Final Report
Award DE-FG02-02ER63473 for:

Factors Affecting the Rate of Penetration of Large-Scale Electricity Technologies: The Case of Carbon Sequestration

Principal Investigator:
Howard J. Herzog

Research Assistant:
James R. McFarland

May 14, 2007

Massachusetts Institute of Technology
Laboratory for Energy and the Environment
Room E40-471
1 Amherst Street
Cambridge, MA 02139

617-253-0688
617-253-8013 (fax)
hjherzog@mit.edu

Overview

This is the final report for the study of factors affecting the penetration rate of carbon capture and storage technologies in the electric power sector (award DE-FG02-02ER63473). This project falls under the Technology Innovation and Diffusion topic of the Integrated Assessment of Climate Change Research Program. Specifically, we are investigating ways of "improving methods and models for assessing innovation and diffusion of technologies that affect the emission of greenhouse gasses" (quote from this year's call for proposals).

Advanced technologies will play a critical role in achieving significant greenhouse gas reductions. Energy-economy models commonly illustrate that the adoption of advanced technology such as carbon capture and sequestration (CCS) is economically attractive under most emission reduction policies. However, embedded within integrated assessment models are ad hoc assumptions on the penetration rate of these advanced technologies. This research seeks to refine our understanding of plausible technology penetration rates and improve the representation of CCS technologies in integrated assessment models.

This study accomplished several research tasks: a survey of the ways modelers currently control penetration rates (task 1), historical analysis of technology adoption (task 2), analysis of factors affecting technology adoption rates (tasks 3-5, comprising industry structure, resources constraints and logistics, and regulations and environmental policy), and the identification of critical factors and their incorporation into integrated assessment models (task 6).

The first two tasks are summarized in sections 1 and 2. Our literature review of empiric and theoretic factors affecting technology adoption rates (tasks 3-5) uncovered several additional factors beyond those identified in the initial proposal. Section 3 summarizes this work. Research to assess the significance and relative importance of these factors involves the development of a microeconomic, system dynamics model of the US electric power sector. The model explicitly represents power sector operation and investment as well as fuel supply and CO_2 storage. By containing more sector-level detail than integrated assessment models, it should generate more plausible estimates of CCS penetration rates. The model is described in section 4. Section 5 summarizes the identification of the factors critical to CCS adoption and our efforts to incorporate a reduced form model into an integrated assessment model.

1. Survey of penetration rate control in integrated assessment models

Six integrated assessment models designed for the study of interactions between energy, climate, and economy were surveyed for how the models control the penetration rates of CCS technologies as listed in Table 1.[1] The models range in construction from bottom-up engineering cost models to top-down macroeconomic computable general equilibrium models. Half of the models are fully dynamic and optimize over all time periods (typically to 2100). The other half is recursive dynamic and maximizes production or minimizes cost for each time period of simulation without regard for conditions in subsequent time periods.

Table 1. Current methods for controlling penetration rates in integrated assessment models

Model, Reference	Description	Method for controlling CCS penetration rates
DNE21 Fujii and Yamaji (1998) Fujii (2003)	Bottom-up hybrid, fully dynamic	Exogenous constraint. CCS decadal capacity addition limited to 20% of total carbon flux from electric power by region.
EPPA McFarland et al. (2004)	Top-down CGE hybrid, recursive dynamic,	Endogenous constraint responsive to carbon price. CCS capacity addition limited to 20% share growth over 20 years (similar to growth of nuclear power in US) at carbon prices of $200/tC.[2]
MESSAGE Riahi et al. (2004), Riahi (2005)	Bottom-up hybrid, fully dynamic	Exogenous constraint. Capacity growth constraint of 20% per annum for niche and demonstration reaching a maximum of 10% per annum during commercialization phase (slightly more than doubling every 10 years).[3]
MERGE Manne and Richels (2004)	Bottom-up hybrid, fully dynamic	Exogenous constraint. Maximum share: 1% in year of introduction, 3% after 10 years, 9% after 20 years, 27% after 30 years, and 81% after 40 years, no limit beyond 40 years.
MiniCAM Brenkert et al. (2004), Edmonds et al. (2004)	Top down partial equilibrium hybrid, recursive dynamic	Exogenous and endogenous. Exogenous constraint on maximum share of electricity generation from a single technology. Share is also endogenously determined as a function of cost differences using a logit specification (see Edmonds and Reilly, 1983).[4]
SGM Sands (2004)	Top down CGE hybrid, recursive dynamic	Endogenous. Share is endogenously determined as a function of cost differences using a logit specification (see Edmonds and Reilly, 1983).[5]

All of the models contain an exogenous or endogenous constraint on the rate of CCS penetration to reflect the historically slow adoption of technologies in the electric power sector. Without such constraints, new technologies would be adopted at unprecedented rates upon becoming economically attractive. The specification of the constraints is summarized in Table 1.

