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Technology learning for renewable energy: Implications for South Africa's long-term mitigation scenarios

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ABSTRACT

Technology learning can make a significant difference to renewable energy as a mitigation option in South Africa's electricity sector. This article considers scenarios implemented in a Markal energy model used for mitigation analysis. It outlines the empirical evidence that unit costs of renewable energy technologies decline, considers the theoretical background and how this can be implemented in modeling. Two scenarios are modelled, assuming 27% and 50% of renewable electricity by 2050, respectively. The results show a dramatic shift in the mitigation costs. In the less ambitious scenario, instead of imposing a cost of Rand 52/t CO_2-eq (at 10% discount rate), reduced costs due to technology learning turn renewables into negative cost option. Our results show that technology learning flips the costs, saving R143. At higher penetration rate, the incremental costs added beyond the base case decline from R92 per ton to R3. Including assumptions about technology learning turns renewable from a higher-cost mitigation option to one close to zero. We conclude that a future world in which global investment in renewables drives down unit costs makes it a much more cost-effective and sustainable mitigation option in South Africa.

1. Introduction

Technology is an important driver of energy development, and technology costs change over time. One of the most important factors shaping the results of energy models are the assumptions they make about technology learning (Energy Innovations, 1997; Fisher and Grubb, 1997; IEA & OECD, 2000, 2006; Repetto and Austin, 1997)—the extent to which technologies get cheaper over time. There is good evidence that the unit costs of new technologies decline as more are built and technology design gets smarter. This article considers technology learning for renewable energy, particularly as it affects climate change mitigation in South Africa, analysed quantitatively through energy modeling.

The article starts with historical evidence for technology learning presented from the international literature. It then considers what drives technology learning and explores, based on spreadsheet analysis, different ways of representing technology learning quantitatively. The results reported here are based on analysis for renewable energy technologies (RETs) which formed part of the energy modeling conducted for the long-term mitigation scenarios (LTMS) for South Africa (Hughes et al., 2007; Winkler, 2007). The base case is briefly introduced, before showing the implications of technology learning for renewable energy and mitigation. Before concluding, we point to some areas for future work.

2. Analysing technology learning

The two central explanatory factors why new technologies get cheaper over time are (i) learning-by-doing and (ii) economies of scale. The first factor suggests that we learn to do things more smartly, garnering the easier cost savings first. The first proto-type is typically much more expensive than later models, which are produced in smarter and more cost-effective ways. Learning by experience reduces costs (Arrow, 1962) and this general finding has been found true for energy technologies as well (IEA & OECD, 2000).

Secondly, later units are often part of larger production runs than the first demonstration modules or pilot plants. Economies of scale often allow savings as well.

The effects of both factors together have been assessed by learning ratios, measuring the reduction of cost per unit of installed capacity for each doubling of cumulative capacity.

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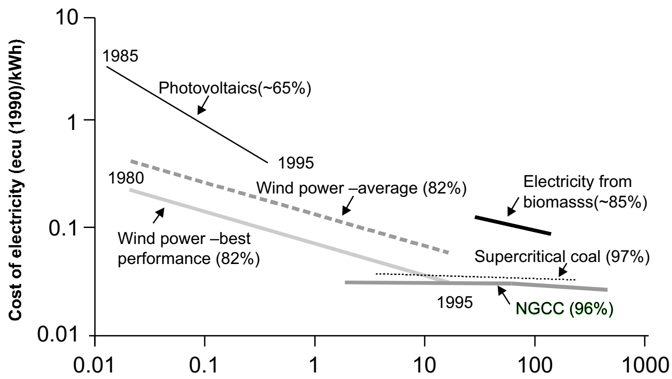

Fig. 1. Learning curves for new and mature energy technologies. Source: IEA & OECD (2000).

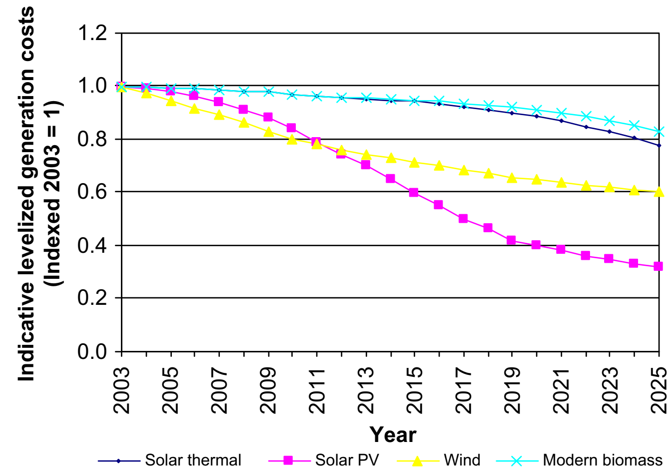

Fig. 2. Reduction in costs, with levelised costs (c/kWh) indexed for base year 2003. Source: UNEP (2006).

2.1. *Evidence for technology learning*

The unit costs of technologies, typically measured in $/installed kW, change over time. A measure of this learning is the 'progress ratio', which is the reduced cost per unit installed for each doubling of global cumulative capacity, given as a percentage of the initial cost. The 'learning ratio' refers to the percentage reduction in cost over the same doubling period (i.e., it is 100% minus the 'progress ratio'). Empirical data on learning for energy technologies have been gathered (IEA & OECD, 2000; Junginger et al., 2004; Laitner, 2002; Nemet, 2006; NREL, 1999; Papineau, 2006; World Bank, 1999). Learning curves show the decline in costs (either in S/kW, i.e. units of installed capacity, or sometimes in levelised costs reported in units of c/kWh for electricity generation technologies) as cumulative electricity production doubles.

