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Growth Dynamics of Energy Technologies: Using Historical Patterns to Validate Low Carbon Scenarios

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Abstract.

Historical growth dynamics of energy technologies reveal a consistent relationship between the extent to which a technology's installed capacity grows and the time duration of that growth. This extent – duration relationship is remarkably consistent across both supply-side and demand-side technologies, and both old and new energy technologies. Consequently, it can be used as a means of validating future scenarios of energy technology growth under carbon constraints. This validation methodology is tested on the extents and durations of growth for a range of low carbon technologies in scenarios generated by the MESSAGE energy system model which has been widely used by the IPCC. The key finding is that low carbon technology growth in the scenarios appears generally *conservative* relative to what has been evidenced historically. This is counter-intuitive given the extremely rapid growth rates of certain low carbon technologies under tight carbon constraints. Reasons for the apparent scenario conservatism are explored. Parametric conservatism in the underlying energy system model seems the most likely explanation.

Acknowledgements.

This work was made possible by the help and advice of colleagues at the International Institute for Applied Systems Analysis (IIASA): Arnulf Grübler in particular; also Peter Kolp, Volker Krey and Keywan Riahi. Detailed review comments from Alex Bowen at the LSE improved this final version; and insightful questions and comments by participants at the ETIP Seminar at Harvard University (April 2009) and the International Energy Workshop in Stockholm (June 2010) also improved earlier drafts. Part of this work was completed while the author was based at the Grantham Research Institute on Climate Change and the Environment and the Centre for Climate Change Economics and Policy at London School of Economics and Political Science.

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1 Introduction

1.1 The discontinuous road to a low carbon future

Scenarios of greenhouse gas constrained futures 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 certain energy technologies. Some scenarios emphasize decarbonising supply-side 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 supply-side and end use technologies, particularly under more stringent greenhouse gas constraints. 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 … Energy efficiency plays a key role across many scenarios for most regions and timescales … For lower stabilization levels, scenarios put more emphasis on the use of low-carbon energy sources ... *In these scenarios 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 italicised 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. This is simply captured by the use of energy and carbon intensities as indicators of change in the demand- and supply-side of the energy system respectively. Energy intensity measures energy use per unit of economic output, and is typically expressed as GJ per $ of GDP. Carbon intensity measures greenhouse gas emissions per unit of energy use, and is typically expressed as tCO_2 or tCO_2-equivalent per GJ.

Historical trends of both carbon and energy intensities have been well documented and explored both nationally and globally (e.g., Grübler 1998; Smil 2000). As a global average, energy intensity has declined at around 1.2% per year over the last few decades; these 'improvements' have been more rapid in industrialised countries (1.7% per year) than in developing countries (1.0% per year). Across a wide range of future scenarios, reducing energy intensity by improving the efficiency of end use technologies provides cheaper and nearer-term alternatives to decarbonising the energy supply (Riahi et al. 2007; Ürge-Vorsatz & Metz 2009). Declining carbon intensity has more consistently characterised the 20th century, but the more stringent the future carbon constraints, the stronger the relative contribution to energy system transformation of accelerated decarbonisation (van Vuuren et al. 2009).

1.2 Validating the technology projections of energy system models

Long range models provide the quantitative basis for the discontinuities in energy and carbon intensity represented in carbon constrained scenarios. These models vary in their level of technological specificity. 'Top-down' macro-economic or econometric models tend to emphasize aggregated metrics and relationships between price, income and energy demand (Azar & Dowlatabadi 1999). In contrast, 'bottom-up' models that simulate or optimise the energy system within specified constraints tend to be rich in technological detail, particularly on the supply-side (van Vuuren et al. 2009). Examples of these latter energy system models include the International Energy Agency's World Energy Model used in the annual World Energy Outlook reports IEA (IEA 2009) and the MESSAGE model developed at IIASA (Messner & Strubegger 1995). (For discussion of different modelling approaches, see, e.g., Nakicenovic et al. 2000; Rivers & Jaccard 2005; van Vuuren et al. 2009).

For the analysis presented in this paper, we used MESSAGE, a bottom-up systems engineering models based on a least cost optimization framework (Messner & Strubegger 1995). The MESSAGE model maps the global energy system from resource extraction, imports and exports, conversion, transport and distribution to end-use services over a centennial timescale. MESSAGE scenarios under carbon constraints have been widely used in the work of the IPCC, including both the Fourth Assessment Report and the earlier Special Report on Emissions Scenarios (Nakicenovic et al. 2000; Fisher et al. 2007). The term 'carbon constraints' is used broadly in this paper, meaning any greenhouse gas-related component of the model's objective function, e.g., mean global temperature stabilisation targets, greenhouse gas concentration targets, emission profiles, and so on. MESSAGE scenarios under carbon, energy security and energy access constraints have also been used in the forthcoming Global Energy Assessment[1].

An essential feature of MESSAGE and other models is that although the objective function or set of constraints under which they are run may be normative (e.g., climate stabilisation at 2^{o}C above pre-industrial), the model results are quantitatively descriptive. *Given the model parameters and structure*, they are also internally consistent and so valid.

Model parameters and structure are empirically-founded and the subject of extensive consideration and review by the parent modelling groups.[2] With regards technology deployment projections, key parameters include costs, efficiencies, performance characteristics, learning rates and resource availabilities. Important structural characteristics of models which influence technology deployment include the treatment of technological diversity, inter-

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[1] For details, see www.iiasa.ac.at/Research/ENE/GEA/index.html

[2] One result is that the models are continually evolving, spawning new variants and updated versions. Using MESSAGE as an example, the original MESSAGE framework has seen iterations to model stochastic learning and returns to adoption (Gritsevskyi & Nakicenovic 2000), technological 'relatedness' and spillovers (Rao et al. 2006), integration with other sectoral models and macro-economic feedbacks (Riahi et al. 2007), and an exploratory agent-based formulation (Ma et al. 2008).

dependence and spillovers, related infrastructures, innovation and learning, energy service demands, macro-economic feedbacks, and so on. Internal validation of model parameters and structure by the parent modelling groups is further supported by comparisons between different model outputs. The US-based Energy Modelling Forum has institutionalised this process (e.g., Clarke et al. 2008) and similar exercises have taken place elsewhere (e.g., van Vuuren et al. 2009), often in the context of assessment processes including the IPCC.

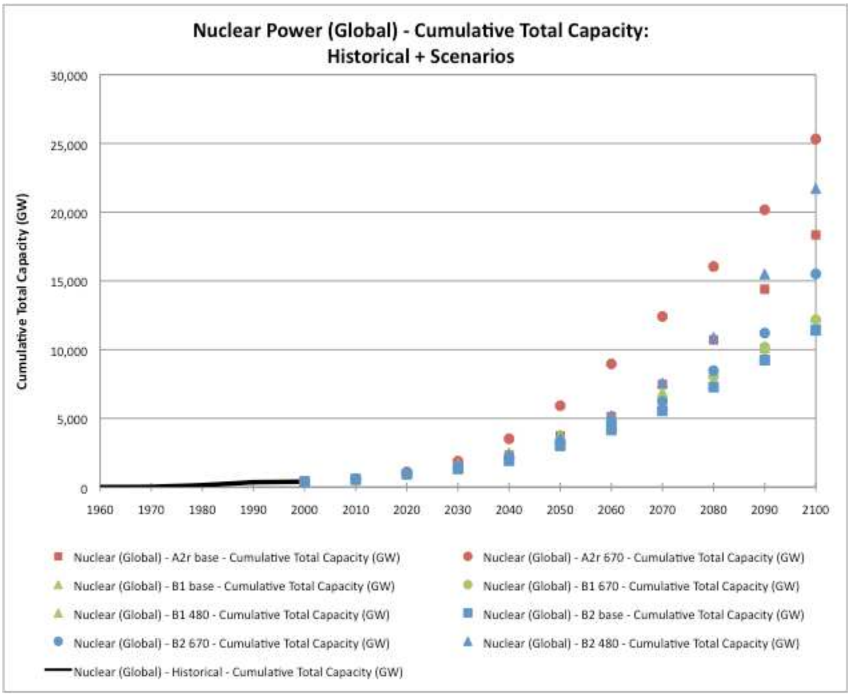
Here, however, the concern with validation is a different one, asking not whether model projections make sense in relation to the model set up or to other model projections, but whether they make sense in relation to what we have observed in the dynamics of energy technology deployment over long timescales historically. Can model projections of technology deployment be assessed independently of the particular model set up? We describe this as an external validation problem.

Focusing the question of external validity on observed decadal and even centennial growth dynamics emphasises two related dimensions of the model projections. The first is *temporal*: according to the models, how rapidly do energy technologies diffuse and for how long is diffusion sustained? This also concerns the form of growth, its pattern over time. The second issue is *spatial or systemic*: according to the models, how much do energy technologies diffuse and what share of the energy system do they come to occupy?

Figure 1 shows the historical growth of nuclear power continuing on into a range of scenario projections from a recent application of the MESSAGE model (Riahi et al. 2007). The similarities and differences in scenario projections are clearly evident. Variable futures are a function of different scenario assumptions and carbon constraints. But *all* scenarios show a substantive expansion of nuclear power compared to historical experience.

The approach taken here to externally validate the projections shown in Figure 1 is to ask: are the growth dynamics of these future scenarios *consistent* with historical experience? Or, more specifically, are the rates, durations and extents of growth consistent with historical experience? These different characteristics of the overall growth dynamic can not be assessed in isolation. Clearly the extent or total installed capacity of nuclear power in the scenarios is not consistent with historical experience. But this same extent as an outcome of long, sustained and gradual growth may embody growth rates that are indeed consistent with what we know to be possible in an expanding energy system.

FIGURE 1. NUCLEAR POWER: HISTORICAL DATA & FUTURE PROJECTIONS.



2 Method & Rationale

2.1 Overview

In this paper, we propose and test a method for externally validating the projections of energy technology capacity growth in long range energy system models under carbon constraints. Our method has two stages. Firstly, we use logistic growth functions to describe the historical diffusion dynamics of a range of different energy technologies. Logistic functions parameterise both the rate and extent of growth as well as how they change over time. Use of a common form of growth - the logistic function - and a common unit of growth - cumulative total capacity - enables comparisons between technologies and time periods. Secondly, we fit the same functional forms to the diffusion dynamics of energy technologies in future scenarios. This method allows us to test the hypothesis that future growth is consistent with historical experience. Specifically, the null hypothesis is that future representations of energy technology diffusion have the same relationship between the duration and extent of growth as that observed historically.