Although many other factors in the models affect the diffusion of CCS technologies (e.g., reference emissions, autonomous energy efficiency improvement, number and relative costs of competing technologies, and capital vintaging), a cursory comparison of the models under 550 ppm CO_2

[1] Energy Technology Perspectives (ETP) model from the IEA will be surveyed in the near future.
[2] Global share of electricity from CCS grows from 10% in 2045 to 80% by 2060 under a 550 ppm stabilization scenario that cuts emission dramatically in the latter half of the century.
[3] Global share of electricity from CCS grows from 10-12% in 2060 to 90% by 2090 under a 550 ppm CO_2 stabilization scenario.
[4] Global share of electricity from CCS grows to 20-55% in 60 years depending upon technology assumptions.
[5] US share of electricity from CCS reaches 35% in 40 years at $200/tC.

stabilization scenarios is revealing. EPPA, with a price responsive constraint, and MESSAGE, with a loose exogenous constraint, show the most rapid adoption of CCS technologies. The share of electricity from CCS technologies grows from 10% to over 80% in less than 30 years. In contrast, MiniCAM and SGM, which rely on logit functions, depict slower share growth, reaching 35% to 50% in 40 years. Such large disparities have significant implications for modeling and climate policy.

2. Empirical assessment of technology penetration rates

Empirical evidence shows that technology diffusion frequently follows an S-shaped logistic curve with three characteristic phases (e.g., Rogers 2003, Stoneman 2002, Grubler et al. 1999, Thirtle and Ruttan 1987). Initially, market penetration is slow as small niche markets are filled and demonstration projects are undertaken. Growth accelerates during the commercialization phase and market share increases rapidly. The rate of growth slows as the size of the non-adopting market declines, the technology matures, and more advanced alternatives become available. This component of the DOE sponsored research has examined technology penetration for: 1) large-scale, networked technologies, 2) nuclear power, and 3) other electric generating technologies. Results are presented below for parts 1 and 2. Empirical penetration rates of other electric generating technologies in the US will be completed as part of the calibration procedure for the system dynamics model as discussed in section 4.

The penetration rate of large-scale, networked technologies has been extensively examined by Grübler et al. (1999). The study characterizes technologies by their relative advantage over competing technologies, scale, infrastructure needs, and technical interdependence. Technologies with great scale, infrastructure needs, and technical interdependence such as coal use, railways, and home electrification required between 44-80 years to move from 10% market share to 90% market share[6]. In the US, railways, telegraphs, oil pipelines, and roads needed 50-65 years to achieve similar changes in market share. The authors also note a wide variation in the diffusion rate with a mean of 41 years and standard deviation of 42 years for 265 processes.

Turning to the expansion of nuclear power, the USA, Japan, and EU-15 required between 9 to 15 years to expand nuclear power from 5% to 20% of their electricity generation (see Figure 1 below). The greatest rate of growth in nuclear power generation occurred from 1974-1988 during the commercialization phase. The diffusion paths for the USA, Japan, and EU-15 excluding France are quite similar as all regions generate between 20-25% of their electric power from nuclear by 1990.[7] France, due to national policy, changed its mix of electricity generation from 10% to 70% in less than a decade.[8]

[6] The authors define this as the diffusion rate.
[7] The research, development, and demonstration phase comprised 15-20 years of low absolute growth but high percentage growth in output.
[8] From 1960 to 2002, France added average of 26,000 GWh/yr while the USA added 77,000 GWh/yr.

