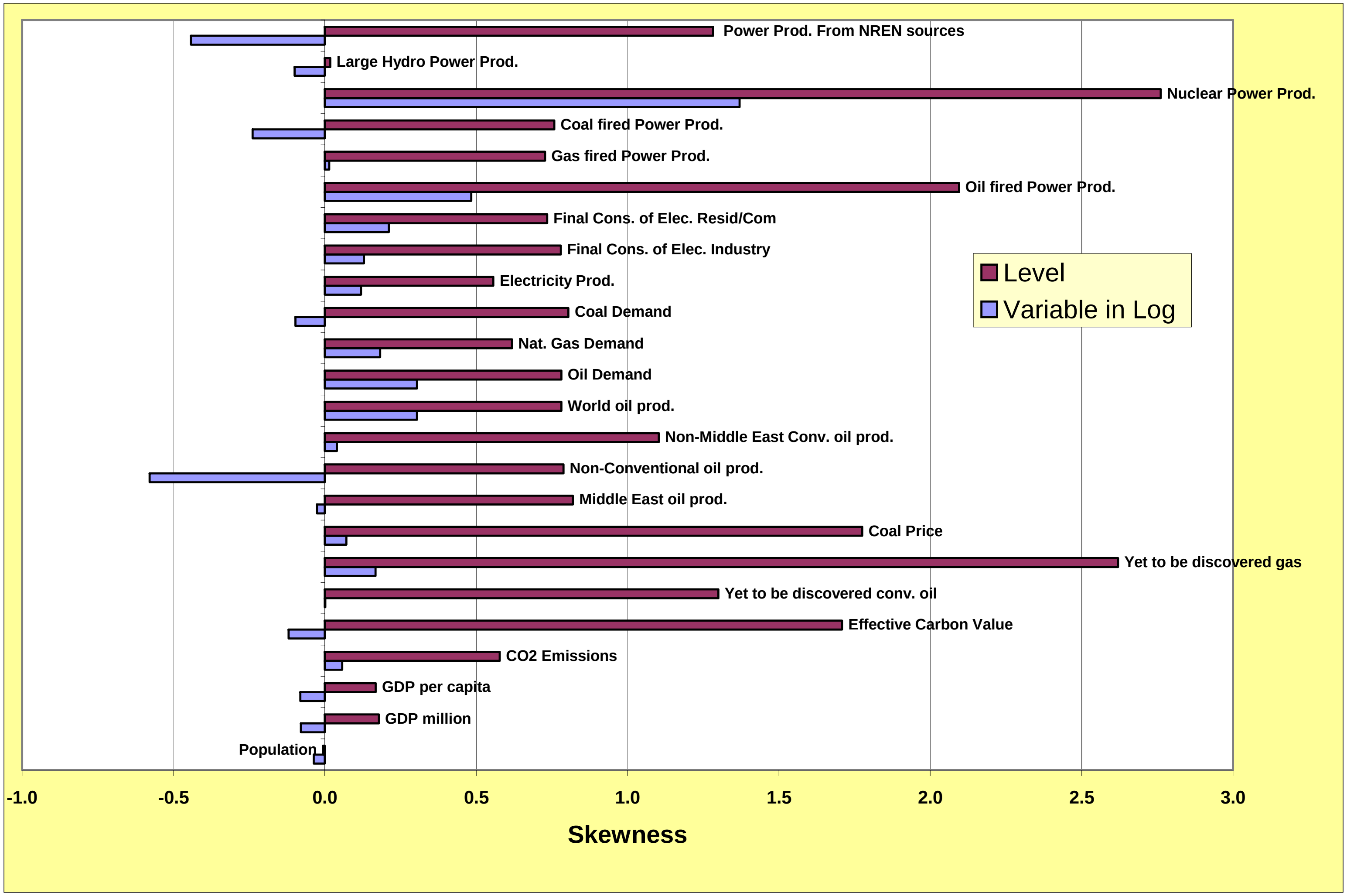


Table 8-6: Correlation matrix between the logarithms of key PROMETHEUS variables (2030)

Correlations between logs of key va	Population	GDP million	GDP per capita	CO2 Emissions	Effective Carbon Value	Yet to be discovered conv. oil	Yet to be discovered gas	World Oil price	Gas Price	Coal Price	Middle East oil prod.	Non-Conventional oil prod.	Non-Middle East Conv. oil prod.	World oil prod.	Oil Demand	Nat. Gas Demand	Coal Demand	Electricity Prod.	Final Cons. of Elec. Industry
Population	1.00	0.13	-0.01	0.13	0.01	-0.04	-0.02	0.10	0.09	0.09	0.11	0.06	0.00	0.10	0.10	0.11	0.09	0.09	0.06
GDP million	0.13	1.00	0.99	0.61	0.00	-0.02	-0.03	0.51	0.49	0.36	0.55	0.34	0.25	0.68	0.68	0.49	0.35	0.61	0.36
GDP per capita	-0.01	0.99	1.00	0.60	0.00	-0.02	-0.03	0.50	0.48	0.35	0.54	0.33	0.25	0.67	0.67	0.48	0.34	0.60	0.35
CO2 Emissions	0.13	0.61	0.60	1.00	-0.48	0.01	0.00	0.51	0.47	0.77	0.58	0.40	0.30	0.75	0.75	0.47	0.88	0.63	0.40
Effective Carbon Value	0.01	0.00	0.00	-0.48	1.00	0.00	0.01	-0.10	-0.08	-0.52	-0.07	-0.18	-0.07	-0.15	-0.15	-0.05	-0.60	-0.05	-0.05
Yet to be discovered conv. oil	-0.04	-0.02	-0.02	0.01	0.00	1.00	0.75	-0.46	-0.42	-0.20	-0.41	-0.42	0.86	0.09	0.09	0.28	-0.11	0.00	0.00
Yet to be discovered gas	-0.02	-0.03	-0.03	0.00	0.01	0.75	1.00	-0.35	-0.40	-0.17	-0.30	-0.30	0.65	0.07	0.07	0.26	-0.12	-0.03	-0.01
World Oil price	0.10	0.51	0.50	0.51	-0.10	-0.46	-0.35	1.00	0.74	0.45	0.77	0.54	-0.18	0.62	0.62	0.12	0.34	0.36	0.21
Gas Price	0.09	0.49	0.48	0.47	-0.08	-0.42	-0.40	0.74	1.00	0.47	0.57	0.51	-0.19	0.47	0.47	0.11	0.39	0.45	0.20
Coal Price	0.09	0.36	0.35	0.77	-0.52	-0.20	-0.17	0.45	0.47	1.00	0.41	0.41	-0.01	0.43	0.43	0.19	0.83	0.43	0.28
Middle East oil prod.	0.11	0.55	0.54	0.58	-0.07	-0.41	-0.30	0.77	0.57	0.41	1.00	0.35	-0.10	0.76	0.76	0.15	0.35	0.40	0.25
Non-Conventional oil prod.	0.06	0.34	0.33	0.40	-0.18	-0.42	-0.30	0.54	0.51	0.41	0.35	1.00	-0.19	0.45	0.45	0.00	0.32	0.25	0.14
Non-Middle East Conv. oil prod.	0.00	0.25	0.25	0.30	-0.07	0.86	0.65	-0.18	-0.19	-0.01	-0.10	-0.19	1.00	0.47	0.47	0.37	0.07	0.18	0.10
World oil prod.	0.10	0.68	0.67	0.75	-0.15	0.09	0.07	0.62	0.47	0.43	0.76	0.45	0.47	1.00	1.00	0.35	0.40	0.49	0.31
Oil Demand	0.10	0.68	0.67	0.75	-0.15	0.09	0.07	0.62	0.47	0.43	0.76	0.45	0.47	1.00	1.00	0.35	0.40	0.49	0.31
Nat. Gas Demand	0.11	0.49	0.48	0.47	-0.05	0.28	0.26	0.12	0.11	0.19	0.15	0.00	0.37	0.35	0.35	1.00	0.22	0.54	0.28
Coal Demand	0.09	0.35	0.34	0.88	-0.60	-0.11	-0.12	0.34	0.39	0.83	0.35	0.32	0.07	0.40	0.40	0.22	1.00	0.49	0.32
Electricity Prod.	0.09	0.61	0.60	0.63	-0.05	0.00	-0.03	0.36	0.45	0.43	0.40	0.25	0.18	0.49	0.49	0.54	0.49	1.00	0.71
Final Cons. of Elec. Industry	0.06	0.36	0.35	0.40	-0.05	0.00	-0.01	0.21	0.20	0.28	0.25	0.14	0.10	0.31	0.31	0.28	0.32	0.71	1.00
Final Cons. of Elec. Resid/Com	0.08	0.59	0.58	0.59	-0.06	0.00	-0.03	0.35	0.47	0.40	0.36	0.24	0.18	0.46	0.46	0.54	0.44	0.83	0.20
Oil fired Power Prod.	-0.01	0.09	0.09	0.41	-0.28	0.19	0.10	-0.10	0.09	0.40	-0.03	-0.09	0.20	0.07	0.07	0.22	0.51	0.50	0.21
Gas fired Power Prod.	0.05	0.17	0.16	0.24	-0.01	0.36	0.30	-0.14	-0.11	0.05	-0.10	-0.15	0.34	0.08	0.08	0.74	0.10	0.44	0.21
Coal fired Power Prod.	0.07	0.42	0.42	0.75	-0.45	-0.18	-0.18	0.43	0.52	0.69	0.42	0.38	0.03	0.46	0.46	0.24	0.77	0.65	0.43
Nuclear Power Prod.	0.08	0.26	0.25	-0.03	0.55	-0.14	-0.14	0.19	0.22	-0.04	0.22	0.06	-0.07	0.15	0.15	0.03	-0.14	0.21	0.17
Large Hydro Power Prod.	-0.03	0.01	0.01	-0.11	0.28	-0.07	-0.09	0.02	0.02	-0.11	0.03	0.01	-0.06	-0.01	-0.01	-0.07	-0.15	0.01	0.01
Power Prod. From NREN sources	0.00	0.24	0.24	-0.13	0.34	-0.03	-0.01	0.13	0.09	-0.19	0.13	0.06	0.00	0.11	0.11	0.00	-0.26	0.25	0.27

The preceding table gives the correlations of the key variables for 2030 as a crude measure of their stochastic interdependence as it arises from PROMETHEUS runs. The logarithms have been used following the evidence presented above that the variables are more likely to be distributed according to Log Normal distribution.

The most notable observation arising from the table is the dominance of positive correlations even between prices and the corresponding consumption categories. This indicates a relative dominance of supply constraints in price formation. Important strategy implications arise from such a state of matters: variability in the future seems to extend predominantly along an axis ranging from low to high activity, energy consumption, GHG emissions and prices.

The tables below highlight in somewhat greater detail the distribution of some macro-economic aggregates as a matter of further illustration

Table 8-7: Correlation matrix Prometheus output (macro aggregates)

	CDP/CAP (World)	GDP/CAP OECD (No Europe)	GDP/CAP OECD (Europe)	GDP/CAP Non OECD Countries	POP OECD (No Europe)	POP OECD (Europe)	POP Non OECD Countries	POP World
CDP/CAP (World)	1.000	0.709	0.634	0.921	0.029	-0.017	-0.026	-0.026
GDP/CAP OECD (No Europe)	0.709	1.000	0.563	0.427	0.028	0.041	0.037	0.042
GDP/CAP OECD (Europe)	0.634	0.563	1.000	0.377	0.024	-0.007	0.006	0.007
GDP/CAP Non OECD Countries	0.921	0.427	0.377	1.000	0.007	-0.059	-0.023	-0.027
POP OECD (No Europe)	0.029	0.028	0.024	0.007	1.000	0.180	-0.012	0.054
POP OECD (Europe)	-0.017	0.041	-0.007	-0.059	0.180	1.000	0.020	0.107
POP Non OECD Countries	-0.026	0.037	0.006	-0.023	-0.012	0.020	1.000	0.994
POP WORLD	-0.026	0.042	0.007	-0.027	0.054	0.107	0.994	1.000

Figure 8-4: Distribution of Annual Percent Growth in population 2000-2030

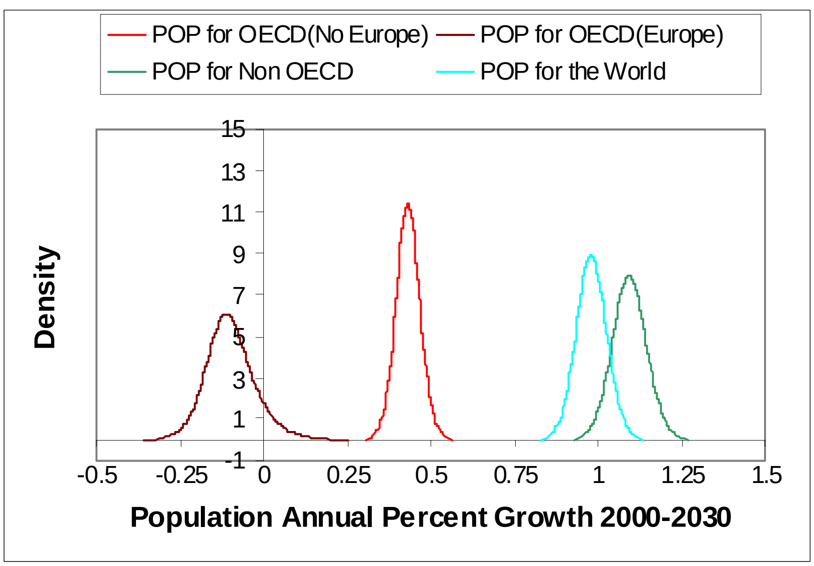
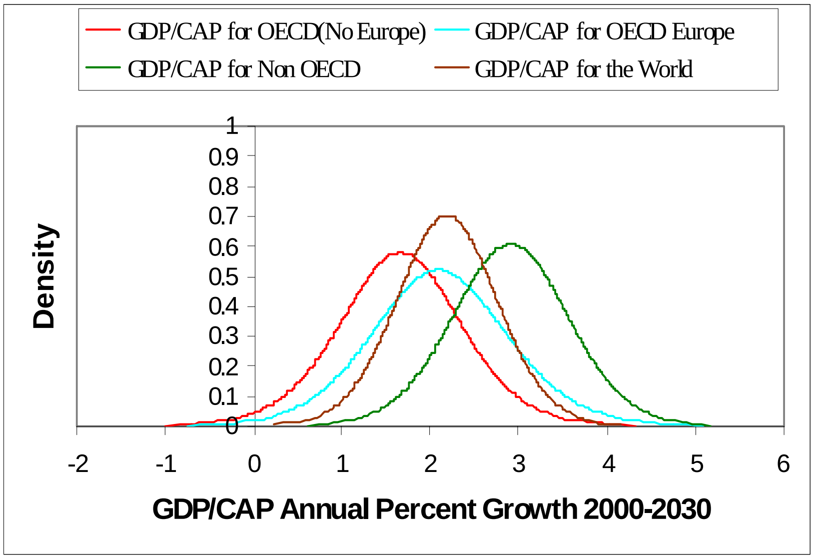
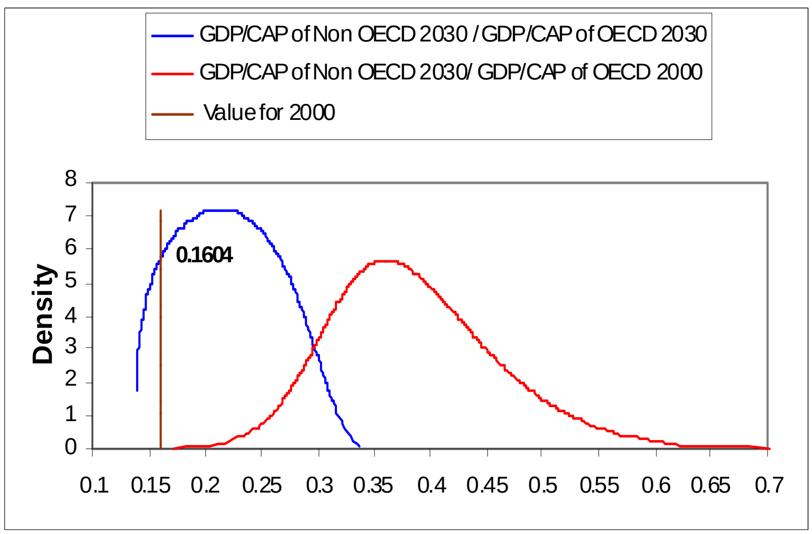


Figure 8-5: Distribution of Annual Percent Growth 2000-2030 of GDP per capita





Following is a review of the objectives partners have decided to retain in the course of the various SAPIENT meetings together with suggestions for their measurement. Needless to say that using common measurements was essential in order to avoid total confusion at the stage of ISPA integration. ICCS/NTUA integrated these objectives in PROMETHEUS in the form that is presented below.

8.8. Implementation and Results of Target Variables

The following section concentrates on the methodology and the measurement of impacts of injecting R&D expenditure shocks on some key energy technologies with respect to the policy objectives specified previously in the course of the ISPA modelling (Section 7.2). Some general considerations with regard to the objective analysis have already been presented in that section. In the course of experimentation with PROMETHEUS however, some additional assumptions had to be specified. Section 8.8.1 below reports on these, while section 8.8.2 presents the PROMETHEUS output for the R&D impacts on the different objectives.

8.8.1. General Considerations

In the course of the various SAPIENT meetings alternative objective measurement options have been analysed along with suggestions for their complete specification. Needless to say that using common measurements was essential in order to avoid total confusion at the stage of ISPA integration.

ICCS/NTUA integrated these objectives in PROMETHEUS having first specified some key assumptions for the analysis.
Regarding the CO2 constraint it was decided in Amsterdam that the IEPE "soft landing" scenario should be used as a kind of expected carbon limitation scenario. Due to poor response to the Delphi vote concerning carbon limitation and after consultations with P. Criqui the following scenario on effective carbon values was formulated for use in PROMETHEUS.

Table 8-8: Probability assumptions on abatement effort

For the period to 2010	Probability that no action is taken	Expected Value in $1995 per Tonne of CO2 in case action is taken
European Union	5%	15
Rest of Annex B	40%	6
Rest of the World	100%	NA

For the period to 2030	Probability that no action is taken	Expected Value in $1995 per Tonne of CO2 in case action is taken
World	20%	33

For the purposes of PROMETHEUS it was assumed that the carbon values were distributed as log normal variates and that regions would not undertake a lesser effort in the period to 2030 than they undertook up to 2010. Furthermore the incidence of carbon values is assumed to be independent of emission outcomes (i.e. a high emission trajectory does not in itself trigger off a tighter abatement policy). This can be considered as a shortcoming and could be corrected in a future version of PROMETHEUS, but the rules of modulation will have to be established before this change is performed.

As far as the baseline Outlook for R&D (private and public) is concerned, all models should use one constant intensity for Public R&D measured on GDP, and another constant intensity for Private R&D measured on sales of equipment. The intensities were calculated from the last available data point in IEPE's data set.

The graphs below give the distributions for the effective carbon value in the world (2030) and the EU and Rest of Annex B to 2010.

Figure 8-6: Distribution of Effective carbon value 2011-2030

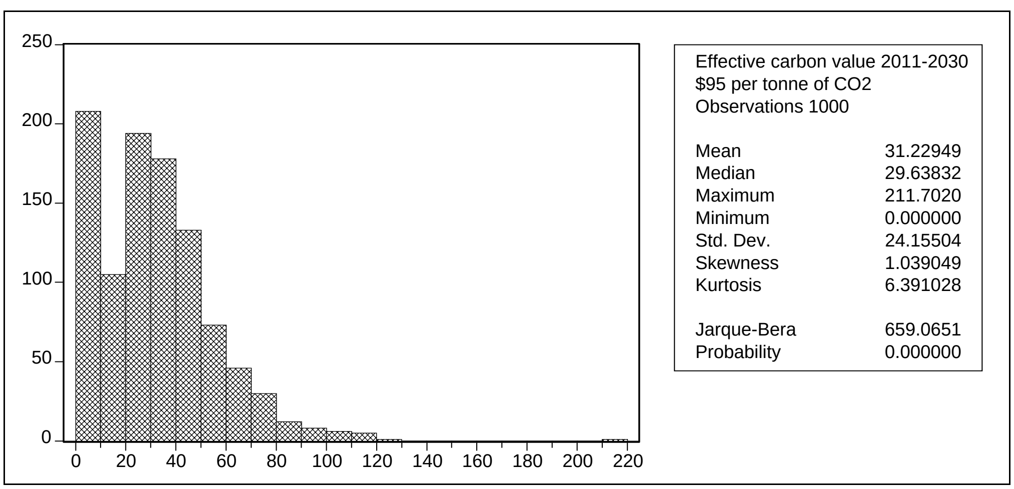


Figure 8-7: Distribution of Effective carbon value for the EU to 2010

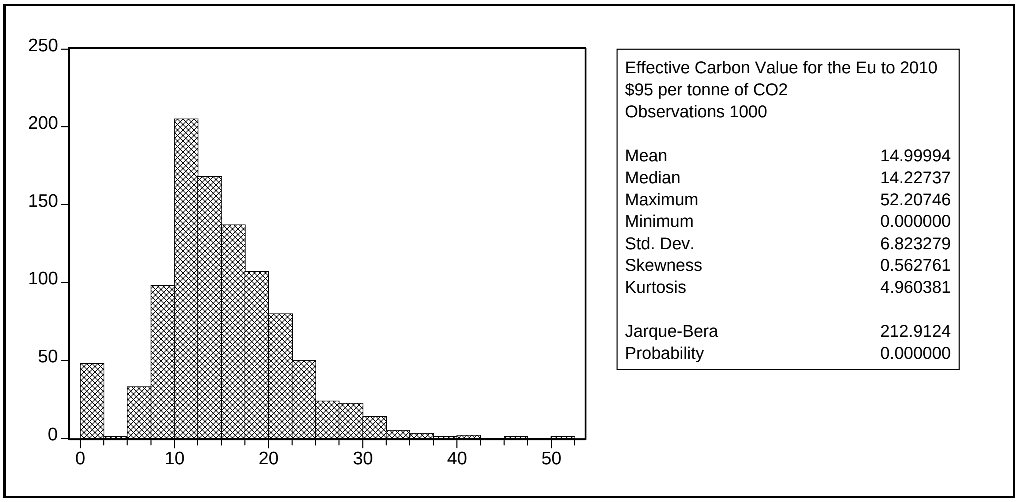
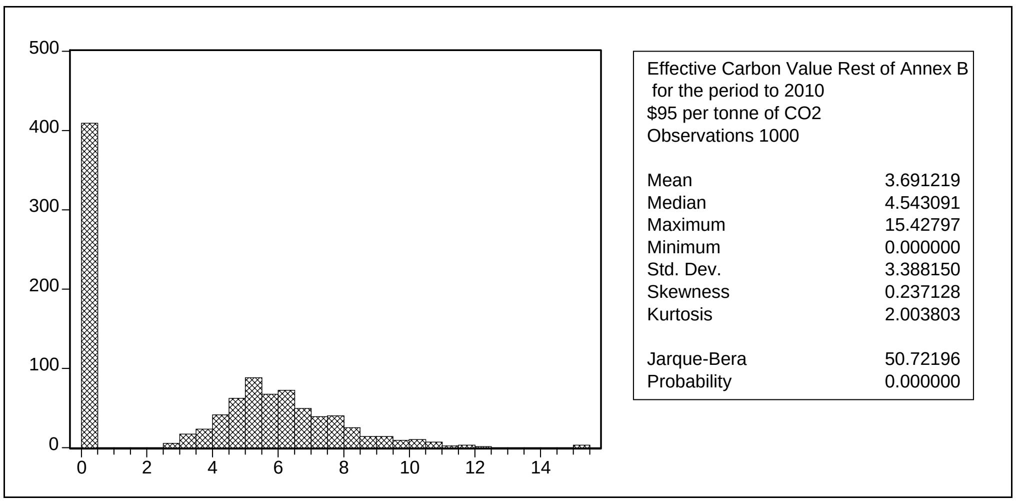


Figure 8-8: Distribution of Effective carbon value Rest of Annex B for the period to 2010



It is important that the model reference cases could incorporate the average abatement policies as appropriate. Failure to do so would imply that experiment results arising from the R&D shocks would not represent expected values in the proper sense (or alternatively that we consider that the probability of any abatement policy to 2030 is zero, which is patently absurd).

8.8.2. PROMETHEUS results on the impacts of the R&D objectives

As shown previously, the final set of policy objectives under scrutiny at the ISPA stage have been integrated in PROMETHEUS and key results have been delivered. In implementing the R&D impact analysis in PROMETHEUS it has been necessary to perform the R&D shocks one by one running a full one thousand experiment Monte-Carlo set for each technology. Specific care has been given to ensuring that all parameter values, stochastic exogenous variables and residuals were identically generated. This has proved necessary since the impact was more often than not small relative to the quantities measured and the additional variation arising from independent experiments would tend to swamp the result.