All technologies selected for analysis, both historical and future, are major components of the energy system. Apart from this similarity of context, we do not control for the myriad factors that drive the growth dynamics of energy technologies. Such factors include cost, efficiency and demand. Rather, these factors are all treated as potential explanatory variables for differences in observed growth dynamics. The method is more akin to a meta-analysis of commonalities in the duration and extents of growth across a range of energy technologies in both the past and future.

An important implication to note at the outset is that the validation method and findings presented below are likely to be primarily of interest to the modelling community. The lack of explicit treatment of the drivers of technology diffusion preclude any insights into the economics of technological change or the role played by policy and regulation. A companion paper which explores historical growth dynamics in more depth may be of more interest to economists and policymakers (Wilson forthcoming).

2.2 Temporal patterns in technology growth

Technology's temporal growth dynamics are succinctly captured as a lifecycle which follows sequential stages of invention, innovation, and diffusion (after, e.g., Schumpeter 1947; Utterback & Abernathy 1975). 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 dynamic is supported by a wealth of historical evidence (Grübler 1990; Grübler 1996; Grübler 1998) and has also been widely observed in the specific case of energy technologies (Grübler et al. 1999). The senescence of a technology sees this growth dynamic mirrored in an S-shaped decline, as increasingly dominant competitors substitute for the incumbent technology (Marchetti & Nakicenovic 1979; Marchetti 1987).

This dynamic of changing growth rates over time is captured in the three parameter logistic function shown in Figure 2, and represented graphically in Figure 3 as a close fit to the observed historical growth in the global cumulative total capacity of nuclear power plants. Figure 2 also highlights the usefulness of the logistic function's parameters in this context. The asymptote parameter, K, represents the saturation level of a technology and can be used as a proxy for the *extent* of growth. The rate parameter, b, describes the steepness of the curve and relates logarithmically to the *duration* of growth expressed as Δt (delta t). Δt represents the time period over which the technology diffuses from 10% to 90% of its final saturation level. This is the part of the curve described clearly by growth: from the initial 'tipping point' at which rapid growth begins, to its inverse slowing point after which growth starts to asymptote.

The logistic function is symmetrical about t_0, the inflection point at which the growth rate is maximal. (The symmetry of the 3-parameter logistic function also means that Δt is equal to the period of diffusion from 1% to 50%, and from 50% to 99%, of the final saturation level). Various alternative S-shaped functions have been proposed, most of which relax the symmetry of the logistic function around the inflection point. Examples include the Gompertz, Sharif-Kabir and Floyd functions. Despite its simplicity, however, the logistic function has been consistently found to be the most representative form of observed dymamics (Grübler 1990).

There are many explanations as to why technology diffusion patterns are logistic, based on information transmission and contagion models, on risk reduction and familiarity, on the changing profile of profitability and compatibility with social norms (for further discussion, see Grübler 1998; Rogers 2003). However, the reasons for logistic growth are not immediately relevant here as the functional form is used only for descriptive and comparative purposes. Of specific interest for the meta-analysis are two parameters of the logistic function fitted to historical and future time series of energy technology deployment:

- K as a measure of the *extent* of growth; and
- Δt as a measure of the *duration* of growth (which is inversely related to the *rate* of growth).

FIGURE 2. THE THREE PARAMETER LOGISTIC FUNCTION.

$$y = \frac{K}{1 + e^{-b(t - t_0)}} \quad \text{(and also : } \Delta t = \frac{1}{b}\log 81\text{)}$$

with :

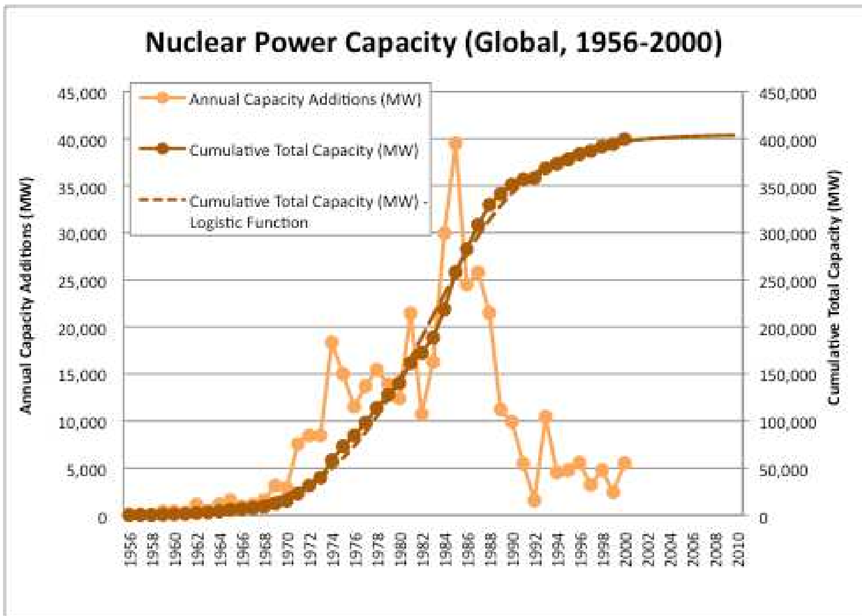
K = asymptote (saturation level);

t_0 = inflection point at K/2 (maximum growth);

b = diffusion rate (steepness);

Δt (delta t) = time period over which y grows from 10% to 90% of K.

FIGURE 3. HISTORICAL GROWTH OF NUCLEAR POWER WITH FITTED LOGISTIC FUNCTION TO CUMULATIVE TOTAL CAPACITY DATA.



2.3 Spatial patterns in technology growth

The logistic function captures changes in a technology's growth dynamic over time. As noted earlier, these growth dynamics also vary spatially. In the initial markets or regions where a technology is first commercialized and diffusion begins, growth tends to be slower but more pervasive (Grübler 1996). In subsequent markets, growth tends to be more rapid but saturates at a lesser extent. Cars provide a good example of this general pattern. Diffusion rates increase and saturation densities (cars per capita) decrease as a log linear function of the introduction date or first commercial sale of the car in different countries (p151, Grübler 1990). Commercialization began in the US in the late 19^{th} century and took over 100 years to move from 10% to 90% of its estimated saturation density (in terms of car ownership per capita). In Japan, widespread commercialization took off in the 1950s and took less than 20 years to achieve the same growth from 10% to 90% of estimated saturation. But the corresponding saturation densities in Japan are also markedly lower: car ownership per capita in the 1990s was similar to that of the US in the 1930s.

Aggregated global technology deployment data miss these spatial differences: growth of a longer duration (slower rate) but to a higher saturation level in initial markets; and growth of a shorter duration (quicker rate) but to a lower saturation level in subsequent markets. In this meta-analysis, therefore, logistic growth functions are fitted to historical and future data disaggregated into three spatial categories: core, rim and periphery markets. These are distinguished by the sequence of widespread diffusion or mass commercialization between countries or regions.

Core, rim and periphery markets vary by technology. The US first saw the mass commercialization of the car; but Denmark was the core market for wind power, and the OECD as a whole saw the take-off of coal power. A similar logic applies to rim and periphery markets. Historically, the former Soviet Union countries were often either concurrent core markets (e.g., nuclear power), or rim markets (e.g., natural gas power). For more recent technologies, the south Asian economies have been rim markets (e.g., the compact fluorescent light bulb). Generally, African and Latin American countries are periphery markets, though not always. Table 1 shows the spatial disaggregation for each technology's historical data series in the meta-analysis.

2.4 Selecting Metrics & Technologies for the Meta-Analysis

Within the constraints of data availability, we selected technologies for the meta-analysis using three criteria. Firstly, we wanted to cover the full range of energy technologies to capture the heterogeneity within the energy system and ensure any results could be generalized. This included both centralised, capital intensive energy supply technologies and distributed, low cost end use technologies. Secondly, we defined a 'technology' as the highest level of complexity and operational aggregation of component parts before the inclusion of distribution infrastructure and market factors: hence, the coal-fired power plant rather than the steam turbine unit (less complex) or the electricity system (more complex);

and the light bulb rather than the filament (less complex) or lighting system (more complex). Thirdly, we required that the energy capacity of each technology was meaningfully related to the provision of a useful service. This meant that end use technologies such as mobile phones or personal computers were excluded as energy metrics do not directly relate to the service provided.

Table 1 summarises the historical time series data compiled and analysed. To the extent possible, data were collected from, or close to, the year of first commercial introduction. Supply-side technologies included were: oil refineries, coal power, natural gas power, nuclear power, wind power, solar photovoltaics. End use technologies included were: passenger jet aircraft, passenger cars, compact fluorescent light bulbs. For full details of the data collection including sources and links to online database, see: (Wilson 2009).

TABLE 1. HISTORICAL ENERGY TECHNOLOGIES INCLUDED IN THE META-ANALYSIS: TIME SERIES, SPATIAL DISAGGREGATION, & LOGISTIC FITS. (SEE TABLE NOTES FOR DATA SOURCES).

Technology			**Spatial Disaggregation**			***Logistic Fits***
		Global	**Core**	**Rim**	**Periphery**	
Data Points (#)		6	8	6	3	
Supply-Side Technologies	Oil Refineries 1940-2000	Global	OECD[i], FSU[i]	Asia (ex. China) MidEast[i], L.America[i]	China, Africa	*Logistic fits to '1st phase' only with asymptote in late 1970s*
	Power – Coal 1908-2000	Global	OECD	(1) FSU *(2) Asia*[ii-a]	Africa, MidEast, L.America	*No logistic fits to exponential growth in rim markets (Asia)*
	Power - Nuclear 1956-2000	Global	OECD	(1) FSU *(2) Asia*[ii-b]	*Africa, MidEast, L.America*[ii-b]	*Insufficient capacity (small n) for logistic fits in rim and periphery markets*
	Power - Natural Gas 1903-2000	Global	OECD	(1) FSU (2) Asia	Africa, MidEast, L. America	*Logistic fits to '1st phase' only with asymptote in late 1970s*
	Power – Wind 1977-2008	*Global*[ii-a]	Denmark	*(1) rest of OECD (2) E. Europe, Asia*	*Africa, MidEast, L.America*	*No logistic fits in all but core market (Denmark, onshore)*
	Power – Solar PV 1975-2007	*Global*[ii-a]	*US*[ii-a]	*(1) Japan, Germany*[ii-a] *(2) rest of OECD*[ii-a]	*Non-OECD*[ii-a]	*No logistic fits: still exponential growth in all regions*
End Use Technologies	Passenger Jet Aircraft 1958-2007	Boeing + Airbus	Boeing	Airbus	*n/a*	*N.B. Regions based on manufacturers not sales; no (reliable) data for FSU*
	Passenger Cars 1900-2005	Global	US	(1) W. Europe, Canada, Japan (2) FSU, minor OECD	*Non-OECD*[ii-a]	*No logistic fits to exponential growth in developing countries*
	Compact Fluorescent Light Bulbs 1990-2003	*Global*[ii-a]	N. America, W. Europe	*Asia*[ii-a]	*Rest of World*[ii-a]	*No logistic fits in all but core market (Western OECD)*

