Climatic Change (2013) 118:381–395
DOI 10.1007/s10584-012-0618-y

Future capacity growth of energy technologies: are scenarios consistent with historical evidence?

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Received: 18 August 2011 / Accepted: 9 October 2012 / Published online: 1 November 2012

Abstract Future scenarios of the energy system under greenhouse gas emission constraints depict dramatic growth in a range of energy technologies. Technological growth dynamics observed historically provide a useful comparator for these future trajectories. We find that historical time series data reveal a consistent relationship between how much a technology's cumulative installed capacity grows, and how long this growth takes. This relationship between extent (how much) and duration (for how long) is consistent across both energy supply and end-use technologies, and both established and emerging technologies. We then develop and test an approach for using this historical relationship to assess technological trajectories in future scenarios. Our approach for "learning from the past" contributes to the assessment and verification of integrated assessment and energy-economic models used to generate quantitative scenarios. Using data on power generation technologies from two such models, we also find a consistent extent - duration relationship across both technologies and scenarios. This relationship describes future low carbon technological growth in the power sector which appears to be conservative relative to what has been evidenced historically. Specifically, future extents of capacity growth are comparatively low given the lengthy time duration of that growth. We treat this finding with caution due to the low number of data points. Yet it remains counter-intuitive given the extremely rapid growth rates of certain low carbon technologies under stringent emission constraints. We explore possible reasons for the apparent scenario conservatism, and find parametric or structural conservatism in the underlying models to be one possible explanation.

Electronic supplementary material The online version of this article (doi:10.1007/s10584-012-0618-y) contains supplementary material, which is available to authorized users.

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1 Introduction

1.1 The discontinuous road to a low carbon future

Climate stabilization scenarios vary widely in their assumptions, storylines, and analytical underpinning. But all share at least one common feature: order of magnitude increases in the deployment of particular energy technologies. Some scenarios emphasize energy supply technologies, such as renewables, nuclear power, bio-energy or carbon capture and storage. Other scenarios depict widespread diffusion of end-use technologies that improve energy efficiency or shift the types and amounts of energy services demanded in buildings, transportation systems, or industrial facilities. Most scenarios focus on both efficient end-use and energy supply technologies.

The conclusion of the IPCC's Fourth Assessment Report in 2007 remains representative of the scenario literature: "The range of stabilization levels assessed can be achieved by deployment of a portfolio of technologies [whose contribution] will vary over time, region and stabilization level … For lower stabilization levels … *improvements of carbon intensity of energy supply and the whole economy need to be much faster than in the past*." [our italics; from p25 of Summary for Policy Makers of (Metz et al. 2007)].

As well as the general need for technology deployment on both supply and demand-sides of the energy system, the italicized sentence at the end of the quotation points to a second recurring theme: discontinuity. Scenarios depict often substantive deviations from the current trends that extrapolate historical experience. The future will not – can not – resemble the past.

1.2 Modeling of future technological growth trajectories

Integrated assessment and energy system models provide the quantitative basis for the discontinuities in energy and carbon intensity seen in climate stabilization scenarios. These discontinuities describe transitions away from the current technological configuration of the energy system. Model outputs are highly sensitive to the parameterization and endogenous representation of technological change (Gillingham et al. 2008). Models used in scenario analysis also vary widely in their resolution of different energy technologies. Top-down models subsume the diffusion of particular technologies into trends in sectoral productivity (Pizer and Popp 2008). Technologically-explicit models depict the capital stock turnover of energy supply technologies given externally specified (exogenous) parameters and internally generated (endogenous) processes. Some technologically-explicit models extend this depiction to end-use technologies, either in particular sectors such as transportation (Azar et al. 2003) or more generally (Kitous et al. 2010).

This 'bottom-up' representation of technologies and their deployment trajectories over time can be differentiated at four levels.

At the first techno-economic level, models consider technologies' capital and operating costs, conversion efficiency, operating lifetime, and other performance characteristics (Barreto and Kemp 2008). The techno-economic parameters of energy technologies are relatively well known and widely documented in the literature, albeit subject to uncertainties and context-dependence.

At the second systems level, models represent competition, synergies, inter-dependencies, and other interactions which ultimately give rise to energy conversion chains through which primary energy resources are converted into end-use services. Based on the techno-economic parameterization within this systems framework, deterministic or optimization models select the lowest cost technologies to fulfill particular energy service demands, subject to resource and other constraints (Ma and Nakamori 2009). This can result in abrupt transitions between new and incumbent technologies as the cost of the new falls below some critical threshold at which it starts to outcompete the incumbent. Such model outputs are at odds with the inherent inertia of a large complex system (Unruh 2000) which gives rise to the relatively smooth transitions observed historically (Grubler et al. 1999). Some models introduce additional features to ensure more realistically heterogeneous technology choices which avoid abrupt transitions as relative costs change (e.g., Rivers and Jaccard 2005; Ma et al. 2009).