The tables following this section present some summary statistics (mean, median, standard deviation, skewness, Kurtosis and a test for normality) as well as correlation matrices for the impacts on the different objectives as developed in this section

TARGET: CUM. CO2 CHANGE

	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Jarque-Bera
Advanced Thermodynamic Cycle (coal)	0.04	0.03	0.22	0.00	0.02	1.59	8.29	1588
Biomass Gasification Gas Turbine	-0.67	-0.37	0.05	-7.18	0.88	-3.29	18.17	11393
CHP with Combined Cycle	0.05	0.03	0.58	-0.05	0.06	2.52	13.86	5979
Decentralised Photovoltaic cells	-0.09	-0.06	0.14	-1.07	0.09	-2.66	18.68	11416
Gas Turbine in Combined Cycle	-0.44	-0.43	0.03	-1.23	0.25	-0.38	2.72	27
Integrated Coal Gasification	0.18	0.16	0.84	-0.04	0.10	1.02	6.11	575
Advanced Lignite	0.07	0.06	0.26	0.00	0.04	0.90	4.24	200
Fuel Cell Power Generation	-0.04	-0.01	1.23	-0.85	0.13	-0.31	18.00	9385
New Evolutionary Nuclear Design	-0.01	-0.01	0.00	-0.10	0.01	-2.60	13.57	5777
Oil Fired Gas Turbine	0.22	0.18	1.43	-0.02	0.17	1.73	8.03	1556
Super Critical Coal	0.42	0.40	1.78	0.01	0.20	1.11	5.98	574
Small Hydro	-8.62	-6.16	1.02	-48.07	8.03	-1.51	5.45	629
Solar Thermal Power	-0.13	-0.05	0.05	-2.08	0.23	-4.21	27.41	27772
Wind Turbines	-0.85	-0.62	0.33	-5.05	0.76	-1.80	7.76	1484

TARGET: CUM. CO2 CHANGE

CORRELATION MATRIX	Advanced Thermodynamic Cycle (coal)	Biomass Gasification Gas Turbine	CHP with Combined Cycle	Decentralised Photovoltaic cells	Gas Turbine in Combined Cycle	Integrated Coal Gasification	Advanced Lignite	Fuel Cell Power Generation	New Evolutionary Nuclear Design	Oil Fired Gas Turbine	Super Critical Coal	Small Hydro	Solar Thermal Power
Advanced Thermodynamic Cycle (coal)	1.000	-0.222	-0.005	0.042	0.059	0.348	0.037	0.036	-0.033	-0.134	0.271	-0.290	0.016
Biomass Gasification Gas Turbine	**-0.222**	1.000	-0.350	-0.083	-0.229	-0.244	0.032	-0.009	-0.158	0.117	-0.205	0.196	-0.051
CHP with Combined Cycle	-0.005	**-0.350**	1.000	0.008	0.072	0.049	-0.026	0.160	0.168	-0.004	0.029	-0.104	-0.065
Decentralised Photovoltaic cells	0.042	-0.083	0.008	1.000	-0.015	-0.053	-0.031	0.015	-0.019	-0.034	-0.023	-0.011	0.105
Gas Turbine in Combined Cycle	0.059	**-0.229**	0.072	-0.015	1.000	0.025	-0.016	-0.132	0.076	-0.163	-0.020	-0.124	0.009
Integrated Coal Gasification	**0.348**	**-0.244**	0.049	-0.053	0.025	1.000	0.083	0.078	-0.035	-0.165	0.481	-0.326	0.022
Advanced Lignite	0.037	0.032	-0.026	-0.031	-0.016	0.083	1.000	-0.056	-0.022	0.071	0.059	0.004	-0.028
Fuel Cell Power Generation	0.036	-0.009	0.160	0.015	-0.132	0.078	-0.056	1.000	0.080	0.073	0.002	-0.060	0.029
New Evolutionary Nuclear Design	-0.033	-0.158	0.168	-0.019	0.076	-0.035	-0.022	0.080	1.000	0.048	-0.041	-0.174	-0.044
Oil Fired Gas Turbine	-0.134	0.117	-0.004	-0.034	-0.163	-0.165	0.071	0.073	0.048	1.000	-0.109	0.098	-0.107
Super Critical Coal	**0.271**	**-0.205**	0.029	-0.023	-0.020	**0.481**	0.059	0.002	-0.041	-0.109	1.000	-0.264	-0.008
Small Hydro	**-0.290**	0.196	-0.104	-0.011	-0.124	**-0.326**	0.004	-0.060	-0.174	0.098	**-0.264**	1.000	-0.045
Solar Thermal Power	0.016	-0.051	-0.065	0.105	0.009	0.022	-0.028	0.029	-0.044	-0.107	-0.008	-0.045	1.000
Wind Turbines	**-0.309**	0.086	-0.132	-0.061	-0.189	**-0.364**	-0.074	-0.119	**-0.209**	0.057	**-0.271**	**0.273**	-0.029

TARGET: "PROFITABILITY"

	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Jarque-Bera
Advanced Thermodynamic Cycle (coal)	0.08	0.06	0.57	0.00	0.07	2.01	8.96	2156
Biomass Gasification Gas Turbine	10.29	6.46	106.04	0.03	12.03	2.68	13.33	5644
CHP with Combined Cycle	0.69	0.43	8.43	0.00	0.82	3.26	20.56	14616
Decentralised Photovoltaic cells	3.18	1.87	50.81	0.00	3.98	3.89	31.80	37076
Gas Turbine in Combined Cycle	10.56	10.13	32.92	0.00	6.54	0.38	2.55	32
Integrated Coal Gasification	3.88	3.29	20.82	0.00	2.85	1.61	7.09	1129
Advanced Lignite	0.20	0.13	1.58	0.00	0.22	2.22	9.58	2625
Fuel Cell Power Generation	3.15	1.47	48.48	0.00	4.94	3.94	24.50	21852
New Evolutionary Nuclear Design	0.02	0.02	0.26	0.00	0.02	3.26	24.03	20205
Oil Fired Gas Turbine	0.87	0.59	7.49	0.00	0.97	2.34	10.79	3443
Super Critical Coal	3.07	2.69	15.13	0.00	2.06	1.17	4.99	395
Small Hydro	266.48	145.86	2668.76	0.82	317.89	2.44	11.20	3792
Solar Thermal Power	6.83	2.60	83.05	0.00	10.84	3.17	16.07	8797
Wind Turbines	22.29	18.82	112.80	0.16	16.92	1.58	6.61	959

TARGET: "PROFITABILITY"

CORRELATION MATRIX	Advanced Thermodynamic Cycle (coal)	Biomass Gasification Gas Turbine	CHP with Combined Cycle	Decentralised Photovoltaic cells	Gas Turbine in Combined Cycle	Integrated Coal Gasification	Advanced Lignite	Fuel Cell Power Generation	New Evolutionary Nuclear Design	Oil Fired Gas Turbine	Super Critical Coal	Small Hydro	Solar Thermal Power
Advanced Thermodynamic Cycle (coal)	1.000	-0.024	0.021	-0.070	-0.071	0.055	0.055	0.030	0.039	0.044	0.056	-0.041	-0.015
Biomass Gasification Gas Turbine	-0.024	1.000	0.125	0.054	-0.063	-0.060	-0.049	0.077	-0.112	-0.087	-0.043	0.301	0.022
CHP with Combined Cycle	0.021	0.125	1.000	0.072	-0.077	0.004	-0.023	0.120	-0.015	-0.016	-0.041	0.024	0.052
Decentralised Photovoltaic cells	-0.070	0.054	0.072	1.000	-0.059	-0.003	-0.034	-0.008	-0.024	0.003	-0.062	0.086	0.150
Gas Turbine in Combined Cycle	-0.071	-0.063	-0.077	-0.059	1.000	-0.035	-0.002	-0.061	-0.008	0.038	0.004	-0.053	-0.019
Integrated Coal Gasification	0.055	-0.060	0.004	-0.003	-0.035	1.000	0.113	-0.037	0.034	0.015	0.204	-0.103	0.035
Advanced Lignite	0.055	-0.049	-0.023	-0.034	-0.002	0.113	1.000	0.003	-0.015	0.084	0.056	-0.068	0.021
Fuel Cell Power Generation	0.030	0.077	0.120	-0.008	-0.061	-0.037	0.003	1.000	-0.027	0.006	0.037	-0.050	0.007
New Evolutionary Nuclear Design	0.039	-0.112	-0.015	-0.024	-0.008	0.034	-0.015	-0.027	1.000	-0.008	0.023	-0.080	-0.019
Oil Fired Gas Turbine	0.044	-0.087	-0.016	0.003	0.038	0.015	0.084	0.006	-0.008	1.000	0.021	-0.084	0.054
Super Critical Coal	0.056	-0.043	-0.041	-0.062	0.004	0.204	0.056	0.037	0.023	0.021	1.000	-0.099	-0.003
Small Hydro	-0.041	**0.301**	0.024	0.086	-0.053	-0.103	-0.068	-0.050	-0.080	-0.084	-0.099	1.000	-0.023
Solar Thermal Power	-0.015	0.022	0.052	0.150	-0.019	0.035	0.021	0.007	-0.019	0.054	-0.003	-0.023	1.000
Wind Turbines	-0.032	**0.311**	0.043	0.167	-0.088	-0.034	0.033	0.025	-0.157	-0.069	-0.071	**0.314**	0.110

TARGET: "SECURITY OF SUPPLY"

	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Jarque-Bera
Advanced Thermodynamic Cycle (coal)	-1.71	-1.23	2.30	-29.78	2.04	-4.35	43.52	71560
Biomass Gasification Gas Turbine	-8.78	-3.08	36.83	-374.92	20.31	-8.29	118.79	570112
CHP with Combined Cycle	3.19	1.77	66.61	-67.37	6.62	1.36	34.20	40869
Decentralised Photovoltaic cells	-0.47	-0.24	3.36	-7.76	0.97	-2.64	16.47	8719
Gas Turbine in Combined Cycle	6.46	4.23	103.22	-69.81	18.20	0.56	7.83	1024
Integrated Coal Gasification	-8.34	-6.17	12.51	-81.58	9.11	-2.35	12.80	4921
Advanced Lignite	-0.85	-0.60	0.23	-9.93	0.96	-3.16	19.59	13129
Fuel Cell Power Generation	2.28	0.64	146.28	-25.18	7.40	9.17	154.55	970938
New Evolutionary Nuclear Design	-0.17	-0.09	0.09	-3.16	0.27	-5.39	45.85	81343
Oil Fired Gas Turbine	20.71	11.28	237.03	-117.03	37.88	1.73	8.72	1862
Super Critical Coal	-16.12	-12.69	14.09	-100.53	15.31	-1.94	8.33	1810
Small Hydro	-79.01	-40.22	129.55	-2098.31	128.14	-6.46	80.41	256662
Solar Thermal Power	-1.17	-0.26	9.05	-55.94	3.12	-7.89	108.49	474004
Wind Turbines	-6.26	-3.58	24.99	-88.73	9.91	-2.88	18.45	11331

TARGET: "SECURITY OF SUPPLY"

CORRELATION MATRIX	Advanced Thermodynamic Cycle (coal)	Biomass Gasification Gas Turbine	CHP with Combined Cycle	Decentralised Photovoltaic cells	Gas Turbine in Combined Cycle	Integrated Coal Gasification	Advanced Lignite	Fuel Cell Power Generation	New Evolutionary Nuclear Design	Oil Fired Gas Turbine	Super Critical Coal	Small Hydro	Solar Thermal Power
Advanced Thermodynamic Cycle (coal)	1.000	0.130	-0.047	0.149	0.010	0.635	0.418	-0.324	0.220	-0.430	0.579	0.266	0.108
Biomass Gasification Gas Turbine	0.130	1.000	-0.219	-0.034	-0.085	0.131	0.111	-0.090	0.066	-0.029	0.143	0.186	-0.010
CHP with Combined Cycle	-0.047	**-0.219**	1.000	-0.065	0.249	-0.006	-0.089	0.235	-0.103	-0.188	-0.002	0.009	-0.222
Decentralised Photovoltaic cells	0.149	-0.034	-0.065	1.000	-0.032	0.251	0.192	-0.056	0.074	-0.111	0.216	0.263	0.183
Gas Turbine in Combined Cycle	0.010	-0.085	0.249	-0.032	1.000	0.106	-0.078	0.226	-0.186	-0.492	0.052	0.016	-0.067
Integrated Coal Gasification	**0.635**	0.131	-0.006	0.251	0.106	1.000	0.527	-0.115	0.264	-0.541	0.749	0.253	0.175
Advanced Lignite	**0.418**	0.111	-0.089	0.192	-0.078	**0.527**	1.000	-0.112	0.214	-0.317	0.565	0.180	0.151
Fuel Cell Power Generation	**-0.324**	-0.090	**0.235**	-0.056	0.226	-0.115	-0.112	1.000	-0.090	0.029	-0.113	-0.118	-0.052
New Evolutionary Nuclear Design	**0.220**	0.066	-0.103	0.074	-0.186	**0.264**	0.214	-0.090	1.000	-0.054	0.292	0.036	0.024
Oil Fired Gas Turbine	**-0.430**	-0.029	-0.188	-0.111	-0.492	**-0.541**	**-0.317**	0.029	-0.054	1.000	-0.530	-0.236	-0.069
Super Critical Coal	**0.579**	0.143	-0.002	**0.216**	0.052	**0.749**	**0.565**	-0.113	**0.292**	**-0.530**	1.000	0.257	0.161
Small Hydro	**0.266**	0.186	0.009	**0.263**	0.016	**0.253**	0.180	-0.118	0.036	**-0.236**	**0.257**	1.000	0.019
Solar Thermal Power	0.108	-0.010	-0.222	0.183	-0.067	0.175	0.151	-0.052	0.024	-0.069	0.161	0.019	1.000
Wind Turbines	**0.217**	0.089	-0.150	**0.263**	0.039	**0.259**	0.151	-0.159	0.042	-0.187	0.195	**0.524**	0.076

TARGET: CHANGE IN EN. COST (EUROPE)

	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Jarque-Bera
Advanced Thermodynamic Cycle (coal)	-0.22	-0.20	0.06	-1.04	0.12	-1.37	7.01	982
Biomass Gasification Gas Turbine	-2.28	-1.23	0.40	-37.07	3.16	-4.13	29.32	31709
CHP with Combined Cycle	-0.51	-0.43	1.93	-3.23	0.60	-0.71	5.45	335
Decentralised Photovoltaic cells	0.53	0.22	9.39	-0.34	0.90	3.50	22.38	17686
Gas Turbine in Combined Cycle	-2.86	-2.80	0.92	-10.31	1.55	-0.60	4.16	117
Integrated Coal Gasification	-1.30	-1.20	-0.16	-4.45	0.57	-1.05	4.94	341
Advanced Lignite	-0.73	-0.70	-0.02	-2.66	0.40	-0.67	3.55	88
Fuel Cell Power Generation	-0.07	0.00	1.85	-3.56	0.50	-2.06	13.67	5447
New Evolutionary Nuclear Design	-0.04	-0.03	0.02	-0.49	0.04	-3.64	25.85	23971
Oil Fired Gas Turbine	2.29	1.89	12.98	-0.08	1.76	1.89	8.93	2060
Super Critical Coal	-2.16	-1.98	-0.34	-6.28	0.96	-0.99	4.21	223
Small Hydro	-14.27	-11.31	29.70	-142.30	16.78	-2.09	12.11	4191
Solar Thermal Power	-0.03	-0.01	2.44	-1.84	0.20	0.71	41.33	61292
Wind Turbines	-2.20	-0.98	4.75	-32.26	3.80	-2.29	10.82	3418

TARGET: CHANGE IN EN. COST (EUROPE)

CORRELATION MATRIX	Advanced Thermodynamic Cycle (coal)	Biomass Gasification Gas Turbine	CHP with Combined Cycle	Decentralised Photovoltaic cells	Gas Turbine in Combined Cycle	Integrated Coal Gasification	Advanced Lignite	Fuel Cell Power Generation	New Evolutionary Nuclear Design	Oil Fired Gas Turbine	Super Critical Coal	Small Hydro	Solar Thermal Power
Advanced Thermodynamic Cycle (coal)	1.000	-0.071	-0.094	-0.044	-0.069	0.369	0.103	0.000	0.018	-0.182	0.361	-0.037	0.130
Biomass Gasification Gas Turbine	-0.071	1.000	-0.057	-0.099	-0.153	-0.068	-0.081	0.028	-0.087	0.082	-0.099	0.130	-0.149
CHP with Combined Cycle	-0.094	-0.057	1.000	-0.122	-0.147	-0.117	-0.061	0.296	-0.069	-0.040	-0.164	-0.012	-0.168
Decentralised Photovoltaic cells	-0.044	-0.099	-0.122	1.000	0.136	-0.058	0.024	-0.118	-0.047	-0.054	0.007	-0.093	0.070
Gas Turbine in Combined Cycle	-0.069	-0.153	-0.147	0.136	1.000	-0.072	0.025	-0.166	0.036	-0.207	-0.034	-0.107	0.069
Integrated Coal Gasification	**0.369**	-0.068	-0.117	-0.058	-0.072	1.000	0.154	-0.017	0.031	-0.135	0.582	-0.039	0.168
Advanced Lignite	0.103	-0.081	-0.061	0.024	0.025	0.154	1.000	-0.027	-0.021	0.020	0.124	0.010	0.035
Fuel Cell Power Generation	0.000	0.028	**0.296**	-0.118	-0.166	-0.017	-0.027	1.000	-0.052	0.014	-0.006	-0.009	-0.019
New Evolutionary Nuclear Design	0.018	-0.087	-0.069	-0.047	0.036	0.031	-0.021	-0.052	1.000	0.025	0.030	-0.041	0.041
Oil Fired Gas Turbine	-0.182	0.082	-0.040	-0.054	**-0.207**	-0.135	0.020	0.014	0.025	1.000	-0.159	0.045	-0.099
Super Critical Coal	**0.361**	-0.099	-0.164	0.007	-0.034	**0.582**	0.124	-0.006	0.030	-0.159	1.000	-0.090	0.177
Small Hydro	-0.037	0.130	-0.012	-0.093	-0.107	-0.039	0.010	-0.009	-0.041	0.045	-0.090	1.000	-0.026
Solar Thermal Power	0.130	-0.149	-0.168	0.070	0.069	0.168	0.035	-0.019	0.041	-0.099	0.177	-0.026	1.000
Wind Turbines	-0.098	0.040	0.085	**-0.275**	-0.152	-0.146	-0.063	-0.011	-0.192	0.046	**-0.218**	0.132	**-0.202**

TARGET: CHANGE IN EN. COST (R.O.W.)

	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Jarque-Bera
Advanced Thermodynamic Cycle (coal)	-0.06	-0.05	0.29	-0.47	0.05	-1.90	14.08	5713
Biomass Gasification Gas Turbine	-0.64	-0.26	0.19	-9.63	1.01	-3.43	19.15	12820
CHP with Combined Cycle	0.08	0.06	0.77	-0.68	0.11	0.28	10.05	2085
Decentralised Photovoltaic cells	0.31	0.19	2.77	-1.05	0.38	2.45	12.14	4480
Gas Turbine in Combined Cycle	-1.52	-1.48	0.04	-4.37	0.67	-0.45	3.21	35
Integrated Coal Gasification	-0.47	-0.42	-0.04	-2.18	0.26	-1.34	6.14	711
Advanced Lignite	-0.06	-0.06	0.00	-0.19	0.03	-0.90	3.99	177
Fuel Cell Power Generation	-0.10	0.00	0.28	-2.99	0.25	-4.08	30.52	34324
New Evolutionary Nuclear Design	-0.01	0.00	0.00	-0.14	0.01	-4.54	37.35	52584
Oil Fired Gas Turbine	0.46	0.39	3.82	-0.07	0.32	2.57	18.61	11251
Super Critical Coal	-0.82	-0.74	1.28	-2.75	0.42	-0.98	5.22	367
Small Hydro	-2.16	-0.22	33.56	-92.42	11.37	-2.88	17.27	9868
Solar Thermal Power	-0.04	-0.01	0.15	-0.63	0.07	-3.47	21.76	16668
Wind Turbines	-0.57	-0.26	1.96	-7.56	0.89	-2.11	10.21	2913

TARGET: CHANGE IN EN. COST (R.O.W.)

CORRELATION MATRIX	Advanced Thermodynamic Cycle (coal)	Biomass Gasification Gas Turbine	CHP with Combined Cycle	Decentralised Photovoltaic cells	Gas Turbine in Combined Cycle	Integrated Coal Gasification	Advanced Lignite	Fuel Cell Power Generation	New Evolutionary Nuclear Design	Oil Fired Gas Turbine	Super Critical Coal	Small Hydro	Solar Thermal Power
Advanced Thermodynamic Cycle (coal)	1.000	0.037	-0.143	-0.059	-0.173	0.276	0.219	-0.035	-0.027	-0.052	0.317	0.076	0.061
Biomass Gasification Gas Turbine	0.037	1.000	-0.022	-0.332	-0.116	0.035	-0.025	0.133	-0.012	0.074	-0.015	0.151	-0.085
CHP with Combined Cycle	-0.143	-0.022	1.000	-0.058	-0.097	-0.195	-0.125	0.126	-0.049	-0.018	-0.235	0.030	-0.110
Decentralised Photovoltaic cells	-0.059	-0.332	-0.058	1.000	0.127	-0.091	-0.073	-0.171	0.014	-0.061	-0.021	-0.132	0.029
Gas Turbine in Combined Cycle	-0.173	-0.116	-0.097	0.127	1.000	-0.129	-0.045	-0.177	0.041	-0.268	-0.106	-0.056	0.037
Integrated Coal Gasification	**0.276**	0.035	-0.195	-0.091	-0.129	1.000	0.225	-0.039	0.028	-0.091	0.584	0.020	0.145
Advanced Lignite	**0.219**	-0.025	-0.125	-0.073	-0.045	0.225	1.000	-0.009	-0.104	-0.032	0.231	0.017	0.063
Fuel Cell Power Generation	-0.035	0.133	0.126	-0.171	-0.177	-0.039	-0.009	1.000	-0.021	0.056	-0.062	0.081	0.043
New Evolutionary Nuclear Design	-0.027	-0.012	-0.049	0.014	0.041	0.028	-0.104	-0.021	1.000	0.004	-0.036	0.066	0.003
Oil Fired Gas Turbine	-0.052	0.074	-0.018	-0.061	**-0.268**	-0.091	-0.032	0.056	0.004	1.000	-0.096	0.027	-0.117
Super Critical Coal	**0.317**	-0.015	**-0.235**	-0.021	-0.106	**0.584**	**0.231**	-0.062	-0.036	-0.096	1.000	-0.046	0.154
Small Hydro	0.076	0.151	0.030	-0.132	-0.056	0.020	0.017	0.081	0.066	0.027	-0.046	1.000	-0.065
Solar Thermal Power	0.061	-0.085	-0.110	0.029	0.037	0.145	0.063	0.043	0.003	-0.117	0.154	-0.065	1.000
Wind Turbines	0.031	0.059	0.006	**-0.290**	-0.097	-0.039	0.023	0.107	-0.049	0.044	-0.093	0.292	-0.122

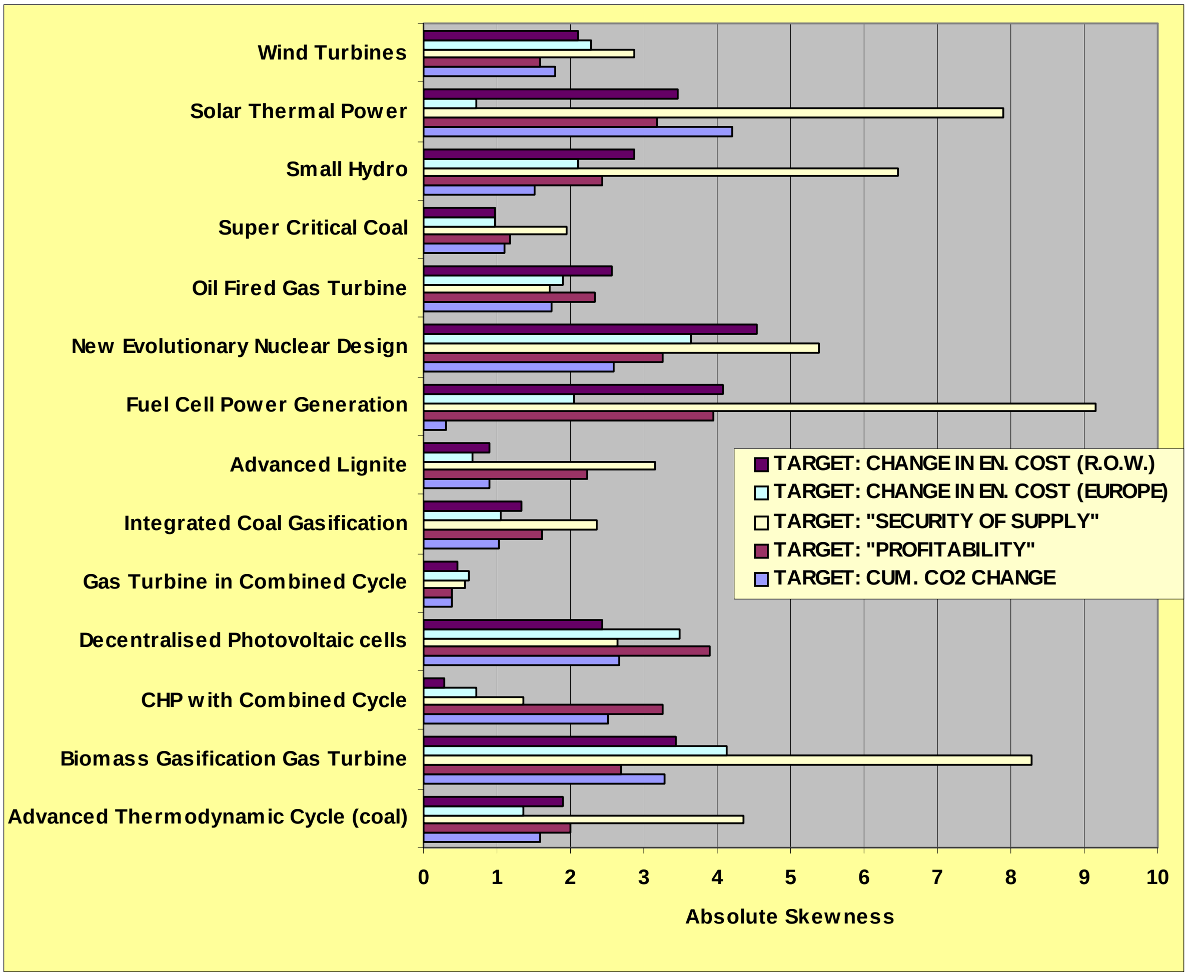
The tables above analytically present the key PROMETHEUS results on the impact of R&D shocks applied to a selection of energy technologies with respect to the above specified R&D objectives. A cursory look at the tables can provide some useful insights to the analysis. Starting with the profitability measure, the results indicate that the impact on this target in general presents high volatility across various technologies. The gas and wind turbines present the highest profitability, followed by the super critical coal, the integrated coal gasification and the decentralised photovoltaic cells to a lesser extent. The solar thermal power also appears highly profitable but with relatively high variability. The resulting figures show that for every € invested in "wind turbines R&D" over 22€ extra will be earned. Correspondingly, for every € invested in the "gas turbine R&D", over 10€ extra will be earned. In all, from an R&D policy point of view, renewable technologies seem to be relatively favoured, followed by gas, coal and PV.

In terms of impact on cumulative CO_2 change, wind turbines display the highest productivity of R&D. Compared to the performance of wind turbines, the Gas turbine in combined cycle displays half the productivity but one third of the variability as measured in terms of standard deviation. Biomass gasification also appears highly productive but with very high variability. Turning to other renewable technologies, the solar thermal power exhibits a restricted impact accompanied with relatively large variability. In terms of impact on security of supply, coal technologies display the lowest variability relative to their mean impacts. In particular, super critical coal displays the optimal relation, with medium variability but more than double the impact of any other productive technology. R&D on integrated coal gasification and biomass gasification gas turbine technologies present almost equal security of supply benefits; the former technology however performs at less than half variability levels, thus displaying a more consistent behaviour. As regards renewable technologies, wind turbines demonstrate the highest productivity in terms of security of supply, which is somehow moderated by the corresponding relatively high variability. With respect to the impact on energy cost reductions to the consumer, R&D investment in the gas turbine in combined cycle produces the highest cost efficiency, followed by the biomass gasification gas turbine, the wind turbines and the super critical coal to a lesser extent.