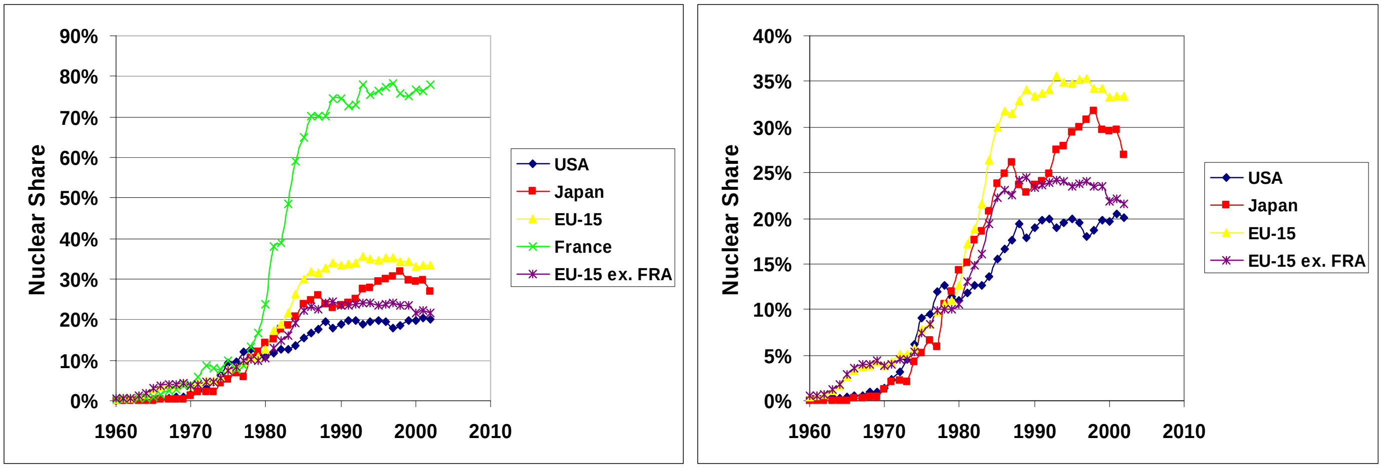

Figure 1. Share of nuclear power generation in the USA, Japan, EU-15, EU-15 excluding France and France (source: IEA, 2004). The right graphic excludes France.

3. Empirical and theoretical analysis of factors affecting technology penetration rates

Our initial proposal identified three factors affecting the rate of CCS diffusion: retrofitability of the existing capital stock, access to CO_2 reservoirs and pipeline infrastructure, and environmental regulation. An extensive survey of the technology adoption and diffusion literature revealed several additional factors that should be considered in a complete analysis of CCS penetration. The factors that determine penetration rates are analyzed by McFarland and Herzog (2006) and may be summarized as follows:

Characteristics of the technology

Perhaps the most obvious and expansive factor influencing technology adoption rates are the technology's characteristics – such as the expected returns and risk relative to existing technologies, the exclusivity of the technology's intellectual property, the degree and form of regulatory barriers, and the complexity relative to existing processes. High expected returns accelerate adoption while risk and regulation deter it.

Characteristics of potential adopters

Empirical studies suggest that firms' size, access to credit, and quality of human capital influence technology adoption. Large firms tend to have a larger capital stock that increases the opportunities to replace aging capital and lowers the risk of investing in a novel technology. Rose and Joskow's (1990) study of electric utilities finds that large firms adopt new technologies earlier than small firms even after controlling for capital stock turnover. Firms with older vintages of capital may find it more profitable to replace that capital with new technology. Heterogeneity across firms may contribute to the historic pattern of S-shaped technology adoption as the largest firms adopt first followed by the majority of mid-sized firms and finally by the smallest firms.

Declining technology costs

McDonald and Schrattenholzer (2002) cite numerous studies of cost (and/or price) reductions in energy-related technologies. Costs may decline via several mechanisms: learning by doing, learning by using, economies of scale in production or unit size, and research and development by the supplier or adopter. Declining costs increase the relative economic advantage of a technology, thus promoting its adoption. This technology characteristic may explain the increasing rates of adoption in the early stages of technology diffusion. Initially, a technology may be economically attractive to only a small set of adopters. As costs decline, the technology appeals to a greater number of adopters. This process of adoption, production, and cost reduction is reinforced until it is no longer profitable for others to switch technologies.

Availability of information

Early models of technology adoption were based on the concept that the dissemination of information explains diffusion (see e.g., Mansfield 1961). Similar to the spread of an epidemic, information spreads slowly from the first adopters then increases geometrically as the number of adopters grows. Adoption slows as the percentage of non-adopters declines. Taylor (2001) describes how information dissemination promoted adoption as well as learning in the development of SO_2 scrubbers. Unlike distributed generation technologies, for example, innovations in large-scale generating technologies typically require several years to test and evaluate.

Industry characteristics

In addition to adopter characteristics, the economic benefits of acquiring a technology are dependent on the industry concentration, industry structure, and business cycle dynamics. The empirical basis of the effect of industry concentration is contradictory, perhaps reflecting countervailing processes. With relatively fewer firms, information flow is facilitated in concentrated industries, yet firm size tends to be highly variable in concentrated industries, which tends to slow diffusion. The competitiveness of the firms supplying and supporting technologies encourages price reductions, and therefore, diffusion. Anex et al. (1999) note that the restructuring of the U.S. electric power sector promoted the adoption of less capital-intensive advanced gas technologies. Business cycle dynamics may lead to erratic rates of investments and technology adoption. As evidenced by Ford (2001), the electricity generating industry is highly susceptible to such behavior.

Specialized resources

The production and operation of new technologies require specialized human or physical capital, such as engineers, tooling equipment or natural resources (e.g., suitable CO_2 reservoirs), the supplies of which are limited in the short term. Thus the availability of these critical resources constrains the profitable level of technology adoption. Over time, the supply of these resources is increased or technology costs decline and adoption resumes.