At the third level of representation, models capture endogenous changes to techno-economic parameters, particularly cost (see (Gillingham et al. 2008) for a review). Endogenous influences on cost include learning processes, and research and development (R&D) investments (Clarke et al. 2008). Learning describes reductions in unit costs as a function of cumulative deployment or experience with a technology (Yeh and Rubin 2012). R&D investments can also reduce a technology's future cost and its availability for widespread diffusion (Ek and Soderholm 2010). 'Perfect foresight' models whose outcomes are based on complete knowledge of future technology and resource characteristics can anticipate the future cost reductions from investing in the R&D or deployment of a new technology. As a result, transitions between technologies tend to be smoother as early investments are used to improve a new technology's techno-economic characteristics before its deployment at scale.

At the fourth level of representation, dynamic constraints on technological growth are used to limit the rate or extent to which particular technologies can scale up. This implies the concurrent deployment of new technologies alongside incumbent technologies, and so again, smoother transitions. In perfect foresight models, growth constraints can result in early investments in new technologies so that they can be deployed rapidly when subsequently needed (so avoiding foreseen potential bottlenecks). The use of dynamic constraints on technological growth is significantly less well substantiated and documented compared to the techno-economic parameterization (first level of representation), systems interactions (second level), and learning processes (third level).

1.3 Model diagnostics & verification

The structural characteristics and parameterization of models are empirically-founded, and the subject of verification and review by their parent modeling groups. Inter-model comparisons are an important additional source of peer review. The US-based Energy Modeling Forum has institutionalized this process (Clarke et al. 2009) and similar exercises have taken place elsewhere (e.g., van Vuuren et al. 2009).

Here, our interest is in an alternative but complementary approach to model verification which uses the past as a comparator for the future. More narrowly, we focus on technological deployment trajectories historically and in scenarios. Comparing future scenarios against the historical record is commonplace for earth system and climate modeling. "*Learning from the past*" is important for testing the feasibility of future scenarios driven by, or contingent on, human behaviors and choices (Cornell et al. 2010). This remains the case even if such scenarios are defined by normative goals (such as climate stabilization targets). As Pizer and Popp (2008) note: "*an important agenda for the modeling community is clearer reporting of benchmark model results … and comparison to historical, empirical data*".

Historical growth rates in energy production can be used to generalize patterns of future growth. Hook et al. (2012) describe this as "*forecasting-by-analogy*". Using historical production data for coal, oil, gas, nuclear, biomass and hydro, they characterize a 'scaling behavior' of technologies as a consistent inverse proportionality between growth rates and energy output.

Kramer and Haigh (2009) posit 'fundamental laws' for new energy technologies which describe two decades of exponential growth (~26 % per annum) until ‘materiality’ is reached at a ~1 % share of the global energy system and growth slows to become linear to an eventual equilibrium market share. Smil (2000) offers a more circumspect view that future potentials for new energy technologies are repeatedly over-estimated. He concludes by cautioning policymakers against relying on “*computerized fairy tales*” (Smil 2008).

In this paper we compare the historical and future dynamics of technological diffusion in the energy system taking into account temporal, systemic, and spatial dimensions. Our temporal comparison asks: how rapidly do energy technologies diffuse and how long is the duration of diffusion? This also concerns the form of growth, its pattern over time. Our systemic comparison asks: to what extent do energy technologies diffuse and what contribution to the energy system do they make? Our spatial comparison asks: how does the sequence of diffusion between regions or markets affect durations and extents of growth? Our overall aim is to demonstrate a methodology for “*learning from the past*” as a contribution to the assessment and verification of climate stabilization scenarios generated by technologically-explicit energy system models. Specifically we are interested in the relationship between the extent of a technology’s growth and the duration of that growth both historically and in future scenarios.

2 Method

2.1 Comparing growth across technologies and time periods

Our emphasis on technological growth dynamics means taking into account both the temporal and spatial characteristics of diffusion. Technology’s temporal growth dynamics are succinctly captured as a lifecycle which follows sequential stages of invention, innovation, and diffusion (Grubler 1996). Over the course of this lifecycle, growth rates are initially slow through an often extended introduction phase, before reaching a take off point after which diffusion is rapid and accelerating. After some time, diffusion starts to slow, passing an inflection point and ultimately starting to saturate. This generalized S-shaped growth, described by a three parameter logistic function (see Box), is supported by a wealth of historical evidence (Grubler 1996; Rogers 2003; Barreto and Kemp 2008), including in the specific case of energy technologies (Grubler et al. 1999).