Some broad preliminary observations can be made concerning the results:

- All impacts for all targets fail the normality test. This is mainly due to pronounced skewness, itself seemingly related to the two-factor learning curve specification (see
- Figure 8-9). Under favourable conditions involving a high response to R&D coupled with reasonable learning by doing effects and a general environment favouring a particular technology (e.g. presence of a high carbon value or its complete absence depending on the technology) it tends to make very significant impacts (sometimes equivalent to "sweeping the board") when as in most cases impacts are rather moderate. As the graph below demonstrates this skewness is particularly pronounced for new technologies like solar thermal power plants, the new nuclear design, fuel cell generation and biomass gasification gas turbines which currently make little or no contribution to power generation and are marked by lacklustre average performance in the reference case and therefore have potential for exceptional performance under exceptionally favourable circumstances. On the other extreme lies the gas turbine in combined cycle technology, which is in any way the winning power technology on average. Among targets skewness seems to be most pronounced with regard to impacts on security of supply seemingly mainly due to the rather "volatile" definition of this target.
- The correlation matrices appear to be surprisingly sparse in view of the stronger correlations identified in the broad energy aggregates. This sparseness is particularly pronounced for the "profit" target but also for the energy costs to the consumer targets. Impacts on security of supply are on the other hand display stronger correlations. In general the clean coal technologies have more closely correlated impacts since they depend on similar configurations for making substantial inroads. A major source of independence of impacts despite the strongly correlated environment seems to be the variation in the parameters of two factor learning curves. In particular learning by research parameters are marked by relatively high variances (tending to dissociate the outcome from the general energy environment), pronounced negative co-variances with their respective learning by doing parameters but so far total independence from TFLCs of other technologies. This latter feature is clearly unrealistic at least for some of the technologies (e.g. those involving gas turbines that are likely to benefit from generic spillovers). It is hoped to remedy this situation by the introduction into PROMETHEUS of technological affinity correlations to be derived by Delphi type consultations.

Figure 8-9: Skewness of distribution of R&D impacts



9. Impact of R&D on policy objectives using deterministic models.

This section concerns the results driven from the large models on the impact of injecting R&D expenditure shocks on specific technologies. In particular, the application of the methodology analysed in Section 7.2 to 14 simulations which correspond to 14 R&D shocks for the 14 (i) technologies produced by increasing PUBINV(i,2000) by 10 %* TOTRD (i,2000).

9.1. POLES (IEPE.CNRS)

The following tables report on the results obtained by POLES.

Table 9-1: R&D Shocks

		R&D shock M€99
Adv Coal Cycle	ATC	321
Supercrit Coal	PFC	423
Int Coal Gasif	ICG	949
Biom Gasif	BGT	386
CHP + CC	CHP	1 377
Gas Turb + CC	GGC	2 949
Oil in Gas Turb	OGC	550
Molt Carb FC	MFC	870
Sol Oxide FC	SFC	870
New Nuclear	NND	2 538
Buildg Int PV	DPV	1 518
Solar Thermal Plant	SPP	359
Wind	WND	755
Small Hydro	SHY	63

Table 9-2: The measure of "profitability" (€/k€)

		R&D shock M€99	Sales
Adv Coal Cycle	ATC	321	21.4
Supercrit Coal	PFC	423	31.8
Int Coal Gasif	ICG	949	7.2
Biom Gasif	BGT	386	15.0
CHP + CC	CHP	1 377	0.2
Gas Turb + CC	GGC	2 949	0.4
Oil in Gas Turb	OGC	550	0.1
Molt Carb FC	MFC	870	0.4
Sol Oxide FC	SFC	870	0.4
New Nuclear	NND	2 538	4.2
Buildg Int PV	DPV	1 518	1.8
Solar Thermal Plant	SPP	359	61.2
Wind	WND	755	26.3
Small Hydro	SHY	63	122.2

Table 9-3: The POLES measure of impact on the CO2 limitation objective

		R&D shock M€99	CO2 red	*Abatement cost (€/tC)*
Adv Coal Cycle	**ATC**	**321**	**-0.003**	*-307*
Supercrit Coal	**PFC**	**423**	**0.051**	*20*
Int Coal Gasif	**ICG**	**949**	**0.002**	*488*
Biom Gasif	**BGT**	**386**	**0.000**	*4 474*
CHP + CC	**CHP**	**1 377**	**-0.001**	*-863*
Gas Turb + CC	**GGC**	**2 949**	**-0.001**	*-910*
Oil in Gas Turb	**OGC**	**550**	**0.000**	*8 712*
Molt Carb FC	**MFC**	**870**	**0.003**	*318*
Sol Oxide FC	**SFC**	**870**	**-0.002**	*-530*
New Nuclear	**NND**	**2 538**	**-0.016**	*-64*
Buildg Int PV	**DPV**	**1 518**	**0.000**	*4 075*
Solar Thermal Plant	**SPP**	**359**	**0.257**	*4*
Wind	**WND**	**755**	**0.020**	*50*
Small Hydro	**SHY**	**63**	**0.068**	*15*

Table 9-4: The measures of POLES cost reductions to the consumer

		R&D shock M€99	Cost Imp EU	Cost Imp DC
Adv Coal Cycle	**ATC**	**321**	**0.22**	**0.06**
Supercrit Coal	**PFC**	**423**	**0.04**	**-2.01**
Int Coal Gasif	**ICG**	**949**	**0.07**	**-0.13**
Biom Gasif	**BGT**	**386**	**1.23**	**0.05**
CHP + CC	**CHP**	**1 377**	**0.06**	**0.00**
Gas Turb + CC	**GGC**	**2 949**	**-0.13**	**-0.27**
Oil in Gas Turb	**OGC**	**550**	**-0.03**	**0.10**
Molt Carb FC	**MFC**	**870**	**0.01**	**0.00**
Sol Oxide FC	**SFC**	**870**	**0.02**	**0.00**
New Nuclear	**NND**	**2 538**	**-0.03**	**-0.04**
Buildg Int PV	**DPV**	**1 518**	**0.01**	**-0.01**
Solar Thermal Plant	**SPP**	**359**	**0.00**	**0.05**
Wind	**WND**	**755**	**0.72**	**0.62**
Small Hydro	**SHY**	**63**	**1.46**	**2.38**

9.2. Impact of R&D 'shocks' on policy objectives using MARKAL [by M. Feber, A. Seebregts, K.L. Smekens and G.J. Schaefer (ECN)]

In the TEEM (Energy Technology Dynamics and Advanced Energy System Modelling) project, the predecessor of SAPIENT, the European MARKAL database was used (Seebregts et al., 2000). For the SAPIENT project, this database has been extended with biomass technologies based on the more detailed MATTER data (Gielen et al., 2000)

9.2.1. Clusters of technologies

The approach followed by ECN Policy Studies on the modelling of technological progress in the MARKAL Europe model uses the concept of "clusters of technologies" (Seebregts et al., 2001). In total, 10 clusters of learning technologies are implemented, representing in total 60 technologies. A "cluster of technologies" is defined as a group of technologies sharing a common essential component.

This component, which can be a technology in itself, is called the 'key technology' and is selected as the learning component in each of the technologies in the cluster. Examples of key technologies and, correspondingly, clusters of technologies are gas turbines, fuel cells, photo-voltaic (PV) modules, wind turbines, burners and boilers.

The existing technologies need to be grouped into clusters of technologies which are similar with respect to their learning behaviour i.e. the development of these technologies is in some way linked to each other.

One technology can appear in more than one cluster. An integrated coal gasification power plant is composed of, among other things, a gas turbine, a steam turbine, a gasifier and a boiler (Seebregts et al., 2000).

To implement the concept of clusters in MARKAL, the following approach has been followed:

1. Identify the clusters and key technologies from the technology database.
2. Review the characteristics of the technologies in each cluster.
3. Add the common component as key technology to the technology database.
4. Make the key technology a learning technology and assign the learning parameters to it.
5. Assign a coupling factor to the key technology and the technologies in the corresponding cluster.
6. Calibrate all learning parameters so that they are in line with the currently available cost and capacity data.
7. Adjust the characteristics of the remaining parts of the technologies in the corresponding cluster.
8. When considered necessary, adjust the bounds (or other parameters) of the key technologies or the technologies in the clusters.

All steps described above have been gone through during the TEEM project in which the concept of clusters of technologies has been tested (Seebregts et al., 1999; Seebregts et al., 2000). During the SAPIENT project the model has been improved. Besides the extension of the number of technologies in the database (as mentioned above), also the number of clusters has been doubled (from five to ten). Therefore, we will now concentrate on step 1 of the approach: identification of clusters and key technologies in SAPIENT.

Identification of clusters

The approach described above was applied for the clusters (last five are new compared to TEEM): wind turbines (WT), solar PV modules (PV), fuel cells (FC), gasifiers (GF), gas turbines (GT), hydro turbines (HY), steam turbines (ST), boiler (BO), combined cycle boiler (CC) and Nuclear Reactor (NU). These ten clusters together represent in total about 60 individual MARKAL technologies. For SAPIENT, these clusters and technologies have also been mapped to the POLES technologies. The mapping from our clusters to the 24 POLES technologies is not a 1-to-1 relationship. The technologies (incl. their codes) considered in MARKAL and POLES are summarized in Annex C.

Table 9-5 summarises the clusters and key technologies used in MARKAL. In total 59 technologies are involved. Because of the fact that some of the technologies belong to more than one cluster, the numbers in Table 9-5 add up to 123.

Table 9-5: Clusters of learning technologies

Code	*Description*	*# technologies in cluster*
ESK	Solar PV modules	5
EWK	Wind turbine	4
FCK	Fuel cell	11
GFK	Gasifier	15
GTK	Gas turbine	23
HYK	Hydro turbine	5
STK	Steam turbine	29
BOK	Boiler	14
CCK	Combined cycle boiler	16
NUK	Nuclear reactor	1

Table 9-6 illustrates the cluster of gasifier technologies. As indicated in Table 9-5, for the key technology ‘gasifier’, the cluster consists of 15 technologies. The cumulative installed capacity for gasifiers is based on the combination of the capacities of these 15 individual technologies. Table 9-6 also clearly illustrates that technologies can belong to more than one cluster.

Table 9-6: Clusters of gasifier technologies

Description	*Key/cluster*
Lignine gasifier large industrial cog.	GTK STK GFK
Wood gasification small industrial cog.	GTK STK GFK
Wood gasification CC power plant	GTK STK GFK CCK
Biomass gasifier dedicated CC (NH)	GTK STK GFK CCK
Biomass gasifier SOFC	GTK STK GFK FCK CCK
IGCC with co-gasification of biomass	GTK STK GFK CCK
Biomass gas turbine plant	GTK GFK
Biomass gasifier dedicated CC (NH) STW	GTK STK GFK CCK
Biomass gasifier FT-fuel/ele co-prod	GTK STK GFK CCK
Integrated coal gasification power plant	GTK STK GFK CCK
Integrated lignite fired power plant	GTK STK GFK CCK
Integrated Coal Gasification SOFC plant	GTK STK GFK FCK CCK
Existing CC power plant	GTK STK GFK CCK
Waste to energy plant (Lurgi gasifier)	STK GFK
Waste to energy plant (Gibros PEC)	STK GFK

Each technology is composed of (or in other words can be coupled to) one or more key technologies. As explained earlier, a key technology is the learning component in each of the technologies in a cluster. However, besides the learning part of a technology (i.e. the part consisting of one or more key technologies), also a non-learning part exists.

As an example of the use of the so called "coupling factors" in MARKAL, we take an integrated coal gasification (or IGCC) power plant. According to Table 9-6 this technology belongs to four clusters of key technologies, i.e. gas turbine, steam turbine, gasifier and combined cycle boiler. Coupling factors "couple" the 10 key technologies to the 60 technologies that are actually learning in MARKAL. The actual value of the coupling factor is based on the output capacity of the technology concerned. For a combined cycle-gasifier combination (as in the example) it is assumed that 60% of the capacity is in the gas turbine and the other 40% is in the steam turbine. Correspondingly, the coupling factor for the gas turbine is 0.6 and for the steam turbine is 0.4.

The coupling factors are for instance used to calculate the (remaining) investment costs of the non learning part for each technology. The investment of the learning part is determined by the combination of key technologies. For the IGCC the breakdown of investment costs is illustrated in Table 9-7.

Table 9-7: Example of cost breakdown IGCC (in €1995/kW installed capacity)

Technology	*Cost*	*Coupling factor*
New integrated coal gasification p.p. (as a whole)	1510	
Gas turbine (as key)	380	0.6
Steam turbine (as key)	300	0.4
Gasifier (as key)	640	1.0
CC boiler (as key)	450	0.4

A complete new integrated coal gasification power plant in total costs 1510 €/kW installed. Of these costs, 0.6*380=228 €/kW is related to the costs of the gas turbine. Correspondingly, 0.4*300=120 €/kW is related to the costs of the steam turbine. The so-called "non-learning part investment cost" is defined as the "total investment costs of a new technology — weighted investment costs of the corresponding key technologies". In this example, the non-learning part (referring to 2000) is then calculated as follows:

$$1510 — \{ 0.6 * 380 + 0.4 * 300 + 1.0 * 640 + 0.4 * 450 \} = 1510 – 1166 = 342$$

The weighted investment costs of the four key technologies sum up to 77% (i.e. 1166/1510) of the total investment costs of the new integrated coal gasification power plant. For 2010 and further, the "non learning part investment cost" in the EU MARKAL database becomes (342/1510=) 0.23 * original value (i.e. the value used before the concept of clusters including the accompanying cost breakdown was introduced; in the case of an IGCC this value is 1510.

Learning Parameters

To the extent possible, learning parameters have been updated and harmonized with IEPE's database (Criqui, 2001). Both the alternative approach of two-factor learning curves in MARKAL and the estimation of the progress ratios for the MARKAL clusters of learning technologies have used IEPE's database as a source of information.

Other learning parameters (i.e. initial and maximum cumulative capacity, growth factors, constraints) have been selected largely based on the original MARKAL TEEM database. Table 9-7 gives an overview of most important learning parameters of key technologies implemented in the SAPIENT database. For clarification, a few definitions will be given below (Seebregts et al., 2000).

Progress ratio

The progress ratio expresses the rate at which the cost declines each time the cumulative capacity doubles. E.g. a progress ratio of 0.8 means that the costs per unit of newly installed capacity decrease by 20% each time the cumulative installed capacity is doubled. The progress ratio thus constitutes a key factor for technological progress because it determines the speed of learning for the technology.

Initial costs

The initial costs form part of the costs of each technology belonging to the cluster. The initial costs (for 1990) are calibrated based on the costs of the technology today (i.e. the cost 2000). The costs 2000 are used to calculate the investment of the learning part of a technology, as was shown in Table 9-7.

Initial cumulative capacity

The initial cumulative capacity of all technologies in a cluster can be derived from the original database (i.e. without learning) by adding the residual capacities for the year 1990 and the capacity installed during the period 1990-1999 of the separate technologies. Current capacity figures (e.g. for wind energy in Western Europe nowadays already 13 GW is installed) have been used to calibrate the initial capacity data.

Maximum cumulative capacity

The maximum cumulative installed capacity is defined for the year 2050. The common value of 1000 GW (except steam turbines, for which 1500 GW was taken) was taken arbitrarily, but turned out well. For each key technology, the cumulative capacity in a certain period is calculated by the weighted sum (based on the coupling factors) of the cumulative installed capacities of the technologies in the specific cluster.

Implied floor costs

The implied floor costs are the costs when the maximum cumulative capacity is reached in 2050, i.e. this is the minimum level of costs that can be reached for a certain technology. The percentage of cost reduction is a good measure for the innovative nature of the technology and hence of its learning potential. E.g. for solar PV modules a cost reduction of approx. 93% is maximally possible.

Table 9-8: Learning parameters of key technologies

Cluster	Progress Ratio [-]	Initial cost 1990 (calibrated) [€95/kW]	Cost 2000 [€95/kW]	Intitial Cumulative Capacity **1990 OR start year** [GW]	Maximum Cumulative Capacity 2050 [GW]	Implied 'floor'-costs 2050 [€95/kW]	**Floor-cost as % of intitial cost** [%]	Maximum Number of doublings [-]
Solar PV	0.82	7500	4000	0.1	1000	537	7.2	13.3
Wind turbine	0.90	1400	800	0.147	1000	366	26.2	12.7
Fuel cell	0.82	2650	1325	0.08	1000	178	6.7	13.6
Gasifier	0.9	800	640	0.65	1000	262	32.8	10.6
Gas turbine	0.87	450	380	31.9	1000	225	50	5
Hydro turbine	0.997	300	300	23	1000	295	98.4	5.4
Steam turbine	0.99	300	300	250	1500	292	97.4	2.6
Boiler	0.99	510	510	122	1000	508	99.6	0.45
CC boiler	0.95	500	450	1.17	1000	331	66.2	8.1
Nuclear	0.99	1940	1940	118	1000	1881	97	3.1

Bounds

It would go too far to elaborate on all the bounds applied in the model. Therefore, only capacity bounds on the key technologies "Solar PV modules" and "Wind turbines" will be briefly discussed here. For a complete overview of individual technology bounds applied, see Annex E.

Solar PV

For Solar PV, a minimum capacity bound of 3 GW (2010) was introduced, corresponding to the EU White Paper (1997). This was modelled as follows:

Table 9-9: Lower capacity bound on total Solar PV in GW (scenario NOREBNDS)

Constraint	*Description*	*1990*	*2000*	*2010*	*2020*	*2030*	*2040*	*2050*
RATSOLARLO	Total Solar PV (= ? ES1-ES5)	0	0	3	3	3	3	3

Wind

The potentials for Wind (onshore and offshore) are based on the latest DG TREN scenarios (LREM modelling, 2002). This was modelled as follows:

Table 9-10: Upper capacity bounds on Wind in GW (scenario NOREBNDS)

Constraint	*Description*	*1990*	*2000*	*2010*	*2020*	*2030*	*2040*	*2050*
RATWTON	Total wind onshore (EW4+5)	1	13	72	103	123	130	136
RATWTOFF	Total wind offshore (EW6+7)	0.09	0.5	6.5	57	103	135	148

For offshore Wind, also a minimum capacity bound of 5 GW (2010) was introduced, based on the prognoses of EWEA (EWEA, 2001). This was modelled as follows:

Table 9-11: Lower capacity bound on offshore Wind in GW (scenario NOREBNDS)

Constraint	*Description*	*1990*	*2000*	*2010*	*2020*	*2030*	*2040*	*2050*
RATWTOFFLO	Total wind offshore (EW6+7)	0	0	5	5	5	5	5

9.2.2. Scenario assumptions

Base cases and variants

The baseline scenario (or the Reference Run) to be used in the model runs is the so called "Market Drive" scenario with high renewables (abbreviated "MD-hr" and described in Seebregts et al., 2000) including CO_2 costs of 15 €/ton till 2010 and 33 €/ton till 2030 (as agreed upon in the project). ECN has not harmonized the MARKAL MD-hr scenario with the POLES reference scenario and IIASA A1B scenario, except for a technology mapping of MARKAL and POLES technologies, and comparison of progress ratios used.

At the request of the European Commission, the overall (social) discount rate used will be 4% throughout. The calculation period is 1990-2050 (7 time periods of 10 years). The results to be used as an input to the ISPA model are reported till 2030. Other results are reported till 2050.

Besides the baseline scenario or Reference Run, the following variants of the baseline will be calculated:

- R&D "shocks" (see below)
- "Constrained CO_2" case translated from the POLES "Soft Landing Stabilisation" scenario (described in Blanchard et al., 2000). This runs are done as a kind of expected carbon limitation scenario, since based on previous ECN experiences (Kram et al., 2001; Gielen et al., 2000; Lako et al., 1998) with the carbon values as agreed (i.e. 15 €/ton till 2010 and 33 €/ton till 2030) no significant CO_2 reduction is achieved. Table 9-12 shows the applied CO_2 constraints in this scenario (from now on referred to as "Soft Landing").

Table 9-12: CO2 constraints in the Soft Landing scenario (as percentage of 1990 level)

	1990	*2010*	*2030*	*2050*
EU MARKAL target CO_2 based on Kyoto 1, 2, 3	100%	92.0%	84.6%	77.9%
EU MARKAL target CO_2 in % 1990 based on POLES reductions Soft Landing Scenario	100%	90.2%	82.2%	78.4%

This leads to 4 cases and variants:

1. Baseline (Reference Run RR)
2. Baseline plus R&D "shocks" (RR+Shocks 1-10)
3. CO_2 constraints according to Soft Landing figures POLES (SL)
4. Soft Landing plus R&D "shocks" (SL + Shocks 1-10)

R&D asssumptions ("shocks")

An additional R&D injection ("shock") will be applied on every key technology separately, i.e. this leads to a total of 10 so-called "shock" runs. The R&D shock will be modelled in the time period designated as 2000. The progress ratio will not change after application of the additional R&D shock.

As stated, the shocks will be applied at cluster level and the magnitude of the shock (in M€) will be fixed so as to achieve a significant effect on the learning rate of the key technology involved. By "significant" we mean a progress ratio improvement of at least 0.03 (but preferably 0.05). This is done to get an effect of the applied R&D-shock in the runs that serve as an input for the ISPA-model. Note that in the ISPA-model, the effect will be calculated *per additional €* of R&D, and therefore the actual size of the applied shock doesn't matter. As was already elaborated in Chapter 2, the additional R&D will have impact on the progress ratio according to relationship following relation: $\Delta PR = \Delta R\&D\text{-intensity} * -0.289$.

Table 9-13 summarizes the resulting shocks as applied at cluster level, including the impact of the additional R&D on the progress ratio (since in the MARKAL model the R&D shock is actually modelled as an "improved" progress ratio). The parameter *n* in the table is defined as the "level of the additional R&D-shock" divided by the "level of the intended cumulative R&D for the period 2001-2010", and is a measure of the relative level of the shock. As can be seen from the table even a twenty fold increase of the cumulative R&D for solar PV does not seriously affect its PR. Furthermore, an additional R&D input of over one 100 billion € for fuel cells has no serious impact on its PR, and consequently *n* is very large. This is due to a very low level of intended cumulative R&D (i.e. projected cumulative R&D 2001-2010, calculated based on the projected cumulative sales in the same time period), and should therefore not be valued as "unrealistic". The same holds for hydro turbines and common boilers.

Table 9-13: New Progress Ratio (PR) after R&D shock (in M$98)

Cluster	*PR*	*R&D Shock*	*N*	*New PR*	**ΔPR**	**ΔR&D Intensity**
Solar PV modules	0.82	355000	21.7	0.792	0.028	0.10
Wind turbine	0.90	22000	2.5	0.85	0.049	0.17
Fuel cell	0.82	100000	654	0.791	0.029	0.10
Gasifier	0.9	1000	1.4	0.85	0.050	0.17
Gas turbine	0.87	5000	1.5	0.82	0.048	0.17
Hydro turbine	0.997	2000	2023	0.94	0.055	0.14
Steam turbine	0.99	6400	5.6	0.901	0.089	0.31
Boiler	0.99	4150	14.7	0.894	0.096	0.33
Combined cycle boiler	0.95	3000	1.0	0.90	0.049	0.17
Nuclear reactor	0.99	17500	1.0	0.94	0.049	0.17

9.2.3. Results

Two sets of runs are discussed here (referred to as “set 1” and “set 2”):

1. Reference Run plus shocks (1-10)
2. Soft Landing plus shocks (1-10)

First the ISPA input will be treated followed by (a selection of) other results.

9.2.3.1. ISPA input

Table 9-14 and Table 9-15 show the values for the ISPA objectives for run sets 1 and 2. The objectives are calculated from the model results as follows (NPV = net present value). All results are calculated for the period 1990-2030.

1. Impact on market profitability (unit M€ /M€):

*NPV_{1990} [(specific technology cost in the “Shock Run” + specific technology cost in the Reference Run) x 10 * (investments in technology in the “Shock Run” — investments in technology in the Reference Run)]} / R&D expenditure shock*

2. Impact on CO2 limitation objective (unit Mton CO2/M€):

*(10 * cumulative CO_2 emissions in the “Shock” Run” — 10 * cumulative CO_2 emissions in the Reference Run) / R&D expenditure shock*

3. Impact on cost reductions to the consumer (unit M€/M€):

*NPV_{1990} (10 * energy system costs of the “Shock Run” — 10 * energy system costs of the Reference Run) / R&D expenditure shock*

The value of the energy system costs is used as a proxy for the costs to consumer.

The factor 10 appears from the fact that individual values reported represent the average of a 10 years’ period, e.g. the value reported for the year ‘2000’ is actually the average of the period 1995-2005.

Table 9-14: Objectives measurement Reference Run + Shocks (1-10)

Case i.e. "shock" on technology …	*New PR (in case)*	*R&D shock M€*	*Impact on market impact ("profitability") M€/M€*	*Impact on CO_2 limitation objective Mton CO_2/M€*	*Impact on cost reductions to the consumer M€/M€*
Reference Run	-	-	-	185277 Mton CO_2	30637 bln €
Solar PV modules	0.792	355000	0.0	0.0	0.0
Wind turbine	0.85	22000	0.0	0.0	0.0
Fuel cell	0.791	100000	0.0	0.0	0.0
Gasifier	0.85	1000	6.1	-0.8	-0.3
Gas turbine	0.82	5000	0.0	0.0	0.0
Hydro turbine	0.94	2000	0.0	0.0	0.0
Steam turbine	0.90	6400	1.3	0.0	-0.2
Boiler	0.89	4150	8.1	0.1	0.1
Combined cycle boiler	0.90	3000	0.2	0.0	0.0
Nuclear reactor	0.94	17500	0.0	0.0	0.0

Profitability

As can be seen from Table 9-14, the impact on profitability in general is negligible: only the boiler, gasifier and, to a lesser extent also the steam turbine are "profitable" in terms of market impact. For every € invested in "boiler R&D" over 7 € extra will be earned. Correspondingly, for every € invested in "gasifier R&D" over 5 € extra will be earned. It must be kept in mind though, that this is not a linear relationship. Results are dependent on the absolute level of the shock applied (i.e. on the progress ratio improvement that is achieved).

It is remarkable that according to these results, renewable technologies (like Solar PV, Wind and Hydro) seem not to be favoured from an R&D policy point of view. Also gasifiers are not used in biomass applications: the majority of the gasifiers installed are in integrated coal gasification power plants.

CO2 emissions

As with profitability, the impact on CO_2 limitation in general is negligible. This can of course be explained by the equally negligible impacts on profitability: if a technology is not implemented (like e.g. in the cases with solar PV modules and wind turbines) emissions won't be effected. In the case of gasifiers, every € invested in gasifier R&D leads to 0.8 Mton of extra CO2 emission reduction. In absolute terms however, this corresponds to 788 Mtons only (i.e. less than 0.5% of the Reference Run emissions).

