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Interim Report **IR-08-021**

Technologies as Agents of Change: A Simulation Model of the Evolving Complexity of the Global Energy System

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September 9, 2008

Revised August 20, 2009

International Institute for Applied Systems Analysis
Registration number: ZVR 524808900

Note: Revised Version of IR-08-021 August 20, 2009.

Continued research on the model revealed a computational mistake in the numerical results reported in the original IR, published in August 2008. We have subsequently rerun all simulations with the corrected model version and have also extended the time horizon of our simulations to 500 (instead of the original 300) time steps. This current version includes revised graphics reporting on the new simulations. Changes are mostly minor and do not affect the discussion and conclusions of the original paper.

TM, AG, BA, NN.

Contents

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Tieju Ma[1,2], Arnulf Grubler[1,3], Nebojsa Nakicenovic[1,4], and W. Brian Arthur [1,5]

1. Introduction

How does technological complexity arise? Before discussing where this paper can be situated within the literature on technological complexity, we first need a working definition of complexity in this context. By technological complexity we understand a system that is characterized by a large number of constituent components that portray a high degree of interdependence (functional interconnections, or interactions). *Complexification* by this definition is a simultaneous increase in both system components and their interdependence (interrelationships) within a given system. This leads to emergent properties that can lead to alternative development paths with similar or even identical initial conditions.

Technological complexity can apply both to individual artifacts ("machines", ranging from tools, to automobiles, all the way up to the space shuttle), as it can apply to combinations of technological artifacts that themselves form technology systems. It is the latter concept of technological systems complexity that is at the core of this paper. We present an agent-based simulation model that emulates the evolution of technological complexification in a stylized model of the global energy system.

Analytical inroads into technological complexification are comparatively few and can be classified into two broad categories: descriptive, and (simulation) model based analyses.

As regards the evolution of complexity of individual artifacts important insights have been provided by both research streams: descriptive, e.g. the work of Saviotti, 1996, or Frenken *et al*., 1999, that analyzed the evolution of technological variety and complexity of aircrafts and helicopters and simulation model based analyses, e.g. the work of Arthur and Polak, 2006 and their model of the evolution of logical circuits, which provided an important inspiration for our model.

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Concerning the issue of complexification of entire technological systems there is a rich tradition in the historical qualitative description of the evolution of technological systems (e.g. the work of Hughes, 1983 and 1986, on the evolution of electricity networks with the introduction of concepts of "seamless webs" to describe complexity comprising technological as well as social and institutional dimensions). Conversely, the (simulation) modeling strategy in the analysis of the complexification of entire technological systems has not been taken up in the literature. A possible exception is a pioneering early study by Frankel, 1955, that however was not followed by further model-based analytical studies. Hence our interest to explore a simulation model based strategy in the analysis of the evolution of complexity of technological systems.

The choice of the case study in the area energy systems evolution was based on prior work of the authors, providing hopefully some insights into the historical evolution of energy systems (e.g. Grubler, 1998 and 2004) and more importantly also resulting in stylized model formulations and numerical data inputs for our simulations drawing on the rich tradition of "bottom-up" energy systems models used to develop long-term energy and climate change scenarios (e.g. Riahi *et al*., 2007). Our case study application is also justified by the policy relevance of a more thorough understanding of the evolution of energy systems that are a main contributor to greenhouse gas emissions and hence human-induced climate change (IPCC, 2007) and the interest in understanding better the systems aspects of major technological shifts, such as the ones that will be required for climate stabilization.

1.1. Model Context

The context of our simulation model is a "resource transformation and distribution system" in which technological components ("conversion technologies") link available (primary) resources (fossil and renewable energies) to societal demands (for energy services such as mobility, illumination, etc.). The critical link between *resources* and *demands* is provided by a combination of (interlinked) technologies that are defined at the level of *conversion facilities* (e.g. power plants or end-use devices such as cars, and that are the customary system boundary for the definition of energy technologies in "bottom-up" energy system models; cf. Messner and Strubegger, 1994). Conversion facilities (or "primary technologies" in our model) form *energy chains*[2] (Figure 1), that either operate in "stand alone" mode or (over time) are increasingly interconnected, resulting in technological complexification.

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[2] As will be discussed later, this choice of the level of aggregation for the definition of technologies has not only advantages (like structural similarity and hence comparability and analogues to conventional energy system models) but also drawbacks. The choice of a resource processing system linking primary resources to final demands through technological combinations forming energy chains in our model and study implies also a dominance of linear structures and combinations in our technological system that are a far cry away from the complexity of real-world or simulated systems (e.g. the ones modeled by Arthur and Polak, 2006).

An energy system consisting of various energy chains forms a network with available resources at the input side and energy services at the output side. Alternative technological combinations or chains can provide the same energy services, and hence they compete, i.e. are subject to an (economic) selection environment in our model, as in the real world.

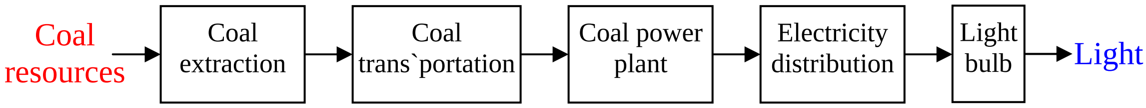

Figure 1. An energy chain for satisfying the demand for illumination.

The emergence of new component technologies as well as their (re-)combination e.g. into new energy chains is essentially conceptualized via a random walk model (reflecting the unpredictability, often serendipity, of technological innovation) subject however to resource constraints and economic incentives. In our model, we assume that the rate of emergence of new technologies and new technological combinations is a function of available (financial and human capital) resources that can "generate" innovations, modeled simply in proportionality to the size of the economy and the resulting demand for energy services. Also, we assume that economic incentives can trigger innovation, e.g. rising energy prices would result in a higher propensity for innovation and hence higher probability of emergence of new technologies.

In other words, we assume that the larger a system (in terms of energy services demanded), the larger the propensity to innovate and the larger the rate of emergence of new technologies and the possibilities for new (re-)combinations would be. Higher energy prices add an additional incentive to increase the dynamics of this process.

Once in existence, new technologies or combinations cannot survive indefinitively. Either technologies are not retained once integrated into existing or emerging technological combinations (chains)[3], or they emerge "prematurely" and cannot be integrated into any available technological combinations. For the former case, the concept of "selection environment" (inspired by the work of evolutionary economists, e.g. Dosi, 1982) is key. We adopt in our model an essentially economic interpretation of the selection environment governing the survival of technologies or their combinations comprising both endogenous (e.g. the evolution of technological process efficiencies and costs) as well as external factors (e.g. a change in relative prices through taxes that reflect environmental and other externalities) that alter the competitiveness of alternative technological combinations and hence over time change the evolution of our technological system.

The selection environment for technologies is characterized by several features, reflecting a number of "stylized facts" emerging from the literature (e.g. Dosi, 2000).

[3] Consider the example of the Stirling engine that despite being known for almost 200 years and demonstrated as feasible (functional toy kits are available on the market) has to date not been integrated into existing energy systems.

First, not only the technological "landscape" but also the characteristics of individual technologies are dynamic. Second, the selection environment is characterized by persistent uncertainty (in both exogenous and endogenous variables). Third, the selection criteria have an important economic dimension, i.e. among alternative choices, the cheaper technological combinations (chains) providing a given service demand will prevail over time. Decisions operate however under uncertainty and with imperfect knowledge and localized "learning", i.e. a given existence of a (functional) technological combination with certain economic attributes (e.g. costs) creates a propensity for adoption that evolves however only gradually as a result of localized learning and its ultimate spillover into the entire system. This is in contrast to traditional deterministic "bottom up" and "top down" energy (and economy) models that assume perfect foresight and thus instantaneous adoption of new technologies and combinations universally. Finally, supply and demand in our model co-evolve. While on the one hand, energy service demands are assumed to be given (represented by an exogenous scenario in our model simulations), new technological combinations can also create new demands. An example is the emergence of electricity, first introduced for substituting town gas as source of illumination and subsequently finding new applications, e.g. in communication (telephone) or mobility (street cars).

We reflect the above "stylized" characteristics of the selection environment by a number of (simplified) model assumptions and formulations. The dynamics of technologies are assumed to be governed by uncertain increasing returns to adoption, i.e. the more a technology is tried, the higher its probability that it actually improves, modeled here via a learning-by-doing (learning curve) formulation that is however treated as uncertain. Localized learning is represented by a kind of probabilistic model representation of the adoption process in which new information on technology characteristics (e.g. their costs) takes time to percolate within a system and the propensity for adoption is assumed to inversely proportional to realized deployment levels. These assumptions imply that recent technologies with highly uncertain characteristics and small market volume will be adopted only very cautiously, yielding the classical slow take-off pattern characteristic of technological diffusion (Grubler, 1991). We also use a variable in the model that represents innovation impatience: modeled via a "retention time" variable for newly emerging technologies that cannot be integrated immediately into new technological combinations but nonetheless "stay around" for a while awaiting potential integration into the technology system. Evidently, with high innovation impatience (short retention time), many new technologies emerge, but subsequently disappear before they can be integrated into new technology combinations.

The key research question in this paper is to understand how a (stylized and highly simplified) energy system bootstraps and evolves. To that purpose we develop a new model for simulating technological complexification that is used to generate alternative "histories" (and futures) of the evolution of the global energy system. We perform a large number of simulations (200) and then analyze the simulation runs for differences, coherent patterns and emerging properties, characterizing technological complexification.

A particularly novel feature of our agent based model is that it treats technologies, or their constituent components, as "agents" while preserving innovation and economic drivers as main components of the evolutionary algorithm underlying a continued (re-)combination of technologies resulting in an emergence and subsequent "organic" build-up of novel systems structures, punctuated by Schumpeterian "gales of creative destruction" (Schumpeter, 1942) resulting from the emergence of new technologies and of new technological combinations.

2. The Model

2.1. Main Characteristics of the Model

In our model, energy technologies, the technological constituents of our system (our "agents"), are defined at the level of a facility/plant or a device that transforms resources or energy flows following both the tradition of activity or process analysis (Ayres and Kneese 1969) as well as that of "bottom-up" energy models (e.g. Messner and Strubegger, 1994). Technologies have characteristics, defined by their resource/energy inputs, outputs, resulting efficiency, and associated emissions, and costs (for sake of simplicity we use levelized costs, i.e. do not differentiate between capital and operating costs of technologies). It is these characteristics of the technologies that govern their long-term survival under the selection environment of our technology system (and not their mere existence).

Energy chains are *linked* energy technologies that connect primary resources or energy sources/forms to the energy service demands of consumers. Energy chains are either new combinations of primary energy technologies or re-combinations of previously existing components (groups of technologies or entire chains). The concept of energy chains is central to the technological system modeled here: It reflects both the necessary supporting "front-" (upstream) and "back-end" (downstream) of individual technologies (e.g. the electricity supply chains necessary to make a light bulb shine). Conversely, it also implies a certain dominance of "linear" combinations of energy technologies, characteristic for systems at our chosen level of aggregation, but that may not necessarily be the case when modeling other technological systems (e.g. the electronic circuits studied by Arthur and Polak, 2006). We contend, that these largely "linear" systems structures emerging from our model simulations are first of all the result of our chosen level of aggregation (energy facilities), but further studies and model extensions will be needed to corroborate this hypothesis.[4]

An *energy system* is a system consisting of an ensemble of energy chains that can satisfy a specified bundle of energy services linking primary energy with combinations

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[4] We plan to relax the simplifying assumptions underpinning our definition of technologies in future modeling studies. E.g. instead of defining a "technology" at the level of a physical plant/facility converting resources or energy carriers (e.g. a coal fired power plant generating electricity), one could also define the technologies of our system at the level of component technologies (e.g. a boiler, steam turbine, and generator, for our coal power plant example), yielding more complex system structures. Lack of suitable data underpinning our simulations have precluded this extension to date.

of technologies to satisfy final human service demands. (A description and graphical overview is given in Section 2.2 below. Numerical details are given in Appendix B.)

In our model, new energy chains are constructed from components that previously exist; and in turn these new chains offer themselves as possible components – building blocks – for the construction of further new chains. In this sense, energy chains build themselves out of themselves changing the morphology of previously existing energy systems. The evolution of an energy system is ultimately driven by final human service demands and by the demands created by new energy technologies/chains. For example, demand for mobility pulls the development of transportation technologies, such as cars; and cars generate a market for gasoline, and the demand for gasoline will further pull the development of technologies such as transport and retail infrastructures, oil refineries, oil extraction, and so on. We also consider the fact that some final human demands are triggered by the availability of new technologies, for example, it is after computers became available that demands for some of the services provided by computers developed.

The emergence of new energy technologies or combinations in the form of new energy chains is a stochastic process, whereas the further existence of existing or newly formed technological combinations (chains) is governed by an evolutionary algorithm of "survival of the fittest" largely based on economic criteria. Costs include both intrinsic characteristics of technologies (initial values as well as possible changes over time, i.e. costs can fall as a function of increasing returns to adoption), as well as external costs (represented in our simple model through a carbon tax to reflect climate change externalities). The simulation model is described in more detail in the following paragraphs.

Consider a following analogy: Energy technologies are cards on a table and final human service demands are cards on a board above the table. Existing technologies and chains can be viewed as face-up cards on the table; there are also potential future technologies/chains (face-down technology "wildcards") which are not available currently. From time to time, some face-down cards will turn over and become existing technologies (at random draw). We start our simulations from a few existing energy technologies (not energy chains) and several energy service demands reflecting the historical situation before the onset of the Industrial Revolution.

