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Long-term performance targets for nuclear energy. Part 2: Markets and learning rates

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Abstract: This paper estimates investment cost targets for future nuclear power plants to be competitive in mid-21st century energy markets and beyond. The point of departure is the nuclear market shares derived from the Special Report on Emissions Scenarios (SRES) of the Intergovernmental Panel on Climate Change. One provocative result is that substantial nuclear expansion does not seem to require big reductions in nuclear investment costs, largely explained by the difference between cost reductions consistent with long-term energy system optimisation based on perfect foresight, and cost reductions necessary to attract private investment in today's deregulating and uncertain energy markets.

Keywords: nuclear power; scenarios; long-term; innovation; performance targets; research; development; demonstration; learning.

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1 Introduction

The objective is to assess cost targets for nuclear energy in competitive mid-century energy markets. The first step is to describe the mid-century energy market in terms of nuclear energy's major competitors, the products that are in demand, the amount of each and the areas where growth is greatest. Rogner et al. (2008) provide such descriptions for four scenarios from the SRES of the Intergovernmental Panel on Climate Change (IPCC, 2000). The costs reductions for nuclear power between now and 2050 in each of these four scenarios are available from the SRES and are reported in Section 3.6.

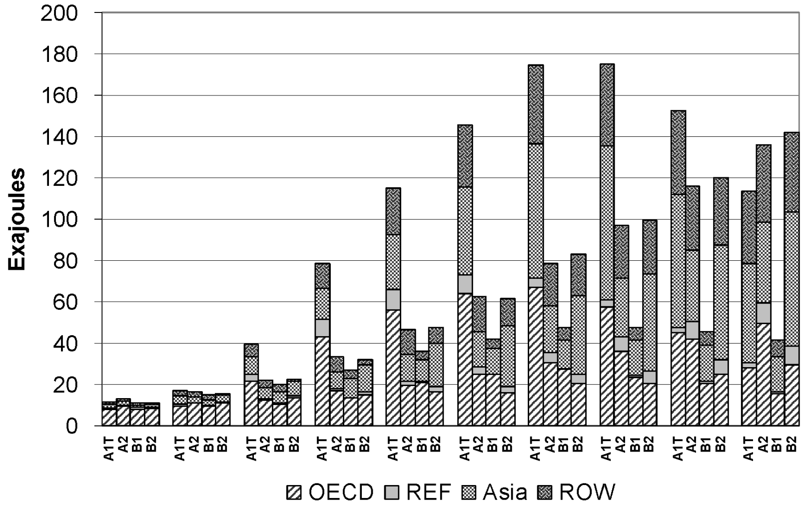
This paper examines how much faster nuclear power's costs might have to decline for it to capture larger shares of the electricity, hydrogen, heat and desalination markets than it does in the four selected SRES scenarios. For each of the four scenarios, a more aggressive nuclear expansion variant is developed. This is done by assuming plausible target shares of its competitors' businesses that the nuclear energy industry might reasonably aspire to capture. Once the target additional market shares of nuclear power are assumed, the rates of technology learning needed to reach those targets are calculated along with the resulting mid-century nuclear energy costs.

2 Estimating potential nuclear markets

Nuclear energy developments in the four SRES scenario quantifications (Rogner et al., 2008) should not be viewed as tight constraints, but as indications of opportunities. This paper seeks to more precisely quantify those opportunities.

Figure 1 summarises the nuclear projections in the four selected scenario quantifications from the SRES using the Model for Energy Supply Strategy Alternatives and their General Environmental Impacts (MESSAGE)[1] (Messner and Strubegger, 1995) of the International Institute for Advanced Systems Analysis (IIASA). Each quartet of bars shows projected nuclear production in a given year for the four scenarios A1T, A2, B1 and B2. Each bar is divided into four segments corresponding to the four regions into which the SRES analysis divides the world. The dark segments include all countries belonging to the Organisation for Economic Cooperation and Development (OECD) as of 1990. The next segments, the REF, are countries undergoing economic reform. Next is 'Asia' that includes all developing countries in Asia. The top light segments cover the Rest of The World (ROW) and include all developing countries in Africa, Latin America and the Middle East. The figure thus corresponds to the results presented in Tables 1–4 of Rogner et al. (2008).

Figure 1 Nuclear primary energy use in four SRES scenarios

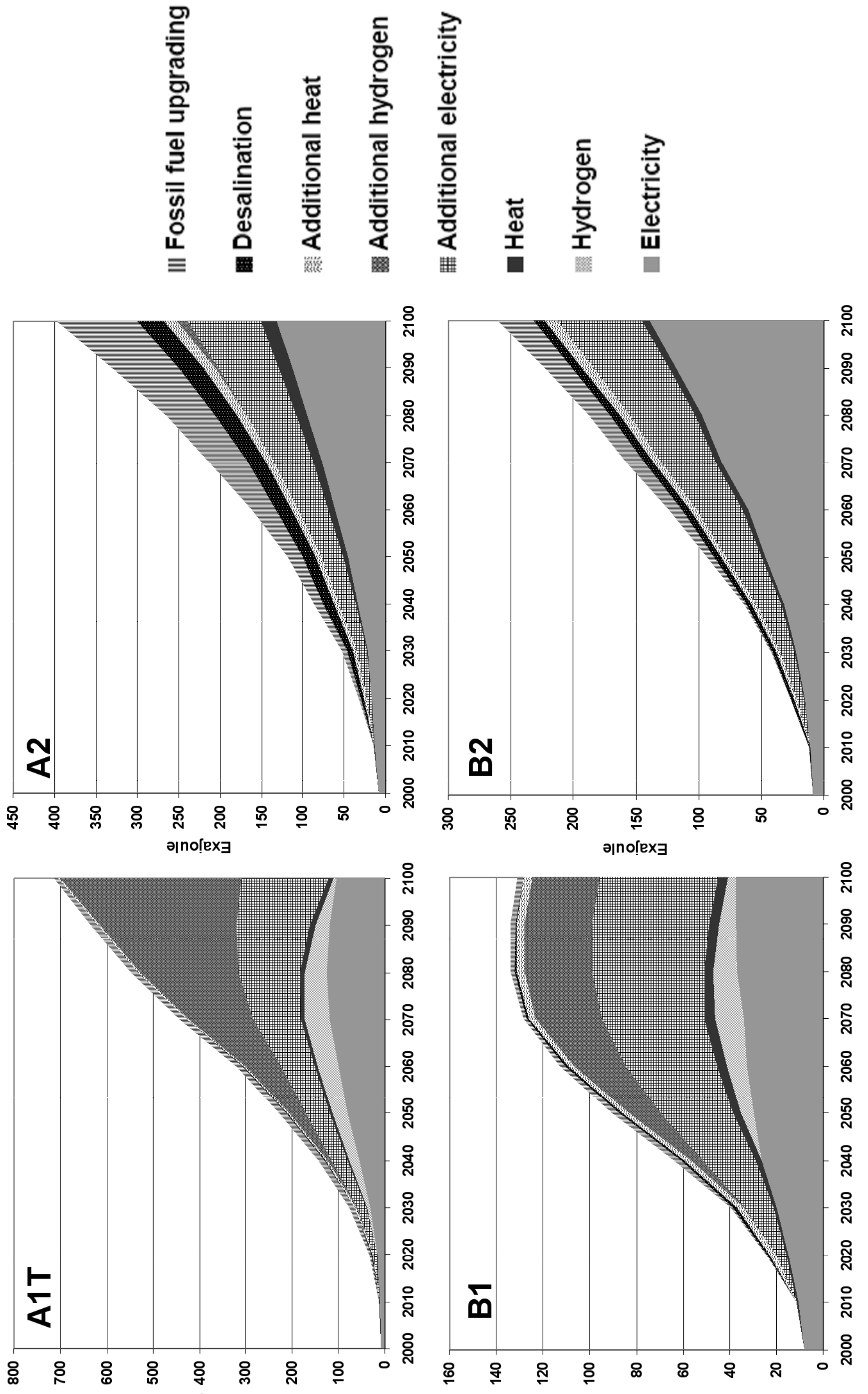


The left bar in each quartet is the A1T scenario. The next bar is the A2 scenario.
The third bar is the B1 scenario, and the right bar is the B2 scenario.