In the case of boilers, R&D shocks lead to an *increase* of CO_2 emissions, so here the effect of R&D shocks is a negative one (though in absolute terms again the effects are marginal, i.e. 0.3% or less). Negative effects (or increasing emissions) are explicable in cases where conventional, fossil fuel based technologies (like boilers) are implemented.

The fact that the effects of R&D shocks are negligble in all cases (i.e. also when renewable technologies are stimulated) clearly demonstrates that the carbon values as applied (i.e. 15 €/ton CO_2 till 2010 and 33 €/ton CO_2 till 2030) are no stimulus for CO_2 reduction. As was stated earlier, this confirms the results of former runs with the EU MARKAL model for different projects, where only at carbon values above 100 €/ton CO_2 emissions are reduced (see e.g. Gielen et al., 2000).

Once again, it is mentioned here that in absolute terms, the total emissions stay more or less constant. The change in cumulative CO_2 emissions (that result from a "shock" run) is in all cases smaller than (plus or minus) 0.5% when compared to the Reference Run. The corresponding amount of CO_2 varies from 508 Mton (in case of boilers) to –788 Mton (in case of gasifiers).

Costs to the consumer

As stated above, the value of the energy system costs is used here as a proxy for the costs to the consumer. As can be seen from Table 9-14, again the impact on cost reductions to the consumer in general is negligible and in none of the cases, the R&D investment is "profitable" in terms of "costs to consumer impact": for every € invested in "technology R&D" either nothing or less than 1 € will be earned (i.e. costs are reduced). In the case of the boiler the costs to the consumer actually increase. A negative value in Table 9-14 corresponds to a reduction in costs when compared to the Reference run.

Table 9-15: Objectives measurement Soft landing + Shocks (1-10)

Case i.e. "shock" on technology …	*New PR (in case)*	*R&D Shock* M€	*Impact on market impact ("profitability")* M€/M€	*Impact on CO_2 limitation objective* Mton CO_2/M€	*Impact on cost reductions to the consumer* M€/M€
Soft Landing	-	-	-	160351 Mton CO_2	30673 bln €
Solar PV modules	0.792	355000	0.0	0.0	0.0
Wind turbine	0.85	22000	0.0	0.0	0.0
Fuel cell	0.791	100000	0.0	0.0	0.0
Gasifier	0.85	1000	12.2	0.0	-0.7
Gas turbine	0.82	5000	0.2	0.0	0.0
Hydro turbine	0.94	2000	0.1	0.0	0.1
Steam turbine	0.90	6400	0.0	0.0	0.0
Boiler	0.89	4150	0.3	0.0	-0.1
Combined cycle boiler	0.90	3000	0.4	0.0	0.1
Nuclear reactor	0.94	17500	0.0	0.0	0.0

Profitability

As can be seen from Table 9-15, the impact on profitability in general is negligible: now only the gasifier is "profitable" in terms of market impact: for every € invested in "gasifier R&D" over 11 € extra will be earned. Unlike in the Reference Run plus shocks, here the gasifier is the *only* profitable technology. Again boilers and turbines have a small positive effect in terms of profitability, but the invested € won't be paid back.

CO2 emissions

In terms of CO_2 limitation, in all cases the R&D shocks have no effect on the CO_2 emissions. This can be explained by the fact that in this case (i.e. Soft Landing scenario) maximum CO_2 emission levels (based on the Kyoto target) are set, which the model has to accomplish (see also Table 9-12).

Costs to the consumer

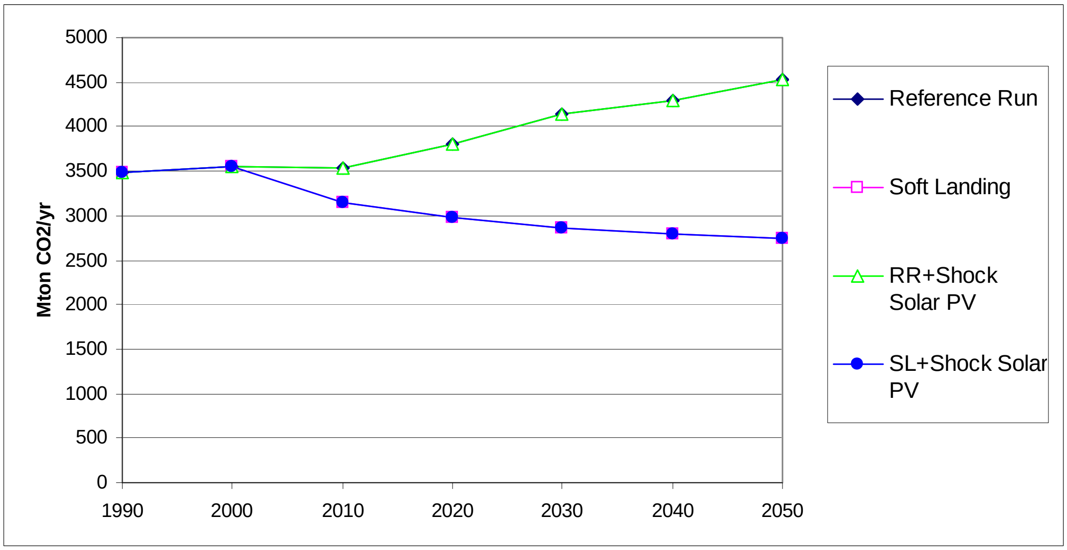
As can be seen from Table 9-15, again the impact on cost reductions to the consumer in general is negligible and in none of the cases, the R&D investment is "profitable" in terms of "costs to consumer impact": for every € invested in "technology R&D" either nothing or less than 1 € will be earned (i.e. costs are reduced). In the cases of hydro turbines and combined cycle boilers the costs to the consumer actually increase. A negative value in Table 9-15 corresponds to a reduction in costs when compared to the Reference run.

Reference Run vs. Soft Landing

By comparing Table 11-14 and Table 11-15, it is evident that in the Soft Landing Scenario the cumulative emmisions are significantly lower than in the Reference Run (difference is 13%). However, this decrease is realized at significantly higher system costs (of 36 billion €, corrresponding to 720 M€/year).

Just as an illustration, CO2 emissions for both runs (Reference Run and Soft Landing) are presented graphically in Figure 11-1. The figure includes the shock runs for Solar PV, but results are not very different for the other cases.

Figure 9-1: CO2 emissions in Reference Run and Soft Landing scenario (incl. shock Solar PV)



9.2.3.2. Other results

Below follows a short overview of other results

1. ***Reference Run + Shocks 1-10 (set 1)***

Table 9-16 gives the cumulative capacities installed of key technologies, both in the Reference Run and Shock Runs. Correspondingly, Table 9-17 gives the specific costs of key technologies.

Table 9-16: Cumulative capacities installed (2050) as % of maximum (GW)

Case	*Maximum*	*Reference Run*	*Shock Run*	*Δ*
Solar PV modules	1000	0.6:	0.6	0
Wind turbine	1000	24.9	24.9	0
Fuel cell	1000	0.0	0.0	0
Gasifier	1000	45.4	47.7	2.4
Gas turbine	1000	59.1	59.1	0
Hydro turbine	1000	18.9	18.9	0
Steam turbine	1500	41.3	59.1	17.8
Boiler	1000	16.5	65.8	49.3
Combined cycle boiler	1000	28.5	28.5	0
Nuclear reactor	1000	6.2	6.2	0

Table 9-17: Specific costs (2050) in €95/kW

Case	*Initial costs$_{1990}$*	*Reference Run*	*Shock Run*	*% of costs$_{RefRun}$*	*Δ*
Solar PV modules	7500	2127	1900	89	-228
Wind turbine	1400	440	245	56	-195
Fuel cell	2650	1217	1193	98	-24
Gasifier	800	310	177	57	-133
Gas turbine	450	243	189	78	-54
Hydro turbine	300	298	256	86	-41
Steam turbine	300	294	243	83	-51
Boiler	510	505	388	77	-117
Combined cycle boiler	500	334	217	65	-117
Nuclear reactor	1940	1919	1869	97	-50

As can be seen from Table 11 17, a R&D impulse in all cases has a positive (in the sense that the costs decrease) impact on the specific costs of the technology. However this does not by definition lead to more installed capacity as is illustrated by Table 11 16. For example, Solar PV modules reach a cost reduction of 11% (compared to costs in the Reference run) but are not installed more. The reason for this is the competition from other technologies: in earlier runs (i.e. when less clusters of learning technologies were implemented) Solar PV as well as Fuel Cells were installed. From this result it can be concluded that the number of learning technologies is important.

Boilers, gasifiers and steam turbines are "winning" technologies in R&D shock runs. As was already concluded renewable technologies do not seem to benefit from the R&D shocks applied (in terms of extra installed capacity). This is importantly explained by the low carbon values applied.

Just as an illustration. Figure 11 2, Figure 11 4 and

Figure 11 6 give cumulative capacities installed (1990-2050) for wind turbines, gasifiers and combined cycle boilers in both sets of runs. Correspondingly, Figure 11 3, Figure 11 5 to Figure 11 7 give the specific technology costs.

Figure 9-2: Cumulative capacity of wind turbines

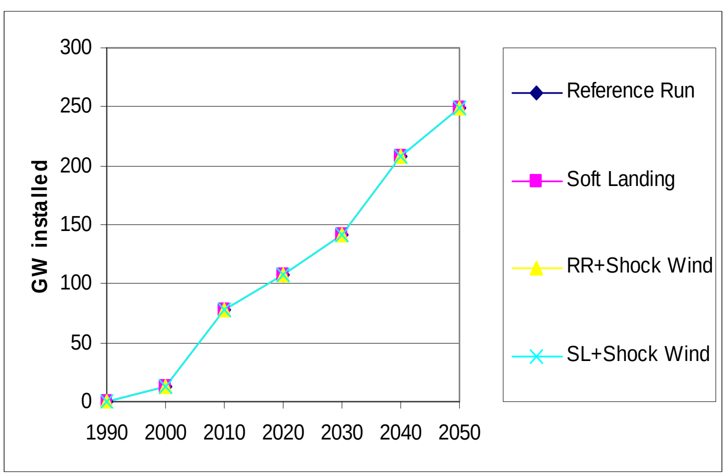


Figure 9-3: Specific costs of wind turbines

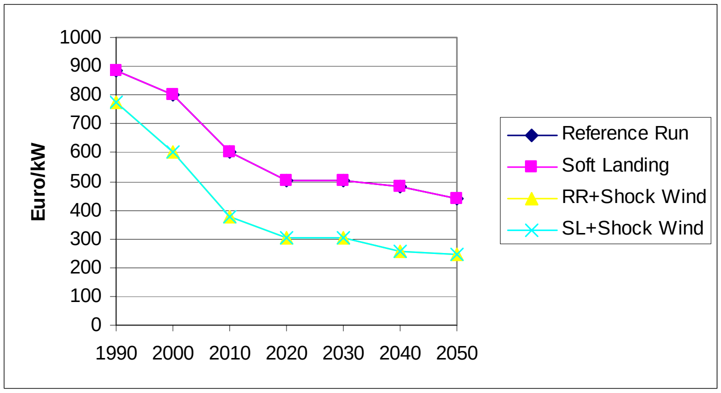


Figure 9-4: Cumulative capacity of gasifiers

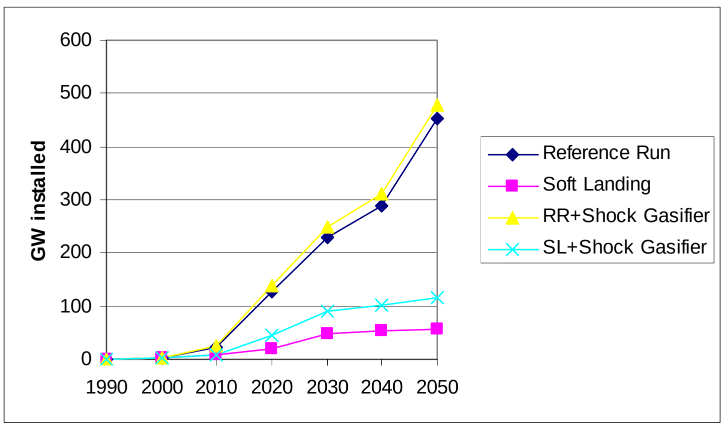


Figure 9-5: Specific costs of gasifiers

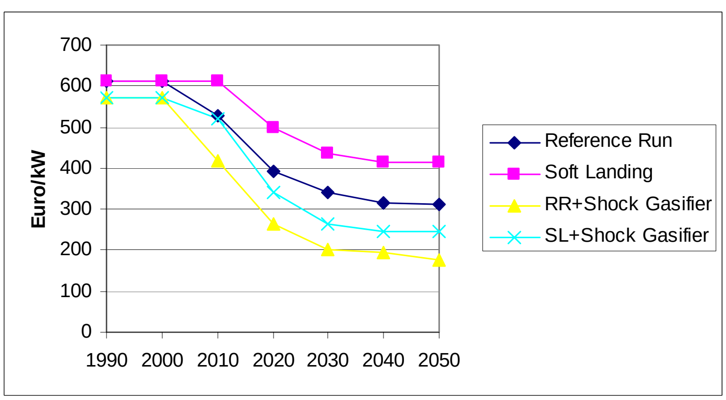


Figure 9-6: Cumulative capacity of combined cycle boilers

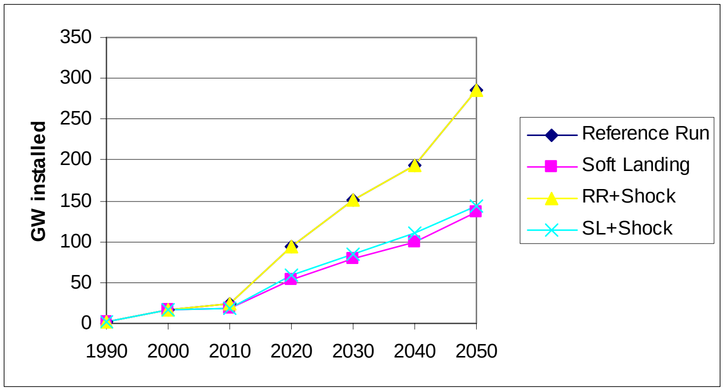


Figure 9-7: Specific costs of combined cycle boilers

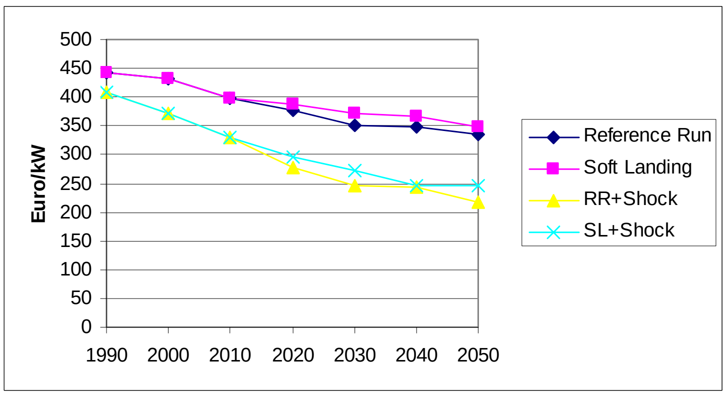


Table 9-18 shows the energy system costs in the Reference and Shock runs. A negative value in the column "Difference" means that the system costs are lower in the Shock run when compared to the Reference Run. As can be seen from this table, in every case the costs in the Shock runs actually are lower than in the Reference Run. The last column "Δ Total costs" adds the absolute level of the shock applied to the cost difference calculated. Calculated like this, we conclude that in 6 out of 10 cases the investment of the R&D shock may be earned back by the decrease in energy system costs.

Table 9-18: Energy system costs (discounted 2050) Reference Run + Shocks (all in M€)

Case	*Costs*	*Difference*	*Shock*	*Δ Total costs*
Reference Run	54978519	-	-	-
Solar PV modules	54977500	-1018	355000	353982
Wind turbine	54962078	-16441	22000	5559
Fuel cell	54978516	-3	100000	99997
Gasifier	54966418	-12100	1000	-11100
Gas turbine	54972475	-6044	5000	-1044
Hydro turbine	54974734	-3784	2000	-1784
Steam turbine	54970688	-7831	6400	-1431
Boiler	54967257	-11261	4150	-7111
Combined cycle boiler	54972194	-6324	3000	-3324
Nuclear reactor	54977949	-569	17500	16931

2. *Soft Landing + Shocks 1-10 (set 2)*

Table 9-19 gives the cumulative capacities installed of key technologies, both in the Reference Run and Shock Runs. Correspondingly, Table 9-20 gives the specific costs of key technologies.

Table 9-19: Cumulative capacities installed (2050) as % of maximum (GW)

Case	*Maximum*	*Soft Landing Run*	*Shock Run*	*Δ*
Solar PV modules	1000	0.6	0.6	0
Wind turbine	1000	24.9	24.9	0
Fuel cell	1000	0.0	0.0	0
Gasifier	1000	5.6	11.7	6.0
Gas turbine	1000	36.7	37.8	1.1
Hydro turbine	1000	49.8	50.2	0.4
Steam turbine	1500	35.8	36.4	0.5
Boiler	1000	14.2	15.6	1.4
Combined cycle boiler	1000	13.6	14.2	0.6
Nuclear reactor	1000	17.7	17.7	0

Table 9-20: Specific costs (2050) in €95/kW

Case	*Initial costs$_{1990}$*	*Soft Landing Run*	*Shock Run*	*% of costs$_{SoftLand}$*	*Δ*
Solar PV modules	7500	2127	1900	89	-228
Wind turbine	1400	440	245	56	-195
Fuel cell	2650	1217	1193	98	-24
Gasifier	800	413	244	59	-169
Gas turbine	450	283	240	85	-43
Hydro turbine	300	296	226	76	-70
Steam turbine	300	294	243	82	-52
Boiler	510	505	458	91	-47
Combined cycle boiler	500	349	247	71	-102
Nuclear reactor	1940	1919	1812	94	-108

As far as the relation between price decreases and installed capacity, the results for the Soft Landing Scenario are comparable with these of the "Reference" Scenario (Table 9 16 and Table 9 17). However, other technologies are now favoured, though the effects (in terms of extra capacity installed) are less pronounced as in the Reference Run. When comparing the Reference Run and Soft Landing Run, the capacities of gasifiers, gas turbines and combined cycle boilers decrease. This is explained by the maximum CO2 emission levels set, which the model has to accomplish (see also Table 9 12). For the same reason the model now "chooses" Hydro and Nuclear Power instead.

In general, the impact of the R&D shocks – in terms of additional installed capacity – is less significant than in the "Reference Scenario". This can be explained by the fact, that already without the shock, a lot of technologies with high learning potential are installed.

Table 9-21 shows the energy system costs in the Soft Landing and Shock runs. A negative value in the column "Difference" means that the system costs are lower in the Shock run when compared to the Reference Run. As can be seen from the table, in every case the costs in the Shock runs actually are lower than in the Soft Landing Run. The last column "Δ Total costs" adds the absolute level of the shock applied to the cost difference calculated. Calculated like this, we conclude that in 4 out of 10 cases the investment of the R&D shock will be earned back by the decrease in energy system costs. When compared to the Reference Run plus shocks, in general the cost differences are lower (with the exception of hydro turbines and nuclear reactors). After addition of the shock level, the technologies that are profitable are the same as in the Reference Run, though in the cases of gas and steam turbines the R&D shocks are not earned back any more in the Soft Landing runs.

Table 9-21: Energy system costs (discounted 2050) Soft Landing Run + Shocks (all in €)

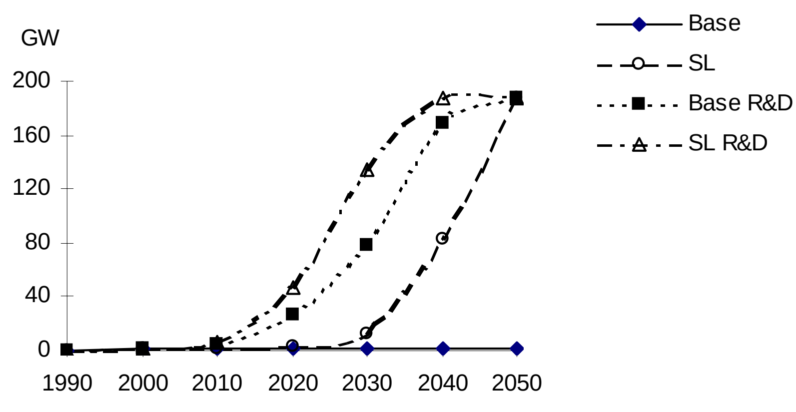
Case	*Costs*	*Difference*	*Shock*	*Δ Total costs*
Soft Landing	55092754	-	-	-
Solar PV modules	55091736	-1018	355000	353982
Wind turbine	55076314	-16441	22000	5559
Fuel cell	55092751	-3	100000	99997
Gasifier	55089715	-3039	1000	-2039
Gas turbine	55088785	-3970	5000	1030
Hydro turbine	55085270	-7484	2000	-5484
Steam turbine	55086848	-5907	6400	493
Boiler	55086845	-5909	4150	-1759
Combined cycle boiler	55089419	-3335	3000	-335
Nuclear reactor	55089755	-3000	17500	14500

9.2.4. Clarification of some results

Lock out effects

As stated before, technologies like Solar PV and Fuel Cells are not installed more despite cost reductions achieved thanks to the R&D inputs (11% in the case of Solar PV). The explanation for this somewhat contradictory result is the competition from other technologies. This can be concluded based on earlier runs, i.e. when less clusters of learning technologies were implemented. At that time, Solar PV modules as well as Fuel Cells were installed. As an illustration, Figure 9-8 shows the former results for Solar PV (relevant are the data labelled as SL and SL R&D).

Figure 9-8: Capacity of Solar PV modules after implementation of 2 clusters



Looking at Figure 11-8, it is very clear that the capacity of Solar PV modules installed (~ 200 GW) is significantly higher than in the latest runs (i.e. after implementation of 10 clusters, see also Table 11 16 and Table 11 17) where the capacity is fixed on the lower bound applied. It can be concluded from this figure, that the number of learning technologies is important.

Influence of Progress Ratio chosen

As a sort of sensitivity analysis, the progress ratio of Solar PV modules was varied in the Soft Landing scenario. The results in terms of cumulative capacity installed are presented in Table 11 22. This clearly shows the importance of the learning potentials and it may be that the progress ratio in case of Solar PV modules has been assumed too pessimistic.Table 11 22: Cumulative capacity (GW) of Solar PV, Soft Landing with varying progress ratios

	1990	*2000*	*2010*	*2020*	*2030*	*2040*	*2050*
PR = 0.82	0.1	0.95	3.1	3.1	3.95	6.1	6.1
PR = 0.792	0.1	0.95	3.1	3.1	3.95	6.1	6.1
PR = 0.70	0.1	0.95	3.1	3.4	3.95	6.1	6.4
PR = 0.66	0.1	0.95	3.1	3.5	7.15	96	246

Influence of Upper Bounds chosen

After former runs, upper capacity bounds for wind turbines were installed on the basis of the latest DG TREN scenarios (LREM, 2002). As a result, wind turbines become less attractive.

9.2.5. Conclusions and Recommendations

Some useful conclusions can be derived from the previous analysis:

1. The fact that in the Reference Run calculations (i.e. with carbon values of 15 €/ton CO2 till 2010 and 33 €/ton CO2 till 2030), the effects of R&D "shocks" on CO2 emissions are negligble in all cases (i.e. also when renewable technologies are stimulated), demonstrates that the carbon values as applied are no stimulus for CO2 reduction. This confirms the results of other studies with the MARKAL Western Europe (see e.g. Gielen et al., 2000).
2. In the Soft Landing Scenario the cumulative emissions are significantly lower than in the Reference Run (difference is 13%). However, this decrease is realised at significantly higher system costs (of 36 billion €).
3. The impact of the R&D shocks – in terms of additional installed capacity – is less significant in the "Soft Landing" than in the "Reference" scenario. This is because of the fact that already without the shock, a lot of technologies with high learning potential are installed. This is necessary in order to accomplish the maximum CO2 emission levels that are set in the Soft Landing scenario.
4. R&D shocks generally have a positive (i.e. price lowering) impact on the specific costs of the technology. However, this does not by definition lead to more installed capacity (e.g. Solar PV and Fuel Cells). The reason for this is the competition from other technologies. It should be kept in mind that both Solar PV and Fuel Cells were attractive in previous MARKAL SAPIENT calculations when only 6 clusters were implemented (so for instance boilers and steam turbines were not yet a learning or key technology). After the addition of the gasifier cluster, Solar PV and Fuel Cells seem to be effectively locked out because implementation of gasifiers becomes more cost effective due to the learning process. This shows the importance of a proper and balanced identification of clusters of learning technologies and the various learning potentials. The learning potential of the more conventional technologies may now be assumed to be too optimistic. It is recommended to review the resulting floor costs of these technologies in more detail: can such cost reductions really be achieved?
5. On the other hand, the learning potentials of renewable technologies like Solar PV modules may be assumed too pessimistic. A quick sensitivity check has shown that with a progress ratio of 0.66 Solar PV are implemented, even in the case of 10 clusters of learning technologies.
6. The indirect approach to 2FLC and the used R&D statistics lead to only marginal changes in progress ratios. So, even beforehand, little impact was to be expected, certainly for the renewable technologies. Comparison with the MARKAL TEEM experiments learns that for instance substantially lower progress ratios and/or a more stringent CO2 policy can make technologies like Solar PV cost-effective. This demonstrates that model assumptions are extremely important for the results.

7. Given the previous conclusions above, one should be very careful to derive very technology specific conclusions from these MARKAL calculations. With other (equally probable or plausible) assumptions, technologies like solar PV and fuel cells could become attractive as well.
8. The MARKAL SAPIENT results indicate that R&D-policy can never stand on its own. R&D can certainly help to reduce specific technology costs, but to get technologies into the market, additional policy measures are needed. Such market policy measures could be upper emission quota or minimum quantity obligations for specific technologies. The combination of the two (a combination of technology push and market pull) might lead to more socially desired outcomes.

References:

Blanchard, O., P. Criqui, L. Viguier, (2000): *Au-dela de Kyoto: enjeux d'équité et d'efficacité dans la negotation sur le changement climatique*, to be published in Economie et Prévision (in French).

Criqui, P. (2001): *Technology Improvement Dynamics database (TIDdb), developed by IEPE under the EU-DG Research SAPIENT project*, IEPE-report, Grenoble, France, July 2001.