[i] OECD = Organisation of Economic Cooperation and Development corresponding to developed countries; FSU = former Soviet Union corresponding to economies in transition, i.e., including Eastern Europe; L. America = Latin America; MidEast = Middle East.
[ii] Logistic function could not be fitted to data series for following reasons: [ii-a] insufficient time series to fit logistic function with reliable asymptote estimate as growth still in exponential phase; [ii-b] insufficient capacity so time series data overly volatile for logistic fit.
Data sources: *Refineries* - (OGJ 1999; OGJ 2000; Enos 2002; BP 2008); *Coal, nuclear, natural gas power* - (Platts 2005); *Wind power* - (BTM_Consult 2002; Danish_Energy_Agency 2008); *Solar*

photovoltaics – (Maycock 2002); *Passenger jet aircraft* - (Jane's 1998) with supplementary data from online sources including www.airliners.net, www.flightglobal.com, www.boeing.com, www.airbus.com; *Passenger Cars* - (AAMA 1980; AAMA 1995; AAMA 1997) with supplementary data from online sources including US National Highways Traffic Safety Agency (www.nhtsa.dot.gov) and European Automobile Manufacturers' Association (www.acea.be); *Compact fluorescent light bulbs* – (IEA 2006). For further details on data sources, see: (Wilson 2009).

Comparing the growth of different energy technologies requires a common metric representing size or extent. We used cumulative total capacity expressed in MW. For the technologies analyzed, capacity data were either directly available or readily derivable. The capacity of power generation and electric end use technologies are naturally expressed in MW; refinery capacity in barrels per day is simply converted as is vehicle engine capacity in horsepower; and so on.

Alternative metrics of size include output / production, investment cost, or metrics of 'effort' including labour requirements, R&D, material inputs, and so on. We selected capacity as it best captured the *potential* contribution of a technology to growth and transformation in the energy system. Using capacity data rather than input or production data also preserves the highest degree of generality. Thus, differences between technologies in terms of efficiency (affecting production) or capital intensiveness and labour productivity (affecting inputs) can be treated as potential explanatory variables for any differences observed.

Cumulative total capacity was preferred to capacity additions for two reasons. (Both are shown for nuclear power in Figure 3). Firstly, cumulative totals contain the whole history of capacity growth. This is appropriate for a comparison of long-term growth dynamics between past and future. Secondly, cumulative totals smooth short-term growth volatility and so lend themselves more readily to fitting a common functional form.

An important consequence is that the cumulative total capacity data used do *not* take into account capital turnover (decommissioning, retirement, substitution, etc.). So differences between technologies in terms of capital stock lifetime and turnover rates are also internalised within the meta-analysis, offering further potential explanations for any differences observed.

Finally, it should be noted that cumulative capacity or production data are not commonly used in logistic function analyses of technology growth dynamics. More common are units of growth which capture annual changes relative to the size of the market, population, economy, etc., as in the car ownership per capita example given in Section 2.3; see also (Marchetti & Nakicenovic 1979; Grübler 1998). In these cases, saturation describes a constant market share or a constant ratio between output growth and 'system' growth. In contrast here, the use of cumulative capacity as the unit of growth means that saturation describes *zero* growth, a complete cessation of capacity additions.

2.5 Fitting the Logistic Functions

For each technology in each of the four spatial regions (global, core, rim, periphery), we tested the fit of logistic growth functions on the historical data series of cumulative total capacity, expressed in MW. We used the "Logistic Substitution Model II" (LSM2) software, developed at the International Institute for Applied Systems Analysis and freely available online.

We used two criteria to define acceptable fits of the logistic functions:

i. goodness of fit measure (adjusted R^2) > 95%;
ii. historical data reaching > 60% of estimated asymptote (K).

The strict goodness of fit criterion ensured that the fitted logistic functions accurately described the historical data. The second criterion required that a technology's *actual* cumulative total capacity had to have passed its maximum growth rate (or inflection point, t_0) and reached at least 60% of its estimated saturation level. This ensured reliable estimates of the asymptote parameter, K.

If historical data extends only through the initial commercialisation and takeoff phases, it is difficult to estimate reliably if and when growth will pass an inflection point and slow, and in particular, the level at which it may finally saturate (Debecker & Modis 1994). For historical data series that not have reached 50% of the estimated asymptote parameter, K, it is not possible to distinguish logistic from exponential growth. Hence the second criterion prevents a high goodness of fit measure (the first criterion) for a falsely precise logistic function. For more details of logistic model estimation and uncertainties, see: (Grübler 1990; Debecker & Modis 1994).

An important consequence of the second criterion is that technologies still experiencing exponential growth in one or more regions had to be excluded from the meta-analysis. These are shown in Table 1 in grey, with corresponding explanatory notes in the final column. Examples include: wind power (all regions except core); solar PV (all regions); compact fluorescent light bulbs (all regions except core).

In general, we fitted logistic functions to the full historical data period available, from first commercial introduction to the present. However, for technologies with distinct, sequential phases of growth, we fitted logistic functions to the '1st phase' of growth if – and only if - it evidenced a clear plateau (or 1st phase asymptote). This was the case for refineries and natural gas power following the 1970s oil shocks. In the case of natural gas power, capacity growth reached a plateau during the late 1970s, most notably in the US where regulations prohibited the use of natural gas for electricity generation given its perceived scarcity against a backdrop of falling demand (Lee & Loftness 1987). In the case of refining in the major OECD & former Soviet Union markets (core region), total industry capacity peaked in 1979 before falling through the 1980s as demand for refinery output fell, utilisation rates of existing regional capacity rose, and capacity expansions in Asia and elsewhere gained market share with a concomitant rise in the international trade of oil products.

So for both natural gas power and refineries, logistic functions were fitted to capacity data in the core markets up to the '1st phase' asymptote of the early 1980s. The same data period was then applied to the rim and periphery markets. The validity of these '1st phase' logistic functions is not affected by the subsequent decline of refinery capacity in contrast to the stabilization and then resurgence of natural gas power.

The same point about '1st phase' growth applies equally to the logistic function shown in Figure 3 to describe the growth dynamic of nuclear power globally from 1956-2000. The fitted logistic function explains over 99% of the variance in the actual cumulative total capacity data (fit criterion 1), and is based on a time series reaching 98% of the estimated asymptote parameter, K (fit criterion 2). The use of this fitted logistic function in the meta-analysis is purely descriptively; it in no way precludes a potential 2nd phase of future growth spurred by greenhouse gas emission constraints or otherwise.

In sum, any period of historical growth described accurately and reliably by a logistic function is included in the meta-analysis. These periods may capture a technology's historical growth dynamic culminating in the present (e.g., nuclear power globally), culminating in the past (e.g., refineries in the OECD and former Soviet Union countries), or showing a distinctive logistic phase nested within a longer dynamic (e.g., natural gas power in the OECD). There is no *a priori* constraint that such periods have to span the time from the first introduction of a technology to its final saturation.

2.6 Controlling for Growth in the Energy System

As the energy system and final demand grows, so too will the total installed capacity of a technology needed to provide a given share of a particular energy service (notwithstanding dramatic offsetting gains in efficiency). Consequently, the *extent* of growth of a technology, measured by the logistic function's asymptote parameter, K, will be positively influenced by the overall size of the system into which the technology diffuses. Comparing the extent of growth between technologies therefore needs to control for these differences in system size.

These differences arise because the commercial energy supply has grown 16-fold over the course of the 20th century (Smil 2000). The historical data used in the meta-analysis include some long established technologies which were first commercialised early in the 20th century (e.g., coal power, cars), and other more recent technologies which began mass diffusion more recently (e.g., wind power, compact fluorescent light bulbs).

To take changes in system size into account, we 'normalise' extents of growth (K) by dividing by the primary energy consumption (in EJ) at the inflection point (t_0) of the fitted logistic function (see Figure 2). As the logistic function is symmetrical about t_0, it provides a common time point for cross-technology comparisons. The resulting normalised extents of growth (K in MW / primary energy in EJ at t_0) are not meaningful in absolute terms, but are useful for comparative purposes between technologies, i.e., should be treated as an index.

Although the normalisation process is important for conceptual consistency, in practice it does not substantively change the relative extents of growth between technologies. This is because the extents of growth vary by 2-3 orders of magnitude (e.g., cars with $K \sim 10^8$ MW vs. nuclear power with $K \sim 10^5$ MW), whereas primary energy consumption at different t_0 values varies by less than 1 order of magnitude.

Other differences in system size arise due to the spatial disaggregation into core, rim and periphery regions; moreover, these may vary between technologies. To match the normalisation process to this spatial disaggregation, primary energy consumption data were similarly disaggregated into 4 regions: OECD, former Soviet Union countries & Asia, and the rest of the world (primarily Africa and Latin America). These 'primary energy regions' were used to normalise the core, rim, and periphery regions respectively.

2.7 Scenario data

This methods section has focused thus far on the historical data. The same process of selecting technologies, collecting time series data, fitting logistic functions based on accuracy and reliability criteria, and normalising extents of growth for differences in system size, were also applied to technology projections in future scenarios under carbon constraints.

