# Modeling Technology Learning for Electricity Supply Technologies

## Phase II Report:

## Implied Learning Rates from REGEN Scenarios and Comparisons with Literature Values

to

Robin Bedilion
Electric Power Research Institute
Palo Alto, California

from

Inês Azevedo[a]
Paulina Jaramillo[a]
Ed Rubin[a,*]
Sonia Yeh[b]

[a] Carnegie Mellon University, Pittsburgh, PA
[b] University of California at Davis, Davis, CA

*Corresponding author: rubin@cmu.edu

June 2013

**[This page intentionally left blank]**

# Table of Contents

# List of Figures

# List of Tables

# Executive Summary

This report compares the technology learning rates found in our Phase I literature review to those implied by the exogenous cost specifications used in EPRI's REGEN model. Results are summarized in Table ES-1. It was found that in a few cases the implied learning rates from REGEN fell within the range of literature values for some (but not all) of the four scenarios examined. Only in two cases, however (onshore wind for the base case and pessimistic scenarios), were the REGEN learning rates similar to the average learning rate from the literature, based on the common one-factor model in which cost reductions are a function of the cumulative installed capacity (or production) of a particular technology. In many cases, the learning rates inferred from REGEN results were outside the range of literature values (either higher or lower). Moreover, since the REGEN cost specifications (as a function of time) are the same for all scenarios, inconsistencies arise wherein cost reductions are greater the less a technology is deployed.

**Table ES-1: Implied and historical learning rates for selected REGEN technologies**

| Technology | Implied Rates for REGEN Scenarios[a] | | | | Literature Values | |
|---|---|---|---|---|---|---|
| | Base Case | CES | CTAX | Pessim. | Range | Mean[b] |
| SCPC without CCS | 0% | 0% | 0% | 0% | 5.6% to 12% | 9% |
| SCPC with CCS | – | – | 0.3% | – | 2% to 4%[c] | *3%* |
| IGCC without CCS | – | – | – | – | 2.5% to 7.6% | *5%* |
| IGCC with CCS | – | – | – | – | 3% to 9%[c] | *6%* |
| NGCC without CCS | 0% | 0% | 0% | 0% | -11% to 34% | 14% |
| NGCC with CCS | – | – | 0.1% | – | 2% to 7%[c] | *5%* |
| Dedicated Biomass | ∞ | 40.7% | 14.2% | – | 0% to 24% | 10% |
| Nuclear | 13.4% | 5.2% | 5.0% | – | -38% [d] to 6% | *-16%*[d] |
| Wind (onshore) | 16.6% | 7.0% | 6.6% | 15.7% | -3% to 32% | 16% |
| Wind (offshore) | -0.5% | 0.4% | 0.5% | 0.4% | – | – |
| Solar PV (rooftop) | 7.6% | 7.2% | 7.0% | 6.8% | 10% to 53% | 22% |

[a]CES= Clean Energy Standard scenario; CTAX=Carbon tax scenario; Pessim.=Pessimistic scenario..
[b]Mean values are from the Phase I report for technologies with many reported values. Values in italics are estimated as the midpoint of the range for technologies with few reported values.
[c]Literature values were based on projections using historical learning rates for similar plant components.
[d]This value was derived in the current study based on data reported in the literature.

At the same time, the literature also recognizes that the level of technology deployment used in the common one-factor learning models is a surrogate for the many factors that influence cost trends. Computer experiments are thus suggested to assess the implications of alternative cost trajectories (based on learning curves) on key REGEN results, including changes in the electricity generation mix, capacity additions of each technology, retail and wholesale electricity prices, total electric sector expenditures, emissions of $CO_2$ and criteria air pollutants, plus GDP for different scenarios.

# 1 Background

In Phase II of the EPRI-sponsored project on "Modeling Technology Learning for Electricity Supply Technologies" we compare the technology learning rates derived from our Phase I literature review to those reflected in EPRI's REGEN model. REGEN does not use endogenous learning curves to estimate future technology costs. Instead, it projects the future costs of power generation technologies based on expert judgments. The capital and operating costs of a given technology are specified at future points in time and these cost trajectories remain constant across different scenarios. Thus, an implied learning curve (and associated learning rate) can be derived by plotting the EPRI cost trajectories as a function of cumulative power plant capacity (rather than time) for a given scenario.

In this report we derive the implied learning rates for several power generation option using data provided by EPRI from recent REGEN runs for the time period 2015 to 2050 for four scenarios:

- Base Case (full portfolio with new nuclear and CCS available in 2020)
- Clean Energy Standard (increasing clean energy requirements through 2050)
- Carbon Tax (starting at $20/tonne rising at 5%/yr real, reaching >$110/tonne in 2050)
- Pessimistic (more pessimistic renewable costs, plus no CCS, no new nuclear, and no new inter-regional transmission available).

We then compare the implicit learning rate values to those obtained from the Phase I literature review. Finally, we present alternative time-dependent cost trajectories that are consistent with the literature values, and which vary across the four EPRI scenarios.

# 2 Capital Cost vs. Cumulative Capacity

Figure 1 shows the capital cost of seven REGEN technologies on the y-axis as a function of its cumulative installed capacity (GW) on the x-axis for the Base Case REGEN scenario. The figure is plotted on a log-log scale, so that a typical one-factor learning curve (of the form: $Y = ax^b$) would appear as a linear relationship on this graph. In the absence of historical data on the true cumulative capacity of each technology (since it was first deployed commercially), the initial values on this graph are taken to be the 2015 installed capacity reported by EPRI. While this assumption can be refined if data on historical retirements become available, it is nonetheless a reasonable estimate for the major renewable technologies that have been deployed only recently. For more mature technologies like NGCC and pulverized coal plants that are already widely deployed (for which REGEN assumes no future cost reductions), the omission of historical retirements is expected to have a relatively small impact on learning curve results.