Fig. 1 from (IEA & OECD, 2000) indicates photovoltaics declined by 35% in price for doublings between 1980 and 1995, wind by 18%, electricity from biomass by 15%; while supercritical coal declined by only 3% and NGCC by 4%. It is clear that newer technologies, be they renewable or otherwise, have higher learning ratios than mature technologies which have integrated most cost savings decades or centuries earlier.

Note that in Fig. 1, both axes are logarithmic and that the learning curves are linear in this log–log space. Shown in 'normal' space, the curves would decline steeply at first, and less steeply later. Regression analysis would give them best fit with logarithmic or exponential curves.

A more recent study focusing on RETs presented learning by indexing all costs for the base year.

Fig. 2 shows which RET costs decline fastest, but loses information about which RETs are more cost-effective overall. All technologies are indexed to 1.0 at the start year, while in unit costs ($/kW) differ substantially.

Most of the literature focuses on learning as a function of global increases in capacity and production of energy technologies. However, there may also be *local* cost reductions that can be achieved, e.g. local manufacture of turbine blades, above a certain threshold of installed capacity. It is possible to include both global and local learning in models, given data on thresholds and associated cost reductions.

In projecting the development of energy technologies into the future, then, one can reasonably assume that technology costs will change over time. The next sections examines how technology learning can be analysed in the context of modeling energy futures, also taking into account limits on growth in capacity.

2.2. *Learning curves and declining unit costs*

The learning curve model has been summarised by Nemet (2006) in three equations:

$$C_t = C_0\left(\frac{q_t}{q_0}\right)^{-b} \tag{1}$$

$$PR = 2^{-b} \tag{2}$$

$$LR = (1 - PR) \tag{3}$$

where C_t (in $/kW) is the unit cost of the technology, q represents cumulative installed capacity, b is the exponent defining the slope of the power function, PR is the progress ratio and LR the learning ratio. The factor b is the central parameter (Nemet, 2006).

Eq. (1) says that the cost at a future time t can be calculated by taking the initial cost (C_0), multiplying that by the ratio of the cumulative installed capacity reached by t, to the power of an exponent b. The exponent, a key parameter, is negative since costs decline. Eqs. 2 and 3 convert this parameter into single percentages. The progress ratio (PR) can be understood as the reduced cost per unit, whereas the learning ratio (LR) is the saved cost for an increase in cumulative output. For example, if after a global doubling of installed capacity, the unit cost of a technology declines from $1.50/kW installed to $1/kW installed, the PR is 67% and the LR 33%.

An important implication is that a single percentage (PR or LR) can show a changing rate of cost reduction over time. Since the percentage enters as an exponent, the resulting cost function is logarithmic.

Given the formulation of the technology learning model, the rate of cost reduction adjusts to changes in the growth of production. The rate of learning declines over time—or rather as capacity doubles. The function graphs as a straight line in log–log space, but in normal space, its logarithmic shape indicates a decreasing rate of learning. A fairly good fit with empirical data has been found (Nemet, 2006).

If technologies cost less per unit, one could expect more of them to be built. A least-cost modeling approach would choose more of cheaper technologies. When used in modeling energy systems into the future, it would be worth considering whether there are any limits to this growth.

Table 1
Range of reported learning ratios for electricity generating technologies.

Energy technology	Solar thermal power (World Bank, 1999)	Concentrating solar power (trough) (NREL, 1999)	Experience curves (IEA & OECD, 2000)	Skip Laitner, US EPA (Laitner, 2002)	Renewables for power generation (IEA, 2003)	Global experience curves for wind (Junginger et al., 2004)	Economic perspective (Papineau, 2006)	Energy Technology Perspectivestechnology perspectives (IEA & OECD, 2006), the figures in brackets indicate assumed future ranges	Changing climate (UNEP, 2006) assumed future[a]
New renewable energy technologies									
Small-scale biomass for electricity[c]			15% (1980–1995)					5% (12–15%)	17% (2003–2025)
Wind			18% (1980–1995)	13% (1995–2010)		19%; (avg% (average PR between 77% and 89%)	10–12% (1990–2000)	5% (4–8%; 15–19%)	40% (2003–2025)
Solar photovoltaic			35% (1980–1995)				17% (1992–2000)	18% (20%)	68% decline from 2003 to 2025 (no.number of doublings not stated)
Solar thermal, parabolic trough	12% (range of 8–15%)	17% historical, estimate 15% future		32% (1997–2020)	15%[d]		10–12% (1990–2000)	5%	22% (2003–2025)
Solar thermal, power tower	12% (range of 8–15%)			11% (1996–2020)	20%		10–12% (1990–2000)	5%	
Geothermal[b]									
Small hydro								5%	
Tidal								5%	
New fossil fueled electricity generation									
Supercritical coal[b]			3% (1980–1995)	7% (1995–2010)					
Natural gas combined cycle			4% (1980–1995)	7% (1995–2010)					

[3]The LTMS study used a learning rate of 25% for PV in the model generally, but also examined a higher rate of 35% in a PV mitigation action, making a more optimistic assumption about future PV costs.

[a] The UNEP study assumed cost reductions for 2003–2025, which could see more than a doubling.
[b] No studies found for some power plants analysed in the LTMS, notably integrated gasification combined cycle, fluidized bed combustion or advanced water reactors.
[c] Small-scale biomass is assumed to be less than 50MWe, and in South Africa would include generation from bagasse.
[d] IEA (2003) gives a general progress ratio of 85% (LR = 15%) for solar thermal generally, but cites a higher learning rate of 20% for concentrating solar power (CSP) systems (p. 94). For dish/engine systems, the range given is 10 to –25%.

