Integrated Assessment of Energy Technologies: An Overview

Investigators
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Introduction

This research involves two related areas of examination. The first, "Assessing the Value of New Energy Technologies" focuses on two main tasks.

- Developing ways to represent the performance and costs of new energy technologies at representative years in the future probabilistically with and without GCEP support.
- Developing a demonstration portfolio valuation model designed to give a probabilistic representation of the contribution of resources invested in each GCEP program area to the overall value of the GCEP portfolio.

The second, "Modeling the Transition to a Hydrogen Economy", focuses on two main tasks:

- Developing a set of unit costs and unit carbon dioxide emissions associated with various technologies that could be used to supply hydrogen for use in light duty vehicles.
- Modeling several quantitative scenarios of the introduction and growth of hydrogen use in light duty vehicles, examining the consequences for economic and environmental impacts as well as impact on other U.S. natural resource use.

These two related areas will be examined separately in the next two sections of this report, entitled "Results: Assessing the Value of New Energy Technologies" and "Results: Modeling the Transition to a Hydrogen Economy". A number of additional sub-projects are described in subsequent sections. Those sections fill out some of the details for items presented in this overview and lay out some future research directions.

Results: Assessing the Value of New Energy Technologies

Assessments of the impacts of new technologies depend on assessments of both their likely cost and performance characteristics (including carbon emissions and other environmental impacts), and their likely market penetration under a wide range of possible energy futures. Approaches to these two tasks are now presented.

Advanced Technology Representation

This task has involved alternative ways of representing the performance and cost of fundamentally new energy technologies with and without GCEP funding. So far this has involved assessments of the probability of demonstrating the technical feasibility of the technology and separate assessments of the probability distributions over the cost and likely environmental impacts of employing these technologies to reduce carbon emissions at future dates of interest. We have experimented with assessing these impacts using a large number of different probability distributions, and different levels of structural modeling of future energy devices and processes.

Also important in projecting the costs of new energy technologies are projected shifts in the assessed distributions over time and decreases in costs with level of implementation resulting from limits on rates of introduction, as well as siting, intermitancy of availability, and resource supply considerations. Land use, water use, and noble metal availability are examples of resources whose prices may increase if demand for them increases significantly to support the wide-scale introduction of new energy technologies.

Obviously these assessments require a great deal of input from technical experts in the areas being assessed. This year we continue to use our strong traditional expertise in probabilistic risk assessment and system economics, but now with much more input from GCEP's central systems group and technology assessment staff to bring in their expertise in technology assessment. We also are increasingly involving experts in specific technologies and relevant areas of scientific research here at Stanford (including GCEP PIs) and the research community at large in this endeavor. Particularly valuable here continue to be input from technical experts at the sponsoring companies. One example of the approach to new technology assessment that we are pursuing is discussed in the sections below on carbon capture and sequestration technologies. Additional examples are given in Weyant, et al. (2005a).

Portfolio Valuation

Given information regarding the characteristics of the new energy technologies resulting from R&D (expressed via ranges or probability distributions over costs and performance at specific future dates of interest), assessments of the value of those specific new technologies depend on what other new technologies have been developed, the rate of improvement in existing technologies, and conditions in energy markets. Conditions in energy markets are reflected in energy prices and depend on many factors including population levels, economic output, the structures of the world's economies, resource availabilities, energy producer (and especially oil exporter) behavior, the set of available technologies for producing, transforming and consuming energy, and government energy, economic, and environmental policies.

The key factors that determine the future value of new energy technologies are highly uncertain and the relationships between them can be quite complex. One approach to energy policy assessment is to run sensitivity analysis on external factors through models of the energy system. Results from these types of exercises are extremely illuminating but generally consider only one reference scenario for one basic set of input and parameter values for each model. There are extremely large uncertainties about both sets of inputs over the course of a century and these uncertainties can have a significant impact on how we value the products of long-term R&D on new energy technologies. During the past year, the elements of this system have been specified in enough detail to allow the development of a full demonstration version of the technology assessment system.

Design Criteria for Evaluation Framework

At the beginning of this project, preliminary design criteria for the evaluation framework were developed. It was recognized that large-scale energy system models are often designed for purposes other than long-run energy technology assessment (e.g., short-run mitigation analyses, assessing international trade impacts of climate policies, emissions target setting and emissions trading analyses) and, therefore, include a level of complexity that makes extensive sensitivity analysis, let alone formal uncertainty analysis, infeasible. The approach employed here is to use reduced-form energy models (calibrated to the more large-scale models) as the central element of an uncertainty-oriented technology evaluation approach. We continue to use literature reviews, structural models, and expert assessments to develop probability distributions about key inputs to the models. This is crucial because these inputs are generally more important determinants of the values of the new technologies than the parameters included in the models.

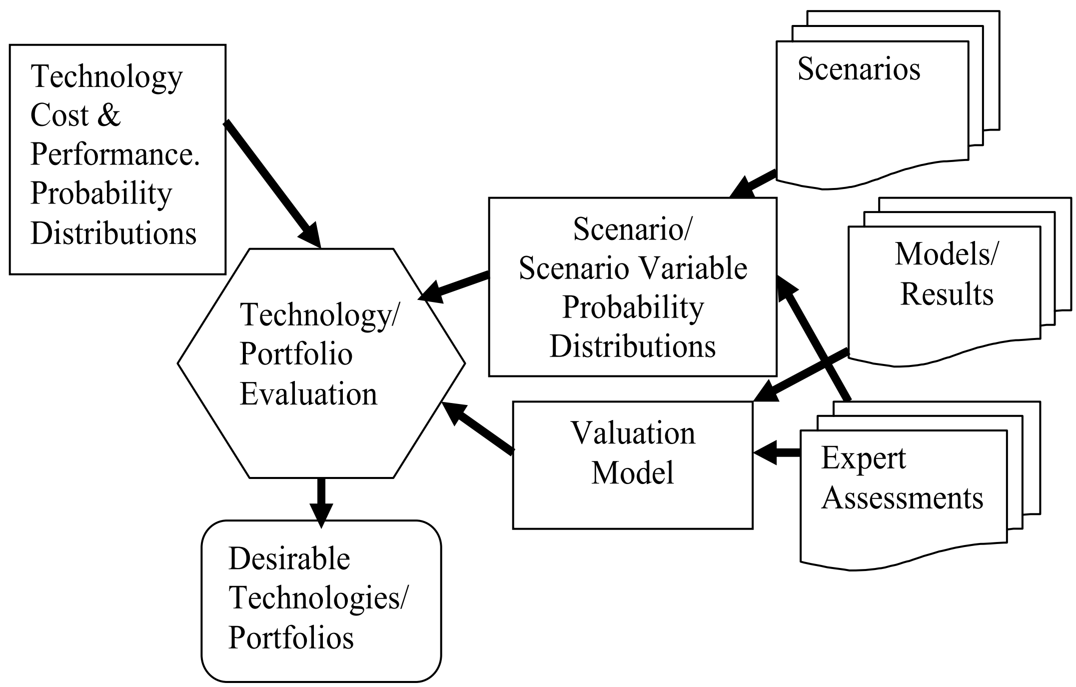

Figure 1: Schematic diagram of technology evaluation process

Based on these assessments, we are working with a set of integrated probabilistic scenarios. These scenarios represent a wide range of future states of the world and are mutually exclusive and collectively exhaustive so that probabilities can be assigned to them. This enables us to compute impact values for the new technologies across a wide range of possible technological and socio-economic futures. Figure 1 shows the key elements of the technology evaluation system.

We designed these scenarios to be as informative as possible about the efficacy of the GCEP R&D portfolio. For example, they range from a (relatively low probability) case where there is no future concern about climate change to one in which (say twenty years from now) where climate change is perceived to be a (relatively low probability, but plausible) much more serious problem than currently expected. In the former case, only a small number of low-/non-carbon emitting technologies (e.g., perhaps advanced-technology combustion engines) will be adopted, whereas in the latter many low-/non-carbon emitting technologies that are more expensive than conventional carbon emitting technologies will be adopted. This comparison illustrates the “option value” associated with the development of new technologies. If new technologies are developed they can be introduced and diffused if they are needed, but kept “on the shelf” (and perhaps put into further development to make them more economical) if they are not needed.

Over the last year, the valuation model has evolved from a simple two sector, two regions, one time period specification to a more sophisticated system with greater detail and inputs calibrated to more complex models, estimated from primary data and/or obtained via expert assessments. Uncertainty about the cost and performance of the technology being evaluated and those of other new technologies are being represented by sampling from the probability distributions for those characteristics. Over time more sophisticated ways of incorporating the actual probability distributions into the analysis have continued to be adopted, and the representation of R&D effort has been broken down into stages, reflecting the technical challenges that need to be met to bring the technology to fruition as well as open up the option of improving it over time. This information will allow us to look at the optimal R&D portfolio more fully as a sequential decision making problem over time where stages of the R&D on a particular technology may be pursued with subsequent stages either canceled or accelerated depending on how the energy system and the climate problem evolve.

Finally the technologies are being evaluated in groups in hopes of finding the most valuable portfolio(s) of technology options given the uncertainties about technology costs and performances, scenario variables, and valuation model parameters. Here we will consider using the whole portfolio as a hedge against future uncertainties as well as using individual elements of the portfolio as hedges against lack of technical or economic success in the other elements of the portfolio.

Demonstration Valuation Framework

Last year a prototype valuation model was formulated and tested. Although this model was not quite ready to be used in the technology assessments, the basic structure seemed workable, developing it revealed a number of challenges that needed to be met to develop a more useful framework, and some basic insights were illustrated semi-quantitatively. This year a more realistic demonstration version model has been developed which is ready to be used as part of technology assessments for GCEP and other interested parties. Although the objectives and philosophy of this framework are consistent with those of the prototype, its structure has evolved to meet the challenges identified last year.

We start with information regarding the characteristics of the new energy technologies resulting from R&D (expressed via probability distributions over costs and performance at specific future dates of interest as described above). Assessments of the value of each new technology depend on what other new technologies have been developed, how fast existing technologies are improved, and conditions in energy markets. Thus, these evaluations require a type of "integrated assessment" of all technologies under all possible market conditions. The basic approach pursued in the design of the prototype evaluation system was initially to divide the world up into two parts: (1) what the GCEP Portfolio can provide in terms of supplies of carbon energy substitutes at various price levels, and (2) what the world might demand of this portfolio under a wide range of future energy market futures. Obviously, both the technology assessments and market assessments are very complex and highly uncertain.

The prototype assessment system started with a highly simplistic and aggregate representation of key elements of the system, but was designed in a way in which more detailed information from any source could easily be added as necessary (in modeling parlance this framework has been designed to be highly scalable). The value of each individual GCEP research program was evaluated in terms of its contribution to the value of the whole GCEP portfolio which was in turn evaluated in terms of its contribution to key energy sectors in key world regions at various times in the future.

The simplest aggregated version of the framework looked at the GCEP enabled supply and rest-of-world demand for non-carbon energy at various future dates of interest. The supply side of that framework consisted of the collection of stochastic GCEP R&D program supply curves described above. These consisted of a single subjective probability of technical success of the program and a probability distribution over the cost of employing the new technology commercially.

The demand for non-carbon energy takes into account possible future conditions in the global energy system including the implications of alternative fuel price scenarios, improvements in non-GCEP technologies (through learning over time, with respect to non-GCEP R&D funding, and with respect to cumulative experience), critical materials or infrastructure constraints on the rates of new technology adoption, economic growth rates, structural changes in the global economy, and government policies including those directly related to climate change. Forecasting how all these factors will work towards creating a market for advanced non-carbon technologies is extremely complicated and highly uncertain. But it is just this wide range of possible outcomes that can create a very large value for advanced technology development.

Conceptually, as observed in last year's report, one could construct these demand curves for non-carbon energy by taking any of the leading global energy models for one set of model parameters, one set of model drivers and one set of policies and add a fictitious source of non-carbon energy at a very low price and observe the demand for it, subsequently increasing the price again and again until more non-carbon energy is demanded. In this way a demand curve for non-carbon energy for one model implemented state of the world could be developed. Since the focus of GCEP is on long-run pre-competitive R&D to help prepare for a very wide range of future states of the energy system it would be cumbersome and probably infeasible to run a large-scale model thousands of times to develop the demand side of the framework. In addition, large-scale models may impose too much structure on the world energy system to be appropriate for this task. Thus, we started with very aggregated energy system models which could be calibrated to the existing set of large-scale energy models, but also took inputs from a number of other sources including relevant empirical work and expert opinion.

Progress

There are two major changes in this year's implementation of the process of projecting the demand for carbon-free energy with respect to last year's prototype model. First, it proved too awkward to represent the full range of technologies (renewable energy technologies, advanced combustion, sequestration, etc.) directly in a simple supply-demand equilibrium like that shown in Figure 2. Instead an equilibrium is now solved for as the result of an optimization formulation where technologies that can satisfy demands compete with each other and are selected to minimize system costs, and demands are adjusted in accordance with the resulting costs of supply. This is an architecture employed in many large-scale general purpose integrated assessment models and allows most of the GCEP portfolio to be represented in terms of modifications to individual technology cost and performance characteristics (including environmental impacts).

The second major change is the use of an existing global energy systems model as the primary source of baseline energy system and energy technology projections. In other words, baseline carbon emissions are calibrated to the baseline emissions produced by the model and most of the baseline technology assumptions come from that baseline or extrapolations from it. The model used for this purpose is the Energy Information Administration's (EIA's) new System for the Analysis of Global Energy (SAGE-EIA, 2003a &2003b). This model was used for the first time to produce the projections included in the EIA's 2004 International Energy Outlook (IEO- EIA, 2004) which was released in April 2004 (IEO 2005 is now scheduled to be released on July 15, 2005). This is a technology rich global model which has grown out of set individual country/regional MARKAL models in the past few years. An early application of a MARKAL type model to national energy R&D planning can be found in Weyant (1984).

The ETSAP (Energy Technology Systems Analysis Programme) network which includes representatives from most of the MARKAL (ETSAP, 2005a) teams has developed a general global energy technology systems modeling framework called the TIMES model (ETSAP, 2005b). This "model" is a set of data files (spreadsheets, databases, simple ASCII files), which fully describes the underlying energy system (technologies, commodities, resources and demands for energy services) in a format compatible with the associated model generator (MARKAL or TIMES). In addition to the SAGE model, instances of global models based on the TIMES architecture include the Energy Technology Perspectives (ETP) project MARKAL model of the IEA, the Global MARKAL-Macro of the Paul Scherrer Institute, and the European Fusion

Development Agreement TIMES model; the national models of the ETSAP partner institutions; and various regional and municipal models developed by other institutions. Each set of files defines one model (perhaps consisting of a number of regional models) and is "owned" by the developer(s).

SAGE was selected here because it is the most public of the existing TIMES variants and as the documentation is brought up to EIA's normal high standards should be the most transparent version. In addition, the baseline and sensitivity cases produced as part of the IEO (including the energy market and technology inputs) are compared with other projections, assessed and debated publicly on a regular basis (EIA, 2004).

Calibrating to – but simplifying from - an existing model like the SAGE model has several other advantages. First, it allows us to focus in on key strategic regions/sectors on relevant time scales and used reduced form representations of the sectors/regions/dynamics not focused on to create a comprehensive picture of how the energy system would affect - and be affected by - new GCEP stimulated technologies.

The second benefit of the scalability provided by the partial co-integration with an existing model is the ability to look at the dynamics of technology development and crucial implications of assumptions about the degree of foresight assumed to be used by the businesses and consumers whose behavior is represented in the models. These dimensions of the technology assessment process are typically not well reflected in existing large-scale general purpose integrated assessment models.

A third benefit of the model integration strategy we are employing is that it allows us to expand rapidly into new areas as the GCEP portfolio expands or as new areas are proposed. For example, the current system focuses on energy conversion/use in key regions for electricity generation, transportation and large thermal uses in the industrial, residential and commercial end-use sectors. Should a more comprehensive and explicit treatment of end-use energy become desirable, the detail in this area included in SAGE could easily be assimilated (and assessed and modified) in a way that would require only minimal modifications to the rest of the system.

In order to be useful for long-run technology portfolio assessment under uncertainty, a number of modifications and simplifications were made to the basic structure of the SAGE model. First, the time horizon of the model was extended to 2100 from the 2050 to which the model has been run for the EIA's International Energy Outlook and the 2025 time frame through which results were reported in that document. Second, in part by lengthening the time periods considered from five years to 25 years each, many of the short-run dynamics in the SAGE model were eliminated or greatly simplified. Finally, much of the detail on the operation of the electricity transmission and distribution system and daily/seasonal patterns of electricity demands were simplified or eliminated because again it is anticipated that these dynamic constraints will not impact the assessments of the introduction of fundamentally new energy technologies over many decades very much. In effect, the assumption made here is that the T&D and scheme for temporal pricing of electricity can be designed around the new technologies given sufficient lead times. These simplifications greatly reduce the time required for a single run of the full SAGE model. Although this has not yet been fully tested, it is estimated that this reduced-form global energy model would run in about .01% to .1% of the time it takes to run the full SAGE model in a comparable computing environment.

This calibration to the SAGE baselines and technology data does not (as will become obvious) preclude adopting model structure, parameters and inputs from other modeling and analysis efforts where appropriate. For example, cost and diffusion parameters for hydrogen fueled vehicles are drawn from National Research Council (2004), and carbon capture and sequestration from Heddle, Herzog, and Klett. (2003), and Dooley and Friedman (2004). This is another advantage of the flexible assessment architecture adopted here. In other words, if the overall architecture of the assessment system was optimization or computable general equilibrium oriented this would immediately limit the types of formulations that could be integrated into it.

Model Structure

The demonstration integrated assessment framework consists of eight regions, five conversion/use sectors, and four time periods. The eight regions are China, India, Other Developing, Former Soviet Union and Eastern Europe, Western Europe, Japan, United States, and Other Developed. This regionalization allows the focus to be on the largest current and likely future GHG emitting countries/regions in a way that is consistent with existing data collection/modeling efforts. Following SAGE we also divide the US into 4 regions and China into two; greater regionalization of China and India will be added in the near future as the requisite data is developed. These sub-country regionalizations are especially important in assessments of the potential of distributed and renewable resources.

The current breakdown of conversion/end-uses includes electricity generation, transportation, industrial steam/process heat, residential and commercial heating, and other non-electric uses. This breakdown is a bit unconventional, but again focuses well on where large reductions in GHG emissions may be possible with very advanced new technologies and where current GCEP R&D programs lie, and would be very easy to re-focus further down stream if necessary.

As in SAGE, demands for the outputs of the first four of the five end-use/conversions sectors are based on computing supply-demand equilibria at projected fuel prices and cost and performance parameters for individual supply technologies. For each level of demand, supplies are produced by the cost-minimizing mix of technologies, given fuel prices. In the other non-electric demands sector fuel demands are computed as reduced-form functions of fuel prices, although individual technology data from SAGE could ultimately be used for these uses as well.

The four time periods considered are 2000-2025, 2026-2050, 2051-2075, and 2076-2100. These time periods are long enough to allow most of the energy producing, transforming, and using equipment to be turned over (excepting some large power plants and other similar scale facilities), which seems appropriate for assessing the impacts of “step out” energy technologies. Despite the length of these time periods, many shorter run capacity and transition limitations can be considered when necessary through the use of growth rate assumptions and various kinds of constraints on the absolute or market share contributions of individual technologies.

While it is not possible to include a comprehensive list of all the technologies and their assumed performance characteristics included in the demonstration assessment framework (see Weyant, et al., 2005a for more detail) here, we can give a flavor for the level of detail employed by briefly describing some of the main SAGE technologies (EIA, 2003a). Technologies for electricity generation, automotive transport, residential space heating, and steam/process heat for ferrous and non-ferrous metals, chemicals, and paper and pulp making are briefly described here.

Table I lists the basic electricity generation technologies included in SAGE. The descriptors consist of the number of the grid within the region where the facility is to be installed (often there is only one), the year of availability, the fuel required, and the basic technology employed. For each technology, the SAGE data base includes its efficiency, annual utilization or capacity factor, lifetime, investment cost, and fixed and variable maintenance costs. For renewable electricity generation from wind, solar and biomass (in both central station and distributed modes) the availability of appropriate resources by quality category (e.g., average wind speed, solar insolation level, and productivity of biomass sources) are also key inputs. Fossil fuel prices come from scenario assumptions modified by aggregate demand changes caused by new technology introductions.

In Table II we show the basic automobile technology options. Other transportation options are included in SAGE (e.g., trucks, airplanes, three wheelers in India and other developing countries), but not listed here. The naming scheme is similar to that for electricity generation: type of technology, year of availability, conventional or advanced categories, fuel consumed, existing characterization and efficiency. Conventional fuels are gasoline and diesel; alternative fuels are LPG, ethanol, natural gas, methanol and electricity. The CAFÉ efficiency standards with numbers appended are more efficient than the CAFÉ standards by that number of miles per gallon. Additional structure included in the SAGE model are mode share constraints which are loosened significantly in our longer term assessment system.

Table III shows the Residential space heating technologies included in SAGE which have descriptors similar to those for the two previous sectors. Electricity demands for heat pumps are added to the overall electricity demand totals.