General equilibrium effects

Significant adoption of technologies that use a particular input will drive up the demand for the input and price of the input. Likewise, as the adoption of new technologies drive output prices down, other firms are pressured to follow suit.

4. Assessing the importance of technology diffusion factors using system dynamics

The primary focus of our work to date has been to develop a system dynamics model of the US electric power sector incorporating the factors discussed in section 3 in order to understand their significance, interactions, and implications for technology and climate policy. This work is documented in McFarland (forthcoming 2007). System dynamics is an appropriate methodology for this endeavor. System dynamics has been used extensively to model energy and electric power systems. Ford (1997) cites 33 system dynamics applications involving electric power. The scope of the work ranges from national energy systems to the investment behavior of individual firms. Furthermore, system dynamics models have successfully represented the boom and bust investment cycles in the utility industry as well as utility responses to rate of return regulation and restructuring (Ford, 1997).

For the purpose of tractability, the model is limited to the U.S. electric power sector. The major drawback of this assumption is that technology spillovers and from other regions of the world cannot be represented in the model.[9] The timeframe of the model is from 2004 through 2100. The longevity of capital life in this sector (20 to 50 years for a power plant) necessitates the lengthy time scale. Table 2 summarizes the model boundaries.

Table 2. Model boundaries

Region	USA
Years	2004 -2100
Key Exogenous Parameters	GDP growth, carbon penalties, regulatory policies (subsidies, demonstration programs, and siting and monitoring requirements)
Key Sub-models	Plant dispatch, electricity demand, capital vintaging, investment, technology supply, resource supply (fossil fuel, renewables, CO_2 storage volume).
Generating Technology Aggregation	
Peak	simple cycle gas/oil
Intermediate	combined cycle gas, pulverized coal, gas CCS, coal CCS
Base	combined cycle gas, pulverized coal, nuclear, hydro, wind, solar, geothermal, gas CCS, coal CCS

Causal loop structure

The factors discussed in section 3 are endogenously represented by the variables and feedback structure of the model. While space limitations prohibit a discussion of how each factor is incorporated into the model, the causal loop diagram below depicts the critical factors and feedbacks represented in the US electricity model.

[9] Once the utility of this technique has been demonstrated for one region, it can be expanded to model multiple regions.