Additional results of this type are shown in Figure 2 for the Clean Energy Standard scenario and Figure 3 for the Carbon Tax scenario. Since the assumed capital cost of each technology in each year is the same across all scenarios (except for renewables cost in the Pessimistic scenario), the only difference across scenarios is the projected cumulative installed capacity. Thus, the key drivers for technology adoptions in Figures 2 and 3 are the regulations imposed in the CES and CTAX scenarios. In the CES case renewable technologies are explicitly favored, while in the CTAX scenario fossil energy has a cost penalty which indirectly aids non-carbon renewables.

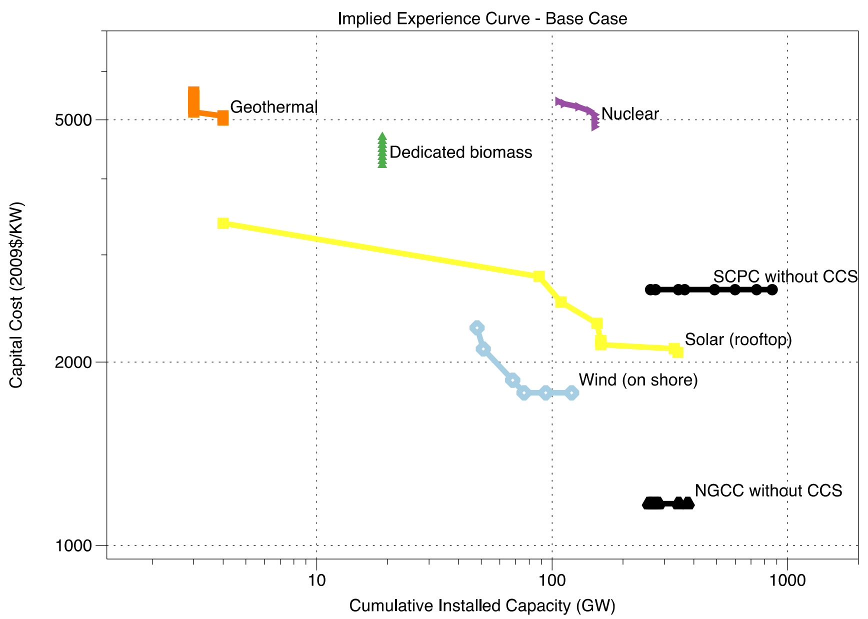


**Figure 1: Capital cost vs. cumulative capacity for the Base Case scenario.**

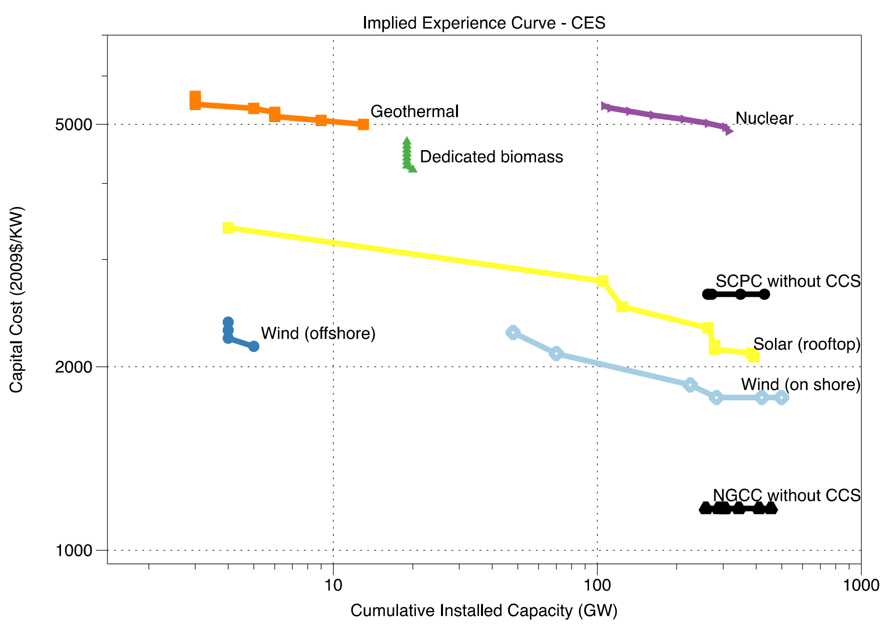


**Figure 2: Capital cost vs. cumulative capacity for the Clean Energy Standard scenario**

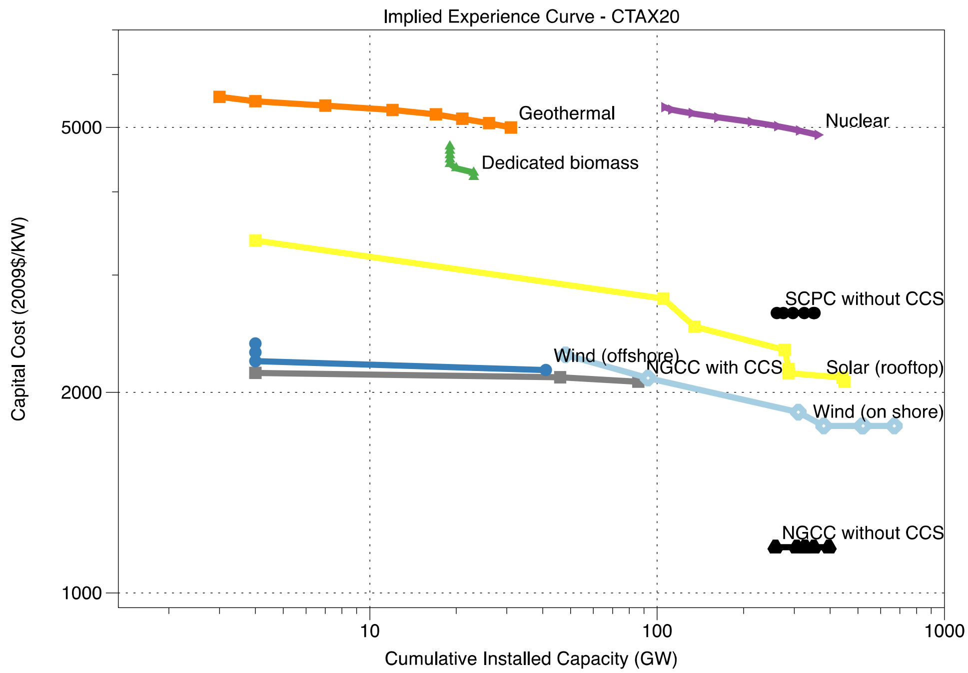


**Figure 3: Capital cost vs. cumulative capacity for the Carbon Tax scenario**

# 3 Implied Learning Rates

The slope of each curve in Figures 1–3 reflects the implied learning rate for that technology based on the assumed cost reduction (y-axis) and market penetration (x-axis). The steeper the slope, the higher the implied learning rate. (Recall that learning rate is defined as the fractional reduction in the unit cost of a technology for each doubling of the cumulative production or capacity. Numerically it is equal to *$(1–2^b)$*, where *b* is the exponent of the learning curve equation shown earlier.)

Since costs over time are fixed across the REGEN scenarios, in general, scenarios with *lower* penetration rates have *higher* implied learning rates. For example, the implied learning rate for onshore wind is highest in the base case scenario, where relatively little wind capacity is deployed, and lowest in the CTAX scenario, where wind systems are more extensively deployed. Results like this seem counter-intuitive—in general one expects greater cost reductions with greater deployment and experience.  However, the literature does not offer a clear conclusion of whether learning rates are determined by the rate and level of technology adoption. As we noted in Section 2.5 of our Phase I report for this project, some studies suggest that cost reductions can occur exogenously over time (CMU, 2013). If that hypothesis is correct, it is possible that the same cost reduction could be achieved during a given time period regardless of the market penetration level achieved in different scenarios.

On the other hand, some implied learning rates (line slopes) observed in Figures 1–3 are far greater than historically observed ranges, while others fall short of past experience. The following section elaborates on these comparisons.