Table I: SAGE Electric Generation Technologies

Technology	Description
Oil	
EOILGBL105 EOILGPL105 EOILSTE105	EPLT: .G1.05.CON.OIL.Generic Dist Gen for Base Load. EPLT: .G1.05.CON.OIL.Generic Dist Gen for Peak Load. EPLT: .G1.05.CON.OIL.Oil Steam.
Gas	
EGASFCE105 EGASSTE105	EPLT: .G1.05.ADV.NGA.Fuel Cells. EPLT: .G1.05.CON.NGA.Gas Steam.
Coal	
ECOAAFB105 ECOACCA105 ECOACCO105 ECOAPFB105 ECOAPUL105	EPLT:G1.05.ADV.COA.Atmospheric Fl Bed. EPLT: .G1.05.ADV.COA.Air Blown IGCC. EPLT: .G1.05.ADV.COA.Oxygen Blown IGCC. EPLT:G1.05.ADV.COA.Pressurized Fl Bed. EPLT: .G1.05.CON.COA.Pulverized Coal.
Mix Oil/Gas	
EGOICCA105 EGOICCY105 EGOITUA105 EGOITUR105	EPLT: .G1.05.ADV.GOI.Gas/Oil Comb Cycle. EPLT: .G1.05.CON.GOI.Gas/Oil Comb Cycle. EPLT: .G1.05.ADV.GOI.Advanced Gas/Oil Turbine. EPLT: .G1.05.CON.GOI.Gas/Oil Turbine.
Hydro	
EHYDDAM105 EHYDRUN105	EPLT: .G1.05.CON.HYD.Generic Impoundment Hydro. EPLT: .G1.05.CON.HYD.Generic ROR Hydro.
Nuclear	
ENUCADV105 ENUCLWR105 ENUCPBM110	EPLT: .G1.05.ADV.NUC.Advanced Nuclear. EPLT: .G1.05.ADV.NUC.Advanced Nuclear LWR. EPLT: .G1.10.ADV.NUC.Advanced Nuclear PBMR.
Biomass	
EBIOCRC105 EBIOCRG105 EBIOGAW105 EBIOMSW105 EBIOSLC105 EBIOSLG105	EPLT: .G1.05.CON.BIO.Crop Direct Combustion. EPLT: .G1.05.CON.BIO.Crop Gasification. EPLT: .G1.05.CON.BIO.Biogas from Waste. EPLT: .G1.05.CON.BIO.MSW Direct Combustion. EPLT: .G1.05.CON.BIO.Sld Biomass Direct Combustion. EPLT: .G1.05.CON.BIO.Sld Biomass Gasification.
Geothermal	
EGEOBIN105 EGEOFLA105 EGEOROC110	EPLT: .G1.05.CON.GEO.Binary Geo. EPLT: .G1.05.CON.GEO.Flash Steam Geo. EPLT: .G1.10.CON.GEO.HotDryRock1 Geo.
Solar	
ESOLPVB105 ESOLPVN105 ESOLTWB105	EPLT: .G1.05.CON.SOL.PV.Solar PV w Backup. EPLT: .G1.05.CON.SOL.PV.Solar PV no Backup. EPLT: .G1.05.CON.SOL.Solar Thermal w Backup.
Wind	
EWINNBU105 EWINWBU105	EPLT: .G1.05.CON.WIN.Wind no Backup. EPLT: .G1.05.CON.WIN.Wind w Backup.
Heat	
HETBIOP105 HETCOAP105 HETGASP105 HETGEOP105 HETOILP105	HPLT: .05.CON.BIO. HPLT: .05.CON.COA. HPLT: .05.CON.NGA. HPLT: .05.CON.GEO. HPLT: .05.CON.OIL.

Table II: SAGE automobile technologies

	Description	Commodity IN
TRT: Autos		
TRTDCA005	CAR: .05.CFV.DST.CAFE.STD.	TRADST
TRTDCA010	CAR: .10.CFV.DST.CAFE.STD.	TRADST
TRTDCA015	CAR: .15.CFV.DST.CAFE.STD.	TRADST
TRTDCA020	CAR: .20.CFV.DST.CAFE.STD.	TRADST
TRTDEG005	CAR: .05.AFV.DEG.ETH/GAS.	TRAETH, TRAGSL
TRTDEG010	CAR: .10.AFV.DEG.ETH/GAS.	TRAETH, TRAGSL
TRTDEG015	CAR: .15.AFV.DEG.ETH/GAS.	TRAETH, TRAGSL
TRTDEG020	CAR: .20.AFV.DEG.ETH/GAS.	TRAETH, TRAGSL
TRTDFL005	CAR: .00.CFV.DST.STD.	TRADST
TRTDMG005	CAR: .05.AFV.DMG.MET/GAS.	TRAMET, TRAGSL
TRTDMG010	CAR: .10.AFV.DMG.MET/GAS.	TRAMET, TRAGSL
TRTDMG015	CAR: .15.AFV.DMG.MET/GAS.	TRAMET, TRAGSL
TRTDMG020	CAR: .20.AFV.DMG.MET/GAS.	TRAMET, TRAGSL
TRTDST005	CAR: .05.CFV.DST.STD.	TRADST
TRTELC005	CAR: .05.AFV.ELC.	TRAELC
TRTELC010	CAR: .10.AFV.ELC.	TRAELC
TRTELC015	CAR: .15.AFV.ELC.	TRAELC
TRTELC020	CAR: .20.AFV.ELC.	TRAELC
TRTETH005	CAR: .05.AFV.ETH.	TRAETH
TRTETH010	CAR: .10.AFV.ETH.	TRAETH
TRTETH015	CAR: .15.AFV.ETH.	TRAETH
TRTETH020	CAR: .20.AFV.ETH.	TRAETH
TRTFUC010	CAR: .10.AFV.FUC.	TRAGSL
TRTFUC015	CAR: .15.AFV.FUC.	TRAGSL
TRTFUC020	CAR: .20.AFV.FUC.	TRAGSL
TRTGAA005	CAR: .00.CFV.GAS.STD.SUBCOMPACT.	TRAGSL
TRTGAB005	CAR: .00.CFV.GAS.STD.COMPACT.	TRAGSL
TRTGAC005	CAR: .00.CFV.GAS.STD.MEDIUM.	TRAGSL
TRTGAD005	CAR: .00.CFV.GAS.STD.FULL.	TRAGSL
TRTGAS005	CAR: .05.CFV.GAS.STD.	TRAGSL
TRTGCA005	CAR: .05.CFV.GAS.CAFE.STD.	TRAGSL
TRTGCA010	CAR: .10.CFV.GAS.CAFE.STD.	TRAGSL
TRTGCA015	CAR: .15.CFV.GAS.CAFE.STD.	TRAGSL
TRTGCA020	CAR: .20.CFV.GAS.CAFE.STD.	TRAGSL
TRTGCB005	CAR: .05.CFV.GAS.CAFE.7.0MPG.	TRAGSL
TRTGCB010	CAR: .10.CFV.GAS.CAFE.7.0MPG.	TRAGSL
TRTGCB015	CAR: .15.CFV.GAS.CAFE.7.0MPG.	TRAGSL
TRTGCB020	CAR: .20.CFV.GAS.CAFE.7.0MPG.	TRAGSL
TRTGCC010	CAR: .10.CFV.GAS.CAFE.3.5MPG.	TRAGSL
TRTGCC015	CAR: .15.CFV.GAS.CAFE.3.5MPG.	TRAGSL
TRTGCC020	CAR: .20.CFV.GAS.CAFE.3.5MPG.	TRAGSL
TRTGCE005	CAR: .00.CFV.GAS.CAFE.STD.	TRAGSL
TRTGFL005	CAR: .00.CFV.GAS.STD.	TRAGSL
TRTHYB005	CAR: .05.AFV.HYB.	TRAGSL
TRTHYB010	CAR: .10.AFV.HYB.	TRAGSL
TRTHYB015	CAR: .15.AFV.HYB.	TRAGSL
TRTHYB020	CAR: .20.AFV.HYB.	TRAGSL
TRTLPG005	CAR: .05.AFV.LPG.	TRALPG
TRTLPG010	CAR: .10.AFV.LPG.	TRALPG
TRTLPG015	CAR: .15.AFV.LPG.	TRALPG
TRTLPG020	CAR: .20.AFV.LPG.	TRALPG
TRTMET005	CAR: .05.AFV.MET.	TRAMET
TRTMET010	CAR: .10.AFV.MET.	TRAMET
TRTMET015	CAR: .15.AFV.MET.	TRAMET
TRTMET020	CAR: .20.AFV.MET.	TRAMET
TRTNGA005	CAR: .05.AFV.NGA.	TRANGA
TRTNGA010	CAR: .10.AFV.NGA.	TRANGA
TRTNGA015	CAR: .15.AFV.NGA.	TRANGA
TRTNGA020	CAR: .20.AFV.NGA.	TRANGA

Table III: Selected SAGE residential space heating technologies

Technology	Description	Commodity IN
RH1, RH2, RH3, RH4: Space heating		
RH1BIO005	RES.HEAT.R1: .05.BIO.INS-REG.WOODSTOVES.	RESBIO
RH1BIO105	RES.HEAT.R1: .05.BIO.INS-35%.WOODSTOVES.	RESBIO
RH1BIO205	RES.HEAT.R1: .05.BIO.INS-47%.WOODSTOVES.	RESBIO
RH1BIO305	RES.HEAT.R1: .05.BIO.INS-50%.WOODSTOVES.	RESBIO
RH1COA005	RES.HEAT.R1: .05.COA.INS-REG.BURNER.	RESCOA
RH1COA105	RES.HEAT.R1: .05.COA.INS-35%.BURNER.	RESCOA
RH1COA205	RES.HEAT.R1: .05.COA.INS-47%.BURNER.	RESCOA
RH1COA305	RES.HEAT.R1: .05.COA.INS-50%.BURNER.	RESCOA
RH1DSA005	RES.HEAT.R1: .05.DST.INS-REG.BURNER.IMP.	RESDST
RH1DSA105	RES.HEAT.R1: .05.DST.INS-35%.BURNER.IMP.	RESDST
RH1DSA205	RES.HEAT.R1: .05.DST.INS-47%.BURNER.IMP.	RESDST
RH1DSA305	RES.HEAT.R1: .05.DST.INS-50%.BURNER.IMP.	RESDST
RH1DSB005	RES.HEAT.R1: .05.DST.INS-REG.BURNER.NEW.	RESDST
RH1DSB105	RES.HEAT.R1: .05.DST.INS-35%.BURNER.NEW.	RESDST
RH1DSB205	RES.HEAT.R1: .05.DST.INS-47%.BURNER.NEW.	RESDST
RH1DSB305	RES.HEAT.R1: .05.DST.INS-50%.BURNER.NEW.	RESDST
RH1DSO005	RES.HEAT.R1: .05.DST.INS-REG.SOLAR.	RESDST
RH1DSO105	RES.HEAT.R1: .05.DST.INS-35%.SOLAR.	RESDST
RH1DSO205	RES.HEAT.R1: .05.DST.INS-47%.SOLAR.	RESDST
RH1DSO305	RES.HEAT.R1: .05.DST.INS-50%.SOLAR.	RESDST
RH1DST005	RES.HEAT.R1: .05.DST.INS-REG.BURNER.STD.	RESDST
RH1DST105	RES.HEAT.R1: .05.DST.INS-35%.BURNER.STD.	RESDST
RH1DST205	RES.HEAT.R1: .05.DST.INS-47%.BURNER.STD.	RESDST
RH1DST305	RES.HEAT.R1: .05.DST.INS-50%.BURNER.STD.	RESDST
RH1EHP005	RES.HEAT.R1: .05.ELC.INS-REG.HEAT PUMP.AIR.STD.	RESELC
RH1EHP105	RES.HEAT.R1: .05.ELC.INS-35%.HEAT PUMP.AIR.STD.	RESELC
RH1EHP205	RES.HEAT.R1: .05.ELC.INS-47%.HEAT PUMP.AIR.STD.	RESELC
RH1EHP305	RES.HEAT.R1: .05.ELC.INS-50%.HEAT PUMP.AIR.STD.	RESELC
RH1ELB005	RES.HEAT.R1: .05.ELC.INS-REG.HEAT PUMP.AIR.IMP.	RESELC
RH1ELB105	RES.HEAT.R1: .05.ELC.INS-35%.HEAT PUMP.AIR.IMP.	RESELC
RH1ELB205	RES.HEAT.R1: .05.ELC.INS-47%.HEAT PUMP.AIR.IMP.	RESELC
RH1ELB305	RES.HEAT.R1: .05.ELC.INS-50%.HEAT PUMP.AIR.IMP.	RESELC
RH1ELD005	RES.HEAT.R1: .05.ELC.INS-REG.HEAT PUMP.AIR.ADV.	RESELC
RH1ELD105	RES.HEAT.R1: .05.ELC.INS-35%.HEAT PUMP.AIR.ADV.	RESELC
RH1ELD205	RES.HEAT.R1: .05.ELC.INS-47%.HEAT PUMP.AIR.ADV.	RESELC
RH1ELD305	RES.HEAT.R1: .05.ELC.INS-50%.HEAT PUMP.AIR.ADV.	RESELC
RH1ELF005	RES.HEAT.R1: .05.GEO.INS-REG.HEAT PUMP.GROUND.STD.	RESGEO
RH1ELF105	RES.HEAT.R1: .05.GEO.INS-35%.HEAT PUMP.GROUND.STD.	RESGEO
RH1ELF205	RES.HEAT.R1: .05.GEO.INS-47%.HEAT PUMP.GROUND.STD.	RESGEO
RH1ELF305	RES.HEAT.R1: .05.GEO.INS-50%.HEAT PUMP.GROUND.STD.	RESGEO
RH1ELS005	RES.HEAT.R1: .05.ELC.INS-REG.SOLAR.	RESELC
RH1ELS105	RES.HEAT.R1: .05.ELC.INS-35%.SOLAR.	RESELC
RH1ELS205	RES.HEAT.R1: .05.ELC.INS-47%.SOLAR.	RESELC
RH1ELS305	RES.HEAT.R1: .05.ELC.INS-50%.SOLAR.	RESELC
RH1ERS005	RES.HEAT.R1: .05.ELC.INS-REG.RESISTANCE.	RESELC
RH1ERS105	RES.HEAT.R1: .05.ELC.INS-35%.RESISTANCE.	RESELC
RH1ERS205	RES.HEAT.R1: .05.ELC.INS-47%.RESISTANCE.	RESELC
RH1ERS305	RES.HEAT.R1: .05.ELC.INS-50%.RESISTANCE.	RESELC
RH1GEO005	RES.HEAT.R1: .05.GEO.INS-REG.EXCHANGER.	RESGEO
RH1HET005	RES.HEAT.R1: .05.HET.INS-REG.EXCHANGER.	RESHET
RH1HET105	RES.HEAT.R1: .05.HET.INS-35%.EXCHANGER.	RESHET
RH1HET205	RES.HEAT.R1: .05.HET.INS-47%.EXCHANGER.	RESHET
RH1HET305	RES.HEAT.R1: .05.HET.INS-50%.EXCHANGER.	RESHET
RH1HFO005	RES.HEAT.R1: .05.HFO.INS-REG.BURNER.	RESHFO
RH1KER005	RES.HEAT.R1: .05.KER.INS-REG.BURNER.	RESKER
RH1KER105	RES.HEAT.R1: .05.KER.INS-35%.BURNER.	RESKER
RH1KER205	RES.HEAT.R1: .05.KER.INS-47%.BURNER.	RESKER
RH1KER305	RES.HEAT.R1: .05.KER.INS-50%.BURNER.	RESKER
RH1LPG005	RES.HEAT.R1: .05.LPG.INS-REG.BURNER.	RESLPG
RH1LPG105	RES.HEAT.R1: .05.LPG.INS-35%.BURNER.	RESLPG
RH1LPG205	RES.HEAT.R1: .05.LPG.INS-47%.BURNER.	RESLPG
RH1LPG305	RES.HEAT.R1: .05.LPG.INS-50%.BURNER.	RESLPG

In Table IV, steam and process heat technologies for the two of the largest energy consuming industries are shown with their descriptions.

Table IV: Selected SAGE industrial energy technologies

Technology	Description	Commodity IN	Commodity OUT
IIS: Iron and steel			
IIS000	Existing Iron and Steel Tech	ISIS	IIS
ISISHFO000	Steam Iron and Steel Heavy Oil Existing	INDHFO	ISIS
ISISDST000	Steam Iron and Steel Distillate Oil Existing	INDOIL	ISIS
ISISNGA000	Steam Iron and Steel Natural Gas Existing	INDNGA	ISIS
ISISCOA000	Steam Iron and Steel Coal Existing	INDCOA	ISIS
IPISHFO000	Process Heat Iron and Steel Heavy Fuel Existing	INDHFO	IPIS
IPISDST000	Process Heat Iron and Steel Distillate Fuel Existing	INDOIL	IPIS
IPISNGA000	Process Heat Iron and Steel Natural Gas Existing	INDNGA	IPIS
IPISCOA000	Process Heat Iron and Steel Coal Existing	INDCOA	IPIS
IPISELC000	Process Heat Iron and Steel Electric Existing	INDELC	IPIS
IPISCOG000	Process Heat Iron and Steel Cokeoven Gas Existing	INDCOG	IPIS
IPISBFG000	Process Heat Iron and Steel Blast Furnace Gas Existing	INDBFG	IPIS
IPISLPG000	Process Heat Iron and Steel LPG Existing	INDLPG	IPIS
IMISHFO000	Machine Drive Iron and Steel Heavy Oil Existing	INDHFO	IMIS
IMISDST000	Machine Drive Iron and Steel Distillate Oil Existing	INDOIL	IMIS
IMISNGA000	Machine Drive Iron and Steel Natural Gas Existing	INDNGA	IMIS
IMISCOA000	Machine Drive Iron and Steel Coal Existing	INDCOA	IMIS
IMISELC000	Machine Drive Iron and Steel Electric Existing	INDELC	IMIS
IMISLPG000	Machine Drive Iron and Steel LPG Existing	INDLPG	IMIS
IEISELC000	Electro-Chemical Process Iron and Steel Electric Existing	INDELC	IEIS
IOISHFO000	Other Iron and Steel Heavy Oil Existing	INDHFO	IOIS
IOISDST000	Other Iron and Steel Distillate Oil Existing	INDOIL	IOIS
IOISNGA000	Other Iron and Steel Natural Gas Existing	INDNGA	IOIS
IOISELC000	Other Iron and Steel Electric Existing	INDELC	IOIS
IOISBIO000	Other Iron and Steel BIO Existing	INDBIO	IOIS
IFISCOK000	Coke consumption in Iron and Steel Existing	COAOVC	IOIS
INF: Non ferrous metals			
INF000	Existing Non-Ferrous Tech	ISNF	INF
ISNFHFO000	Steam Non-ferrous metals Heavy Oil Existing	INDHFO	ISNF
ISNFDST000	Steam Non-ferrous metals Distillate Oil Existing	INDOIL	ISNF
ISNFNGA000	Steam Non-ferrous met Natural Gas Existing	INDNGA	ISNF
ISNFCOA000	Steam Non-ferrous metals Coal Existing	INDCOA	ISNF
IPNFHFO000	Process Heat N-ferrous met Heavy Fuel Existing	INDHFO	IPNF
IPNFDST000	Process Heat N-ferrous met Distillate Fuel Existing	INDOIL	IPNF
IPNFNGA000	Process Heat N-ferrous met Natural Gas Existing	INDNGA	IPNF
IPNFCOA000	Process Heat N-ferrous met Coal Existing	INDCOA	IPNF
IPNFELC000	Process Heat N-ferrous met Electric Existing	INDELC	IPNF
IPNFLPG000	Process Heat N-ferrous met LPG Existing	INDLPG	IPNF
IMNFHFO000	Machine Drive N-ferrous met Heavy Oil Existing	INDHFO	IMNF
IMNFDST000	Machine Drive N-ferrous met Distillate Oil Existing	INDOIL	IMNF
IMNFNGA000	Machine Drive N-ferrous met Natural Gas Existing	INDNGA	IMNF
IMNFCOA000	Machine Drive N-ferrous met Coal Existing	INDCOA	IMNF
IMNFELC000	Machine Drive N-ferrous met Electric Existing	INDELC	IMNF
IMNFLPG000	Machine Drive N-ferrous met LPG Existing	INDLPG	IMNF
IENFELC000	Electro-Chemical Process N-ferrous met Electric Existing	INDELC	IENF
IONFHFO000	Other N-ferrous met Heavy Oil Existing	INDHFO	IONF
IONFDST000	Other N-ferrous met Distillate Oil Existing	INDOIL	IONF
IONFNGA000	Other N-ferrous met Natural Gas Existing	INDNGA	IONF
IONFELC000	Other N-ferrous met Electric Existing	INDELC	IONF
IONFBIO000	Other N-ferrous met BIO Existing	INDBIO	IONF

With 8 regions, five energy uses and four time periods included, 160 sets of constrained technology comparison/optimizations (each with dozens of technology options) must be computed, although only about 10% of these strongly influence the results obtained. Thus, additional simplifications like scaling results from one region to another or from one time period to another can sometimes be employed without biasing the results.

In the assessments, fuel demand interactions and feedbacks are captured by integrating the fuel demands from the optimal mix of energy technologies in each sector region and time period with the simple fuel supply functions. For example, if there is a large increase in the demand for natural gas because it is the most economic way to make hydrogen fuel cell vehicles this will lead to an increase in natural gas prices and a decrease in gasoline prices. These adjustments in fuel prices will make gasoline fueled cars somewhat less expensive and hydrogen fuel cell vehicles somewhat more expensive with respect to the case where fuel price feedbacks are ignored. At present, land, water and noble metal usages are calculated, but feedbacks from those markets are not yet accounted for.