2.3. *Comparing estimates of technology learning*

Several studies have examined learning across a range of technologies. Some of these have focused on *types* of energy technologies, and particular focus has been given in the literature to RETs. Table 1 compares learning ratios from studies that have examined more than one energy technology, as well as others that have focused on particular technologies.

As shown in Table 1, technology learning ratios were not found for all technologies. Applying learning to only some technologies will favour those technologies to which it is applied. Future work should apply technology learning more comprehensively and include all end-use technologies in the model to which it applies.

Values were chosen for use in this study, based on range cited in the peer-reviewed literature cited above. Table 2 summarises the learning ratios for new electricity generating technologies assumed in the LTMS study (Hughes et al., 2007; Winkler, 2007).

Table 2
Learning ratios for this study and summary of ranges in the literature.

Energy technology	Range of learning rates in the literature* (%)	Learning ratios, this study (%)
Wind	5–40	19
Solar photovoltaic	17–68	25 35
Solar thermal, parabolic trough	5–32	15
Solar thermal, power tower	5–20	20
Geothermal		
Small hydro	5	5
Biomass	5–17	15
Tidal	5	5
Supercritical coal	3–7	4
Natural gas combined cycle	4–7	5

2.4. *Learning ratios constant over time*

Does the rate of technology learning remain constant over doublings? A single number such as the learning ratio can represent changing costs over time, including multiple doublings. Historical evidence for PV supports this. "Between 1968 and 1998, PV module costs declined by an average rate of 20.2% each time the total cumulative installed capacity doubled (for a total of greater than thirteen doublings)" (Harmon, 2000). Harmon (2000) goes on to suggest continued investment can achieve future PV module cost reductions. Other findings indicate that annual

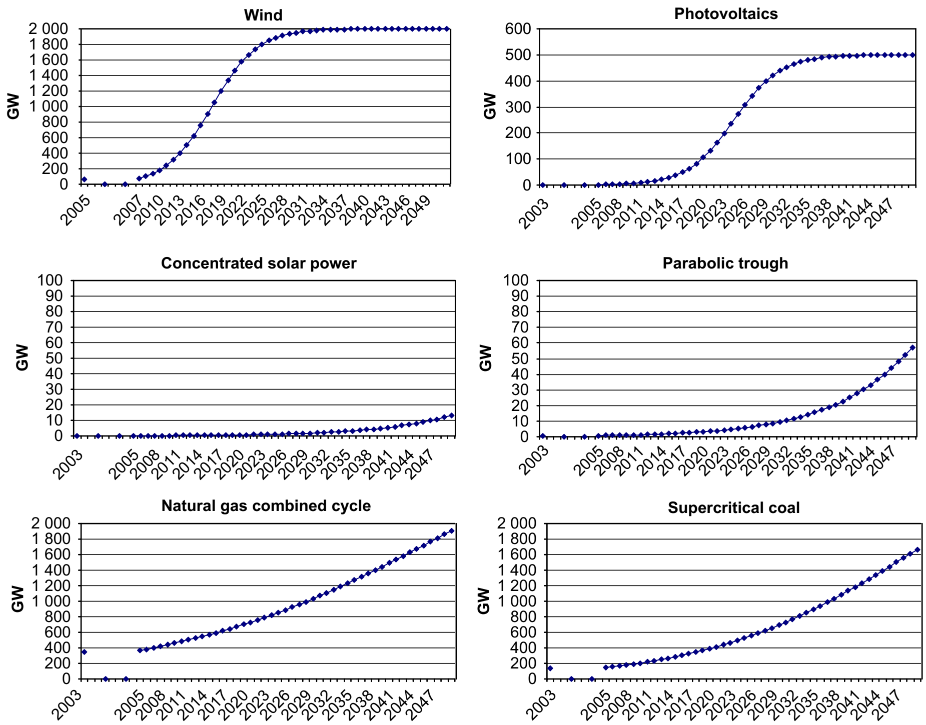

Fig. 3. Growth in global capacity for different technologies.

growth rates for PV have reduce costs by a nearly 100 times over half a decade (Nemet, 2006).

A further question is whether the doubling time remains constant. Since each time, twice the capacity needs to be installed to achieve a further doubling, that doubling could take longer. The approach taken in this study is to increase the doubling time by 1.5 for each doubling, i.e. half-way between 1.0 (same doubling time for each successive doubling) and 2.0 (twice as long each time).

2.5. Upper limits on growth of capacity

One might expect technologies to grow rapidly in installed capacity while they are new, but at some point limits may emerge. Constraints such as available materials, suitable sites or limited energy resources may contribute to an upper limit. The growth of capacity and doubling time for each technology also depends on diffusion or market penetration of the technology. Competition among different technologies, economical competitiveness, physical or social constraints on the technology build up, or alternatively certain considerations for capacity expansion, determine the rate of market penetration. Detailed examination of technology-specific factors is beyond the scope of this paper.

Upper limits in the growth of installed capacity can be represented in a logistic function. These functions are typically S-shaped, that is their growth does not stop, but slows down at higher levels. For technology learning, it is worth considering upper limits on global installed capacity.

$$\frac{dC}{dt} = rC\left(1 - \frac{C}{K}\right) \tag{4}$$

Here C is capacity (in kW installed in this case), K is maximum capacity (kW installed) and r is the annual growth rate. The second term, in brackets, on the right-hand side, effectively limits growth from becoming exponential. As the installed capacity approaches its maximum, C/M approaches 1, the right-hand side approaches zero and there is no further change in costs (dC/dt).