# 4 Comparison with Historically Observed Learning Rates

We fit least-square linear regressions to the "implied experience curves" discussed above to determine the implied learning rate parameter value for each technology in each scenario. This is consistent with the way that learning curves are derived from historical data based on a one-factor log-linear model. The results for several key technologies are summarized in Table 1 below. The first four columns show the implied learning rates calculated from results of REGEN scenarios. The last two columns show the ranges and mean values of historical learning rates reported in the literature, based on our Phase I report.

**Table 2: Implied and historical learning rates for selected REGEN technologies**

| Technology | Implied Rates for REGEN Scenarios[a] | | | | Literature Values | |
|---|---|---|---|---|---|---|
| | Base Case | CES | CTAX | Pessim. | Range | Mean[b] |
| SCPC without CCS | 0% | 0% | 0% | 0% | 5.6% to 12% | 9% |
| SCPC with CCS | – | – | 0.3% | – | 2% to 4%[c] | *3%* |
| IGCC without CCS | – | – | – | – | 2.5% to 7.6% | *5%* |
| IGCC with CCS | – | – | – | – | 3% to 9%[c] | *6%* |
| NGCC without CCS | 0% | 0% | 0% | 0% | -11% to 34% | 14% |
| NGCC with CCS | – | – | 0.1% | – | 2% to 7%[c] | *5%* |
| Dedicated Biomass | ∞ | 40.7% | 14.2% | – | 0% to 24% | 10% |
| Nuclear | 13.4% | 5.2% | 5.0% | – | -38% [d] to 6% | *-16%*[d] |
| Wind (onshore) | 16.6% | 7.0% | 6.6% | 15.7% | -3% to 32% | 16% |
| Wind (offshore) | -0.5% | 0.4% | 0.5% | 0.4% | – | – |
| Solar PV (rooftop) | 7.6% | 7.2% | 7.0% | 6.8% | 10% to 53% | 22% |

[a]CES= Clean Energy Standard scenario; CTAX=Carbon tax scenario; Pessim.=Pessimistic scenario..
[b]Mean values are from the Phase I report for technologies with many reported values. Values in italics are estimated as the midpoint of the range for technologies with few reported values.
[c]Literature values were based on projections using historical learning rates for similar plant components.
[d]This value was derived in the current study based on data reported in the literature.

Table 1 shows that REGEN assumes no future cost reductions through 2050 for fossil fuel technologies like supercritical PC and NGCC plants. However, historical and projected learning rates for these systems (with or without CCS), indicate a potential for further cost reductions. Similarly, there is little learning in REGEN for coal or gas-fired plants with CCS, whereas the literature again suggests a greater potential for future cost reductions.

For renewables, REGEN is also conservative in its projections for solar PV cost. The average learning rate reported in the literature is roughly three times greater than the implied REGEN rates for the four scenarios in Table 1. Rates for wind are consistent with the average literature value for two of the four scenarios. However, the implied REGEN learning rates are only half as large for the two scenarios in which wind systems are most widely deployed (CES and CTAX).