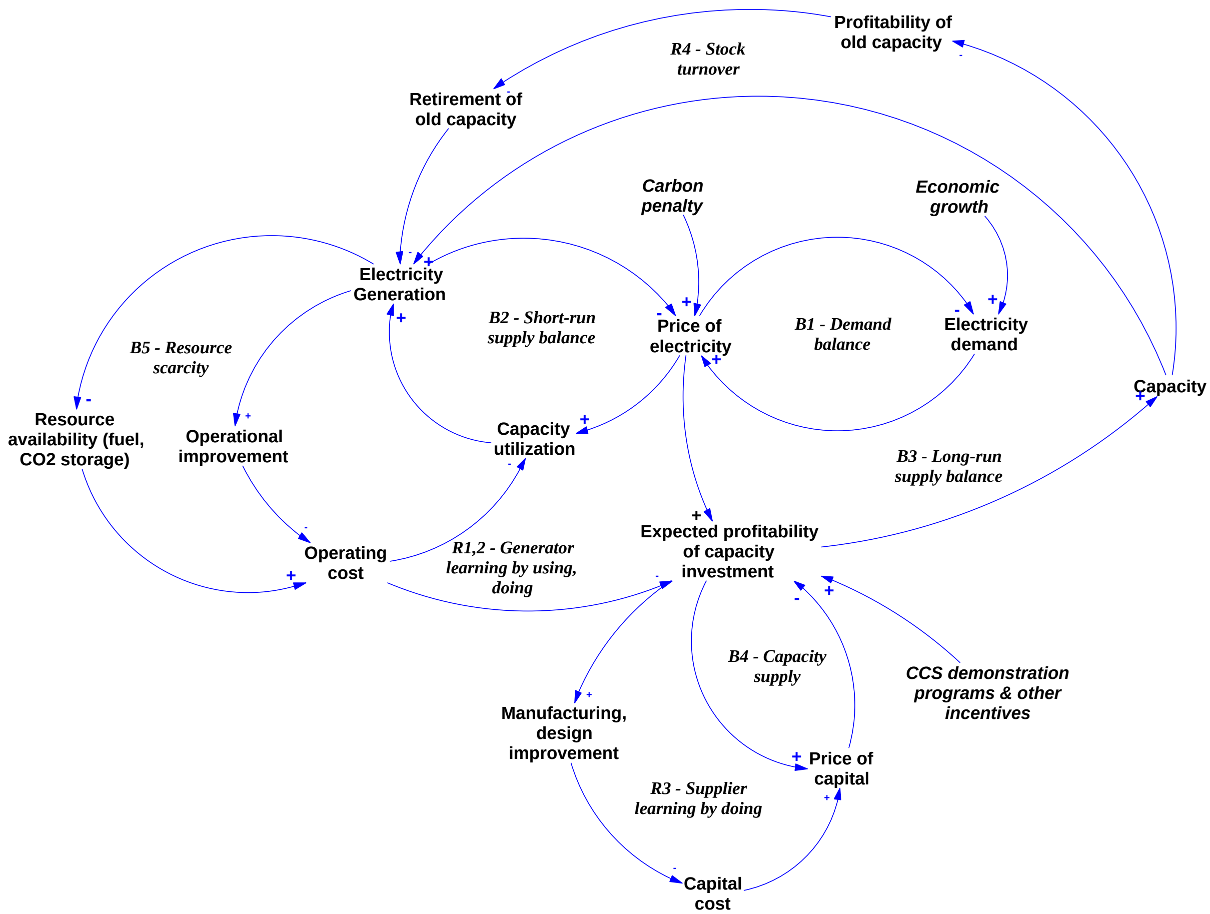

Figure 2. Causal loop diagram of technology adoption in the electric power sector

The loops in such a diagram are labeled as "balancing" or "reinforcing". Balancing loops stabilize variable values at a dynamic equilibrium, at least in the long run, while reinforcing loops create exponential growth or decay. The "plus" and "minus" signs on the arrows indicate the relationship between the variables. The "plus" sign from electricity demand shows that higher demand leads to higher prices. The "minus" sign from electricity price to demand indicates that an increase in price lowers demand. A discussion of these feedback loops provides an overview of the model. Three exogenous variables (economic growth, carbon penalty, and demonstration programs and incentives) have important effects on model behavior but are not contained in the feedback loops.

The majority of the balancing loops represent the economic relationship between supply and demand. Demand balance (B1) captures the short and long-run price responsiveness of consumer demand to electricity prices. As prices escalate, consumers use less electricity. Similarly, short-run supply balance (B2) and long-run supply balance (B3) depict increases in electricity output as electricity price rises. The short-run effect involves bringing idle capacity on-line and increasing the capacity factor of plants that are already in operation. Plant dispatch is treated endogenously in the model. The long-run effect of an electricity price increase leads to a higher expected profitability, more capacity investment, and subsequently higher output. As capacity investment outstrips the short-run ability of equipment suppliers to deliver the products, the price of capital equipment will rise to slow investment (B4) until additional manufacturing capacity is available to meet demand.

Resource scarcity (B5) depicts the rising costs of physical resources (coal, gas, CO_2 storage areas, pipeline right of ways, etc.) as those resources with the highest quality or easiest access are used. We will use the Carbon Management GIS or similar system to produce supply curves for CO_2 transport and storage costs. Resource extraction and depletion models will be based on previous system dynamics models (see e.g., Naill 1973). Omitted from the diagram, but not from the final model is technological progress in resource discovery, extraction, and utilization that has historically outstripped depletion costs for most raw materials in the 20th century.

Causal loops leading to exponential growth in technology adoption in this model involve cost-reducing innovations that are generally classified as learning effects. Generating entities lower costs through operational improvements (i.e., learning by using R1) and through reapplying knowledge from repeated acquisition of a particular technology (i.e., learning by doing R2). These cost reductions enhance the expected profitability of future investments, which leads to greater capacity acquisition and further learning. A similar phenomenon exists for the technology supplier (R3). Higher cumulative production leads to standardization of designs, innovations in manufacturing, and the streamlining of organizational processes which in turn lower costs. This increases demand for the technology to the extent that such cost reductions are passed along to the buyers. Although not depicted in the diagram, economies of scale may also play a reinforcing role in these three areas of technology cost reduction.

The last reinforcing loop involves capital stock turnover (R4). As new capacity comes on line, the profitability of older vintages of capital declines. Lower profitability leads to less investment in operations and maintenance and eventually translates into the retirement of older capacity. With less system capacity during peak demand periods, prices will spike higher which in turn makes new capacity investment more attractive. Unlike most other models with capital vintaging, investment decisions regarding existing capacity are endogenous to the model. For each of the three vintages per technology, the economic decision will be made regarding whether or not a technology should receive a life extension, CCS retrofit, or retirement. The option to life extend is believed to be important as much of the existing coal-fired capacity in the US will soon surpass its design life, yet few plants are expected to be retired.

Example of stock and flow structure: capacity

To offer a sense of the level of detail within the model, we describe the stock and flow structure of generating capacity, one of the macro-level variables presented in Figure 2 above. As Figure 2 illustrates, capacity is a component of the long-run supply balance (B3) and stock turnover (R4).