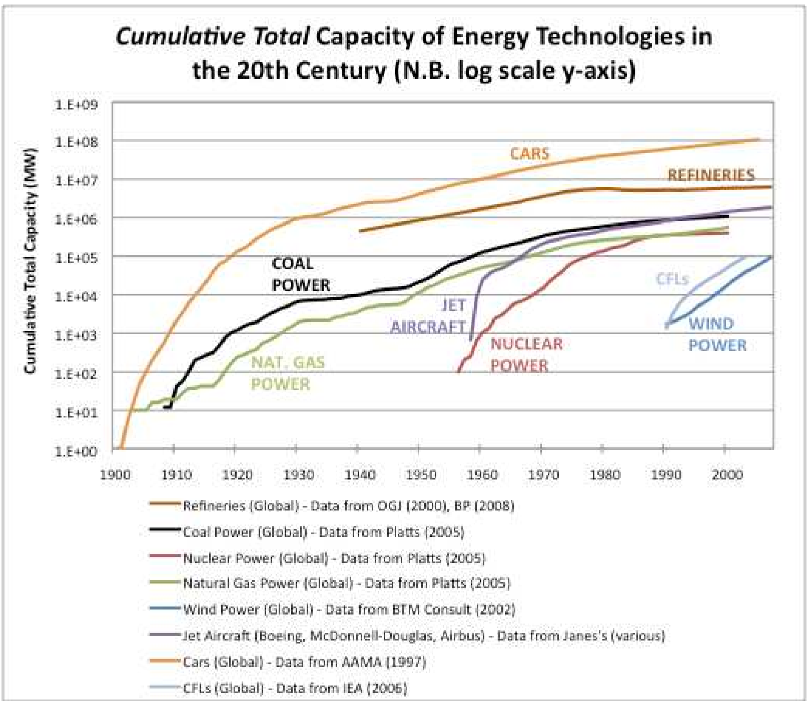
The principal difference is self-evident: future data were derived from energy system model projections not the historical record. Data availability was therefore determined by model structure and technological resolution. An important consequence was that only supply-side power generation technologies could be included in the scenario data analysis as the future deployment of specific end use technologies is not modelled explicitly. Further details on the scenarios and technologies analysed are included in Section 4.

3 Historical Analysis

3.1 Relationship between Extent & Duration of Growth

Figure 4 shows the historical data series of cumulative total industry capacity for the energy technologies shown in Table 1. Fitting logistic functions to these data controls for the changing dynamic of growth over time (and over the lifecycle of a technology). The K and Δt parameters of the fitted logistic functions then allow the *extents* and *rates* of growth to be compared for different technologies. As noted in Section 2.6, the extents of growth are normalised for changes in the size of the energy system into which the different technologies diffuse.

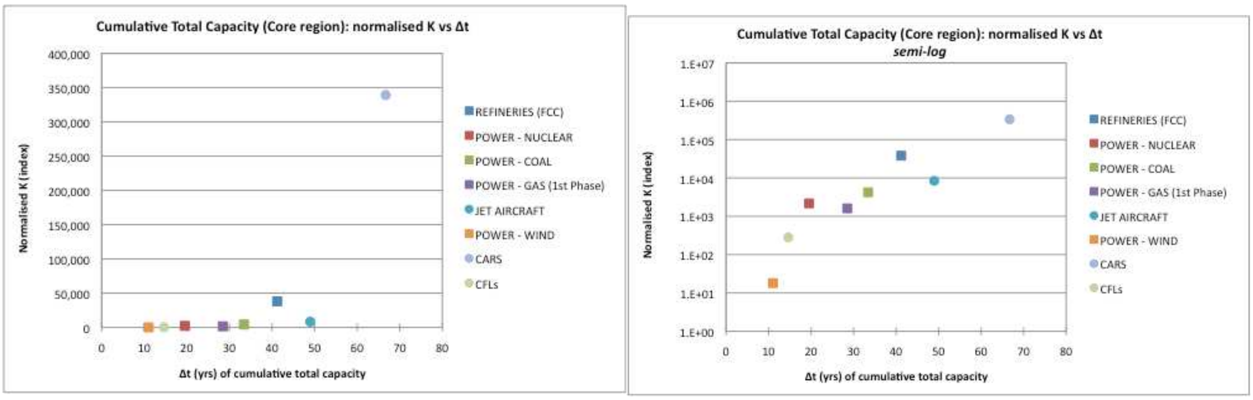
FIGURE 4. CAPACITY GROWTH OF SELECTED ENERGY TECHNOLOGIES IN THE 20TH CENTURY.



Intuitively, and in general, a technology should take longer to diffuse to a greater extent. Part of the explanation for the greater extents of growth for cars and refineries shown in Figure 4 is their longer time horizons. (The first refineries date back to the 1860s, but data are only available from 1945). So the extent and duration of growth should be positively correlated, notwithstanding the many factors that affect growth dynamics (Grübler et al. 1999).

Figure 5 confirms this basic intuition by plotting the normalised K and Δt parameters of the fitted logistic functions for 8 energy technologies in their respective core regions. The left-hand graph shows the relationship on linear axes. The distorting effect of the very high relative extent of growth of cars is 'corrected' in the right-hand graph which shows the same data but on a log y-axis. The core region is used as it has the most number of data points (see Section 2.3 for details of the regional disaggregation). Logistic functions can be more reliably fitted to capacity growth which has passed its initial exponential growth phase; this is more likely in core regions where the growth dynamic first began.

FIGURE 5. RELATIONSHIP BETWEEN EXTENT AND DURATION OF GROWTH FOR 8 ENERGY TECHNOLOGIES IN THEIR CORE REGIONS. (BOTH GRAPHS SHOW SAME DATA; RIGHT-HAND GRAPH HAS LOG Y-AXIS).



The right-hand graph of Figure 5 confirms the intuition of a positive correlation between the extent and duration of growth. Surprising, however, is the remarkable consistency of the extent – duration relationship between both end use and supply-side technologies of markedly different characteristics and vintage. An exponential best fit line explains 85% of the variance between the 8 data points shown (normalised K = $21.4\Delta t^{0.16}$).

3.2 Regional Analysis of Extent – Duration Relationship

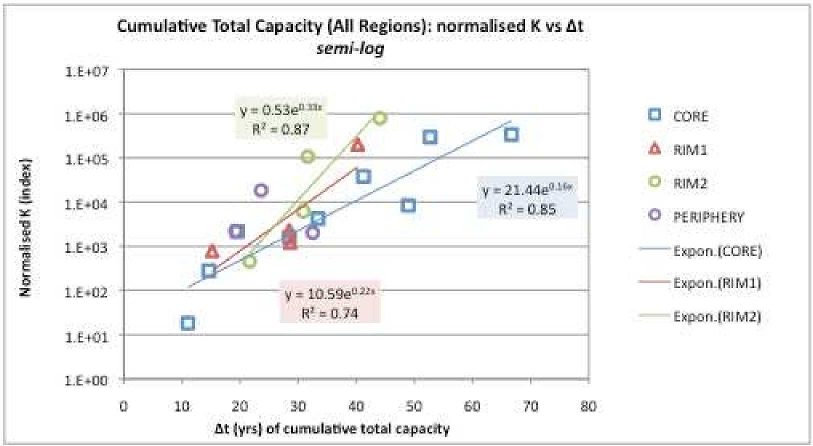
The extent - duration relationship in the core region also holds for other regions although the number of data points become sparser. Figure 6 plots normalised K against Δt for all the data points available. The rim region is split into 'rim1' for former Soviet Union countries and 'rim2' for all other countries as 20th century energy technologies tended to diffuse in OECD countries and former Soviet Union countries either sequentially or concurrently, and then subsequently into non-OECD countries. Isolating the former Soviet Union countries also allows for structural differences in technologies' diffusion context to be explored.

The best fit lines for the technology data points in the core, rim1 and rim2 regions are consistently exponential (see Figure 6). Also observable is the increasing rate of growth as a technology diffuses spatially. In other words, from the core to rim1 to rim2 regions, a given extent of growth requires a shorter duration of growth, confirming established theory (see Section 2.3).[3]

[3] The best fit line for the global data might be expected to lie somewhere between the core and periphery regions in terms of steepness. However, it is actually slightly flatter than the best fit line for the core region data. The durations of growth (Δt) globally and in the core region are very close as diffusion in the core region strongly influences the overall global growth dynamic (in terms of the time taken to diffuse from 10% to 90% of the final saturation density). The extent of growth (K) is much larger globally than in the core region. However, the normalized extents are generally lower globally than in the core region which pulls the extent – duration relationship downwards. As the global growth dynamic is 'stretched out' in time at the tail by the inclusion of

No best fit line is shown for the periphery region which has only 3 data points. The rightmost data point with a Δt of over 30 years is for coal power, and is biased rightwards by the inclusion of South Africa in the periphery region (as part of Africa) despite its long history of coal exploitation under the trade restrictions of the apartheid era. A best fit line through the 2 remaining data points would be slightly steeper than the rim2 line as would be expected.

FIGURE 6. REGIONAL COMPARISON OF RELATIONSHIPS BETWEEN EXTENT AND DURATION OF GROWTH.



3.3 Cross-Technology Consistencies in the Extent – Duration Relationship

As noted above, the positive relationship between the extent and duration of growth shown in Figure 5 is intuitive; however, the striking consistency of this relationship across different technologies is not. The technology lifecycles of refineries, power plants, jet aircraft, cars and light bulbs are characterised by distinctive cost and efficiency profiles, capital intensiveness, turnover rates, market niches, regulatory contexts, manufacturing bases, and so on. The technologies analysed also serve different functions within the energy system, converting primary energy to energy carriers or directly servicing end user needs. Any or all such differences would be expected to influence the extent and duration of a technology's growth.

But the observed consistency in the extent – duration relationship suggests influences on growth act proportionally on both Δt and log K (to preserve the linear relationship on a semi-log plot). As an example, a strongly supportive regulatory context for a technology may successfully reduce the duration of growth (shorter Δt) but in so doing also reduces the potential extent of growth (lower K) possible during that shorter duration. Conversely, demand for a technology which is dispersed and only incrementally increasing may imply slow growth rates and so a longer duration of growth (longer Δt) but an associated

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the periphery region, the inflection point, t_0, at which primary energy is measured for the normalization is delayed, meaning the energy system is relatively larger and so the normalized extent relatively lower.

potential for growth to be much more pervasive (higher K). This simple relationship between Δt and K describes the inherent inertia of a large, complex, inter-related system of technologies, infrastructures and end user needs.

It is worth recalling that the extent – duration relationship is for cumulative total capacity data. *So the observed consistency across both technologies and spatial scales describes the energy system's ability to accumulate energy conversion potential over time;* or alternatively, the ability of actors within an energy system to manufacture and install capital stock. A full discussion of historical growth dynamics can be found in (Wilson 2009; Wilson forthcoming). Some of the main observations are summarised here.

Firstly, final demand for energy technologies converting electricity and oil products into useful services has grown inexorably over the 20th century. This in turn has fed the demand for technologies to extract, process, transport and convert primary energy. A consistent extent – duration relationship may simply describe the dynamics of demand growth. How rapidly and how extensively demand changes is both driven and constrained by the adaptability of end user needs and wants, which are embedded in practices, routines, social networks, organisational structures and so on. Technology diffusion models emphasize the importance of reducing perceived uncertainties and risks as innovators and then early adopters seed an often lengthy process of social learning (e.g., Rogers 2003). Thus the inherent inertia to change in technological systems is similarly found in social systems: arguably, the two are inseparably entwined. The consistent extent – duration relationship suggests both face the same trade-off between rapid growth and pervasive growth.