The use of nuclear energy rises most rapidly in the A1T scenario to more than 14 times its level of the year 2000 in 2050. Initially, the expansion is driven by the OECD, but after 2040 expansion is greatest in Asia. Nuclear energy then peaks around 2070 and 2080 and declines by the end of the century. The pattern is similar in the B1 scenario but at a much reduced level. Nuclear use in 2050 is slightly less than five times the current level. The pattern is very different in the A2 and B2 scenarios. Expansion is slower than in the A1T scenario, but it is steady and continuous. By 2050, nuclear use is almost six times its current level, and by 2100 it has passed the level in the A1T scenario and is still growing.

Key questions emerge. First, what additional market potential might there be for nuclear energy beyond what is shown in Figure 1 if the nuclear industry were to reduce nuclear costs, relative to its competitors, more quickly than is assumed in the SRES calculations? Second, how quickly must the industry innovate to capture significantly larger future market shares? To answer these questions and develop cost reduction targets, an 'aggressive nuclear' variant was developed for each of the four SRES scenarios discussed above. The assumptions underlying these aggressive nuclear variants are described in Sections 2.1–2.4. The results are shown in Figure 2.

Figure 2 Potential global markets through 2100 for nuclear electricity, hydrogen, heat and desalination for aggressive nuclear variants of four selected SRES scenarios



The vertical scales are different.

2.1 Electricity

If the nuclear industry were to reduce nuclear costs faster than assumed in the SRES, or if its competitors were to reduce their costs more slowly, nuclear energy would make inroads into the market held by its competitors starting with those parts of competitors' market shares that are most expensive. Consider first competition from coal-fired electricity generation. In the SRES scenarios, coal resources are divided into five cost categories. The SRES calculates consumption in each category for each region and scenario. In general, consumption early in a scenario concentrates on lower cost categories and, as these are depleted, moves to higher cost categories in later parts of the scenario. In detail, the patterns are more complex, incorporating as they do regional differences in resources, trade and infrastructural inertia – i.e., new plants, mines, transportation systems and processing facilities do not replace old ones overnight, but are phased in at different rates in different regions.

We assume that even aggressive nuclear cost reductions would be unlikely to displace electricity produced by coal in the two least expensive coal categories. Electricity from coal in these categories is simply too cheap an option. But the three higher-cost categories are more vulnerable to inroads from nuclear cost reductions that are faster than those assumed in the SRES. We therefore assume that aggressive nuclear improvements would allow nuclear power to capture 50% of the market share (in each region in each scenario) that corresponds to electricity from coal in these categories.

In each scenario and region, multiplying the percentage of coal use that comes from these three categories by 50% gives the numbers in the 'coal' column in Table 1. The first, 17% for Asia in the A1T scenario, means that the estimated potential nuclear market in that region and scenario adds to what the SRES reports for the nuclear potential (Figure 1) an amount equal to 17% of the SRES's estimate for coal-fired electricity. The rest of the column should be interpreted similarly.

For natural gas, the assumptions parallel those for coal. The SRES scenarios divide gas resources into eight categories, the first four of which are assumed to be too cheap for even aggressive nuclear cost reductions to displace. However, 50% of unconventional gas consumption from the more expensive categories is assumed to be vulnerable to more accelerated nuclear cost reductions than assumed in the SRES scenarios. The numbers in Table 1's 'natural gas' column were calculated, and should be interpreted, in the same way as the numbers in the 'coal' column.

Biomass and waste are not divided into cost categories in the SRES like coal and natural gas. But the same principle should hold – even aggressive nuclear cost reductions would be unlikely to dislodge the cheapest biomass and waste from the electricity market, but should make inroads at the expensive end of the biomass/waste market share. Since the SRES estimates the total potential availability of biomass and waste, we assume that any use that exceeds 60% of this total potential would fall into the high-cost, vulnerable category. Table 1 thus shows the percentages of the SRES's estimates for biomass/waste-fired electricity that are included in the target nuclear market potentials assuming aggressive nuclear improvements.

The SRES divides hydroelectricity into a 'high-cost' category and a 'low-cost' category. Only the high-cost category is considered vulnerable to inroads by nuclear energy. In the OECD and REF regions, we assume that nuclear energy could capture 50% of the high-cost hydroelectricity calculated by the SRES. In the Asia and ROW regions, where nuclear energy faces greater infrastructural challenges even in the event of aggressive improvements, we assume that it could only capture 33% of the high-cost hydroelectricity calculated by the SRES.

In the SRES scenarios, solar electricity is divided into three categories based on whether it is generated by centralised solar thermal plants, centralised photovoltaic plants or decentralised onsite production (mostly from small photovoltaic systems). Only the two centralised categories were considered vulnerable to displacement by nuclear energy. The numbers in Table 1 assume nuclear energy captures 50% of their market as calculated by the SRES.

For wind and geothermal, the SRES includes no cost categories. Based on the expectation that, with aggressive improvements, nuclear energy could displace a share of the more expensive end of the wind/geothermal market share, Table 1 indicates that 25% (half of half) of the complete wind/geothermal electricity shares calculated by the SRES is assumed vulnerable to nuclear inroads.

Table 1 Percentage of SRES-calculated electricity markets assumed to be captured by nuclear energy in the event of aggressive nuclear cost reductions

	Coal (%)	*Gas* (%)	*Biomass/Waste* (%)	*Hydro* (%)	*Solar* (%)	*Wind/Geothermal* (%)
A1T						
Asia	17	30	35	30	25	25
ROW	0	18	0	20	20	25
REF	1	8	0	15	40	25
OECD	0	23	31	0	33	25
A2						
Asia	36	27	40	30	33	25
ROW	21	16	40	25	20	25
REF	18	11	40	15	26	25
OECD	5	28	40	6	16	25
B1						
Asia	11	27	16	30	34	25
ROW	0	14	0	20	27	25
REF	3	5	0	15	34	25
OECD	0	24	26	8	37	25
B2						
Asia	17	32	40	30	26	25
ROW	0	18	40	20	20	25
REF	6	9	40	10	40	25
OECD	0	30	37	5	28	25

2.2 Hydrogen

Table 2 quantifies the assumptions used for hydrogen production in the aggressive nuclear variants of the SRES scenarios. Hydrogen in the SRES scenarios can be produced in six ways. For the first three, hydrogen is produced directly from carbon fuels – coal, natural gas and biomass. The fourth option is electrolysis, and the fifth and sixth are thermochemical production from high-temperature nuclear and solar cycles. Of the six, the first three are the cheapest, and are assumed to be less vulnerable to inroads from nuclear energy. Any nuclear inroads into electrolytic hydrogen production are assumed to be already accounted for in Table 1, where nuclear power displaces the contributions of competitors to the overall electricity mix. Thus the only potential additional hydrogen market share to capture is that from thermochemical solar hydrogen production. Assuming again that the more expensive end of solar's market share is most vulnerable to displacement, Table 2 assumes nuclear hydrogen production displaces any solar hydrogen production in excess of 60% of the total solar potential estimated by the SRES.

Table 2 Percentage of SRES-calculated hydrogen production from solar power that could be displaced by nuclear energy in the event of aggressive nuclear performance improvements

A1T	%	*A2*	%
Asia	40	Asia	10
ROW	40	ROW	40
REF	25	REF	6
OECD	40	OECD	39
B1	%	*B2*	%
Asia	0	Asia	7
ROW	40	ROW	40
REF	0	REF	0
OECD	0	OECD	15

2.3 Heat

This section addresses additional applications of nuclear energy for district heat (i.e., centralised heat generation), heat for upgrading unconventional oil, for liquefying and gasifying coal, and for producing synfuels from coal.