In each year (represented by a simulation step), a certain number of “draws” and “combinations” will be carried out. Here *draws* mean the introduction of new technologies. At each draw, with a certain probability, a future technology is randomly selected and becomes an existing one. *New combinations* emerge when existing technologies or entire chains are melded together to form new chains. For each attempt of combination, the model randomly selects any two energy technologies and/or chains from the table to see whether they can be linked – by linking the output of one technology (chain) to the input of another technology (chain). If they can be linked, the model checks whether the technological combination(s) can satisfy at least one kind of energy service demand. If a technology combination can satisfy an energy service demand, that combination is added as "existing" to the portfolio of technological combinations/chains characterizing the energy system at a particular point in time of our simulations (i.e. it is added to the "table" as an existing technology combination/chain). In case a new technological combination/chain creates a new demand (out of a range of pre-specified potential demand categories), the new demand is retained as well (i.e. added to the "board").

The number of draws and combinations in each year is responsive to the two most pertinent variables affecting technological change: available resources (financial and human capital) and prices. Thus, as the size of the economy grows (approximated by the growth of energy service demands in our model) or prices increase rapidly, the search for new technologies will be higher than in small-size economy/low price scenarios. Thus, the number of "innovation draws" and of technological combinations is a combined function of size of the system and energy prices [see Eq. (10) in Appendix A].

As the simulation progresses, any given final energy service demand could be satisfied by several viable energy chains. A viable chain is defined here as a combination of technologies that can link primary energy resources with final human service demands. For a newly formed viable chain, we assume a small market share, no matter how expensive it may be. This reflects our interpretation of the history of technological innovation that is governed by *expectations* (e.g. of future cost reductions, or market viability under possible external constraints, e.g. carbon taxes in our case).

The cost of technologies and their combination into energy chains are treated as dynamic due to technological learning and resource depletion. We also consider in a stylized fashion that demand quantities interact with prices (reflected in the costs of our technology chains), adopting the concept of income and price elasticity of demand into our simulation model [see Eq. (4) in Appendix A]. These three basic assumptions governing the relative economics of technological combinations and the dynamics of the technology portfolios of evolving energy systems, reflect our interpretation of the most salient economic drivers in the long-term evolution of energy systems (see Nakicenovic *et al.,* 2000; Grubler *et al.,* 1999): resource discovery and depletion, dynamic costs of energy technologies due to (uncertain) increasing returns to adoption (uncertain "learning" effects), and in turn their feedback on energy service demands (via price elasticity in addition to income elasticity).

The next issue is to address the nature of the genetic algorithm that simulates the survival and competition among alternative technology combinations/chains satisfying particular service demands. We assume that relative costs govern the long-term "survival of the fittest" technologies. At each step, if one viable chain is cheaper (considering both internal as well as external [environmental externality] costs) than the weighted average cost of all viable chains satisfying the energy service demand [see Eq. (5) in Appendix A], its share will increase, where the degree of market share gain is assumed to be proportional to the respective cost differences. The bigger the difference (i.e. compared to the average costs), the bigger the market share increase will be. The share of chains more expensive than the weighted average will decrease as well. The mathematical expression of the dynamics of chain market shares is given by Eq. (5 to 7) in Appendix A.

For the dynamics of final service demands in our model, we assumed first an exogenous rate of increase for the aggregate economy that yields increases in income and hence (with an assumed income elasticity) an exogenous increase in service demands. Energy service demands are also influenced by the price for satisfying them, which is calculated by the weighted average cost of viable chains satisfying a particular energy service demand. Changes in prices translate into changes in service demands via price elasticities. Each final energy service demand is recalculated with the assumed price elasticities at every simulation step [5]. Thus final energy service demands are determined both exogenously and endogenously in our model.

As concerns resource depletion, we simply assume the cost of extracting primary energy resources increases with cumulative extraction. We draw on the quantifications of cumulative resource extraction cost curves of Rogner (1997) for our model parameterization. Of course, things could be more complex in reality: As new energy resources are discovered, or resource extraction costs are lowered due to technological change (which is not modeled here), extraction costs could well be constant or even decrease over time, as opposed to the increasing trends due to resource depletion suggested by our simple model.

Finally, costs of technologies or of technological combinations/chains are considered dynamic in the simulations reported here. Again this reflects our interpretation of one of the most important "stylized facts" in the historical evolution of energy systems (Fisher, 1974, Grubler *et al*., 1999). We assume the existence of learning effects for new primary energy technologies, which means costs can decrease with cumulative experience (technology deployment or adoption). Technological learning is a classical example of increasing returns (see Arthur 1983 and 1989). However, technological learning is also highly uncertain, evidenced by both empirical (e.g. see IIASA-WEC, 1995 and Nakicenovic *et al*., 1998) as well as modeling studies (Gritsevskyi and Nakicenovic, 2000; Grubler and Gritsevskyi, 2002). In our model, we assume that potential future learning rates of new technologies are random values around mean expected values (with lognormal distributions) following Grubler and Gritsevskyi (2002).

Appendix A summarizes the mathematical expressions and numerical values of above genetic algorithm governing competition and ensuing growth, survival, and decline of technological combinations/chains in our simple simulation model.

2.2. The Reference Energy System

For our simulations, we use a hypothetical, simplified, but to a certain degree realistic representation of the global energy system as it has evolved since the Industrial Revolution. The constituents (technologies) of the energy system are represented by customary engineering and economic variables that are treated as dynamic in the

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[5] This explains the pattern of drastically reduced service demands in some of the simulations reported below as a function of increasing costs (e.g. due to resource depletion and under absence of potential learning [i.e. cost lowering effects] of new technological combinations/chains).

simulations. A schematic overview is given in Figure 2 depicting the reference energy system at step 300 of our simulations.

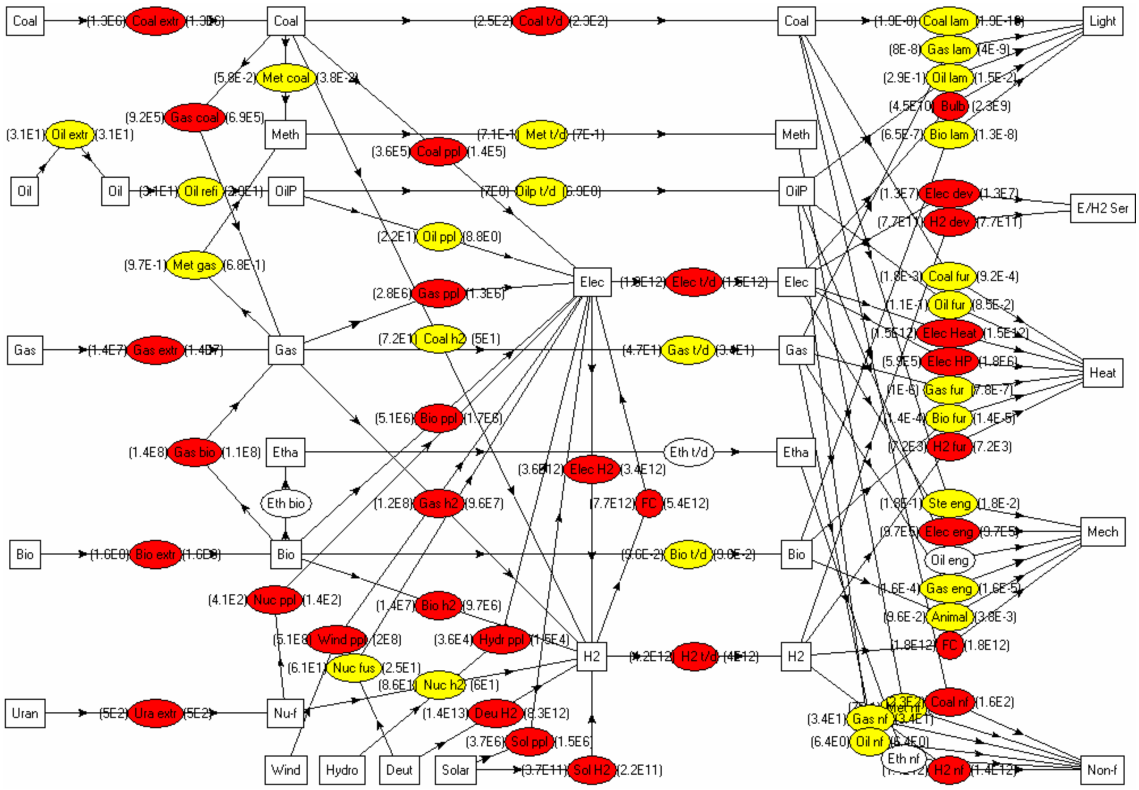

Figure 2. An overview of the simplified reference energy system in the model simulations. Squares denote energy resources, energy carriers, or energy service demands (always shown in white color). Ellipses represent primary energy technologies, the basic constituents of the model that combine into alternative energy chains. The technology color codes indicate the level of deployment of various technologies ranging from large (red), very small (either emerging embryonic technologies or technologies being phased out, yellow) to technologies not used at all (white). Arrows indicate the direction of linkages, whereas the extent of linkage is given as numerical values of the corresponding energy flows. For high resolution pictures and dynamic simulations see http://www.iiasa.ac.at/Research/TNT/WEB/ABES_08/

Our simplified energy system is composed of 62 primary energy technologies which are stored in a "technology base" at the beginning of the simulations. The 62 primary technologies are classified into three groups. The first group consists of 5 very basic technologies -- biomass extraction, biomass transport and distribution, biomass burning for providing illumination, biomass furnaces for providing heat, and (biomass [feed] fuelled) horses that provide mobility. Technologies in this group are all available at the beginning of the simulation, as representing the main energy technologies extant before the onset of the Industrial Revolution. The second group consists of 49 "traditional" technologies related to the application of fossil fuels and also hydropower. They become available randomly after our simulation starts, with 0.01 probability (at each step) that one of them is drawn out from the "technology (knowledge) base". The third group of technologies consists of 8 so-called "advanced" technologies, such as hydrogen fuel cells. They are assumed to start to become available randomly after some 130 simulation steps, also with 0.01 probability that one of them is drawn out from the "technology base". Finally, we also deploy the concept of "backstop" technologies, i.e. technologies that are assumed to exist and can be taken "off the shelf" in case they are needed (especially to assure a feasible model solution). The existence of "backstop" technologies is an optional feature in our model; simulations can be performed with or without the availability of "backstops" (see Section 3 below). All the technologies, except resource extracting technologies, are assumed to exhibit uncertain technological learning effects, i.e. a technology's cost will decrease with its cumulative output.[6]

Our simplified energy system is in addition defined by the following 5 energy service demands:

- illumination (light);
- specific services provided by devices consuming electricity or hydrogen (in addition to other energy services), e.g. telecommunication (E/H2 Ser);
- heat;
- mobility and/or mechanical energy (Mech);
- industry feedstocks, i.e. energy used for non-energy purposes (Non-F).

Simulations start initially for the four energy service demand categories excluding E/H2, with the latter only emerging once corresponding supply technologies become available.

At the resource side, we consider 9 kinds of natural resources: biomass, coal, oil, gas, uranium, hydro, wind, solar, and deuterium. We assume the first 5 resources are depleteable, which means their extraction costs will increase with (cumulative) extraction; hydro and wind are treated as renewable, without depletion effects but with upper limits on their annual supply potential; solar and deuterium are considered as backstop resources, without any depletion effects or upper limitations on their annual potentials.

Figure 2 shows the energy system at the end of a simulation, with the 9 resources at the left side and the left-bottom, the 5 energy services at the right side, and the 62 primary technologies forming a network to link energy services to resources. Details and numerical parameters of the simplified energy system and of our model can be found in Appendix B.

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[6] As modeling simplification we simply assume that historically new technologies, when they emerge are a factor 3 higher compared to the period of their maximum use and exhibit a mean learning rate of 10% per doubling of cumulative output. For the 8 current advanced technologies we assume a mean learning rate of 30% and initial cost estimates are derived from the scenario literature (Nakicenovic *et al.,* 2000). All learning rates are treated as uncertain. Cost of extraction technologies are assumed to be determined soley by resource depletion and are modeled after the data given in Rogner, 1997.

3. Model Simulations

For exploring the evolution of the energy system, we first run 200 base case simulations with base-line parameter values as specified in Appendix B. We run each simulation for 500 (time) steps (akin to years[7]). We then perform additional sensitivity runs, altering model assumptions to explore their influence on the evolution of the energy system.

We report below some persistent patterns and robust features ("stories") that emerge in our model simulations and that characterize the long-term evolution and complexification of the stylized global energy system of our model.

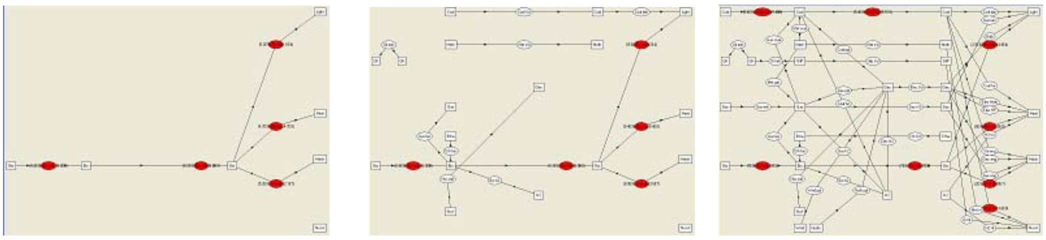
3.1. Bifurcation, Lock-in, and Path Dependence

One of the most intriguing findings from our simulations is the degree of chance and serendipity characterizing the evolution of our simulated technology system. With identical initial conditions, identical suite of potential technologies that can emerge (be discovered), and identical technological and economic characteristics of technologies and drivers (e.g. service demands), nonetheless different system's structures emerge across the simulations. Alternative histories and futures unfold in different simulations, providing numerical illustrations for both counterfactual historical thought experiments and alternative future scenarios.

