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Conceptual Design of an Integrated Technology Model for Carbon Policy Assessment

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Conceptual Design of an Integrated Technology Model for Carbon Policy Assessment

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Abstract

This report describes the conceptual design of a technology choice model for understanding strategies to reduce carbon intensity in the electricity sector. The report considers the major modeling issues affecting technology policy assessment and defines an implementable model construct. Further, the report delineates the basis causal structure of such a model and attempts to establish the technical/algorithmic viability of pursuing model development along with the associated analyses.

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Section 1: Overview

This report describes the conceptual design of a technology choice model for understanding strategies to reduce carbon intensity in the electricity sector. The methodology and approach are readily extendable to industrial, commercial residential and transportation technology choices. This effort focuses on the electric generation sector because this sector most clearly contains the dynamics that potentially confound the assessment of low-carbon technology policy.

Several issues motivate this work. The transition to low-carbon energy supplies is a dynamic process. Human behavior, market competition, and feedback within the economy can produce a dramatic divergence between the desired, optimal path into the future and the actual evolution of the path.

Since the 1973 OPEC crisis, economic analyses indicated there would be a rapid change toward greater energy efficiency and renewable energy. But the market response has been slow, minimal, and fraught with reversals (Jaffe 1994). With concerns of both peak-oil and climate change (Farrell 2006, Hirsh 2005), the energy transition process has again become a focus of energy policy. Idealized assumptions about markets and human behavior are at odds with actual responses (Sutherland 1991, Kahneman 2003, Palmer 2010). The feedback delays among energy investments, material suppliers, and operating production, could produce bottlenecks that prevent the realization of any preconceived technology portfolio and lead to a conflicting technology mix with elongated timing and market overshoot (Kenny 2010, Kramer 2009). The investments of the transition will transiently and dramatically increase carbon usage while stressing international supply-chains and possibly stressing the rest of the U.S. economy (Chandler 2009, Hall 2008, Kenny 2010). The interaction among decision makers, support industries, and the rest of the economy produce countervailing dynamics neglected in many current analyses (Jacobson 2010, Kypreos 2007, Anadarajah 2010, Enkvist 2007). Further, policy options affect how various technologies will compete in the marketplace. Studies addressing specific (e.g. wind) or even families (e.g. renewable energy) technologies in isolation cannot capture the interactions that may produce results considerably different from those of a ceteris paribus approach. As will be noted in the ensuing sections of the report, this modeling effort focuses on determining the impact of those issues noted above.

The modeling approach of the work treats the “cost of carbon” as a “control signal” to the market rather than as an optimized value that minimizes social impacts. The social cost of carbon is based on achieving a desired future with minimized cost using presumably understood and directly controllable technology options (Ackerman 2010, DOE 2010a). With idealized market assumptions, both “cap & trade” and carbon taxes produce the desired results -- with “cap & and trade” providing more options to accommodate perceived policy (political) constraints. However, many researchers now recognize the ability to distort carbon markets in a cap & trade” regime, with the resulting volatility paralyzing investment decisions (Green 2007, Nordhaus 2009, Reuven 2009, Economist 2009).

Carbon taxes produce stable price signals for long-term investments, whereas carbon markets cause volatility emphasizing short-term decisions. Carbon taxes can have a largely neutral affect on the economy depending on the method of recycling revenue (for example, by reducing income and labor taxes – Barker 1995,1996). More importantly, the level of a carbon tax changes the relative cost of using a (low-carbon) technology compared to conventional fossil-fuel based technologies. Additionally, the level of tax provides the incentive to reduce the carbon footprint of energy production and energy usage. In essence it can play the same role in the technology markets as the federal discount (interest) rate plays in the financial markets. Its value lies in its capability of controlling and ensuring the achievement of a low-carbon goal (despite uncertainty and changing conditions) rather than as a social marker of what the idealized cost to reach a carbon goal *should* be. Thus, the logic of our model explicitly uses a carbon tax and attempts to capture all the consequences it has for technology decisions and technology implementation.