An unexpected change in the fuel price outlook has occurred since last year's report due to the persistence of higher oil and gas prices than anticipated. We were considering a wide range of future price expectations last year, but the level of oil and gas prices over the last year has lead some observers to conclude that current price levels may be sustained for the next several decades. While we do not believe that is the most likely scenario, it is more likely than last year, leading to an increase in the high end of our price range and a higher probability attached to that range (see Weyant, et al., 2005a).

There are uncertainty representations (i.e., probability distributions) for energy demand levels, fuel prices, and climate policies that are similar to the new technology supply uncertainty specifications described above. Given probability distributions for the demand for energy and constraints on carbon emissions in the future and for the supply of each technology included in the GCEP portfolio, stochastic simulation techniques are used to generate thousands of possible supply demand-equilibria each including a level of contribution by each technology in the portfolio for each simulated state of the energy system.

At this point another modeling challenge comes into play – how much foresight and rationality to attribute to the firms and consumers whose behavior is represented in the analysis. Typical modeling practice has been to assume either no foresight, meaning the actors whose behavior is being represented make their investment decisions assuming that current prices and technologies will prevail into the indefinite future (this is sometimes referred to as a "recursive dynamic" formulation, reflecting the carry-forward of capital equipment), or that they have perfect foresight based on perfect forecasts of future fuel prices and technologies. In the first case we can add the uncertainties in after the decisions are made to get distributions over actual market outcomes, while in the second we apply the probabilities to the perfect decisions that are ultimately made to find out what our uncertainties as analysts imply about the distributions over key outputs (like carbon emissions or net surplus). As these two sets of assumptions are typical modeling practice we explore the implications of both in our integrated assessment framework.

On the other hand, neither of these two sets of polar opposite assumptions seems completely realistic – firms and consumers probably do have some foresight in making energy investment decisions, but it is far from perfect over the several decades much energy capital equipment lasts. Thus, decisions are made under uncertainty and investors will hedge against bad outcomes by investing in technologies that are robust over outcomes on market conditions and technology performance weighted by their probabilities. Model formulations that reflect this approach to investment decision making are rare and have generally been limited to considering only two or three uncertainties. In addition, here we separate the investment uncertainty from the R&D uncertainty by conditioning the investment uncertainty on whether the technical uncertainties have first been resolved (no success at that stage means no new technology to invest in) and the resulting cost projected for the technology. The R&D investment reduces, but does not eliminate, uncertainty about the cost of the new technology. Using advanced flexible optimization techniques like approximate dynamic programming, neural networks and genetic algorithms (see, e.g., Bertsekis and Tsitsiklis, 1996; Bertsekis, 2000; Davis, 1991, Goldberg, 1989, and Whinston, 2000) we are able to analyze the implications of this set of assumptions regarding foresight and decision making strategies to compare the results obtained and implications for advanced technology research investing with the other two setups. We are grateful to Sam Savage of Stanford University, and S. Christian Albright and Wayne Whinston of the University of Indiana for numerous helpful suggestions on the design of all three of these approaches to uncertainty modeling and for providing software to help implement them.

Impact Measures

There are a wide range of benefit measures that could be used to quantify the benefits of the GCEP portfolio for each supply and demand realization. Given GCEP's objectives, one important metric is the reduction in carbon emissions attributable to the new technologies that are developed. In making such assessments, though, it is important to include not only a range of possible energy sector futures, but also a range of outcomes regarding the costs, performances and contributions to carbon emission reductions of other new energy technologies. These carbon emission reductions come from efficiency improvements, sequestration of carbon emissions and fuel substitutions.

Another frequently used benefit metric is the increase in net surplus to the economy resulting from the new technologies. For simple supply and demand curves such as those shown in Figure 2, the net social surplus gain can be computed as the area under the demand curve less the area under the supply curve for energy in each region/sector considered. The area under the demand curve represents the total value of energy to consumers and intermediate goods producers while the area under the supply curve represents the total draw on societal resources required to produce the alternative energy. Net social surplus is maximized at the point where supply equals demand (also know as the market equilibrium) because to the left of the point the marginal area under the demand curve exceeds the marginal area under the supply curve and that relationship reverses to the right of the market equilibrium point.

In the demonstration model the market equilibrium is found by solving a linearized optimization problem represented by the area under the demand curve for energy in the region/sector less the least-cost mix of energy supply options given the availability of new (and old) technologies and any constraints on the energy supply system.

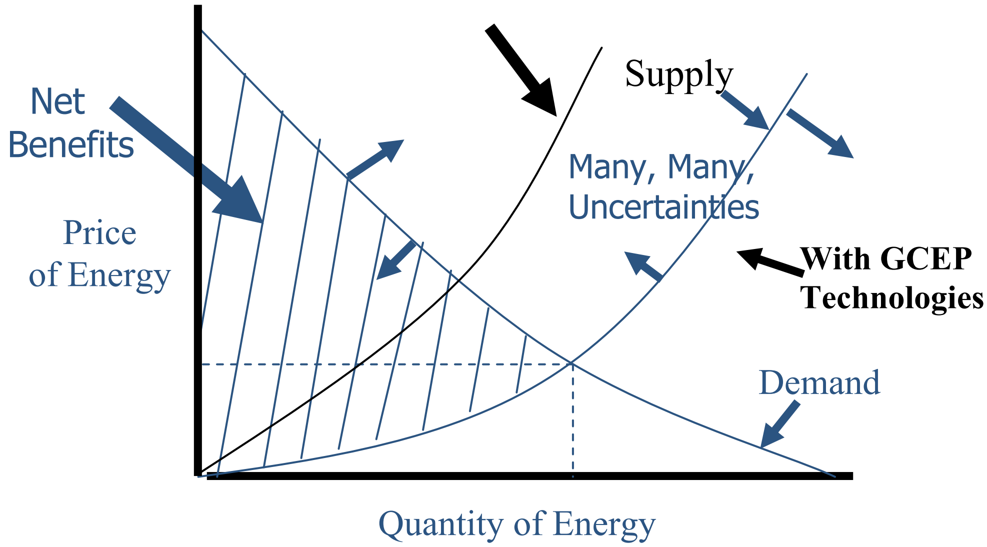

Figure 2: GCEP Technology Assessment: Conceptual Overview

In Figure 2 we can see how net surplus is reduced as carbon emissions are constrained because many of the least expensive energy supply options produce carbon emissions. The inclusion of new technologies resulting from GCEP research leads to increases in net benefits in two ways: (1) providing lower cost ways to reduce carbon emissions (for example, via coal-fired electricity generation with carbon capture and sequestration); and (2) possibly providing lower-cost sources of non-carbon energy than some of the original carbon emission producing sources (the goal of the project is break-through technologies after all).

Using the net benefits triangle, it is thus easy to calculate the net benefits of the GCEP portfolio for one particular set of technology outcomes and one particular future state of the world energy system. Given the complexities and uncertainties involved though this set of calculations might need to be repeated thousands to millions of times to capture the effect of the full range of outcomes.

This capability is being implemented through Monte Carlo Simulation in which each probability distribution is sampled through the use of appropriate random number generators to sample from the GCEP technology and market environment probability distributions. For example, if an R&D project on a new technology has a .2 chance of demonstrating the technical feasibility of a new carbon free energy technology, a random number between 0 and 1 is generated and the technical demonstration is assumed to be successful if that number is .2 or less and unsuccessful otherwise. Then the cost of the new technology is determined by another random draw used to pick an outcome corresponding to that probability number in the cost distribution for that technology. For example, if .5 is drawn the mean of the probability distribution over future costs is selected. The process is repeated over all the uncertainties many times over to generate probability distributions over various output measures, including the net benefits of what ever portfolio is being analyzed. Further details on the evaluation system can be found in Weyant, et al., 2005a).

Example Results

In this section we illustrate a few of the different uses of the demonstration evaluation system. More detailed examples with regional and sectoral disaggregations are given in Weyant, et al. (2005b). Figure 3 shows a range of calibrations to the 2004 IEO cases. The Reference, High and Low Baselines are based on the IEO reference, high and low economic growth rate assumptions. Here we use the GCEP fuel price uncertainties, but (as in the IEO) do not assume any additional climate policies. The reference baseline reaches 25 GT of carbon emissions in 2100, while the high and low scenarios reach 37

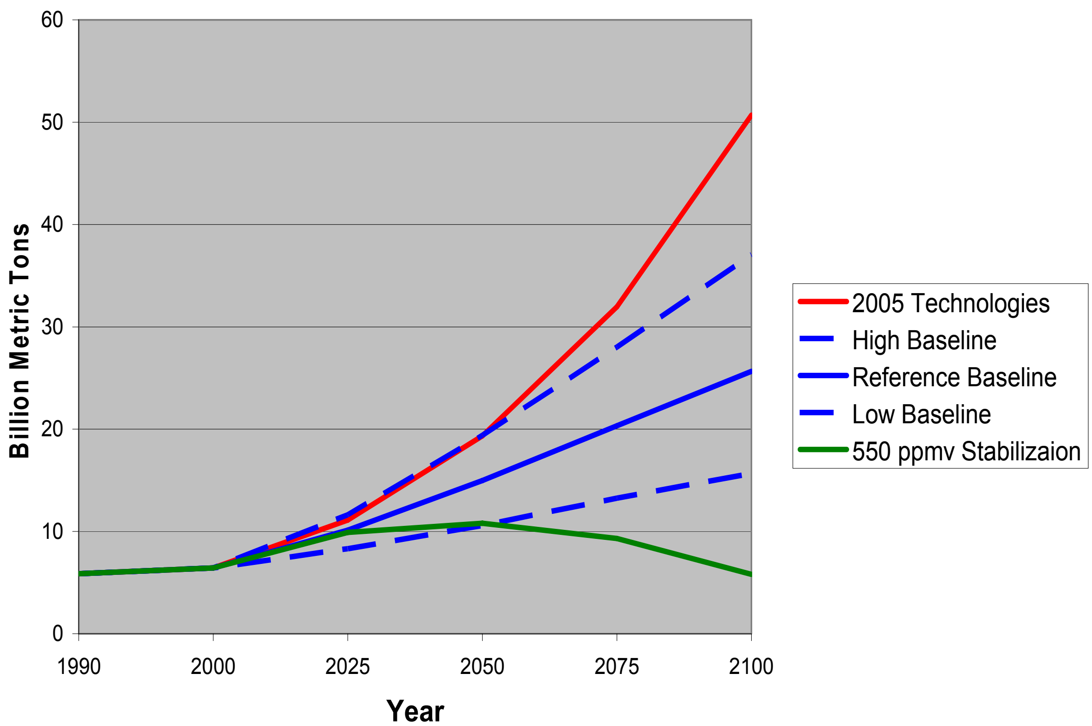

Figure 3. Alternative Global Carbon Emission Projections

GT and 16 GT in that year, respectively. These results are very similar to those included in the IEO for the first half century. Also shown are the emissions projections that result from the baseline reference assumptions with technologies frozen at their 2005 efficiency and cost levels, and the WRE carbon emissions trajectory which is projected to lead to a CO_2 concentration in the atmosphere of 550 ppmv. The former case leads to slightly over 50 GT of carbon emissions in 2100, while the latter shows emissions by that date at 5.8 GT and heading down.

The R&D evaluation framework is not designed primarily to make small sets of carbon emissions projections like those shown in Figure 3, but to assess the impacts of new technologies over a plausible range of energy market futures determined by economic growth rates, fuel prices, and climate policies. A sample probabilistic range covering 84 percent of the possible outcomes is shown in Figure 4. Here we use the IEO economic growth rates cases probabilistically (with 50% weight on the reference level and 25% on each of the high and low assumptions) as well as fuel price and climate policy uncertainties. This lowers the mean of the distribution down to slightly over 20 GT of global carbon emissions in 2100, with the 9th percentile at about 14 GT and the 93rd percentile at about 30 GT by that date. This means there is a 9% change actual emissions will be below 14 GT in 21000 and a 7% chance they will be over 30 GT by the end of the century.

From these carbon emission scenarios we can project the carbon emission reductions that would be expected to result from the GCEP R&D portfolio. These results are shown in Figure 5.

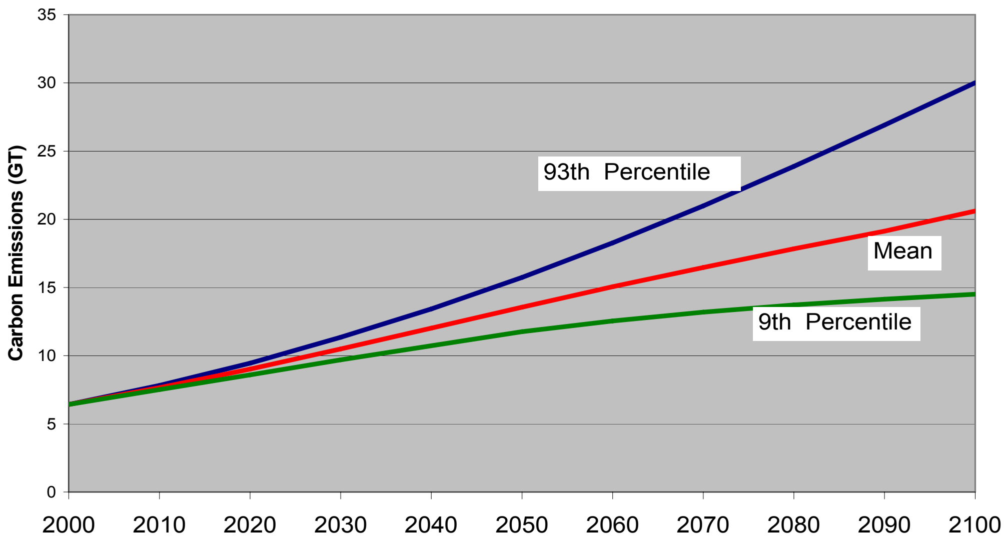

Figure 4. Projected Probabilistic Range of Global Carbon Emissions

Recall the high low and reference refer to the economic growth levels, with each projection resulting from a range of fuel price and climate policy assumptions. Here we use the decision making under uncertainty formulation to model investments in energy using plant and equipment. By 2100 reference case carbon emissions are lowered from a little over 20 GT to about 10GT, in the high case the reduction in carbon emissions is from 30 GT to 13 GT, and in the low case from 14 GT to 8.5 GT. Over the century these expected reductions are all fairly substantial.

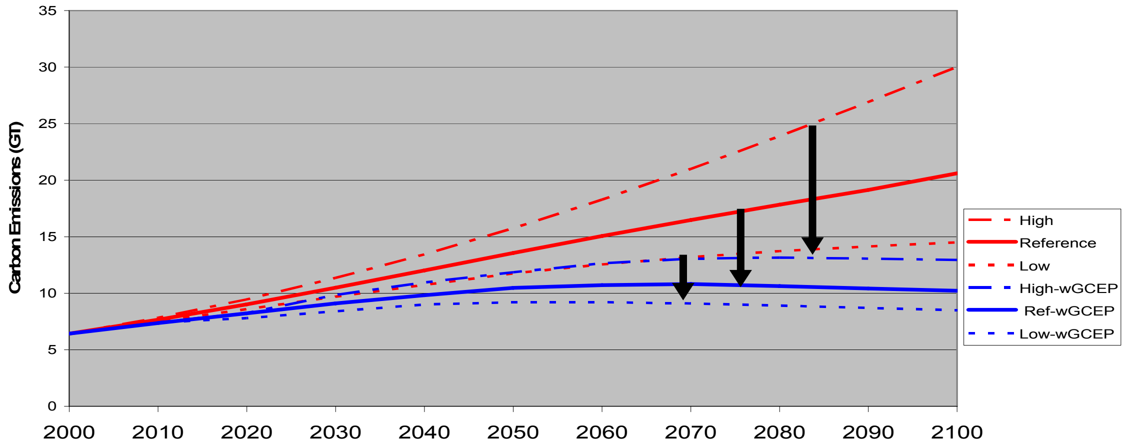

Figure 5. Projected Range of Impacts of GCEP Program on Global Carbon Emissions

In Figure 6 the contributions of the different technology areas to the emissions reductions in the reference scenario are shown. Although each technology area contributes many Giga-tons in reductions, the timing of the areas is somewhat different with the advanced combustion program making the largest initial contributions, followed by sequestration in scenarios where there are constraints on carbon emissions. The renewable technology area does not make a Giga-ton contribution until about mid century, but after that their contribution rises to about 3 GT in 2100. Hydrogen lags even further behind, but again is expected to make a major contribution during the second half of the century.

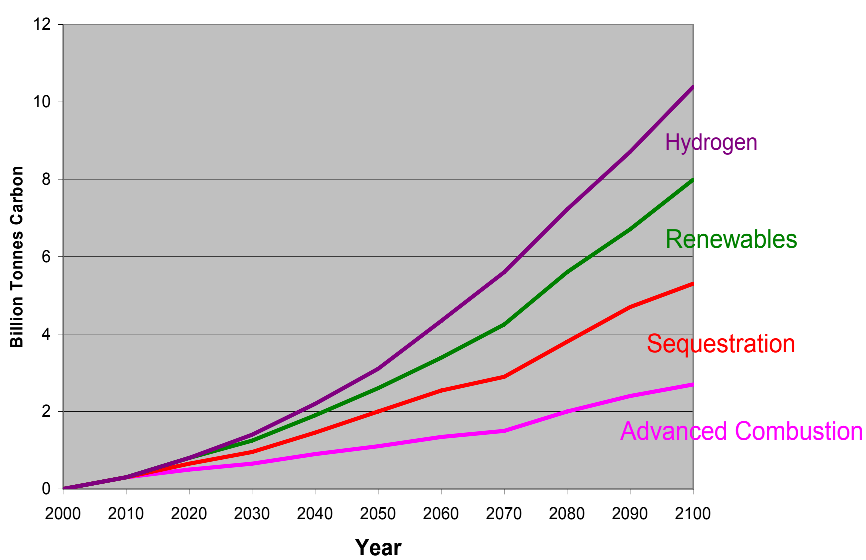

Figure 6. Contributions of GCEP Technologies to Carbon Emission Reductions

An example of net surplus benefits for the three scenarios of the GCEP portfolio is shown in Figure 7. That the expected benefits are on the order of trillions of dollars per year by the end of the century is impressive although the uncertainty about achieving them is considerable.

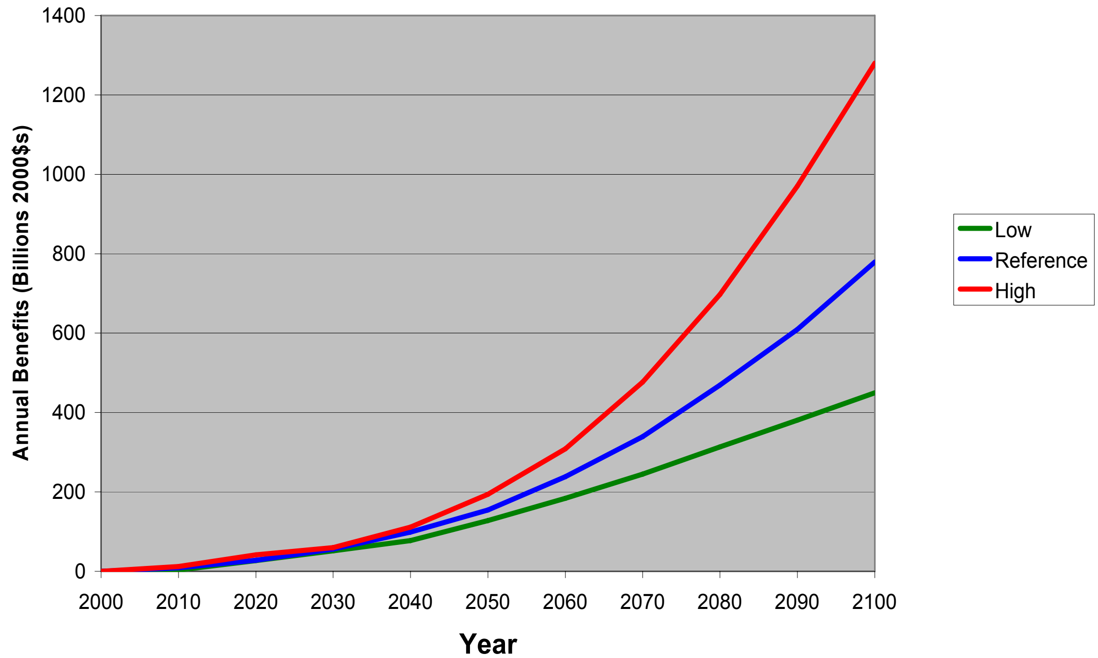

Figure 7. Expected Economic Benefits of GCEP Portfolio wrt Reference, Low and High Cases

These simple global emission and technology introduction projections are still not the main objectives of the technology assessment system; they only set the stage for integrated technology assessments. As a simple example of the overall evaluation methodology, consider the case where world energy demand is aggregated and there are only four technology areas in the GCEP portfolio – renewable energy, advanced combustion, hydrogen and carbon sequestration. The distribution of benefits for the renewable technology area alone is shown in Figure 8. Although the expected level of benefits for this technology in Figure 9 shows results for another example portfolio consisting of the advanced combustion, carbon capture and sequestration, renewables, and hydrogen technology research areas. This collection of technology programs is referred to as a "mini" portfolio here because although it only includes 4 of the 11 GCEP areas – they are the ones in which there are currently the most active R&D projects. Here the payoff is higher, but not dramatically than that for the renewables program on its own because there is substitution between the payoffs of the different elements of the portfolio. The expected level of carbon emission reductions for this portfolio is a little over 400 GT.