District heat supplies are included as a separate category in the SRES calculations, but they are not broken down into cost categories. Paralleling the logic applied to wind and geothermal electricity generation above – that nuclear energy could displace a share of the more expensive end of the market – we assume in the aggressive nuclear variants of the SRES scenarios that nuclear district heat could capture 25% of the total district heat use calculated in the SRES.

Oil resources in the SRES, like coal and gas resources, are divided in cost categories. Oil resources in the four highest cost categories (out of eight) are all unconventional. In the SRES, the heat needed to upgrade oil in these categories comes from the oil itself, and thus shows up in the calculations as a conversion loss. Similarly, in coal gasification and liquefaction, and in synfuels production from coal, the necessary heat comes from the coal and shows up as a conversion loss. The assumption used in the aggressive nuclear variants of the SRES scenarios is that improvements would allow nuclear energy to supply heat for these purposes equal to 50% of the conversion losses calculated by the SRES.

2.4 Desalination

The SRES scenarios do not elaborate on future water demand and supply. However, studies indicate that freshwater demand may well exceed sustainable supply in the near-term future (Falkenmark, 1997; Gleick, 2000; Seckler et al., 1998; WRI, 1998; UNCSD, 2005). Indeed, in areas of North Africa, the Middle East and certain parts of Asia, this is already the case now. For the purposes of this analysis, overall water demand was estimated based on the demographic developments underlying the SRES scenarios, a daily diet of at least 2,700 kcal per person per day, an average water demand of households and industry of 400 m^3 per person per year, and rates of productivity in improving water use derived from the SRES storylines. Regional water availability was taken from a variety of sources (Falkenmark, 1997; Gleick, 2000; Seckler et al., 1998). A sustainable share of 40% of total water availability was assumed for all regions, as was a 25% potential share of nuclear power in the future water desalination market.

2.5 Results

The potential global markets for nuclear electricity, hydrogen, heat and desalination for the resulting aggressive nuclear variants of the four SRES scenarios are shown in Figure 2. (Note that the vertical scales differ.) The lower three areas in each panel show the SRES projections for nuclear-generated electricity, hydrogen and heat. Together these values correspond to the nuclear totals for the SRES scenarios shown in Figure 1. The other areas show the additional nuclear-generated electricity, hydrogen, district heat and desalination based on the assumptions above.

The four IIASA-SRES scenarios depict future worlds of alternative market conditions and technology environments. Hence, the potential of nuclear technologies to gain additional shares differs considerably across the scenarios. First, this is due to the variation of the scenarios' socio-economic assumptions, which result in considerably different energy demand projections. Second, the scenarios differ also with respect to technology assumptions, which drive the evolution of the energy system in alternative directions. By analysing the scenarios, key markets are identified for additional nuclear shares compatible with the given path-dependent development in each of the four SRES worlds.

The main markets for the expansion of nuclear capacities are electricity and heat generation, hydrogen supply and desalination. The scenario-specific characteristics for possible additional nuclear shares beyond the levels depicted by each of the four SRES scenarios are as follows:

A1T

The A1T scenario depicts a world of high economic growth and rapid increase of energy demand. The comparatively fast turnover of capital promotes the expansion of nuclear energy. In the original SRES A1T scenario, nuclear energy contributes more than 100 EJ to the global hydrogen and electricity production in 2050. Based on our assumptions (see Tables 1 and 2), nuclear may increase its contribution by an additional 90 EJ in 2050. In the very long term, the energy supply of the A1T scenario shifts from fossil-based energy production toward renewable sources of hydrogen. The additional market potential for nuclear is vast and could increase to 400 EJ of hydrogen and 200 EJ of electricity in 2100. Nuclear energy's biggest competitor is solar-based hydrogen production. Hence, nuclear energy strategies that focus on the 'buy down' of costs in the hydrogen sector are most promising. Due to the phase-out of coal and comparatively little use of other fossil fuels, there is only limited additional potential for nuclear in the heat sector.

A2

The A2 scenario is characterised by heavy reliance on coal and relatively modest assumptions for economic growth. The scenario illustrates the long-term implications of quickly 'running out of conventional oil and gas' combined with slow progress in developing alternatives. In the original SRES A2 scenario, nuclear technologies are predominantly used for power generation, increasing their contribution from 45 EJ in 2050 to 130 EJ in 2100. The main competitors for nuclear energy are coal technologies. In the electricity sector, nuclear power could gain additional market shares of about 30 EJ in 2050 and up to 90 EJ in 2100. In the non-electric sectors, nuclear technologies could supply process heat for coal-based gasification and liquefaction processes. Following the assumptions reflected in Tables 1 and 2, nuclear energy could increase its contribution to heat supplies in the A2 scenario by more than a factor of six in 2100, which would correspond to additional heat generation of about 110 EJ.

B1

The B1 world describes a rapidly converging world, characterised by 'dematerialisation' and the introduction of clean technologies. The slow growth of energy demand and the focus on decentralised energy supply strategies hinder the diffusion of nuclear technologies. This results in the smallest contributions of nuclear energy across all four SRES scenarios (30 EJ in 2050 and 40 EJ in 2100). In the long run, the energy system is dominated by hydrogen and electricity from renewables and natural gas. The main competitors for nuclear energy are solar technologies in the hydrogen sector and natural gas and renewable power generation in the electricity sector. Strategies to promote nuclear technologies (see Tables 1 and 2) could increase the contribution from nuclear energy by more than a factor of two. By 2100, this would correspond to additional gains for nuclear energy of about 30 EJ of hydrogen and 50 EJ of electricity. Due to the phase-out of coal and comparatively little use of other fossil fuels, there is only limited additional potential for nuclear energy in the heat sector.

B2

The B2 scenario describes a world based upon 'dynamics as usual' assumptions with intermediate economic growth. Due to the focus on local rather than global solutions, the energy system in the B2 scenario develops very heterogeneously. Hence, major competitors for nuclear energy differ from region to region, depending on regional circumstances such as resource and technology availability. In the original SRES B2 scenario, nuclear technologies are predominantly used for power generation, and increase their contribution from 45 EJ in 2050 to about 140 EJ in 2100. Based on the assumptions reflected in Tables 1 and 2, electricity generation from nuclear energy could be expanded by another 30 EJ in 2050 and 70 EJ in 2100, respectively. These additional shares for nuclear energy would result in slower market penetration for coal in Asia; for natural gas and biomass technologies in the developing world; and, to a lesser extent, for solar power generation globally. In addition to electricity, nuclear technologies could also supply considerable amounts of process heat for the production of synthetic fuels and upgrading of fossil fuels (10 EJ in 2050 and 40 EJ in 2100).

The results for particularly the aggressive nuclear variant of the A1T scenario, in which nuclear energy grows from a contribution of less than 10 EJ today to 700 EJ in 2100, immediately raise the question of whether uranium resources are adequate. Total conventional uranium resources accessible at less that US$ 130/kg are currently estimated to be sufficient for 270 years of nuclear power production at the current global level (9.4 EJ) assuming present light water reactor (LWR) technology and a once-through fuel cycle (OECD/NEA-IAEA, 2006)[2]. Adding unconventional uranium resources associated with phosphates (currently accessible at US$ 60–US$ 100/kg) increases the longevity of estimated uranium resources to 675 years, again assuming current uranium production rates and a once-through fuel cycle. But the rapid steady expansion of nuclear energy in the A1T scenario would use up all 675 years' worth of uranium by 2050, and, as is evident from Figure 2, the second half-century of the A1T scenario will place an even greater demand on uranium resources than the first half-century.