Box. Three-parameter logistic function describing S-shaped growth.

$y = K / (1+e^{-b(t-t0)})$ and $\Delta t = \log 81.\ b^{-1}$
with:
K = asymptote (saturation level)
b = diffusion rate (steepness)
Δt (delta t) = time period over which y grows from 10% to 90% of K
$t0$ = inflection point at $K/2$ (maximal growth)

The logistic function captures changes in a technology’s growth over time, but this growth dynamic also varies spatially. In the initial ‘core’ markets or regions where a technology is first commercialized and diffusion begins, growth tends to be slower but more pervasive (Grubler 1996). In subsequent ‘rim’ and then ‘periphery’ markets, growth tends to be more rapid as the accumulated experience from core markets is transferred and applied (‘knowledge spillovers’). But this more rapid growth in later markets tends also to saturate at lower levels. One reason is that the institutions and infrastructures on which the technology depends are themselves less developed.

2.2 Logistic function parameters

Using a common growth form fitted to time series data enables cross-technology comparisons over different time periods (past and future). We use logistic functions to standardize the form of growth, and to parameterize the extent and duration of growth (see Online resource 1 for details). We fitted logistic functions to time series data globally, and disaggregated into core, rim, and periphery regions for each technology depending on the sequence of diffusion spatially. In each case, we tested various other saturating (Gompertz, Sharif-Kabir, Floyd) and non-saturating (exponential, linear) growth functions (see (Hook et al. 2011) for a review). However, we found the logistic function consistently provided the best fit to the data, a finding born out in other studies of energy technologies (Grubler et al. 1999).

We used two logistic function parameters in our analysis:

- K, the asymptote parameter, as a measure of the *extent* of growth;
- Δt, the time between 10 % and 90 % of the asymptote, as a measure of the *duration* of growth.

A comparison of the extent to which energy technologies diffuse at different time periods (past and future) also needs to control for changes in the size of the energy system as a whole. For each technology, we normalized the extent of growth (K) using total primary energy consumption measured at the inflection point of the fitted logistic function. As the K parameter is expressed in MW (see below) and primary energy is in EJ, the normalized Ks are not meaningful in absolute terms nor as percentage shares of the energy system. Rather, normalized K should be treated as an index against which data points for different technologies are meaningful relative to one another. Although normalization is conceptually necessary, our findings are very similar whether K or normalized K is used (see Online resource 1).

2.3 Growth metric

To enable comparisons between technologies, a common metric of growth is needed. We use energy-conversion capacity as our metric to describe the *potential* contribution of a technology to growth and transformation in the energy system. Specifically, we use cumulative total capacity expressed in MW. We preferred cumulative total capacity to installed capacity or capacity additions for two reasons. First, cumulative totals smooth short-term volatility and contain the whole history of capacity growth which provides an appropriate comparison of long-term growth dynamics. Second, cumulative totals are used as a proxy for experience or accumulated knowledge in learning curve analyses (Yeh and Rubin 2012).

Using a capacity metric also ensures a high degree of generality for cross-technology comparisons as differences between technologies in terms of efficiency (affecting outputs), operating lifetime (affecting capital stock turnover), or capital intensiveness and labor productivity (affecting inputs) are all explanatory variables for observed differences in capacity growth. However, by not controlling for the many factors which drive capacity growth (e.g., cost, efficiency, demand), we preclude any substantive insights into the economics of technological change. Rather, we are concerned with demonstrating a method for cross-technology comparisons of historical and future extents and durations of change in the energy system.

3 Data

3.1 Historical data

Table 1 summarizes the historical capacity growth trajectories compiled and analyzed. Energy supply technologies include oil refineries, coal power, natural gas power, nuclear power, and wind power. End-use technologies include passenger jet aircraft, passenger cars, and compact fluorescent light bulbs. For full details of the data collection including sources and links to the datasets used, see Online resource 1 and (Wilson 2009).

3.2 Scenario data

For future time series data we used capacity growth trajectories generated by MESSAGE, a bottom-up systems engineering model of the global energy system based on a least cost optimization framework over a centennial timescale (Messner and Strubegger 1995). The MESSAGE model is widely used in the work of the IPCC and in inter-model comparison studies (e.g., van Vuuren et al. 2009).