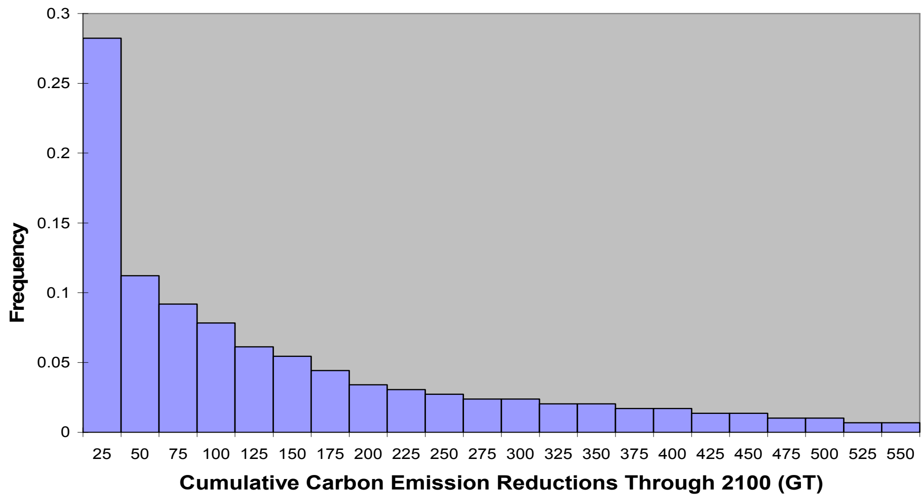

Figure 8. Carbon Emission Reductions Resulting From GCEP Renewables R&D

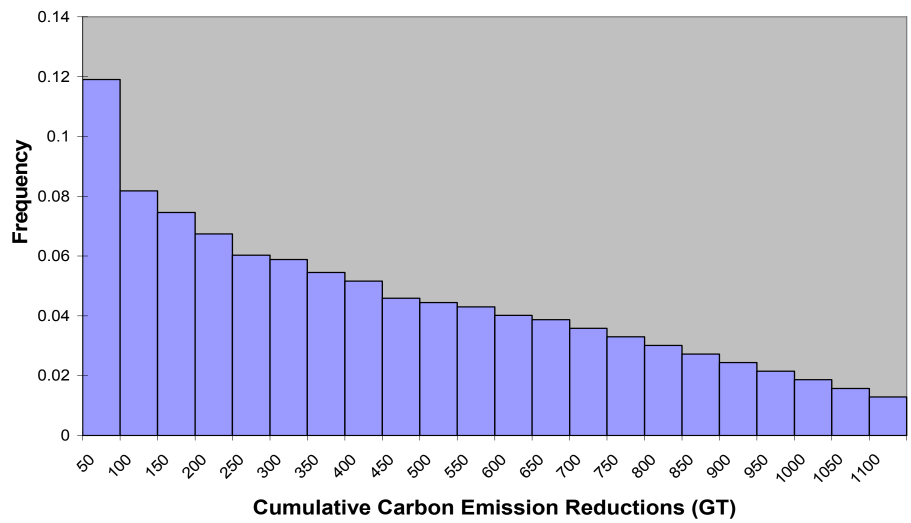

Figure 9. Carbon Emission Reductions Resulting From GCEP R&D Portfolio

There is also much less chance of a no payoff from the program which results from diversification: that is, the probability of all projects in all four technology areas proving to be technically infeasible (about a 2% chance) is much less than any individual technology program proving to be infeasible. Finally the probability of very large benefits is very large (about 1.0% terms of carbon emission reductions is impressive (about 141 billion metric tons of carbon over the century, there is a 1% chance they will be greater than 500 billion tons. Very large benefits occur when the cost of the new technology is very low and the demand for it very high because of, e.g., high baseline carbon emissions, high fossil fuel prices, poor success in the develop of other alternative sources of energy by GCEP or anybody else, and a high policy induced financial penalty on carbon emissions for cumulative carbon emissions of 1000 giga-tons) as it is better to have two or more areas with chances at a technically feasible and relatively low cost carbon free technology than only one area when the demand for carbon free energy is simultaneously high due to high economic growth, tight fossil fuel market conditions and public policies designed to reduce carbon emissions significantly.

As another example we show the distribution of projected carbon emission reductions for the sequestration R&D program alone in Figure 10. In cases where there is a positive price on carbon and carbon sequestration is publicly accepted, the resulting emissions reductions from this technology can be substantial with an expected value of 145 GT over the century and a 3% chance of 425 GT or greater. In this case most of the reductions come from the sequestration of power plant emissions. If the hydrogen R&D program is added to the portfolio (Figure 11), the possibility of generating hydrogen from fossil fuels and sequestering the carbon makes both the hydrogen and sequestration programs more valuable. Advanced combustion is the final program area and it has a high value across many sectors in many regions for a number of time periods. The distribution of carbon emissions reductions over the century attributable to the work in this area is shown in Figure 12. The emission reductions over the century are 157 giga-tons, with a 3% chance of 450 GT or greater. The expected benefits also start accruing earlier than for the programs in any of the other areas.

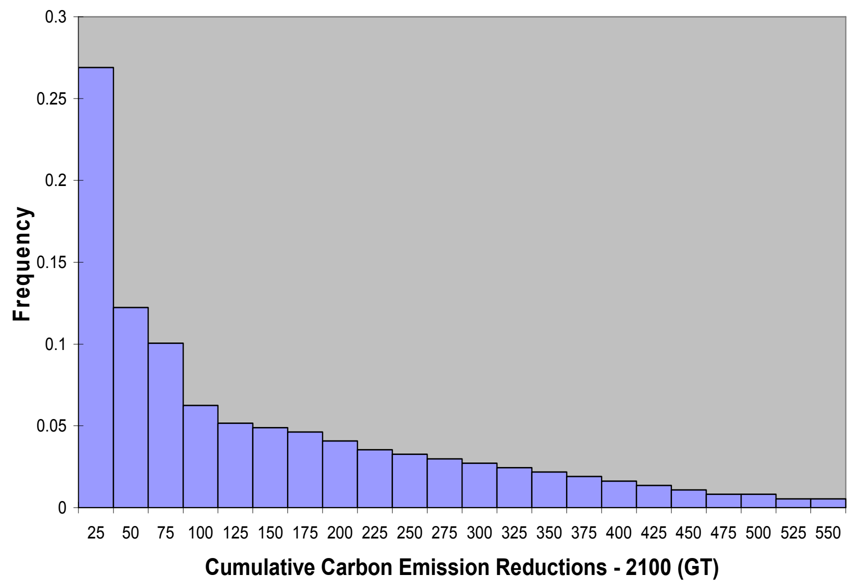

Figure 10. Carbon Emission Reductions Resulting From GCEP Sequestration R&D

Finally, Table V shows the expected carbon emissions reductions for each of the areas conditional on already having none, one, two or three of the other areas in the portfolio. The subscripts in Table represent 25th and the superscripts 90th percentile values for projected carbon emission reductions. For example, if the sequestration program is added to a portfolio that already includes renewables the expected additional carbon emission reductions during the century is 103 GT, there is a 75% chance that it will be greater than 7 GT, and a 10% chance it will be greater than 267 GT.

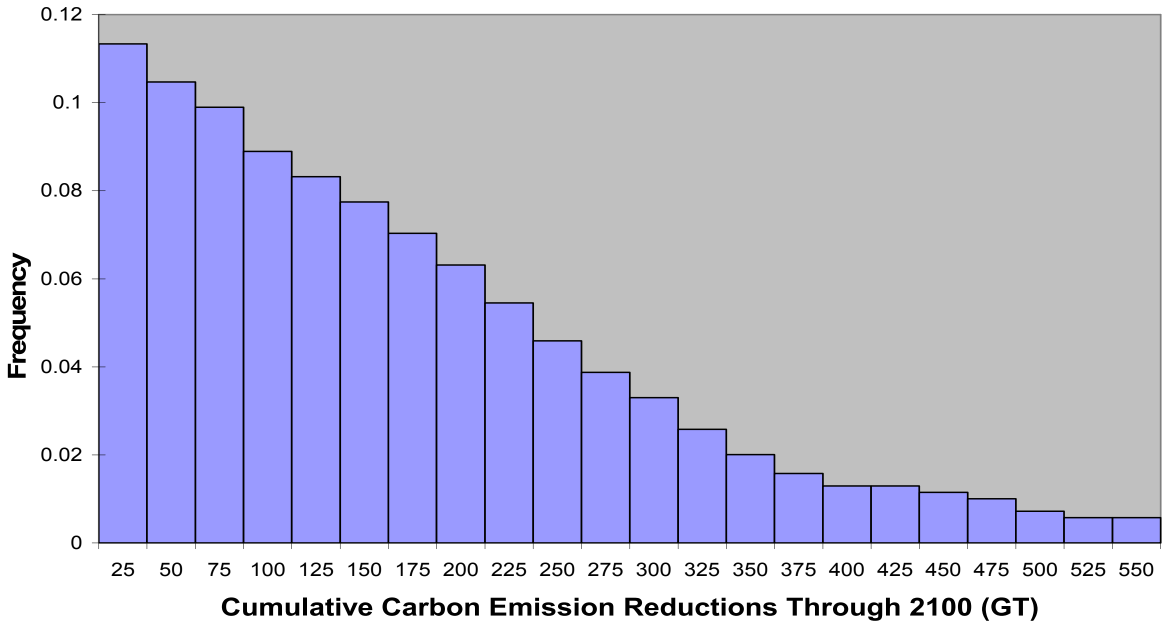

Figure 11. Carbon Emission Reductions Resulting From GCEP Sequestration and Hydrogen R&D Programs

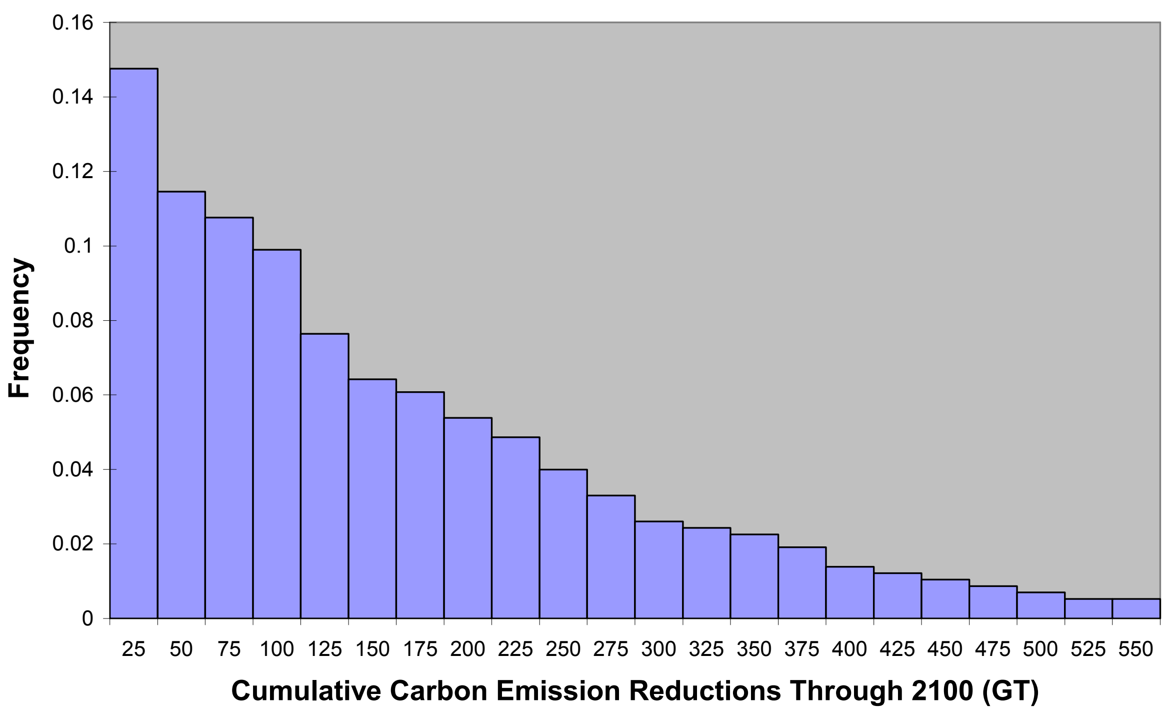

Figure 12. Carbon Emission Reductions Resulting From GCEP'SAdvanced Combustion R&D Program

Table V: Incremental contributions of GCEP R&D areas to cumulative carbon emission reductions (GT Carbon)

	R&D Area Added to Portfolio			
Areas Already in R&D Portfolio	Adv. Comb.	Sequestration	Renewable	Hydrogen
Nothing	$_{65}157^{305}$	$_{12}143^{317}$	$_{45}141^{378}$	$_{15}90^{253}$
Adv. Comb.	-	$_{10}134^{301}$	$_{23}123^{314}$	$_{13}80^{179}$
Sequestration	$_{43}142^{277}$	-	$_{9}92^{67}$	$_{15}118^{240}$
Renewables	$_{40}140^{282}$	$_{7}103^{267}$	-	$_{15}84^{189}$
Hydrogen	$_{57}133^{291}$	$_{8}141^{345}$	$_{32}157^{356}$	-
Adv Comb, Sequestration	-	-	$_{7}73^{233}$	$_{14}105^{176}$
Adv Comb, Renewables	-	$_{5}85^{233}$	-	$_{13}83^{179}$
Adv Comb, Hydrogen	-	$_{7}121^{273}$	$_{22}137^{309}$	-
Sequestration, Renewables	$_{31}130^{263}$	-	-	$_{12}95^{165}$
Sequestration, Hydrogen	$_{34}112^{259}$	-	$_{5}72^{242}$	-
Renewables, Hydrogen	$_{28}121^{261}$	$_{4}87^{242}$	-	-
Adv Comb, Sequestration,Renewables	-	-	-	$_{12}79^{151}$
Adv Comb, Sequestration, Hydrogen	-	-	$_{3}53^{217}$	-
Adv Comb, Renewables, Hydrogen	-	$_{3}81^{221}$	-	-
Sequestration, Renewables, Hydrogen	$_{23}99^{232}$	-	-	-

Future Plans

The sectoral, regional, time and technology disaggregation of the demonstration evaluation framework seems adequate for placing approximate values on R&D in the technology areas, and for developing useful insights regarding the design of the R&D portfolio. Nonetheless, improvements in the representation of the dynamics of new technology introduction and diffusion would help improve the realism of the system and lead to refinements in the portfolio valuations as well as additional insights. An approach to improved dynamics for the electricity sectors of the U.S. and China is described in the "A Global Portfolio Strategy for Climate Change Technology Development" section below.

Another area of active research is improvements in the assessment of the results of the GCEP R&D technology areas. Including more technological process detail drawn from thermodynamics, petroleum geology, electro-chemistry, biology, bio-engineering and other relevant disciplines in the assessment process will continue to be a fruitful area for future research. The "Carbon Capture and Storage – Estimating the Costs" section below describes a structured approach to carbon capture and sequestration cost assessment, while the "Quantifying the Leakage Rate Associated with Carbon Storage" section below describes an approach to a combined structural/expert assessment approach to assessing the leakage rates from carbon sequestration sites.

Results: Modeling the Transition to a Hydrogen Economy

In addition to updating last year's systematic assessment of scenarios for the introduction of hydrogen fuel cell vehicles in the U.S. and completing a paper describing the modeling methods and the results (Sweeney, 2005), this year's work included two new research directions: (1) identifying barriers and opportunities for the introduction of hydrogen internal combustion engines, and (2) an exploration of the causes of – and potential solutions to- the "chicken and egg problem" that pertains to the incentives for fuel supplies, transporters and distributors, car manufacturers to all wait for each other to commit R&D and investment funding to the development of a hydrogen economy: if no one (or no group of participants) commits first, then no egg is hatched, no chickens develop and so on. An overview of research in these two areas follows.

Hydrogen Internal Combustion Engine Vehicles: Identifying Opportunities and Barriers

In recent years, there has been increasing interest in the promising concept of a hydrogen economy, where our transportation sector would be powered by hydrogen rather than oil. The heart of this promise lies in the possibility of producing hydrogen from low-emission, domestic energy sources, and using that hydrogen in high-efficiency vehicles. But, there are many obstacles that must be overcome before this opportunity can be realized. For example, considerable technological development remains to be done before cost-effective hydrogen fueled vehicles are ready to hit the road at a large scale. Moreover, it is not entirely clear which technological avenue to pursue.

Hydrogen vehicles powered by fuel cells have received the greatest attention, but other technology options are also being developed, the most prominent of which is the hydrogen internal combustion engine (ICE) vehicle. The Ford Motor Company has developed a prototype hydrogen ICE vehicle, the "Model U," which it believes is a viable alternative to hydrogen fuel cell vehicles. But, open questions remain about the potential of hydrogen ICE technology relative to hydrogen fuel cell technology.

This research project aims to address some of these open questions through an in-depth examination of the hydrogen ICE technology, with an eye to the relative merits of hydrogen ICE when compared to the existing gasoline hybrid technology and the future hydrogen fuel cell technology. This examination involves both the characteristics of the technology and the economics of an application of these technologies at the large scale. As such, this research agenda fits squarely in the first of the two of the three primary objectives of the Stanford Global Climate and Energy Project (GCEP): (1) "identify promising opportunities on technologies for low emissions, high-efficiency energy supply," (2) "identify barriers to the application of these new technologies at large scale," and (3) "conduct research into technologies that will help to overcome barriers and accelerate global applications."

More specifically, this research aims to address the following questions: (1) what are the key technological characteristics that define hydrogen ICE vehicles; (2) how do these characteristics compare with those of other technology options; (3) what are some plausible scenarios of hydrogen ICE adoption; (4) what are the barriers that would need to be overcome for these scenarios to occur; and finally (5) what are the economic and environmental consequences of hydrogen ICE adoption? In concert, these questions aim to provide basis for assessing the desirability of promoting hydrogen ICE technology relative to other promising vehicle technologies.

What are the key technological characteristics of hydrogen ICE vehicles?

There is a long history of using hydrogen in internal combustion engines, beginning in 1807, when Issac de Rivas built the first hydrogen internal combustion engine. Indeed, hydrogen in internal combustion engines even predates gasoline in internal combustion engines (Taylor 1985).

However, there are difficulties to running ICE vehicles on hydrogen that only recent technological developments have begun to overcome. Many of these difficulties stem from critical tradeoffs between different desirable attributes. Understanding these tradeoffs is essential to understanding of the economics and market potential for hydrogen ICE vehicles.

The first important relevant tradeoff is whether to run the hydrogen ICE *lean* (with a low density of hydrogen to air), or at a higher hydrogen-air ratio. This amounts to a tradeoff between higher engine efficiency and lower criteria air pollutant emissions (e.g., nitrous oxides) with a lean fuel mixture, and greater power with a higher density fuel mixture. The higher emissions associated with a fuel mix that provides more power can be reduced by the use of technologies such as three-way catalysts, but at the cost of higher manufacturing costs. With higher engine efficiency, a smaller fuel tank is also possible, which ties in directly with the tradeoff between fuel tank size and vehicle range. Depending on the fuel economy of hydrogen ICE vehicles, a very large tank size may be required to achieve a marketable vehicle range (Kliesch and Langer 2003).

As the hydrogen ICE technology is further developed, engineers will have to reconcile these competing demands. How this is accomplished will have a considerable influence on the application of the new technology on a large scale. This research includes a detailed examination of the technical details of hydrogen in ICEs, insofar as they are relevant to the effects of a large-scale application of hydrogen ICE vehicles.

How do these characteristics compare with those of other technology options?

An important element in this research is to provide a sense of the relative merits of hydrogen ICE vehicle technology in comparison to other prominent competing technologies. Specifically, the characteristics of hydrogen ICE vehicles are compared to those of conventional gasoline vehicles, hybrid gasoline vehicles, and future hydrogen fuel cell vehicles. While many of the details of how the technology will progress in each of these areas is highly uncertain and endogenous to the policy process, rough estimates of the characteristics of each of these vehicles types can be found or derived.

As such, Table VI provides a comparison of the salient characteristics of each vehicle type. Note that several of the quantitative estimates are highly uncertain. In particular, the fuel economy estimates are rough approximations of what the average on-the-road vehicle fleet fuel economy might be in the relatively near future if the technologies are developed as hoped for or expected. Several points brought out in Table 6 are worth highlighting. First, due to the nature of using hydrogen in the vehicle, both hydrogen ICE vehicles and hydrogen fuel cell vehicles are most likely to also be using a hybrid transmission with an electric motor, much as today's hybrid gasoline vehicles do. Second, hydrogen ICE vehicles are likely to have an engine efficiency advantage over today's gasoline hybrid vehicles, although not as great of an advantage as hydrogen fuel cell vehicles would enjoy.