On the other hand, implied learning rates for biomass-powered plants are substantially greater than literature values. For the base case scenario the implied REGEN rate is effectively infinite since the assumed cost reduction occurs with no new deployment of the technology. A small increase in deployment for the CES scenario implies a learning rate four times larger than the average literature value, while a somewhat larger deployment in the CTAX scenario lowers the implied learning rate to a value slightly larger than the literature average (14% vs. 10%).

For nuclear plants the projected cost reductions in REGEN imply a learning rate for the base case (13.4%) that is more than twice as large as the most optimistic value in the literature (5.8%, reported in one study for OECD countries from 1975 to 1993). That upper-bound literature value is similar to the implied values for REGEN scenarios with increased nuclear deployment. Other historical studies, however, show significantly *increasing* costs for nuclear plants in the U.S. and France, corresponding to *negative* learning rates. Although no numerical values of these negative learning rates were reported in the study cited, the data presented on cost vs. cumulative capacity allowed us to calculate a learning rate of -38% for the U.S. for the period 1972-1996. Thus, it remains to be seen whether future generations of U.S. nuclear plants can achieve long-term cost reductions, as modeled in REGEN.

Finally, Figures 4–8 show REGEN cost trajectories by scenario for each of several technologies. These trajectories are compared to the cost trends based on the lower bound, upper bound and (where available) mean learning rates observed for that technology based on our literature review. This provides a graphical illustration of the extent to which the REGEN cost trends are consistent with, or different from, projections based on historical learning rates. Overall, the greatest discrepancies—where REGEN cost trends fall outside the range of literature values—are seen for NGCC plants with CCS (Figure 4), nuclear plants (Figure 5), dedicated biomass plants (Figure 6), and rooftop solar PV systems (Figure 8). For NGCC-CCS and solar PV the specified REGEN costs fall more slowly than the learning curve literature would predict, while for biomass the REGEN costs fall much more rapidly and without any significant deployment. The latter phenomenon—while not consistent with the common one-factor learning curve based on cumulative capacity—*would* be consistent with multi-factor learning models that employ additional variables such as R&D expenditures or exogenous change factors, which allow costs to fall with no incremental capacity. (See the Phase I report for further discussion of multi-factor learning models.) In the case of nuclear plants, the base case cost trajectory also shows cost reductions with no incremental deployment in the later years of that scenario. In other scenarios where new nuclear plants are deployed the cost trajectory is just inside the envelope based on literature learning rates, but far from the end of that range where future costs increase rather than decrease.

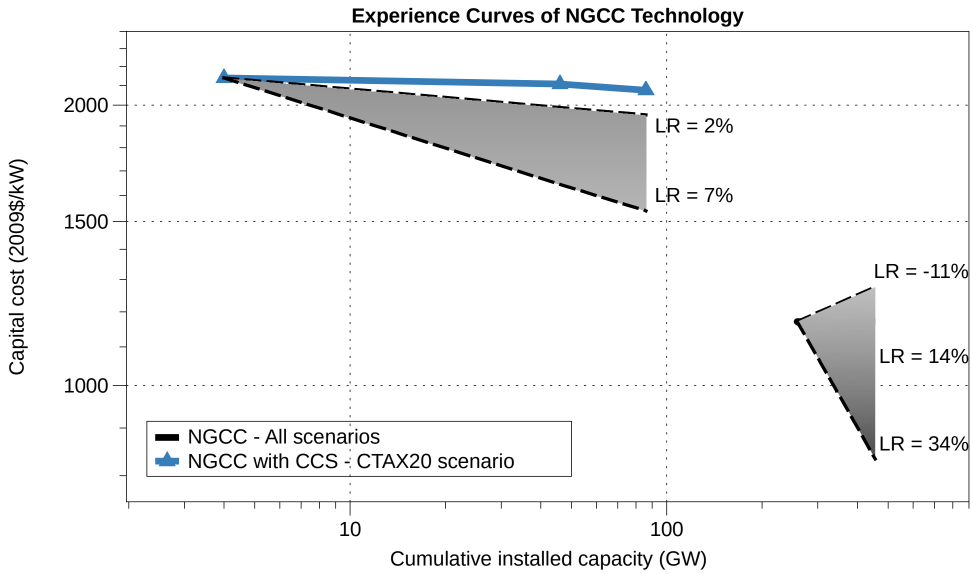


**Figure 4: REGEN cost trends compared to learning rate projections based on literature values for NGCC technology. Dashed lines show the range of costs based on upper and lower bound learning rates; the dotted line is based on the mean learning rate.**