The model design described in the subsequent sections is relatively uncomplicated for a system dynamics model and it only aspires to a national level detail with an adequate portrayal of and number of technologies to address the primary considerations affecting technology policy decisions. The model includes a feedback representation of interacting demand, economy, capacity expansion, and capacity use/retirement dynamics. While it does contain some distinct levels (state variables) to capture capital-turnover, most phenomena with filtering or delay attributes are represented as simple exponential-delay functions. The model uses generic Qualitative Choice Theory (QCT - McFadden 1974,1982,1986) algorithms for technology choices, which often incorporate simple exponential-forecasting among modeled decision-makers. As an accounting simplification, the model generates instantaneous realizations of secondary carbon-emission effects of investment decisions via I/O tables (that capture the chain of causality across the U.S. and Rest-of-World economies). The model does include secondary industry constraints, economies of scale, and learning curve dynamics. It has an elementary financial structure to capture investment and price dynamics (including changes in the cost of capital). An unpretentious demand and economic sector uses elasticities and delays representing consumer decisions and capital turnover, respectively. Energy price is endogenous to the model – assuming regulated ratemaking rules for electricity and depletion-driven effects for fossil fuels. The primary control lever is the carbon tax, but other policy variables such as R&D are testable via sensitivity-analysis scenarios.

While the proposed model simulates the impacts of carbon and technology policy on the technology investments and energy costs, the actual determination of appropriate policy (under the uncertainty of assumptions and parameters) would use the SNL DAKOTA optimization application (Eldridge 2006, Adams 2009) as a shell to the model described here.

Appendix B contains a much longer list of issues that a realistic model could consider, but the description above represents the current thinking on those issues most critical to evaluating technology policy.

Section 2: Establishing a Model Design

The sections below consider each of the basic sectoral components within the proposed modeling framework. Before providing an overview of the model, a few underlying concepts need elucidation. A single structure needs to consider multiple technologies, affecting multiple economic and environmental pathways. The impacts may be local to the U.S. but may also spill-over to the Rest-of-the-World (ROW), e.g., the impact of biofuels subsidies on world food prices. Conversely, ROW supply chain constraints and material constraints, such as on rare-earth minerals, can cause significant changes in technology costs and, thereby, dramatically affect the U.S. market dynamics of technology implementation. As such, essentially all variables in the model represent arrays, with many connecting-variables being sums across the arrays. For example, investment is by technology and load, but the impact on interest rates is a function of the total investment. Still, many values are just averages, such as the price of electricity as a composite cost over all technology costs.