Table VI: Comparison of different vehicle types

	Gasoline ICE	*Gasoline Hybrid*	*H2 ICE*	*H2 Fuel Cell*
Engine Type	spark-ignition	spark-ignition & electric motor	compression-ignition with electric motor	electric motor
Average engine efficiency	~30%	~30%	~40%	~55%
Max engine efficiency	32.5%	32.5%	~40%	~65%
Transmission Type	standard	hybrid	hybrid	hybrid
Transmission efficiency	~40%	~60%	~60%	~60%
Fuel Economy (mpg equival.)	21	31	41	51
Power	As much as needed, at the cost of mpg	Some efficiency improvements over gas ICEs are lost with increased power	Efficiency losses or higher emission control costs to increase power	Increasing power may be expensive, requiring additional FCs
Fuel Tank Size (constant range)	Moderate	Small	Large	Large; smaller than H2 ICE
Cost of Fuel	Currently low	Currently low	Currently high; but would be slightly lower than H2 FC	Currently high
Criteria Pollutant Emissions	Meets emission standards	Lower than gasoline ICE	Likely low; but higher than H2 FC	Very low
State of technology	developed	developed, and in diffusion stage	Could be developed quickly	Earlier in the research process

Third, under high loads (e.g., towing a boat up a hill), both gasoline vehicles and hydrogen ICE vehicles are likely to be able to provide sufficient power. Issues of efficiency losses and increased criteria pollutant emissions would need to be worked out for hydrogen ICE vehicles, but the potential would still be there to provide the power. In contrast, hydrogen fuel cell vehicles would be constrained by the number of fuel cells—once all fuel cells are working at capacity, very little additional power can be squeezed out. Unfortunately, the only solution to this issue for fuel cell vehicles is to add more fuel cells, which happen to be one of the most expensive components of the engine.

Finally, the concept of hydrogen in internal combustion engines is reasonably well understood. While much additional research would need to be done before commercialization of a hydrogen ICE vehicle, the technology is much closer to commercialization than hydrogen fuel cells, which remain prohibitably costly and with a short life-span.

Analyzing the differences between the technological characteristics of the leading competing options with hydrogen ICE vehicles provides insight into the value of promoting each technology, and the relative consequences of a wide-spread introduction of each.

What are plausible scenarios of hydrogen ICE introduction and how might they occur?

This research builds upon knowledge of the technical characteristics of the different vehicle types to develop plausible scenarios of wide-spread introduction hydrogen ICE vehicles. In the development of these scenarios, the most important barriers to the introduction of hydrogen ICE vehicles become apparent, many of which appear to be more closely related to the lack of a hydrogen infrastructure than to the vehicle technology itself. These barriers also hold for hydrogen fuel cell vehicles, so it may be that if infrastructure issues are solved, a critical barrier to hydrogen ICE vehicles is competition from hydrogen fuel cell vehicles.

What are the economic and environmental consequences of hydrogen ICE vehicle introduction?

Given these scenarios of hydrogen ICE vehicle introduction, this research goes on to examine the economic and environmental consequences of these scenarios. Of particular interest is how these consequences compare to a baseline of all conventional vehicles, a scenario of wide-spread introduction of hybrid vehicles, and a scenario of wide-spread introduction of hydrogen fuel cell vehicles. These other three scenarios are taken from the National Research Council (2004) Report on the Hydrogen Economy. Relevant metrics used to compare the different scenarios include fuel economy, total gasoline use, and carbon dioxide emissions.

This component of the research agenda provides insight into the relative value of promoting each of the competing technologies, as well as a deeper understanding of the economics of hydrogen ICE vehicles.

Research Methodology and Tentative Conclusions

Thus far, the first elements of this research have relied heavily on interviews with experts in the field, as well as technical papers that address some of the critical questions about the details of hydrogen ICE technologies. The economic scenario analysis components of the research have followed the methodology of the NRC (2004) Report, providing a similar economic and environmental analysis.

While this research is still in progress, it appears that hydrogen ICE vehicles may have a place in a future hydrogen economy, although it is likely to be limited, depending on the technology advance of fuel cell vehicles. The same difficulties in implementing the hydrogen economy will equally apply to hydrogen ICE vehicles and hydrogen fuel cell vehicles, but the potential fuel economy improvement benefits are greater for fuel cell vehicles. However, the expense of adding additional fuel cells on vehicles that face high load demands (e.g., trucks, buses) may imply that it would be more cost-effective to utilize hydrogen ICE technology in those cases.

That said, the questions raised above have not yet been fully answered, leaving room for additional research into the conditions under which this conclusion makes the most sense. This research promises to provide insight into the relative merits of vehicle technologies, allowing for a more refined understanding of the most valuable technologies to promote.

A "Chicken and Egg Problem" That Could Impede the Development of a Hydrogen Economy

CEP has three main objectives: (1) "identify promising opportunities on technologies for low emissions, high-efficiency energy supply," (2) "identify barriers to the application of these new technologies at large scale," and (3) "conduct research into technologies that will help to overcome barriers and accelerate global applications."[i] Thus far, hydrogen vehicles have been identified as a low emission, high-efficiency energy option. Fuel cell vehicles are more energy efficient than conventional automobiles and emit only water vapor. The hydrogen that fuels the vehicle can be produced from clean, domestically available, renewable sources. However, barriers exist hindering the adoption of hydrogen vehicles. A commonly identified barrier is the "chicken and egg" problem. This research project aims to determine whether or not the chicken and egg barrier exists, and thus fits with the second goal of the GCEP project.

The hydrogen economy has been classified as a chicken and egg problem. Car manufacturers do not want to alter their production facilities and mass produce hydrogen fuel cell vehicles until hydrogen fuel is widely available at a reasonable cost for fear that consumers will not purchase the vehicles. Consumers cannot purchase vehicles until they are produced, and will be unwilling to purchase vehicles in the absence of fueling stations selling competitively priced fuel. Should fuel suppliers invest in a fueling station infrastructure, these fueling stations would operate well below capacity in the early years due to insufficient demand. This excess capacity would lead suppliers to want to charge a higher price for hydrogen in order to prevent a profit loss. However, consumers will be unwilling to pay such a price. Thus, fuel suppliers would rather wait until enough vehicles are in the market to warrant operating at full capacity. As Daniel Sperling explains, "fuel suppliers condition their investment decisions on the existence of a fuel market, and automakers condition their investment decisions on the supply of fuel with the combined result of investment paralysis; no one is willing to make the initial commitment."[ii]

Currently, efforts are underway to spur investment and end the paralysis through the creation of both national and statewide programs. Many of these programs rely on public-private partnerships and government funding to encourage the adoption of hydrogen technologies and speed the transition to a hydrogen economy. For example, the recently released blueprint for the California Hydrogen Highway calls for a $10,000 per vehicle subsidy and 50/50 cost sharing on hydrogen fueling infrastructure.[iii] The goal of this research is to determine whether such government intervention is necessary. The specific question asked is whether a fuel supplier can economically justify undertaking the burden of building a hydrogen fueling infrastructure and offering hydrogen at a cost comparable to that of gasoline. In the California Hydrogen Highway Net Blueprint, the economy team found that the cost of the hydrogen infrastructure was too large to be economically justified by the private sector without government funding. Their analysis assumes a short time frame during which all hydrogen suppliers charge a price equivalent to the prevailing gasoline price. The analysis conducted for this research extends the time frame and explores higher hydrogen price in future years. The idea is that if a fuel supplier can differentiate its product and build a loyal customer base, it can charge a higher price in later years and earn a positive economic profit. In this research, several questions are raised: (1) can suppliers differentiate their products, (2) will the purchasers of hydrogen exhibit brand loyal behavior, (3) can hydrogen fuel suppliers charge a price above cost for hydrogen, (4) what profit is necessary to offset the short-term subsidy, and (5) is it possible for a supplier to earn this needed profit?

Can suppliers differentiate their products?

While the hydrogen itself may be a homogenous commodity, suppliers can potentially differentiate their product through differences in the fueling station itself – e.g. better customer service, cleaner restrooms, convenience stores, etc. In the U.S. gasoline industry, firms often partner with other companies (e.g. Subway, Dairy Queen, etc.) to help distinguish themselves. Furthermore, the US gasoline industry spends millions on advertising to create brand recognition. In 1999, eighteen firms spent a combined total of $179 million on advertising.[iv]

Will the purchasers of hydrogen exhibit brand loyal behavior?

The concept of brand loyalty arises when consumers have a decision to make between purchasing a product from several different firms. Brand loyalty is a conscious choice to purchase of a particular brand as opposed to other brands over a period time.[v] Product differentiation, whether perceived or actual, tends to increase brand loyalty. Furthermore, brand loyal buyers are not easily influenced by price oscillations and are "committed to the value and price appeal of the brand."[vi] Several factors can lead to brand loyalty. In some cases, consumers may not want to spend time searching for a better alternative and instead continue to purchase from the brand from which they initially bought the product.

In other cases, switching costs deter customers from trying a new product. Consumers must learn new information to gain the same experience from the product and are thus reluctant to switch brands. These costs are more significant in new and emerging product markets.[vii] The hydrogen economy is an emerging market with the potential for product differentiation and therefore has the factors affiliated with brand loyal markets. However, whether or not customers in the hydrogen fuel market will exhibit brand loyalty is unknown. Thus, this research project explores differing degrees of brand loyalty and compares the findings to a base case that assumes no brand loyalty.

Can hydrogen fuel suppliers charge a price above cost for hydrogen?

Because the hydrogen economy is not yet established, the answer to this question is unknown. The ability to price above cost depends on the market power a particular firm exhibits. Determining market power depends on the industry structure, pricing behavior of the firms in the market, and brand loyalty. Industry structure and with it pricing behavior are the most important determinants of market power. For example, if the hydrogen fueling station industry develops into a perfectly competitive industry without product differentiation or brand loyalty, in equilibrium, all fuel suppliers will be forced to price hydrogen at cost. The presence of entry barriers, limiting the number of firms in the industry, however, may allow firms to charge a price above cost. Furthermore, the presence of product differentiation and brand loyalty will accentuate a firm's market power and allow it to charge an even higher price.

What profit is necessary to offset the short-term subsidy?

The answer to this question depends on how many years gasoline needs to be subsidized and how many firms are in the market. For example, using the National Research Council's hydrogen cost and demand estimates,[1] a 7% discount factor, and assuming that two firms will supply the expected hydrogen demand of the United States at gasoline prices[2] for a period of 10 years starting in 2015 leads to a subsidy of approximately $3.6 billion. Assuming that ten firms are in the market, a subsidy of approximately $721 million is necessary.[3] In both cases, a firm will need to expect to earn at least the subsidy amount in future years in order to justify investing in the hydrogen economy.

Is it possible for a supplier to earn this needed profit?

The ability to earn a substantial profit depends on the ability to price above cost. For instance, to earn enough profit to justify paying the subsidy in the ten firm example ($721 million), each firm would need to set the hydrogen price 1.2% above the average cost of hydrogen. As before, these estimates use the NRC costs and demand, a 7% discount rate, and assume that the ten firms evenly divide the market. The price markup is for the years

[1] Costs used are for distributed generation. The demand used is the estimated demand from the NRC report, computed at the NRC's costs, not the lower gasoline prices used here. Thus, using this demand assumes that hydrogen demand is insensitive to price.

[2] Gasoline prices assume that the price of oil is $50/bbl, and then are adjusted to incorporate the increased efficiency of fuel cell vehicles. This method is the same as used in the NRC report with a different oil price.

[3] These estimate assume that market share is divided evenly among firms.

2015 to 2050. Whether or not firms can charge the prescribed markup depends on the characteristics of the industry.

Precisely how the hydrogen fueling station industry will develop is unknown. One could assume that the hydrogen fuel supply market will develop much like that of gasoline, into an oligopoly, dominated by a few firms.[4] Game theory is often used to determine production and pricing decisions in an oligopoly. This method is invoked in this research project. Specifically, equilibrium behavior is found by making an assumption about one's rivals' behavior, and then choosing a best response given that assumption. Two classic oligopoly models, Bertrand and Cournot, are implemented for this problem.

In the Bertrand model, a firm assumes that its rivals face an infinitely elastic demand curve (i.e. the rival charges the same price regardless of the decision firm's action). Without product differentiation, the Bertrand model leads to a surprising result; with only two firms, a competitive pricing scheme arises. In this competitive pricing scheme, a firm earns a long-run profit of zero. Thus, if a fuel supplier expects a homogenous product Bertrand scenario to arise, a hydrogen subsidy is not economically justified. However, the presence of product differentiation, allows firms in a Bertrand competition to exude some market power, the extent of which depends on the number of rivals and degree of substitutability among products.

In the Cournot model, a firm assumes that its rivals face an inelastic demand curve (i.e. the rival produces a particular quantity regardless of price). In such a model, the price elasticity of demand becomes important. Assuming a demand elasticity of zero (i.e. consumers by a particular quantity regardless of price) allows a firm to charge an infinite price. The inclusion of a non-zero price elasticity reigns prices in to a more reasonable level.

A Cournot competition will lead to higher prices than those of Bertrand Competition. For instance, in the ten firm example without brand loyalty, the Bertrand model results in an equilibrium price of $3.23 in 2025. This price is equivalent to the cost per unit of hydrogen in that period. The Cournot model, however, results in an equilibrium price of $5.78. Thus, while the Bertrand model has zero long-term economic profits, the Cournot model leads to positive profits.

As is shown in the examples above, the belief a firm forms about its rivals heavily influences the resulting decision. Thus, a variety of beliefs are explored and the resulting pricing and production decisions compared.

Thus far, the research conducted has been focused on the United States as a whole, taking information and assumptions from the NRC's Hydrogen Report. However, with the recent release of the California Hydrogen Highway Blueprint Cal. EPA, 2005), the project will be altered to concentrate on California specifically. The Blueprint concludes that state funding is necessary to spur investment in hydrogen infrastructure. This

[4] According to the EIA, in the US in 1999, 62% of gasoline sales were to branded firms.

research project explores whether or not that conclusion is true. Is government funding needed or will fuel suppliers have incentives to finance the investment on their own?

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Carbon Capture and Storage – Estimating the Costs

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Introduction

This section examines the cost structure of Carbon Capture and Storage (CCS). The analysis highlights the highly heterogeneous nature of Carbon Capture and Storage. Capturing this heterogeneity in a cost distribution is important as results using average values of the cost of carbon capture and storage in economic models may under or overestimate the role of CCS as a mitigation option in both the short and the long run.

This procedure overcomes the difficulty in arriving at overall cost estimates in the absence of detailed data. From underlying component distributions of cost, an aggregate marginal cost curve is built for carbon capture and storage that can be used in larger economic or dynamic system models.

Background

Carbon Capture and Storage is an add on strategy to mitigate climate change, i.e. it adds on top of the existing fossil-fuel technology set rather then replaces elements in that set. It allows the continued use of the existing fossil fuel base at lower emissions.

The overall cost of CCS technologies can be disaggregated into (1) the energy cost of CO_2 capture (2) capital costs for the CO_2 capture /separations unit, and (3) the cost of CO_2 transport and storage.

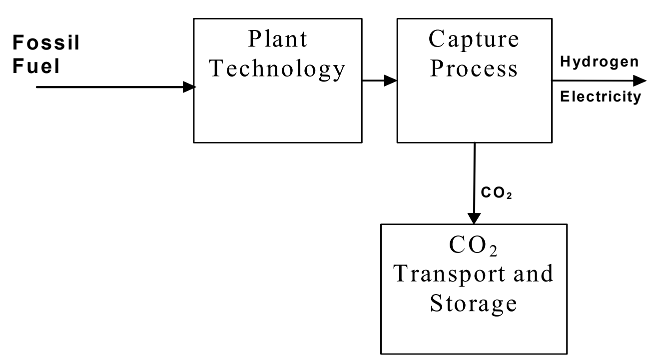


Figure 1: CCS Cost Chain

The Total Cost of Carbon Capture and Storage can be expressed simply as the Cost of Capture + Cost of Transport + Cost of Storage. As shown in Figure 1, the individual costs depend on the specific source, capture technology, distance to storage reservoir, and type of reservoir. There are therefore many combinations possible in this cost chain leading to several sequestration pathways.

Calculating Costs

The following functional relationships give the costs for each element in the chain:

- Cost of Capture = Capital Costs + Energy Penalty = *f(plant type, technology)*
- Cost of Transport = *f(distance to sink, location, volume)*
- Cost of Storage = Cost of Injection + Monitoring & Verification = *f (reservoir type, reservoir characteristics, volume, location)*.

The next sections will examine each element in greater detail.

Capture Costs

One of the key barriers to the introduction of CO_2 capture and storage technology has been identified as the high cost of capture. The high cost is principally associated with the extensive equipment required to scrub the CO_2 from exhaust gas streams from power plants whose exhaust streams contain CO_2 in low concentrations (8-14% by volume). However, many industrial processes generate exhaust gas streams that can contain high purity (>90%) CO_2, which means that the capture costs will be significantly lower.

Electric Power Sector - The electric power sector accounts for a substantial portion of greenhouse gas emissions in the developed world and a growing fraction in developing countries. In the U.S., electricity generation accounts for about one-third of all greenhouse gas emissions. Table I shows reference capture costs for three main plant types. The three main plant types considered are: 1) natural-gas-fired combined cycle (NGCC), (2) integrated gasification combined cycle (IGCC), and (3) pulverized coal (PC). The cost of carbon capture can be calculated by attributing the additional cost of power generation from plant fitted with separation technology to the carbon dioxide captured.

Capture Cost = $(P_c - P_{nc})/(E_{ct} - E_c)$ where

P_c = generation cost from plant with carbon dioxide capture ($/kWh)
P_{nc} = generation cost without capture ($/kWh)
E_{nc} = emissions from plant without capture (kg/kWh)
E_c = emissions from plant with capture (kg/kWh)
E_{ct} = quantity of carbon dioxide produced in plant with capture (kg/kWh)

Carbon Dioxide Produced $(E_{ct}) = E_{nc} \times G_{nc}/G_c$ where

G_c = generation efficiency with capture technology fitted
G_{nc} = generation efficiency without capture technology fitted

Table I: Cost of CO_2 Capture for different plant types.

Plant Type	Cost of CO_2 removal (/tCO_2)	Emissions without CO_2 Capture (kg/MWh)	Emissions w CO_2 Capture(kg/MWh)
PC plant	$35	800	80
IGCC plant	$25	670	67
NGCC plant	$28	370	37

Source: Bechtel Corp 2002.

The total costs of sequestration for old coal-fired plants will be much higher as PC fired coal plants would have almost twice as much CO_2 to sequester than an equivalent gas fired plant because of the greater carbon content of the fuel. Therefore under an actual carbon tax regime, it may be more cost-effective in the long term to fuel-switch, load balance or build new gas-fired power plants instead of retro-fitting old coal fired power plants.

Non electric sources - Recent estimates state that globally there are more than 14,600 large CO_2 point sources. More than 45% of these point sources are from various industrial plants and not such as cement kilns, steel mills, chemical refineries, gas processing facilities, etc., that could also be addressed via the deployment of CCS technologies. (Dooley 2002).[5] These non-electric power CO_2 point sources potentially represent early opportunities for capturing CO_2 at low cost.

Transportation Costs

The total annual transportation cost per tonne of CO_2 is found by annualizing the construction cost using a capital charge rate of 15 percent per year and adding this to the annual O&M cost. Pipeline costs are estimated to be of the order of $1/tonne CO_2/100 km. For the Weyburn project, the CO_2 is being supplied via a 205 mile (325 km) long pipeline (costing 100 million US$) from the lignite-fired Dakota Gasification Company synfuels plant site in North Dakota to the Weyburn oilfield in Canada. The total project would add 20 Mt of CO_2 over its lifetime (IEA).

Storage Costs

As shown in Table II, storage costs show great variability even within a reservoir class. The lowest possible costs can be achieved by using CO_2 in value added markets viz. Enhanced Oil Recovery (EOR) and Enhanced Coal Bed Methane (ECBM) where CO_2 can be used to displace previously unrecoverable oil and gas. The use of CO_2 for EOR will provide early sequestration opportunities at negative cost as EOR operations currently purchase CO_2 for around 50 $/tC (Heddle et al. 2003). While there is much less industry experience with ECBM than with CO_2-EOR, it appears that ECBM provides substantial potential for CO_2 sequestration at low cost. The cost for EOR and ECBM depends on many factors including injection well depth, formation thickness and permeability, reservoir geometry, CO_2 effectiveness, recycle rate, no. of injection wells etc. With large numbers of abandoned wells in depleted oil and gas reservoirs, work over,

[5] IEA GHG has inventoried all large CO_2 point sources worldwide. The total emission of the inventoried sources (14 652 in total) sums up to 13.5 Gtonnes of CO_2 per year. This amounts up to about 60% of the estimated total anthropogenic emission worldwide (22.6 Gtonnes).

monitoring and verification costs can increase substantially. Higher oil and natural gas prices expand the scope for EOR and ECBM.

Table II. Storage costs. Source (Herzog 2004)

Storage Type	Cost $/tCO_2$
EOR	Range: -$91 to $74, Base: -$12
ECBM	Range: -$6 to $26, Base: -$18
Depleted Oil/Gas Reservoir	Range : $2 to $20, Base: $5
Saline Aquifer	Range : $1 to $12, Base: $3
Ocean	Range : $10 to $25, Base: $15
Mineral Carbonates	$70?

The cost steadily increases moving to storage in saline aquifers and oceans although the variability decreases. Finally one could also consider permanent storage in mineral carbonates although with current technology, the cost is quite prohibitive.

Total Cost

Putting the cost chain together, Figure 2 shows the total cost for different CCS system configurations. For example an NGCC plant disposing of CO_2 in the deep ocean 400 miles away in the North Sea for example would incur a total cost of $50/t$CO_2$ whereas a PC plant injecting CO_2 for ECBM would incur a total cost of $15/$CO_2$.