For this analysis, we selected a set of eight MESSAGE-generated scenarios from a broader 'Integrated Assessment Modeling Framework' study (hereafter: MESSAGE-IAMF) which linked the technologically-explicit representation of the energy system with other greenhouse gas emitting sectors, including industry, agriculture and forestry (Riahi et al. 2007). The eight MESSAGE-IAMF scenarios selected span the widest range of low carbon technology trajectories across three scenario families (A2r, B1, B2) and carbon stabilisation targets (baseline and 670 ppmv CO_2-equivalent concentrations for all 3 families, and 480 ppmv CO_2-eq. for the B1 & B2 families). Technology trajectories differ according to each scenario family's exogenously-specified technological preferences. The B1 scenarios, for example, respond to carbon constraints with strong growth in renewables, particularly solar; the A2r scenarios rather emphasize nuclear, bio-energy, and carbon capture and storage (see (Riahi et al. 2007) for details).

For each of the eight scenarios selected, cumulative installed capacity data were extracted for low carbon technologies resolved by the MESSAGE model. As specific end-use technologies are not modeled explicitly in capacity terms, this limited the analysis to six alternative forms of electricity generation for which technology-specific data were available: nuclear, natural gas, coal CCS (carbon capture and storage), all fossil CCS (i.e., coal CCS + natural gas CCS), wind, solar PV (photovoltaic, centralized + decentralized).

Logistic functions fitted to the combined historical + future scenario data for each technology accurately describe capacity growth (minimum adjusted R^2=98 %). These combined historical + future time series all run to the year 2100, but began as early as the 1900s (natural gas and coal power), the 1950s (nuclear power), the 1970s (wind power and solar PV), or the 2020s or later (CCS).

4 Historical analysis

4.1 Relationship between historical extents & durations of growth

Figure 1a (left panel) shows the historical data series of cumulative total capacity for the energy technologies shown in Table 1 (note log-scale y-axis). The K and Δt parameters of the fitted logistic functions then allow the *extents* and *durations* of growth to be compared for different technologies. The core region is used as it has the most number of data points,

Table 1 Historical energy technologies analyzed. See Online resource 1 for details and data sources

Technology	Time series	Regions with logistic growth (*included in analysis*)				Regions with non-logistic growth[a] (*excluded from analysis*)
		Global	Core	Rim	Periphery	
Oil refineries[b]	1940–2000	Global	OECD + FSU	Middle East, Asia (ex. China), L.America	China, Africa	–
Coal power	1908–2000	Global	OECD	(1) FSU	Middle East + L.America + Africa	Rim (non-FSU)
Nuclear power	1956–2000	Global	OECD	(1) FSU	–	Rim (non-FSU), Periphery
Natural gas power[b]	1903–2000	Global	OECD	(1) FSU (2) Asia	Midde East+L.America+Africa	
Wind power	1977–2008	–	Denmark	–	–	Global, Rim, Periphery
Solar PV	1975–2007	–	–	–	–	Global, Core, Rim, Periphery
Passenger jet aircraft[c]	1958–2007	Global	Boeing	Airbus	–	Periphery
Passenger cars	1900–2005	Global	US	(1) FSU (2) OECD ex. US	–	Periphery
Compact fluorescent light bulbs	1990–2003	–	N.America + W.Europe	–	–	Global, Rim, Periphery

[a] Either growth still in exponential phase reducing reliability of logistic fit, or insufficient data

[b] For technologies with distinct, sequential phases of growth, logistic functions were fitted to the '1st phase' of growth if it evidenced a clear plateau

[c] Boeing sales used as proxy for core region; Airbus sales for rim region; Boeing & Airbus combined for global data

OECD Organization of Economic Cooperation and Development (corresponding to developed countries); *FSU* former Soviet Union (corresponding to economies in transition); *L.America* Latin America

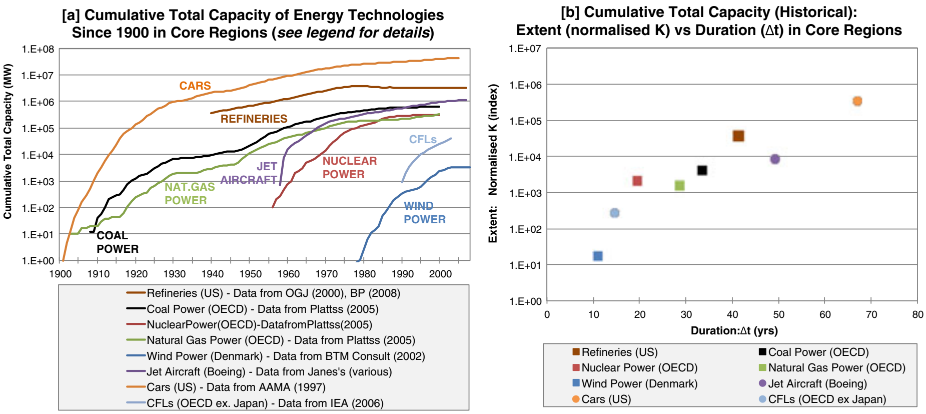

Fig. 1 Capacity growth of 8 energy technologies in the 20th century in their respective core regions (**a** *left panel*) with extent vs. duration of growth using fitted logistic parameters (**b** *right panel*). Source: see figure legend (and Online Resource 1 for details)

as growth is more likely to have passed its initial exponential phase so allowing more reliable logistic fits. Figure 1b (right panel) shows normalized K plotted against Δt (note log scale y-axis). K is normalized to account for changes in the size of the energy system into which each technology diffused.