ETSAP (1999): *Dealing with uncertainty together*, Summary of Annex VI, ECN, Petten, The Netherlands. Downloadable from: http://www.ecn.nl/unit_bs/etsap/reports/annex6.html

European Commision (1997): *EU White paper on renewable energy*.

EWEA (2001): http://www.ewea.org/, website last updated July 2001.

Gielen, D.J., A.J.M. Bos, M.A.P.C. de Feber, T. Gerlagh (2000): *Biomass for greenhouse gas emission reduction; Task 8: Optimal emission reduction strategies for Western Europe*, ECN-C-00--001, ECN, Petten, The Netherlands.

Grübler, A. (1998): *Endogenous Technological Change*, Proceedings of the Workshop on Modeling Technological Learning, March 19-21, 1998, IIASA, Laxenburg, Austria.

International Atomic Energy Agency (1989): *Evaluating the Reliability of Predictions Made Using Environmental Transfer Models*, Safety Series No. 100, Vienna, 1989.

Junginger, M. (2000): *Experience curves in the wind energy sector – Use, analysis and recommendations*, Utrecht University, NWS-I-2000-29.

Kann, A., Weyant, J.P. (2000): *Approaches for performing uncertainty analysis in large-scale energy/economic policy models*, Environment Modeling and Assessment 5 (2000) 29-46.

Kram, T., A.J. Seebregts, G.J. Schaeffer, A.J.M. Bos, S. Kypreos, L. Barreto, S. Messner, L. Schrattenholzer (2000): *Technology dynamics in energy systems models with perfect foresight*, Int. J. Global Energy Issues, Vol. 14, Nos. 1-4, pp. 48-64, 2000.

Kram, T., D.J. Gielen, A.J.M. Bos, M.A.P.C. de Feber, T. Gerlagh, B.J. Groenendaal, H.C. Moll, M.E. Bouwman, B.W. Daniëls. E. Worrell, M.P. Hekkert, L.A.J. Joosten, P. Groenewegen, T. Goverse (2001): *THE MATTER PROJECT, Integrated energy and materials systems engineering for GHG emission mitigation*, Dutch National Research Programme on Global Air Polution and Climate Change, Report no.: 410 200 055 (2001), Bilthoven, The Netherlands.

Lako, P., Ybema, J.R, Seebregts, A.J. (1998): *The long-term potential of fusion power in Western Europe; MARKAL scenarios until 2100*, ECN-C--98-071, ECN, Petten, The Netherlands.

Lange, de T.J., L. Crommentuijn (2000): *Fotovoltaische zonne-energie – Achtergrondnotitite behorend bij de rapportage: Klimaat en verzuring in 2030: Oplossingsrichtingen voor energie en mobiliteit*, ECN/RIVM-N-2000-6, Petten, Bilthoven, the Netherlands (in Dutch).

LREM modelling (2002): *Data factsheets for latest DG TREN scenarios*, to be published at ECN, Petten, The Netherlands.

McDonald, A., L. Schrattenholzer (2001): *Learning rates for energy technologies*, Energy policy 29 (2001) 255-261.

Seebregts, A.J., G. Goldstein, K. Smekens (2001*): Energy/Environmental Modelling Using the MARKAL Family of Models*, Article selected for publication in the Proceedings of the OR2001 Conference, Energy and Environment Session, September 3-5, 2001, Duisburg, Germany (to be published by Springer Verlag). Also at: http://www.ecn.nl/library/reports/2001/rx01039.html

Seebregts, A.J., T. Kram, G.J. Schaeffer, A.J.M. Bos (1999): *Modelling technological progress in a MARKAL model for Western Europe including clusters of technologies*, Proceedings European IAEE/AEE Conference 'Technological Progress and the Energy Challenge', 30 Sep - 1 Oct 1999, Paris, France (also as ECN-RX--99-028), August 1999.

Seebregts, A.J., T. Kram, G.J. Schaeffer, A.J.M. Bos (2000): *Endogenous learning of technology clusters in a MARKAL model of the Western European energy system*, Int. J. Global Energy Issues, Vol. 14, No.1-4, pp. 289-319.

Winston W. (1999): *Simulation Modeling Using @RISK*, Palisade Corp. New York, 1999. http://www.palisade.com/html/risk/facts.html

Ybema, J.R, Bos, A.J.M., Seebregts, A.J. (1998): *Incorporating the long term risk for deep emission reduction in near term CO2 mitigation strategies*, Journal of Hazardous Materials 61 (1998) 217-227.

Ybema, J.R., Lako, P., Gielen, D.J., Oosterheert, R.J., Kram, T. (1995): *Prospects for Energy technology in the Netherlands – Volume 1 Evaluation of the cost-effectiveness of energy technologies under a range of long term future conditions*, ECN-C--95-002, ECN, Petten, The Netherlands, August 1995.

ANNEX C: Overview of technologies considered

Table C.1 Technologies in MARKAL

Code	*Corresponding technology*
BD1	Lignine boiler large industrial cog.
BD2	Lignine gasifier large industrial cog.
BE1	Wood gasification small industrial cog.
BE2	Wood gasification CC power plant
BE3	Biomass gasifierdedicated CC (NH)
BE4	Biomass gasifier SOFC
BE5	Co-firing wood chips in coal fired plant
BE6	IGCC with co-gasification of biomass
BE7	Biomass gas turbine plant
BE8	Biomass gasifierdedicated CC (NH) STW
BE9	Biomass gasifier FT-fuel/elec. co-prod
BI4	HTU oil/CC power plant
EC2	Existing pulverised coal fired p.p.
EC3	Existing lignite fired power plant
EC4	New pulverised coal fired power plant
EC5	Integrated coal gasification p.p.
EC6	New lignite fired power plant
EC7	Integrated lignite fired power plant
EC8	Integrated Coal Gasification SOFC plant
ECA	Coal FBC CHP plant
ED0	Existing oil fired power plant
ED1	New oil fired power plant
ED2	Oil gasification combined cycle p.p.
EG0	Existing gas fired power plant
EG1	Gas turbine peaking plant
EG2	Existing CC power plant
EG3	New CC power plant
EG4	Combined cycle SOFC power plant
EGA	Existing gas turbine CHP plant
EGB	Existing CC CHP plant
EGD	New gas turbine CHP plant
EGE	New CC CHP plant
EGG	HERON SOFC total energy for H, C and A
EH0	Medium and high head hydro
EH1	Low head hydro
EH2	Hydro pumped storage
EH3	Archimedes Wave Swing
EH5	Hydro Iceland for Aluminium smelters
EI1	Waste to energy plant (incinerator)
EI2	Waste to energy plant (Lurgi gasifier)
EI3	Waste to energy plant (Gibros PEC) (PEC = Product and Energy Plant)
EN0	LWR power plant
ES1	Solar PV in Northern Europe
ES2	Solar PV roofs southern ESP, IT, GR
ES3	Solar PV in Central Europe
ES4	Solar PV roofs/barren land cent. ESP, IT
ES5	Solar PV: import from North Africa
EW4	Large onshore wind turbine – inland
EW5	Large onshore wind turbine - shore

Table C.2 Technologies in POLES

Code	*Corresponding technology*
HYD	Large Hydro
NUC	Nuclear LWR
NND	New Nuclear Design (Evolutionary type)
LCT	Lignite Conventional Technology
CCT	Coal Conventional Technology
PFC	Pulverized Fuel Supercritical Coal
ICG	Integrated Coal Gasification
ACT	Advanced Thermodynamic Cycle
OCT	Oil Conventional Technology
OGT	Oil in GTCC
GCT	Gas Ccnventional Technology
GGC	Gas in GTCC
CHP	CHP
SHY	Small hydro
WND	Wind
SPP	Solar Thermal Power Plant
DPV	Decentralised PV (building integrated)
RPV	Rural PV (electrification in LDCs)
BF2	Electricity production from waste
BGT	Biomass gasification + GTCC
FCV	Fuel Cell Vehicle (PEMFC) (PEM = Proton Exchange Membrane)
SFC	Solid oxide FC
MFC	Molten Carbonate fuel cells

ANNEX D: Summary of coupling factors used

Table D.1 Selected MARKAL technologies/processes

Description ↓ Key technologies →	*ESK*	*WTK*	*FCK*	*GFK*	*GTK*	*HYK*	*STK*	*BOK*	*CCK*	*NUK*
Lignine boilerlarge industrial cog.							1.0	1.0		
Lignine gasifierlarge industrial cog.				1.0	0.6		0.4			
Wood gasificationsmall industrial cog.				1.0	0.6		0.4			
Wood gasificationCC power plant				1.0	0.6		0.4		0.4	
Biomass gasifierdedicated CC (NH)				1.0	0.6		0.4		0.4	
Biomass gasifierSOFC			0.6	1.0	0.2		0.2		0.2	
Co-firing wood chips in coal fired plant							1.0	1.0		
IGCC with co-gasification of biomass				1.0	0.6		0.4		0.4	
Biomass gas turbine plant				1.0	1.0					
Biomass gasifierdedicated CC (NH) STW				1.0	0.6		0.4		0.4	
Biomass gasifier FT-fuel/ele co-prod				1.0	0.6		0.4		0.4	
HTU oil/CC power plant					0.67		0.33		0.33	
Existing pulverised coal fired p.p.							1.0	1.0		
Existing lignite fired power plant							1.0	1.0		
New pulverised coal fired power plant							1.0	1.0		
Integrated coal gasification p.p.				1.0	0.6		0.4		0.4	
New lignite fired power plant							1.0	1.0		
Integrated lignite fired power plant				1.0	0.6		0.4		0.4	
Integrated Coal Gasification SOFC plant			0.6	1.0	0.2		0.2		0.2	
Coal FBC CHP plant							1.0			
Existing oil fired power plant							1.0	1.0		
New oil fired power plant							1.0	1.0		
Oil gasification combined cycle p.p.				1.0	0.6		0.4		0.4	
Existing gas fired power plant							1.0	1.0		
Gas turbine peaking plant					1.0					
Existing CC power plant					0.67		0.33		0.33	
New CC power plant					0.67		0.33		0.33	
Combined cycle SOFC power plant			0.8		0.12		0.08		0.08	
Existing gas turbine CHP plant					1.0					
Existing CC CHP plant					0.67		0.33		0.33	
New gas turbine CHP plant					1.0					
New CC CHP plant					0.67		0.33		0.33	
HERON SOFC total energy for H, C and A			0.8		0.2					
Medium and high head hydro						1.0				
Low head hydro						1.0				
Hydro pumped storage						1.0				
Archimedes Wave Swing						1.0				

*) Because transport (demand) technologies have a special unit in the EU MARKAL model (PJ to the wheels rather than vehicle kilometers) and because of lifetime/replacement considerations of the fuel cell stacks, these coupling factors have calculated differently than for other technologies

ANNEX E: Overview of bounds applied

Table E.1 Upper bounds on capacity in scenario NOREBNDS (in GW)

Code	*Description*	*1990*	*2000*	*2010*	*2020*	*2030*	*2040*	*2050*
BE1.UP	Wood gasificationsmall industrial cog.	-	10	12.14	14.29	16.43	18.57	20.71
BE2.UP	Wood gasificationCC power plant	0.1	0.55	1	13	25	25	25
BE3.UP	Biomass gasifierdedicated CC (NH)	-	2	8.5	15	15	15	15
BE5.UP	Co-firing wood chips in coal fired pl.	-	0.1	25	25	25	25	25
BE6.UP	IGCC with co-gasification of biomass	-	4	47	90	-	-	-
BE7.UP	Biomass gas turbine plant	5	15	25	25	25	25	25
BE8.UP	Biom. gasifierdedicated CC (NH) STW	-	2	6.33	10.67	15	15	15
BE9.UP	Biomass gasifier FT-fuel/ele co-prod	-	17.33	33.67	50	62.5	75	87.5
BI4.UP	HTU oil/CC power plant	-	0.1	1	13	25	25	25
EC2.UP	Existing pulverised coal fired p.p.	115.8	94.72	45.95	0.002	0.002	0.002	0.002
EC3.UP	Existing lignite fired power plant	38.7	25.56	14.34	0.002	0.002	0.002	0.002
EC4.UP	New pulverised coal fired power plant	-	14.68	-	-	-	-	-
EC5.UP	Integrated coal gasification p.p.	-	4	47	90	-	-	-
EC6.UP	New lignite fired power plant	-	4.36	-	-	-	-	-
EC7.UP	Integrated lignite fired power plant	-	1	15.5	30	-	-	-
ECA.UP	Coal FBC CHP plant	4.58	4.5	-	-	-	-	-
ED2.UP	Oil gasification combined cycle p.p.	-	1	15.5	30	-	-	-
EG0.UP	Existing gas fired power plant	43.41	44.86	-	-	-	-	-
EG2.UP	Existing CC power plant	1.7	1.31	0.91	0.456	0.002	0.002	0.002
EG3.UP	New CC power plant	-	36.31	-	-	-	-	-
EGA.UP	Existing gas turbine CHP plant	7.18	5.18	5.18	2.59	-	-	-
EGB.UP	Existing CC CHP plant	0.67	0.67	0.67	-	-	-	-
EGC.UP	Exist. gas eng. gen. set for H, C and A	0.98	0.98	0.002	0.002	0.002	0.002	0.002
EGD.UP	New gas turbine CHP plant	-	13.59	24.34	25.12	25.9	25.9	25.9
EGE.UP	New CC CHP plant	-	6.83	7.5	7.68	7.85	7.85	7.85
EGF.UP	New gas eng. gen. set for H, C and A	-	12.11	21.2	21.63	22.05	22.05	22.05
EI1.UP	Waste to energy plant (incinerator)	0.565	1.98	2.93	3.99	5.14	6.32	7.23
EN0.UP	LWR power plant	118.4	126.7	126.7	126.7	107.7	107.7	107.7

Table E.2 Overview upper bounds on investment in scenario NOREBNDS (in GW)

Code	*Description*	*1990*	*2000*	*2010*	*2020*	*2030*	*2040*	*2050*
ED0.UP	Existing oil fired power plant	-	-	-	-	0.001	0.001	0.001
EGA.UP	Existing gas turbine CHP plant	-	-	-	-	0.001	0.001	0.001
EGB.UP	Existing CC CHP plant	-	-	-	0.01	0.01	0.01	0.01
EN0.UP	LWR power plant	37.77	8.31	2.63	45.04	45.41	38.92	32.44

Table E.3 Lower capacity bound solar PV in scenario NOREBNDS (in GW)

Constraint	*Description*	*1990*	*2000*	*2010*	*2020*	*2030*	*2040*	*2050*
RATSOLARLO	Total Solar PV (= ? ES1-ES5)	0	0	3	3	3	3	3

Table E.4 Upper capacity bounds wind in scenario NOREBNDS (in GW)

Constraint	*Description*	*1990*	*2000*	*2010*	*2020*	*2030*	*2040*	*2050*
RATWTON	Total wind onshore (EW4+5)	1	13	72	103	123	130	136
RATWTOFF	Total wind offshore (EW6+7)	0.09	0.5	6.5	57	103	135	148

Table E.5 Lower capacity bound solar PV scenario NOREBNDS (n GW)

Constraint	*Description*	*1990*	*2000*	*2010*	*2020*	*2030*	*2040*	*2050*
RATWTOFFLO	Total wind offshore (EW6+7)	0	0	5	5	5	5	5

9.3. Estimation of R&D indicators using the MESSAGE model [IIASA]

MESSAGE was used to estimate the impact of R&D for only two of the indicators; (1) measuring the impact of R&D expenditures on cumulative emissions, (2) measuring the impact of R&D expenditures on costs to the consumer. In this Section, we describe step by step how these indicators were calculated for specific electricity generation technologies using MESSAGE.

As an initial step, a set of scenarios was developed, which explore alternative development pathways for the electricity technology mix and future carbon emissions. They serve as the basis for the analysis exploring the effectiveness of R&D. Next, we performed a sensitivity analysis of R&D effectiveness for the electricity sector as a whole. By calculating the R&D requirements for different LSRs (learning-by-searching rates) in each scenario, we quantified the relationship between the LSRs and the R&D indicators (indicators are defined as the numerical values of specific impacts) for the electricity sector as a whole. Finally, the R&D indicators for each specific technology were estimated, based on the values for the parameter *b* of the R&D elasticity for individual technologies given by IEPE. For the quantification of the R&D indicators for the ISPA runs, we assumed an R&D shock of +10% compared to the cumulative R&D expenditures up to the year 1997.

MESSAGE is a linear programming model (LP) of the global energy system operating on 11 world regions. Technological learning is exogenous to the model. For example, cost improvements of technologies are introduced at pre-specified rates over time. The integration of the 2FLC is not possible within an LP formulation, because doing so would specify a non-convex problem too large to be tackled by existing solvers with Mixed-Integer Programming (MIP) capabilities. Illustrative and stylised MIP versions of MESSAGE that endogenise technological change through uncertain returns from learning have been developed (Messner, 1997), but it would be computationally infeasible to use the same method for a detailed scenario that includes over 400 energy technologies and operates on 11 world regions, as in the SAPIENT scenarios here. Consequently, R&D indicators (measuring the impact of technology-specific R&D on the policy variable, e.g., carbon emissions) are calculated ex-post, based on the scenario results for installed capacities and the assumed cost improvements for each technology.

The remainder of this Section is structured into three subsections. Subsection 9.3.1 gives an overview of the scenarios, which were used for the calculation of the R&D indicators. Subsection 9.3.2 describes how the R&D indicators for the electricity sector were measured, and Subsection 9.3.3 presents the results for specific technologies, which were used for the ISPA policy analysis.

9.3.1. Scenario development

The IIASA modelling team developed a set of global energy-environment scenarios of high economic and energy demand growth in which technological change unfolds in alternative "path dependent"" directions. The scenarios share common demographic, economic, and energy demand developments, but explore alternative development pathways for the technology mix and future carbon emissions. For the estimation of the specific impacts ("shocks") reported here, four alternative pathways, according to different resource and technology development assumptions were used:

- MESSAGE-baseline: "Balanced technology" future; the scenario assumes "balanced" progress across all resources and technologies from energy supply to end use.
- MESSAGE-C: This scenarios relies mainly on "Clean coal" technologies that are generally environmentally friendly with the exception of carbon emissions;
- MESSAGE-G: This scenario describes a "Oil and gas"-rich future, with a swift transition from conventional resources to abundant unconventional resources including methane hydrates ("clathrates");
- MESSAGE-T: This scenario features a "Post-fossil" future, with rapid development of solar and new nuclear technologies on the supply side, and mini-turbines and fuel cells used in energy end-use applications.

The main commonalities of the scenarios are summarized in . Most important of these is that the scenarios have identical electricity demand. More importantly, however, they show major differences with respect to the development of the technology mix in the electricity sector. This is mainly due to diverging assumptions for the learning of electricity generating technologies. An overview of the main differences in the scenario drivers and results is given in Table 9-24.

Due to the different assumptions on technological learning, the scenarios result in diverging energy supply structures and, hence, a largely different future CO_2 emissions. These emissions are the highest in the

MESSAGE-C and MESSAGE-G scenarios, both of which describe future worlds heavily relying on fossil-fuel technologies. In contrast, carbon emissions are lowest in the MESSAGE-T scenario, which assumes highest learning rates for advanced renewable and clean technologies.

The scenarios describe futures for alternative directions of capacity expansion, and hence, investment decisions. In particular, investment requirements in R&D in order to achieve the assumed technology improvements in the scenarios differ significantly. However, the question remains as to how much R&D has to be spent to steer technological change in the electricity sector away from carbon-intensive futures C and G to a sustainable path described by scenario T. This is the focus of the analysis in the following subsection, where the effect of the R&D expenditures across the scenarios on cumulative emissions and the cost to the consumer is estimated. Due to the high uncertainty associated with the effectiveness of R&D, we calculated, for each scenario, a range for R&D investments representing different assumptions for the R&D elasticity.

Table 9-22: Overview of main commonalities in the scenario drivers, and results of the four SAPIENT scenarios created with the MESSAGE.

Commonalities of the MESSAGE Scenarios for SAPIENT (Baseline, C, G, T)	
Population, in billion	Low. IIASA (Lutz *et al*., 1996) 8.7 billion by 2050, 7.1 billion by 2100
Economic Growth GWP (gross world product at market exchange rates)	Very high. 1990-2020: 3.3 % 1990-2050: 3.7 % 1990-2100: 3.0 %
Per-capita income, GWP/cap in US$/GDP (at market exchange rates)	Very high. In 2100: US$ 109,500 in Annex I countries, US$ 69,800 in Non-Annex I countries.
Final-energy use (annual)	High. Increase from 275 EJ in 1990 to 1743-1769 EJ by 2100 for baseline, G and C. 1270 EJ in T by 2100.

Table 9-23: Overview of main commonalities in the scenario drivers, and results of the four SAPIENT scenarios created with the MESSAGE.

Commonalities of the MESSAGE Scenarios for SAPIENT (Baseline, C, G, T)	
Population, in billion	Low. IIASA (Lutz *et al*., 1996) 8.7 billion by 2050, 7.1 billion by 2100
Economic Growth GWP (gross world product at market exchange rates)	Very high. 1990-2020: 3.3 % 1990-2050: 3.7 % 1990-2100: 3.0 %
Per-capita income, GWP/cap in US$/GDP (at market exchange rates)	Very high. In 2100: US$ 109,500 in Annex I countries, US$ 69,800 in Non-Annex I countries.
Final-energy use (annual)	High. Increase from 275 EJ in 1990 to 1743-1769 EJ by 2100 for baseline, G and C. 1270 EJ in T by 2100.

Table 9-24: Overview of main differences in the scenario drivers, and results of the four SAPIENT scenarios created with the MESSAGE model.

	Cumulative Hydrocarbon Resource Use (1990-2100)	Technology Improvements in the Electricity Sector				Primary Energy Use (in 2100)	CO_2 * Emissions (in 2100)
		Coal	Oil	Gas	Non-fossil		
Baseline scenario	Oil: Medium, 25.4 ZJ Gas: High, 31.3 ZJ Coal: Low, 19.7 ZJ	High	High	High	High	Very high, 2,681 EJ. Low energy intensity of 4.9 MJ/US$	Median, 14.0 GtC. Cumulative (1990 - 2100): 1,517 GtC
G-scenario	Oil: High, 34.5 ZJ Gas: Very high, 50.3 ZJ Coal: Low, 19.8 ZJ	Low	Very High	Very High	Median	Very high, 2,715 EJ. Low energy intensity of 4.9 MJ/US$	High, 27.7 GtC. Cumulative (1990 - 2100): 1,872 GtC
C-scenario	Oil: Medium, 18.5 ZJ Gas: Medium, 20.5 ZJ Coal: Very high, 48.4 ZJ	High	Low	Low	Low	High, 2,325 EJ. Low energy intensity of 4.2 MJ/US$	High, 32.7 GtC. Cumulative (1990 - 2100): 1,999 GtC
T-scenario	Oil: Medium, 20.8 ZJ Gas: Medium, 25.0 ZJ Coal: Very Low, 11.7 ZJ	Low	High	High	Very High	High, 2,021 EJ. Very low energy intensity of 3.7 MJ/US$	Low, 4.9 GtC. Cumulative (1990 - 2100): 1,076 GtC

* CO_2 emissions from fossil fuels and industrial processes.

9.3.2. Measuring aggregated R&D indicators for the electricity sector as a whole

This subsection summarizes how the MESSAGE scenarios were used to calculate aggregated R&D indicators for the whole electricity sector. The results from this analysis were used to assess R&D indicators for specific technologies, described later.

In order to measure the aggregated effect of the R&D expenditures on the policy objectives (reduction of carbon emissions and cost to the consumer), we first calculate the cumulative R&D requirements for each of the scenarios. Then, we compare the R&D requirements in the scenarios with respect to their impacts on the policy objectives. For the assessment of the impact indicator we use the following formulation:

The calculation of the R&D expenditures is done ex-post, based on the scenario results for installed capacities and the assumed cost improvements for each technology. In addition, we use different capacity elasticities[20] for each individual technology, but for each calculation a single R&D elasticity, which we vary from 5 percent to 20 percent[21] for each scenario. By doing so, we get a distribution of response functions for the two indicators illustrating the effect of the R&D expenditure on the policy variable (indicator) in relation to the assumed R&D elasticity (see Figure 9-9 and Figure 9-10).

Figure 9-9 depicts the response functions for carbon reductions per unit of R&D for the MESSAGE-T scenario compared to the MESSAGE baseline, C, and G scenarios. As illustrated by the figure, the higher the assumed R&D (absolute) elasticities are, the higher the effect on the carbon emissions. Still, there is a paramount difference in the effect of the R&D across scenarios. E.g., for an assumed R&D elasticity of 20

[20] To simplify the sensitivity analysis, we used the negative of the learning-by-searching elasticity as the independent variable. The learning-by-searching elasticity –b is related to the learning-by-searching rate LSR in the following way: $LSR=1-2^{-b}$. For example, for an elasticity of –10% we get an LSR of 6.7%.

[21] For easier readability, we refer to an elasticity of –0.2 by writing "20 percent".

percent, the T-scenario achieves a carbon reduction of 0.05 tons per dollar R&D (tC/$) relative to the C-scenario, but achieves approximately 0.2 tC/$ relative to the baseline and G scenarios.

Figure 9-10 presents the response functions for the reduction of investment costs per unit of R&D for the MESSAGE-T scenario compared to the MESSAGE baseline, C, and G scenarios. Due to the definition of this indicator, the effect of R&D results in negative values illustrating savings in investments per dollar R&D spent. As for carbon emissions, the effect on the investment requirements is higher, the higher the assumed R&D elasticities are. Again, there is a significant difference in the effect of R&D across scenarios. E.g., for an assumed R&D elasticity of 20 percent, the T-scenario achieves a reduction of investment costs of about -4 dollars per dollar R&D ($/$) relative to the C-scenario, but approximately -10 $/$ relative to the baseline and -15 $/$ relative to the G-scenario.

The response functions illustrate aggregated impacts of R&D for the electricity sector as a whole. They serve as the basis for the calculation of technology-specific impacts, which are presented in the next section.

Figure 9-9: Carbon reduction per dollar R&D spent in relation to the assumed R&D elasticity. The lines show the carbon reductions per unit R&D in the MESSAGE-T scenario relative to the MESSAGE baseline, C, and G scenarios.