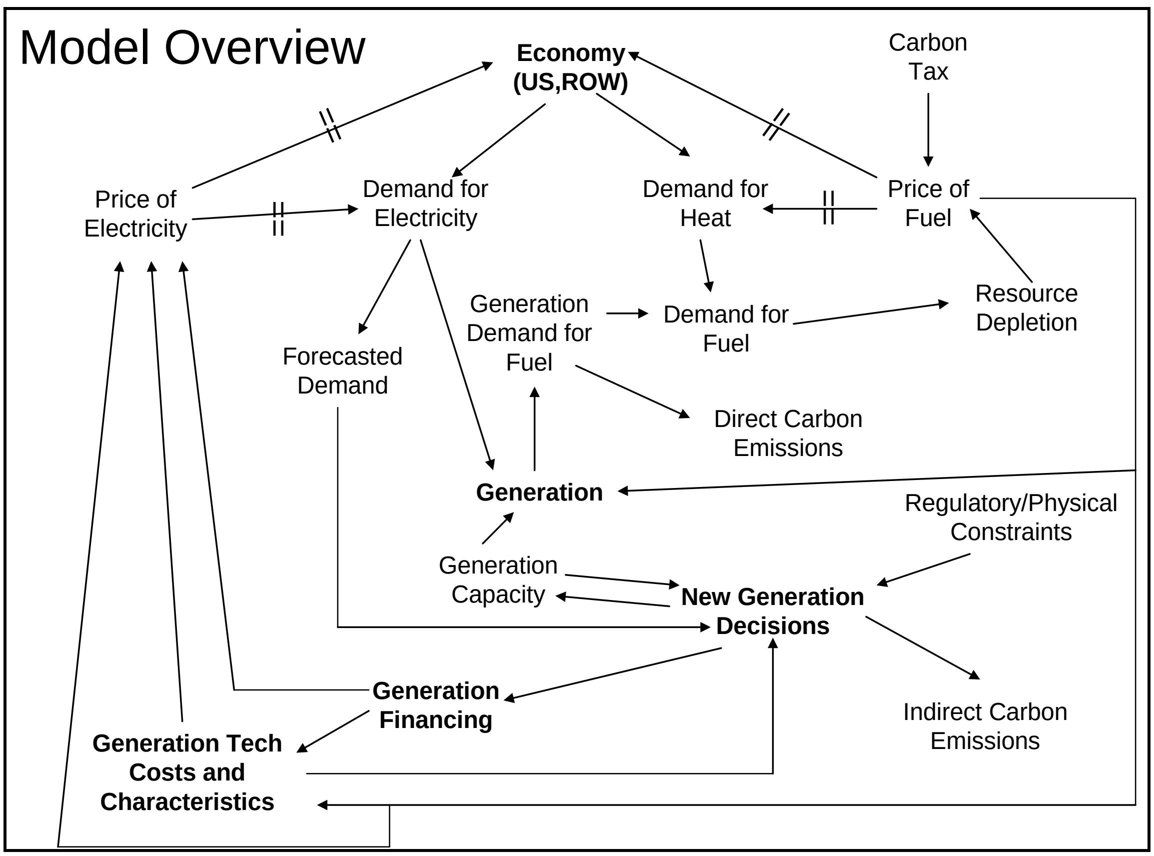

Figure 1: Model Overview. Bold components are expanded in following sections.

Figure 1 above shows the overview of the model. Energy demand drives the need for energy supply. The economy determines the need for energy. Energy prices affect the consumer decisions for process and device energy efficiency. The efficiency (energy intensity per unit of economic output), in combination with the level of economic activity, determines the total demand for energy -- here separated into demands for fuel and electricity. With this model definition, fuel use includes combined, aggregate process heat and transportation service demands for the economy -- which are influenced by the price of oil, coal and natural gas. Electricity includes electromotive and lighting (and some heating) demands and uses many varied sources for generation.

The double bars in the diagram above represent delays. In causal modeling, as practiced within the system dynamics (Sterman 2000) and econometric cointegration (Engle 1987,1971, Granger 1981, Hendry 1993,2000,2001) paradigms, there can be no simultaneity among the feedback interactions of a system. The delays include state-variables (integrations) that mathematically (and causally) depict the lag between the instantiation of information and the acting upon that information.

The model emphases the electricity side of the energy system, but because electricity and the economy use other fuels, the model must include a basic representation of fossil fuel price dynamics. Although the model will capture short-term dynamics caused within the electric industry, endogenously capturing short-term dynamics for other fuels (i.e. global oil markets) is well outside the scope of the current effort (other than through exogenous sensitivity analysis). Nonetheless, the long-term aspects of resource depletion and technological advance do affect electricity decisions and, therefore, warrant inclusion in the model.

Because of the construction delays within the electric industry (and the secondary impact of pricing on investment due to regulatory requirements), the utility must plan capacity expansion based on a necessarily imperfect forecast of future demands (Sterman 1988). The new generation choice is based on the understanding of technology characterization, particularly risk and costs. The choices become investments; the investments ultimately become added generation capacity to serve load. For many technologies, the act of generation involves the use of fossil fuels that then directly produce carbon emissions.

The new facilities also have many indirect effects on emissions. The production, refining, and shipping of fossil fuels themselves produce emissions. As another example, biomass generation can lead to the exploitation of marginal land and increased energy-intensive fertilizer use. Additionally, construction requires the use of steel and concrete, whose manufacture is energy-intensive. Labor used for construction also demand fuels, and most components at the construction-site require shipment over long distances. As noted in Section 1, it is likely that the more rapid the transition to low-carbon energy technology, the larger the transient increase in GHG emissions and energy use to from construction and from the industries supporting the construction (Kenny 2010). Faced with goal of reducing emissions by 80% over today's levels, and given the continuing delay in climate legislation, the pressures for and complication of an extreme and rapid transition could be large (Galiana 2009). Section 5 presents a detailed view of the generation component which includes a construction component.