In general, a technology should take longer to diffuse to a greater extent notwithstanding the many factors that affect growth (Grubler et al. 1999). Figure 1 confirms this basic intuition; surprising, however, is the consistency of the extent – duration relationship between historical energy technologies of markedly different characteristics and vintage. An exponential best fit line to the 8 data points has an R^2 of 84 % (normalized $K=25.74e^{0.15\Delta t}$).

The consistent extent - duration relationship shown in Fig. 1b (right panel) for the core region also holds globally, and for the rim and periphery regions although the number of data points become sparser (see Online resource 1 for details and figures).

Refineries, power plants, jet aircraft, cars and light bulbs are characterized by different energy service demands, and have distinctive costs and efficiencies, capital intensiveness, turnover rates, regulatory contexts, and so on. Infrastructure requirements also vary widely. Yet observed consistencies between extents and durations of capacity expansion historically suggest influences on growth (including R&D, learning, and knowledge spillovers) act proportionately on both log K and Δt, so preserving the exponential relationship seen in Fig. 1b (see Online resource 2 for further discussion).

5 Scenario analysis

5.1 Relationship between future extents & durations of growth

The consistent extent - duration relationship shown in Fig. 1b provides a historical comparator for technological trajectories in future scenarios. We analyzed the scenario data using the same methodology applied to the historical time series, extracting K and Δt parameters from logistic functions fitted to cumulative total capacity data and subject to goodness of fit and reliability criteria. K parameters were similarly normalized, using primary energy consumption data from each scenario measured at the inflection point of each fitted logistic function.

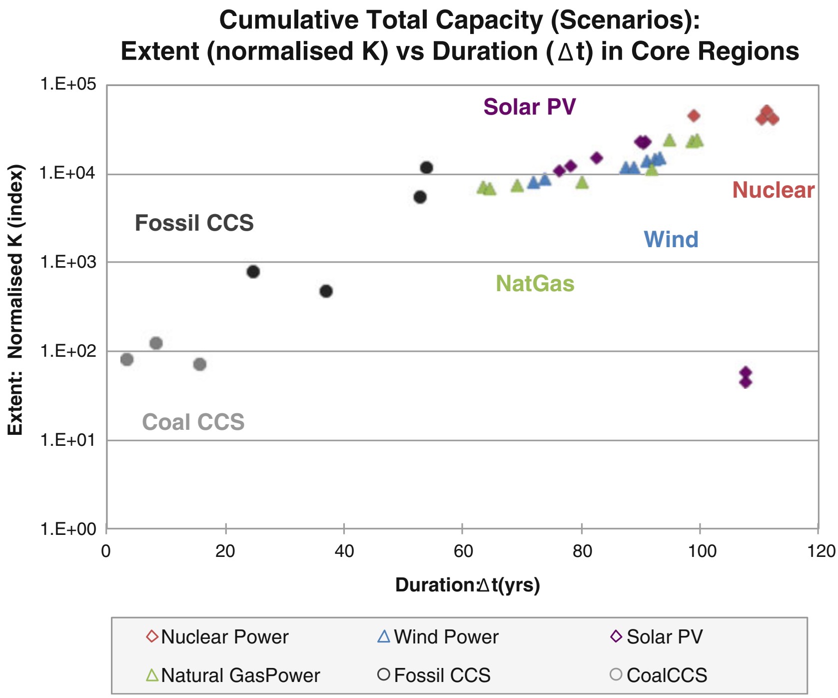

Fig. 2 Capacity growth of 6 energy technologies in 8 future scenarios of the 21st century in their respective core regions: extent vs. duration of growth using fitted logistic function parameters

The extent - duration relationship (normalized K vs. Δt) describing capacity growth of six low carbon electricity generation technologies in each of the eight scenarios analyzed is shown in Fig. 2 for each technology's core region. This is the scenario equivalent of the historical data shown in Fig. 1b (right panel).

As in the historical data, the extent – duration relationship in the scenarios is consistent across the different technologies. The dispersion of data points is greater between technologies for a given scenario than between scenarios for a given technology. Differences between scenarios are greatest for fossil CCS and solar PV which, by design, have low extents of growth in the B1 and A2r scenario families respectively. Two solar PV data points corresponding to the A2r baseline & 670 ppmv CO_2-eq. scenarios are clear outliers with long durations of growth (Δt) but low extents (normalized K).