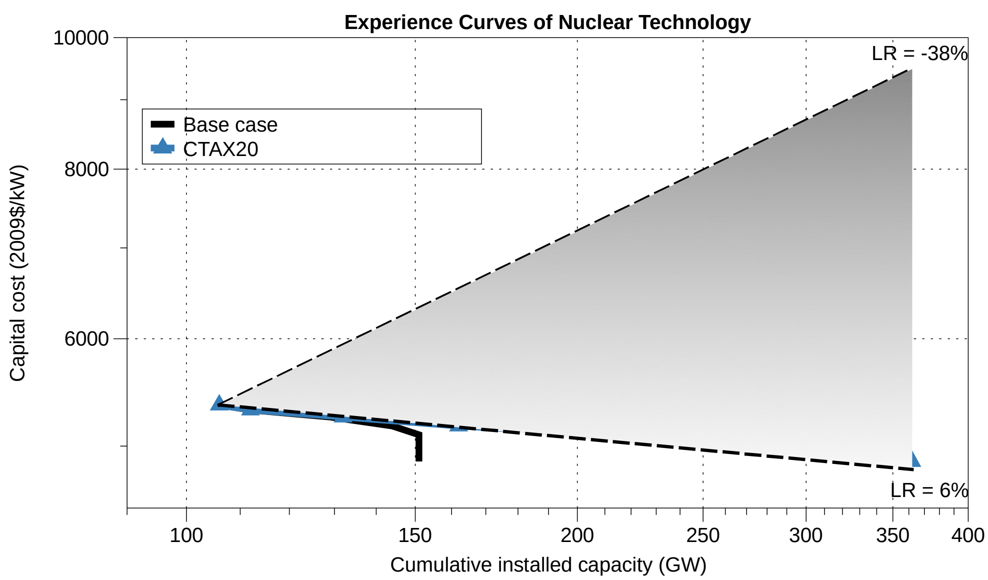


**Figure 5: REGEN cost trends compared to learning rate projections based on literature values for nuclear technology. Dashed lines show the range of costs based on upper and lower bound learning rates; the dotted line is based on the mean learning rate.**

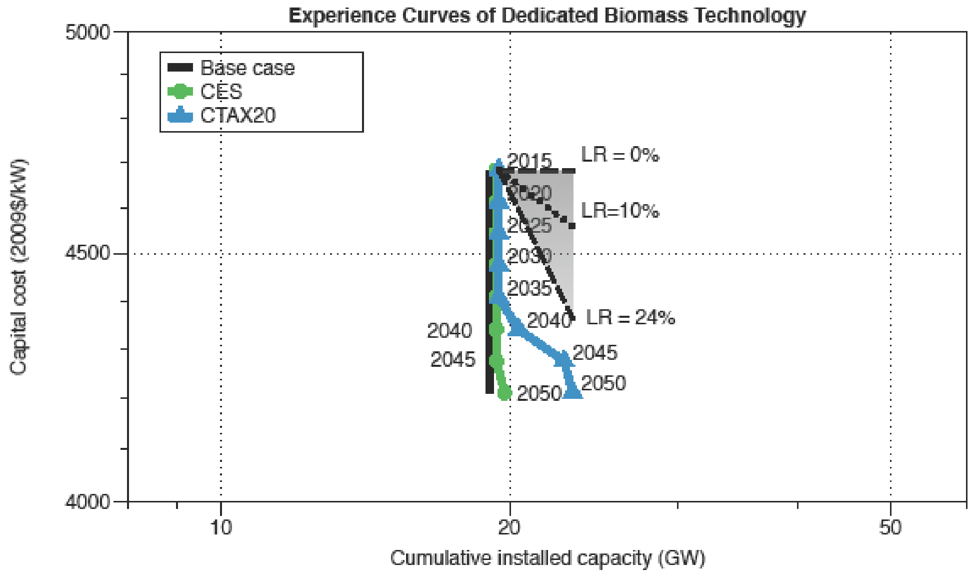


**Figure 6: REGEN cost trends compared to learning rate projections based on literature values for dedicated biomass technology. Dashed lines show the range of costs based on upper and lower bound learning rates; the dotted line is based on the mean learning rate.**

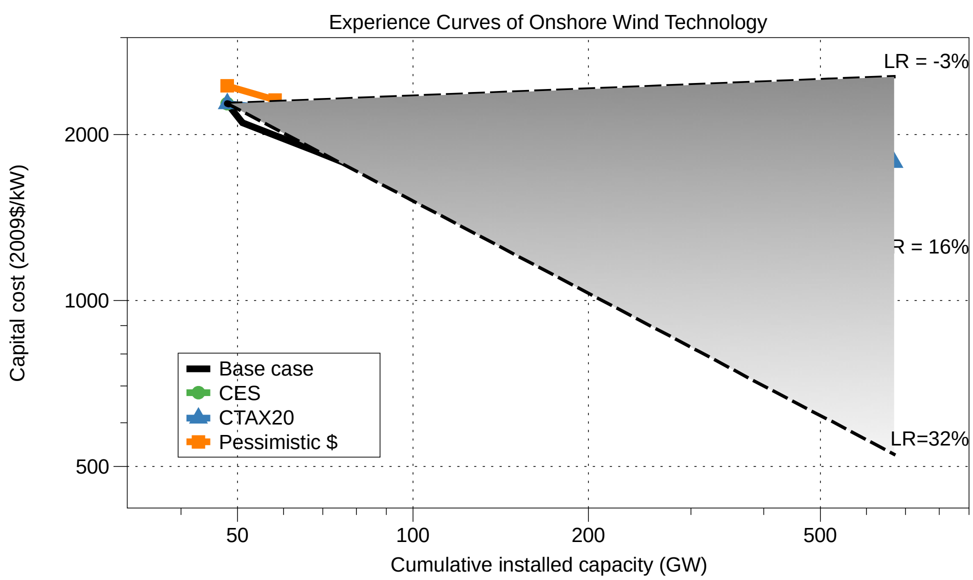


**Figure 7: REGEN cost trends compared to learning rate projections based on literature values for onshore wind technology. Dashed lines show the range of costs based on upper and lower bound learning rates; the dotted line is based on the mean learning rate.**