Building new generation requires new investment funding that must be recouped as fixed costs over the life of the facility. The cost of the investments per kilowatt is dependent on the technology chosen. The variable fuel costs, if any, depend on the heat-rate and technology choice, as well as possible carbon costs. The sum of the variable and fixed costs over all generation determines the electricity price in a regulated environment.

The following sections contain detailed diagrams of the components depicted in Figure 1. Except for dispatch and market-share procedures, each item in the diagrams represents a single equation and all items together represent all the major equations of the model except for minor auxiliary equations and the defining of parameters.

Section 3: The Economy and Demand Component

Figure 2 details the economy and demand components of the model. For illustrative purposes, a complete example set of equations corresponding to Figure 2 appears in Appendix 1.

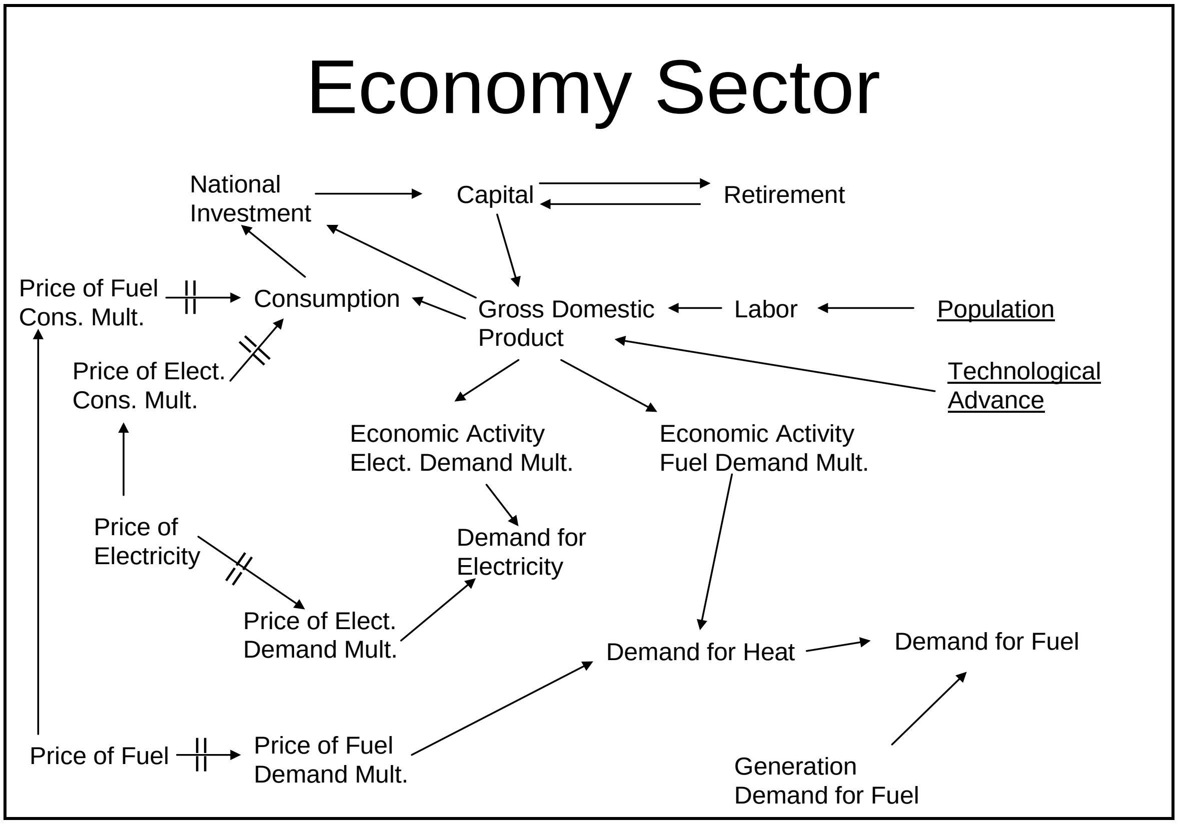

Figure 2. Economy and Demand Diagram

For the purposes of the proposed analysis, the model contains an economy represented as a simple one-sector production function. The current design assumes a Cobb-Douglas (CD) function, but a Constant Elasticity of Substitution (CES) or some other approach is also possible. The CD output, as the Gross Domestic Product (GDP), is only a function of capital, labor, and technological advance. Labor is a constant fraction of the population unless exogenously modified for sensitivity testing. Technological advance in the overall economy is an exogenously specified exponential function of time.