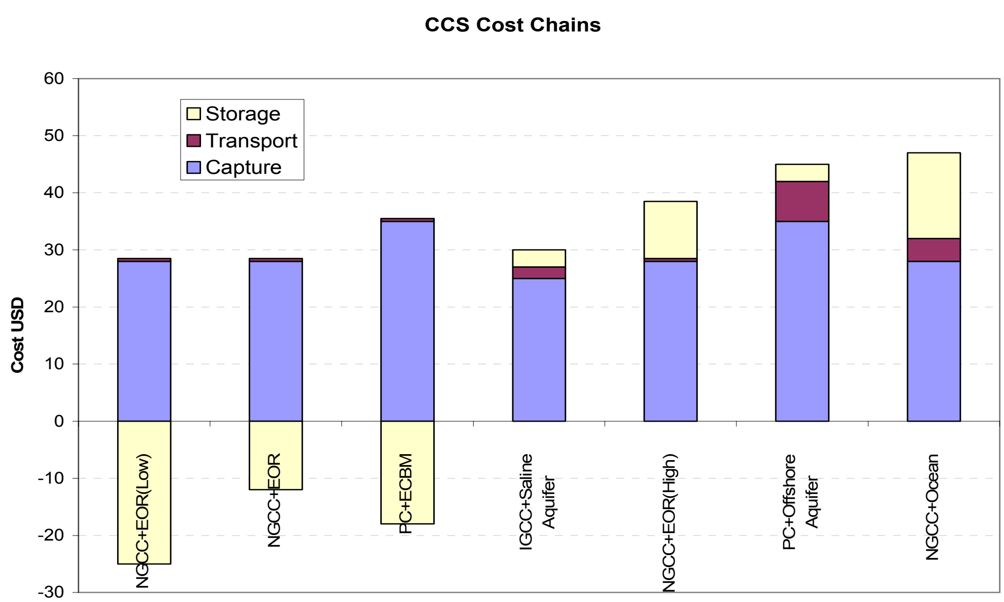


Figure 2: Total cost of different CCS configurations

Therefore in building a marginal cost curve for CCS deployment a bottom up source-sink modeling approach may be more appropriate. In this model as shown in Figure 3, the most appropriate or least-cost source sink pairs are matched up for a region. Once the sink capacity is consumed, we would have to move to the next most expensive grade of reservoir. (Fig. 4). The marginal cost then at a certain level of CO_2 sequestered Q will be equal to the cost of the least cost source-sink available pair at that point. i.e. $MC(Q) = C(u_i v_j)/Q$.

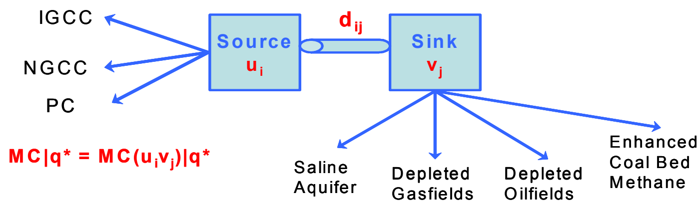


Figure 3: Source sink matching

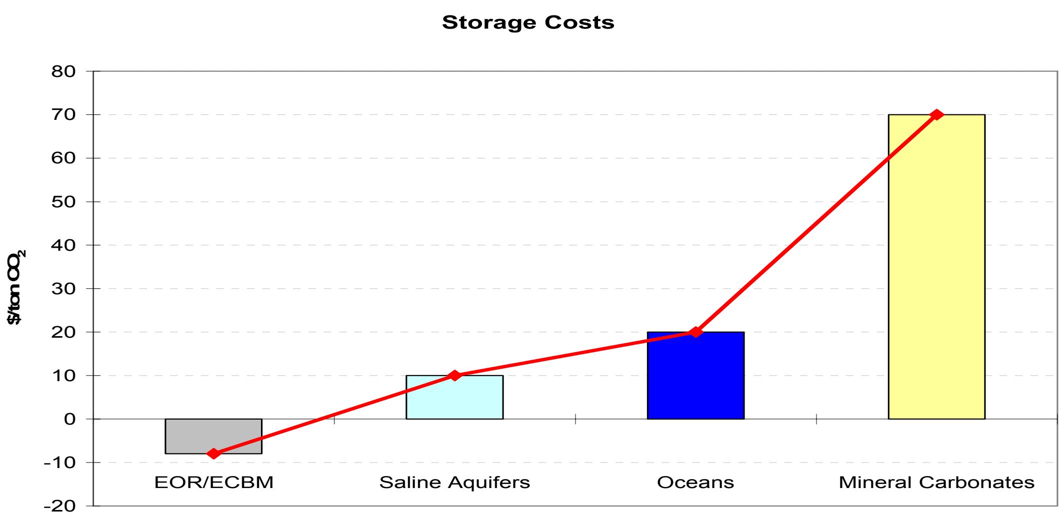


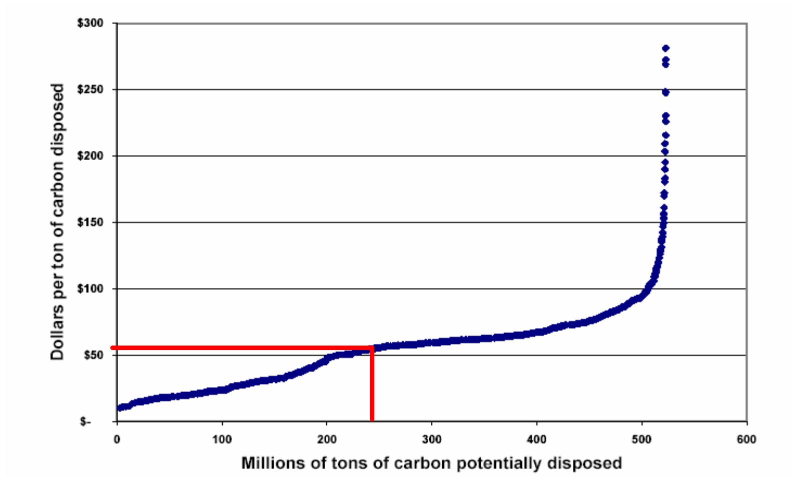
Figure 4: Storage Costs. Red line mirrors a rising marginal cost of storage as each reservoir option is exhausted.

Modeling Heterogeneity and Uncertainty

It is important to distinguish between heterogeneity and uncertainty. Heterogeneity in the case of CCS refers to the variety and spatial distribution of storage options available as well as the number of source types and capture technologies. Uncertainty on the storage side exists around the characterization of storage reservoirs and consequently the fate of CO_2 migration and leakage. On the capture side there is uncertainty in the evolution of capture technology.

Most macro broad based or 'top down' economic studies analyzing the potential of carbon capture and sequestration technologies (CCT) have used either a single cost based on a reference case or average costs (Dooley 2002). However, as is evident from the preceding analysis that – 1) the availability and cost of geological storage is highly variable and site-specific and 2) CCT technology will change with time and adoption = *f(R&D) +f(Quantity Sequestered = f(cumulative Installed Capacity))*.

Bottom-up engineering models have greater spatial and temporal detail. In the case of CCS, a full-scale Geographic Information System (GIS) model would be needed to determine the most appropriate source-sink connections. Dooley, Dahowski et al. have developed a tool to facilitate the analysis of sources and geologic reservoirs for the long-term storage of CO_2 in the United States. Figure 5 shows a very rough cost curve for the 185 existing coal- and natural gas-fired power generation units in the United States located in Illinois, Indiana, Ohio and West Virginia assuming that they can not transport their CO_2 more than 100 miles from the power generating unit (Dooley 2002). At a carbon tax of $50/ton, approximately 250 million tons of CO_2 can be sequestered out of approximately 600-700 million tones emitted, roughly 40% of total emissions.



Source: Dooley, J.J., R.T. Dahowski, and M.A. Wise. 2003. "Modeling Carbon Capture and Storage Technologies in Energy and Economic Models." IPCC Expert Meeting on CO2 Removal and Storage, Canada.

Figure 5: Marginal cost curve for MAAC region

Even with a GIS model there is the practical difficulty of estimating the actual cost of storage associated with a certain reservoir or storage site. This is akin to the inverse problem of petroleum resource extraction where it is difficult to estimate cost before an actual survey is conducted. Reservoir data does exist for depleted oil and gas reservoirs but for coal beds and saline aquifers little data is available.

To bridge this practical difficulty, a cost distribution for each of the source and sink types can be estimated using the studies, data, information, models and expert assessments currently available. These individual cost distributions can be combined in a statistical mixture model to generate an aggregate marginal cost curve for each region. As more information from experiments, CO_2 sequestration demonstration projects, simulations and assessments become available, the cost distributions can be updated. Broadly speaking this modeling approach belongs to the Bayesian school of thought. Its advantage lies in its ability to generate aggregate instead of site-specific information that can be used in economic models. Figure 7 illustrates this conceptual framework.

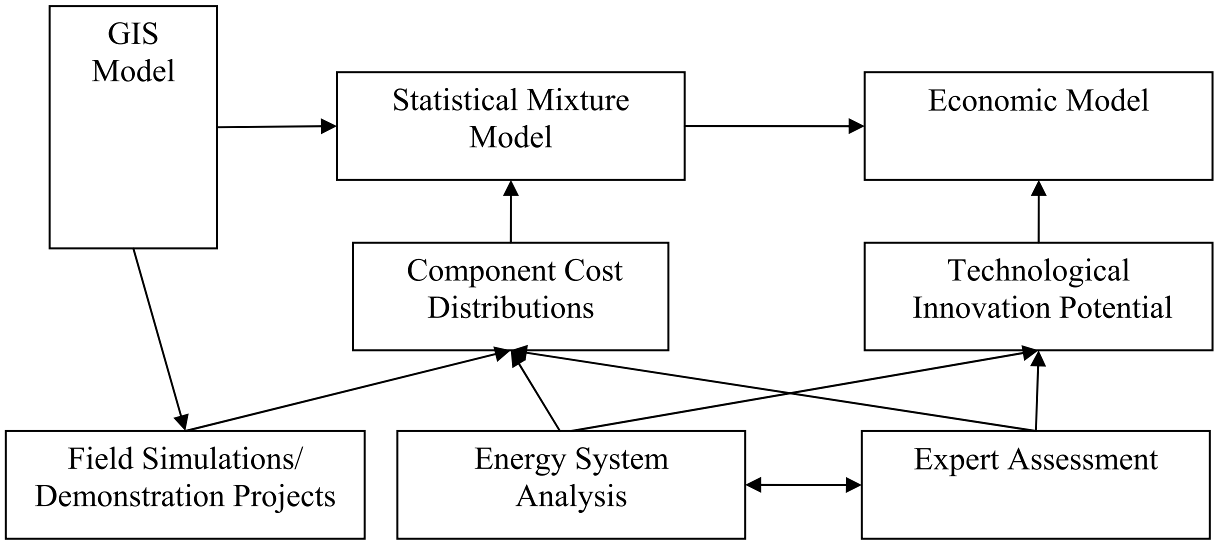


Figure 7: Conceptual Model of the CCS Analysis Framework

Using a Mixture Model to Capture Heterogeneity

Mixture modeling refers to modeling a statistical distribution by a mixture (or weighted sum) of other distributions.

Basic definition of a mixture model

A mixture model is given by the observation of *n* independent random variables $x_1, x_2, ..., x_k$ from a *k*-component mixture density:

$$f(x_i) = \sum_{j=1}^{k} p_j f_j(x_i), i = 1, ..., n,$$

$$p_j > 0, \qquad j = 1, ..., k; \qquad p_1 + ... + p_k = 1$$

$$f_j(x) \geq 0, \qquad j = 1, ..., k.$$

The parameters p_1, p_2.., p_k are called the mixing weights and $f_1(x)$, ... $f_k(x)$ are the component densities of the mixture.

In our mixture model, the mixing weights are the proportions of the available reservoir storage types and CO_2 source-capture technology combinations. The cost distributions for the storage and capture components are the component densities of the mixture. These cost distributions are modeled by prior Bayesian probability distributions.

Methodology

The prior cost distributions are built for each geological storage type and for each of the capture technologies, both current and future, in the technology cost chain. It is assumed that any type of source or sink can be matched up, i.e. source sink groups are independent of storage type and source type. In practice, important criteria for a source-sink match-up is proximity, storage capacity, seal integrity and cost. These factors are implicit in the cost estimates being used (Herzog et al. 2004). The distribution of total cost is then obtained by sampling from the individual technology distributions and the reservoir costs in the cost chain and summing over those costs. Cost distributions for this study have been built using a Bayesian approach. The Bayesian approach combines sample information with other available and pertinent prior information. The actual cost estimates have been based on the cost analysis conducted by Herzog et al. (2004). In their study Herzog et al used 'rules of thumb' to define the engineering parameters needed to estimate costs. These 'rules of thumb' were derived based on information from experts in the field and the literature (Table II). Using the high, low and base cases triangular distributions were generated for each of the storage types.

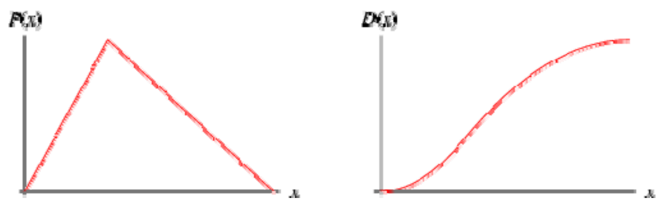


Figure 8: Triangular distribution

The triangular distribution is a well known distribution in quantitative risk analysis/ estimation and is commonly used in the absence of hard data. Its advantages are that it is simple to use and intuitively plausible. The weight for each storage component is equal to its percentage of the total available storage. Available storage refers to storage site within an acceptable distance from a source. Similarly on the capture side one would need to know what percentage of CO_2 emitters are coal plants, natural gas plants etc. This is where aggregate statistics from a GIS model would be very useful. A GIS model could answer questions like: What percentage of storage is located close enough to sources and far away enough from populated areas such that they are not a major risk – both for environmental and safety reasons? What percentages of reservoirs are large enough, i.e. greater than the threshold storage capacity?

Monte Carlo Sampling - A Monte Carlo sampling procedure is used to draw from each of the underlying probability density functions in the ratio of their respective weights. In the analysis for the United States weights of 20% EOR, 20% ECBM, 60% Aquifer and Depleted Oil and Gas Reservoirs are chosen.

The results of the mixture model analysis are shown in Figures 9 and 10. Figure 9 describes the cumulative distribution of storage costs for each of the storage classes – EOR, ECBM, Aquifer, Depleted Oil and Gas, as well as for the overall mixture, i.e. Total Storage. The results show that up to approx. 26% of available CO_2 storage capacity can be filled at negative cost. The curves for each of the storage classes basically indicate the cumulative distributions of cost if 100% of storage capacity were contained in that class.

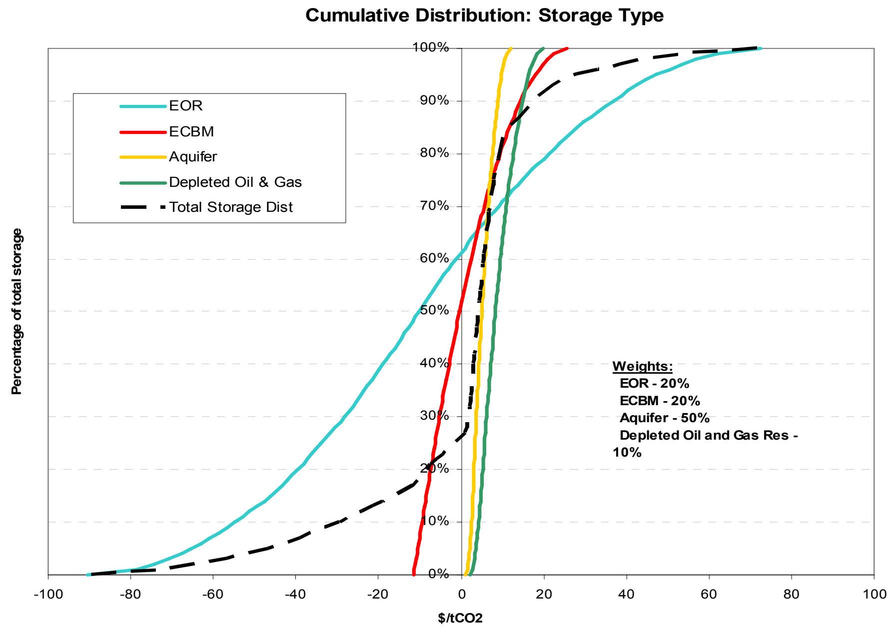


Figure 9: Cumulative distribution of cost by storage class

The storage class with the widest range is EOR and the narrowest, Saline Aquifer. It is expected that after 'value added' early opportunities like EOR and ECBM, the Saline Aquifer class will dominate CO_2 storage, the primary reason being the abundance and uniform distribution of saline aquifers across most regions.

Figure 9 shows the marginal cost curves for storage and for total cost (= storage + capture) respectively. The marginal cost curve is obtained by inverting the cumulative distribution of cost. This is based on the premise that the lowest cost options will be deployed first. The storage cost curve in effect is the lower limit of the total cost curve since it is not expected that the geological storage costs of CO_2 will decrease with time substantially, at least not in the near future. The CO_2 capture costs on the other hand are expected to be a decreasing function of time through R&D and learning. Figure 11 shows the 10-50-90 distribution. In the case selected, 80% of the cost of storage falls within the range of -$18 to $20.

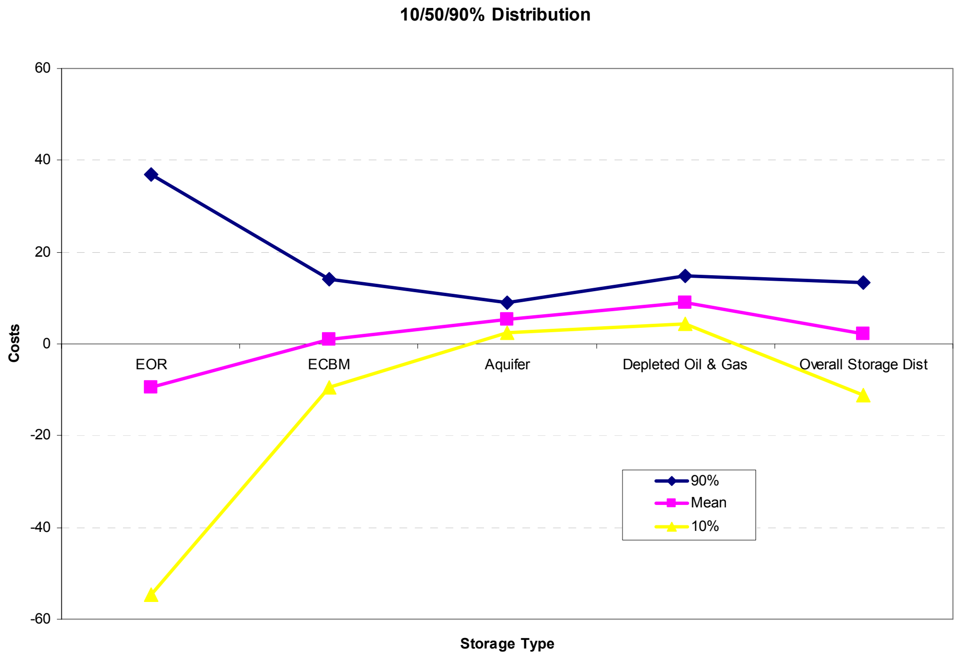


Figure 11: 10/50/90 curve by storage class

Extensions and Future Work

Modeling Technological Change

Modeling technological change is a complex task. Technological change responds to policy, is highly uncertain and technological diffusion differs in time and between countries and regions (Clarke and Weyant 2002). The most important question we would like to answer is how costly will CCT be in the future. Rubin et al (2002) have used the concept of 'learning' in modeling technological change. They used experience over the past 30 years in the U.S. and other countries with reducing emissions of sulfur dioxide (SO_2) using flue gas desulphurization (FGD) systems (also commonly known as SO_2 "scrubbers") to serve as a guide to technological progress in managing CO_2 emissions. This was plausible since SO_2 "scrubbers" and currently commercial CO_2 capture systems have similar principles of operation. For CCT a combination of learning and subjective probability assessment may be more appropriate, especially since these technologies have not yet been deployed at any significant scale. Since initial conditions have not exactly been set, it is worth considering a portfolio of several distinct technological possibilities incorporating spillover effects from advances in other areas like materials, nanotechnology etc. In the case of CO_2 separation, operating cost is closely linked with the energy penalty of the particular separation method. An energy assessment (thermodynamic potential) can give us a good estimate of the minimum cost or technical limit associated with any future separation technology.

Incorporating the results of scientific research

If geologic storage of CO_2 is to take place at large scale the issue of leakage risk seems very important - 1) when accruing for storage, monitoring and verification costs 2) regarding the location and appropriateness of sites and 3) calculating environmental and political cost. For example in the case of EOR, not all oil and gas reservoirs are good candidates for CO_2 flooding. Fluid properties are important. Heavy oil is more amenable to steam flooding than CO_2 flooding. It is also well known from the oil and gas industry that stress changes associated with injection or depletion can affect the integrity of the geologic seals that contain the fluid. Highly fractured carbonate reservoirs such as those in California may not be good CO_2 seals. Much less is known about coal beds and saline aquifers. It is evident from these issues that domain specific scientific knowledge is important in examining the role of CCS as a viable climate change mitigation option. How can scientific research be integrated into our modeling efforts?