Secondly, meta-analyses of energy technologies and innovation have found a common set of underlying mechanisms that shape innovation, market formation and early diffusion (Grübler 1998; Grübler et al. 2011). These include R&D investments, learning and scale effects, knowledge spillovers (and knowledge depreciation), entrepreneurialism, actor networks, demonstration activities, niche market applications, and so on. A consistent extent – duration relationship for different technologies may signal limitations in the capability of these underlying mechanisms to support technologies through into the mass market. Thereafter, growth rates are influenced by factors including relative advantage over incumbent technologies, inter-dependencies with other technologies and infrastructures, the size and growth of niche markets (see above) (Grübler et al. 1999). But these factors may equally influence potential growth extents.

Thirdly, the technologies analysed here are biased in two ways. They are all 'winners', having successfully grown and approached (or reached) saturation. They also have growth dynamics that can be reliably and accurately described *in hindsight* by logistic functions. A consistent extent – duration relationship may only describe this biased sample of all energy technologies and so may not be generalisable. However, our interest is in applying the extent - duration relationship to future winners based on scenario depictions. So a similar *future* hindsight bias also describes the following analysis.

4 Scenario Analysis

4.1 Validating Future Scenarios Against Historical Evidence

The consistent extent - duration relationship for energy technology growth shown in the previous section provides a historical comparator for externally validating the projections of energy system models (see Section 2.1). The null hypothesis is that projected growth dynamics are consistent with those evidenced historically in terms of their logistic form, and in terms of the relationship between the duration and extent of growth. Testing this hypothesis is a means of validating the quantitative model outputs used to enrich carbon constrained scenarios.

As noted in Section 2.7, this means analysing technologically-explicit future scenarios in an identical manner to the historical data sets, by:

i. compiling time series data of cumulative total capacity (in MW) for energy technologies in future scenarios;
ii. fitting logistic functions to the time series data subject to a goodness of fit criterion (adjusted $R^2 > 95\%$) and a reliability criterion (maximum capacity data > 60% of estimated asymptote);
iii. normalising extents of growth for differences in energy system size by dividing K by primary energy consumption at t_0 of the logistic function (using primary energy data from the same scenario);
iv. plotting the extent – duration relationship, and comparing with the historical data.

4.2 Selecting Scenarios & Technologies for the Meta-Analysis

We used carbon constrained scenarios generated by the MESSAGE energy system model as part of an 'Integrated Assessment Modelling Framework' 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). A wide range of scenarios were generated within different scenario families and under different carbon constraints. Table 2 shows the full set of combinations; the 8 scenarios selected for this external validation exercise are marked in bold.

The global A2r, B1 and B2 scenario families vary across a range of exogenous drivers (including economic growth, population growth, rates of technological change, and energy intensity improvements) and so describe a wide range of greenhouse gas emission profiles and stabilisation scenarios over the period 2000-2100 (Nakicenovic et al. 2000). In the 'Integrated Assessment Modelling Framework' analysis used here, the A2r family has the highest baseline emissions, and its most constrained stabilisation scenario is 670 ppmv (see Table 2). The B1 family has the lowest baseline emissions and stabilisation scenarios between 480 and 670 ppmv.

Table 2. MESSAGE-Generated Scenarios as Part of the Integrated Assessment Modelling Framework (Riahi et al. 2007). Scenarios in Bold are Used in the Meta-Analysis.

Scenario Family	***Carbon Constraints* stabilisation target for 2100 in CO_2-equivalent ppmv***								***No Constraints***
A2r				**670**	820	970	1090	1390	**baseline**
B1	**480**	520	590	**670**					**baseline**
B2	**480**			**670**					**baseline**

* i.e., stabilisation targets of atmospheric CO_2-equivalent concentrations measured in parts per million by volume.

For the purposes of the meta-analysis, scenarios were selected to examine and compare the widest possible range of low carbon technology projections. This meant the least constrained scenario in each scenario family (the 3 baselines), the most constrained scenario in each family (B1 & B2 480 ppmv, A2r 670 ppmv), and the most constrained scenario shared by all families (670 ppmv). The most extensive deployment of low carbon technologies is found in the most constrained scenarios, although the specific technology or technologies which are emphasized varies between scenario. For example, the B1 scenario family responds to carbon constraints with strong growth in renewables, particularly solar; the A2r scenario family rather emphasizes nuclear, bio-energy, and carbon capture and storage.

For each of the 8 scenarios selected (see bold cells in Table 2), cumulative installed capacity data were extracted for low carbon technologies resolved by the MESSAGE model. This limited the analysis to alternative forms of electricity generation for which technology-specific data were available:

- nuclear power;
- natural gas power;
- coal power with carbon capture and storage (coal CCS);
- coal and natural gas power with carbon capture and storage (fossil CCS);
- wind power;
- solar PV power (centralised + decentralised).

4.3 Fitting the Logistic Functions to Scenario Data

For each of the 6 * 8 technology-scenario combinations, cumulative total capacity data for 2000 – 2100 were recalibrated so they continued from the historical data series up to the year 2000.[4] As with the historical data, capital stock lifetime and turnover were not treated explicitly; rather they are internalised within the cumulative total capacity data and so may potentially explain differences in modelled growth dynamics between technologies. Each data series was compiled globally, and for selected technology-scenario combinations was then disaggregated into core, rim and periphery regions (respectively: OECD, former Soviet Union + Asia, rest of the world).

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[4] The decadal time steps in MESSAGE start from 1990. Cumulative total capacities are initialized at the net installed capacities for 1990 (i.e., no pre-1990 installed capacity is carried over into the model).

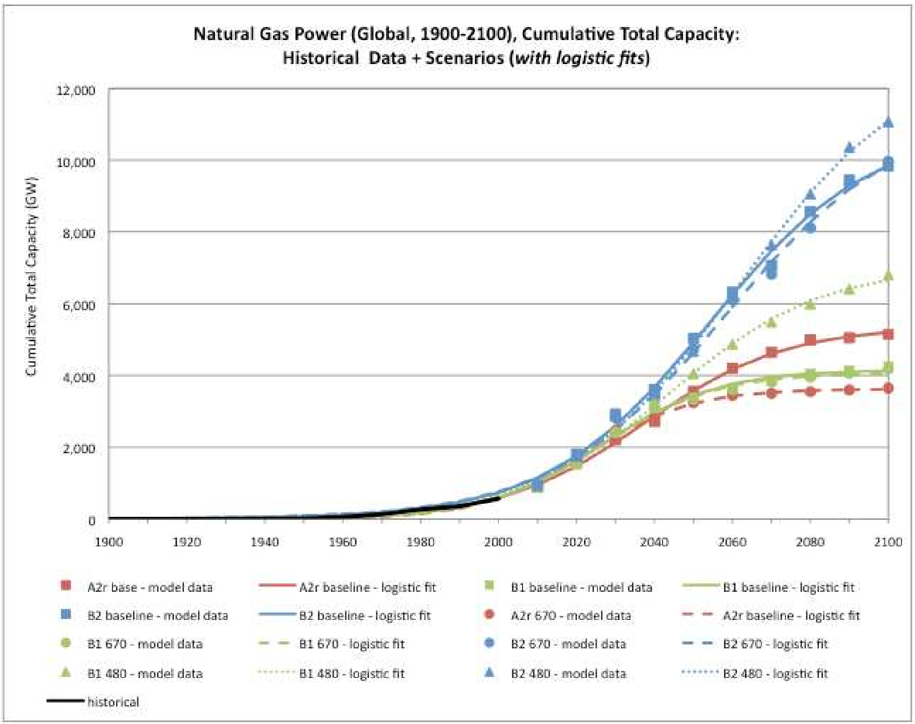
Logistic functions were fitted to the cumulative total capacity data describing the combined historical + future time series. In almost all the technology-scenario combinations, logistic functions accurately and reliably described the modelled growth dynamic. In a few cases, the projected growth was still exponential in 2100 and so the extent of growth from the model output was less than 60% of the fitted asymptote value (the 2nd fit criterion, see Section 2.5). Selected results are shown below; for full details of the scenario data and fitted logistic functions including all underlying data, see (Wilson 2009). Although the historical analysis presented data for the core region as it maximised the number of data points, here, global data are presented. In the scenario analysis, no further information is gained by moving to the regional level, and all results were found to be independent of the spatial disaggregation.

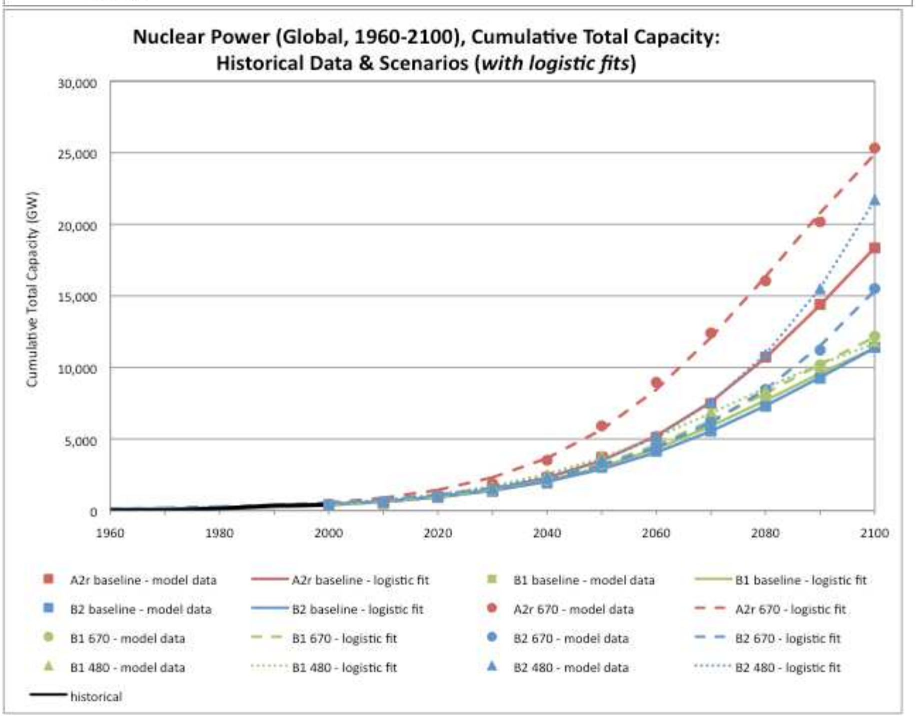
Figure 7 shows an example of the combined historical + scenario time series data for natural gas power and nuclear power globally (data points) together with the fitted logistic functions (lines). The correspondence of the logistic functions with the underlying data is clear.