Capital is tautologically defined as the integral of investments and retirements (all endogenous to the model). In this initial conceptualization, investment is the residual of consumption (i.e., savings). As was the approach in early DOE NEMS (NEMS 2009) modeling work, the price of energy primarily has its effect on the economy by changing consumption directly. As a one-sector economy, consumption includes that of the government, industry, and citizenry.

In its default configuration, the model emphasizes domestic funding rather than international funding for two reasons: 1) to endogenously capture any investment edge-out effects within the domestic economic and the impact on interest rates; 2) the (un-modeled) international financial markets will possibly be enduring even larger stresses for ROW investment needs to make the energy transition and should not be assumed to be anymore available than domestic funds. For sensitivity and testing purposes, the model readily allows implicit access to international markets by specifying the fraction of required financing that could come from international sources.

Relative to GDP impacts, imports and exports are implicitly held proportionally constant in this formulation. However, the model does calculate the increased need for imported materials in response to domestic energy-supply pressures caused by the transition.

As noted above, the price of energy and the level of economic activity affect the demand for energy. While there is some need for self consistency between the effect of energy on total economic consumption and on energy demand, the shifting of consumption patterns, warrants the separation of phenomena as shown in Figure 2.

At the economy level, the model simulates energy demand responses using simple price and income elasticities, because the focus is on the technology choice process – wherein the full qualitative choice detail is relevant. Other modeling efforts have considered the detained assessment of industrial, commercial, residential, and transportation responses to climate policy using QCT (ICF 2008, AQB 2010)

Several previous studies have considered the impact of energy and climate change on economic conditions (Nabors 2002, Backus 2010).

Section 4: The Electricity Generation Finance Component

New technologies must compete in the marketplace as new generation capacity. Financial constraints and accounting rules determine the impact of new electricity generation on the price of electricity. Figure 3 shows the logic of the Electric Finance component of the model.