This differential equation can be solved, yielding

$$C_t = \frac{e^{rt}}{(1/C_0) - (1/M) + (e^{rt}/M)} \tag{5}$$

where C_t is the installed capacity at a future time, C_0 is the initial capacity in year 0, and time t is measured in years. This formula can be used to project future capacity growth, based on the growth rate r, initial capacity C and maximum capacity M. How these equations translate into figures for different energy technologies is illustrated below (see Figs. 3 and 4), using data presented in the following sections.

Where maximum global potentials were not found in the literature (IEA & OECD, 2000; Junginger et al., 2004; Laitner, 2002; Nemet, 2006; NREL, 1999; Papineau, 2006; World Bank, 1999), they were estimated. The maximum global capacities used for this study are reported in Table 3.

Using these maximum global potentials, the growth of technologies can be represented in the form of a logistic equation, i.e. one that does not increase exponentially forever, but slows as it approaches an upper limit and eventually flattens out. If global cumulative capacity approaches an upper limit, the rate of growth in installed capacity will slow, and consequently learning would slow accordingly. In addition, there is information on the rate of the doubling based on the historical growth rates. These doubling times can be used to cross-check doubling resulting from the logistic equation.

2.6. Estimates of doubling times

Since the reduction in unit costs is a function of a doubling of global cumulative production, it is helpful to know the time in which a technology might be expected to double its capacity. The production of all new energy technologies does not increase at the same rate. This is reflected in Table 4, showing information from various sources on

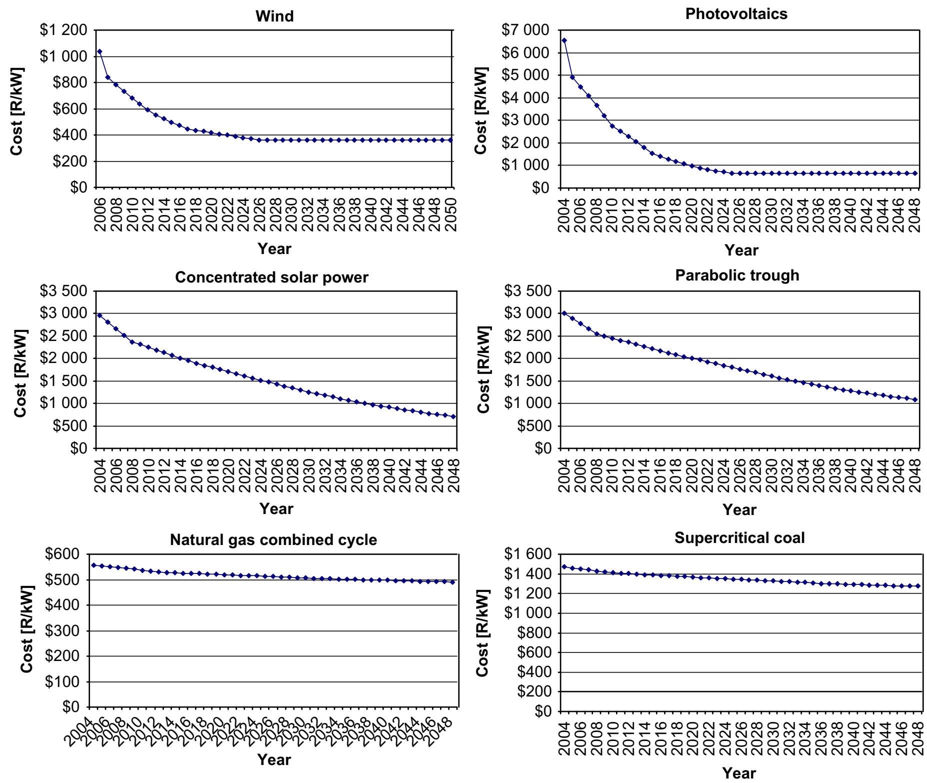

Fig. 4. Cost reductions for RETs.

Table 3
Estimated maximum global capacity.

Energy technology	Maximum level this technology can reach globally (GW)
Wind	2000
Solar photovoltaic	500
Solar thermal, parabolic trough	500
Solar thermal, power tower	500
Geothermal	
Small hydro	
Biomass	
Tidal	
Supercritical coal	3072
Natural gas combined cycle	3773

Table 4
Current status of renewable energy technologies.

Technology for electricity generation	Increase in installed capacity in past five years (%/yr)	Number of years for doubling at historical rate	Operating capacity, end 1998 (GWe)
Wind	~30	3	10
Solar photovoltaic	~30	3	0.5
Solar thermal, parabolic trough	~5	14	0.4
Solar thermal, power tower	~5	14	0.4
Geothermal	~4	17	8
Small hydro	~3	23	23
Biomass	~3	23	40
Tidal	0	–	0.3

Sources: (Laitner, 2002; NREL, 1999; UNDP, UNDESA & WEC, 2000).

the current status of RETs, based primarily on data from the World Energy Assessment (UNDP, UNDESA & WEC, 2000) supplemented and updated with information from more recent sources.

The past is not always a good predictor of the future, but it provides an empirical basis to distinguish between different doubling rates. The use of global energy models would be an alternative methodology. The implied time of doubling in the exponential function could be checked against expectations of doubling based on past experience. The number of years for doubling are given by ln(2)/growth rate, e.g. ln(2)/3% for biomass yields 23 years.