There are three possibilities: (1) using thorium and additional unconventional uranium resources beyond those in phosphates; (2) introducing a closed fast reactor fuel cycle with reprocessing and recycling of spent fuel, or (3) both. The principal additional unconventional source of uranium is seawater. The uranium concentration is low (~3 ppb), but the quantity is vast – 4,000 million tonnes or two orders of magnitude greater than the total from conventional sources and phosphates (OECD/NEA-IAEA, 2004). Current estimates of future recovery costs range from US$ 80/kg to US$ 300/kg (Nobukawa et al., 1994; Charpak and Garwin, 1997). For thorium, exploration has been limited because of limited demand, but thorium is estimated to be three times as abundant in the Earth's crust as uranium. Reprocessing and recycling of spent fuel would increase the energy extracted from uranium by a factor of 60–70.

Either the uranium from seawater or the multiplier of 60–70 associated with a closed fuel cycle implies resources well in excess of those needed for at least the first century of the A1T scenario. Together they imply more than several centuries worth of nuclear fuel resources even with continued steady nuclear energy expansion beyond 2100.

3 Estimating cost targets

Economic competitiveness is a moving target simply because technology and experience are constantly improving. Leading the market today means nothing if a firm or industry is not improving cost-effectiveness at least as rapidly as its competition. As the ancient Greek philosopher Heraclitus purportedly said, "Nothing endures but change". Or put in a more modern time frame, "Even if you're headed in the right direction, if you stand still you'll get run over".

Since competitiveness targets are forever moving, this paper's focus is on rates of improvement rather than unmoving cost targets at specific dates. The measure of the improvement rate used here is the learning rate.

Section 3.6 illustrates how a learning rate target can be converted into specific cost targets at specific dates for the aggressive nuclear expansion scenarios presented in Section 2. This has to be done in an energy system context as nuclear power cannot reasonably be analysed in isolation. But more important than hitting any particular isolated cost target at one point in time is establishing a consistent pattern of continuing cost improvements to keep pace with the market. Thus the focus in the body of the section is on rates of continuous improvement – not static targets – and specifically learning rates.

3.1 Learning rate approach

The concept of technological learning was first introduced over 60 years ago (Wright, 1936). As used here, it assumes that a technology's performance improves as experience with the technology accumulates. The concept can be used with a variety of different indicators of technological performance and experience, but the focus here is on specific capital costs as the performance indicator and total cumulative installed capacity as the experience indicator. In this case, technological learning is defined by the following power function:

$$\text{Cost} = A \times \text{Ccap}^{b} \qquad (1)$$

where

Cost: specific capital costs (US$/kW)

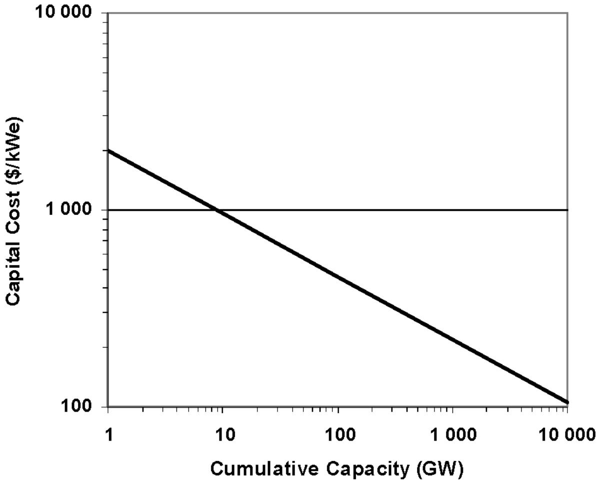
A: specific capital costs at a total (initial) cumulative capacity of 1

Ccap: total cumulative installed capacity (GW)

b: learning elasticity (a constant).

It follows from this definition that a doubling of total cumulative capacity reduces specific costs by a factor of 2^b. In the usual case, where b is negative, 2^b (labelled the progress ratio, pr) is between zero and one. The complement of the progress ratio (1 – pr) is called the learning rate (lr).[3] A learning elasticity of –0.32, for example, yields a progress ratio of 0.80 and a learning rate of 20%. This means that the specific capital cost of newly installed capacity decreases by 20% for each doubling of total installed capacity. On a double logarithmic scale, the decrease in cost appears as a straight line (Figure 3).

Figure 3 Double-log plot of a learning curve example with a first-unit cost of US$ 2,000/kWe and a learning elasticity of –0.32, corresponding to a learning rate of 20%



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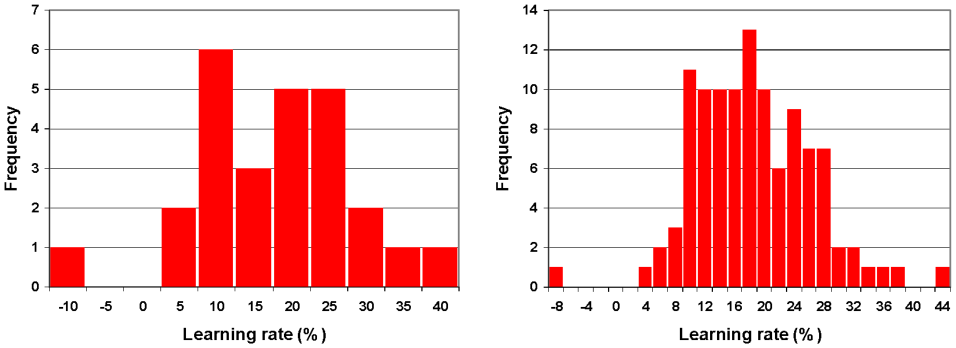
For orientation, empirically estimated learning rates are presented in Figure 4. The right panel shows a compilation of learning rates for over 100 different production programmes in individual manufacturing firms (Dutton and Thomas, 1984). The left panel shows a compilation of 26 estimated learning rates for various energy technologies (McDonald and Schrattenholzer, 2001). The median value of 16–17% for energy technologies is not far below the 19–20% median for the manufacturing firms, and the ranges are comparable, from below zero (i.e., 'forgetting rates') to above 35% in both studies.

Figure 4 Distribution of learning rates observed for energy technologies (left panel) (McDonald and Schrattenholzer, 2001) and for general industry (right panel) (Dutton and Thomas, 1984) (see online version for colours)



3.2 *Learning in the SRES scenarios*

Implied learning rates were estimated for the four SRES scenarios. The term 'implied' is used because learning, as described in equation (1), is not explicitly included in the version of the MESSAGE model used in the SRES. Instead, the cost data input to MESSAGE for the SRES scenarios assumed decreases in technological costs as a function of time, not as an explicit function of experience (cumulative capacity). However, because cumulative capacity increases with time in each scenario, a plot of a technology's cost as a function of its installed capacity in a given SRES scenario will yield downward sloping lines on a double-log plot, as shown in Figure 5 for the A1T scenario. The lines in Figure 5, and comparable plots for the other three SRES scenarios, are not perfectly straight, but implied learning rates can be inferred by fitting the curves from the SRES scenarios with straight lines and calculating their slopes. The results of this exercise are presented in Table 3 that compares implied learning rates for the four original SRES scenarios for each of the principal power generation technologies.