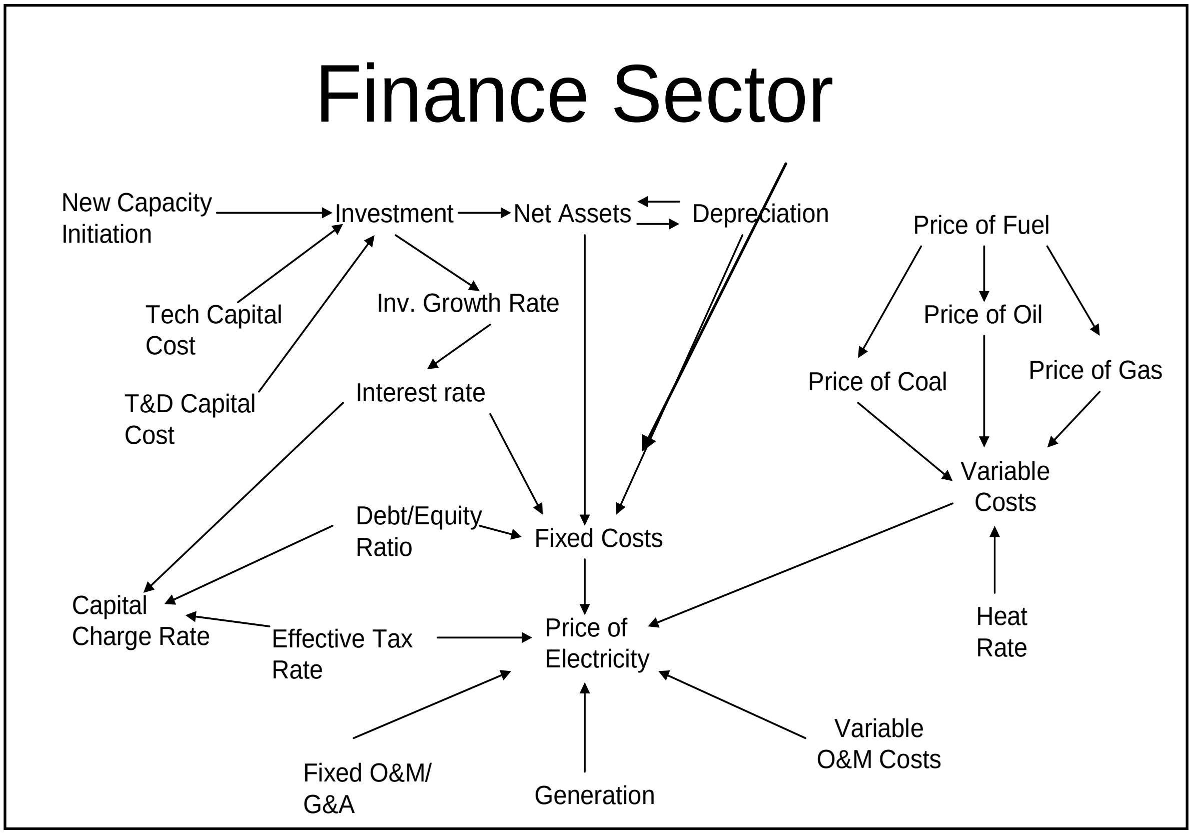

Figure 3. Electricity Generation Finance Diagram

New generation requires not only the financing of the generation construction, but also the Transmission and Distribution (T&D) costs for using the new generation. These costs and the amount of new capacity, by technology, determine the new investments. As a simplification in this modeling framework, the new investments immediately become new financial assets. There are many assets in an electric utility's accounts. All are subsumed in the "Net Assets" account explicitly used here. In essence, investments increase Net Assets and depreciation decreases it. The Net Assets reflect the amount of debt and equity financing within the asset portfolio. (The modeled debt to equity ratio is a constant, as is the difference between the regulated return on equity and the interest rate on debt.)

Depreciation, with the effective tax rate (the marginal tax rate corrected for accelerated depreciation methods), along with interest payments and allowed returns on equity, determines the total amount of fixed cost that the generation must cover.

The Capital Charge Rate (see Appendix D) is the annualization factor used to determine the expected cost of the new technologies per unit of generation (Kwh) as shown in Figure 6. It has all the same components as the fixed cost, except it is an accounting estimate of the long-term average conditions, rather than a refection of actual financial conditions.

Variable costs are those associated with each Kwh of generation, primarily fuel costs with some variable Operating and Maintenance costs. The model uses a single measure of fuel price (tied to changing oil resources) and derives, via a proportionality constant, the delivered market price of oil, gas, and coal to the utility sector – as based on parameterization using actual historical data. Operationally, carbon taxes would appear as an addition variable cost. For construction, carbon taxes would increase the costs of equipment.

The heat rate determines how much fuel is used per Kwh generated. Because the heat rate is different for new plants versus old plants, the model needs to separate old from new investments (by artificially using a different technology class designations) to make marginal and average heat rate adequately consistent.

Each plant also has fixed cost (operating and maintenance—O&M) expenses, and the utility itself has general and administrative (G&A) expenses that are also part of the electricity price.

A unique aspect of this component is the internal determination of interest rates. Because of the capital-intensity of modern generation technologies, their competitiveness is very sensitive to the interest rates (and, consequently, inflation). If (exogenous) mitigation scenarios cause dramatic increase in the demand for investments funds (not shown), or the investment in new electric generation dramatically exceeds historical growth rates, the model can convert the added funding pressure into increased interest rates. The data for this process are limited, but the feedback dynamic is too important to neglect. If policy too strongly promotes investment in capital-intensive technologies, the increase in interest rates may edge out other technologies as well as conventional investments in the broader economy that affect GDP growth.

Except for the impact of rapid investment growth on interest rates, the equations of this component are all uncomplicated and tautological.

Section 5: Electricity Generation Component

Figure 4 displays the generation component of the model. This component focuses on the generation capacity and the actual generation of electricity from it.