The annual total potential generating output (see top of Figure 3) is a product of the total capacity, plant availability, and the hours in a year. Total capacity is the sum of six vintages of capital: three vintages of capital that have not been retrofit with carbon capture and storage (or cannot be retrofitted, e.g., wind, hydro, and nuclear) and three vintages of fossil plants that have been retrofitted with carbon capture and storage technology. At the completion of new construction, new capacity is added to the stock of vintage 1 capacity.

As the capital ages, it is moved to vintages 2 and 3, respectively, based on an average physical life that varies by technology. The rate of capacity aging is specified as the stock of capital divided by the average life of capacity for that vintage. For each vintage of capacity, an investment decision is made as to whether some or all of the capacity should be given a life extension or retrofit with carbon capture and storage technology. If the capacity is retrofit with CCS technology, it continues to age and is subject to life extensions. A separate, parallel structure, called a co-flow, tracks the heat rate and operations and maintenance requirements for each plant type and vintage.

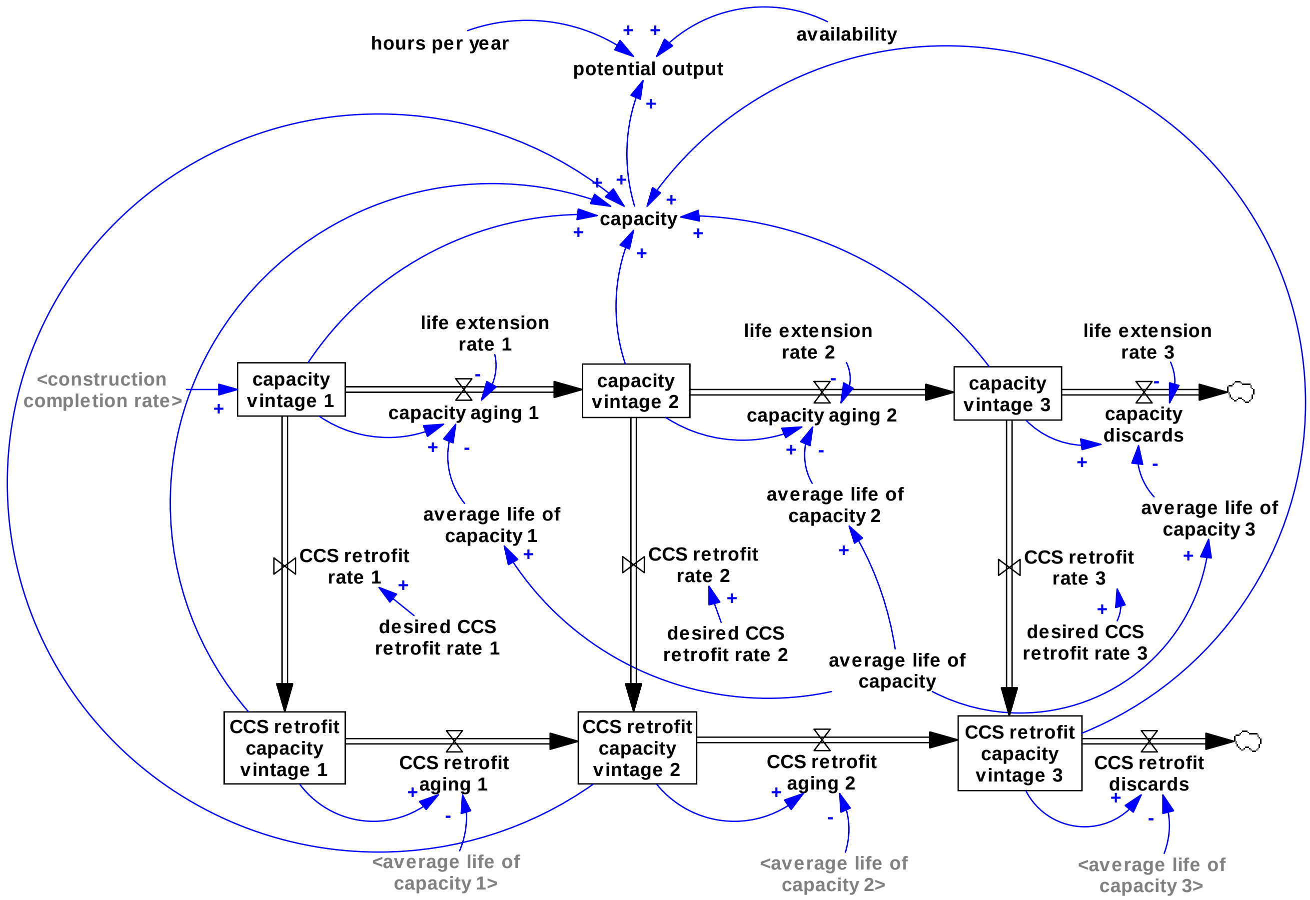

Figure 3. Stock and flow structure of generating capacity

To date, the majority of the feedback loops have been incorporated into the model. More work is needed to characterize natural resource sector (coal, oil, and gas supply). The model is calibrated to 2004 data for power plant characteristics and electricity demand. Estimates of model parameters (e.g., plant construction times, profitability hurdle rates, and demand expectations) have been obtained from the literature, econometric analysis when possible, and expert elicitation or judgment.