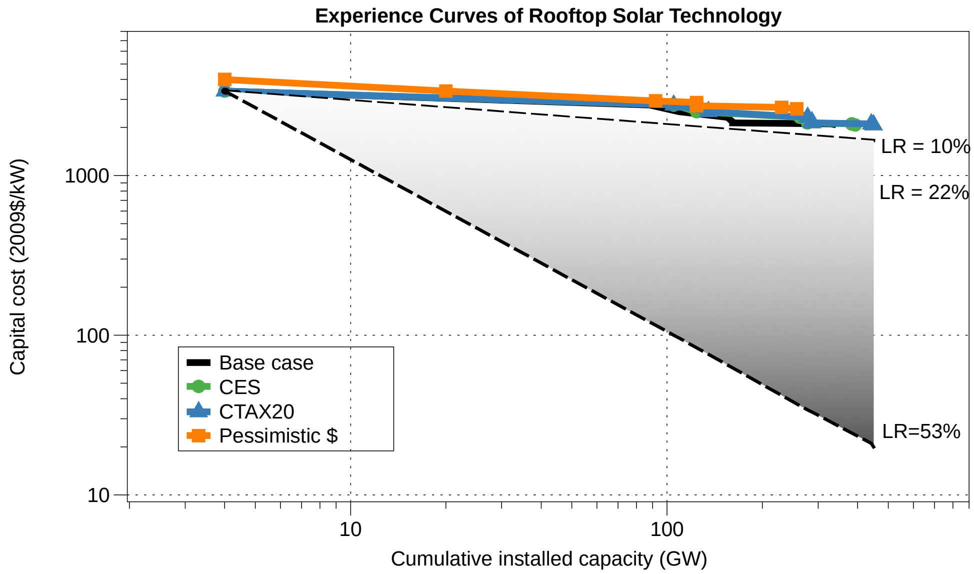


**Figure 8: REGEN cost trends compared to learning rate projections based on literature values for rooftop solar PV technology. Dashed lines show the range of costs based on upper and lower bound learning rates; the dotted line is based on the mean learning rate.**

# 5 How Much Do These Differences Matter?

In light of the many discrepancies noted above between cost projections based on historical learning rates and the exogenous specifications used in recent REGEN runs, it is reasonable to ask how key results from REGEN would have changed had endogenous learning rates been used instead. While REGEN is not designed to incorporate endogenous learning explicitly, some relatively simple computer experiments can give an indication of the difference this alternative approach would make.

Approximating endogenous learning would require an iterative series of model runs in which the time-dependent cost trajectories are adjusted to values that are consistent with a specified learning rate for the technology. Based on a given learning rate, the current REGEN cost values for each technology would be adjusted based on the cumulative capacity predicted at different points in time for a given scenario. These new cost profiles would be used in a new iteration of REGEN, yielding a new set of capacity predictions over time. Those new capacity values would be used with the learning rate model to estimate a new set of costs. REGEN would be run again, and the process repeated until a stable solution is found.

Short of a complete analysis of this type, a simpler and less time-consuming experiment would examine the effects on REGEN results of only one or two iterations for just one or two scenarios (e.g., the Base Case and the CTAX scenario). Key output variables of interest would include changes in the generation mix, capacity additions of each technology, retail and wholesale electricity prices, total electric sector expenditures, emissions of $CO_2$ and criteria air pollutants, plus GDP for different scenarios. Results that are found to be highly sensitive to the technology cost projections should be distinguished from those that are found to be more robust. Overall, this would contribute to a more complete characterization of the uncertainty and variability in REGEN results for the range of scenarios modeled.

Table 2 below presents a set of revised time-dependent technology capital costs for the four REGEN scenarios based on the average learning rates from the literature (see Table 1) and the cumulative capacity values from REGEN runs, as presented above. For nuclear, however, a zero learning rate was assumed, keeping costs constant. These cost trends would be used in a new iteration of REGEN to determine their effect on key model results, as noted above. Ideally (if time and resources permit), the new set of cumulative capacity values would then be used in the one-factor learning model to further modify the cost profiles for additional iterations of REGEN.

**Table 3: Revised capital cost values ($/kW) for four scenarios based on mean learning rates from the literature and cumulative capacity projections from current REGEN runs**

| Technology | 2015 | 2020 | | | | | 2025 | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | Initial cost | Original EPRI | Base Case | ALT 1 -CES | ALT 2 -CTAX | ALT Base | Original EPRI | Base Case | ALT 1 -CES | ALT 2 -CTAX | ALT Base |
| SCPC without CCS | 2,631 | 2,631 | 2,613 | 2,631 | 2,612 | 2,617 | 2,631 | 2,535 | 2,631 | 2,585 | 2,552 |
| NGCC without CCS | 1,171 | 1,171 | 1,166 | 1,144 | 1,129 | 1,145 | 1,171 | 1,161 | 1,133 | 1,113 | 1,130 |
| Natural Gas Turbine | 827 | 827 | 827 | 827 | 827 | 827 | 827 | 827 | 827 | 827 | 827 |
| Dedicated Biomass | 4,682 | 4,612 | 4,682 | 4,682 | 4,682 | 4,682 | 4,543 | 4,682 | 4,682 | 4,682 | 4,682 |
| Nuclear | 5,361 | 5,316 | 5,361 | 5,361 | 5,361 | 5,361 | 5,253 | 5,361 | 5,361 | 5,361 | 5,361 |
| Wind (on-shore) | 2,277 | 2,102 | 2,242 | 2,071 | 1,930 | 2,171 | 1,868 | 2,083 | 1,544 | 1,425 | 2,123 |
| Solar PV (central station) | 2,254 | 1,844 | 2,254 | 2,254 | 2,254 | 2,254 | 1,674 | 2,254 | 2,254 | 2,254 | 2,254 |
| Solar PV (rooftop) | 3,381 | 2,766 | 1,129 | 1,061 | 1,060 | 1,916 | 2,511 | 1,045 | 999 | 970 | 1,111 |