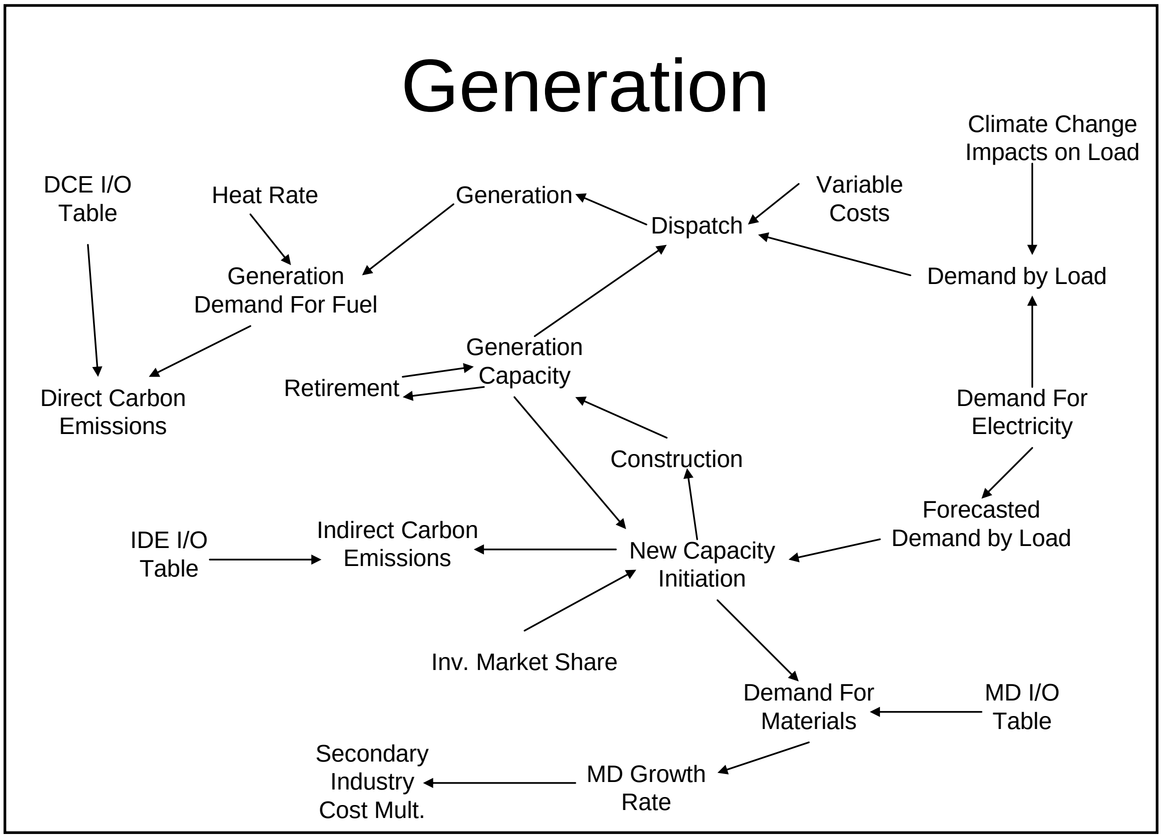

Figure 4: Generation Component Diagram

The demand for electricity is not a constant over each day, week, or season. In utility parlance, the demand represents a "load" whose value changes over time. Some load (demand) is present constantly and is called the minimum or base load. Some load (such as air conditioning) only occurs for a few hours a day and, on the hottest days, leads to the need for utilizing nearly all the available capacity. The maximum demand for energy is the peak load.

A load duration curve portrays the load over the number of hours for which it exists, for example, the base load exists for 8760 hours per year. Figure 5 depicts an illustrative representation of a load duration curve that only contains historically conventional generation. Hydro generation has the lowest variable costs (in the example of Figure 5) and runs to match base load. Nuclear power, being the next least-expensive to operate, serves the next increments of base load. Coal has some load-following capability and has higher variable costs than nuclear plants, so it fills in the middle portion of the curve. Oil and gas generation is expensive, but gas turbines can quickly respond to changes in demand to serve the peak load.

Thus, technologies need to be designated by their load-following capability (base, intermediate, and peak) and demand needs to be converted to a load duration representation.