Given identical initial conditions, the energy system self-organizes into alternative different structures, evolves ("locks-in") into alternative different directions that persist. This feature of bifurcation, path-dependence and emergent properties is a result of the randomness of the innovation process combined with a random walk model of increasing returns to adoption is a dynamic behavior that to our knowledge has not been described in any energy model to date. The state of art describes such bifurcations usually by varying exogenous assumptions across different simulations (scenarios), while in our case differences emerge endogenously with identical assumptions and initial conditions. Figure 3 provides an illustration of this bifurcation and path-dependence showing the results from two simulations (Sim159 and Sim53) at identical time steps (1, 20, and 50).[8]

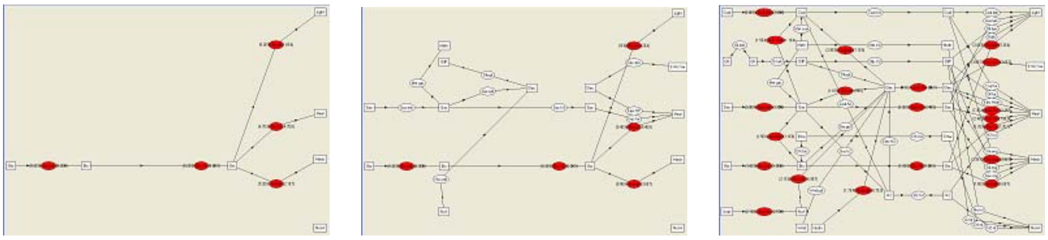
[7] Readers wishing to position our simulations in "real", historical time should consider the present anyway between simulation time step 100 to 120 in our "simulated, virtual" years of the evolution of the global energy system.
[8] The full results of all 200 simulation runs over 500 time steps can be accessed at http://www.iiasa.ac.at/Research/TNT/WEB/ABES_08/

Simulation ID = 24 (Sim24).



Step = 1 Step = 20 Step=50

Simulation ID = 50 (Sim50).



Step = 1 Step = 20 Step=50

Figure 3. Alternative structures of the energy system evolving in two illustrative simulations: Sim24 versus Sim50 for three time steps. Red ellipses denote technologies in actual use.

Since the two simulations start with identical initial conditions, the structures of the energy system at step 1 are identical as well, basically describing an energy system as it prevailed before the advent of the Industrial Revolution. With the random emergence of new technologies and a selection environment characterized by uncertainty, localized learning and (uncertain) increasing returns to adoption, available technologies as well as their deployment levels are radically different. For instance at time step 20 *Gas bio* (gas from biomass) are available in Sim159 while not available in Sim53, while *Oil ppl* (oil power plant) and *Gas ppl* (gas power plant) are available in Sim53 while not available in Sim159. At step 50, although available technologies in the two simulations are almost the same (except *oil lam* [oil lamp]), *oil fur* [oil furnace for heating] and *Oil eng* [oil engines for motive power] which are still not available in Sim159, the structures of the energy system in the two simulations are nonetheless quite different. In Sim159, the energy system relies on coal and biomass; while in Sim53, besides coal and biomass, (natural) gas and (nuclear) uranium are also used, and various electricity generating technologies are applied to generate electricity from coal, gas, biomass, uranium, and hydro with electricity beings used to power end-use devices such as *Elec HP* (Electric air-condition).

Figure 4 plots the dynamics of resource extraction from time step 50 to step 160 for our two illustrative simulations Sim159 and Sim53. In Sim53, nuclear dominates from around time step 70 to around 110; in Sim159, over the same period, coal dominates initially, with the system switching to a diversified resource portfolio relying on nuclear, gas and coal.

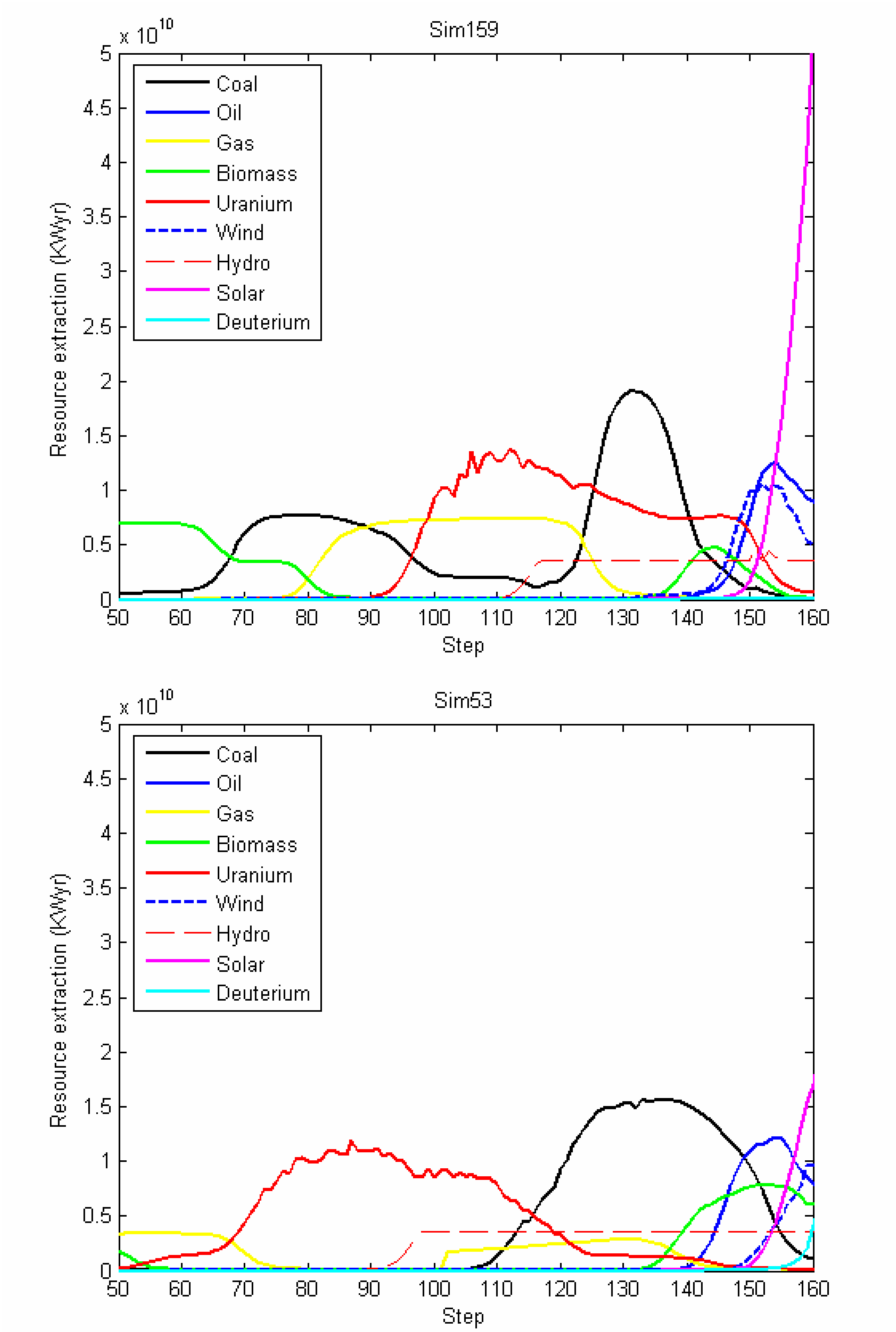


Figure 4. Dynamics of resource extraction (in KWyr) in two simulations: Sim24 versus Sim50 over time steps 50 to 160.

Over the very long-term (300 simulation years) the energy system invariably shifts to solar or deuterium (or both) due to depletion effects for fossil resources and limits on the harnessing of the conventional renewable resources wind and hydro (Figure 5). Technologies relying on deuterium or solar (fusion or solar power plants) can be considered as the long-run "backstop" technologies of the energy system in the sense that even when all other resources are depleted, the energy system can always rely on those technologies. Figure 5 is an example of “path-dependence” of the model – with the exactly same initialization, Sim159 ends with a *solar-dominated*, while Sim53 ends with *deuterium-dominated* energy system, albeit at different levels of resource use and energy service demands. This indicates a pattern in which the long-term evolution of energy systems, both in terms of resource use (and the corresponding environmental externalities, such as carbon emissions) as well as energy (service) demands are *technologically constructed*, indicating the importance of technology as policy leverage in coming to grips with the negative environmental consequences of global change.

Many other simulations end with a combination of both *deuterium and solar-dominated* technologies. As such, the hypothesized (Haefele *et al.*, 1981) emergence of "*Solfus"* as ultimate long-term "winner" in a resource constrained global energy system appears corroborated by our simulations.

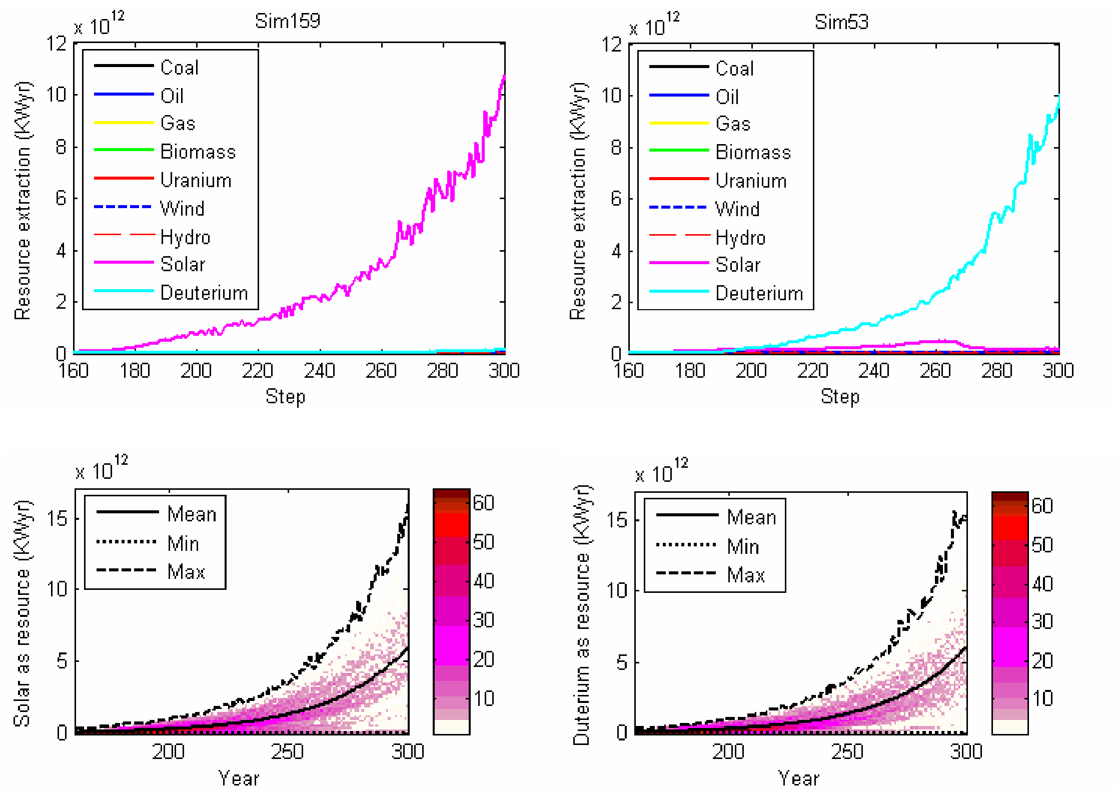


Figure 5. Long-term bifurcation of the energy system into reliance on alternative “backstop” technologies solar or fusion (extraction rates in kWyr): Sim159 (left) versus Sim53 (right) over time steps 160 to 300 (top panel) and distribution of long-run extraction rates for solar(left) and fusion (deuterium, right) across all 200 simulations (bottom panel).

Readers might object to above conclusions on the importance of historical or future *alternative* contingencies, i.e. the powerful effects of small random events that can "tilt" the system into persistent, alternative directions (and thereby permanently exclude the possibility of some futures). However, our results rather suggest the importance of human agency (intentionality and choice) in the long-run evolution of technological systems that even if represented as being random in the model, nonetheless lend itself to policy intervention in the real world. Imagine Thomas Edison (and many of his contemporaries like Nikola Tesla) never existed, or alternatively, that he would have been instead a contemporary of James Watt. Would we expect the energy system of today in its current configuration? Our results indicate not. Perhaps the most important lesson to draw from our simulations is the potential of policy interventions that can trigger long-run bifurcations in large technological systems such as energy: nurturing the emergence of alternatives and influencing the selection environment through policy signals (cf. the discussion of the influence of a carbon tax below), that when measured at the scale of the system at stake, might appear minor "perturbations", but could nonetheless provoke lasting long-term bifurcation effects.

An important conclusion from our model simulations is that random perturbations over short periods of time have little long-lasting effects. For instance, increasing randomly enormously the rate of emergence of new technologies for a limited period of time (e.g. through an R&D effort of the size of the Apollo Project), is unlikely to trigger long-term bifurcations in energy systems.[9] Providing incentives for an incremental increase in the propensity to innovate across the entire technological "landscape", coupled with consistent signals to change the economic incentives prevailing in the technological selection environment (e.g. through carbon taxes) *might* result in drastic system transformations.

3.2. Complexification versus technological "denudation"

Starting initially with only 5 primary technologies, the structure of the energy system becomes invariably more complex in all simulations, as new technologies appear and become integrated into the system by recursive combinations with existing technologies and chains as well as competing with each other. However, while complexification is a powerful tendency, the simulations reveal as well that complexification cannot unfold indefinitely, nor that it is preordained. Technological systems complexification emerges as a consequence of both the characteristics governing technology dynamics as well as that of the selection environment. More and more complex in terms of technology is therefore not a safe bet to use in historical as well as prospective studies of the global energy system without a careful consideration of both the endogenous and exogenous environment under which technological complexity evolves.

[9] In a sensitivity analysis we increased the probability of emergence of a subset of new technologies (i.e. of group 2, that represent current technologies [the largest number of technologies in our model], i.e. excluding pre-industrial as well as advanced future technologies) by a factor of 5. Nonetheless, despite this simulated "innovation frenzy" the impact on technological complexity remains very small, cf. Figure 6 below.

As measure of complexity, we simply use the notion of *viable energy chains* characterizing an energy system. A viable chain means a full energy chain which starts from extracting resource and satisfies a final energy service demand. When a viable chain has a market share above 0.1%, it is considered to be in use. As aggregate measure of complexity, we simply consider the number of viable energy chains in use and that characterize different energy systems over time. Given that we have run 200 simulations it is necessary to summarize their diversity into simpler aggregates. To that end Figure 6 below summarizes our simulations in terms of the average over 200 simulations. (For a full display of heterogeneity see Figure 7 below).