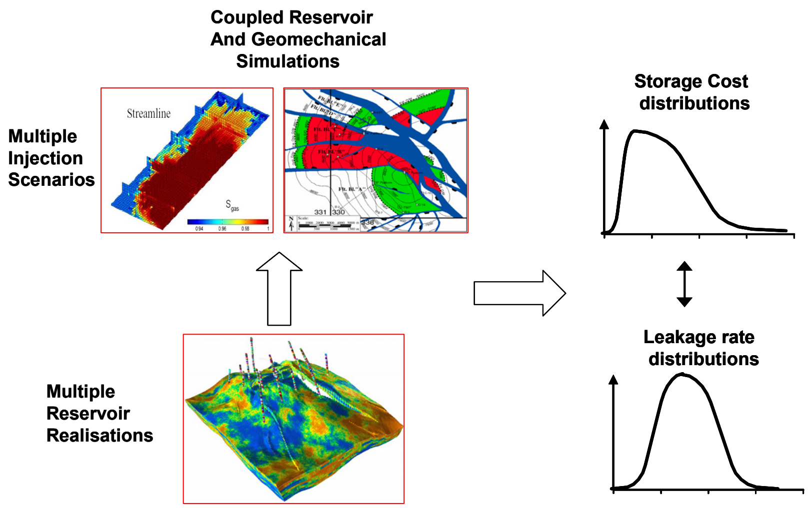


Figure 12: Using Simulation to determine leakage rate distributions

Simulation - One option is to run coupled reservoir-geomechanical simulations to determine leakage rates and CO_2 movement for a set of reservoir characterizations spanning the range of reservoir parameters and injection scenarios – Figure 13. This will allow us to determine leakage rate distributions for a set of reservoir classes. The results of the simulations can also show us the temporal profile of CO_2 migration and leakage which will be important in determining monitoring and verification costs. This is especially useful since monitoring and verification costs have not yet been treated with any significant rigor in the costing literature.

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Quantifying the Leakage Rate Associated with Carbon Storage

Investigators
James Sweeney, Professor of Management Science and Engineering; John Weyant, Professor of Management Science and Engineering; Oscar Mascarenhas, Graduate Researcher.

Introduction

Establishing the permanence of geological storage of CO_2 is critical to the deployment of Carbon Capture and Storage. Leakage rates must be acceptable from the perspectives of climate change, the environment and human health and safety. On a global level, slow leaks could eventually build up to current fossil emissions levels. A 1% leakage rate from one trillion tons of sequestered fossil carbon sequestered carbon would create ten billion tons of annual emissions, comparable to the current annual total of seven billion tons. On a local level, leaking CO_2 can contaminate of drinking-water aquifers. The quantification of leakage risk and leakage rate is however yet to be rigorously analyzed and quantified on the macro scale. Studies evaluating the feasibility and potential of Carbon Capture and Storage have suggested a maximum leakage rate of approximately 0.001 – 0.01 % taking into account possible scenarios for future CO_2 emissions through fossil fuel usage (Benson, 2002) A leakage rate of 0.01 % would ensure that 90 % of the carbon dioxide would remain underground over a 1000 year time period. Leakage rates of 1 % imply that most of any stored carbon dioxide would return to the atmosphere after only 400 years (Benson, 2002). This emphasizes the need for the quantification of leakage risks.

Background

Leakage pathways

Several pathways exist for possible leakage both 'natural' and 'anthropogenic'. These include:

1) Diffuse leakage across caprock formations,
2) Concentrated leakage through natural faults and fractures, and
3) Leakage through human-made features such as wells: Depleted oil and gas reservoirs have large numbers of abandoned wells greatly increasing the potential for leakage. In areas where little oil and gas exploration has occurred, there are relatively few existing wells, and potential for leakage through existing wells is not a major concern.

Trapping CO_2

There are several trapping mechanisms to store CO_2 in the subsurface:

1) Structural Trapping
2) Geochemical Trapping
    a. Solubility trapping
    b. Ionic trapping
    c. Mineral trapping
3) Residual Gas trapping

Structural trapping

Structural trapping refers to permeability and capillary barriers created by the formation caprock. Trap effectiveness depends on the specific geometry and structure of the reservoir as well as the caprock type which can broadly be classified under shale, clay or carbonates. Permeability barrier effectiveness varies with rock properties increasing from gravel and coarse sands to clay and shales. Capillary barrier effectiveness increases moving from shales to carbonates. Structural traps are classified under: 1) Closed Traps and, 2) Open traps.

Closed traps physically retain the CO_2. These include structures such as anticlines, unconformities, sealed faults and facies changes.
Open traps permit lateral migration of the CO_2 but prevent rapid upward migration of CO_2. Open trap structures include synclines and transmissive faults.

Geochemical trapping

Geochemical trapping broadly refers to chemical reaction of the CO_2 with brines and rock to form stable carbonates. The effectiveness of this trapping mechanism is determined by the volume and the rate of chemical reactions which are dependent on formation chemistry.

Residual Gas trapping

Residual gas trapping refers to the trapping of gas as it flows through the porous medium. Once the gas in injected, there is a hysteresis loss and some of it cannot flow out. Residual gas trapping depends on both pore-network characteristics and gas saturation.

Overall Reservoir trapping potential

Potential leakage rate is therefore a function of the overall trapping potential of the reservoir or more precisely - a function of the structural, geochemical and residual gas trapping potentials. The trapping mechanisms are however not necessarily independent of one another. A strong structural seal allows more time for geochemical reactions to take place further reinforcing the geochemical trap. In practice however, strong structural and geochemical traps may not coexist. Carbonate reservoirs have high geochemical trapping potential but are highly fractured in nature allowing concentrated high permeability pathways for CO_2 leakage.

Uncertainty

The uncertainties involved in the storage of CO_2 are of two main types (Figure 1) – the first type represents the inherent variability associated with geologic storage which includes the spatial heterogeneity of intrinsic permeability and porosity, the multiplicity of rock types and structural geometries and the randomness of external events like earthquakes. The other type of uncertainty also termed as epistemic uncertainty stems from an incomplete knowledge of the fundamental phenomena involved such as geochemical degradation of the reservoir or induced seismicity. In order to capture epistemic uncertainty, risk scenarios must be constructed on a set of all known hypotheses regarding the nature of fundamental mechanisms (Paté-Cornell, 1996). These mechanisms must be structured as a set of mutually exclusive and collectively exhaustive elements in accordance with the fundamental laws of probability.

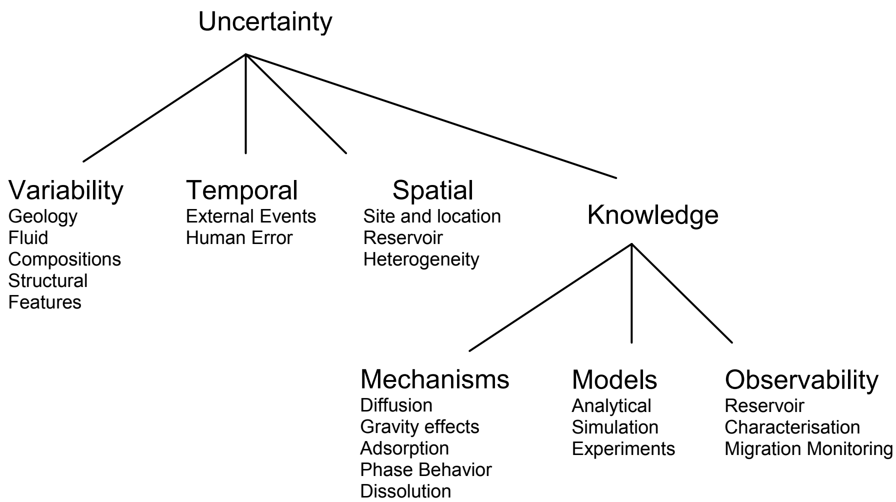

Figure 1: Uncertainty taxonomy for the geological storage of CO_2

Simulation - One option is to run coupled reservoir – geomechanical simulations to determine leakage rates and CO_2 movement for a set of reservoir characterizations spanning the range of reservoir parameters and injection scenarios. All of these data and parameter uncertainties create a problem that has a complex multi-dimensional parameter space with potentially wide ranges of possible values along the parameter axes. Because of the scale disparity and the large degree of uncertainty, and the resultant large number of simulations that will be needed to perform a risk analysis, computational efficiency of models becomes a concern, and different modeling options need to be considered. A systems approach is described in the following section.

A Systems Approach to Modeling

The complexity of geological storage of CO_2 makes it a good candidate for a 'Systems' approach to modeling. A systems model divides a system into a collection of components or elements linked together by form, process or function. The system can be expressed in terms of an input-output model and characterized by state variables at any point in time.

Model Structure

At a high level, a typical CO_2 reservoir system can be divided into blocks or zones as shown in Figure 2. CO_2 will be initially trapped beneath a relatively impermeable layer. Driven by diffusion, buoyancy, and regional hydraulic gradients, the CO_2 will move. Some will dissolve or become trapped beneath the caprock. The CO_2 that escapes will do so if the caprock fractures or when the moving front encounters a conduit such as a fault or an abandoned well with a failed concrete seal. It will then migrate upward, spreading horizontally as it moves, until it encounters another relatively impermeable layer, and the whole process will begin again, similar to a jump-diffusion process. A fraction will never escape and the rest will escape with a distribution of time lags. The amount of CO_2 retained and the distribution of time lags will vary from reservoir to reservoir.

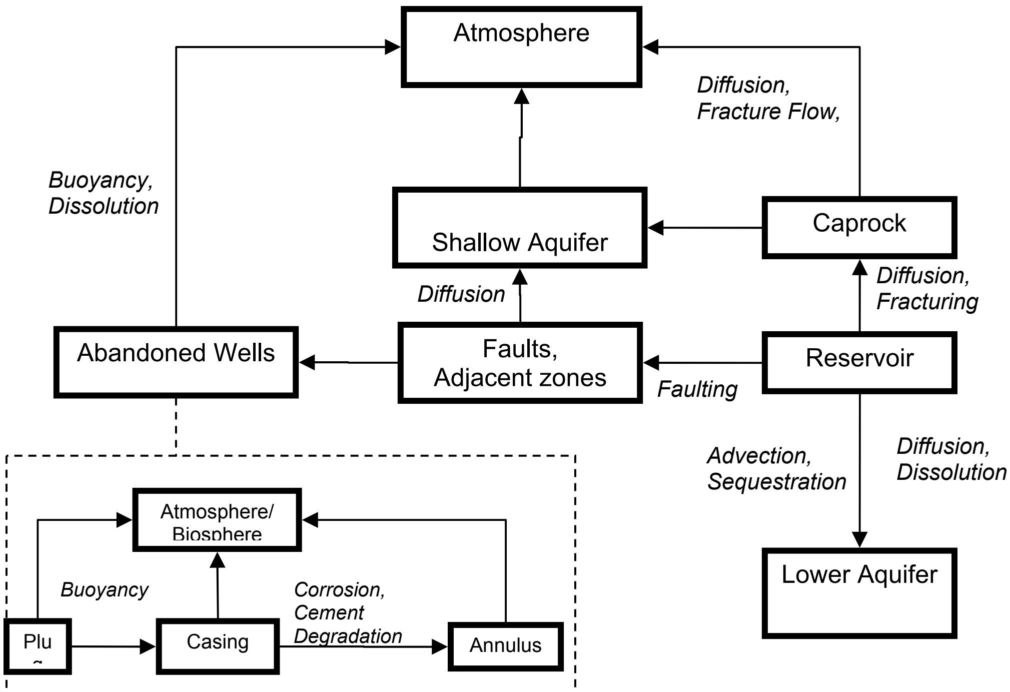

Figure 2: CO_2 reservoir systems model

In reality, a real reservoir would contain many confining layers ad copartmente. The reservoir system can be decomposed still further into contiguous blocks both conceptual and physical. The flow or transfer or migration or 'leakage' of CO_2 between these system blocks can be expressed by a probability $P_{ij}(t)$ that can be interpreted as the expected fraction of flow between the ith and jth blocks. The transition probabilities P_{ij} form the elements of a stochastic matrix P. The matrix **P** essentially represents system structure.

$$\begin{bmatrix} P_{11} & P_{12} & . & . & . & P_{1n} \\ P_{21} & P_{22} & . & . & . & P_{2n} \\ . & . & . & & & \\ . & . & & . & & \\ . & . & & & . & \\ P_{n1} & P_{n2} & & & & P_{nn} \end{bmatrix} \qquad \sum_{j=1}^{n} P_{ij} = 1 \quad \text{for all } i = 1, 2, \ldots, n$$

Figure 3: System Matrix P

The sum of all elements in each row of **P** sums up to 1. Each row of matrix **P** is a called a probability vector because of this property. This representation is essentially a

Markov chain or a special class of a dynamic system that evolves probabilistically. The possible locations for the migrating at each step in time CO_2 can be thought of as states of the system. The future evolution of the process is described by a vector of probabilities at each step in the process. Successive probability vectors are generated by the recursion:

$$\mathbf{x}(k+1)^T = \mathbf{x}(k)^T \mathbf{P}(k)$$, where k is the time step of evolution.

Note that the transition probabilities depend on the number of steps (k) that have occurred in the evolution or in other words are a function of time. This follows from the physics of CO_2 migration and the timescales involved with the analysis.

This formulation allows a rich set of analyses drawing on the theory of Markov processes. One example is the computation of the probability that a specified state location will ultimately be reached. Another is the average length of time to reach a specified state or group of states. This opens up interesting application possibilities, one of which is in the design of an optimal risk monitoring and control regime.

A systems analysis approach to assessing risk has been successfully applied to the field of radioactive waste disposal (Stenhouse et al., 1993). A central part of this approach is a rigorous and exhaustive documentation of the 'FEP's' to describe the disposal concept which is to be evaluated. FEP's are *features, events, and processes* relevant to the assessment of the behavior of a carbon dioxide disposal system.
Features of the sequestration system could include rock and fluid properties, reservoir geometry, cement quality, such as unsealed or inadequately sealed boreholes, the quality (composition) of CO_2, undetected geological structures, etc.
Events include seismic events, faulting, human error, etc.
Processes include the mechanisms that govern the evolution of the disposal system, such as flow and diffusion of CO_2, chemical reactions with reservoir and cap rock etc. The transition probabilities are in essence functions of the 'features, events and processes' of the system components and their interfaces.

Motivation for a probabilistic approach

The CO_2 disposal system can be classified as an organized complex system or a system with structure – one involving large numbers of non-linear differential equations with many interactions among a large number of components and variables that define the system. Problem solutions related to such models of organized complexity tend to converge to statistically meaningful averages (Klir and Wierman, 1998). This sets the basis for a probabilistic approach to modeling this complex system.

Assessing Probabilities

Influence Diagrams

In order to assess probabilities, the dependencies between the key variables that represent the system FEP's should be established. For example, the solubility of CO_2 in water may influence the degradation of borehole seals. An influence diagram can graphically represent this relationship between system variables, both uncertain and deterministic. It is an intuitive way of capturing complexity in a concise graphical form. Influence diagrams also serve to reduce the uncertainty space associated with the problem. The development of an influence diagram involves identifying the system state variables, deciding on appropriate states, determining the dependencies among events, and assigning likelihoods to the states. Uncertainties are represented by ovals. The uncertainty to be estimated the - leakage through the well is represented by a hexagon. An event with no predecessors, that is, no arrows pointing to it, is an independent variable. An arrow pointing to an uncertainty represents probabilistic dependence. Consider the influence of diagram shown in Figure 4 that represents a simple probabilistic model of leakage through an abandoned well. It is plausible that a migrating CO_2 plume can contact an abandoned well especially in areas like Texas which have close to a million wells drilled. Leakage through a wellbore will depend on the reactivity of CO_2 which are influenced by the cement quality, the materials used, well completion standards etc. all of which are believed to show a high degree of variability. (Norbotten et al., 2005).

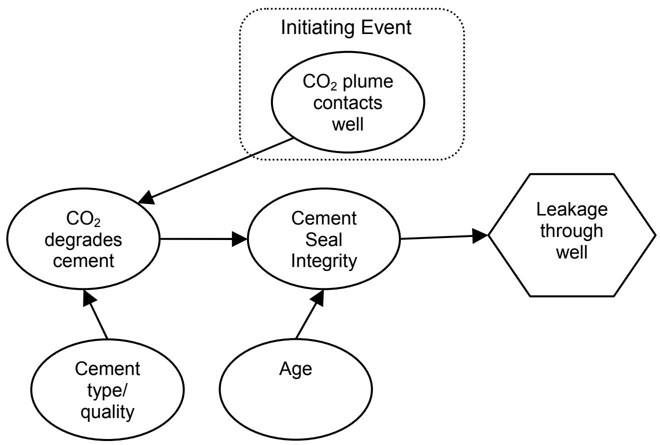

Figure 4: Influence diagram for wellbore leakage

Expert Assessment

The high uncertainty, variability and system complexity limits analytic modeling and makes simulation modeling a time intensive process. Since policy decisions need to be made in a timely manner, we have decided to conduct an expert assessment to assess probabilities.

Using much of the structure and modeling tools outlined in the previous sections, the CO_2 storage system will be broken down into well-defined components, lower level probabilities assessed, and then combined mathematically to arrive at a distribution of leakage rates. A Bayesian approach to assessing probability allows the incorporation of all available evidence including statistical data, physical models and expert opinion. Specific techniques will be used to account for motivational and cognitive biases and resolve differences of opinion.

The assessment meeting will comprise three stages. Participants will:

1) Assess the current state of knowledge and available evidence; Identify and address the key questions and issues related to CO_2 migration and leakage.
2) Agree on a structural model of leakage in the form of an influence diagram.

3) Identify leakage scenarios and quantify key uncertainties in the form of probability distributions. The uncertainty is propagated through a probabilistic model to obtain an overall distribution over leakage.

We will limit the assessment to sites that are suitable candidates for CO_2 disposal in North America. The reservoir classes considered will be 1) Depleted Oil and Gas Reservoirs, 2) Saline Aquifers, 3) Coal Beds. It is reasonable to assume that sites will be selected to minimize the risk of leakage and unsuitable sites will not be considered. The major requirement is suitable geology. An injection reservoir must generally have:

1) Sufficient depth (generally greater than about 2,500 ft) to maintain the injected fluid as a supercritical liquid,
2) Enough thickness and lateral extent to provide capacity for large injection volumes,
3) Sufficient porosity and permeability to accept injection fluids,
4) Impermeable caprock layers above the injection layer to provide containment,
5) A structurally sound setting free of faults and fractures, and
6) Suitable chemistry to prevent adverse interaction between the rock and injection fluid.

Since we are estimating likely leakage rates given suitable geology, we will therefore need an expert assessment of the proportion of available reservoir storage likely to be suitable, thereby obtaining a constraint on storage.

Scenarios

A set of scenarios will form the basis for the quantification of risks. Assuming a structurally sound storage site is selected free of any known fractures and faults, a scenario for leakage could be that a fault remained undetected during the site characterization process, CO_2 contacts this fault, the fault turns out to be active, serving as a conduit for the CO_2 that migrates to adjacent zones and seeps to the surface through the overburden.

External events

External events can include natural events like earthquakes, the movement of old faults, the creation of new fractures and geochemical changes that destabilize the reservoir. Manmade changes include wellhead failures, pipeline ruptures and leakage through wells. The injection of large volumes of CO_2 at high pressures can induce micro-seismicity and subsidence due to dissolution (for example in carbonate aquifers).

Evidence

Evidence selected for the assessment will include:

1) Evidence from analogues such as naturally occurring CO_2 reservoirs and natural gas reservoirs.
2) The results of experiments, analytical models and simulations.
3) Results from demonstration projects. A set of 3-6 cases that span the range of reservoir types could be selected for review. These could be for proposed sites such as the Ohio River Valley reservoir; and ongoing demonstration projects such as Weyburn and Sleipner. Results from the Weyburn risk assessment (IEA GHG 2004) estimate that after 5000 years, the average cumulative release of CO_2 to the

atmosphere is predicted to be 0.2% of initial CO_2 in place with a 95% confidence interval of 0.005% to 1.3% of initial CO_2 in place.

Extensions and Future Work

The assessment meeting at Stanford is tentatively scheduled for mid to late summer depending on the level of preparation and availability of the participants. After this stage, the assessment will be extended to external participants. The results will serve to integrate the current state of knowledge regarding the long-term viability of CO_2 storage, and provide insights into the relative magnitudes of uncertainty in different parts of the system. This will be important from a risk monitoring and control perspective for which there are many potential applications of our work.

A natural next step is to determine the impact on the future evolution of Carbon Capture and Storage. The treatment of risk in global economic models will need to be carefully considered in the light of risk-cost tradeoffs, mitigation options and future technological change. Future researchers should look at:

1) The interplay between risk and the regulatory framework - In most countries, the lack of regulatory framework may delay the application of CO_2 capture and storage. It is expected however that the regulatory framework will evolve through cooperation between government, industry, and other stakeholders as the number of demonstration and commercial projects increases. (Opinion of Carbon Capture Project policy team, personal communication, 2004)
2) Public perception and risk communication - A study conducted by Howard Herzog and Tim Curry of the MIT Laboratory for Energy and the Environment on “Public Opinions on Carbon Capture and Storage”, concludes that public awareness of CO_2 capture and storage technology is low to non-existent; therefore gaining public acceptance is likely to be challenging and will depend to a large part on how the benefits and risks of Carbon Capture and Storage are communicated to the public.