5.2 Learning from the past

Figure 3a (left panel) compares the scenario data points in Fig. 2 with the historical data points using core region data in both cases. Exponential best fit lines are included for both historical (black) and scenario (grey) data points. As all scenario data points describe power generation technologies, an additional best fit line is included for historical power generation technologies only (dotted black). These best fit lines should not be over-interpreted: they describe only the aggregate relationship between the extent and duration of capacity growth for different energy technologies. For the scenario data points, this aggregate relationship is further generalized across a range of possible futures.

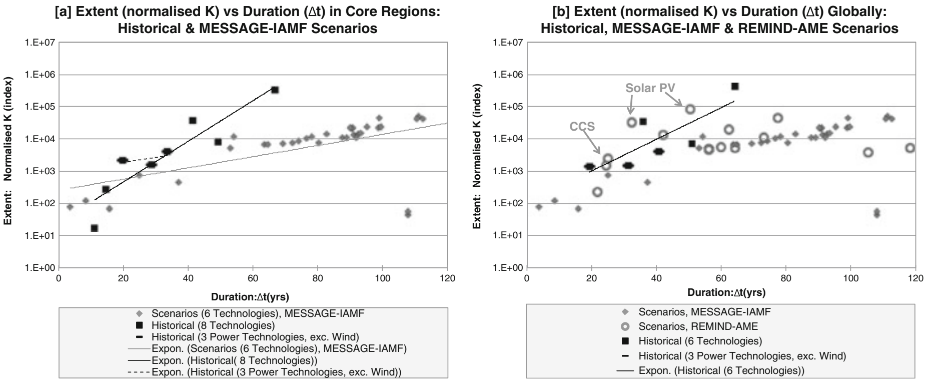

Fig. 3 Extent - duration relationships of capacity growth historically & in scenarios using fitted logistic function parameters. *Left panel* **a** shows core region data historically and for MESSAGE-IAMF scenarios. *Right panel* **b** shows global data historically and for MESSAGE-IAMF and REMIND-AME scenarios

The surprising implication of Fig. 3a is that capacity growth in the scenarios appears generally more conservative than is evidenced in the historical record. By conservative, we mean requiring a longer duration of growth (Δt) to reach a given extent of growth (normalized K). With the exception of some of the low growth CCS data points, all the scenario data points lie below and to the right of the historical pattern.

This general finding of apparent scenario conservatism is weaker if the historical comparator for the scenarios is limited to power generation technologies only (coal, natural gas, nuclear). Their extent – duration relationship is less steep than for all historical technologies although this trend should be treated with some caution due to the small number of data points.

As with the historical data, the patterns observed for the core region in Figs. 2 and 3a (left panel) hold whether the data are global or disaggregated regionally (see Online resource 1 for figures).

The main difference between the observed historical record and future scenarios is the longer durations of growth for low carbon technologies in the scenarios. In the case of nuclear power globally, for example, Δts in the scenarios are all longer than 85 years, compared to the historical Δt of 19 years. Although cumulative total capacity in the scenarios is projected to grow by two orders of magnitude (from ~0.4 TW in 2000 to 11-25 TW in 2100), once this huge increase in extent is normalized for growth in the overall energy system, the duration or timescale over which it takes place is much longer than historical growth dynamics suggest is possible. To bring the scenario data points for nuclear power in line with the historical extent – duration relationship, either the extent of growth (normalized K) would have to increase by another 3 orders of magnitude, or the duration of growth (Δt) would have to halve.

The extent – duration relationship in the scenarios for CCS is closer to the historical trend. In particular, CCS has a shorter duration of growth for a given extent of growth (i.e., a lower Δt for a given normalized K). Globally, coal CCS has Δts in the range of 7–41 years, and all fossil CCS has Δts in the range of 27–76 years. This is similar to the historical range of Δts across all technologies of 19–64 years (with nuclear power and cars as the minimum and maximum respectively). The relatively compressed duration of CCS deployment in the scenarios results from its particular technology characteristics. Under less stringent carbon constraints (e.g., 670 ppmv CO_2-eq.), its high cost and commercial immaturity relative to other low carbon electricity generation technologies means it is deployed only later on in the 21st century. Under more stringent carbon constraints (e.g., 480 ppmv CO_2-eq.), its compatibility with the dominant fossil-based power system infrastructure means it is deployed early on but is then phased out as residual emissions from the overall supply chain (mining, transport, combustion, capture, storage) make it less attractive. In both cases, CCS capacity growth is limited to a ~50 year period.