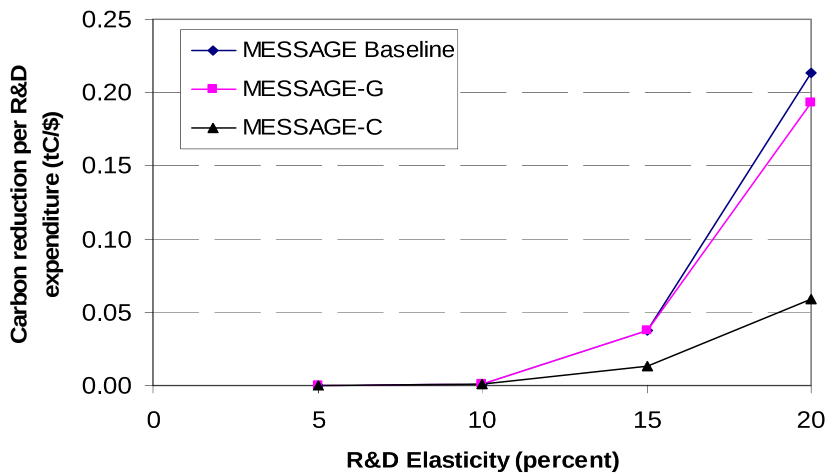
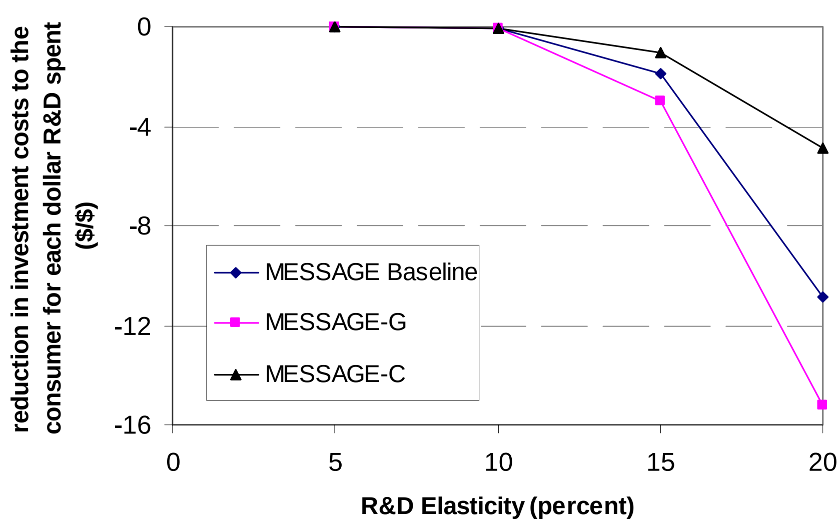


Figure 9-10: Cost reductions to the consumer per dollar R&D spent in relation to the assumed R&D elasticity. The lines show the cost reductions in the MESSAGE-T scenario relative to the MESSAGE baseline, C, and G scenarios.



9.3.3. Measuring R&D indicators for specific technologies

The calculations of the R&D indicators for specific technologies are based on the response functions presented in Section 9.3.2. For each technology and indicator, we first quantify the impact per unit of R&D spent. Next, we calculate technology-specific impacts for a +10% R&D shock assuming that cumulative R&D expenditures for the next 50 years will be 10% higher than the cumulative R&D expenditures until 1997. The result from this analysis may be used as direct inputs to the multi-objective policy analysis with the PROMETHEUS and ISPA modelling framework.

Each technology is characterized by a specific R&D elasticity, estimated by IEPE. The elasticities are calculated for each individual technology and are used to define technology-specific indicators for the R&D impact on "cost reduction to the consumer" and "cumulative carbon emissions". The relationship between the indicators and the R&D elasticity for individual technologies is given by the response functions (see Figure 9-9 and Figure 9-10). By looking at matching pairs of indicators and elasticities, according to the response functions, we derive the technology-specific R&D impacts. For each indicator we estimated three response functions (see Figure 9-9 and Figure 9-10), high, medium, and low, for each assumed value of the elasticity.

Table 9-25 presents R&D elasticities and the resulting range of R&D indicators for a selected set of electricity generation technologies. Relatively high R&D elasticities are given for the molten carbon fuel cells (MFC) and the photovoltaic technologies (DPV, RPV). Consequently, R&D expenditure in these technologies shows comparatively high impacts on the policy objectives (see the indicators in Table 9-25).

Table 9-25: Low, median, and high estimates for technology-specific R&D indicators measuring the reduction in investment costs and in carbon emissions per dollar R&D spent.

Reduction in investment costs to the consumer per dollar R&D spent, $inv/$R&D

Technology abbreviation[a]	R&D elasticity (percent)	R&D indicator ($inv/$R&D)		
		low	median	high
CHP	6	-0.01	-0.01	-0.02
SHY	20	-4.88	-10.87	-15.22
WND	19	-4.12	-9.07	-12.77
SPP	8	-0.03	-0.03	-0.06
DPV	30	-12.51	-28.83	-39.64
RPV	40	-20.14	-46.80	-64.07
BF2	1	-0.0000004	-0.000001	-0.000001
BGT	5	-0.000002	-0.000003	-0.000003
MFC	30	-12.51	-28.83	-39.64
SFC	5	-0.000002	-0.000003	-0.000003
FCV	5	-0.000002	-0.000003	-0.000003
NUC	20	-4.88	-10.87	-15.22
HYD	20	-4.88	-10.87	-15.22

Reduction in carbon emissions per dollar R&D spent, tC/$R&D

Technology abbreviation[a]	R&D elasticity (percent)	R&D indicator (tC/$R&D)		
		low	median	high
CHP	6	0.0001	0.0002	0.0002
SHY	20	0.059	0.193	0.214
WND	19	0.050	0.162	0.178
SPP	8	0.0003	0.0006	0.0007
DPV	30	0.151	0.502	0.567
RPV	40	0.242	0.811	0.920
BF2	1	0.00000001	0.00000001	0.00000001
BGT	5	0.00000003	0.00000004	0.00000004
MFC	30	0.151	0.502	0.567
SFC	5	0.00000003	0.00000004	0.00000004
FCV	5	0.00000003	0.00000004	0.00000004
NUC	20	0.059	0.193	0.214
HYD	20	0.059	0.193	0.214

For the policy analysis with the ISPA model, we calculated technology-specific R&D impacts, given a +10 percent R&D shock. We assumed that cumulative R&D expenditures for each individual technology until 2050 will be ten percent higher than the cumulative R&D expenditures of the past (until 1997). The impact on cumulative reductions of investments and carbon emissions was calculated with the following formula:

*Cumulative impact = Delta cumulative R&D expenditures due to the R&D shock * R&D indicator (see Table 9-25).*

The table below shows the cumulative R&D requirements for a +10 percent R&D increase ("shock"). Also given is the impact of the R&D on the cumulative carbon emissions and cumulative investment requirements per technology. R&D investments are not equally distributed across technologies. In particular, nuclear power generation (NUC) accounts for a comparatively high share of the total R&D, and hence, shows high impacts on cumulative emissions and investments. As mentioned before, most promising options with high impacts due to R&D investments are molten carbon fuel cells (MFC) and photovoltaic technologies (DPV, RPV).

Table 9-26: Low, median, and high estimates for the cumulative impact of a 10% R&D shock on cumulative investment costs and cumulative carbon emissions.

Cumulative impact on investment costs to the consumer for a 10% R&D shock, M$

Technology abbreviation[a]	Cumulative R&D expenditures for a 10% R&D shock (M$)	Δ cumulative R&D (M$)	R&D impact (M$)		
			low	median	high
CHP	14650	1332	-12	-14	-25
SHY	670	61	-297	-662	-926
WND	7736	703	-2898	-6380	-8984
SPP	3873	352	-10	-11	-20
DPV	16621	1511	-18904	-43567	-59902
RPV	14462	1315	-26475	-61524	-84233
BF2	11963	1088	-0.0004	-0.0006	-0.0007
BGT	4119	374	-0.0007	-0.0011	-0.0013
MFC	9118	829	-10370	-23900	-32861
SFC	9118	829	-0.0016	-0.0023	-0.0028
FCV	8933	812	-0.0015	-0.0023	-0.0027
NUC	63231	5748	-28073	-62478	-87472
HYD	10798	982	-4794	-10669	-14938

Cumulative impact on carbon emissions for a 10% R&D shock, MtC

Technology abbreviation[a]	Cumulative R&D expenditures for a 10% R&D shock (M$)	Δ cumulative R&D (M$)	R&D impact (MtC)		
			low	median	high
CHP	14650	1332	0.1	0.3	0.3
SHY	670	61	3.6	11.7	13.0
WND	7736	703	34.9	113.7	125.4
SPP	3873	352	0.1	0.2	0.3
DPV	16621	1511	227.5	758.2	856.5
RPV	14462	1315	318.6	1066.2	1209.5
BF2	11963	1088	0.00001	0.00001	0.00001
BGT	4119	374	0.00001	0.00001	0.00002
MFC	9118	829	124.8	416.0	469.8
SFC	9118	829	0.00003	0.00003	0.00004
FCV	8933	812	0.00003	0.00003	0.00003
NUC	63231	5748	337.8	1107.2	1228.3
HYD	10798	982	57.7	189.1	209.8

[a] For a definition of the technology abbreviations seeTable 9-27 below.

Table 9-27: Definition of technology abbreviations

Technologies	Abbreviation
Conventional Large Hydro	HYD
Conventional Nuclear	NUC
Combined Heat and Power	CHP
Small Hydro	SHY
Wind	WND
Solar Power Plants	SPP
Decentral Photovoltaics to Grid in Buildings	DPV
Rural Photovoltaics in Developing Countries	RPV
Biomass Gasification for Gas Turbines	BGT
Biofuels	BF2
Solid Oxide Fuel Cell	SFC
Molten Carbonate Fuel Cell	MFC
Fuel Cell Vehicle	FCV

9.4. An evaluation with MERGE-ETL and ERIS-2FLC

MERGE-ETL and ERIS have been used to assess the impact of R&D spending per technology on various policy objectives: CO2 reduction, technology profitability and cost reductions to consumers.

9.4.1. Evaluation with MERGE-ETL

Orthogonal R&D shocks have been applied by doubling the R&D spending of a given learning technology. This has been more precisely done for the six learning power plants considered by MERGE-ETL: GCC (gas turbine combined cycle), GFC (gas fuel cell), IGCC (integrated coal gasification with combined cycle), NNU (new nuclear designs), WND (wind turbine) and SPV (solar photovoltaic). In all these cases, a carbon control strategy has been assumed where the following regional carbon tax is imposed:

Table 9-28:Assumed regional carbon tax (in USD 1990 per ton C)

	2010	2020	2030	2040	2050
USA	19	61	104	139	173
OECDE	47	76	104	139	173
CANZ	19	61	104	139	173
JAPAN	19	61	104	139	173
EEFSU	19	61	104	139	173
CHINA	0	52	104	139	173
INDIA	0	52	104	139	173
MOPEC	0	52	104	139	173

The following sections detail the different indicators per technology.

i. Impact on the CO_2 limitation objective

Table 9-29 gives this impact per technology.

Table 9-29: Impacts on the CO2 limitation objective (in ton CO2 per Euro 95)

GCC	GFC	IGCC	NNU	SPV	WND
-0.48	-1.03	-6.53	-6.13	-3.89	-2.10

ii. Market impact ("Profitability")

Table 9-30 gives this impact per technology:

Table 9-30: Market impacts

GCC	GFC	IGCC	NNU	SPV	WND
12.02	9.90	18.93	24.95	39.91	13.39

iii. Cost reductions to the consumers

Table 9-31 gives the cost reductions to consumers in Europe:

Table 9-31: Cost reduction to consumers in Europe

GCC	GFC	IGCC	NNU	SPV	WND
1.76	0.11	-5.71	-7.26	-0.62	0.22

Finally, Table 9-32 gives the cost reductions to consumers in the (current) developing regions (China, India, MOPEC, ROW).

Table 9-32: Cost reduction to consumers in the developing regions

GCC	GFC	IGCC	NNU	SPV	WND
2.20	0.23	-6.15	-8.50	-0.24	0.12

9.4.2. Evaluation with ERIS-2FLC

PSI also implemented the global version of the ERIS-2FLC model to define the impacts for the policy objectives of interest for the SAPIENT project by applying orthogonal R&D shocks to power generation technologies for which a 2FLC relation is defined.

The formulation with exogenous budget allocation defines fixed R&D shocks per technology and year, ARDte,t. Adding them up over time, fixed cumulative R&D expenditures per technology and time period (CRDte,t) are obtained as:

$$CRD_{te,t} = dcrd_{te} + \sum_{\tau=1}^{t} ARD_{te,\tau} * \Delta_{\tau}$$

where:

$dcrd_{te}$ is the initial cumulative R&D expenditures per technology, and

Δt is the length of the period.

Therefore a 2FLC formulation is to be applied with known cumulative R&D spending. In such a case only the cumulative capacity installations remain free decision variables to be defined by solving a modified "learning by doing" problem.

It is well known that perfect foresight optimisation models with endogenous learning are forced to apply a MIP approximation of learning together with market allocation growth constraints. Otherwise, without these constraints, the algorithm will try to introduce the maximum possible capacity aiming at obtaining high productivity returns even during the first time period of analysis.

The consequence of these unavoidable market constraints is that we find all competitive technologies to be on their (maximum penetration) bounds while the orthogonal R&D shocks applied to these technologies are not showing any extra returns.

We have tried to avoid the above problem by increasing the market penetration of competitive technologies based on a logit function. The function was introduced as to distribute extra market shares to competitive technologies. First experiments with the logit function were not always robust and the overall algorithm was unstable. This means that the MIP solution was quite different than the final NLP solution of the problem with no indication if the final solution is a global optimum.

Finally, a robust approach is adopted that defines the market penetration for technology j and period t based on the following function:

$$Cap_{j,t} \geq Cap_{j,t-1} \cdot \exp rate_j \cdot (1 + 0.5 \frac{R\,\&\,Dshock_{j,t-1}}{R\,\&\,Dreference_{j,t-1}}) + 0.01 \cdot \sum_r Cap_{r,j,t-1}$$

This expression allows tripling the installed capacity between periods under a reference budget ($\exp rate = 2$). In the case of twice as high R&D shocks as in the reference budget of 2010, we quadruple the expansion rate. We have isolated the effect of the budget-shocks in the first period. The last term introduces a global spillover effect on capacity expansion, important in the multi-regional version of the model. This approach has the caveat that competitive technologies will be found again on their new upper bounds. But this new formulation, as it changes penetration rates of all technologies, shows significant changes in market shares allowing to competitive systems to growth faster displacing second and third best technologies out of the market.

The carbon tax applied in ERIS corresponds to the "soft landing" scenario. It is relatively low but applies to all world regions. Results are shown in Table 9-33 for the definition of impacts as explained before. Since the regional scale of the two models (MERGE-ETL and ERIS) is different, and since the underlying cost and learning data are not the same, results show significant differences. This refers mainly for the impacts of the SPV system as well as the high level of profitability estimates in ERIS.

Table 9-33: Indicators estimated with global ERIS-2FLC for the carbon tax case

	New nuclear	Advanced coal	Gas turb. CC	Wind	Gas fuel cell	Solar PV
Profitability	12.05	16.85	37.20	32.10	38.50	0.02
Impact on CO_2 objective (t CO_2 per €95)	-1.21	-0.42	-2.29	-1.19	-0.90	0.0
Cost reductions to consumers	-3.75	-10.88	-8.66	-11.4	-3.24	-2.36

9.5. TIMES-WEU (Western Europe) [by M. Blesl, A. Das, U. Fahl and U. Remme (IER)]

9.5.1. Introduction

The present report has been carried out by IER jointly with ECN, Netherlands. IER used a new energy system model called TIMES (The Integrated MARKAL-EFOM System) covering Western Europe (hence onwards will be referred as TIMES-WEU) to compute the R&D impacts on different technologies to be used in ISPA**.** R&D impacts considered are as follows:

1. The impact on market profitability which is defined as (discounted R&D induced technology cost – reference technology cost) x change in equipment sales volume) / (R&D expenditure shock).
2. The impact on CO_2 emissions which is defined as (change in cumulative CO_2 emissions) / (R&D expenditure shock)
3. The Cost reduction to the consumers which is defined as ((R&D induced total discounted system costs – reference total discounted system costs) / (R & D expenditure shock).

TIMES is an advanced modelling tool and a possible successor of MARKAL model. A brief description of the model is given in Annex F. The following tasks are carried out here:

1. Generating TIMES-WEU model from MARKAL-WEU model
2. Implementing endogenous technology learning and clustering in TIMES-WEU
3. Scenario construction and model run to get the required input for ISPA model
4. Results analysis and conclusion

The TIMES-WEU model has been generated from MARKAL-WEU model based on the database MARKAL-SAPIENT 0.2 provided by ECN, Netherlands. Although a software called M2T (abbreviation of 'MARKAL to TIMES') is applied for the conversion process, however, because of complex nature of the MARKAL-WEU model which has about 700 different processes, some amount of manual adjustments have been needed. For example, while MARKAL can accept same product as both input and output, that is not possible in TIMES. One example is refinery gas. This is an output of the refinery and is recycled back to the refinery to be used as fuel. It has been tackled in TIMES by defining a dummy process and dummy output.

Figure 11-1 presents how this process has been modelled in MARKAL and TIMES. M2T software does not generate any error message for this and this error can be rectified only from the 'infeasibility finder' generated by CPLEX solver used by GAMS (Generalised Algebraic Modeling System) software.

Residual capacity of some of the processes in MARKAL-database is not compatible with their life. Capacity continues beyond their life and MARKAL ignores this error. However, since M2T generates the phasing of the past capacity based on the life and the residual capacity of the technology, it encounters with error (it gives error message) which need to be corrected. Another problem encountered which is very model database specific is to make the activity level of a process compatible between two models. As stated earlier, the current MARKAL database includes many complex processes with multiple inputs and outputs. Sometimes, activity level of this process is normalised as 1 or sometime it has been represented in terms of one output as one unit in MARKAL database (please see). For example, in case of the process catalytic reformer (OCR), the activity level has been for the whole process OCR and in terms of 1 PJ. The process has four different outputs namely DSL (diesel), GAS (gas), GSL (gasoline), LPG. If the model decides OCR to produce 1 PJ, contributions from different outputs will be respectively 0.48 PJ by DSL, 0.06 PJ by GAS, 0.4 PJ by GSL and remaining 0.06 PJ by LPG. Consider another process 'petrochemical naphtha cracker (INA), which has six outputs, FOL, GAS1, GSL, LTS, MPE and MSE. The activity level of this process on the other hand, is defined in terms of the output MSE as 1 PJ. Therefore, if model decides INA to produce 1 PJ of MSE, production of other outputs will be scaled up or down proportionately. INA will consequently produce, 2 PJ of FOL, 11.5 PJ of GAS1, 9 PJ of GSL etc. M2T cannot make this differentiation in defining activity level of a process. It makes mistake in defining activity level for TIMES and incurs wrong activity cost. Therefore, activity of a large number of processes was adjusted manually in TIMES. There is no way to identify this error. It can only be detected by comparing the results on process-wise activity level of both the models in VEDA (a software useful for post-optimal analysis).

Figure 9-11: Process representation in two models

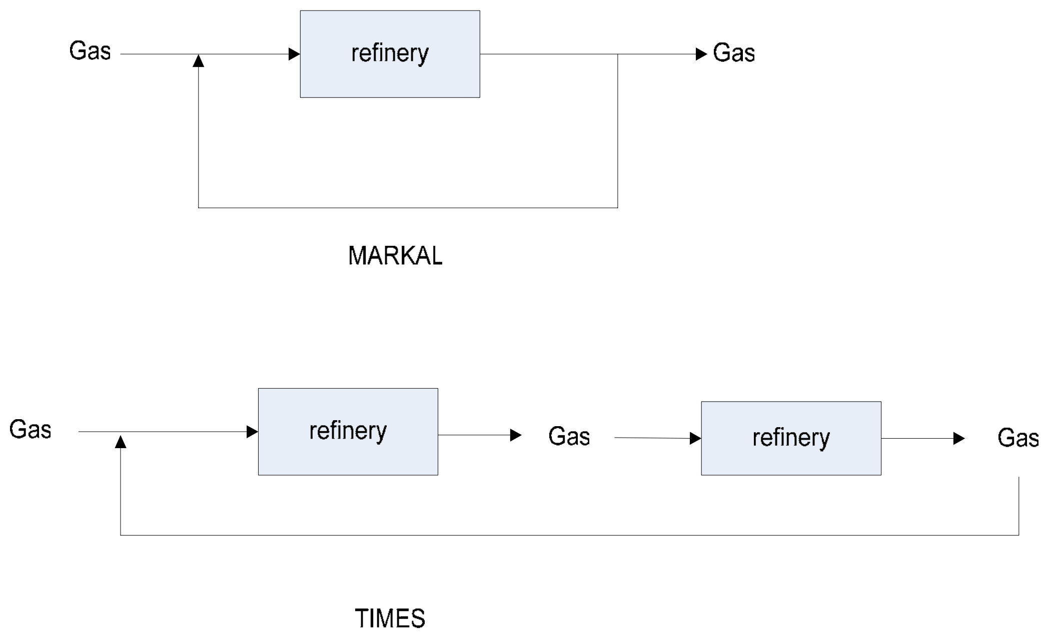


Table 9-34: Activity level of different processes used in MARKAL database

Process	Output	PJ	Process	Output	PJ
Catalytic reformer (OCR)	DSL	0.48	Petrochemical naphtha cracker (INA)	FOL	2
	GAS	0.06		GAS1	11.5
	GSL	0.4		GSL	9
	LPG	0.06		LTS	5
				MPE	0.49
				MSE	1
Activity		Normalised as 1			represented by the output of MSE

This particular MARKAL database contains CHP technology in back pressure mode. M2T cannot transform some of the parameters associated to this process appropriately into TIMES. These parameters are calculated in EXCEL spread-sheet and fed into the TIMES database.

This conversion process also helped to eliminate some of the bugs in the TIMES software. For example, mistake in formation of electricity peak demand-supply equation was detected and corrected. TIMES-WEU is running for the model horizon 1990-2100. At aggregate level, results of TIMES-WEU are quite similar to MARKAL-WEU. However, about 20% of technologies are not matching exactly in terms of their activities which can be explained by the methodological differences between two models in terms of treatment of processes, costs etc.

9.5.2. Endogenous Technology learning and clustering in TIMES-WEU

At the second step of the study, endogenous single factor technology learning has been introduced in TIMES-WEU. A learning or experience curve, describes the specific cost as a function of the cumulative capacity for a given technology. The cumulative capacity is used as a measure of the knowledge accumulation occurring during the manufacturing and use of one technology. An experience curve can be expressed as follows:

$$SC(C) = a \times C^{-b}$$

where:

SC: Specific cost

C: Cumulative capacity

b: Learning index (constant)

a: Specific cost for the first unit (constant)

The learning index b defines the effectiveness with which the learning process takes place. The learning index b can be derived from the progress ratio. The progress ratio (PR) is defined as the rate at which the cost declines each time the cumulative production doubles. It can be expressed as a function of the learning index as:

$$PR = 2^{-b}$$

It constitutes one of the key parameters because it defines the speed of learning for the technology. Mixed-integer programming approach is used to incorporate learning in TIMES (Kypreos et al, 2000; Seebregts et al, 1998).

R & D investment is a very important contributing factor towards the technological progress. SAPIENT project demands for a 2-factor learning curve (2-FLC) approach which relates specific cost for a technology with cumulative capacity and R & D investment. The 2-factor learning curve for the specific investment cost of a given technology is specified as:

$$SC(C, CRD) = a \times C^{-b} \times CRD^{-c}$$

where:

C: Cumulative capacity

CRD: Cumulative R & D expenditures

b: Learning by doing index

c: Learning by searching index

a: Specific cost at unit cumulative capacity and unit cumulative R & D expenditures.

Given the short time frame, IER didn't investigate the two factor learning relationship for technologies. Additionally, for a large size model like TIMES-WEU model (with about 67000 equations and similar number of variables), the non-linearities introduced by two-factor learning curve is difficult to tackle. Therefore, IER used the same R & D intensity approach as adopted by ECN team for MARKAL (Feber et al, 2002) to capture the R & D investment impact. This approach is as follows:

- The model uses the overall progress ratio that includes all factors of learning including R & D impact.
- Additional R & D budget will lead to an increase in the R & D intensity of the technology. R & D intensity is defined as (amount of R&D)/ (amount of R&D + turnover).
- An increased R & D intensity will lead to a lower progress ratio.
- This updated progress ratio is used in the model to study the overall impact of R&D.

Feber et al. estimated the following quantitative relationship between R & D intensity and the change in the progress ratio based on the data of three technologies fuel cell, solar PV and wind turbine:

PR = -0.29 * R & D intensity + 0.9451.

This equation indicates that for one % point increase in R & D intensity lowers (improves) the progress ratio by 0.29% point. This relationship is used to estimate the new progress ratio due to the R & D shock. However, IER recognises the shortcoming of this approach. It may not be appropriate to apply the relationship of R & D intensity and PR which is estimated based on pooled data of three technologies, to all technologies. There is a possibility that this equation may not translate the relationship between PR and

R & D intensity accurately. However, carrying out a detail analysis or exploring for an alternative approach would require much longer time.

Similar to MARKAL, a clustering approach has been used to analyse the learning behaviours of a large number of technologies (Feber et al, 2002). Six technologies are chosen as key components. These are gas turbine, steam turbine, gasifier, fuel cell, solar PV and wind turbine. Cluster technologies are limited only to power generation and 49 of them are considered. Table 9-35 presents the number of technologies clustered with each key components. It should be noted that since one technology can have more than one key components and therefore, belongs to more than one cluster. This makes the total number of technologies in Table 9-36 81 (and not 49).

Table 9-35: Key components and number of cluster technologies

Key component	Number of technologies
Gas turbine	20
Steam turbine	33
Wind turbine	4
Gasifier	14
PV	6
Fuel cell	4

Same data on progress ratio, investment cost, maximum cumulative capacity for key components, and bounds on cluster technologies as used by MARKAL are also applied for TIMES Table 9-36 and Table 9-37.

Table 9-36: Data on technology learning parameters

Key component	Progress ratio	Initial cost 1990 (calibrated) € 95/kW	Initial cum. capacity (GW) 1990	Maximum cum capacity for 2050 (GW)
Solar PV	0.82	7500	0.100	1000
Wind turbine	0.90	1400	0.147	1000
Fuel cell	0.82	2650	0.080	1000
Gasifier	0.90	800	0.650	1000
Gas turbine	0.87	450	31.900	1000
Steam turbine	0.99	300	250.000	1500

Source: (Feber et al, 2002)

Table 9-37: Capacity bounds (GW) on technologies

Technology	2010	2020	2030	2040	2050
Lower capacity bound					
Solar technologies with PV as module	3	3	3	3	3
Upper capacity bound					
Total wind onshore	72	103	123	130	136
Total wind offshore	6.5	57	103	135	148

Source: (Feber et al, 2002)

One important assumption is made on Balance of System (BOS) associated to solar PV module. For 1990, BOS costs has been assumed as 40% of the total PV system costs (Harmon, 2000). It is recognised that the BOS also learns (IEA, 2000). Probably the cost of the BOS has decreased as rapidly as modules for sometime. However, detail cost analysis has not been carried out. For 2000, as brought out by an ECN study, we assume the cost for BOS as € 1350/kW (€ 1313/kW in 1995 price) (Lako, 2002). However, same study comments that impressive cost reductions of the BOS cannot be expected for the next few decades. We assume a PR of 0.9 for 2010 for BOS (Lako, 2002). Same ECN study has made an assessment that 3 GW of solar PV capacity to be achieved in 2010. Based on these information on PR and capacity, we estimate the cost of BOS as € 861/kW in 2010 and assume to remain same beyond 2010.