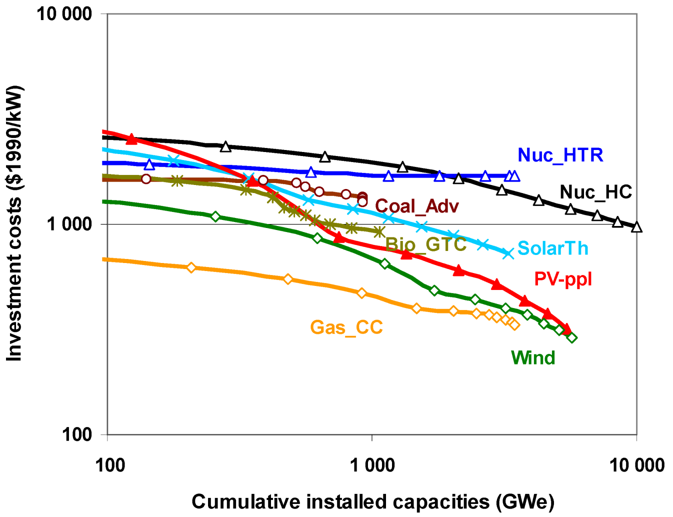
The results in Table 3 generally show lower learning rates for established technologies and higher learning rates for new technologies. That is consistent with the notion of knowledge depreciation, which refers to the fact that experience gained ten years ago is not as valuable as experience gained yesterday. This can be reflected by modifying equation (1) as follows:

$$(\text{Cost})_t = A \times (Q_t)^b \tag{2}$$

$$Q_t = \lambda Q_{t-1} + q_t \quad 0 \le \lambda \le 1$$

where q_t is the production at time t and λ is the knowledge depreciation parameter.

Figure 5 Declining investment costs for selected power generation technologies in the SRES A1T scenario (see online version for colours)



See Table 3 for a description of technology abbreviations.

Table 3 Learning rates for the principal power generation technologies in the AIT, A2, B1 and B2 scenarios

		Learning rates in the SRES scenarios (%)				*Endogenous technological learning*
Abbreviation	*Technology description*	*A1T*	*A2*	*B1*	*B2*	
CoalStdu	Coal power plant, no FGD, no DENOX	0	0	0	0	–
CoalStda	Coal power plant, 90% FGD, 50% DENOX	0	0	0	0	–
CoalAdv	Advanced coal power plants; e.g., integrated gasification combined-cycle (IGCC)	2	2	2	1	√
Coal_FC	Coal-based high temperature fuel cells	1	0	0	0	–
Oil	Oil power plants	0–2	0	0	0	–
GasStd	Gas power plant (standard steam cycle)	0	0	0	0	–
GasCC	Gas combined-cycle power plant	13	3	14	12	√
GasReinj	Combined cycle power plant with no CO_2 emissions (re-injected for enhanced recovery at field, efficiency reduced by 1%)	12	0	20	0	√

Table 3 Learning rates for the principal power generation technologies in the AIT, A2, B1 and B2 scenarios (continued)

Abbreviation	*Technology description*	*Learning rates in the SRES scenarios* (%)				*Endogenous technological learning*
		A1T	*A2*	*B1*	*B2*	
Gas_FC	Natural-gas-based high temperature fuel cells	3	0	0	0	√
BioSTC	Biomass power plant (standard steam cycle)	4	2	5	2	–
Bio_GTC	Biomass gasification power plant	14	6	15	5	
Waste	Waste power plant	0	0	0	0	–
Nuc_LC	Conventional nuclear power plant, low costs, low performance	0	0	0	0	–
Nuc_HC	Conventional nuclear power plant, high costs, high performance	5	1	4	1	√
Nuc_HTR	Nuclear high temperature reactor, cogeneration of hydrogen and electricity	4	0	0	0	√
Nuc_FBR	Nuclear fast breeder reactor	0	0	0	0	√
Hydro	Hydroelectric power plant	0	0	0	0	–
SolarTh	Solar thermal power plant with storage, and solar thermal power plant for H_2 production	10	4	9	5	√
PV-ppl	Solar photovoltaic power plant (no storage)	15	10	13	10	√
Wind	Wind power plant	14	6	10	6	√
Geothrm	Geothermal power plant	0	0	0	0	–
PV-ons1	Photovoltaic onsite electricity production in the residential/commercial sector	15	10	13	10	√
PV-ons2	Photovoltaic onsite electricity production in the industry sector	15	10	13	10	√

The right column identifies those technologies that are fully endogenised in the new version of the MESSAGE model described in Section 3.3.1.

FGD: Flue Gas Desulphurisation; DENOX: flue gas denitrification.

At the extremes, if $\lambda = 1$, there is no knowledge depreciation, and knowledge equals cumulative production (or capacity) as in equation (1). If $\lambda = 0$, there is no knowledge accumulation, i.e., no learning. Knowledge depreciation has the effect of causing learning curves to flatten (learning rates to decline) at increasingly high cumulative capacity levels. McDonald and Schrattenholzer (2001) cited knowledge depreciation as one possible reason why empirical learning rates for established technologies in their data set (i.e., technologies with high cumulative capacities) are often lower than learning rates for new technologies (i.e., those with low cumulative capacities).

Interestingly, although the general pattern of inferred learning rates in Table 3 is consistent with knowledge depreciation, the same cannot be said for the downward bend in most of the curves in Figure 5. Knowledge depreciation would cause the curves to flatten, not steepen, as cumulative capacities increase. Their downward bend reflects the absence of learning in the MESSAGE model used in the SRES and indicates that the exogenously assumed cost improvement rates are too fast in later periods to be consistent with both the learning model of equation (1) and the ever increasing increments that are needed to constitute 'capacity doubling' as cumulative capacity grows.

3.3 Target learning rates for aggressive nuclear cost improvements

The estimation of target learning rates consistent with aggressive nuclear cost improvements was a two-step process. First, a variation of the IIASA MESSAGE model was developed that incorporates endogenous learning (i.e., technology costs decrease as a function of experience rather than time), both for nuclear technologies and for competing energy technologies such as solar power, other renewable technologies and fossil-fuelled technologies. Second, a variety of improved (i.e., faster) learning rates were tested using this new model to identify those most consistent with the results presented in Section 2.5 for the aggressive nuclear variants of the four SRES scenarios. Although in terms of endogenised technological change the new model developed for this study is more sophisticated than the original MESSAGE model used in the SRES, in other respects it is simplified in order to match the resources available for this study. The model simplifications, as well as new model features relevant to learning, are described in the next section.

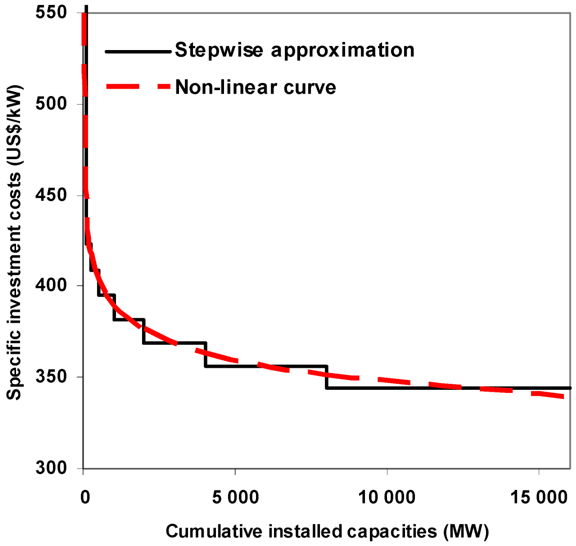
3.3.1 Building a model that incorporates learning

The new model with endogenised learning developed for this analysis is a simplified version of the large-scale model MESSAGE, a dynamic systems-engineering optimisation model that is used for medium- to long-term energy planning, energy policy analysis and scenario development (Messner and Strubegger, 1995). At the core of MESSAGE is a Reference Energy System (RES), which includes the full menu of primary energy options, conversion technologies, transmission and distribution infrastructures, and final energy forms. The RES includes fossil resources (such as coal, oil and gas), nuclear and various renewable energy sources. Final energy is produced as liquid, solid and gaseous fuels, electricity and district heat. Methanol and hydrogen are alternative options to currently established fuels. Energy demands are exogenous to the model. They can be defined on the level of final or useful energy. In the latter case, demand distinguishes between thermal and specific (mostly electricity) uses in the industry and residential/commercial sectors, and between passenger and freight transport demands. MESSAGE results include optimal (i.e., least-cost) energy supply and utilisation structures, resource extraction profiles, marginal cost and quantities of energy traded internationally, investment requirements in the energy sector and pollutant emissions. Energy supply responds to relative energy prices in MESSAGE in the form of substitution effects guided by the overall optimisation procedure. In its most common form, MESSAGE includes separate variables for each of 11 world regions covering the entire world. These world regions are linked by international trade of primary and/or final energy. Typically, a world region includes approximately 150 technologies. In addition, the model includes variables describing energy conversion from resource extraction and imports up to final utilisation in the end-use sectors. Altogether, the 11-region version of MESSAGE has approximately 35,000 variables and 50,000 constraints, depending on the number of new technologies included.