An invariable pattern emerging from our simulations is that of a "complexity peak". Whereas initially technological complexity in terms of number of energy chains in use increases, it reaches a peak around time step 150, and declines thereafter. Increasing complexity is the result of recursive combinations of technologies, whereas decreasing complexity is the result of “lock-out” effects of technologies or Schumpeterian “creative destruction”: Newly formed viable chains with advanced technologies increasingly squeeze out existing viable chains that are progressively loosing their economic competitive edge due to resource depletion. Since in our simulations the system does not have an infinite suite of new technologies that can be introduced, after some time (i.e. around step 150), technological “lock-out” effects start to dominate over recombinatory (complexification) effects. The end result is a drastic decline in technological complexity. After some 400 time steps (or years), the level of complexity of the energy system in our model is back where it started at the onset of the Industrial Revolution. Evidently this result could to a certain degree be an artifact of our modeling protocol (innovations can only randomly appear out of a pool of pre-defined technologies that ultimately becomes exhausted). But there is also a deeper reason as well: resource depletion. With the onset of depletion effects (increasing resource costs), increasingly fossil fuel technologies and energy chains, that have traditionally provided for much of technological variety and complexity in the energy landscape become "locked out" and the systems relies increasingly on the two major "backstop" resources: *solfus* (solar and fusion) and the corresponding key conversion technologies for electricity and for liquid fuels (hydrogen). The significantly higher (in fact the highest) complexity of the model simulations without available backstop technologies (Figure 6) reconfirms this notion. This increasing dependence of a few key technologies over the very long-term was hypothesized as early as 1956 by Harrison Brown, who referred to it as *"technological denudation."*

3.3. Increasing returns and crowding out

Another interesting finding from our simulations is that complexity and increasing returns to adoption are to a certain degree at odds with each other. In order to analyze this effect we have performed a sensitivity analysis of 200 additional simulations with a drastically lowered mean learning rate parameter.[10] In the "low learning" case,

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[10] In the baseline simulations we have assumed mean learning rates of 10% for existing, and of 30% for the 8 advanced technologies. In the "low learning" simulations we assume mean

technological complexity of the energy system is both higher in absolute terms as well as exhibiting a substantially later peak (at time step 190, as opposed to 150 in the baseline simulation) before eventually also entering the pathway towards technological denudation as a result of resource depletion. Figure 7 shows the full results of all 200 simulations for both the baseline and the low learning case. The calculated averages are reproduced in Figure 6 to allow easier comparison with other model sensitivity runs on the evolution of technological complexity.

The effects of increasing return ("learning") phenomena on the economics of large technological systems are well established and important in our simulations as well (see Figure 8). However, the effects of increasing returns on energy systems complexity and variety need also attention. On one hand, evidently the economic benefits of an increased reliance on a few key technologies that exhibit increasing returns to adoption are substantial (a factor of more than 100 in our simulations, cf. Figure 8 below), and the corresponding lower level of technological complexity could also have some risk benefits as well (lower vulnerability to disruptions of interconnections between technologies and energy chains). However, lower complexity also means less variety in the system and thus increased vulnerability in case of a sudden change in external conditions or the selection environment. It remains an open research question of how to weigh the respective economic benefits of increasing returns with the corresponding disadvantages of less complexity and variety due to the increasing "lock out" of alternative technologies and of technological combinations.

Even with a stylized and simplified model, we nonetheless offer a final observation that may be useful in directing future research into the historical evolution of energy systems. In our baseline simulations we have assumed a mean learning rate of 10% (per doubling of cumulative output). Combined with our assumed rate of appearance of new technologies and the resulting propensity for new combinations to emerge, our simulations suggest both many alternative development pathways and comparatively little pre-mature technological lock-in (at least in the first 150 years of our simulations), which is in stark contrast to the historical record.

This contrast between the model simulations of many possible development paths and the history of energy systems “lock-in” lends itself to two possible interpretations. Either, history is indeed an almost random realization of many potential alternative histories that could have unfolded under a different combination of small random events. Or, alternatively, the historical record of technological "lock-in" (first in a coal dominated steam economy in the 19th century, and then an oil dominated internal combustion/electricity dominated one in the 20th) suggests that historically our baseline model assumptions do not hold. Either the rate of appearance of innovations is far more discontinuous and clustered than suggested in the smoothly growing trajectory of our model simulations, or the mean learning rate (i.e. extent of increasing returns to adoption) is significantly higher than the 10% assumed here for the technologies characteristic of the 19th and 20th century global energy system. Or, the historical

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learning rates of 1% and 3% respectively. As mentioned above, learning rates are treated as uncertain, however we have not varied the uncertainty surrounding learning rates in this sensitivity analysis, just the mean.

record is a result of a combination of both phenomena, a hypothesis which we suggest as worth exploring further in future studies.

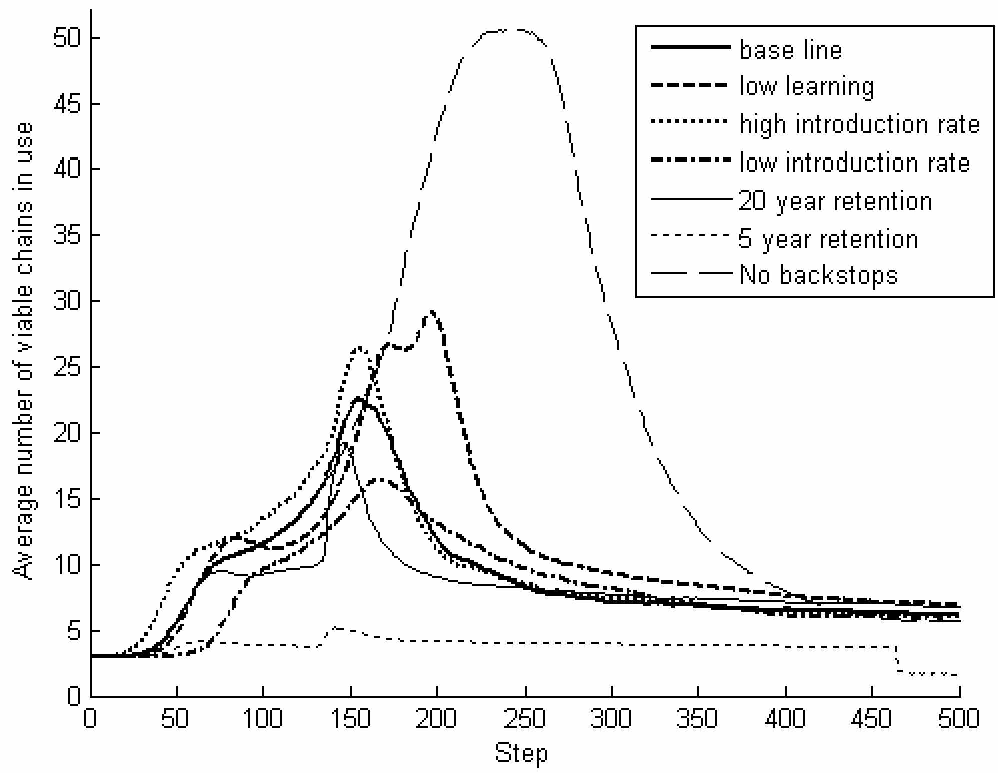

Figure 6. Complexification of the simulated global energy system (average of 200 simulations each) as a function of varying characteristics of technological evolution and of the selection environment. The scenarios shown include: base line simulation (with parameters set as given in Appendix A and B), lower learning rates (smaller increasing returns to adoption), changing the rate of emergence of new technologies (low and high introduction rates), reducing "innovation patience" (i.e. the retention rate of new technologies in the system to allow for emerging new combinations) parameter from 500 years (base line) to 20 and 5 years respectively, and finally, exclusion of "backstop" technologies. The biggest impact on technological complexity results from varying the "innovation patience" parameter, followed by learning rates, and the availability of backstops. Conversely, the impact of varying the rate by which innovations emerge (i.e. are randomly drawn out of a pre-defined "pool" of potential technology-knowledge base) is comparatively limited.

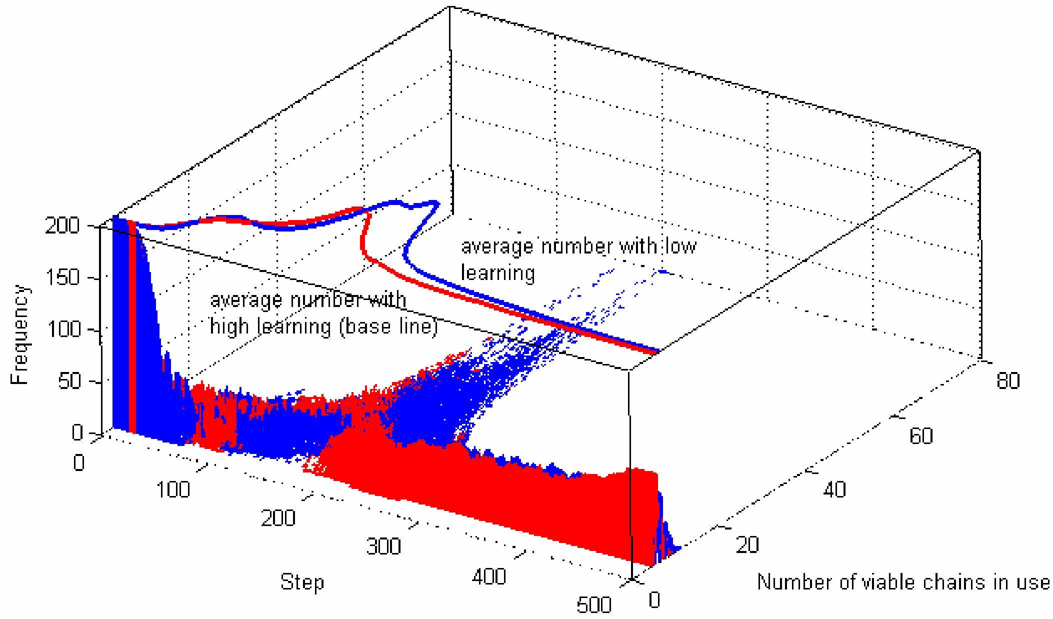

Figure 7. Effects of different learning rates on technological complexification for 200 simulations with 500 time steps each. Note in particular the decrease in complexity in the high learning (baseline) case.

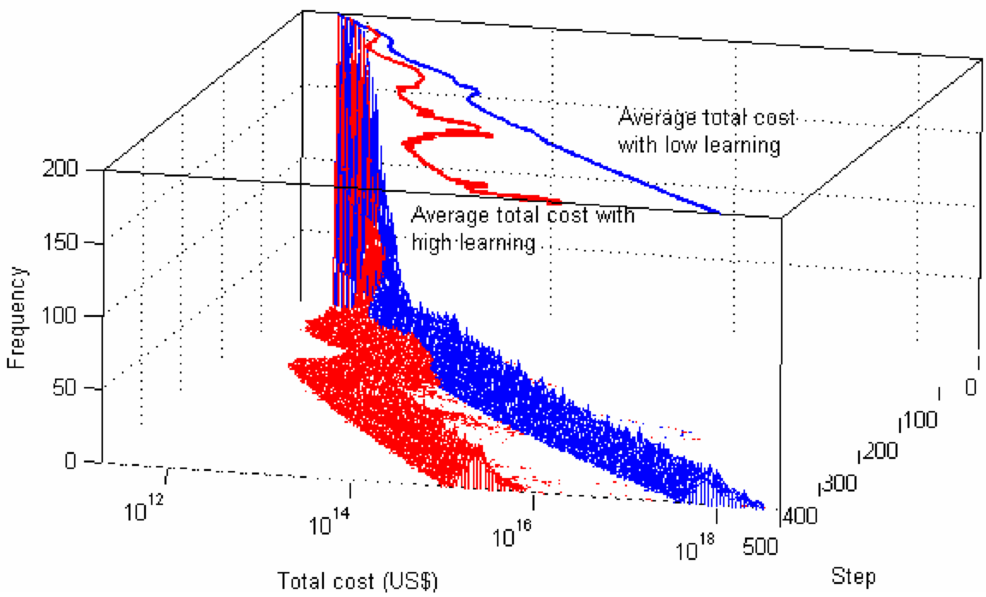

Figure 8. Energy systems costs for two different learning rate scenarios for 200 simulations with 500 time steps each. Note in particular the two orders of magnitude difference in energy systems costs between the two learning rate scenarios at the end of the simulation time period.

3.4. Innovation impatience, recharge, and "forgetting by not doing"

One of the key variables in our (re-)combinatorial evolutionary model of energy technologies and systems is the assumption that once a technology is discovered, knowledge about it will persist and hence this technology is available for new (re-)combinations into the technological landscape quasi indefinitely. There are, however, reasons to challenge this assumption. First, evidently even given the existence of new technological knowledge by someone somewhere does not mean it is available to be integrated into the technological landscape by someone else at another location. Given however the high level of aggregation of our simulation model, we cannot meaningfully address this issue of actor and spatial heterogeneity here. However, we can look at the impacts of relaxing our assumption on the "innovation retention time" in the technological system.

The historical record of technologies provides many examples of the entire disappearance of technologies along with the associated knowledge for their production and use. The famous Sheffield (crucible) steel, whose manufacturing secrets were so well guarded that the technology actually never diffused outside the original innovation center (Tweedale, 1986), no longer exists and the tacit knowledge of its production is no longer available.[11] Thus the corollary of "learning-by-doing" might indeed be "forgetting-by-not-doing" (an adage attributed to the technology economist Gerhard Rosegger [1991]).