3. Technology learning in energy modeling

The information presented in Section 2 was translated in LTMS into an energy modeling framework. First, however, the modeling framework is briefly introduced.

3.1. MARKAL model

Energy modeling provides a useful tool to explore the implications of technology learning, allowing different assumptions about the future to be tested. Energy models are a powerful way to explore various alternative energy futures quantitatively, but it is important to understand the limitations of each tool. For the LTMS, we used the MARKAL (short for Market Allocation) model.[1]

[1] The MARKAL modeling framework was developed by the International Energy Agency; the database used for LTMS was developed at the Energy Research Centre over several years and projects.

MARKAL is an optimising model, meaning that, subject to available resources, a set of energy supply and use technologies, and a set of required energy services and constraints, the model determines the optimal configuration of an energy system that will meet the demand for energy services. Optimisation follows an objective, usually to minimize costs. The model is demand-driven, in that it must meet projections of useful energy demand. Working with a system model means that various balances are maintained, e.g. that energy demand is met; that a specified reserve margin is maintained; that plants for peak and base-load are distinguished; that technologies have a limited life, etc. A full description of the model used is contained in Hughes and Haw (2007).

The strength of the MARKAL models lies in the ability to identify the most cost-effective technology solutions for energy systems. Constraints, which temper the drive to least cost, can include environmental factors (e.g., emissions), limits on resource availability and – relevant to this article – the penetration rates of technologies.

MARKAL requires a large set of data, which can be divided into several kinds:

1. Data on energy technologies—transformation (e.g., power plants, refineries), distribution (e.g., pipelines) and end-use (e.g., motors, lights) technologies—which would include efficiency, capital cost, operation and maintenance costs, equipment life, and environmental impacts/emissions.
2. Independent variables such as GDP and population that drive demand.
3. The structure of the energy system.
4. Historical data on the existing energy infrastructure.

In MARKAL a 'base case' is constructed, against which other scenarios are compared. The base case in LTMS is effectively a simulation of the development of the energy system into the future, and is tightly constrained to represent a 'business as usual' scenario.

The major drivers include GDP, population and technology assumptions, reported fully in the LTMS technical report ((Winkler, 2007); a fuller description of the energy system, the characteristics of key energy technologies (such as power plants), various cost components (captital, fixed and variable O&M) efficiencies, fuel prices and other factors can be found in the same report, as well as the energy modeling input (Hughes et al., 2007)).

3.2. Learning ratios into modeling

Combining the information on learning ratios, historical growth rates and maximum capacity globally, allows growth paths for different RETs to be plotted. They are compared to existing coal and gas-fired electricity generating technologies.

In interpreting Fig. 3, it should be noted that the scales of capacity for various technologies differ and that the underlying assumption is learning continues at historical rates into the future. On that basis, the capacity of wind and PV might grow rapidly enough to reach limits. Concentrated solar power and parabolic trough come off such low bases that capacity remains small—growth rates would have to increase before they would reach an upper limit. Mature technologies, coal and gas start from high installed capacity.

Adding estimates of current installed capacity, costs and learning ratios to the data shows cost curves for the RETs in Fig. 4

The difference between quite rapid declines in unit costs for some newer, RETs, and the mild reductions for mature types of technologies are clearly illustrated in Fig. 4, for example, third generation fossil fuel technologies. The latter went through their learning curves in previous centuries. Photovoltaics show the steepest decline in unit costs, followed by wind. Between the two solar thermal electricity technologies considered, concentrated solar power is expected to decline quicker and further than the parabolic trough, based on the stated assumptions (see Table 2 above).

The cost reductions shown in Fig. 4 were applied in the MARKAL modeling. In particular, the reductions in unit costs were applied to the capital costs (the MARKAL parameter INVCOST) of the relevant technologies over time.

The remainder of this article focuses on the implications of technology learning as applied in the South African MARKAL model. It considers the application of technology learning both to the base case and to policy cases, in which RETs are modeled as climate change mitigation options.

3.3. Learning in the base case?

An important question is whether to include technology learning in the base case. The base case is the modelers' reference case, to which all other cases are compared. The question is essentially whether one is comparing apples to oranges.

Including technology learning in the base case assumes that business as usual will include technology learning. If the scenarios then also include technology learning comparatively, the choice of technologies by the model will be unaffected by the technology learning as the costs of the technologies remain the same across scenarios. In this case you would be comparing "apples with apples". But will decision-makers base their decisions on projected future costs of technology?

A base case including technology learning may be 'optimal', but does it reflect future expectations? In the study for LTMS, when technology learning was included in the base case, the choice of technologies that make up the least-cost solution to meet the demand for electricity shifts from what one would expect to see, a base case dominated by coal, to a base case dominated by renewables towards the end of the time horizon. The expansion plan with learning was not 'plausible' in the sense of looking very different to official projections (DME, 2003a; NER, 2004).

The matter was further complicated, in this study, by not having the available data to apply technology learning to all technologies in the MARKAL model. It is applied to a sub-set of electricity generating technologies wind, two kinds of solar thermal, photovoltaics, super critical coal and natural gas combined cycle. Due to lack of data, technology learning is not applied to fluidised bed combustion, IGCC or nuclear. This sub-set of electricity generating technologies therefore has an advantage not only over other electricity generating technologies, but also over other end-use technologies such as solar water heating or technologies that could be used to improve energy efficiency that do not have technology learning specified within the model. So, not all apples are treated equally.