Differing technological responses to carbon constraints between the scenario families are also clear: the A2r scenarios see more nuclear power whereas the B2 scenarios rely more on natural gas. Similar differences exist for other technologies depending on the scenario family storyline and the more specific technological cost, performance, learning and other inputs used to model the scenarios (see Riahi et al. 2007 for more details). In the case of nuclear power, future growth to a cumulative total capacity of 10 - 25 TW by 2100 renders barely visible the '1st phase' of logistic growth to the current level of 0.4 TW cumulative total capacity (see Figure 3).[5]

[5] This is similar, though not quite as marked, for natural gas power which reaches a cumulative installed capacity of 4-11 TW in 2100 compared to 0.6 TW in 2000. Other technologies assessed in the scenarios - CCS, wind power, and solar PV – all have very low cumulative total capacities in 2000.

FIGURE 7. GROWTH IN CUMULATIVE TOTAL CAPACITY GLOBALLY OF NATURAL GAS POWER (1900-2100) & NUCLEAR POWER (1960-2100).



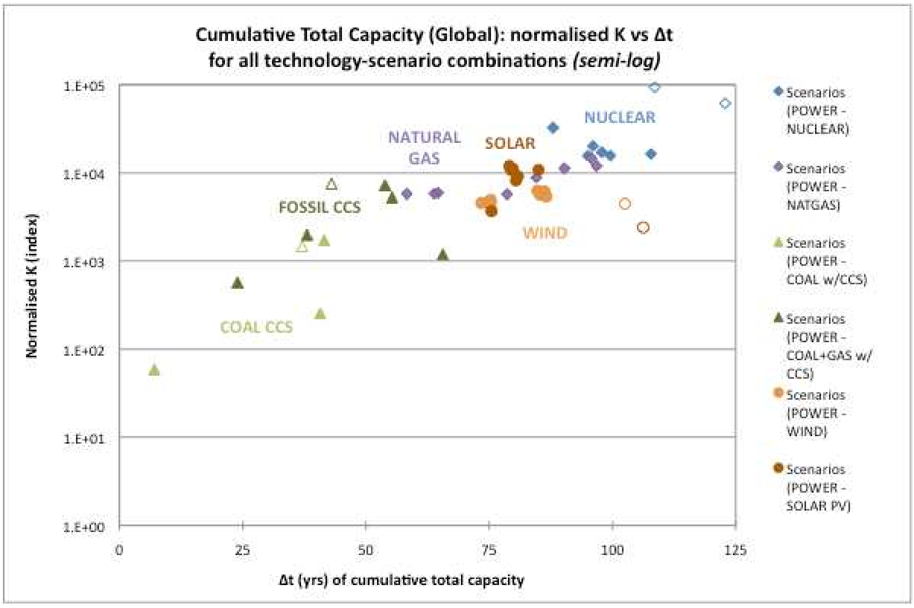


4.4 Relationship between Extent & Duration of Growth in the Scenarios

4.4.1 Global Data

The relationship between the extent and duration of growth globally (normalised K vs. Δt) for the 6 low carbon energy technologies in each of the 8 future scenarios is shown in Figure 8. Different data points are used for each of the 6 technologies; specific scenarios are not distinguished. Unfilled data points (in outline form only) are for technology-scenario combinations for which projected capacity in 2100 had not yet reached 60% of the estimated asymptote (K), and so had breached the reliability criterion (see Section 2.5). These unfilled data points are included for indicative purposes only. As with the historical data, the asymptote parameter, K, from the fitted logistic function was divided by primary energy consumption in year t_0 (the inflection point of the logistic curve) to normalise for differences in system size. Primary energy data were taken from the same scenario as the technology growth projection (e.g., B1 670 primary energy projections were used to normalise extents of growth for technologies in B1 670 scenarios).

FIGURE 8. RELATIONSHIP BETWEEN EXTENT AND DURATION OF GROWTH GLOBALLY FOR 6 LOW CARBON ENERGY TECHNOLOGIES IN FUTURE SCENARIOS



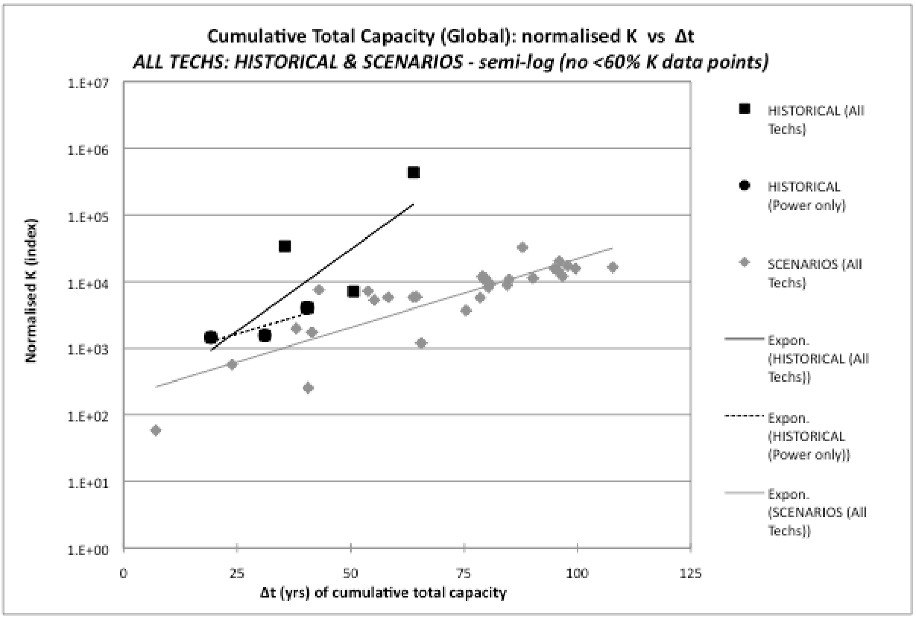
Various points are salient in Figure 8. Firstly, the extent – duration relationship is again consistent across the different technologies along an exponential trend line. Secondly, the dispersion of data points is much greater between technologies than between scenarios. The data points for each technology are relatively well clustered, though the two CCS technologies (coal and fossil) are more dispersed as CCS makes a relatively low contribution (and so low extent of growth) in the B1 scenarios. The exceptionality of CCS is discussed further below. Thirdly, nuclear power is generally projected to grow to the greatest extent (in terms of MW of cumulative total capacity), followed by the intermittent renewables (solar PV and wind), followed by the fossil fuels (natural gas, gas + coal with CCS, just coal with CCS). Again, these relative contributions to low carbon growth – in terms of cumulative total capacities - are broadly consistent across the widely different scenarios.

Figure 9 shows the same data points as Figure 8 but without the colour distinctions between technologies and without the unfilled (unreliable) data points. Also included are exponential best fit lines for all the historical technologies (black squares, solid black line), for only the historical power generation technologies (black circles, dotted black line), and for all the scenario technologies (grey diamonds, solid grey line). We emphasize that the best fit lines only describe the general relationship between the extent and duration of growth for energy technologies. In the case of the scenarios, this relationship is also further generalised for different future scenarios. The patterns shown are therefore at a high level of aggregation.

The important, and surprising implication of Figure 9, is that *the scenario projections of energy technology growth appear generally more conservative than the historical record suggests possible*. By conservative, we mean requiring a longer duration of growth to reach a given extent of growth, i.e., towards the bottom right hand corner of Figure 9. With the exception of some of the low CCS data points, all the scenario data points lie below and to the right of the historical data points.

This general finding holds if the historical comparator for the scenario data points is limited to power generation technologies (coal, natural gas, nuclear). Their extent – duration relationship is less steep than for all historical technologies (i.e., slower rate of growth) as shown by the dotted black best fit line. Although, this trend should be treated with some caution due to the small number of data points, almost all the scenario data points still lie below and to the right, i.e., are more conservative.

FIGURE 9. COMPARISON OF EXTENT – DURATION RELATIONSHIP GLOBALLY: HISTORICAL EVIDENCE & SCENARIO PROJECTIONS

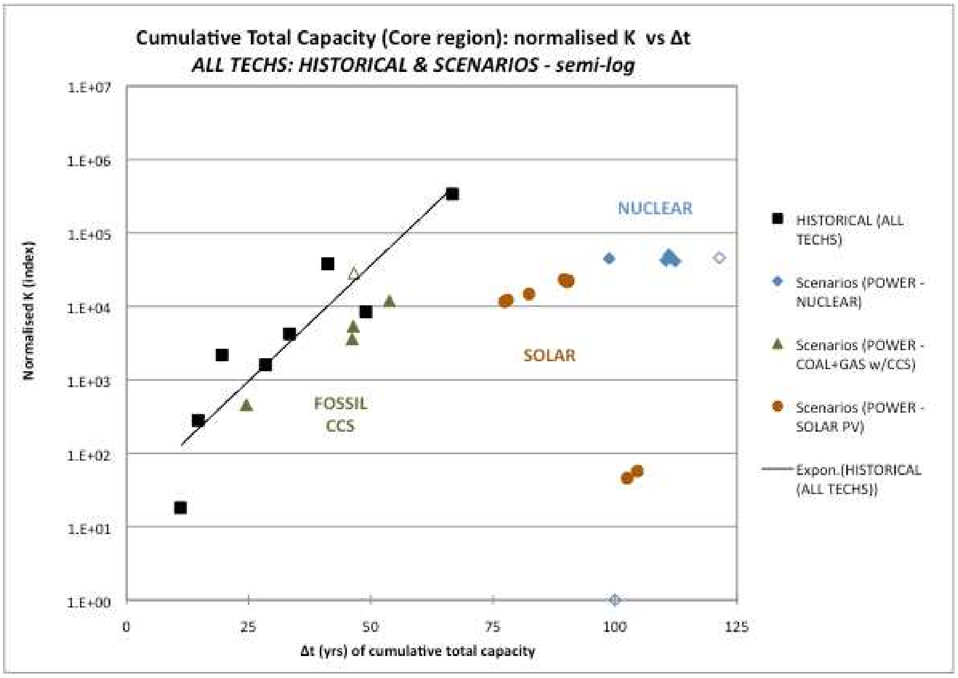


4.4.2 *Core Region Data*

As with the historical data, the patterns observed in Figure 8 and Figure 9 hold if the global data are disaggregated regionally. Figure 10 shows the same plot as Figure 9 but for the core region rather than globally, and for a reduced number of scenario technologies: nuclear power, fossil CCS and solar PV.