Exploring the effects of "forgetting-by-not-doing" is straightforward in our model. We simply vary the "retention time" of newly emerging technologies in the system from quasi infinite (500 time steps) down to 20 and 5 time steps respectively, again performing 200 simulations, whose averages are summarized in Figure 6 above. For an empirical interpretation of our "retention time" variable, consider the case of laser, where several decades passed before an actual application (i.e. an integration into the existing technology system) of this scientific breakthrough was found.

Reducing the innovation "patience" (time) to 5 simulation time steps (years) has an indeed drastic impact on lowering technological complexity. Too little time is left to allow for technologies to combine, chains to be integrated, for bootstrapping of the system in general. The end result is an almost entire lack of evolution of the system and an extremely low level of complexity. Even considering a retention time of 20 time steps (years) that would otherwise be considered generous, we nonetheless observe reduced complexity levels of about one fourth (and with higher energy systems costs as well). The conclusion from our simulations is to highlight the importance of innovation "patience" preserving technological innovation diversity much like biological diversity, as diversity is the ultimate resource from which new combinations and changing practices can be built. Evidently important trade-offs are involved: the extra (current)

[11] Another example of “lost" technology is *Tang San Cai*, Tri-color Glazed Pottery, a gem of ancient Chinese art, which reached its peak during the Tang Dynasty (618-907), in order to entirely disappear under the Song Dynasty (960-1279), cf. see Wang and Zhang (2006).

costs of preserving technological diversity (innovation patience) need to be contrasted with (unknown) future benefits from a larger innovation “gene” pool that nurtures technological change.

Finally, we have also examined the implications of lowering or increasing the innovation rate, i.e. the rate at which random new technologies appear and become available as potential new building blocks for an ever evolving energy system. In a sensitivity analysis we have lowered and increased the introduction (or rather the random sampling) rate of new technologies to 10 percent or 200 percent of that of the baseline simulation and again carried out 200 simulations for each of the two scenarios. The effect is noticeable in Figure 6 above, albeit asymmetrically. Quite counter-intuitively, lowering the innovation rate has a bigger impact on technological complexity, than increasing it, but in both cases it is less drastic than the effect of lowering the innovation retention time. If this pattern would indeed be generic for technological systems, it would suggest a quite stark policy conclusion. From an evolutionary perspective of technological complexity, it is far less important how much resources are used as input to the innovation process (that produce the continuous "recharge" of innovations assumed as an exogenous variable in our model) -- provided that it is maintained. Instead, far more important is to assure innovation "patience", i.e. avoiding knowledge depreciation or forgetting-by-not-doing for extended periods of time in order to increase the chances that new solutions can ultimately be combined into new system components and integrated into the technological landscape.[12]

Perhaps, the most drastic model experiment on technological recharge is to conduct sensitivity analyses on the implications of the unavailability of our combined long-term energy systems backstop technologies under the collective name "solfus". As progressive resource depletion sets in, energy prices soar, which in turn accelerate the rate of introduction of new technologies and of combinations at least temporarily. From all simulations performed, this resource constrained system without long-term viable alternatives (the backstops) turns out to be the most complex in the medium term (reaching a complexity peak some 50 time steps after the baseline simulations and at more than twice its level (cf. Figure 6 above). This increasing complexity is simply due to the absence of "lock-out" effects of the backstop technologies as well as the enormous energy price increases associated with progressive resource depletion. Our simulations illustrate a basic feature of technological innovation: Even embracing an induced innovation perspective, in which innovativeness responds to economic and policy signals, this potential response only materializes in case earlier innovation "recharge" replenishes the pool of potential technological solutions. In the absence of innovation recharge, induced innovation triggers a frantic search, but that cannot find new solutions as these have not been generated previously.

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[12] Using the popular (even if imperfect) metaphor of the "valley of death" of technological innovation our findings suggest that R&D expenditures are less important than keeping the outputs of the innovation process *"alive"* to allow for emerging new combinations. As the above metaphor suggests, nurturing a technological "baby" (innovation through R&D) might be quite useless if later on it is left to peril in the valley of death where the innovation does not find any commercial applications.

3.5. Gales of Creative Destruction

In symmetry to the recursive combinations of new technologies into new energy chains that characterize the growth component of technological evolution, there is also death that does not strike only individual technologies, but entire combinations or chains as well. As increasing returns to adoption favor new technological combinations, these in turn will "squeeze out" existing combinations. Like technological growth, also technological death is characterized by non-linear, avalanche effects. This "fading out" of technological combinations represents the Schumpeterian "gales of creative destruction" in our simulation model. Since the number of new technologies that can eventually emerge is finite in our modeled technology system, at some point in time "gales of creative destruction" will become more prevalent than the technological growth components that lead to increasing "conversion deepening" [13] and complexification. The end result is a decreasing complexity of technological systems.

Figure 9 summarizes all 200 simulations by showing the total number of primary technologies in use as well as the total number of technologies exiting the system, killed by competition of newer technologies and technological combinations. Like emerging technological combinations and systems complexification that come in spurts, also exiting technologies exhibit discontinuous rates and clustering, i.e. *gales of creative destruction*, albeit for different reasons at different periods in time.

Prior to simulation time step 150, increasing death rates of technologies mirror the ascent of more competitive technological combinations, whose competitive advantages evolve non-linearly due to increasing returns. After about simulation time step 150, the mortality of technologies and of technological combinations is increasingly determined by resource depletion effects in addition to innovation effects, but again technological "exit" proceeds discontinuously much like "entry". This clustering effect of technological "exits" is best visible for individual simulations (shown for simulation run 150 at the bottom panel of Figure 9, as the top panel summarizes all technological exits of our 200 simulations). These clustering effects in technology exit emerge from the twin evolutionary drivers modeled explicitly here: (deterministic) technological interdependence, as well as (uncertain) increasing returns to adoption.

[13] Conversion deepening refers to the increasing lengthening of energy chains, which is one of the two components of technological complexification (in addition to the emergence of ever larger number of energy chains).

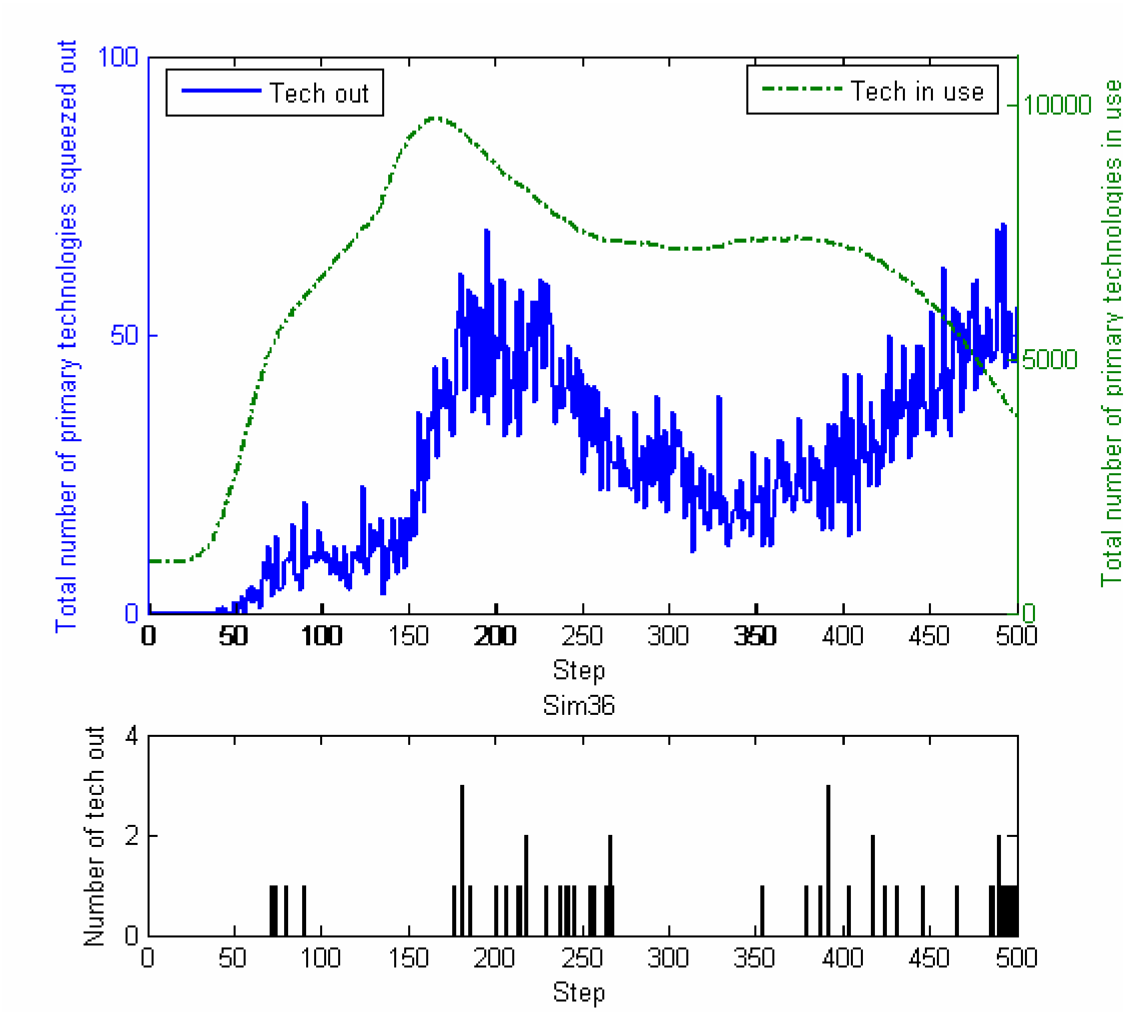
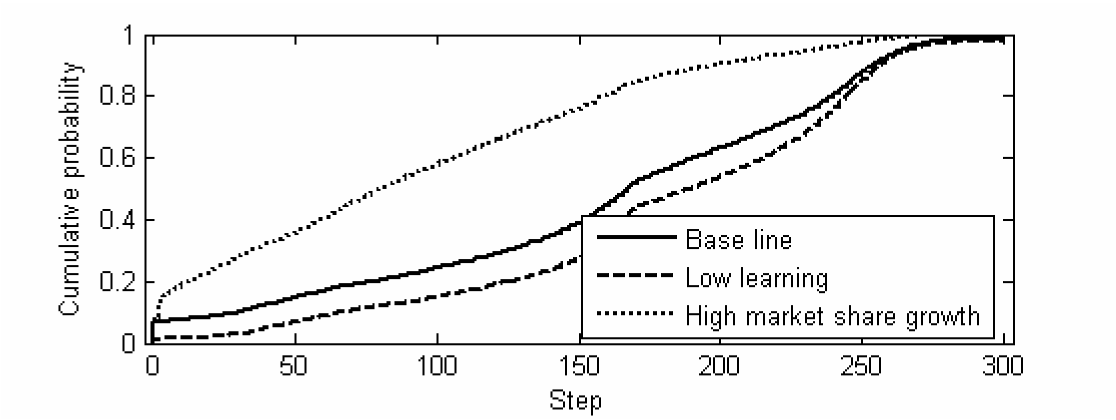


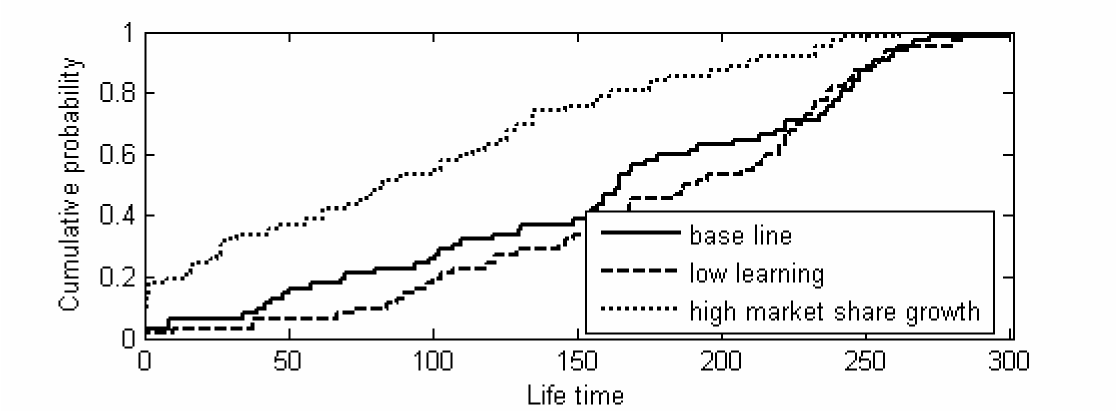
Figure 9. Number of technologies squeezed out versus number of technologies in use, total number of primary technologies in use and exiting the system, totaled over 200 simulations (top panel). The discontinuous nature of technology death is illustrated on the bottom panel for an illustrative simulations (Sim36) showing the number of primary technologies exiting the energy system as the simulation time steps progress. Note in particular the "clustering" of the exit of technologies at time step 100, 200, and 250-270: Gales of creative destruction.

3.6. Methusalem technologies

The above discussion of technological mortality and "exits" should not lead to the conclusion that the "lifetime" of technologies in our system is short. Rather our model simulations indicate the contrary (Figure 10). When analyzing the cumulative distribution of the number of simulation steps/years technologies stay active in the system almost all technologies exhibit a quite surprising degree of longevity. For the base case simulations with higher learning rates, 80% of all primary technologies stay in the system for more than 50 years (simulation time steps), and in the low learning rate simulations with their significantly higher levels of technological complexity, around 95% of primary technologies stay in the system for more than 50 years. By allowing market share growth rates to be as large as possible in another 200 simulations, we found that still around 70% of the technologies stay in the system for more than 50 years.



Life time distributions of all 200 simulations



Life time distributions of average of 200 simulations

Figure 10. Active life of primary technologies: Cumulative probability distribution for base line with high learning rates, sensitivity runs with low learning rates, and sensitivity runs without limitation on market share growth of new technologies and technological combinations (i.e. on instantaneous "flip-over"). Summary distributions are for all primary technologies for 200 simulations each for the three scenarios.