Endogenising technological learning in a technology-oriented model requires a representation of changing technology cost parameters as a consequence of the learning process. The measure used for cumulative knowledge acquired in the learning process is cumulative installed capacity. The specific investment costs are a function of the cumulative capacity (see equation (1)). This formulation implies that the new objective function is not only non-linear but also non-convex. Conventional linear programming (LP) cannot be used in this case, and non-linear programming (NLP) has to deal with the local minima problem. Hence, mixed-integer programming (MIP) techniques were used, which permit the linearisation of the non-convex, non-linear problem, and thereby make it possible to find a solution consistent with the global optimum. Technological learning was endogenised by a piece-wise approximation of the total cumulative cost curve using integer variables to control the sequence of segments along the curve (see Figure 6).

An additional feature of the new MESSAGE-ETL^4 (compared to earlier models of endogenous learning, such as Messner, 1997) is that it considers the spillover of technological improvements from one technology to the next. In other words, the accumulation of experience in one technology affects the 'buy-down' of technology costs for other related technologies within the same technology cluster – e.g., the expansion of capacities for solar PV onsite technologies in the residential/commercial and industry sectors also results in cost reductions for centralised PV power plants and vice versa.

Figure 6 Illustrative example for the stepwise approximation of the investment cost curve in MESSAGE-ETL (see online version for colours)



To obtain scenario results consistent with the four SRES scenarios analysed in this paper, technological learning was endogenised for the 13 power generation technologies checked in Table 3, using the learning rates shown in the table. The model also includes endogenous learning for nuclear and solar technologies in the hydrogen supply sectors. Resource assumptions for fossil and renewable energy, and performance and cost improvement rates for other conversion and distribution technologies, were taken from the original four SRES scenarios. The results were four scenarios including endogenised technological change with the long-term development of the energy system consistent with the aggregated global developments in the respective SRES scenarios.

3.3.2 Scenario results

The aim of the scenario analysis is to obtain quantitative estimates for economic requirements for nuclear technologies to meet the developments depicted by the aggressive nuclear cost improvement scenarios of Section 2, shown in Figure 2. For this purpose, for each of the four scenarios run with MESSAGE-ETL including endogenised technological change, a sensitivity analysis was performed for the diffusion of nuclear technologies under alternative learning rate assumptions. From each sensitivity analysis, for example for the A1T scenario, the learning rate was determined for which the expansion of nuclear capacity over time best matched the expansion shown in Figure 2 for the aggressive nuclear cost improvement version of that scenario (in this case, A1T in upper left panel of Figure 2).

The resulting nuclear learning rates necessary to generate the faster and more extensive nuclear build-up trajectories corresponding to the four aggressive nuclear variants were higher than the nuclear learning rates for the original four SRES scenarios (Table 4) and are broadly consistent with historically observed rates for energy technologies (McDonald and Schrattenholzer, 2001).

Table 4 Learning rates as implied by the four selected SRES scenarios and as required to match the aggressive nuclear variants of these scenarios

Scenario	*Implicit learning rate in the original SRES scenario* (%)	*Learning rate to match "aggressive nuclear improvement" variant* (%)
A1T	4–5	10
A2	0–1	6
B1	3–4	10
B2	0–1	8

3.4 Policy options

A focus on learning rates suggests two general categories of policy options. The first includes policies to speed progress down the learning curve, i.e., to speed the rate at which experience is accumulated in order that costs drop more quickly. The second category includes policies to steepen the learning curve by increasing the learning rate.

Policies in the first category – aimed at speeding progress down the learning curve – are based on the premise that people with limited planning horizons will tend to underinvest (from the long-term global perspective) in new energy technologies that are currently expensive.[5] Where the market fails to serve perceived social interests, governments can compensate. This is the logic behind government subsidies for new technologies, promotional government procurement policies (e.g., new-technology buses for public transportation systems) and government technology mandates (e.g., green certificates). In the first instance, subsidies will lower the consumer's price and encourage use. Expanded use means quicker progress down the learning curve. In the second instance, government purchases directly increase use and thus speed progress down the learning curve. In the third instance, mandates that force consumers to buy more of a new technology than economic considerations would warrant also increase use and accelerate progress down the learning curve.

Policies in the second category – aimed at increasing learning rates – focus on factors in addition to experience accumulation that might lead to cost reductions. Possibilities include research and development (R&D) investment, corporate structure, market structure, patent law, regulatory oversight, and education and training. If the impact of each of these on cost reductions (on the slope of the learning curve) were well understood, it would be possible to identify cost-effective government (or corporate) policies to steepen learning curves consistent with government (or corporate) objectives. Unfortunately, despite an expanding body of research, the impacts of such factors on cost reductions are not yet understood well enough to prescribe here policies to reach target learning rates. What can be offered in the sections below are brief summaries of ongoing research, including key references as starting points for readers interested in greater detail.

3.4.1 Research and Development investment

Equation (1) above is a one-factor learning curve – cost reductions are a function only of cumulative capacity. To incorporate the effects of R&D investments, Kouvaritakis et al. (2000) proposed a two-factor learning curve, with cumulative R&D investments being the second factor. Miketa and Schrattenholzer (2004) modified Kouvaritakis et al.'s formulation by replacing cumulative R&D with the notion of 'knowledge stock,' which includes R&D expenditures but also takes into account depreciation and time lags. Clear quantitative empirical results are still elusive, although some qualitative insights are available from stylised model runs to test the sensitivity of policy recommendations to variations in assumed 'learning by doing' rates (reflecting cost reductions due to experience accumulation) and 'learning by searching' rates (reflecting cost reductions due to R&D investments).

3.4.2 Organisational behaviour

There is a substantial body of research on ways to enhance learning (i.e., steepen the learning curve) within private sector firms and other organisations. Indeed, individual firms are well aware of the variation in learning rates illustrated in Figure 4, even within a single industry, and recognise the importance of being a fast learner on the right side of the distribution rather than a slow learner (or worse, a 'forgetter') on the left side. Argote and Ingram (2000) analysed a firm's knowledge in terms of three categories – knowledge embedded in people, knowledge embedded in tools (e.g., machines and software) and knowledge embedded in tasks (e.g., standard operating procedures). They reviewed the research on mechanisms for transferring knowledge in different categories and the importance of the networks that connect different categories – for example, if success is partly dependent on finding the right person for a given task, then transferring just a successful person or just a successful operating procedure might not successfully transfer knowledge. Argote (1999) examined additional research on both knowledge acquisition at the firm level (from customers, suppliers, competitors, and academic, government and in-house research) and internal knowledge transfer.

Much organisational research is focused on incremental short-term learning by individual firms and thus not fully applicable to long-term governmental strategies to promote innovative change. But much of this research is more broadly applicable to a wide range of organisations – including government and corporate R&D organisations. Lessons from research focused on the knowledge embedded in people and on ways to expand, transfer and exploit that knowledge to stimulate creativity and innovation might be especially valuable for steepening the nuclear learning curve.