Two observations from Figure 10 are salient. Firstly, the historical data points and scenario data points for each technology have the same relative position in the core region as globally. The findings above relating to the global data apply equally to the regional data. Secondly, the fossil CCS data points are again the closest to the historical pattern, and in some cases are overlapping. The exceptionality of CCS is discussed further below.

FIGURE 10. COMPARISON OF EXTENT – DURATION RELATIONSHIP IN THE CORE REGION: HISTORICAL EVIDENCE & SCENARIO PROJECTIONS



4.4.3 *Explaining Extent – Duration Relationships in the Scenarios*

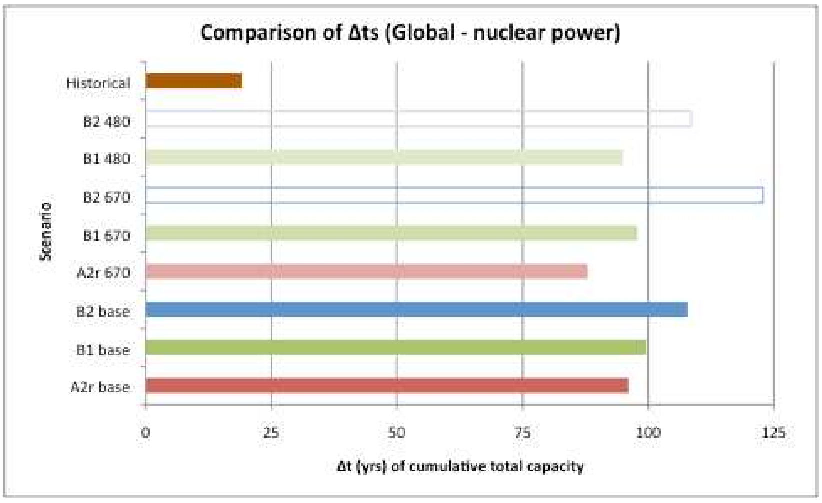
The main difference between the historical record and future scenarios is the longer durations of growth for low carbon technologies in the scenarios. In contrast, extents of growth in the scenarios are broadly in line with those experienced historically once growth in the energy system as a whole is controlled for. These normalised Ks range from 3 to 5 orders of magnitude, with the data point for cars as a high outlier historically, and a few CCS data points as low outliers in the scenarios. (Recall that these normalised Ks are meaningful only relative to one another, and not in absolute terms; see Section 2.6 for discussion).

Figure 11 shows the duration of growth for nuclear power globally, measured by the Δt of the fitted logistic functions to both historical data and scenario projections. The two unfilled bars (in outline form only) are not considered reliable as the projected capacity in 2100 had not yet reached 60% of the estimated asymptote (K), and so had breached the reliability criterion. These unfilled data points are included for indicative purposes only.

Figure 11 clearly shows the substantially longer durations of growth of nuclear power capacity in all the scenarios (all Δt > 85 years), compared to the growth evidenced historically (Δt = 19 years). A similar pattern is found with the durations of growth for other low carbon technologies in the scenarios (to the extent that a technology has an historical analogue).

In the scenarios, nuclear power is projected to grow by two orders of magnitude in terms of cumulative total capacity (from ~0.4 TW in 2000 to 11-25 TW in 2100). But once this huge increase in the extent of nuclear power capacity is normalised for growth in the overall 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 shown globally in Figure 9, either the extent of growth (normalised K) would have to increase by another 3 orders of magnitude, or the duration of growth (Δt) would have to halve.

FIGURE 11. DURATIONS OF GROWTH FOR NUCLEAR POWER: HISTORICAL EVIDENCE & FUTURE SCENARIOS



4.4.4 *CCS Exceptionality*

The extent – duration relationship in the scenarios for CCS is closer to the historical pattern than for the other low carbon technologies analysed. In particular, CCS has a shorter duration of growth for a given extent of growth (i.e., a lower Δt for a given normalised K). Globally, coal CCS and all fossil CCS have Δts in the range of 24 – 66 years compared to the historical range of Δts across all technologies of 19 – 64 years (with nuclear power and cars as the minimum and maximum respectively).

This arises because the models treat CCS as a backstop technology, i.e., one whose relative attractiveness in terms of cost or other performance characteristics become secondary to the need to meet specified carbon constraints by a given point of time. As a result, growth in CCS capacity is concentrated in the second half of the 21st century, so compressing its duration measured by Δt. This delayed growth is a function of the cost characteristics of CCS used in the models which only become attractive when discounted over long time frames. Additional deployment constraints may be used to reflect the technology's relative immaturity and lack of demonstrated viability at scale.

5 Discussion: Why do the Scenarios Appear Conservative?

5.1 Key Findings

The comparative analysis of energy technology growth dynamics described in Sections 3 & 4 centres on the relationship between the extent of growth and the duration of growth. These are measured respectively by the asymptote parameter, K, and the value of Δt from logistic functions fitted to both historical and scenario data expressed in terms of cumulative total capacity (in MW). Only those logistic functions that meet stringent criteria of accuracy and reliability are included. We emphasize again that logistic functions are used simply to *describe* observed historical trends or modelled future trends and are in no way predictive. As explained in Section 2, the reason logistic functions are used is to control for the changing dynamic of growth over time and so enable comparisons between technologies and time periods.

The striking finding from this meta-analysis is that projected capacity growth in carbon constrained future scenarios appears conservative relative to what has been evidenced historically. Specifically, a given extent of growth for a technology in the scenarios requires a longer duration of growth than has been the case historically, once changes in the overall size of the energy system are taken into account. We caveat this finding by noting that the historical data points are relatively sparse, particularly in the electricity generation sector from which the scenario data are drawn.

Here, we posit and test various hypotheses to explain this apparent scenario conservatism. These are summarised here, and discussed further below:

i. *Past - Future Comparability (see Section 5.2)*:
   - the historical data on technology growth can not be directly compared with scenario data as past and future are discontinuous.

ii. *Time Series Artefact (see Section 5.3)*:
   - a single time series combining historical and future capacity data inherently shows longer durations of growth than the shorter periods used in the historical analysis.

iii. *Model Conservatism (see Section 5.4)*:
- the MESSAGE model, or technologically-explicit energy system models in general, is run using conservative parameter estimates and/or deployment constraints for low carbon technologies.

5.2 Past – Future Comparability

The need for discontinuities in the trends of both energy and carbon intensity was discussed in the introduction. So: do fundamental differences between the historical and future contexts of energy technology growth mean the historical record is not a meaningful comparator for scenario data?

The future represented in the scenarios tends to describe a world with carbon constraints, policies for inducing low carbon technological change, more globally-integrated technology markets and so more rapid spatial diffusion, and stronger regional growth in Asia. All these differences in the future context for energy technology growth would seem to imply more aggressive not more conservative extent – duration relationships for low carbon technologies such as wind, solar PV, nuclear, and CCS.

Conversely, however, relying on regulation, externality pricing, and other supporting policies to drive low carbon growth may be slow or inadequate. The current dominance of fossil fuels relates to their relative advantages over low carbon technologies in terms of cost, energy density, convenience, versatility and substitutability (Smil 2003). Moreover, a transition away from the energy infrastructures and institutions which have co-evolved with fossil fuels over the last century or more carries its own costs and inertias (UnRuh 2000). The fossil fuel present arrived through a centennial process of incrementally innovating and building "on the shoulders of giants" (Acemoglu et al. 2009); the magnitude of decarbonisation required in the future affords no such gradualism. Although resource constraints may play an increasing role in driving this transition, such considerations would seem to support conservatism in the scenarios. Accelerated policy-induced technology deployment without lengthy formative periods of experimentation and testing also implies additional risks (Wilson forthcoming).

But despite these competing arguments, it is important to note that whether discontinuities between past and future imply faster or slower growth potentials for energy technologies is not of immediate relevance. This is because the apparent scenario conservatism is not observed between past and future, but between past and *energy system model representation of the future*. The issue, therefore, is the extent to which MESSAGE takes into account the various future influences supporting either faster or slower technology growth. Here the argument is clearer as there is no obvious discontinuity between past and *model representation of the future* that can explain why projected growth appears conservative relative to the historical record. MESSAGE bases its mechanisms and drivers of technology deployment on historical evidence.[6] The same is true of technology-specific parameters such as cost, efficiency, inputs, outputs, and so on. As an example, unit cost assumptions for a technology are derived from extrapolations of historical trends and industry surveys of current practice; and unit costs fall over time as a function of cumulative deployment according to empirically-founded learning rates.

5.3 Time Series Artefact

The logistic functions fitted to scenario data described the growth in capacity over the combined historical + future time series, i.e., the full course of a technology's (future) history. These combined time series all ended in 2100, but began as early as the 1900s (natural gas and coal power), or the 1950s (nuclear power), the 1970s (wind power and solar PV), and the 2020s or later (CCS). They ranged in length, therefore, from 80-200 years. For all 6 of the low carbon technologies analysed across the range of 8 scenarios, logistic functions were very accurate fits for this combined historical + future time series (the lowest adjusted R^2 was 98%).

But the historical analysis showed that logistic functions also describe growth dynamics for natural gas power from 1903 to the late 1970s (a '1st phase' of growth) and for nuclear power from 1956 to 2000 (similarly a '1st phase' of growth if nuclear power is again deployed at scale). In other words, the *centennial* pattern of logistic growth in the combined historical + future time series incorporates - and hides - at least one, and potentially more *episodic* periods of logistic growth.

So: do the *centennial* logistic functions used in the scenario analysis inherently mean longer durations of growth (and so higher Δts) than the *episodic* logistic functions used in the historical analysis? In other words, is the observed scenario conservatism simply an artefact of the length of time series data used in the scenario analysis?

Again, we reject this argument for two reasons. Firstly, longer durations of growth (higher Δt) should also mean greater extents of growth (higher K). Ultimately it is the extent – duration relationship which is conservative, not the duration in isolation. As shown in Section 4.4, scenario data points show substantially longer durations of growth for similar extents of growth as those evidenced historically, after controlling for changes in the size of the energy system.

However, this does assume that the K and Δt parameters of the logistic function are affected proportionately by different time frames of analysis, and specifically in this case, the move from an *episodic* to a *centennial* time frame. Do longer time

[6] Note that this does not mean MESSAGE can faithfully reproduce historical dynamics, not least because MESSAGE is an optimisation model implicitly representing the perspective of a cost minimising social planner. This structural characteristic of MESSAGE should also make technological growth projections more aggressive rather than more conservative.

frames increase Δt proportionately more than K, and so inherently result in slower growth rates?