| Technology | 2030 | | | | | 2035 | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Original EPRI | Base Case | ALT 1 -CES | ALT 2 -CTAX | ALT Base | Original EPRI | Base Case | ALT 1 -CES | ALT 2 -CTAX | ALT Base |
| SCPC without CCS | 2,631 | 2,514 | 2,631 | 2,553 | 2,520 | 2,631 | 2,416 | 2,627 | 2,528 | 2,390 |
| NGCC without CCS | 1,171 | 1,153 | 1,129 | 1,112 | 1,114 | 1,171 | 1,153 | 1,129 | 1,112 | 1,111 |
| Natural Gas Turbine | 827 | 827 | 827 | 827 | 825 | 827 | 827 | 827 | 827 | 825 |
| Dedicated Biomass | 4,475 | 4,682 | 4,682 | 4,682 | 4,682 | 4,407 | 4,682 | 4,682 | 4,682 | 4,682 |
| Nuclear | 5,174 | 5,361 | 5,361 | 5,361 | 5,361 | 5,097 | 5,361 | 5,361 | 5,361 | 5,361 |
| Wind (on-shore) | 1,781 | 2,032 | 1,458 | 1,353 | 2,061 | 1,781 | 1,922 | 1,320 | 1,253 | 1,954 |
| Solar PV (central station) | 1,544 | 2,254 | 2,254 | 2,254 | 2,254 | 1,446 | 2,254 | 2,254 | 2,254 | 2,254 |
| Solar PV (rooftop) | 2,316 | 922 | 762 | 748 | 999 | 2,169 | 910 | 748 | 739 | 999 |

| Technology | 2040 | | | | | 2045 | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Original EPRI | Base Case | ALT 1 -CES | ALT 2 -CTAX | ALT Base | Original EPRI | Base Case | ALT 1 -CES | ALT 2 -CTAX | ALT Base |
| SCPC without CCS | 2,631 | 2,351 | 2,618 | 2,525 | 2,314 | 2,631 | 2,285 | 2,529 | 2,525 | 2,236 |
| NGCC without CCS | 1,171 | 1,148 | 1,101 | 1,095 | 1,110 | 1,171 | 1,099 | 1,059 | 1,067 | 1,080 |
| Natural Gas Turbine | 827 | 827 | 827 | 827 | 825 | 827 | 764 | 744 | 738 | 770 |
| Dedicated Biomass | 4,341 | 4,682 | 4,681 | 4,649 | 4,682 | 4,276 | 4,682 | 4,681 | 4,572 | 4,682 |
| Nuclear | 5,020 | 5,361 | 5,361 | 5,361 | 5,361 | 4,945 | 5,361 | 5,361 | 5,361 | 5,361 |
| Wind (on-shore) | 1,781 | 1,921 | 1,320 | 1,253 | 1,954 | 1,781 | 1,921 | 1,320 | 1,250 | 1,954 |
| Solar PV (central station) | 1,424 | 2,254 | 2,254 | 2,254 | 2,254 | 1,404 | 2,254 | 2,254 | 2,254 | 2,254 |
| Solar PV (rooftop) | 2,137 | 910 | 748 | 739 | 999 | 2,105 | 703 | 667 | 633 | 800 |

| Technology | 2050 | | | | |
|---|---|---|---|---|---|
| | Original EPRI | Base Case | ALT 1 -CES | ALT 2 -CTAX | ALT Base |
| SCPC without CCS | 2,631 | 2,238 | 2,459 | 2,525 | 2,178 |
| NGCC without CCS | 1,171 | 1,079 | 1,035 | 1,067 | 1,072 |
| Natural Gas Turbine | 827 | 751 | 738 | 734 | 754 |
| Dedicated Biomass | 4,212 | 4,682 | 4,667 | 4,557 | 4,677 |
| Nuclear | 4,871 | 5,361 | 5,361 | 5,361 | 5,361 |
| Wind (on-shore) | 1,781 | 1,803 | 1,264 | 1,174 | 1,874 |
| Solar PV (central station) | 1,383 | 2,254 | 2,254 | 2,254 | 2,254 |
| Solar PV (rooftop) | 2,075 | 694 | 660 | 629 | 769 |

A graphical depiction of the revised cost trends is shown below in Figure 9. For comparison the original REGEN cost specifications (labeled "original EPRI") also are shown.