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[i] Stanford Global Climate and Energy Project
[ii] Sperling. Page 366.
[iii] California Hydrogen Highway Blueprint
[iv] EIA Gasoline Restructuring.
[v] Jacoby and Kyner. Page 2.
[vi] Day. Page 153-4.
[vii] Gabszewicz, Pepall, and Thisse. Page 398

A Global Portfolio Strategy for Climate Change Technology Development

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Introduction

The field of climate policy has examined many aspects of an optimal response to global climate change as a result of anthropogenic greenhouse gas emissions. Among the difficulties posed by this problem are long timeframes, pervasive uncertainty, extremely high potential costs of mitigation and damages, and a global scale requiring unprecedented institutional coordination. The majority of climate policy studies have focused on the optimal choice of market-based instruments to induce appropriate internalization of the costs of emissions in private energy supply and demand decisions. Many economic and physical processes influence these calculations, but one of the most central is the future state of technology. The process by which carbon-free or carbon-reducing energy technologies are made available is a powerful lever for lessening the economic impact of a given level of abatement, or conversely for reducing the environmental risks of a given level of abatement expenditure. However, the nature of this process is not well understood, and in particular the role of a strategy to control it has not been directly analyzed. A significant body of work has examined the extent to which technological change is accelerated by private actors in response to the introduction of an internalization policy, but this work does not address the current problem faced by a public research and development (R&D) manager[1] under uncertain policy conditions.

In this project we propose a novel formulation of a decision problem in R&D strategy. The problem is motivated by and applied to the context of global climate change, but is characterized in general by an aggregate R&D decision-maker with a social welfare objective, and technology diffusion markets subject to externalities in which private costs are minimized. Of particular interest in this study is the *allocation* of the R&D investment portfolio and its effect on the expected value of research outcomes. We also examine the relationship between technology strategy, defined as the choice of the allocation vector, and market-based internalization policies such as emissions permits or taxes. The dynamic nature of this problem is emphasized in our methodology in order to properly account for several structural features, including the time lag between R&D investment and technology diffusion, the uncertainty in both technological and environmental factors, and the extended time horizon for climate change induced damages.

Background

This work draws upon three distinct areas of the literature. The first is a series of studies in the economics field concerning the dynamic optimization of R&D investment. These studies provide useful templates for framing our analysis, but none has considered the particular

[1] We will use the term 'public R&D' to refer not necessarily to R&D conducted by governments, but more generally to any R&D effort that generates knowledge which is treated as a public good.

setting we propose here. Secondly, the real options literature is helpful in describing the way in which R&D investment provides value. The benefits of technological advance over a long time horizon with evolving resolution of uncertainty often take the form of options, which fundamentally affects the valuation process for near-term research portfolios. Finally, this project both depends heavily on and seeks to extend the integrated assessment techniques used in climate policy analysis. While we use traditional integrated assessment modeling to evaluate technological developments, our work further attempts to embed the treatment of technology strategy within the broader assessment context. Recently, climate policy researchers have become increasingly interested in the role of technological change. However, most studies have examined the impact of a policy-induced price signal on contemporaneous learning or R&D by industry actors, a process known as endogenous technical change (ETC). This framework does not apply to more long-term radical developments requiring many years of basic research, since they cannot be motivated by current emissions penalties.

A small number of studies within the last year have addressed elements of the public basic research decision problem. Miketa and Schrattenholzer (2004) use a learning curve approach to model the influence of aggregate R&D in the diffusion of renewable energy technologies such as photovoltaics and wind [1]. This paper focuses more on the learning-based ETC that arises as a result of an R&D stimulus than on the R&D investment decision itself. Baker et al. (2005) provide a comparative statics analysis of the response in various types of technology R&D to increases in risk [2]. This paper emphasizes the role of uncertainty in assessing the value of an R&D investment, but it does not provide a decision framework for an R&D portfolio. There have also been numerous integrated assessment modeling studies which compare the costs and benefits associated with greenhouse gas abatement under alternate technological scenarios. While these comparisons begin to establish guidelines for the magnitude of the benefits of new energy technologies, they cannot assess the allocation problem: Developments in individual technologies, subsets of technologies, and issues of timing, staging, and dynamic flexibility are not considered. Our work is thus a unique extension of ongoing effort to characterize a technology portfolio strategy for global climate change. For a detailed review of the relevant literature, please see the authors' background paper [3].

Results

The first main result of this project is the formulation of a theoretical model of the R&D process. After describing the model, we present the analytical solution mechanism and the optimality conditions. Finally, a simple example of the model is provided to elucidate the insights yielded by our approach.

The Model

We propose a model of sequential innovation with T periods and n research programs available in each period. Each research program represents a technology, or class of technologies, with the potential to mitigate an environmental externality in the end-use market. The decision variable is the level of aggregate investment in public research allocated to each program in each period, subject to a budget constraint which may or may not be binding. In a given period, each program has set of possible technological outcomes, which depend on the state of the program's technology at the beginning of the period. The probability distribution across the outcome space is conditioned on the level of investment in the program. This relationship will be referred to as the *innovation production function*. A fundamental assumption is that the relationship between research investment and the probability of success is increasing, but exhibits decreasing returns to scale. However, this does not necessarily imply that the relationship between research investment and the *value* of success has decreasing returns to scale, since the benefits of an advance may be highly nonlinear. Value is measured by the technologies' performance in the market, and by the realization of an uncertain damage function associated with an environmental externality.

The economic system into which the developing technologies are diffused evolves in parallel with the research programs. Given the state of the economic system at the beginning of a period, defined by the market shares of the technologies associated with the research programs, the state of the system at the beginning of the next period is modeled as the result of private cost minimizing decisions by the relevant industries. These decisions describe diffusion as a deterministic function of the state of technology in the current period (but *not* of the outcomes of the concurrent research programs), a set of exogenous parameters such as demand conditions and environmental damages, and the existence and extent of an internalization policy.[2] The policy may be endogenous to the R&D decision problem (i.e., influenced by the state of technology). The evolution of the economic system can also contribute to the state of technology in the next period; there is strong empirical evidence that increased deployment of a technology leads to improvement via learning effects. These effects, combined with the existence of research efforts outside the scope of the public decision-maker (which may or may not be proportional to deployment), admit the possibility of advance independent of the investment allocation. In particular, the probability of independent advance in a given technology is at least partially increasing in its market share. Thus the probability distribution across the outcome space is conditioned on both the innovation production function and the diffusion pattern in the economic system.

Because the R&D decision-maker is concerned with maximizing social benefit, the problem's objective function includes measures of the utility of consumption, economic abatement costs, and environmental damages associated with the state of the economic system and the exogenous parameters. Consumption utility is defined as the aggregate utility in the system associated with private consumption *before* any environmental mitigation is enforced. This baseline is included to capture the value of technological development independent of its impact on abatement costs. These costs are measured as the reduction in aggregate utility of consumption as the result of an optimal internalization policy, but are calculated net of any emissions penalties imposed by the policy.[3] Finally, unless the policy-maker finds it optimal

[2]The diffusion of new technology is typically viewed as a highly uncertain process subject to attributes of the economic system not modeled here, including firm size, industry structure, and institutional barriers. The representation here was chosen to focus the analysis on technological, environmental, and policy uncertainties.

[3]In some cases, such as grandfathered permits, these penalties are in fact costless. In other cases, such as auctioned permits or taxes, the penalties are simply a transfer and do not affect the net social cost of the policy. Moreover, some economists have suggested that emissions taxes can actually reduce social costs by offsetting revenues from other, more distortionary taxes. This so-called 'double dividend' effect is not considered here.

to abate fully, there will remain a certain level of emissions associated with the policy-controlled economic system, whose environmental costs depend on the realization of an uncertain damages function. From the perspective of the R&D decision-maker, value is calculated as expected utility net of the sum of economic and environmental costs, taking into account the policy-maker's choice.[4] The decision-maker's problem is therefore to allocate investment across the programs in each period, and at each node in the outcome space, so as to maximize the expected value of the system's evolution over the time horizon. The solution is found with a dynamic programming recursion, and thus takes the form of a dynamic, adaptive strategy that specifies optimal investment at the present moment, and in every possible future scenario.

The Solution

The problem is solved using a dynamic programming recursion over the finite time horizon. In the final period, each possible state is evaluated. A state in the final period is represented by s_T, which encompasses a particular path through time T of the three state variables: technology, socio-economic conditions, and knowledge about climate damages. Every s_T is evaluated based on the state of the economic system, y^t, in each period t in the time horizon, which is calculated as deterministic function of s_t, the path of the state variable up to time t. The value of y^t is determined by the difference between the utility of consumption in the absence of a carbon policy, U^t, minus the costs of mitigation undertaken in the period, C^t. The emissions level e^t is also determined by y^t. Finally, the value V^T of s_T is calculated as the difference between the discounted sum of net economic benefits and the function D, which represents the discounted sum of damages from carbon emissions throughout the time horizon, and is not known with certainty until the final period. The following equation describes this first step in the dynamic solution:

$$V^T(s_T) = \sum_{t=1}^{T}(1-\delta)^t \left(U^t(y^t) - C^t(y^t)\right) - D(e^1, \ldots, e^T) \tag{1}$$

From the value assigned to the entire path, the dynamic programming recursion can be established by working backward in time. Let $V^t(s_t)$ be the value of any partial path through the state space to time t. This value is determined by optimizing the choice of the R&D investment allocation vector. The allocation of investment to program i in period t is given by α_i^t, and $\alpha^t = \{\alpha_1^t, \ldots, \alpha_n^t\}$ represents the overall investment allocation in period t. Total R&D investment in period t is denoted $A^t = \sum \alpha_i^t$; the budget for period t is denoted B^t. At any node in the state space, that is, at any possible state s_t, the allocation vector is chosen to maximize the expected value of the next period's state, V^{t+1}, less the cost of the investment. Since V is based on a discounted sum of utility and costs across all periods, the research investment must also be discounted back to the present. The expected value of V^{t+1} has three dimensions, representing each of the state variables. In the case of socio-economic conditions and knowledge about climate damages (denoted by ω and ψ, respectively), the expected value of next period's state is determined entirely by the current state. However, the expected value

[4] The value associated with a *particular* R&D investment is calculated as the difference between expected value with and without the investment.

of next period's technology state, denoted by θ, is a function of both the current state *and* R&D investment. This is the crucial element of the technology strategy problem. The probability density function f associated with each possible state of technology in period $t+1$ (the entire set is denoted by Θ_{t+1}) depends upon the choice of α^t. Therefore we define the recursive objective function as follows:

$$V^t(s_t) = \max_{\alpha^t} \left(\sum_{\theta \in \Theta_{t+1}} f\left(\theta; \alpha^t, \theta_t\right) \mathrm{E}_{\omega_{t+1}} \mathrm{E}_{\psi_{t+1}} V^{t+1}(s_{t+1}) - (1-\delta)^t A^t \right) \tag{2}$$

The solution will take the form of a policy α^*, consisting of an optimal allocation vector $\alpha^{t*}(s_t)$ for every possible s_t in each period. Because of the one-period lag between R&D investment and outcomes, there is no investment in the final period. In the first period, there is a single optimal investment allocation, since there is only one current state. The optimization problem at an arbitrary stage in the dynamic program had the following first order condition, with time subscripts removed:

$$\frac{\partial V_0}{\partial \alpha_i} = \sum_{\theta \in \Theta} \frac{\partial f}{\partial \alpha_i}(\theta; \alpha, \theta_0) \mathrm{E}_{\omega,\psi} V(\theta, \omega, \psi)) = 1 - \delta \tag{3}$$

Without a budget constraint, investment in each program is increased until the marginal benefit equals the discounted opportunity cost. Although the criterion for the marginal condition is independent of investment in other programs, the benefit function depends on these variables, so the n-equation system must be solved simultaneously. The balance between research programs will depend on the response in f to changes in investment, the influence of the various programs on the value function, and interdependence among the programs. When a budget constraint is applied, the first order conditions are adjusted slightly to include the budget's shadow price, λ, to which the marginal benefit in each program must be equalized.

$$\frac{\partial V_0}{\partial \alpha_i} = \frac{\partial V_0}{\partial \alpha_j} = \lambda + 1 - \delta, \forall i, j, \tag{4}$$

$$\sum_i \alpha_i \leq B \tag{5}$$

In optimality, the usual complementary slackness condition holds. If the budget constraint is binding, $\lambda > 0$; when the constraint is slack, the optimal level of investment is less than B, and $\lambda = 0$.

Progress

To better understand the optimality conditions and the insights they provide into the formation of a technology strategy, a simple example is analyzed. Let n and T both equal 2, so that there is only one decision, the allocation of the budget between two research programs at the beginning of the time horizon. Suppose each program may succeed or fail, and the probability of success in program i is determined by a function $f_i(\alpha_i)$. Similarly, suppose there is a single exogenous parameter which may assume either a high level with probability μ

or a low level with probability $1-\mu$. Thus there are eight possible scenarios for the evolution of the economic system in the second period, or eight instances of s_2. The absolute value function V^2 is defined as follows:

Table I: Example Scenario Values

θ_2	ω, ψ	
	High	Low
Both Fail	$\mathcal{U}^h$	$\mathcal{U}^l$
Program 1 Succeeds	$\mathcal{U}^h + \mathcal{V}_1^h$	$\mathcal{U}^l + \mathcal{V}_1^l$
Program 2 Succeeds	$\mathcal{U}^h + \mathcal{V}_2^h$	$\mathcal{U}^l + \mathcal{V}_2^l$
Both Succeed	$\mathcal{U}^h + k^h(\mathcal{V}_1^h + \mathcal{V}_2^h)$	$\mathcal{U}^l + k^l(\mathcal{V}_1^l + \mathcal{V}_2^l)$

Here $\mathcal{U}^h$ and $\mathcal{U}^l$ represent the net welfare over both periods in the baseline case with no technological advance when the level of the exogenous parameter is high and low, respectively. $\mathcal{V}_i^h$ and $\mathcal{V}_i^l$ represent the *increase* in net welfare in the case of an advance in *only* technology i in the two exogenous states.[5] Finally, the scalars k^l and k^h represent the nature of the additivity of welfare gain when *both* programs succeed. When the $k > 1$, the technologies associated with the programs are complements; when $k < 1$, subsitutes.[6]

Subtracting the term $\mathrm{E}_{\omega.\psi}\mathcal{U} = \mu\mathcal{U}^h + (1-\mu)\mathcal{U}^l$ from each to normalize the value of the no advance case to zero, we evaluate the objective function in Equation 2 to obtain:

$$\begin{aligned} V \;=\; & f_1(\alpha_1) * (1 - f_2(\alpha_2)) * (\mu\mathcal{V}_1^h + (1-\mu)\mathcal{V}_1^l) + \\ & (1 - f_1(\alpha_1)) * f_2(\alpha_2) * (\mu\mathcal{V}_2^h + (1-\mu)\mathcal{V}_2^l) + \\ & f_1(\alpha_1) * f_2(\alpha_2) * (\mu k^h(\mathcal{V}_1^h + \mathcal{V}_2^h) + (1-\mu)k^l(\mathcal{V}_1^l + \mathcal{V}_2^l)) \end{aligned} \tag{6}$$

To solve the problem in this example, V is maximized subject to $\alpha_1 + \alpha_2 = B$. Note that no discount factor is required since all the value nodes occur in the same period. The objective may be reduced to an equivalent form:

$$V = f_1(\alpha_1)[\mathrm{E}_{\omega,\psi}\mathcal{V}_1 + f_2(\alpha_2)K] + f_2(\alpha_2)\mathrm{E}_{\omega,\psi}\mathcal{V}_2 \tag{7}$$

Where

$$K = \mu k^h(\mathcal{V}_1^h + \mathcal{V}_2^h) + (1-\mu)k^l(\mathcal{V}_1^l + \mathcal{V}_2^l) - (\mathrm{E}_{\omega,\psi}\mathcal{V}_1 + \mathrm{E}_{\omega,\psi}\mathcal{V}_2) \tag{8}$$

K quantifies the impact of the technologies' success on each other. If the technologies are complements, K is positive, and if they are substitutes, K is negative.[7] When the

[5]Technological advance is assumed to have a strictly positive welfare impact.

[6]While k^l and k^h are assumed to be either both greater than 1 or both less than 1, they need not, and likely will not in most cases, be identical.

[7]Enforcing a lower bound on k^l and k^h such that the value when both technologies succeed is at least as great as the value in either individual success scenario limits the substitution effect so that $K > -E\mathcal{V}_1$ and $K > -E\mathcal{V}_2$.

technologies are independent, K vanishes, and the objective function is separable in the decision variables. From the form in Equation 7, the first order condition in Equation 4 (accompanied by the budget constraint) is readily derived:

$$f_1'(\alpha_1)[\mathrm{E}_{\omega,\psi}\mathcal{V}_1 + f_2(\alpha_2)K] = f_2'(\alpha_2)[\mathrm{E}_{\omega,\psi}\mathcal{V}_2 + f_1(\alpha_1)K] \tag{9}$$

This differential equation describes the optimal choice of α_1 and α_2. For further insight into its meaning, let us suppose that the innovation production function f takes the following form:

$$f_i(\alpha_i) = \rho_i(1 - e^{\frac{-\alpha_i}{\beta}}), \text{ for some } \rho_i < 1 \tag{10}$$

This form satisfies the decreasing returns to scale assumption, and is a suitable probability mapping, since $f_i(0) = 0$, and the limit as α_i approaches infinity is $\rho_i < 1$. This parameter represents the best possible success rate achievable in the program, and β is a scaling parameter common to both programs. Note that this functional form assumes no exogenous probability of advance from learning effects. Substituting Equation 10 into Equation 9, the first order condition is reduced to:

$$\alpha_2 - \alpha_1 = \beta \ln\left(\frac{\rho_2\mathrm{E}\mathcal{V}_2 + \rho_1\rho_2 K}{\rho_1\mathrm{E}\mathcal{V}_1 + \rho_1\rho_2 K}\right) \tag{11}$$

Thus when the budget constraint is binding, the optimal solution is defined by a simple linear system. Moreover, the research programs may be rank-ordered according to the value $\rho_i\mathrm{E}\mathcal{V}_i$, and the first-ranked program receives a stricly larger share of the budget. In the case of a tie, the difference evaluates to zero, and an equal allocation is optimal. If the budget is less than the constant on the RHS of Equation 11, the first-ranked program receives the entire allocation. When the budget is greater than this amount, all investment up to the level of the constant is allocated to the first-ranked program, and the remainder is split evenly. When the budget constraint is not binding, the optimal level of investment is determined by setting the marginal benefit expression (either side of Equation 9) equal to $1 - \delta$.

The threshold constant, or difference between the investment in the two programs, also has an intuitive interpretation. When the expected values of the technology developments on their own in the best case (i.e. with probability ρ_i) are equal, the optimal values of α_1 and α_2 are also equal, regardless of K, the level of interaction. When one expected best case value is larger, that program receives more funding, but the difference in funding depends not only on the difference in expected value, but also on K. All else equal, the difference is decreasing in K when the technologies are complements and increasing in $-K$ when they are substitutes. These comparative statics suggest that the stronger is a complementarity effect, the more evenly investment should be allocated, but the stronger is a substitution effect, the technology that appears more favorable on its own receives an increasingly larger share of the investment.

When more than two programs are considered, the expression for marginal benefit (which is to be equalized across programs) will include a K term for each combination of successful programs. However, the insights from the two-program case, in terms of a rank-ordering and successive inclusion in the portfolio up to the budget constraint, will continue to apply. This example therefore primarily illustrates the effects on portfolio diversification of the decreasing returns to scale assumption. Also, the influence of heterogeneous applications is also demonstrated, to the extent that programs aimed at different applications will have values of K close to zero, avoiding the concentration caused by strong subsitution effects. However, the effects of risk and uncertainty are not apparent here, because these require multiple periods to manifest. When more than two periods are considered, the model in the example is applied in the penultimate period, and its optimal solutions become the value nodes for the preceding period. The results suggested by the optimality confition in Equation 11 will be complicated in this case by the ability to 'explore' in early periods. Finally, when research programs may result in more than two outcomes, the interaction space is expanded as when more programs are added. This extension may be handled similarly by including additional K terms, but in none of these cases is the model fundamentally altered.

Future Plans

In order to provide more concrete technology strategy recommendations, we intend to implement the methodology described here for the electric power generation sector. Carbon intensity reductions can be achieved in this sector by three broad classes of technological developments: (1) Renewable technologies, including wind, photovoltaic cells, solar thermal, biomass, and fuel cells using a non-fossil fuel source, such as biologically produced hydrogen;[8] (2) Carbon capture and sequestration, considered separately from other renewable technologies because of its interaction with conventional fossil generation; and (3) Efficiency improvements in fossil fuel generation. Because the value of a technology portfolio is linked to the diffusion of developments, the pre-existing characteristics of the market landscape are influential. Many of these characteristics are geographically differentiated, so we plan to consider the three technology classes of electric power generation in two distinct, but important, global regions: the United States and China. Several factors suggest that the most effective suite of mitigation technologies will be different for the two regions, and this will influence the allocation of R&D investment. Finally, a streamlined integrated assessment model is being developed to evaluate the developments described here. Key features of the model are rapid computation, since the dimensionality of the dynamic programming approach requires a very large number of model runs, and capital vintage accounting, because of the current system's inertia with respect to diffusion.

Publications

1. Blanford, G.J. and J.P. Weyant, A Global Portfolio Strategy for Climate Change Technology Development, Proceedings of the 28th Annual Conference of the International Association of Energy Economics, Taipei, Taiwan, June 2005.
2. A similar paper will be presented at the International Energy Workshop in Kyoto, Japan in July 2005.

[8]Other zero carbon generation technologies have been omitted. The extent of hydroelectric and geothermal generation is assumed to be constrained by physical resource availability and therefore relatively unresponsive to technological improvements. Similarly, the use of nuclear generation is more sensitive to political constraints than to the state of technology.

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