These results suggest that once a technology is introduced into the energy system, it is most likely that it will stay there for a long period of time which adds an important element of technological inertia slowing down radical systems transformations. Our results are in conformity with the characteristic rates of global energy systems transformations that typically take 7 decades up to a century to fully unfold (Marchetti and Nakicenovic, 1979, Grubler *et al.*, 1999). Accelerated rates of radical systems changes and transformation beyond historical experience appear thus only possible if an explicit policy mechanism of Schumpeterian "gales of creative destruction" can be found.

3.7. Environmental uncertainty: Carbon emissions and uncertain carbon-taxes influencing the technological selection environment

Of all environmental externalities, energy-related carbon emissions are recognized as a major source of past as well as future climate change (IPCC, 2007; Riahi *et al.*, 2007). As carbon emissions are endogenously calculated in our simple model we illustrate both their uncertainty as well as their (uncertain) response to environmental regulation (modeled here via an uncertain carbon tax). Carbon emissions are the product of levels of primary energy use times the carbon intensity of primary energy. As levels of energy use are very different across our 200 simulations, we focus below on an analysis of the carbon intensity of primary energy as most succinct variable illustrating the different degrees of environmental climate change externalities associated with the alternative energy systems emerging from our evolutionary model.

As in our previous simulation results, the uncertainty, even given identical initial conditions as well as potential suite of primary technologies available, is substantial (Figure 11) as a result of alternative evolutionary combinations of energy technologies and chains. When comparing our results with historical studies that have described a slow, but steady "decarbonization" of global energy systems (i.e. a declining carbon intensity, cf. Grubler and Nakicenovic, 1996) readers are advised to be cautious: Following standard practice, we have modeled biomass energies as "carbon neutral" in our base-line simulations here, an assumption that seems little warranted from a historical perspective. Including biomass carbon emissions increases our carbon intensity across all simulations (right panel in Figure 11) and shows a persistent trends toward "decarbonization" as the energy system evolves. The mean "decarbonization" rate of the average of our 200 simulation is around 0.3 percent per time step (year), in line with the historical record when including biomass carbon emissions.

Next we analyze the impact of adding a carbon tax. We assume that such a tax is phased in after simulation time step 50 at a range of initial starting values, in order to increase thereafter at an average rate of 2 percent/year, roughly in line with the mean growth of energy demand across our simulations. Figure 12 illustrates the impact of varying the carbon tax from initial levels of 10, 20, 50, 100, and 200 $/tC respectively (while always retaining the assumption of a 2%/yr growth rate in the tax level). It comes as no surprise that the resulting carbon intensity of our energy system is the lower, the higher is the assumed carbon tax.

What is less intuitive, is that the generic pattern of initially increasing, peaking and ultimately declining carbon intensity is unaffected by the different tax levels, although peak levels as well as peak timing are responsive (i.e. occur at lower levels and earlier) to increasing carbon taxes. Apparently, the systems advantages of fossil fuel technologies substituting traditional biomass use[14] and technologies (in terms of energy

[14] Biomass emissions are by accounting convention not included in our base line calculations of the carbon intensity -- hence the initially rising carbon intensities in Figures 11 (left panel) and in Figure 12.

services rendered, efficiencies and costs) are so prevalent as to only be gradually influenced by a carbon tax, even at high levels.

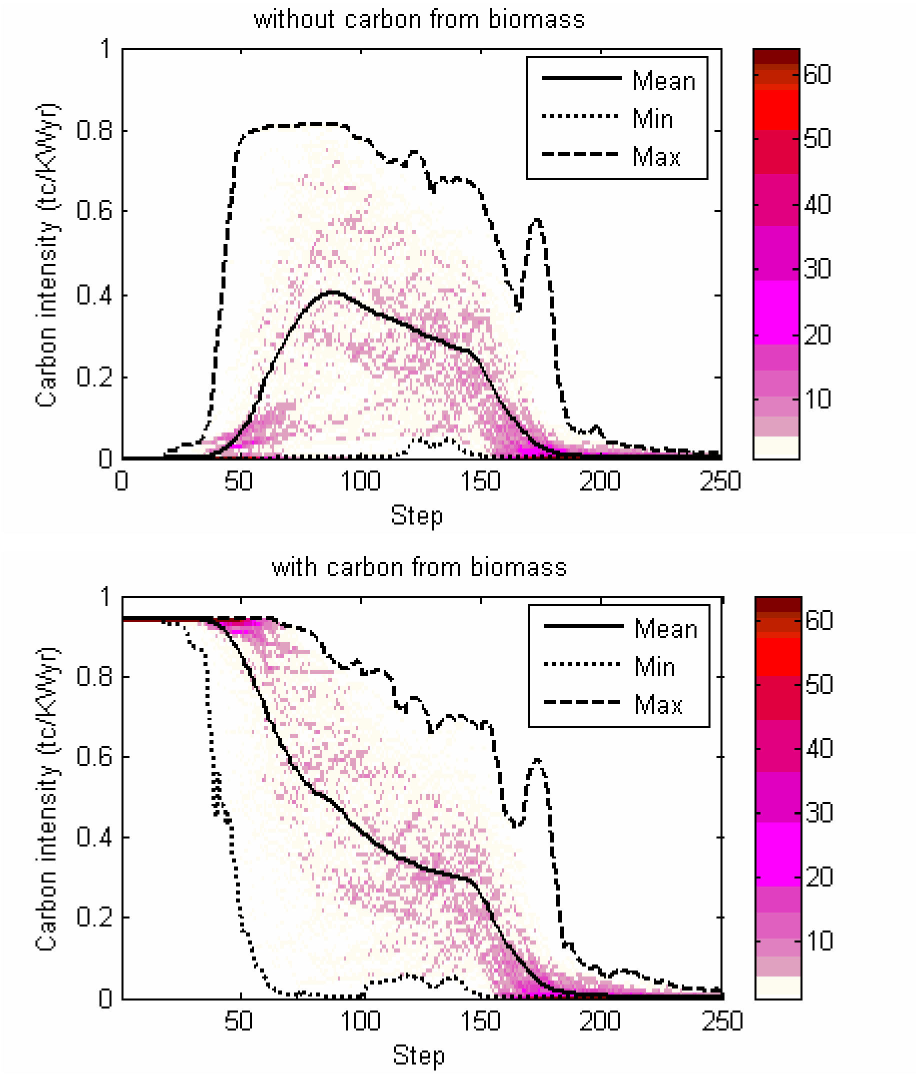


Figure 11. Carbon intensity of primary energy (in tons elemental carbon per kWyr primary energy) in the 200 base line simulations considering biomass as "carbon neutral" (left panel) and in 200 simulations including the CO_2 emission from biomass in the corresponding carbon intensity of the energy system (right panel), mean and min/max of 200 simulations each. The color scheme denotes the frequency at each carbon intensity level across the simulations.

Our simulations suggest that even pricing in environmental externalities in form of a carbon tax as early as in the 19th century would not have essentially changed the course of the take-off of the Industrial Revolution, which appears primarily as technologically driven, i.e. by the creation of new technological combinations enabling new energy services and/or vastly improved efficiencies and costs of delivering traditional energy services as a result of technology improvements and increasing return phenomena.

This conclusion on the technological "pre-ordainment" of the long-term evolution of the energy system is corroborated by our simulation results on the influence of a carbon tax on the aggregate level of complexity of the global energy system and the corresponding distribution of technological "lifetimes", i.e. years technologies remain in active use (Figure 13).

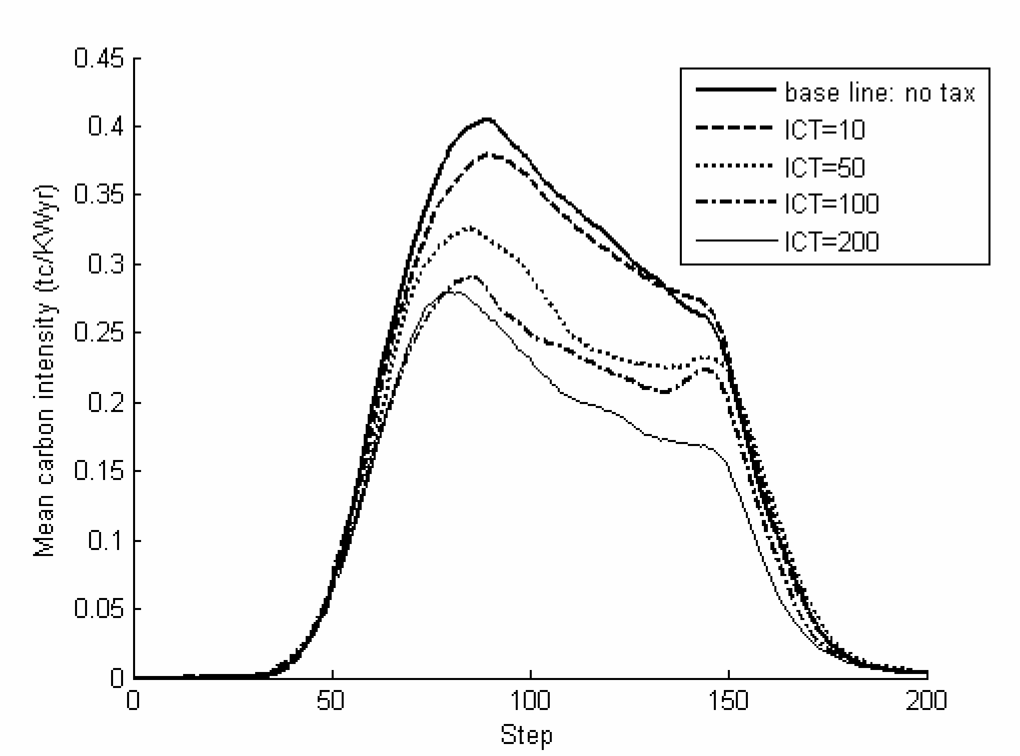
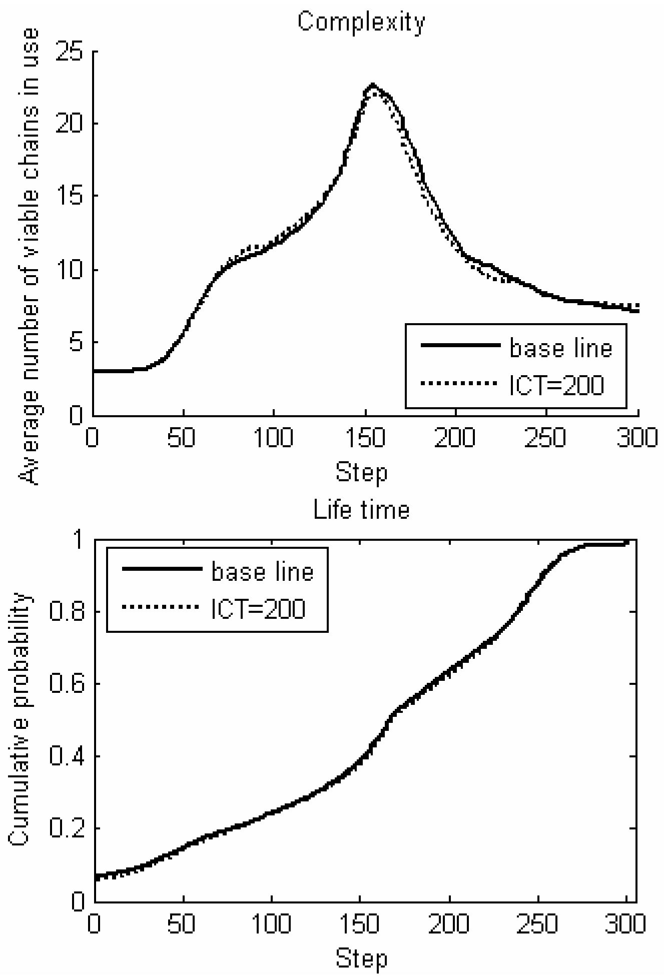
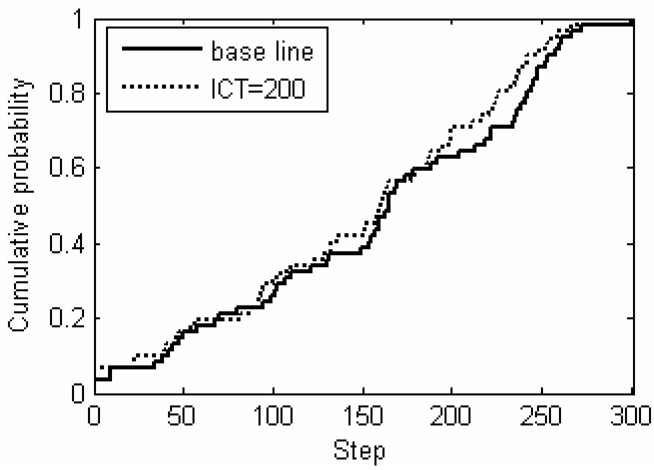


Figure 12. Carbon intensities (mean across 200 simulations respectively, in tC/kWyr, assuming carbon neutrality for biomass) versus alternative carbon taxes (in $/tC), starting at various initial carbon tax levels (ICT at 10, 50, 100, and 200 $/tC respectively) at time step 50 and increasing with 2%/year thereafter.



Life time distributions of all 200 simulations



Life time distributions of average of 200 simulations

Figure 13. Average of 200 simulations without (baseline) and with an initial carbon tax (ICT, starting at 200 \$/tC at simulation time step 50 and increasing with 2%/yr thereafter): Technological systems complexity (average number of chains in use, left panel) and technological lifetime distribution (in years of active use of technologies

plotted as a density function of 200 simulations,upper panel) for the two scenarios. Note in particular only the gradual shift even in the case of a rather extreme carbon tax level.