9.5.3. Scenarios

The baseline or reference scenario has been kept same as defined by ECN (Feber et al, 2002). Modeling period is 1990-2050 with 7 time periods of 10 years. A general discount rate of 4% has been used as desired by the European Commission. Prices are at € 1995. Baseline scenario has been run with the value of progress ratio and other learning parameters as given in Table 9-36.

Regarding the CO2 constraint it was decided in the SAPIENT meeting at Amsterdam that the IEPE "soft landing (SL)" scenario should be used as a kind of expected carbon limitation scenario. CO2 targets in different time periods are given in Table 9-38. Same technology learning parameters as used in Baseline scenario are applied for SL Scenario also.

Table 9-38: CO2 targets in Soft landing Scenario

	1990	2010	2020	2030	2040	2050
CO_2 emissions as % of 1990 emissions	**100.0**	**90.2**	**86.2**	**82.2**	**80.3**	**78.4**

Same amount of R & D shocks and corresponding PR values as used for MARKAL are used for TIMES (Table 9-39). R&D shocks are transmitted to the cluster technologies through key components. As per the project requirement, R & D shocks are applied for one technology at a time and therefore, generating 6 runs altogether for 6 key technologies.

R & D shock amount associated to a key technology is included in the model as one- time lump-sum investment in the beginning of the modelling horizon (1990). Objective function is modified to include this investment. R & D investment is made only when the technology is chosen by the model. Same integer variable dealing with the experience curve to choose the capacity segment for a particular technology for the first period is used to include the investment.

Table 9-39: R & D shock and new progress ratio for key components

Key component	R & D shock (million €)	New progress ratio
Solar PV	355000	0.792
Wind turbine	22000	0.850
Fuel cell	100000	0.791
Gasifier	1000	0.850
Gas turbine	5000	0.820
Steam turbine	6400	0.901

Source: Feber et al., 2002

R & D shock runs are executed for the Baseline as well as the CO2 constrained scenario and from the model results R & D impacts as defined in the beginning have been estimated. Altogether 14 runs are obtained:

1. Baseline scenario without R & D shocks (one run)
2. Baseline + R & D shocks (six runs)
3. SL Scenario without R & D shocks (one run)
4. SL + R & D shock (six runs)

9.5.4. Analysis and Results

This section has been divided into two parts, 1) analysis of TIMES-WEU results and comparison with MARKAL-WEU, 2) analysis of R & D shock runs.

9.5.4.1. Analysis of TIMES-WEU results

Sector-wise final energy demand is presented in Table 9-40. Total demand increases initially till 2030, however after that it almost remains stagnant. Final demand for residential sector declines over time because of energy conservation and penetration of efficient technologies like electric heat pump for water heating etc. Because of structural changes, energy conservation, and efficient process use, final demand for industrial sector remains almost stagnant throughout the modelling period. Growth in energy demand during the modelling period is mainly contributed by the commercial and transport sectors. Some differences occur across the sectors if results of the two models are compared which are mainly due to variations in technology choice. These differences arise because of the differences in costing methodologies and process modelling between two models. For example, while TIMES calculates the cost on annual basis, MARKAL estimates the cost of middle year of a period as an average for the whole period.

Table 9-40: Sectoral final energy demand (PJ)

Sector	1990		2000		2010		2030		2050	
	MARKAL	TIMES	MARKAL	TIMES	MARKAL	TIMES	MARKAL	TIMES	MARKAL	TIMES
Residential	8517	8520	8285	8160	8227	8357	8343	8100	7924	7979
Commercial	4619	4613	5246	5225	5689	5565	6631	6450	7473	7086
Industry	15237	15518	14774	15257	15240	15265	16702	15726	16004	14652
Transport	12615	12615	13881	13881	14576	14576	15836	15836	16497	16497
Agriculture	912	912	1017	1017	1007	1007	988	988	968	968
Total	41899	42177	43203	43540	44740	44770	48499	47099	48866	47182

Table 9-41: Primary energy production, import and consumption (PJ)

Fuel	1990		2000		2010		2030		2050	
	MARKAL	TIMES	MARKAL	TIMES	MARKAL	TIMES	MARKAL	TIMES	MARKAL	TIMES
Production										
Coal	10185	10006	4802	4884	1303	1240	1335	1335	878	878
Oil	11413	11916	12187	17125	7500	7500	655	500	30	1250
Gas	6570	6570	8300	8300	7950	7950	6300	6300	4500	4500
Nuclear	8423	8423	9333	9333	10104	10104	2020	1300	840	840
Renewables	11496	10431	13465	11773	13087	12359	13449	13028	14138	13481
Total	48087	47346	48088	51415	39944	39154	23760	22463	20385	20949
Import										
Coal	2085	2063	4824	5014	6501	6209	10789	12362	14631	16352
Oil	14000	14000	15040	10000	20205	19834	30614	29483	30192	27102
Gas	3100	3100	3900	3900	6200	6200	7601	7601	7901	7901
Nuclear										
Renewables	-2368	-1046	-2354	-1416	-2209	-951	-909	-1094	-498	-432
Total	16817	18117	21411	17498	30698	31292	48095	48353	52226	50922
Gross Inland Consumption										
Coal	12270	12069	9626	9898	7804	7449	12124	13697	15509	17230
Oil	25413	25916	27228	27125	27705	27334	31269	29983	30222	28352
Gas	9670	9670	12200	12200	14150	14150	13901	13901	12401	12401
Nuclear	8423	8423	9333	9333	10104	10104	2020	1300	840	840
Renewables	9128	9385	11111	10357	10878	11408	12540	11934	13639	13049
Total	64904	65463	69499	68913	70642	70446	71854	70816	72611	71871

The table above presents the primary energy supply and consumption during the modelling period. Domestic production of fossil fuels in Western Europe decreases over time. Because of penetration of more efficient and cost effective fossil fuel technologies, use of nuclear declines over time. Mainly coal (IGCC (Integrated Gasification Combined Cycle) technology) replaces nuclear. Its consumption, while decreases till 2010, increases again from 2030 onwards. Absolute consumption of renewables grows from 9385 PJ in 1990 to 13049 PJ in 2050, about 39% increase. However, fossil fuels dominate the primary energy consumption with share of coal, oil and gas together increases from 71% in 1990 to 80% in 2050.

Reduction in domestic fossil fuel production and nuclear use, leads to a rapidly increasing import dependence. Increasing use of CHP and more efficient power generation technologies like IGCC (Integrated Gasification Combined Cycle) results into stabilisation or in marginal reduction in primary energy consumption in the later periods of the modelling horizon. Average thermal efficiency of coal based power plant increases from 38% in 1990 to 60% in 2050. During the same period, average gas based power plant's thermal efficiency increases from 42% to 63%. While comparing results of the two models, TIMES projections on total primary energy consumption is about 1% less than the MARKAL projections. There are some discrepancies in coal, oil and gas consumption which arise mainly because of differences in technology options made by the two models.

Table 9-42 presents the total power generation capacity as well as new capacity created in the different periods of the modelling horizon. During 1990-2050, total capacity requirement increases by about 128 GW, about total 21% increase from 1990 level. As stated earlier, because of availability of more efficient and cost effective fossil fuel technologies, nuclear capacity almost vanishes from the power generating system with its capacity falling from 118 GW in 1990 to 9.3 GW in 2050. However, supply constraint on gas leads to entry of nuclear again at the end of the time horizon. Oil also follows the same trend as nuclear. However, power generating system of Western Europe mainly becomes fossil fuel dependent, solid fuel (coal, lignite and biomass) and gas together account for about 65% of total capacity in 2050. In absolute term, increase in capacity of solid fuel and gas based technology together is about two-fold. Entire coal based capacity in 2050 is based on IGCC technology. Similarly entire gas based capacity in

2050 is combined cycle type, gas turbine for peaking which had about 28% share in 1990 in total gas based capacity, vanishes completely. Capacity contribution from large hydro increases from 166 GW in 1990 to 189 GW in 2050. There is a large increase in capacity from renewables, from meagre 1 GW in 1990 to 64 GW in 2050, contributing about 11% in total capacity. This consists of mainly wind which accounts for about 94% of the total renewable capacity. Higher availability of wind as compared to solar PV makes wind as an preferable option by lowering the cost of generation. Some amount of differences are observed between two models in terms of capacity mix projections, particularly at the later periods of the model horizon. TIMES projection on gas based capacity is about 28 GW less than that of MARKAL and it is compensated with coal and renewables.

Notable differences are observed between two models in terms of investment decision on new power generation capacity (). Differences increase over time and can be explained largely by the variations in cost treatment between two models as brought out earlier.

Table 9-42: Power generation capacity (total and new capacity added during the periods) in GW

	1990		2000		2010		2030		2050	
	MARKAL	TIMES	MARKAL	TIMES	MARKAL	TIMES	MARKAL	TIMES	MARKAL	TIMES
Total capacity										
Coal, lignite and biomass	160.05	160.05	141.64	141.64	83.98	83.58	200.10	237.93	301.31	306.68
Gas	71.55	71.55	131.16	131.16	128.75	136.86	188.71	160.37	156.13	128.94
Oil	67.33	67.33	46.87	46.87	30.01	28.22	14.40	13.50	9.30	5.81
Nuclear	118.41	118.41	126.66	126.66	124.03	124.03	23.39	15.09	9.30	9.30
Large hydro	166.59	166.59	171.74	171.74	184.93	184.93	188.72	188.72	189.17	189.17
Renewables	1.03	1.03	7.80	7.80	16.39	16.39	42.51	42.51	46.85	64.86
Waste	1.80	1.80	3.00	3.00	3.00	3.00	3.00	3.00	3.00	3.00
Total	586.76	586.76	628.86	628.86	571.09	577.01	660.32	660.63	714.07	706.76
New capacity	1985-1995		1995-2005		2005-2015		2025-2035		2045-2055	
Coal, lignite and biomass	57.62	57.62	16.24	16.84	4.80	4.40	142.08	105.63	93.26	165.11
Gas	32.25	32.25	74.48	74.48	30.45	38.57	40.88	62.41	75.20	55.45
Oil	25.38	25.38	0.00	0.00	4.63	2.84	0.00	0.00	6.67	5.81
Nuclear	37.77	37.77	8.31	8.31			0.5	0.5	0.25	9.25
Large hydro	23.44	23.44	28.33	28.33	36.39	36.39	24.59	24.59	23.43	23.43
Renewables	0.34	0.34	6.84	6.84	9.20	9.20	18.96	18.96	14.65	24.46
Waste	0.80	0.80	1.45	1.45	0.75	0.75	1.45	1.45	0.80	0.80
Total	177.59	177.59	135.64	136.24	86.22	92.14	227.97	213.05	214.01	275.05

Electricity generation by sources is showed in . Total electricity generation increases by about 50% during 1990-2050, from 2265 TWh in 1990 to 3383 TWh in 2050. Generation from nuclear falls drastically from 700 TWh to 70 TWh during 1990-2050 since new coal or gas based technologies with cheaper generation cost are available. Oil also follows the same trend. Solid and gas together replace nuclear and oil for power generation and contribute about 74% of the total generation in 2050. Large hydro is another significant contributor, accounts for about 18% of the total generation in 2050. Although generation from other renewables increases enormously from 5 TWh in 1990 to 155 TWh in 2050, however, its share remains only 5% in the total generation. Comparing the results of two models, throughout, TIMES projections on generation remains slightly higher than the MARKAL projections.

It should be noted that while total installed capacity growth during 1990-2050 is only about 21%, total generation increases by about 50% in the same period. This is partially due to the assumption on improvement in availability of power generation capacity and partly because of models's decision on higher utilisation of some capacity between 1990 and 2050 (). Solid (coal, lignite and biomass) increases from 52% in 1990 to 74% in 2050. As stated earlier, entire solid based capacity is IGCC type, assumption in higher availability factor and reduction in generation cost favours the higher utilisation. During the same period utilisation of gas based capacity grows from 26% to 44% because of increasing use of gas combined cycle plants which offer higher availability factor. In case of nuclear, it is due to the assumption made by the model which leads to improvement in utilisation.

Table 9-43: Electricity generation in TWh

	1990		2000		2010		2030		2050	
Source	MARKAL	TIMES	MARKAL	TIMES	MARKAL	TIMES	MARKAL	TIMES	MARKAL	TIMES
Coal, lignite and biomass	755	731	616	680	520	534	1273	1545	1880	1996
Gas	118	161	302	301	492	557	770	673	492	493
Oil	180	180	111	111	125	114	79	73	56	32
Nuclear	700	700	776	776	840	840	168	108	70	70
Large hydro	484	472	511	518	532	555	499	534	565	611
Renewables	5	5	20	20	43	43	105	105	117	155
Waste	16	16	26	26	26	26	26	26	26	26
Total	2257	2265	2363	2432	2578	2668	2920	3063	3205	3383

There is marginal increase for large hydro. However, utilisation of renewables falls from 52% in 1990 to 27% in 2050. Higher capacity utilisation in 1990 is due to the higher share of waste plant in the total renewables capacity (1.8 GW out of total renewable capacity of 2.8 GW) which assumes relatively higher capacity utilisation. However, the share of waste plant becomes marginal at the later periods. On the whole, average capacity utilisation improves from 44% in 1990 to about 55% in 2050.

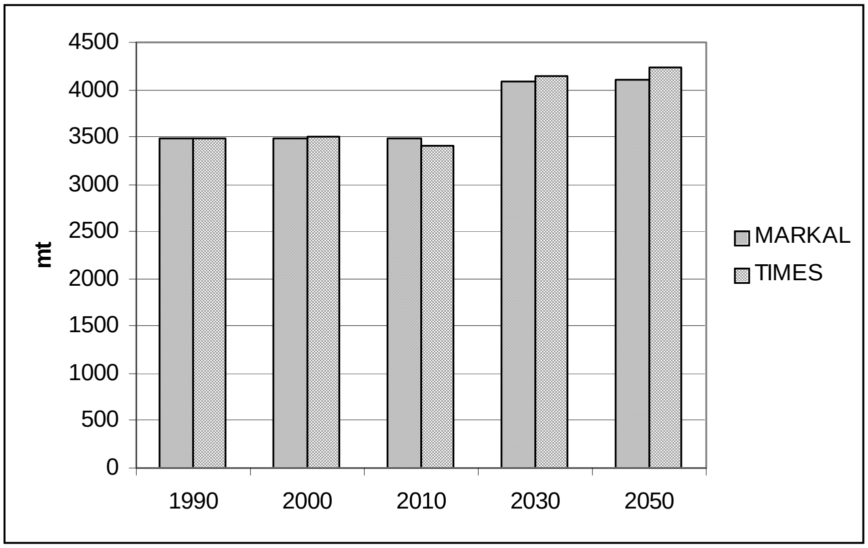
Table 9-44: Utilisation of power generation capacity (%)

Technology	1990		2000		2010		2030		2050	
	MARKAL	TIMES	MARKAL	TIMES	MARKAL	TIMES	MARKAL	TIMES	MARKAL	TIMES
Coal, lignite and biomass	53.8	52.1	49.7	54.8	70.7	72.9	72.7	74.1	71.2	74.3
Gas	18.9	25.6	26.3	26.2	43.6	46.5	46.6	47.9	36.0	43.7
Oil	30.5	30.5	27.0	27.0	47.7	45.9	62.2	61.4	68.8	62.3
Nuclear	67.5	67.5	69.9	69.9	77.3	77.3	81.9	81.7	85.6	85.6
Large hydro	33.2	32.4	34.0	34.4	32.9	34.3	30.2	32.3	34.1	36.9
Renewables	51.9	52.0	29.9	29.9	29.7	29.7	28.1	28.1	28.5	27.2
Waste	99.7	99.7	99.7	99.7	99.7	99.7	99.7	99.7	99.7	99.7
Total	43.9	44.1	42.9	44.2	51.5	52.8	50.4	52.9	51.2	54.6

Both the models project CO_2 emissions from the energy system remains to be same at 1990 level till 2010 (Figure 9-12). After that in 2030 and 2050, it increases by 19% and 21% respectively as compared to 1990 emissions. Because of TIMES larger dependence on coal in primary energy consumption, emissions in 2050 are 3% higher than the same of MARKAL.

TIMES projects the discounted energy system costs as 5555 billion euro for the whole time horizon of 1990-2050, which is about 4% higher than the MARKAL's projection on the same.

Figure 9-12: CO2 emissions



9.5.4.2. Shock-runs analysis

Baseline Scenarios and shock-runs

presents the cumulative capacity and specific cost for the years 1990 and 2050 in the Baseline Scenario. Specific cost reduction depends upon the initial cumulative capacity and the progress ratio. PV, wind turbine and gasifier showed about 65%, 69% and 61% reduction in specific cost in 2050 compared to 1990. PV hits the lower bound imposed on installed capacity of 3 GW in 2010 and beyond which helps in forced cost reduction. The assumption on BOS costs along with its availability factor, perhaps play an important role in model's decision on PV capacity addition. Because of high progress ratio or low learning rate, specific cost reduction is only 1.5% for steam turbine during the period 1990 to 2050. Fuel cell remains cost in-effective for the whole modelling horizon, there is no new capacity addition and hence no reduction in specific cost during the whole modelling period 1990-2050.

Table 9-45: Cumulative capacity and specific cost in Baseline Scenario

	Cum. Capacity (GW)		Specific cost (Euro/kW)		Specific cost in 2050 as
Key component	1990	2050	1990	2050	fraction of 1990
PV	0.10	6.10	7500	2648	0.35
Wind turbine	0.15	250.15	1400	439	0.31
Fuel cell	0.08	0.08	2650	2650	1
Gasifier	0.65	421.96	800	314	0.39
Gas turbine	43.10	535.76	450	254	0.56
Steam turbine	391.59	665.27	300	296	0.985

It can be seen from that excepting gasifier, cumulative capacity in 2050 in R & D shock run remains same as baseline scenario for all key technologies. Gasifier shows a marginal increase in capacity addition. Specific cost falls because of lower progress ratios or higher learning rates for all key components excepting fuel cell. Even higher learning rate couldn't boost the capacity addition for fuel cell throughout the whole modelling horizon and therefore, specific cost does not fall.

Table 9-46: Cum. Capacity and specific cost in baseline vis-à-vis R & D shock run in 2050

	Cum. Capacity (GW) in		Specific cost (€/kW) in	
	Baseline	Shock-run	Baseline	Shock-run
PV	6.10	6.10	2648	1948
Wind turbine	250.15	250.20	439	241
Fuel cell	0.08	0.08	2650	2650
Gasifier	421.96	424.76	314	189
Gas turbine	535.76	535.76	254	190
Steam turbine	665.27	665.27	296	259

The table above presents the impact of R & D shocks on different objective measurements. Additional R & D investment does not improve the market profitability of any of the key technologies since specific cost falls at a higher rate and cumulative capacity remains same (or increases marginally for gasifier) in the 'shock run' compared to the baseline scenario. Concerning CO_2 emissions, shock run for wind turbines shows a marginal, about 13 mt reduction (about 0.05%) in cumulative emissions from baseline scenario. This is due to higher capacity addition in 2040 of 212 GW in shock run as against 207 GW in baseline scenario. Impact on CO_2 emissions is worked out as 0.01 tonne per euro for the whole period. R & D shock for gasifier causes a reduction in cumulative CO_2 emissions of 2.7 million tonnes which is mere 0.1% of the cumulative emissions of the baseline scenario. Consequently, impact on CO_2 emissions is worked out as 0.03 tonne per euro for the whole period. None of the other key technologies shows any impact on CO_2 emissions.

Concerning impact on energy system cost or cost to the consumer due to the R & D shocks, it should be noted that in the shock run, the objective function includes the R & D investment associated to a specific key technology. Therefore the value of the impact as 1 implies there is no change in the energy system cost (excluding R & D investment) in the shock run. In other words, R & D investment does not cause any reduction or increase in the energy system costs. Therefore, R & D investment on solar PV and fuel cell does not cause any benefit to the energy system. The value of the impact as less than one implies R & D investment causes some amount of reduction in energy system costs, but reduction in total energy system costs is less than the R & D investment made. In other words, R & D investment is not fully recovered through energy system cost reduction. This is observed for three technologies, wind turbine, gas turbine and steam turbine. For these technologies, each euro investment in R & D causes reduction in energy system cost by respectively 0.04 euro, 0.08 euro and 0.02 euro. The impact value zero implies reduction in total energy system cost is same as the R & D investment made for the technology. Therefore, R & D investment is fully recovered through cost reduction, however it does not cause any additional benefit. For gasifier, R & D investment of 1000 million euro causes total energy system costs reduction by almost same amount. In other words, one euro of R & D investment causes one euro reduction in energy system costs.

Table 9-47: Impact of R&D shocks on different objectives

Key technology	Impact on market profitability(€/€)	Impact on CO_2 (t/€)	Impact on Cost (€/€)
PV	0.00	0.00	1.00
Wind turbine	0.00	-0.01	0.96
Fuel cell	0.00	0.00	1.00
Gasifier	0.00	-0.03	0.0
Gas turbine	0.00	0.00	0.92
Steam turbine	0.00	0.00	0.98

SL Scenario and shock runs

Cumulative CO_2 emissions in SL Scenario during the period 1990 to 2050 are about 15% less as compared to the same in the Baseline Scenario. Constraint on CO_2 leads to higher penetration of wind in the SL Scenario as compared to the Baseline Scenario and lowers the capacity addition based on coal and gas (). As a result, requirement of gas and steam turbine and gasifier falls. CO_2 constraint plays tremendously to boost the penetration of solar PV and fuel cell based more efficient combined cycle gas power plant in SL Scenario. While solar PV capacity increases from 6 GW in Baseline Scenario to 164 GW in SL Scenario in 2050, for fuel cell it is from almost no capacity to 27 GW in the same year. In this scenario, wind also hits it maximum upper limit.

Table 9-48: Key component capacity in Soft landing Scenario vis-à-vis Baseline Scenario

	Gas turbine		Steam turbine		Wind turbine		Gasifier		PV		fuel cell	
	Baseline	SL	Baseline	SL	Baseline	SL	Baseline	SL	Baseline	SL	Baseline	SL
1990	43	43	392	392	1	1	1	1	0.1	0.1	0.08	0.08
2000	95	95	439	439	13	13	3	3	0.2	0.2	0.08	0.08
2010	115	116	442	443	77	79	8	10	3.1	3.1	0.08	0.08
2020	272	242	501	501	109	161	101	52	3.1	3.1	0.08	0.35
2030	360	320	547	546	141	239	209	72	3.3	123.5	0.08	8.94
2040	413	382	587	575	207	337	274	88	6.1	140	0.08	15.63
2050	536	493	665	641	250	393	422	164	6.1	159	0.08	26.82

The table below presents the specific cost in Baseline vis-à-vis SL scenario. While specific costs for fuel cell and solar PV fall significantly in SL scenario because of significant increase in capacity installation, cost increases for gasifier and gas turbine due to the reduction in their cumulative capacity. Specific cost for wind turbine and steam turbine remains same.

Table 9-49: Specific cost (euro/kW) in Baseline vis-à-vis SL Scenario for 2050

Key component	Baseline	SL
PV	2648	803
Wind turbine	439	417
Fuel cell	2650	507
Gasifier	314	357
Gas turbine	254	267
Steam turbine	296	296

The table below presents the cumulative capacity and specific cost for the year 2050 in SL Scenario and R & D shock applied to SL Scenario. Solar PV and gasifier show an increase of respectively 6 GW and 3 GW in cumulative capacity in shock run as compared to the SL Scenario. Wind turbine, gas turbine and steam turbine, each of them shows a very nominal increase of 1 GW capacity in the shock run. Cumulative capacity for fuel cell remains same. Because of higher learning rate, specific cost falls in R & D shock run as compared to the SL Scenario.

Table 9-50: Cumulative capacity and specific cost in 2050 in SL scenario and R & D shock run

	Cum. capacity (GW)		Specific cost (euro/kW)	
Key component	SL	Shock run	SL	Shock run
PV	159	165	803	568
Wind turbine	393	394.65	439	241
Fuel cell	26.82	26.8	507	380
Gasifier	164	167	357	238
Gas turbine	493	494	267	204
Steam turbine	641	642	296	259

As far as R & D impacts are concerned, there is no gain in terms of market profitability or in reduction in CO_2 emissions (Table 9-51). Concerning impact on consumer costs the same interpretation as made earlier is valid as well. R & D investment on PV and fuel cell is not desirable at all since it does not reduce the energy system costs. R & D investment on wind turbine and gas turbine can be recovered partially through energy system cost reduction. Each euro of R & D investment on these two technologies causes energy system cost reduction by 0.07 euro. For steam turbine the recovery is only 0.02 euro, while it is 0.35 euro for gasifier.

Table 9-51: Impact of R&D shocks on different objectives

Key component	Impact on market profitability(€/€)	Impact on CO_2(t/€)	Impact on Cost (€/€)
PV	0	0	1.00
Wind turbine	0	0	0.93
Fuel cell	0	0	1.00
Gasifier	0	0	0.65
Gas turbine	0	0	0.93
Steam turbine	0	0	0.98

9.5.5. Conclusions

Gas turbine which is already cost-effective, shows tremendous potential for capacity installation during the modelling period of 1990 to 2050 in the Baseline Scenario with PR of 0.87. During the modelling period, cumulative capacity increases by more than 12 times, from 43 GW in 1990 to 536 GW in 2050 and specific cost falls by 44%. Additional R & D investment does not enhance the capacity installation, however it contributes in specific cost reduction from 254 euro per kW in 2050 in the Baseline scenario to 190 euro per kW in the same year in the shock run. CO_2 constraint reduces the capacity installation from 536 GW in Baseline Scenario in 2050 to 493 GW in SL Scenario in the same year and consequently specific cost is higher in SL Scenario as compared to the Baseline Scenario.

Although cumulative capacity for steam turbine increases significantly from 391 GW in 1990 to 665 GW in 2050 in the Baseline Scenario, due to the very low learning rate of 1%, specific cost reduction is only 1.5% during the whole period. R & D shock does not enhance the capacity installation but specific cost falls by 12.5% in 2050 as compared to the Baseline Scenario due to the higher learning rate used. CO2 constraint reduces the installation of steam turbine from 665 GW in 2050 in Baseline Scenario to 641 GW in SL Scenario in the same year since use of fossil fuels (coal, gas) fall for power generation.