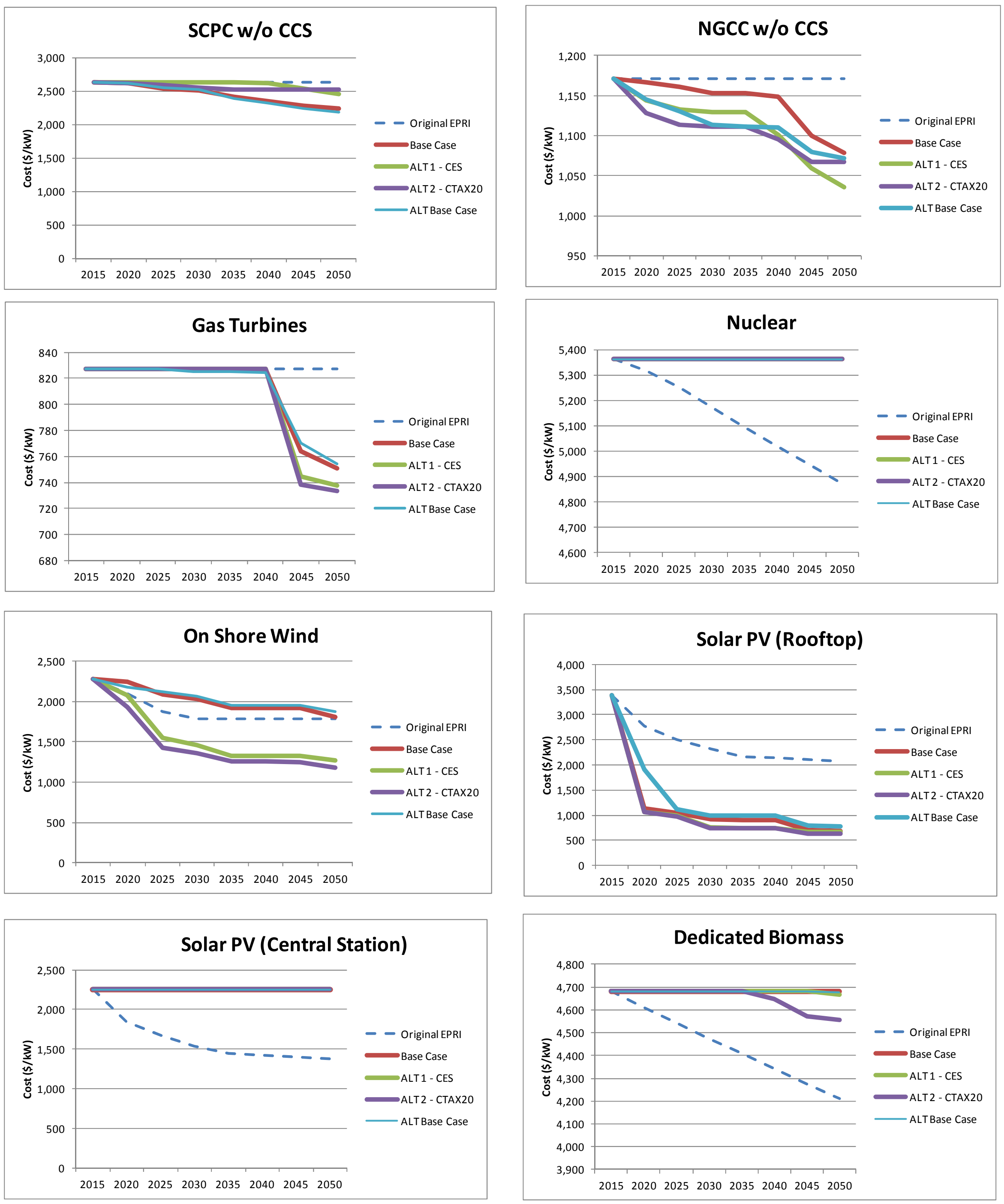


**Figure 9: Original and revised cost trajectories for several technologies (from Table 2).**

# 6 Conclusion

This report has compared the technology learning rates found in our Phase I literature review to those implied by the exogenous cost specifications used in EPRI's REGEN model. It was found that in a few cases (such as for NGCC, nuclear, biomass, and onshore wind technologies) the implied learning rates from REGEN fell within the range of literature values for some (but not all) of the four scenarios examined. Only in two cases, however (onshore wind for the base case and pessimistic scenarios), were the REGEN learning rates similar to the average learning rate from the literature, based on the common one-factor model in which cost reductions are a function of the cumulative installed capacity (or production) of a particular technology. In many cases, the learning rates inferred from REGEN results were outside the range of literature values (either higher or lower). Moreover, since the REGEN cost specifications (as a function of time) are the same for all scenarios, inconsistencies arise wherein cost reductions are greater the less a technology is deployed—a result contrary to findings in the literature.

At the same time, the literature also recognizes that the level of technology deployment used in the common one-factor learning models is a surrogate for the many factors that influence cost trends. Some multi-factor learning models attempt to capture other factors explicitly, with mixed success, often due to data limitations. Thus, the modeling of technological change remains an active area of study.

To better understand the implications of alternative learning and cost trajectory assumptions, we suggest that EPRI conduct some simple computer experiments in which the current set of exogenous cost specifications in REGEN are replaced with cost trends based on the prevailing learning rate models (experience curves). Toward this end, we developed an initial set of revised time-dependent cost trajectories for eight power generation technologies for each of the four REGEN scenarios for which data was provided by EPRI. These new cost trajectories are based on the average learning rates in the literature. Their use in REGEN would yield a new set of results—including new levels of capacity deployments—which could then be used for additional iterations of REGEN. Ideally this would continue until a stable solution is found.

Short of a complete analysis of this type, a simpler and less time-consuming experiment would examine the effects on REGEN results of only one or two iterations for just one or two scenarios (e.g., the Base Case and the CTAX scenario). Key output variables of interest would include changes in the generation mix, capacity additions of each technology, retail and wholesale electricity prices, total electric sector expenditures, emissions of $CO_2$ and criteria air pollutants, plus GDP for different scenarios. Results that are found to be highly sensitive to the technology cost projections should be distinguished from those that are found to be more robust. Overall, this would contribute to a more complete characterization of the uncertainty and variability in REGEN results for the range of scenarios modeled. Further work to develop a more rigorous method of employing expert judgment as an alternative to learning curves also has merit and is recommended.

# 7 Acknowledgements

We are grateful and indebted to our EPRI Project Manager Robin Bedilion and to Francisco de la Chesnaye for their invaluable assistance and support throughout this project.

# 8 References

CMU, 2013. *Modeling Technology Learning for Electricity Supply Technologies, Phase I Report: Literature Review*, Report to Electric Power Research Institute, Palo Alto, CA, Prepared by I. Azevedo, P. Jaramillo, E.S. Rubin and S. Yeh, Carnegie Mellon University, Pittsburgh, PA, May.