6 Discussion

6.1 Apparent conservatism in future extent - duration relationships

Projected capacity growth of energy technologies in future scenarios appears conservative relative to what has been evidenced historically. We caveat this finding by noting that the historical data points are sparse, and that like-for-like comparisons of electricity generation technologies only are more closely aligned between historical and scenario data.

Why do the scenarios appear conservative? We suggest three explanations. First, the apparent conservatism is without substance: either historical and future capacity growth, or different energy technologies, are inherently incomparable. Second, the apparent conservatism is a statistical artifact of using different lengths of time series data. Third, the apparent conservatism is generated by parametric or structural conservatism in energy system models used to generate future technology trajectories. We discuss each explanation in turn (with further material in Online resource 2).

6.1.1 Past - future comparability

Historically, growth in energy conversion capacity has been driven by energy service demands met by technologies with ever-improving market performance and ever-falling relative costs (Fouquet 2010). In future scenarios, technologies' environmental characteristics play a driving role in a selection environment increasingly dominated by regulation and policy inducements (Acemoglu et al. 2009). If novel and cheaper energy services characterized the past, then carbon pricing characterizes a low carbon future.

But the question here is not one of consistency between past and future, but between past and *model representation of the future*, and by extension, whether models like MESSAGE account for the future drivers of growth - policies, resource constraints, cost improvements, or otherwise. As noted in the introduction, models have substantially improved the extent to which technological change is endogenised (Clarke et al. 2008), although this remains an active frontier of model development and research in which gaps still remain (Barreto and Kemp 2008; Pizer and Popp 2008). Exogenous parameterization of different technologies' cost, performance, availability, and other characteristics is founded on historical evidence, although the challenge of building and maintaining data sets of technology-specific and potentially context-specific observations is formidable. Yet neither of these caveats suggests an obvious discontinuity between the past and model representations of the future that can explain the apparent scenario conservatism.

6.1.2 Cross-technology comparability

An additional question concerns the use of historical data on a wide range of *energy technologies* (both energy supply and end-use) as a comparator for scenario data on *electricity generation technologies*. Figure 3a shows that the scenario data (grey trend line) align more closely with the historical data if these are limited to electricity generation technologies (dotted black trend line).

But with the exception of nuclear and all fossil CCS, future portfolios of electricity generation technologies are weighted towards decentralized renewable energy technologies, particularly solar PV and thermal systems. These have technological and manufacturing characteristics more similar to the end-use technologies included in the historical data.

Indeed distributed generation technologies and end-use technologies might be expected to have a steeper extent – duration relationship as they tend to have shorter lifetimes, faster turnover rates, lower conversion efficiencies, standardized production, and manufacturing scale economies which - *ceteris paribus* - all imply more rapid growth in installed capacities on a cumulative basis. Yet this does not appear to be the case.

6.1.3 Time series artifact

Do the centennial logistic functions in the scenario analysis inherently mean longer durations of growth (and so higher Δts) than the decadal logistic functions in the historical analysis? There is no obvious reason why moving from decadal to centennial time frames for fitting logistic functions should affect the K and Δt parameters disproportionately (see Online resource 2 for discussion). As shown in Fig. 3a, scenario data points show substantially longer durations of growth for similar extents of growth as those evidenced historically (once changes in the size of the energy system are controlled for). It is the scenarios' extent – duration relationship which is conservative, not the duration in isolation.

6.1.4 Parametric conservatism in models

Optimization models such as MESSAGE operating under conditions of perfect foresight (as for the MESSAGE-IAMF scenarios) require potential rates of technology deployment to be constrained. In the absence of any limiting factors, small changes in the exogenously-specified characteristics of a technology can result in dramatic changes in its selection by the model for capital stock replacements and additions (Grubler and Messner 1996). MESSAGE prevents such unrealistic outcomes by imposing market penetration constraints (maximum of x% growth in installed capacity of a technology over time period t). These are estimated based on observed historical trends, although as noted in the introduction, the challenge of using historical data to generalize growth constraints for potentially hundreds of technologies across very different adoption environments is significant. These exogenous growth constraints may be overly restrictive over the centennial time frames of the scenario analyses giving rise to a *parametric conservatism* (see Online resource 2 for further discussion).

6.1.5 Structural conservatism in models

The use of growth constraints under conditions of perfect foresight also means low carbon technologies may be selected early to maximize their contribution to emission reduction targets, particularly if these are stringent. This was illustrated in Fig. 2 and discussed in the case of CCS in the 480 ppmv MESSAGE-IAMF scenarios. This may in turn imply a *structural conservatism* with respect to rapid capacity expansions. In other words models may prefer gradual centennial growth within a portfolio of concurrent technologies, rather than punctuated decadal growth for successive technologies.