Both wind and gasifier show a tremendous learning potential even in the Baseline scenario with PR of 0.9. Cumulative capacity of these two technologies increases respectively 0.15 GW and 0.65 GW in 1990 to 250 GW and 422 GW in 2050. Consequently, specific cost of these two technologies fall by respectively 70% and 60% during the modelling period. In R & D shock run, while wind capacity remains same, there is marginal increase of about 3 GW in cumulative capacity of gasifier. However, R & D shock helps in further reduction in specific costs. In SL Scenario, while CO2 constraint further boosts the additional capacity installation for wind, it drastically reduces the capacity addition for gasifier from 422 GW in 2050 in Baseline Scenario to 164 GW in the same year in SL Scenario. In R & D shock run on SL Scenario, only marginal increase in cumulative capacity is observed.

Fuel cell shows a very pessimistic future in Baseline Scenario with PR of 0.82. There is no new capacity addition during the whole modelling horizon. Even additional R & D investment in the form of higher learning rate of 0.791 could not boost the installation. However, CO2 constraint leads to capacity enhancement from 0.08 GW in 2050 in the Baseline Scenario to 27 GW in the same year in SL Scenario leading to a drastic reduction in specific cost from 2650 euro in 2050 in Baseline Scenario to 507 euro in the same year in SL Scenario. R & D shock run on SL Scenario does not cause any change to the cumulative capacity installation.

Solar PV is not very promising in the Baseline Scenario with a PR of 0.82 or a learning rate of 18%. Cumulative capacity is projected as 6.1 GW in 2050 which is also forced by imposing a lower bound. CO2 constraint leads to an enormous penetration of solar PV from 6 GW in Baseline Scenario to 159 GW in SL Scenario in the year 2050. This results into a tremendous fall in specific cost from € 2648/kW in Baseline Scenario to € 803/kW in the SL Scenario in the same year. R & D investment increases the cumulative installation marginally by 6 GW in 2050 and lowers the cost by 30% because of higher progress ratio.

None of the key components shows market profitability in Baseline as well as in SL Scenario. In the Baseline Scenario, wind and gasifier show some impact on CO2 emissions. Emissions are reduced by 0.01 tonne and 0.03 tonne per euro additional R & D investment on these two technologies. In SL Scenario, there is no impact on CO2 emissions in shock runs. Concerning consumer costs reductions, R & D investment on solar PV and fuel cell does not cause any reduction in energy system cost in neither Baseline nor SL Scenario. However, for solar PV, it should be noted that assumptions on BOS costs may have considerable influence in this conclusion. For gasifier, in Baseline Scenario, R & D investment can be recovered fully energy system cost reduction, i.e one euro investment in R & D causes one euro reduction in energy system cost. However, only partial recovery of 0.35 euro per euro of R & D investment is possible in SL Scenario. Energy system costs reduction due to the R & D investment is nominal for other three technologies.

The results obtained from the analysis need to be treated with caution. It may be possible R & D intensity approach which is used here is not successful to translate the relationship between R & D investment and capital costs via progress ratio appropriately. It is recognised that applying the R & D elasticity of progress ratio which has been obtained based on the pooled data of three technologies (fuel cell, solar PV and wind turbine), to all the technologies has its limitation or may not be appropriate. However, for a large scale model like TIMES (about 67633 equations and 67832 variables), it is difficult to tackle non-linearity introduced by two-factor learning curve. Additionally, given time-frame was short to analyse the two-factor learning curve relationship in detail as well as to explore a better approach to implement it in a large scale energy system model. SAPIENTIA will hopefully help to take these areas of research to one step further.

References:

Feber M. A. P. C de, Seebregts A. J., Schaeffer G. J., Smekens K .E .L., Enhancements of endogenous technology learning in the Western European MARKAL model, Contributions to the EU SAPIENT Project, Draft version, March 2002.

Harmon. C., 2000, Experience curves of photovoltaic technology, IIASA, Austria.

IEA, 2000, Experience curves for energy technology policy, International Energy Agency, Paris.

Kypreos, S., Barreto, L., Capros P., Messner, S., (2000), ERIS: A model prototype with endogenous technological change, International Journal Global Energy Issues, Vol. 14, No. 1-4.

Lako, P., 2002, Learning and diffusion for wind and solar power technologies, ECN-02-001, Netherlands.

Seebregts A J., Kram T., Schaeffer G., J., Stoffer A., Endogenous technological learning: experiments with MARKAL, ECN, Netherlands, 1998.

Annex F: The Integrated MARKAL-EFOM System

TIMES[22] is a new mathematical modeling scheme for representing, optimizing and analyzing energy systems on local, regional, national and global scales. It follows a so-called bottom-up system engineering approach, which allows a detailed technical description of the energy system by equalities and inequalities. TIMES has been developed over the last two years by a working group including IER under the auspices of the International Energy Agency (IEA) within the Energy Technology Systems Analysis Programme (ETSAP). It still continues undergoing developments and refinements and is anticipated to replace the widely used MARKAL approach, which has achieved rather unprecedented longevity in the analysis of energy, environmental and economic (E3) issues. MARKAL suffered from inflexibility - TIMES has been and is being developed for readily adaptable future modeling paradigms.

TIMES is based on the concept of a reference energy system (RES). The RES describes the energy system as a network of processes and commodities being interconnected by commodity flows. One characteristic aspect of an RES is that in most cases a process does not depict a single plant, but rather an entire technology type being available in the energy system. Another typical feature of an RES is that it may contain technologies that are not yet utilized in the real-world system.

TIMES establishes out of the RES abstraction a core of mathematical formulas considering the following relationships:

- Mass or energy balances for the commodities are created.
- Transformation equations for a process relate the input to the output flows. The possibility of specifying fuel and process dependent efficiencies enables a flexible process description avoiding the need for dummy processes as used in MARKAL.
- Capacity-activity relationships do limit activities of processes by their available capacities.
- A generic equation framework allows the generation of non-standard, user-defined equations; e.g. a dynamic constraint limits the investment in a new technology for the current period to a percentage of the existing capacity of the previous period.
- Bounds can be set on variables or ratios of process input and output flows.

The design of TIMES is based on the “reference technology” concept, where costs and emission factors from different technologies are used in the modeling process. Thus, the cost of abatement can be estimated as a function of a movement between technologies from older, less expensive but more polluting technologies towards newer, cleaner, more expensive technologies. These abatement costs feed into the modeling process for energy supply and energy demand.

The output of TIMES are energy balances (for primary and final energy demand), capacity balances (for power generation) and emission balances – always total or by sector. Based on this results marginal abatement costs, exchanged quantities between sectors etc. might be calculated.

[22] TIMES has been implemented in GAMS (General Algebraic Modelling System), a standard modelling environment for optimisation problems, that by separating model formulation, input data and solution method from each other allows changes in the input database without changing the model equations. In addition, GAMS provides easy access to several commercial solvers. One disadvantage of GAMS however is that because of its open architecture it possesses no graphical user-interface. Thus, to support data handling and analysis of the results, the integration of TIMES within the MESAP architecture is in preparation.

10. Exploring R&D Budget Options using ISPA [by N. Kouvaritakis, V. Panos, (ICCS-NTUA)]

The main thrust of the research undertaken within the SAPIENT project has been the construction of the ISPA tool and its use for energy R&D budget exploration. In principle such use would implicate interactions with decision makers involved in R&D policy formulation. However the SAPIENT methodology is essentially still experimental and direct involvement of policy makers at this early stage risked becoming a confusing and inconclusive exercise. The exploration was therefore carried out by project partners and in particular the project co-ordinators in order to familiarise themselves with the properties of the tool and evolve methods for its interactive use in preparation for future applications. The section below summarises some of the experiences gained and results obtained in such proxy exercises.

The first task in ISPA utilisation is the definition of a feasible set. This consists in specifying for each objective retained thresholds for the impact of R&D and minimum probabilities that they will be exceeded. For meaningful exploration the initial set should be sufficiently large to allow for contrasting solutions as the exploration proceeds by increasing levels of ambition concerning specific targets. At the same time it should not be so large that it renders most of the probability constraints redundant (signifying that the given objective is completely inoperative in the exploration).

For an initial set of exploration exercises the feasible set was defined as follows:

The probability that the R&D budget results in:

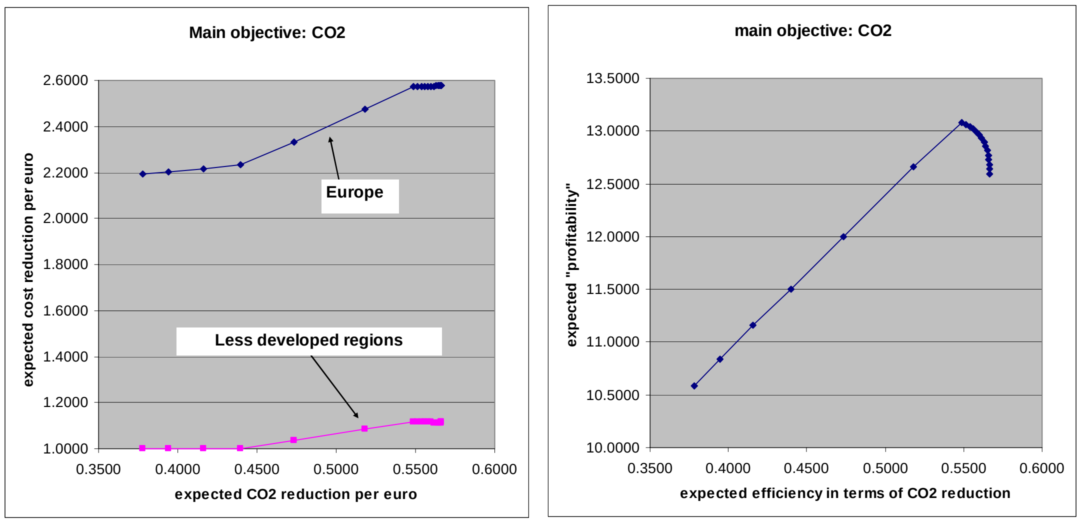
- A reduction of cumulative CO2 emissions should be greater than 90%
- An improvement in security of supply should be greater than 50%
- A reduction in the EU annual energy bill in 2030 of one Euro for every Euro spent in R&D now should be greater than 90%
- A reduction in the annual energy bill in less developed countries in 2030 of one Euro for every Euro spent in R&D in the EU now should be greater than 50%
- A profit rate (as defined within the SAPIENT project) greater than 200% should be more than 95%

10.1. Initial set of R&D exploration exercises

For the initial exercise profitability (a crucial but more conventional target) was used as the main objective while the sustainable development objectives operating via the constraints. The profitability threshold was raised in small steps from 200% to 1280% (beyond this value the character of the solution changed from hedging to “gambling”). Clearly as the profitability threshold is raised the probability of exceeding it declines: slowly at the beginning (from 98% for a threshold of 200% to 90% for a threshold of 560%) and more precipitously as the ambition increases (from 80% for a threshold of 800% to 60% for a threshold of 1150%). At low levels of profit ambition the constraint on energy costs in less developed countries is binding when as beyond a threshold of 550% the constraint on energy costs in the EU becomes increasingly important to the point that the solution virtually stabilises in an effort to satisfy it. At a low level of ambition the portfolio is diversified with many technologies with relatively modest profit prospects in the horizon to 2030 (fuel cells for power generation, integrated coal gasification- ICG and solar thermal power) maintaining budget shares through statistical independence of their prospects contributing to the maximisation of the probability that the profit threshold will be exceeded. ICG is a case of particular interest attracting more than 20% of the budget at low ambition levels because apart from profit hedging it facilitates the satisfaction of the probability constraint on the energy costs in third countries. Beyond a level of ambition of 550% all the modest profit prospect options are eliminated and the budget concentrates on four technologies: GCC (gas turbines in combined cycles) with allocations of over 55% wind turbines (over 25%), biomass gasification (10% to 13%) and supercritical coal (7.5% to 5.5%). Supercritical coal (with modest profit prospects) plays the role of facilitating the satisfaction of the cost to the EU requirements hedging against high hydrocarbon prices. Biomass gasification (BGT) steadily gains share as the ambition is increased because it is characterised by relatively high albeit more uncertain profit prospects.

Placing cumulative CO2 reduction as the main objective the threshold measured in terms of tonnes per R&D euro (99) was raised in small steps from zero to 0.54 (beyond this value the character of the solution changed from hedging to "gambling"). Unlike the case of the exploration using profitability as the main objective the security of supply constraint is binding for the whole range of emission reduction thresholds. This means that all solutions obtained are neutral with respect to energy security (they maintain a 50% probability of a deterioration in energy security as defined within SAPIENT). The energy cost to the EU consumer constraint is also operative for thresholds higher than about 0.1 tonnes per euro. The combined effect of these constraints is the maintenance of supercritical coal as an R&D option for hedging purposes alongside BGT, wind and GTCC. An interesting finding within this set of exercises has been the broad synergy between ambition on CO2 reduction on the one hand and profitability and consumer cost reductions on the other as long as the threshold for CO2 reduction was maintained below 0.18 tonnes of CO2 for each R&D euro spent. This synergy is illustrated in the pay-off curves presented below.

Figure 10-1: Pay-off curves of the CO_2 reduction objective.



It should be noted that values refer to expectations and are different than the thresholds which represent minimum requirements associated with a given probability. For example the first value of the threshold for productivity in terms of CO2 reduction is zero but the expectation associated with it is just under 0.38 tonnes per euro spent on R&D. An inspection of the pay-off curves indicates that there is a clear discontinuity around the seventh point illustrated. Beyond this point, for example the average impact in terms of CO2 reduction can be improved only at the expense of expected profitability (though the drop in the latter is initially rather small). Likewise the expected impact on energy costs does not increase beyond the seventh point. It could be argued that the drops in profitability are small enough to justify a higher impact in terms of CO2 but it should be noted that the gains themselves are very modest and are additionally associated with higher risks. It is for such reasons that such discontinuities on pay-off schedules indicate good candidates for compromise solutions (no or low regret solutions). The budget allocation on the seventh point on the graphs is 55% for GTCC 24% for wind 17% for BGT and 4% for supercritical coal. It is worth noting that a large share goes to a technology which is more or less neutral in terms of CO2 (relatively low emissions with large and reasonably secure market penetration prospects) a relatively new renewable source (wind) which is poised to gain considerable market share if its technical and economic characteristics permit it, a more speculative renewable technology (BGT with large but rather uncertain potential) and a clean coal technology for hedging against supply insecurity and high energy costs. The expected productivity of R&D is .59 tonnes per euro while the probability of exceeding 0.18 tonnes per euro is maximised and stands at 98.7%.

In setting the other targets at the main objective position some of the constraints tended to dominate as follows:

- The CO2 reduction probability constraint when the cost to the European consumer was the main objective (for thresholds of less than two euro reduction for every euro of R&D spent)
- The profitability and security of supply probability constraints when the cost to the consumer of less developed regions was the main objective

- The CO2 reduction and the cost to the consumer of less developed regions probability constraints when security of supply was the main objective

The table below summarises the approximate optimal budgets obtained in this set of exercises:

Table 10-1: Approximate optimal budgets

Main Objective	Cost to EU Consumer	Cost to Consumers in Less Dev. Regions	Security of Supply
Biomass Gasification	10%		12%
Gas Turbine Combined cycle	42%	68%	34%
Supercritical Coal	38%	25%	39%
Wind Turbines	10%	7%	15%

10.2. A second set of R&D exploration exercises

A general remark arising from all the exercises as reported in the previous section was the quasi dominance of gas turbines in combined cycles for R&D funding. This group of technologies is expected to dominate new plant markets both in developed and developing regions in the ISPA horizon to 2030. Improvements in this technology could increase competitive advantage and hence provide very good profitability prospects. This market dominance also means that expected impacts of improvements on electricity consumer costs are very important especially in less developed regions where most of the capital turnover and hence renewal is expected to take place. With regard to CO2 though GTCC produces emissions it does so at a lower rate (per KWh) than almost all of the other fossil fuel options. It is only in terms of security of supply that this technology is potentially disadvantageous as it encourages gas use leading to vulnerability to supply disruptions (hence the smaller budget shares obtained when security of supply was given priority as an objective). It should be noted that despite this dominance diversification is an integral ISPA characteristic through the mechanism of hedging on the main objective itself but also the probability requirements on the other objectives. This diversification notwithstanding, it could be argued that a technological option with such market potential would anyway attract sufficient private R&D to ensure considerable improvements. Taking a public R&D perspective a second set of exercises using ISPA was performed excluding the GTCC option.

In attempting to carry out the policy exploration with this modification a series of problems were encountered regarding feasibility or sufficient size of the feasible region to enable meaningful threshold variation. The technology that was excluded (GTCC) played a key role in terms of profitability and energy cost reduction and some diminution in the ambition concerning these objectives seemed necessary. After a series of test runs the feasible set for the new series of exercises was defined as follows:

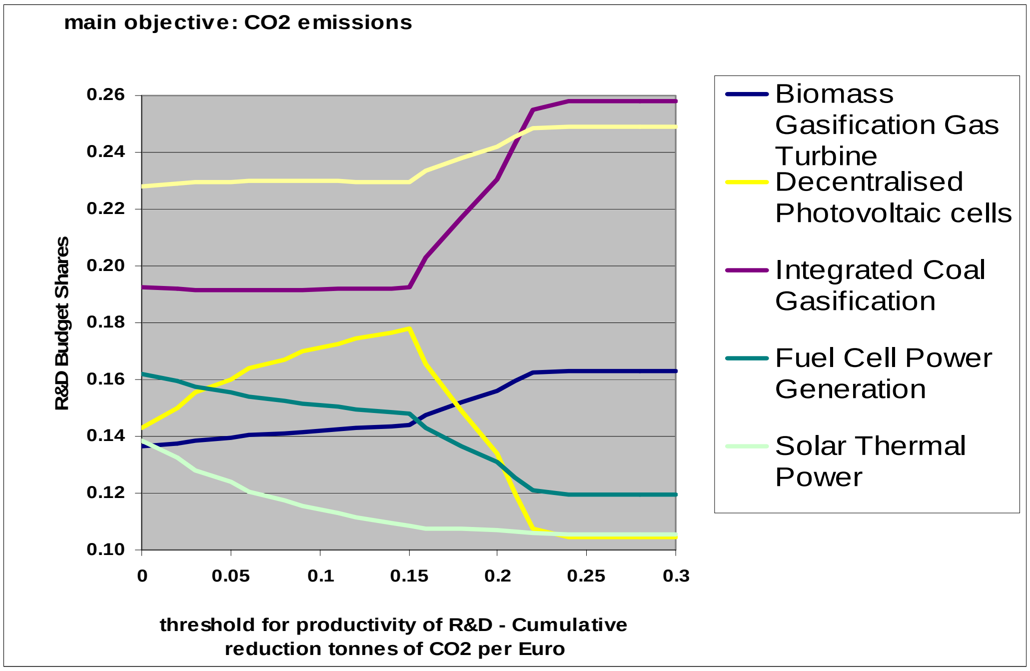
The probability that the R&D budget results in:

- A reduction of cumulative CO2 emissions should be greater than 90% as in the first set of exercises
- An improvement in security of supply should be greater than 50% as in the first set of exercises
- A reduction in the EU annual energy bill in 2030 of one Euro for every Euro spent in R&D now should be greater than 50% (instead of 90% in the first set of exercises)
- A reduction (just any reduction) in the annual energy bill in less developed countries in 2030 should be greater than 50%
- A profit rate (as defined within the SAPIENT project) greater than 50% (instead of 200% as in the first set of exercises) should be more than 95%

The modified set represents considerable downgrading in terms of profit expectation and hedging. Even so the relaxed profit constraint was found to be binding in all cases where the other targets were placed as main objectives and was even operative when increasing the profitability threshold beyond 400%: maximising the probability of exceeding this threshold was in conflict with the maintenance of a 95% probability of exceeding the revised “minimum” of 50% “profitability”.

As could be expected the removal of a dominant technological option and the changes in the feasible area has resulted in radically different budget allocations for all exercises examined. In general more technologies were retained even at high levels of ambition. Furthermore the budgets were more balanced in that there emerged no dominant option. As an example the case of the CO2 reduction target as the main objective is discussed briefly below. The graph presents the budget allocation as the threshold (level of ambition) regarding CO2 reduction is raised up to 0.3 tonnes per euro of R&D.

Figure 10-2: Budget Allocation given a threshold regarding CO_2 reduction.



It is noteworthy that six technologies figure with shares of more than 10% throughout the range of thresholds. There appear to be three phases in the allocation as the threshold is increased. The first (up to a threshold of 0.15 tonnes of CO2 per euro) is characterised by a high degree of diversification. Photovoltaic power (with relatively small expected impact to 2030) and fuel cells (with more uncertain prospects and a less than clear cut impact on CO2) are maintained at high budget levels for hedging purposes. The same is true of solar thermal power though its clearly smaller prospects mean that its share starts declining even for modest increases in CO2 reduction ambition. From 0.15 to 0.22 tonnes per euro there is a rapid reversal. Wind power and biomass increase their share to facilitate meeting the more ambitious target. The profitability constraint which is operative throughout the exercise meaning that this increase in renewable energy funding must be accompanied by an increase in integrated coal gasification (ICG) funding. This seeming paradox is explained by the fact that ICG is potentially the most efficient (and hence lowest emitter) among the clean coal technologies considered and at the same time its profitability prospects are negatively correlated with the prospects of renewable power technologies that are rising in this phase. Photovoltaic power and fuel cells must give way to allow for the above developments. Beyond a threshold of 0.22 tonnes of CO2 per euro the constraint on the minimum probability requirement becomes operative: any further increase in BGT or Wind (not to talk of ICG) increases the risk that the CO2 objective collapses (the probability that the R&D budget results in an increase in cumulative CO2 emissions would be higher than the stipulated 10%). The solution therefore stabilises with ICG retaining 26%, wind turbines 25%, BGT 16%, fuel cells 12% and Solar thermal and photovoltaic power 10.5% each.

10.3. Summary Overview of Results

A summary view of the budget results arising from the whole range of exercises leads to some robust observations on the different power technologies as candidates for R&D funding:

- Some technologies that were included as candidates failed to attract any funding irrespective of the target that was placed as the main objective or whether the GTCC option was excluded. These were:
    - CHP the technical / economic characteristics and general prospects of which are closely correlated with GTCC. When the latter was excluded and the profitability constraint became binding throughout CHP was excluded because of lower profit prospects than all the other technologies included.

  - Advanced Thermodynamic cycle (hard coal) and Advanced Lignite the prospects of which are strongly correlated with the other clean coal technologies (ICG and SCC) while their expected performance was substantially inferior on every one of the objectives explored.
  - New Evolutionary Nuclear design because of poor learning by research characteristics: according to the Technology Database this technology has attracted considerable R&D effort while displaying little improvement in economic performance, a fact that is reflected in the learning curve relationship used for the analysis.
  - Oil fired gas turbine because of relatively poor profitability performance and negative expectations with regard to all other targets
- GTCC (when included) dominated the budget for reasons exposed in an earlier paragraph. Its share was highest in all cases and ambition levels with the exception of the case where priority was given to security of supply when it was overtaken by supercritical coal but still maintained close to one third of the budget.
- Clean coal technologies featured strongly in almost all the cases examined including those that gave priority to CO2 reduction. Their prospects being independently or negatively correlated with those of renewable and gas based power options their funding constitutes a major hedging instrument especially with regard to meeting binding probability constraints on secondary objectives. Of the two technologies featuring in the solutions ICG has more attractive prospects in terms of profitability (higher learning potential) and CO2 (higher efficiency potential) while SCC is more effective in terms of the other objectives because of its higher expected market impact especially in less developed regions. Consequently ICG dominates the clean coal choices when priority is given to the CO2 reduction or profitability. SCC dominates when energy cost to consumers in LDCs is set as a priority. In all other cases its shares are markedly lower in cases where GTCC is excluded because of the importance of the profit probability constraint that characterises them.
- The key renewable power sources that attract funding in the exercises carried out are wind and biomass gasification. In the absence of GTCC they figure with high percentages whatever the target that is set as the main objective and in most cases they do not crowd each other out as the level of ambition regarding a target variable is modified. In the presence of the GTCC option in general they tend to get somewhat lower shares and very low funding when energy costs to the consumer are set as the main objective.
- Photovoltaic cells (DPV) and fuel cells represent the more speculative options in the portfolios explored. Their prospects to the 2030 horizon are rather limited and there is considerable uncertainty surrounding them yet they offer vehicles for diversification once the basic risk conditions are satisfied. In the presence of the GTCC option they are almost completely crowded out but in the second set of exercises one or the other or even both featured in the solution even when high levels of ambition regarding the objectives were set. DPV was particularly favoured when security of supply was given priority while fuel cells attracted more funding when energy costs were the dominant concern. In almost all cases these two technologies acted antagonistically crowding each other out as the level of ambition regarding a target variable is modified.

The table below summarises the ranges for the budget shares attributed to the different technologies for both sets of exercises.

Table 10-2: Ranges for the budget shares attributed to the different technologies

Technology share (in %) of budget over the whole range of ISPA experiments Main objective:		Gas Turbine in Combined Cycle (GTCC)	Wind Turbines	Biomass Gasification Gas Turbine (BGT)	Solar Thermal Power (SPP)	Integrated Coal Gasification (ICG)	Super Critical Coal (SCC)	Decentralised Photovoltaic cells (DPV)	Fuel Cell Power Generation
CO_2	*(incl. GTCC)*	50 - 55	13 - 24	9 - 26	0 - 13	1 - 14	-	1 - 5	-
	(without GTCC)	-	23 - 25	16 - 22	10 - 14	19 - 26	-	10.5 - 18	12 - 16
Profitability	*(incl. GTCC)*	50 - 57	14 - 26	6 - 14	0 - 5	0 - 23	0 - 7	-	0 - 3
	(without GTCC)	-	19 - 27	11- 13	11 - 13	27 - 29	-	9 - 14	11 - 16
Energy cost to consumer (Europe)	*(incl. GTCC)*	42 - 67	4 - 9	8 - 10	-	-	20 - 38	-	-
	(without GTCC)	-	25	15 - 16	14	26	-	6	13
Energy cost to consumer (Rest of the World)	*(incl. GTCC)*	68	7	-	-	-	25	-	-
	(without GTCC)	-	18 - 36	11 - 14	15 - 23	25 - 28	39	0 - 6	13 - 21
Security of Supply	*(incl. GTCC)*	34	15	12	-	-	39	-	-
	(without GTCC)	-	22 - 24	11 - 15	14 - 16	20 - 30	0 - 5	17 - 26	0 - 2

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