An iterative exercise in fitting logistic functions to increasingly long periods of the same underlying data series offers only a partial answer to the question. Figure 12 shows two different sets of logistic functions. Each set shows 5 different logistic functions fitted to increasingly long time frames of an underlying data series which is also logistic in form.[7] The underlying data series is analogous to the *centennial* logistic functions from the scenario analysis. The 5 fitted logistic functions are analogous to the *episodic* logistic functions from the historical analysis. And all 5 accurately describe the time frame of the underlying data series over which they are fitted.

Figure 13 then shows the corresponding extent – duration relationships for both sets of logistic functions. The first set (left-hand graphs) clearly show a flattening of the K – Δt relationship as the time frame lengthens; Δt increases proportionately more than K (on a semi-log plot). The second set of logistic functions (right-hand graphs) clearly show a consistently straight K – Δt relationship independent of the time frame; Δt and K increase proportionately (on a semi-log plot).

As both sets of 5 logistic functions accurately describe their respective underlying data series (Figure 12), this simple exercise suggests there is no inherent reason why a longer time frame should increase Δt proportionately more than K (on a semi-log plot). So the flatter extent – duration relationship of technology growth in future scenarios compared to the historical pattern is not simply an artefact of the methodology. However, as the first set of fitted logistic functions show (left-hand graphs), neither can it be ruled out as a potential explanation for apparent scenario conservatism.

Figure 14 shows the same graphs as Figure 12 but with a log y-axis to emphasize the goodness of model fits over shorter time frames. All fitted functions should describe the initial period of growth in the underlying data series (from t=0 to around t=15). Figure 14 shows that this initial period is weakly described, particularly in the first set of functions (left-hand graphs). But this initial period is also the most relevant part of the overall data series as it corresponds to the time frame for the historical analysis. In part, therefore, this is an issue of function fitting accuracy and subjectivity.

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[7] Note that the *episodic* and *centennial* logistic functions describe the same initial growth, but differ thereafter in terms of rate, timing of the inflection point, and final saturation density. This distinguishes this exercise from the more common problem of identifying sequential logistic growth phases that are combined into an overall non-logistic growth pattern (Meyer 1994).

FIGURE 12. FITTING LOGISTIC FUNCTIONS OVER DIFFERENT TIME FRAMES. (EACH LOGISTIC FUNCTION SHARES THE SAME INITIAL GROWTH, BUT DIFFERS THEREAFTER IN TERMS OF RATE, INFLECTION POINT, AND ASYMPTOTE).

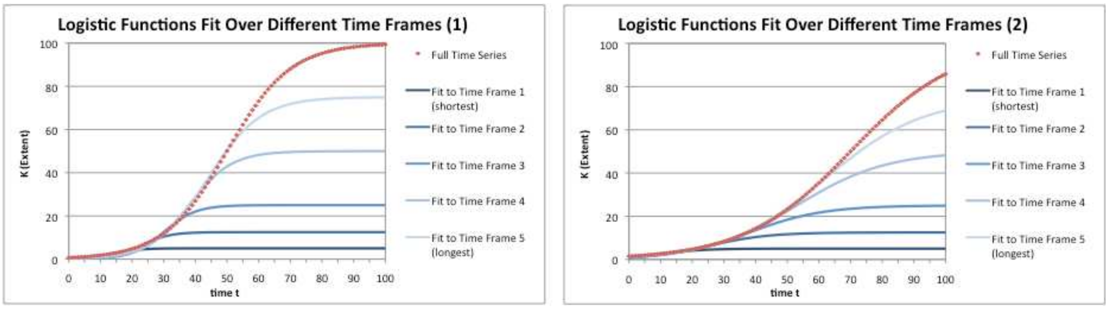


FIGURE 13. EXTENT – DURATION RELATIONSHIPS FOR LOGISTIC FUNCTIONS FIT OVER DIFFERENT TIME FRAMES.

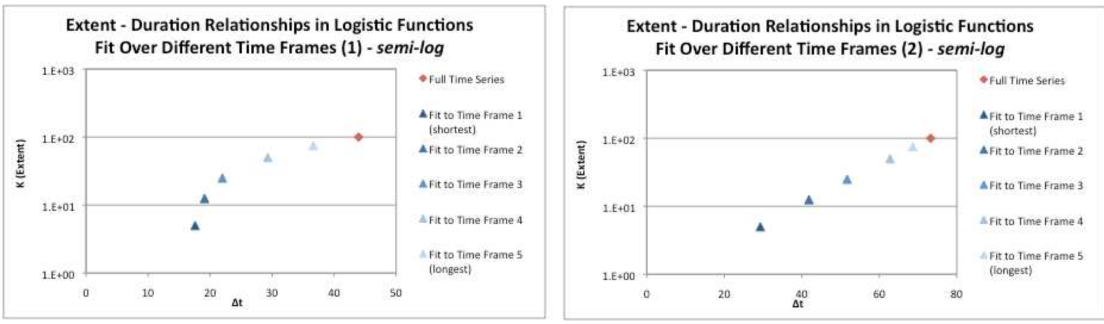
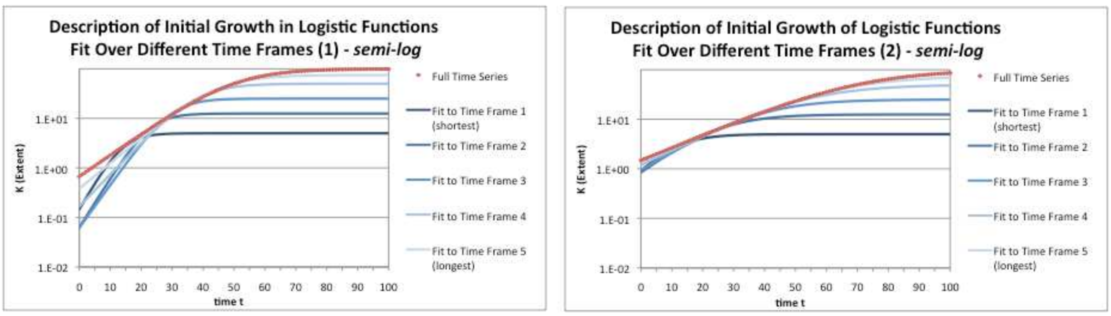


FIGURE 14. UNCERTAINTIES IN LOGISTIC FUNCTIONS FIT OVER DIFFERENT TIME FRAMES. (LOG Y-AXIS EMPHASIZES UNCERTAINTIES DURING INITIAL GROWTH PERIOD AT LOW T).



5.4 Model Conservatism

Optimisation models such as MESSAGE are typically set up with constraints on technology deployment to prevent dramatic changes in model output as input parameters vary (Grübler & Messner 1996). This ‘flip-flopping’ behaviour is exacerbated by perfect foresight, i.e., models’ knowledge of expected technology cost trends throughout the scenario time frame. As a result, a cost minimal solution for a given set of model conditions may swing from a dominant market position of technology A to a dominant market position of technology B if technology B's relative cost is reduced only marginally or technology B's relative learning rate is increased only marginally. To prevent such unrealistic outcomes, MESSAGE uses market penetration constraints for technologies: e.g., maximum of x% growth in installed capacity over time period y. These constraints are based on observed trends and realistic extrapolations.

So: are these market penetration constraints the reason for scenario conservatism? A similar argument applies to the cost and performance parameters used in MESSAGE for specific technologies. For example, capital cost reductions over time are derived from historically evidenced learning rates and scale economies, but these may be conservative over the *centennial* future time frames of the scenario analyses.[8]

5.5 Summary & Further Research

In sum, none of the hypotheses to explain the apparent scenario conservatism can be roundly rejected. The centennial timescales of future scenarios, the limits represented in MESSAGE on the potential for policy to induce a transition away from relatively advantageous fossil fuels, and the possible structural or parametric conservatism of MESSAGE with respect to technology growth in general, may all help explain the findings.

On balance, the evidence points towards model conservatism as the most likely explanation, though as noted, CCS is an exception here (see Section 4.4.4). Model conservatism could be further investigated by incrementally relaxing market penetration constraints and/or increasing learning rate assumptions for a particular technology. This should result in a more extensive and shorter duration growth dynamic. The relevant data points in Figure 8 & Figure 9 should swing up and to the left, towards the historical extent - duration relationship. Taking the market penetration constraints as an example, a sensitivity analysis could estimate how low constraints on specific technologies' growth would have to be in order to bring the extent – duration relationship in the scenarios in line with historical data (see Figure 9). These minimal constraints (and ditto with cost or learning rate assumptions) could then be compared with observed data to revisit their basis and determine whether they are overly restrictive.

6 Conclusions

The methodology set out in this paper is a means of externally validating the technology projections in future scenarios by comparing the relationship between extents and durations of growth with the historical record. The approach used should be of interest to the energy system modelling community as it provides a way to test model structure and parameters against

[8] Learning can be modelled endogenously, but not in perfect foresight models as technologies are simply selected based on their (known) expected future costs. For further discussion, see (Gritsevskyi & Nakicenovic 2000; Ma & Nakamori 2009).

observations. The analysis is first-order; potential explanatory variables for both observed and modelled growth dynamics, including the relative costs, efficiencies, and lifetimes of different energy technologies, are not addressed explicitly. It should also be emphasized that model output can only be assessed *ex post*; the method developed can not be used for *ex ante* evaluations of potential growth rates or likely successes of specific technologies. Consequently, no implications should be drawn for policymakers seeking insights into technology selection or R&D portfolio design.

Two key findings emerge. Firstly, the extent – duration relationship for 8 different energy technologies historically is consistent. Secondly, the analogous extent – duration relationship for 6 different low carbon technologies in a range of future scenarios is also consistent, but more conservatively so. The scenarios depict longer duration growth to reach a given extent of growth compared to the historical data. These findings are interesting precisely because they are largely robust across different technologies in different regions at different times.

However, the inherent generality of the meta-analysis means that the observed consistency of the historical and scenario extent – duration relationships shown in Figure 9 should not be imbued with false precision. In particular, more historical data points covering a wider range of technologies are needed than those shown in Figure 5 to provide a reliable trend against which scenarios can be compared.

The meta-analysis is also predicated on technologies that have 'succeeded' and that are 'mature' enough to have exhibited signs of saturation (so allowing reliable logistic function fitting). Although the validation methodology's reliance on logistic functions is a strength in that it provides a common growth form with both extent and duration parameters, its weakness is that it excludes technologies early in their lifecycle and/or technologies still growing exponentially. This in turn makes the findings more robust in initial or core markets compared to later or periphery markets. Findings should not be generalised beyond successful, mature technologies (whether these are historically-evidenced, or represented in models).

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