If, in fact, the base case does not include technology learning but is compared to an action case with technology learning, is that a fair comparison? Clearly the technologies which have learning in the policy case would have an advantage, given a least-cost optimising context. Comparing action case with learning to base case without compares apples to oranges.

It is worth considering the role of the base case in this respect. The base case should be optimised, given best information. Excluding technology learning from the base case, when we know that in future the cost of technologies will likely change over the planning period does not allow us to adapt and use the best information that we have at hand to inform an optimal future path. Today's least-cost solutions may not remain the least-cost technologies over the modeling time horizon. This was pertinent in the context of LTMS.

The LTMS study was faced with options to (1) include technology learning in both the base case and policy cases; or (2) exclude technology learning from all cases. Given the advantages and disadvantages of both options, as examined here, neither seemed attractive. The solution adopted for the LTMS analysis was to conduct most of the analysis without learning in either the base or policy (mitigation) cases. However, an additional variation of the base case with technology learning was run, and policy cases for technologies for which learning data was available were reported against this base case. The next section examines the results for RETs as a mitigation option in South Africa.

4. Technology learning and mitigation costs for renewables

Various policy options are available to increase the share of renewable energy in the fuel mix (Winkler, 2005). In 2003, South Africa adopted a renewable energy target: "Government is setting as its target 10,000 GWh (0.8 Mtoe) renewable energy contribution to final energy consumption by 2013, to be produced mainly from biomass, wind, solar and small-scale hydro" (DME, 2003b). Increasing the share of renewable electrical generation technologies beyond these levels was among the mitigation option chosen for analysis in the LTMS process. In order to assess the impact of increased utilisation of renewable technologies on GHG emissions, various levels of penetration of renewables for electricity generation were considered.

4.1. Twenty-seven percent of electricity generated by renewables

In this scenario, 15% of electricity dispatched must come from domestic renewable resources by 2020. The technologies available include South African hydro, wind, solar thermal, landfill gas, PV and biomass. This is extrapolated to 27% by 2030, and remains at 27% until 2050. Each of these technologies has an upper limit of capacity that can be built over the period, and a maximum rate at which capacity can be added to any single technology type each year.

This scenario sees the introduction of solar power towers, parabolic trough and wind. The extent to which each is introduced can be seen in Fig. 5. The solar power tower comes into the mix from 2014 and reaches its limit of 30 GW in 2045. The trough starts off much smaller, but reaches 16 GW by 2050. Wind comes in gradually, mostly at 25% availability, reaching a peak of 15 GW installed capacity in 2030, but declining to 7 GW by 2050 likely due to other renewable options becoming more economically viable and the relatively short life-time of wind turbines.

Fig. 5 shows installed capacity (GW), not electricity generated (kWh). Since RETs generally have lower availability factors (with the exception of the power tower at 60%), more capacity needs to be built for the same electricity output than for a high-availability plant; thus the size of the grid in this case is 140 GW, 20 GW larger than in the base case.

Table 5 below shows that the emission reductions in add up to 2010 Mt CO_2 over the period. The cost of mitigation (or reducing emissions through policy, technology and other measures) is the taken as the difference in emissions with and without the policy; divided by the difference in the costs. Since costs vary over time, the discount rate affects the cost significantly, and it reported at 3% (recommended for long-term mitigation); 15% (closer to a commercial rate of return) and the intermediate 10% (often used for public investments in South Africa). The results for energy system costs and as a share of GDP are reported for the central value of 10% only (Tables 5–8).

The mitigation cost is R52/ton CO_2-eq at a 10% discount rate, reducing emission on average by 42 Mt CO_2-eq per year. Fig. 6 shows the emission reductions in the renewable energy scenario, without technology learning.

If technology learning is assumed for both the base case and the renewable case, the mitigation costs decline significantly, becoming negative at −R143/t CO_2-eq. The total emission reductions are also increased to 2757 Mt CO_2-eq over the period.

Emission reductions increase with learning, even when compared to the base case with learning (see Fig. 7). Annual emission reductions are 15 Mt CO_2-eq higher if technology

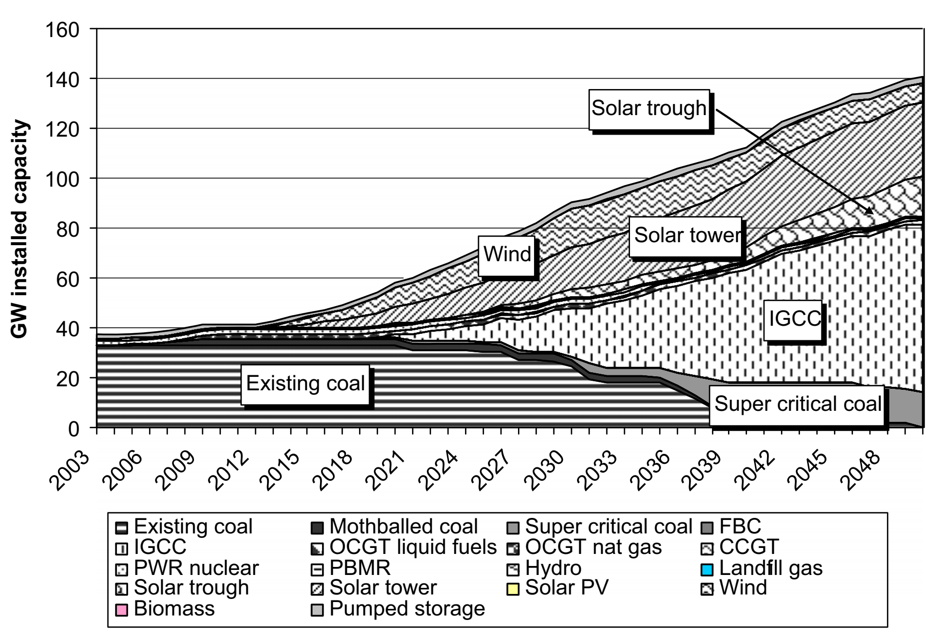

Fig. 5. Electricity generating capacity for renewables with learning.