The result of this effort is a bottom-up model of the US electric power sector that incorporates all of the empirical and theoretical factors affecting technology penetration rates as discussed in Section 3. The model offers insights into the interactions between penetration rate factors for a given carbon price path using reference parameter estimates. For example, although the some features of the model are not complete, the adoption of CCS technology is much slower in the bottom-up, system dynamics model than in the EPPA model. For a carbon tax beginning in 2010 at $25/t$CO_2$ and growing at a real rate of 4% per year the EPPA model shows the share of CCS generation climbing from 5% to 65% in 20 years. In contrast, the system dynamics model requires 35-40 years for CCS to gain such high shares of generation. This difference is partly due to the greater technology disaggregation in the bottom-up model as well as the supply chain delays.

5. Identification of critical variables and incorporation into integrated assessment models

Upon completion of the model, we plan to use it to identify the most critical factors influencing technology penetration, and to incorporate the important feedbacks into at least one integrated assessment model. These results will be presented in McFarland (2007).

Through sensitivity testing, we plan to determine which exogenous factors (e.g., carbon price, subsidies, demonstration programs, learning rates, resource estimates) and endogenous feedback loops (e.g., learning by doing for technology supplier and user, stock turnover, and resource scarcity) have the greatest influence on the CCS technology penetration path. Different variables will have greater influence at different stages of market penetration. For example, demonstration programs may accelerate initial penetration, but will not likely have as great an impact on the long-term rate of commercialization. The same holds true for the endogenous feedback loops. Initial tests of the model suggest that the exogenous factors have the greatest effects followed by capital stock turnover and technology supply.

Having identified the critical variables and feedbacks, we plan to place probability distributions on the key parameters[10] and use Monte Carlo techniques to establish confidence intervals around the CCS adoption pathways. The probability distributions for parameters may be derived from the literature where possible and expert elicitation. We plan to develop a reduced-form fit of CCS penetration as a function of carbon prices by developing confidence intervals around the CCS adoption path for a variety of carbon price paths.

We have incorporated several important feedbacks into one integrated assessment model, the recursive version of the MIT Emission Prediction and Policy Analysis (EPPA) model (Paltsev et al., 2005). In Otto et al. (forthcoming), we examine the effects of capital vintaging, learning, and adjustment costs on the adoption of CCS technologies. As we have shown in the bottom-up model, the short-run supply of specialized resources (e.g., natural resources, human or physical capital) constrains the optimal level of investment in a new technology. The novel piece of this analysis was constructing an endogenous specification of adjustment costs[11]. To accomplish this, we have developed a method that endogenously incorporates the real costs of short-run resource supply constraints. In this version of the model, as the level of investment in CCS technologies exceeds the specialized resource base, the cost of the technology increases thus tempering demand for the technology. The current version of EPPA controls the penetration rate of CCS technologies using a specialized resource factor that grows as a function of technology output in the previous period. By modifying the parameters of this endogenous specification we can match CCS adoption in EPPA's USA region to the reduced-form fit of the system dynamics model.

[10] This does not include policy parameters such as the carbon price or subsidies.
[11] Earlier work (Jacoby et al. 2006 and McFarland et al. 2004) examine the effects of learning and capital vintaging.

This work should facilitate the incorporation of CCS penetration rates into other models as well. The reduced-form fit of CCS adoption as a function of carbon price can be directly implemented in bottom-up models with fully exogenous constraints (e.g., DNE21, MESSAGE). Similarly, we believe that models with endogenous constraints based on logit specifications can adjust the "elasticity" parameter as function of carbon price to simulate the reduced-form behavior. Having established a calibration procedure for the US and conducted a sensitivity analysis, similar work can be readily repeated for other regions.

Bibliography

Publications from this work:

Jacoby, H.D., J.M. Reilly, J.R. McFarland, and S. Paltsev, Technology and technical change in the MIT EPPA model. (2006). Energy Economics. 28:610-31.

McFarland, J.R. (expected 2007). The Governing Dynamics of Technology Adoption: The Case of Carbon Capture and Storage Technologies. MIT PhD Dissertation.