3.4.3 Unit size

For countries with large fleets of nuclear power plants, the historical trend has been toward larger units to capture economies of scale. More recently, advocates for smaller units have argued that among their advantages are 'economies of scope.' Their argument is that because 1,000 MWe of capacity made up of 100 MWe modules generates the experience of building ten modules, while 1,000 MWe of capacity from one 1,000 MWe unit generates the experience of building only one module, cost decreases will be faster if capacity is added in smaller chunks. This is fully consistent with the learning model of equation (1), and the higher the learning rate the greater the 'economies of scope.' The influence of knowledge depreciation is more complex but, generally, for a given learning rate, the faster knowledge depreciates, the greater the economies of scope.

3.4.4 Market structure

The inferred learning rates in the SRES scenarios are regularly higher in the globalisation scenarios (A1T and B1) than in the regionalism scenarios (A2 and B2) (Table 3). This is consistent with the storylines underlying the scenarios, in which the relatively more open markets and more open borders of the globalisation scenarios foster a more rapid diffusion of technologies and efficient practices than do the relatively less open markets and less open borders of the regionalism scenarios. While the SRES scenarios are not themselves empirical evidence that the openness of the A1T and B1 scenarios will necessarily steepen learning curves, they suggest that policies to promote such openness are good candidates to steepen learning curves. For a more detailed exploration of such candidate policies, the references provided by the SRES report in support of faster learning in more open scenarios would be one useful starting point.

In addition to market openness, market price levels can also create strong incentives to learn faster (using all the knowledge acquisition and transfer mechanisms studied by the organisational behaviour researchers cited above). In particular, if there is substantial money to be made by producing low carbon electricity because of new carbon constraints, the financial incentive can be expected to motivate faster learning in lower-carbon technologies. In this connection, we recall the discussion above about the consistency of the A1T and B1 scenarios with carbon constraints consistent with the United Nations Framework Convention on Climate Change (UNFCCC) carbon stabilisation objective. Thus one mechanism with the potential to steepen the nuclear learning curve is a carbon constraint.

3.5 Conclusions about learning rates

We have emphasised the importance of long-term continuous cost improvements, and analysed learning rates as a helpful mechanism for setting targets, judging policy alternatives and eventually measuring progress. We have steered largely clear of shorter-term issues like prices (as opposed to costs), including the impacts of policy options like subsidies, guaranteed loans, regulated rates of return, tax breaks or price supports that change the prices, cost structure and risks facing an investor. Such policies are common features of national energy policies around the world, and, despite periodic rhetoric calling for the abolition of all energy subsidies, it can be projected with high confidence that, in general, they will continue for many decades to come. Specifics are much more difficult to project. They are driven by an unpredictable mix of changing political pressures and can vary rapidly with respect to a time scale focused on cost targets for mid-century. That is one reason why they have not been emphasised here. The second reason is our conviction that, while such government policies can make a lot of difference in the short term and can move a technology down its learning curve faster by accelerating experience accumulation, it is the long-term improvements in underlying costs that matter over the time span of half a century. Subsidies can prop up a persistently slow-learning technology only for a limited period. Without fundamental long-term continuous cost improvements, no technology will survive long.

Turning to the specific results, there is little work and even less agreement on empirical learning rates for nuclear power plants. Kouvaritakis et al. (2000) present OECD data from 1975 to 1993 that imply a learning rate of 5.8%, which is not too different from the A1T scenario's 4–5% in Table 4 or the B1 scenario's 3–4%. But the OECD data's remarkable linearity with time and our inability to find out more about their origin makes them somewhat suspect.

One difficulty in estimating nuclear learning rates is the changing nature of the product over time. Consider the 1973–1995 OECD data. A nuclear plant built at the end of this period, in 1995, after both the 1979 Three Mile Island accident and the 1986 Chernobyl accident, was certainly a different plant than one built at the beginning of the period in 1973. Given the relatively small number of nuclear plants built (for example, compared to cars or telephones), it is difficult to find a time series of cost data reflecting increasing experience in producing an unchanging product. And it is not clear how existing data might be corrected to eliminate the impact of product changes on costs.

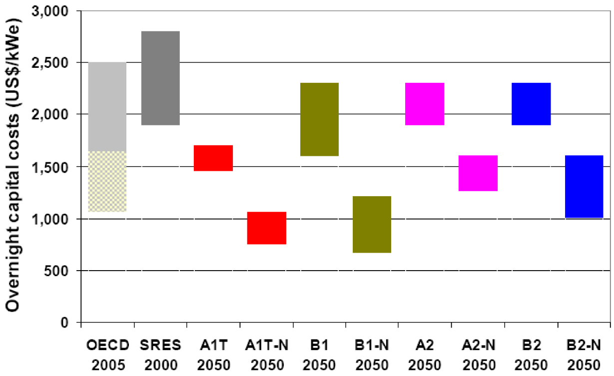
With those caveats in mind, a comparison of the learning rates in Table 4 and Figure 4 suggests that the learning rates necessary to reach any of the aggressive nuclear improvement scenarios should be well within reach. All the values in Table 4 are below the 16–17% median value of the Figure 4 data.

Rather than focussing on specific learning rate values, it may be wiser to emphasise the relative increase in the nuclear learning rate needed to reach the aggressive nuclear improvement nuclear expansion trajectories in Figure 2. Thus even if a reader considers the SRES authors to have been too conservative in their assumed cost improvements, if that conservatism is uniform across technologies, conclusions about the relative increases in learning rates would still be useful. With this in mind, the relative increases between the learning rates of the SRES scenarios in Table 4 and the aggressive nuclear improvement scenarios range from a factor of two to a factor of more than eight.

3.6 Converting learning rate targets to cost targets by 2050

Given a specified learning rate and a trajectory for capacity expansion over time, one can calculate the implied costs for each scenario as a function of time. Figure 7 shows the results for overnight costs per kilowatt (electric) in 2050 for all eight scenarios discussed above. The range in the year 2000 is also from the SRES scenarios. The bar labelled 'OECD' shows the range of current capital costs presented in Projected Costs of Generating Electricity: 2005 Update (OECD/NEA/IEA, 2005). The lower end of the OECD range was considered optimistic (see the shaded area of the OECD data range in Figure 7). Possibly it reflects questionnaire responses based on 'nth-of-a-kind' costs, i.e., cost levels some distance down the learning curve from the cost of the initial 'first-of-a-kind' unit). Such low-priced designs are either not yet available on the market or are not being bought. Costs reported in the press for Olkiluoto-3, the new 1,600 MWe Finnish reactor on which construction began in 2005, were in the order of US$ 2,000/kWe, and initial construction problems to date may push that higher in the end. In the USA, where the 2005 Energy Act has created a flurry of industry initiatives for new construction, the estimated costs of the designs under consideration range from US$ 1,600–US$ 2,000/kWe (MacLachlan, 2006).

Figure 7 Ranges for specific capital costs in 2050 for nuclear power plants in eight scenarios (see online version for colours)

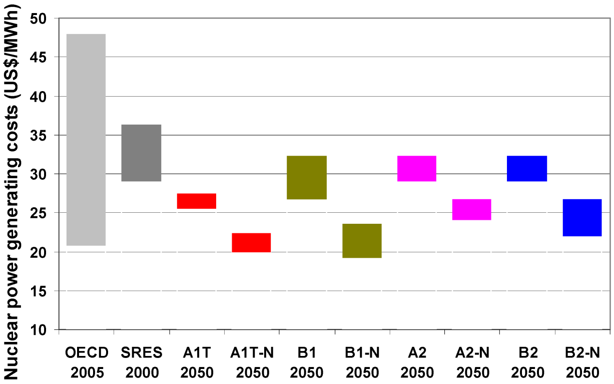


The bars '-N' indicate the cost ranges in the aggressive nuclear variants of the corresponding original SRES scenarios.