Table 5
Mitigation and costs for 27% renewable electricity[a] scenario without technology learning.

Discount rate	3%	10%	15%
Annual CO_2-eq saving (Mt/yr)			
	42		
Incremental Annual Costannual cost (R millions)	4177	2165	1241
Cost effectiveness (R/t CO_2-eq)	100	52	30
Total CO_2-eq saving (Mt,; 2003––2050)		2010	
% increase in energy system costs (at 10% discount rate)		0.63	
% of GDP (at 10%)		0.13	

[a] 'Renewable electricity' is used as a short-hand for electricity generated from renewable energy sources; electricity itself being an energy carrier.

Table 6
Mitigation and costs for 27% renewable electricity scenario with technology learning.

Discount rate	3%	10%	15%
Annual CO_2-eq saving (Mt/yr)			
	57		
Incremental Annual Costannual cost (R millions)	−11,087	−8208	−7557
Cost effectiveness (R/t CO_2-eq)	−193	−143	−132
Total CO_2-eq saving (Mt,; 2003–2050)		2757	
% increase on energy system costs		−2.13	
% of GDP		−0.38	

Table 7
Mitigation and costs for 50% renewable electricity scenario without technology learning.

Discount rate	3%	10%	15%
Annual CO_2-eq saving (Mt/yr)			
	68		
Incremental Annual Costannual cost (R millions)	20,276	6310	2872
Cost effectiveness (R/t CO_2-eq)	296	92	42
Total CO_2-eq saving (Mt,; 2003–2050)		3285	
% increase on energy system costs		2.64	
% of GDP		0.56	

learning is assumed. The dip in emission reduction towards the end of the period is due to the increased uptake of renewables towards the end of the period in the base case. In a world where technology learning reduces costs globally, South Africa benefits from the lower unit costs, and in a least-cost modeling framework, more of these technologies are taken up yielding greater emission reductions (Figs. 8 and 9).

A dramatic shift in the mitigation costs can be seen–from imposing a cost of R52/t CO_2-eq (at 10% discount rate), including assumptions about technology learning turns renewables into negative cost option, *saving* R143 per ton reduced.

The conclusion is that, if South Africa found itself in a world in which new technologies got cheaper due to investment globally, emission reductions from renewable electricity would be more cost-effective, and still deliver significant reductions. For a scenario assuming 27% of electricity was generated from renewable energy sources, technology learning flips the costs from positive to negative. Instead of imposing incremental costs (higher than the base case), renewables can reduce costs.

4.2. *Fifty percent of electricity generated by renewables*

In this scenario, electricity dispatched from domestic renewable resources is extended to 50% by 2050. Total emission reductions increase to 3285 Mt CO_2-eq, but at a higher mitigation costs of R92/t CO_2-eq.

When taking learning into consideration, mitigation costs are R3/t CO_2-eq, with annual emissions reductions of 83 Mt CO_2-eq. A total of 3990 Mt is mitigated over the period.

For the mitigation costs of RETs, assumptions about learning are clearly important.

Mitigation costs of R92/t CO_2-eq decline to just R3 per ton when we factor in technology learning. In the 50% renewable electricity scenario, the change is not from incremental costs to savings, but still from a much higher cost to one close to zero (i.e., comparable to the base case).

Table 8
Mitigation and costs for 50% renewable electricity scenario with technology learning.

Discount rate	3%	10%	15%
Annual CO_2-eq saving (Mt/yr)			
	83		
Incremental Annual Costannual cost (R millions)	527	278	79
Cost effectiveness (R/t CO_2-eq)	6	3	1
Total CO_2-eq saving (Mt,; 2003–2050)		3990	
% increase on energy system costs		0.07	
% of GDP		0.02	

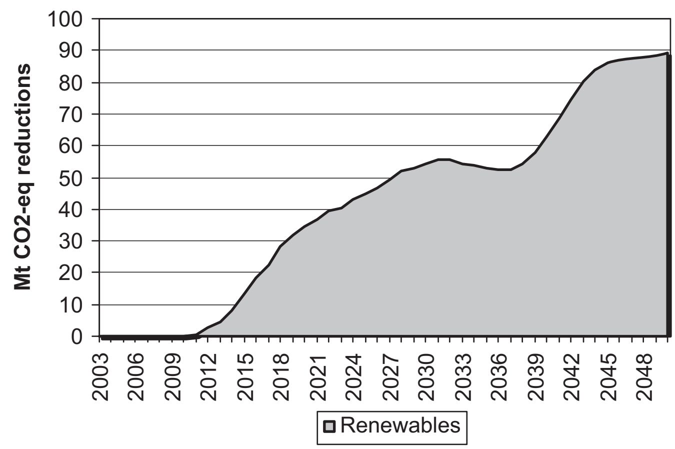

Fig. 6. Emission reductions from 27% renewables compared to the base case, both without technology learning.

5. Future work

The approach to technology learning extends previous approaches to energy modeling (Alfstad, 2005; Howells and Solomon, 2002), which have been used as inputs to integrated energy planning (DME, 2003a). Nonetheless, there are limitations to the approach taken here, which are areas for further work.