McFarland, J.R. and H.J. Herzog. (2006). Incorporating Carbon Capture and Storage Technologies in Integrated Assessment Models. Energy Economics. 28:632-52.

McFarland, J.R., H.J. Herzog and H. Jacoby. (2004). The future of coal consumption in a carbon constrained world. Presented at the Seventh International Conference on Greenhouse Gas Control Technologies, Vancouver, Canada, September.

Otto, V., J.R. McFarland, S. Paltsev, J.M. Reilly, M. Babiker. (forthcoming). MIT Joint Program Working Paper.

References Cited in Report:

Anex, R.P., Velnati, S., Meo, M., Ellington, R. and Sharfman, M. (1999). Innovation and the transformation to clean technologies: life cycle management of gas turbine systems. *Proceedings of the 1999 NSF Design & Manufacturing Grantees Conference*, Long Beach, CA, January 5-8.

Brenkert, A.L., R.D. Sands, S.H. Kim, H.M. Pitcher (2004). Model Documentation: The Second Generation Model. PNNL-14256. October.

Edmonds, J. and J. Reilly (1983). A long-term global energy-economic model of carbon dioxide release from fossil fuel use. *Energy Economics* April, 74-88.

Edmonds, J.A., J. Clarke, J. Dooley, S.H. Kim, S.J. Smith (2004). Stabilization of CO2 in a B2 world: insights on the roles of carbon capture and disposal, hydrogen, and transportation technologies. *Energy Economics* 26:517-537.

Ford A. (1997). System dynamics and the electric power industry. *System Dynamics Review* 13: 57-85.

Ford, A. (2001). Conservation in an Era of Boom and Bust, presented at the Conference on Conservation or Crisis: A Northwest Choice, Portland, Oregon, 24 September.

Fujii, Y. and K. Yamaji (1998). Assessment of technological options in the global energy system for limiting the atmospheric CO_2 concentration. *Environmental Economics and Policy Studies*. 1:113-139.

Fujii, Y. (2003). Personal communication.

Grübler, A., N. Nakićenović, and D.G. Victor (1999). Dynamics of energy technologies and global change, *Energy Policy* 27:247-280.

IEA (2005). Energy statistics of OECD countries (2004 edition).

Joskow, P.L. and N.L. Rose. (1990). The diffusion of new technologies: evidence from the electric utility industry. *Rand Journal of Economics*. 21(3):354-373.

Manne, A. and R. Richels (2002). The impact of learning-by-doing on the timing and costs of CO_2 abatement. *Energy Economics* 26:603-619.

Mansfield, E., (1961) Technical change and the rate of imitation, *Econometrica*, 29:741-765.

McDonald, A. and L. Schrattenholzer (2002). Learning curves and technology assessment. *International Journal of Technology Management* 23(7/8):718-745.

McFarland, J.R. and H.J. Herzog (2003). Incorporating carbon capture and storage technologies in integrated assessment models. Presented at the EMF Workshop on Climatic Change Impacts and Integrated Assessments, Snowmass, Colorado, July 28-August 7.

McFarland, J.R., H.J. Herzog, and J.M. Reilly (2004). Representing energy technologies in top-down economic models using bottom-up information, *Energy Economics* 26:685-707.

Naill, R. (1973). The discovery life cycle of a finite resources: a case study of US natural gas. *Toward Global Equilibrium*, ed. D. Meadows and D. Meadows. Wright-Allen Press.

Paltsev, S., J.M. Reilly, H.D. Jacoby, R.S. Eckaus, J. McFarland, M. Sarofim, M. Asadoorian & M. Babiker (2005). The MIT Emissions Prediction and Policy Analysis (EPPA) Model: Version 4. MIT Joint Program Technical Report.

Riahi, K., Rubin, E.S., Taylor, M.R., Schrattenholzer, L., Hounshell, D. (2004) Technological learning for carbon capture and sequestration technologies, *Energy Economics* 26:539-564.

Riahi, K. (2005). Personal communication.

Rogers, E.M. (2003). *The Diffusion of Innovations*, New York: Free Press, 5th ed.

Sands, R.D. (2004). Dynamics of carbon abatement in the Second Generation Model. *Energy Economics*. 26:721-738.

Stoneman, Paul (2002). *The Economics of Technological Diffusion*, Malden, Mass.: Blackwell Publishers.

Taylor, M.R. (2001). The influence of government actions on innovative activities in the development of environmental technologies to control sulfur dioxide emissions from stationary sources. Ph.D. Thesis, Carnegie Mellon University, Pittsburgh, PA, Jan. 2001.

Thirtle, C.G. and V.W. Ruttan (1987), “The Role of Demand and Supply in the Generation and Diffusion of Technical Change”, Fundamentals of Pure and Applied Economics, vol. 21. New York: Harwood Academic Publishers.