Even when changing the economics of the selection environment of technologies in our evolutionary model of the global energy system (via a carbon tax), its long-term characteristics in term of complexity and life spans of technologies remain nonetheless largely unchanged. This result is less surprising considering that the fundamental systems dynamics of technological evolution encompass many more dimensions and variables beyond influencing the economics of technology adoption. Rates of emergence of new technologies (innovations), "residence" time of innovations to allow for an ultimate "discovery" of technological linkages and hence integration of innovations into large technical systems, as well as the natural rhythms of technological obsolescence and "gales of creative destruction" remain as fundamental divers. Unless clear linkages between economic environmental policies (such as taxes) and these fundamental drivers of the long-term evolution of technological systems can be established, it appears difficult to argue for the sufficiency of such measures in triggering much needed large-scale technological transitions.

4. Summary and Conclusion

In this paper we have developed an agent-based simulation model of the evolution of a large and complex technological system using the example of energy. Our research objective was to improve our understanding on how such a complex system evolves from "within", bootstrapping itself, evolving into ever higher levels of systems complexity.

A distinguishing and novel feature of our model is that our "agents" are *technologies*, while the model preserves innovation and economic drivers as main components of the evolutionary algorithm underlying a continued re-combination of technologies that result in an "organic" build-up of novel systems structures, punctuated by Schumpeterian "gales of creative destruction".

Technologies in our model emerge, combine, compete, and ultimately disappear from the technological landscape under a combination of interacting drivers: innovation emergence and retention time in the system; evolutionary endogenous traits in changing technological characteristics (most notably uncertain increasing returns to adoption) as well as in the morphology of the technological landscape summarized here under "complexification"; and finally the evolution of the selection environment, governing technological competition and ultimate technological senescence, interactions with demand, as well as due to exogenous constraints such as resource depletion, or carbon taxes. Despite its stylized nature and many simplifications, our model nonetheless provides a number of important insights.

One of the most intriguing findings from our simulations is the degree of chance and serendipity characterizing the evolution of our simulated technology system. With identical initial conditions, identical suite of potential technologies that can emerge (be discovered), and identical technological and economic characteristics of technologies and drivers (e.g. technology costs, energy service demands), nonetheless different system's structures emerge across the simulations. Alternative histories and futures unfold in different simulations providing ample illustrations of path dependence and technological "lock-in". This feature of bifurcation and path-dependence as a result of the stochastic nature of the innovation process combined with a random walk model of increasing returns to adoption is a dynamic behavior that to our knowledge has not been described in any energy model to date.

Another insight provided by our model simulations is that despite heterogeneity in alternative development pathways, the system is characterized by a persistent pattern towards increasing complexity. However, while complexification is a powerful tendency, the simulations reveal as well that complexification does neither unfold indefinitely, nor that it is preordained, as levels of complexity respond to changes in the evolutionary environment governing technology selection, competition, and survival or exit. An invariable pattern emerging from our simulations is that of a "complexity peak". Whereas initially technological complexity in terms of number of energy chains in use increases, it reaches a peak around time step 150, in order to decline thereafter. Increasing complexity is the result of recursive combinations of technologies, whereas decreasing complexity is the result of “lock-out” effects of technologies via "crowding out" due to increasing returns of newer competing technologies. Long-run resource depletion ultimately leads to drastically reduced system's complexity or to technological "denudation" as Harrison Brown has called it.

A powerful mechanism in our model that influences technological complexity is increasing returns to adoption (technological learning), that however can lead to both complexification and/or simplification depending on the timing and systems structure in our model simulations. Generally, increasing returns tend to lower systems complexity as certain technological combinations forge ahead, out-competing alternatives that then gradually disappear. System's complexity tends therefore to be higher in simulations that assume low increasing returns. Our model results thus suggest a certain tension between the desirable effects of increasing returns (e.g. drastically lowered costs) and potential negative effects, such as lowered technological diversity that might increase the vulnerability of the systems to external shocks or changes in the selection environment.

In both complexification as well as simplification of technology systems, development pathways are far from gradual and smooth. Emerging technological combinations and systems complexification come in spurts, and exiting technologies exhibit also discontinuous rates with clustering and avalanche effects: Schumpeterian "gales of creative destruction".

In terms of the evolution of systems complexity our simulation results suggest asymmetrical, non-linear responses to a) varying the rate of emergence of innovations and b) their rate of the retention in the system to allow for the emergence of new technological combinations. Lowering the innovation introduction rate below base-line values drastically lowers systems complexity; whereas increasing the introduction rates drastically above base line values has only a gradual effect. Conversely, the single most important variable for system complexity in our model is "innovation patience", i.e. the time new innovations remain in the system (even if not yet integrated into viable energy chains) and during which new combinations can emerge. The evolution of our system in terms of complexity responds most dramatically to a lowering of this innovation "residence" (or innovation "patience") time.

The policy implications of above findings are interesting, as extending much of the current debate on technology policy in a climate constrained world. An important conclusion from our model simulations is that random perturbations over short periods of time have little long-lasting effects. Even increasing systematically innovation efforts above a critical baseline innovation "recharge" (R&D) level, e.g. through an additional R&D effort of the size of the Apollo Project, is unlikely to trigger long-term bifurcations in energy systems. Instead our simulations suggest a much more critical role for innovation "patience" that preserves innovation diversity. Sustained and cumulative R&D efforts appear to be more important than shorter-term spurts even if very high. Much like in biology, technological diversity is the ultimate resource from which new combinations and changing practices can be built.

Our simulations have also revealed a surprising longevity of individual technologies and of technological combinations. Its main influencing variables are the degrees of increasing returns to adoption (that accelerate "crowding out" of technologies) as well as accelerated rates of market penetration (i.e. removing the effects from localized learning und persistent uncertainty that lead only to cautious and gradual adoption of new technologies in our model[15]). 70% to 95% of all technologies in use stay in the system for more than 50 years across all sensitivity analyses performed. This is a theoretical corroboration of the observed slow turnover rates in energy systems (Grubler *et al.*, 1999) that exceed well over 5 decades. Accelerated rates of radical systems changes beyond historical experience appear thus possible less from the "cradle" end of the technology life cycle (innovation rates and increasing returns) but rather from the "grave" end, i.e. the exit of technologies from the system. From the perspective of this modeling exercise, accelerated systems transformation would only be possible if an explicit policy mechanism of Schumpeterian "gales of creative destruction" can be found.

Finally, with respect to environmental issues, our simulations provide for two important conclusions. First, in all simulations there is a powerful tendency towards "decarbonization", i.e. a decrease in the carbon intensity of energy systems that emerge entirely endogenously in our model without external constraints. Evidently, both absolute emissions as well as emission intensities are highly uncertain, reflecting the multitude of alternative pathways and technological combinations emerging from different simulations. Pricing in environmental externalities (through a carbon tax) has an important effect on emissions and carbon intensities, but only a gradual effect on systems complexity and longevity of technologies. Thus, it appears difficult to argue that economic policy signals alone will result in a drastic transformation of the energy technology landscape.

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[15] This is the most significant difference in the technology dynamics between our model when compared to deterministic models that display instantaneous technological "turn-overs" (usually moderated by exogenous market penetration constraints in the models).

Our simulation modeling results indicate both important areas of future research as well as the need to enlarge the environmental policy "tool kit" in a climate constrained world in the direction of targeted technology measures both at the "cradle" as well as at the "grave" of technological life cycles. How to trigger accelerated innovation efforts, increased innovation "patience", as well as speedier retirement of old, but long-lived capital vintages and infrastructures and how to weigh costs and benefits of such technology measures might indeed the most challenging, but also most fruitful, avenues for technology research in a warming world.

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Appendix A – Main Mathematical Formulations of the Model

Suppose an *energy chain* (i.e. a combination of [conversion] technologies enabling to link primary resources to demands for energy services) is composed of *n* primary energy technologies (defined here in analogy to activity/process analysis at the level of an industrial plant [facility]). We number the technologies from the end to the beginning of an energy chain as 1, 2, … *n*. The cost of the chain can be calculated as Eq. (1)

$$C^t = \sum_{i=1}^{n} \frac{1}{\prod_{j=1}^{i} eff_j} \left(c_i^t + \phi e_i \right), \tag{1}$$

where t denotes the time step of the simulation, C^t denotes the total cost of the chain for producing one unit output at step t, eff_j denotes the (energy input-output) efficiency of technology j, c_i^t denotes the levellized cost of technology i at step t, ϕ denotes the carbon tax per emission (US$/ct), and e_i denotes the emission of technology i for producing each unit output (tC/kWyr).

Cost are dynamic in our model via increasing returns to adoption, i.e. technological learning, that are calculated at the primary technology level and then aggregated to chain levels according to Eq. (1). A primary technology's learning rate (cost reductions) is modeled as a function of its cumulative output. With technological learning effects, a technology's levellized cost will decrease with an increase of cumulative output. Technological learning rates are treated as uncertain, with random values around a mean assumed learning rate of 10% (for old) and 30% (for new technologies) respectively, with uncertainties characterized by lognormal distributions.

Thus a technology's levellized cost at time t, c_i^t, can be calculated as Eq. (2)

$$c_i^t = c_i^0 \left(\bar{I}_i^t \right)^{-b_i(\omega)}, \tag{2}$$

where $b_i(\omega)$ is a random value with ω denoting an element from a probability space that is characterized by a lognormal distribution, $2^{b_i(\omega)}$ is the progress ratio ($1-2^{-b_i}$ is the learning rate) of technology i, c_i^0 is the initial cost of technology i, and $\bar{I}_i^t$ is the cumulative installed output of technology i at step t, and

$$\bar{I}_i^t = \sum_{j=0}^{t} I_i^j, \tag{3}$$

where I_i^j is the installed output of technology i at step j. In our model, technology outputs at a certain time step depend on the evolution of energy service demands. It is possible that a technology is deployed as a component in several different energy chains for satisfying final energy service demands. I_i^j in this case is the sum of output capacities required in each chain at step j.

For the dynamics of the final energy service demands, we assumed an exogenous increasing rate for the economy, say, income, with each demand category having a fixed income elasticity. A demand is also influenced by the price/cost for satisfying it. According to the definition of price elasticity, it is easy to get Eq. (4) which describes the dynamics of energy service demands.

$$d_i^{t+1} = (1+\alpha_i)d_i^t \frac{(1-e_i^p)p_i^{t+1} + (1+e_i^p)p_i^t}{(1+e_i^p)p_i^{t+1} + (1-e_i^p)p_i^t} \tag{4}$$

where d_i^t and d_i^{t+1} denote the demand for energy service i at step t and $t+1$, respectively; p_i^t and p_i^{t+1} are energy service i 's prices at t and $t+1$, respectively; α_i is an exogenous increasing rate of the demand for energy service i, and e_i^p is price elasticity of demand for energy service i. With Eq. (4), the dynamics of demands are partly exogenous and partly endogenous in our model.

The price for satisfying a final energy service demand is calculated by weighted average cost of viable chains which can provide the energy service required (we ignore mark-ups and profits in our simple model). Suppose at step t, there are h viable chains for satisfying demand *i*, and $s_j^t (j=1,\cdots h)$ is the share of each chain at step t, and C_j^t is the cost of chain j, then the price of energy service i is calculated as Eq. (5)

$$p_i^t = \sum_{j=1}^{h} s_j^t C_j^t . \tag{5}$$

Chain j 's share before normalization in the next step $\hat{s}_j^{t+1}$ is calculated according to Eq (6)

$$\hat{s}_j^{t+1} = s_j^t \left(1 + \max\left\{\tau, \frac{p_i^t - C_j^t}{p_i^t}\right\}\right) \quad (-1 < \tau < 0). \tag{6}$$

The reason why t is introduced in Eq. (6) is to prevent negative market shares. With Eq. (5) and Eq. (6), the growth/decrease of a viable chain's market share is not only governed by the difference between its cost and the weighted average cost (the price variable in our model), but also governed by its current market share since its current share is used as a weight for calculating the price in Eq (5). With Eq. (5) and Eq. (6), the sum of all viable chains' shares for a demand should be more or less than one. In addition, there could be new formed viable chains which will get an initially small market share. So we need to normalize viable chains as in Eq. (7)

$$s_j^{t+1} = \begin{cases} \dfrac{\hat{s}_j^{t+1}}{\sum_{k=1}^{h} \hat{s}_k^{t+1} + h'\xi} & (\text{for existing viable chains}) \\[2ex] \dfrac{\xi}{\sum_{k=1}^{h} \hat{s}_k^{t+1} + h'\xi} & (\text{for new formed viable chains}) \end{cases} , \quad (j = 1, \cdots, h+h') \tag{7}$$

where h' denotes the number of new formed viable chains, and ξ is a small number assigned to a new formed viable chain which thus will have an initial small market share only.

Since every chain's share is always normalized the sum of all viable chains market shares for a demand equals 1 (i.e. 100%), so we can not set the exact upper or lower limit on the change of relative market shares. But we can adjust τ to control the market share dynamics, e.g. $\tau = -0.9$ allows for bigger market share gains per simulation step than $\tau = -0.1$.

In our simulations, we assume resource depletion, i.e. the cost of extracting resources increases with cumulative extraction. For resource *i*, its extraction cost at time t is calculated as Eq. (8)

$$R_i^t = \beta_i \times 2.718^{\overline{E}_i^t / \gamma_i}, \tag{8}$$

where β_i and γ_i are model parameters. β_i is the initial extraction cost of technology *i* and γ_i governs the speed of increase of technology *i*'s extraction cost. $\overline{E}_i^t$ is the cumulative extraction of resource *i* by step t, and

$$\overline{E}_i^t = \sum_{j=1}^{t} E_i^j , \tag{9}$$

where E_i^j denotes the extraction of resource *i* at time t.

The number of drawing and combinations of technologies/chains at each step is a combined function of the size of the economy and the resulting demand for energy services, treated as exogenous in our model, and also a function of energy prices (which are endogenous in our model. For the illustrative simulations reported here we simply assume that energy service demands grow at an annual rate of 2%, roughly in line with the long-term global growth rate in final energy demand.

$$N^t = Min\left(25000, \varepsilon \frac{\sum_{i=1}^{m} \left(d_i^t p_i^t \right)}{\sum_{i=1}^{m} \left(d_i^0 p_i^0 \right)} \right) \tag{10}$$

where ε is a model parameter, d_i^t and p_i^t denote demand and price of energy service *i* at time t, and d_i^0 and p_i^0 denote demand and price of energy service *i* at time 0, and m denotes the number of various final energy service demands. 25000 is considered sufficiently large for the number of draws. If we do not add this upper limit, the N^t might be very big slowing down the simulation beyond practical limits.