The limits on upper capacity and doubling times might be derived from running a global energy model (see Section 2.6). Currently, no such models are run in South Africa, making this an area to be explored in future work. Depending on the model structure, such further work could consider in greater detail technology-specific factors, including market conditions, physical and social constraints.

Another important extension of the work would be to apply learning to a wider set of new technologies. The focus in the work reported in this article has been mainly on renewable energy, and

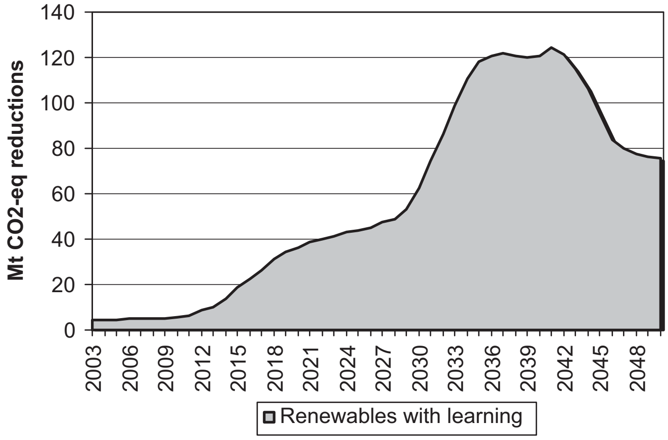

Fig. 7. Emission reductions from 27% renewables compared to the base case, both with technology learning.

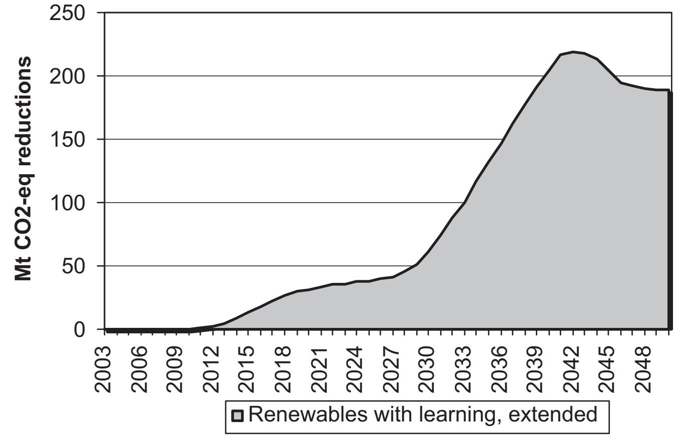

Fig. 9. Emission reductions from 50% renewable electricity, with learning.

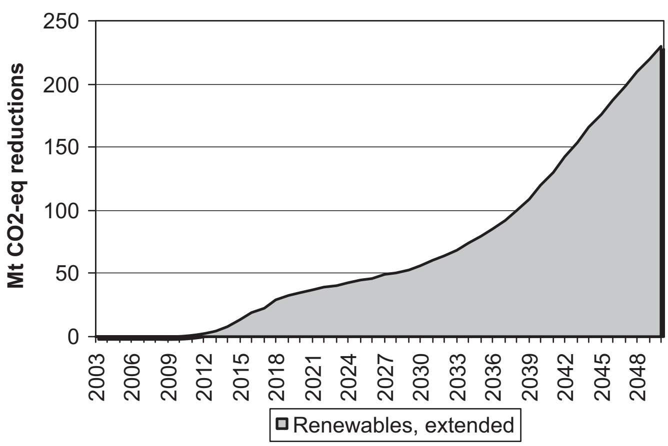

Fig. 8. Emission reductions from 50% renewable electricity, without learning.

results were compared to a version of the base case that also included learning. Learning rates for other electricity generating technologies were considered—but found to be low. Further work could examine learning rates for technologies in other demand and supply sectors. Eventually, this would enable both the base case or modelers reference case and *all* policy cases to reflect technology learning.

6. Conclusion

It matters what world we inhabit. In this study of renewables for mitigation in South Africa, it matters in particular whether our scenarios play out in a future world that invests in renewables or not. The benefit of a world in which global investment in renewable energy reduces the unit costs would clearly be seen in South Africa. What might seem like an expensive mitigation option might in such a future become the preferred, low-cost option.

The earlier sections of this article examined both the empirical evidence of learning in RETs and theoretical aspects. Having applied this to scenarios of renewable electricity as a mitigation option in South Africa, it is clear that technology learning matters greatly.

A dramatic shift in the mitigation costs was found in both scenarios—for 27% and 50% of electricity from renewable energy sources, respectively. For the less ambitious case, mitigation costs, in Rand per ton of CO_2-equivalent reduced—change from adding costs (positive cost) to saving relative to the base case (negative cost). At the higher penetration rate, there is not a change of sign in the costs, but still a very significant reduction—from incremental costs of R92/t CO_2-eq to close to zero with technology learning.

Savings or reduced costs would promote the sustainability of renewables as a solution. By including technology learning in scenarios for renewable electricity in South Africa, the mitigation costs are dramatically reduced, or even provide a saving relative to business-as-usual. If such scenarios materialised, it would no longer take legislation to mandate shares of renewables, but greater uptake should be driven by economic incentives.

Overall, reductions in unit costs will be driven by global levels of investment in renewables and overall installed capacity. South Africa itself may well be part of the global investment in renewable energy. Policy may promote climate-friendly technologies and make the country a place that manufactures and indeed exports RETs.

The conclusion is that, if South Africa found itself in a world in which new technologies got cheaper due to investment globally, emission reductions from renewable electricity would be more cost-effective, or even be more cost-effective than business-as-usual.

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