MESSAGE-ETL recognises that, in any given year, both the operating fleet of reactors and any new reactors installed in that year include a mix of technologies. The most expensive reactor among the new additions is probably cheaper than the operating reactor with the highest original cost, which is at least several decades old. Figure 7 shows the ranges from the least to the most expensive nuclear technology added in 2050, i.e., the range in which nuclear power plants are found by the model to be attractive investments.[6] In the A1T and B1 scenarios (and in the base year 2000) the top of the bar corresponds to high-temperature reactors capable of cogenerating electricity and hydrogen. The bottom of each bar corresponds to simpler nuclear technologies generating only electricity.

Figure 8 presents comparable targets for the levelised cost of nuclear electricity generation in 2050 including capital, fuel, operating and maintenance expenditures. Levelised costs are not calculated explicitly in the SRES. The values shown here, and the values shown for the aggressive nuclear variants, are estimated using the overnight costs from Figure 7, and adding interest during construction, operation and maintenance costs, as well as fuel costs based on the general patterns reported in OECD/NEA/IEA (2005).

Figure 8 Ranges for electricity production costs in 2050 for nuclear power plants in eight scenarios (assuming a 5% discount rate)



The bars with '-N' indicate the cost ranges in the aggressive nuclear variants of the corresponding original SRES scenarios.

4 Discussion and conclusions

Should RD&D strategists consider the results in Figures 7 and 8 as cost targets for competitive nuclear designs in 2050? Not yet. Although these results are indeed the cost ranges in which the scenarios find nuclear technologies to be attractive investments relative to competing alternatives, they need further work before they can serve as good targets for new designs. However, they already appear to support the case for near-term government subsidies of new nuclear power plants.

Before looking at what more needs to be done before the results can serve as cost targets for new nuclear designs, we should recall how far we have come. The starting point was scenarios because they are the best mechanism for systematically incorporating a host of uncertain factors when estimating the capital and operating cost levels likely to make an innovative nuclear reactor an attractive investment in 2050. Such factors include how much populations grow around the world; how much economies grow and change; how lifestyles evolve and how that is reflected in changing market demands and changing safety, environmental and non-proliferation constraints; how extensive various energy resources prove to be; how quickly alternative technologies advance; and how quickly ideas, money, people and technologies move around the world. Scenarios incorporate all these – and more – consistently and systematically.

The best pedigreed independent set of scenarios available was therefore chosen from the SRES and the relevant capital costs were extracted for nuclear technologies that those scenarios consider attractive investments in 2050. Those costs are shown by the bars labelled A1T, B1, A2 and B2 in Figures 7 and 8. Throughout the analysis, the concept of technological learning measured by learning rates was emphasised in order to focus on the need for continuous learning and improvement if a future technology is to be consistently competitive.

The nuclear costs in the SRES scenarios for 2050 (the A1T, B1, A2 and B2 bars in Figures 7 and 8) are, however, not as low as expected. Below are two possible explanations related to idealisations incorporated in the MESSAGE model. An additional reason is that the figures' cost ranges are those for which nuclear power is attractive based on fossil fuel costs in 2050, not 2000. Although the SRES scenarios do not deplete oil and gas resources as quickly as in standard applications of the Hubbert curve (Hubbert, 1956), due mainly to the unconventional fossil resources in the scenarios, depletion definitely takes place. Fossil fuels extracted in 2050 therefore come from higher cost categories than the cheaper fossil fuels against which nuclear energy is competing today. Other things being equal, this means that nuclear costs would not have to be as low in 2050 to be competitive as they must be today.

Of the two explanations related to idealisations in MESSAGE, the first is that the model optimises total energy system costs through 2100 using a discount rate of 5%. The current front-loaded cost structure of nuclear technologies (and renewable technologies), with their high initial capital costs and low long-term costs, is therefore less of a disadvantage in the scenarios than it would be for an investor in a liberalised energy market who faces higher financing charges than 5% and needs a rapid return on his investment. Thus MESSAGE is likely to still 'buy' nuclear technologies (and renewable technologies) with high capital costs even when a private investor in a liberalised market might not. It is recognised that not all prospective investors will be private companies seeking quick returns in fully liberalised markets. Many are likely to be governments that can focus on longer-term returns and for whom low discount rates are appropriate. But if the objective is a design attractive to private investors in liberalised markets, the cost targets should probably be lower than those extracted directly from the SRES scenarios.

A second related consideration is that in MESSAGE investments are essentially risk-free and benefit from the model's 'perfect foresight'. Given the investment risks that exist in actual markets, both for private investors and governments, costs may need to be lower than shown in Figures 7 and 8 for nuclear technologies to still be attractive investments once investment risks are taken into account.

Although these comments are directed to the four original SRES scenarios, they also apply to the four aggressive nuclear variants.

As for near-term policy implications, one way to interpret the higher than expected numbers in Figures 7 and 8 (at least for the A1T, B1, B2 and A2 scenarios) is that the incentives of today's 'deregulating' and uncertain energy markets will not lead to the best (least-cost) long-term evolution of the energy system. If the A1T, B1, A2 and B2 cost ranges in Figures 7 and 8 are too high to attract nuclear investments (at the levels in the scenarios) in today's 'deregulating' and uncertain energy markets, that means investment that should be going into nuclear energy is inefficiently going elsewhere – probably to natural gas and, where gas is less available, to coal. This would hardly be the first case of market incentives motivating investments that, while they make perfect sense from the perspective of the individual investor, are not the best in terms of the greater national or international interest. If one accepts that the long-term evolution of the energy system is something where broader national or international interests might sometimes trump the sanctity of investor independence, then there is a case for governments intervening in markets to bring the incentives perceived by investors more into line with those broader national or international interests. In practical terms this means government subsidies for new nuclear plants to prompt expansion, even based on relatively high capital cost nuclear designs. Where governments are direct investors, the results suggest they could justifiably invest in relatively high capital cost nuclear plants, even when these are not always the least-cost option available.

Governments also have an interest in the maintenance and preservation of nuclear expertise. The best assurance of such expertise is a growing nuclear sector that expands experience and attracts talent. Although MESSAGE assumes that unused skills never get rusty and new talent will still flock to even stagnant technologies, reality is different. Government subsidies to assure nuclear expansion in the long-term national interest may in fact be a more cost-effective way to maintain expertise than allowing nuclear stagnation and then spending on compensatory programs to assure expertise.

In interpreting the higher-than-expected numbers for the A1T, B1, A2 and B2 scenarios as support for government subsidies and investment to help new nuclear power plants over the up-front cost hump that discourages today's private investors, we note that a comparable analysis of renewables in the scenarios would likely provide similar support for subsidies for renewable technologies, which also have an up-front cost hump.

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Notes

[1] The SRES report presents energy and emission trajectories for six illustrative marker scenarios based on four different models. The marker scenarios use harmonised assumptions on global population, gross world product and final energy, while the remaining 34 scenarios explore additional uncertainties associated with the future development of the main driving forces for energy demand, supply and GHG emissions. In this study, only the MESSAGE model was used because of the authors' easy access to and familiarity with the model. This facilitated additional model applications for this study that go well beyond the scope of the SRES work.

[2] For reference, at the end of May 2007 the uranium spot market price was US$ 325/kg.

[3] For some data sets, estimating a learning curve leads to values of b equal to or greater than zero. Thus costs stagnate or increase with cumulative experience. In these cases, the terms 'progress ratio' and 'learning rate' are still used, although they are no longer as intuitively descriptive.

[4] ETL: endogenous technology learning.

[5] This paragraph borrows extensively from McDonald and Schrattenholzer (2002).

[6] The one exception is the bar for the B1-N scenario. In 2050, the model is still 'buying' the last few new units of an old US$ 1,600/kWe reactor technology. Because new additions of this old technology are phased out shortly thereafter, the top of the bar represents the next most expensive nuclear technology still being 'bought' by the model as a better indicator of the upper bound for competitive costs in 2050.