This preference for portfolio diversity may be further reinforced in the present analysis as the scenario data describe electricity generation technologies which are more or less ready substitutes both for the incumbent fossil generators, and for each other. Substitute technologies generally diffuse more rapidly (Grubler et al. 1999), but across the electricity generation sector as a whole, the availability of more substitutes may also mean discrete technologies diffuse concurrently rather than successively.

Applying the Shannon index as a measure of diversity to the global electricity generation mix (Kruyt et al. 2009), we estimate that a gradual rise in technological diversity over the 20th century is mirrored in a gradual decline in diversity over the 21st century in the MESSAGE-IAMF scenarios, although this varies depending on scenario assumptions (see Online resource 2 for details). As a first order indication, however, this suggests that models' preference for a diverse portfolio of substitute technologies does not explain the apparent conservatism observed in the extent - duration plots.

6.1.6 Inter-model comparisons to test for conservatism

One way of testing for potential parametric and structural conservatism is by comparing MESSAGE-IAMF output to that of other integrated assessment models with different set ups. We replicated the analysis using data from the REMIND integrated assessment model (Leimbach et al. 2010). Like MESSAGE, REMIND has been widely used by the IPCC and in other inter-model comparison studies (e.g., Edenhofer et al. 2010). REMIND is also a perfect foresight model but treats the inertia of capacity expansion differently through its use of flexible 'adjustment costs' in lieu of fixed market penetration constraints (see (Pizer and Popp 2008) for other examples).

We extracted cumulative total capacity data for 11 electricity generation technologies in both baseline and 450 ppmv CO_2-eq. stabilization scenarios. These scenarios were developed as part of the Asian Modeling Exercise, an international inter-model comparison study, and are labeled hereafter: REMIND-AME (Luderer et al. 2012). As shown in Fig. 3b for the global data, the findings are broadly consistent with those described using MESSAGE-IAMF. The main exception is that the solar PV data points from REMIND-AME are in line with the historical extent – duration relationship, but at much higher extents and durations than the CCS data points from MESSAGE-IAMF. The same basic pattern was found for the regional analyses. In general, the REMIND-AME comparison suggests that possible parametric or structural conservatism may not be specific to the MESSAGE model.

7 Conclusions

The methodology set out in this paper allows projected capacity expansions of low carbon energy technologies to be compared against historically-evidenced diffusion. This provides a first-order verification of model output against the observed historical record.

There are two key findings. First, the extent – duration relationship for the capacity expansion of eight different energy technologies historically is consistent. Second, the analogous extent – duration relationship for a range of low carbon electricity generation technologies in a range of future scenarios is also consistent, but more conservatively so. The scenarios depict longer durations of capacity growth to reach a given extent of growth compared to the historical pattern. These findings are interesting precisely because they are largely robust across different technologies in different regions at different times.

There is no single clear explanation for this apparent scenario conservatism. Either the centennial timescales of future scenarios or the use of historical energy technologies to construct a comparator for future electricity generation technologies may mean this finding is a methodological artifact. Another explanation is that energy system models may be either parametrically conservative (in terms of growth constraints or other exogenous technology parameters) and/or structurally conservative (in terms of the endogenous drivers of, and constraints on, rapid capacity expansion).

We note three important caveats. First, potential explanatory variables for both observed and modeled growth dynamics, including the relative costs, efficiencies, and turnover rates of different energy technologies, are not addressed explicitly. The cross-technology analysis means that the observed consistency of the historical and scenario extent – duration relationships is inherently general. Second, more historical data points covering a wider range of technologies are needed to provide a reliable trend against which scenarios can be compared. Similarly the scenario data could be extended to include end-use technologies from models with more detailed resolutions of end-use sectors (e.g., Kitous et al. 2010). Third, the methodology's reliance on logistic functions is a strength in that it provides a common growth form with both extent and duration parameters which allows cross-technology comparisons. But its weakness is the exclusion of technologies early in their lifecycle and/or still growing exponentially. This means the findings are more robust in initial or core markets compared to later or periphery markets.

In conclusion, our main contribution has been to propose, develop and apply a method for using historical technology growth dynamics as a basis for assessing model-generated future trajectories. This complements the use of inter-model comparison studies and other verification and review processes to substantiate model output.

Acknowledgements Peter Kolp at the International Institute for Applied Systems Analysis (IIASA) provided invaluable technical support. Earlier drafts were much improved by insightful comments from Alex Bowen at the LSE, and from participants at the ETIP Seminar at Harvard University (April 2009) and the International Energy Workshop in Stockholm (June 2010).

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