At each draw, the probability of success is assumed to be μ which means at each draw, the probability of the emergence of a new technology (randomly out from the "technology base" until the "technology base" is empty) is μ. Any new technologies or combinations will stay in the system for potential further combination or use for κ time steps (which is a parameter used to represent innovation [im-]patience in our model).

Appendix B – The Reference Energy System

Table 1 gives the details of the 62 primary energy technologies in our simplified global energy system. The "Input ID" and "Ouput ID" are denoted by codes whose detailed information can be found in Table 2. "Efficiency" denotes the ratio of output per unit input. "Cost" denotes the levellized cost assumed for a technology for generating a unit "Output". "CO2 Emission" denotes the CO2 emitted when generating a unit "Output". (Values in parentheses refer to biomass CO2 emissions as occurring at the point of energy conversion, but that are balanced by CO2 uptake from biomass growth if produced sustainably. In the default model simulations we simply assume the carbon neutrality of biomass over all simulation time steps, but equally document the model simulations for not assuming carbon neutral biomasss [e.g. when resulting from deforestation].)

The 62 primary technologies are classified into three groups. "Group ID" in Table 1 denotes the group they belong to. "Group" assignment also roughly determines when a technology will become available. "LBD" denotes the technological learning effect. If LBD = 0, then there is no learning effect (and the only dynamic cost influence are resource depletion effects); if LBD = 1, then the technology has a relatively low learning rate (mean of 10%); and if LBD = 2, then the technology has a high learning rate (mean of 30% cost decline per doubling of cumulative output). The costs of extraction technologies are governed by the resource depletion function (Eq. 8 in Appendix A) with different parameter values shown in Table 3. For technologies with learning potential (LBD = 1 or 2), their initial levellized cost are assumed to be 3 times larger than the levellized costs shown in Table 1.

Table 2 gives the details of energy forms. Energy forms are clustered into five levels – resource, primary, secondary, final and useful energy. "Resource" means natural resources, and "useful" describes the final energy service demands expressed at the useful energy level. The reason why we distinguish additional three levels is that for the same energy form energy vectors are treated differently in the model and thus need specific designations. For example, the codes "0 3", "1 3", "2 4", "3 5" denote – the same energy currency – *gas*. But "0 3" denotes the gas available in nature, "1 3" denotes the gas extracted from nature; "2 4" denotes the gas available at the locations for further processing; and "3 5" denotes the gas transported into locations for providing the final energy services, for example, gas in residential housing that can be used for heating purposes.

For a new circular energy chain, e.g. from hydrogen (H2) to electricity and then from electricity again back to produce H2 (here H2 and electricity are modeled at the same level, i.e. the secondary energy level), we set its share to 0, because of the intrinsic substantial economic penalty associated with the incurred conversion losses when compared to simpler linear chains. (In real technology systems obviously, such circular chains and their additional conversion losses are entirely plausible. Consider for instance the case where hydrogen would be used for electricity storage. We plan to include such circular chains and the need for energy storage in future extensions of our model.)

Table 3 summarizes the values of parameters related to the demand for energy services (Eq. 4), resource depletion (Eq. 8), and number of technology draws and combinations (Eq. 10) used in our base case model simulation and Table 4 summarized our assumptions on upper resource extraction limits for renewable resources. Finally, Table 5 summarizes other salient parameters used for the reported here.

Table 1. Definition of the 62 primary energy technologies in the reference energy system.

ID	Name	Description	Input ID	Output ID	Efficiency	Levellized Cost (US$/kWyr)	CO_2 Emissions [16] (tC/kWyr)	Group ID	LBD
1	Coal extr	Coal extraction	0 1	2 1	1	30	0	0	0
2	Oil extr	(Crude) oil extraction	0 2	1 2	1	40	0	0	0
3	Gas extr	Natural gas extraction	0 3	2 4	1	45	0	0	0
4	Bio extr	Biomass extraction	0 4	2 6	1	10	0	0	0
5	Ura extr	Uranium extraction	0 5	2 7	1	2.5	0	0	0
6	Oil refi	Crude oil refining	1 2	2 3	0.95	37	0.032	2	1
7	Gas bio	Gas from biomass	2 6	2 4	0.75	328	(0.580)	2	1
8	Eth bio	Ethanol from biomass	2 6	2 5	0.56	623	(0.489)	2	1
9	Met coal	Methanol from coal	2 1	2 2	0.65	547	0.403	2	1
10	Gas coal	Gas from coal	2 1	2 4	0.75	397	0.451	2	1
11	Met gas	Methanol from gas	2 4	2 2	0.7	319	0.041	2	1
12	Coal ppl	Coal power plant	2 1	2 8	0.38	612	0.814	2	1
13	Coal h2	H2 from coal	2 1	2 9	0.7	512	0.814	2	1
14	Oil ppl	Oil power plant	2 3	2 8	0.4	375	0.631	2	1
15	Gas ppl	Gas power plant	2 4	2 8	0.45	366	0.482	2	1
16	Gas h2	H2 from gas	2 4	2 9	0.8	227	0.482	2	1
17	Bio ppl	Biomass power plant	2 6	2 8	0.33	591	(0.942)	2	1
18	Bio h2	H2 from biomass	2 6	2 9	0.7	422	(0.942)	2	1
19	Nuc ppl	Nuclear power plant	2 7	2 8	0.33	1013	0	2	1
20	Nuc h2	H2 from nuclear power	2 7	2 9	0.7	1153	0	3	1
21	Sol ppl	Solar power plant	0 8	2 8	0.4	4338	0	3	1
22	Sol H2	H2 from solar	0 8	2 9	0.6	1496	0	3	2
23	Wind ppl	Wind power plant	0 6	2 8	0.4	3850	0	2	1
24	Hydr ppl	Hydro power plant	0 7	2 8	0.4	886	0	2	1
25	FC	H2 power pl. (fuel cell)	2 9	2 8	0.7	2346	0	3	2

[16] Emission factors in parenthesis refer to biomass whose emissions can be considered either as carbon neutral (i.e. zero) or be included alongside fossil fuel emissions (values) in the model.

ID	Name	Description	Input ID	Output ID	Efficiency	Levellized Cost (US$/kWyr)	CO_2 Emissions[16] (tC/kWyr)	Group ID	LBD
26	Nuc fus	Nuclear fusion	0 9	2 8	0.4	4338	0	3	1
27	Elec H2	H2 from electricity	2 8	2 9	0.95	172	0	2	1
28	Coal t/d	Coal T&D[17]	2 1	3 1	0.95	60	0	2	1
29	Met t/d	Methanol T&D	2 2	3 2	0.98	60	0	2	1
30	Oilp t/d	Oil products T&D	2 3	3 3	0.98	60	0	2	1
31	Gas t/d	Gas T&D	2 4	3 5	0.72	122	0	2	1
32	Eth t/d	Ethanol T&D	2 5	3 6	0.98	60	0	2	1
33	Bio t/d	Biomass T&D	2 6	3 7	1	20	0	1	0
34	Elec t/d	Electricity T&D	2 8	3 4	0.85	396	0	2	1
35	H2 t/d	H2 T&D	2 9	3 8	0.935	152	0	2	1
36	Oil lam	Oil lamp	3 3	4 1	0.05	30	0.631	2	1
37	Gas lam	Gas lamp	3 5	4 1	0.05	30	0.482	2	1
38	Coal lam	Coal illumination	3 1	4 1	0.01	60	0.814	2	1
39	Bio lam	Biomass illumination	3 7	4 1	0.02	2	(0.942)	1	0
40	Bulb	Electric light bulb	3 4	4 1	0.05	403	0	2	2
41	Coal fur	Coal furnace (heat)	3 1	4 3	0.50	30	0.814	2	1
42	Oil fur	Oil furnace (heat)	3 3	4 3	0.75	30	0.631	2	1
43	Gas fur	Gas furnace (heat)	3 5	4 3	0.75	30	0.482	2	1
44	Bio fur	Biomass furnace (heat)	3 7	4 3	0.1	10	(0.942)	1	0
45	H2 fur	H2 furnace (heat)	3 8	4 3	1	1204	0	2	1
46	Ele Heat	Electric heat (direct)	3 4	4 3	1	30	0	2	1
47	Elec HP	Electric heat pump	3 4	4 3	3	602	0	2	1
48	Ste eng	Steam engine	3 1	4 4	0.1	2422	0.814	2	1
49	Oil eng	Oil engine	3 3	4 4	0.1	7785	0.631	2	1
50	Gas eng	Gas engine	3 5	4 4	0.1	7785	0.482	2	1
51	Animal	Draft animals (transp.)	3 7	4 4	0.04	10000	(0.942)	1	0
52	Elec eng	Electric engine	3 4	4 4	1	4830	0	2	1

[17] T&D: Transport and distribution

ID	Name	Description	Input ID	Output ID	Efficiency	Levellized Cost (US$/kWyr)	CO_2 Emissions[16] (tC/kWyr)	Group ID	LBD
53	FC	H2 engine (fuel cell)	3 8	4 4	1	4830	0	3	2
54	Elec dev	energy services from electricity (e.g. IT)	3 4	4 2	1	3885	0	2	2
55	H2 dev	energy services from H2 (e.g. IT)	3 8	4 2	1	3885	0	3	2
56	Coal nf	Coal for feedstock	3 1	4 5	0.7	3	(0.814)	2	1
57	Oil nf	Oil for feedstock	3 3	4 5	1	3	(0.631)	2	1
58	Gas nf	Gas for feedstock	3 5	4 5	1	3	(0.482)	2	1
59	Met nf	Methanol for feedstock	3 2	4 5	1	3	(0.549)	2	1
60	Eth nf	Ethanol for feedstock	3 6	4 5	1	3	(0.549)	2	1
61	H2 nf	H2 for feedstock	3 8	4 5	1	3	0	2	1
62	Deu H2	H2 from deuterium	0 9	2 9	0.6	1496	0	3	2

Table 2. Energy forms/flows/currencies of the model.

ID	Name	Label	Level		ID	Name	Label	Level
0 1	Coal	Coal	Resource		2 8	Electricity	Elec	Secondary
0 2	Crude oil	Oil	Resource		2 9	Hydrogen	H2	Secondary
0 3	Gas	Gas	Resource		3 1	Coal	Coal	Final
0 4	Biomass	Bio	Resource		3 2	Methanol	Meth	Final
0 5	Uranium	Uran	Resource		3 3	Oil Products	OilP	Final
0 6	Wind	Wind	Resource		3 4	Electricity	Elec	Final
0 7	Hydro	Hydro	Resource		3 5	Gas	Gas	Final
0 8	Solar	Solar	Resource		3 6	Ethanol	Etha	Final
1 2	Crude oil	Oil	Primary		3 7	Biomass	Bio	Final
2 1	Coal	Coal	Secondary		3 8	Hydrogen	H2	Final
2 2	Methanol	Meth	Secondary		4 1	Light	Light	Useful
2 3	Oil Products	OilP	Secondary		4 2	E/H2 Services	E/H2 Ser	Useful
2 4	Gas	Gas	Secondary		4 3	Heat	Heat	Useful
2 5	Ethanol	Etha	Secondary		4 4	Mechanical	Mech	Useful
2 6	Biomass	Bio	Secondary		4 5	Non-Fuel	Non-f	Useful
2 7	Nuclear fuel	Nu-f	Secondary					

Table 3. Parameter values of energy service demands, resource depletion, and number of technology draws and combinations.

<table>
<tr><td colspan="4">Parameters related to demand for energy services in Eq. 4</td></tr>
<tr><td>Service demands (useful energy)</td><td>d_i^0 (initial demand) (KWyr)</td><td>a_i (annual growth rate)</td><td>e_i^p (price elasticity)</td></tr>
<tr><td>Light</td><td>10^4</td><td>4%</td><td>0.2</td></tr>
<tr><td>Ele/h2 Service</td><td>5×10^6 (at emergence)</td><td>4%</td><td>0.2</td></tr>
<tr><td>Heat</td><td>4.6×10^8</td><td>2%</td><td>0.5</td></tr>
<tr><td>Mechanical</td><td>2×10^7</td><td>3%</td><td>0.3</td></tr>
<tr><td>Non-Fuel</td><td>3.5×10^6</td><td>3%</td><td>0.3</td></tr>
<tr><td colspan="4">Parameters related to resource depletion, in Eq. 8 in Appendix A</td></tr>
<tr><td>Resources</td><td colspan="2">b_i (initial extraction cost)</td><td>g_i (speed of cost increase)</td></tr>
<tr><td>Coal</td><td colspan="2">16.97</td><td>10^6</td></tr>
<tr><td>Crude oil</td><td colspan="2">50</td><td>1.2×10^6</td></tr>
<tr><td>Gas</td><td colspan="2">80</td><td>1.5×10^6</td></tr>
<tr><td>Biomass</td><td colspan="2">8</td><td>3×10^6</td></tr>
<tr><td>Uranium</td><td colspan="2">100</td><td>8×10^6</td></tr>
<tr><td colspan="4">Parameters related to number of draws and combinations, in Eq. 10</td></tr>
<tr><td colspan="4">$\varepsilon = 66.7$</td></tr>
</table>

Resource extraction costs are estimated based on Rogner (1997).

Table 4. Assumed upper limits on the annual use of biomass, hydro, and wind.

renewable resources	Upper limit on annual use (kWyr)
Biomass	2.6×10^{10}
Hydro	3.6×10^9
Wind	9.5×10^9

Table 5. Other model parameter values used in base line simulations

Design parameters	values
t Eq. (6) (limit on market share change)	-0.1
x Eq.(7) (initial share of a new technology)	0.0001
m (probability of a successful draw)	0.01
k (retention time of a technology/chain)	$k >$ 300 time steps