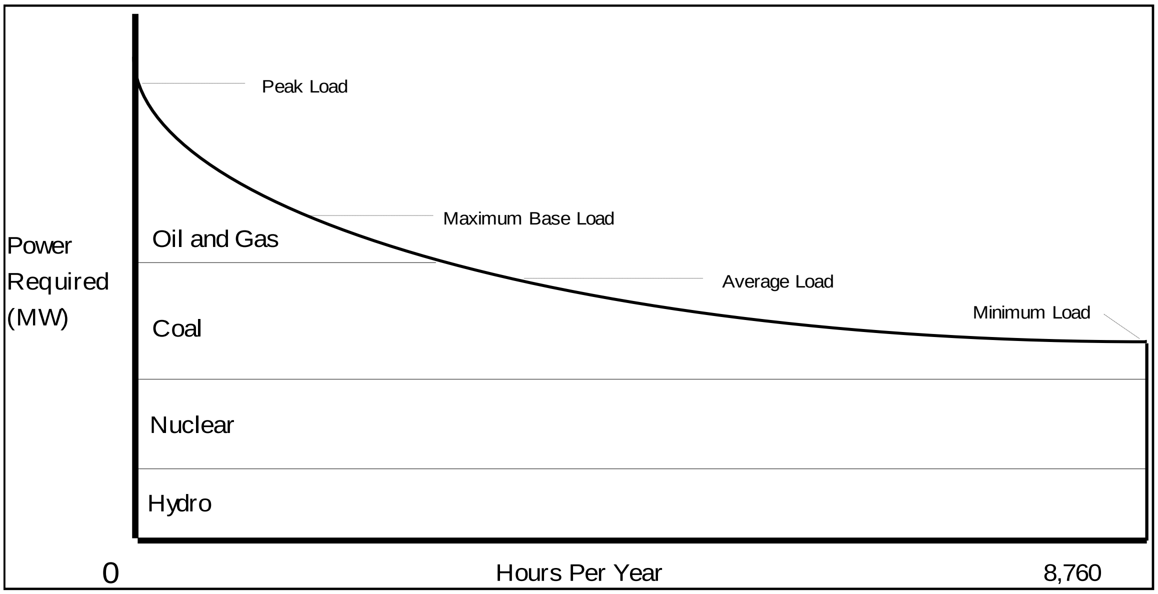

Figure 5: Illustrative Load Duration Curve

The variable costs determine the dispatch. If the generation is energy limited or stochastic, the calculations become more complicated. Nonetheless, several variants of the dispatch algorithms used in other models (Ford 1983, Backus 1995) would work in this model.

Note that climate change can make the load curve even sharper at the top by increasing the peak needs for cooling (or heat, due to extreme weather). Increased peak power with possibly reduced base loads, would require added capacity that would be seldom utilized. In such situations, the technology serving the peak must have low capital costs.

For most technologies, generation uses fuel. The burning of the fuel currently causes the release of GHG emissions. Engineering (such as sequestering) can reduce the emissions at the cost of increased heat-rates. Input-output (I/O) tables would capture these considerations. Such indirect emission (IDE) tables are readily obtainable from Life-Cycle Assessment (LCA) studies on generation technologies (Kenny 2010, White & Kulcinski 1998).

As noted in the section 2, the forecasted demand determines the need for new capacity initiation. After the construction delay, the new capacity becomes part of the overall generation capacity, to be used for generation, but eventually retired. New capacity initiation must consider upcoming retirements. The technologies selected for new capacity depend on their market share (discussed in the next section).

New capacity construction demands many materials. If the demand for specific materials grows too quickly, industry can not easily serve the demand and prices rise. The demand for materials is captured with a separate (MD) I/O table. MD I/O information is also available in LCA (Kenny 2010, White & Kulcinski 1998, 2000) and through the use of economic I/O tables (DOC 2010). The impact of increasing materials demand on price is modeled as a secondary market process. The changes in cost then affect the selection the technology in the next time period. The interaction of the secondary industry cost multiplier and its effect on capital costs is shown in Figure 6.

As also discussed earlier, the construction process and the use of the new facility can have consequences in other parts of the world economy that can lead to increased (or decreased) emissions.

As noted previously, the choice of new technology is based on detail QCT assessment (Ben-Akiva 1985, also see Appendix C). QCT allows the explicit and consistent simulation of competition among all the technology options as a function of not only costs, but also perceptions and policy actions.

Section 6: Electricity Technology Characterization and Choice

The last component evaluates the technical and economic characterization of electricity generation technologies, along with determining the market share each technology should garner for new investments. Figure 6 shows the logic of this component.

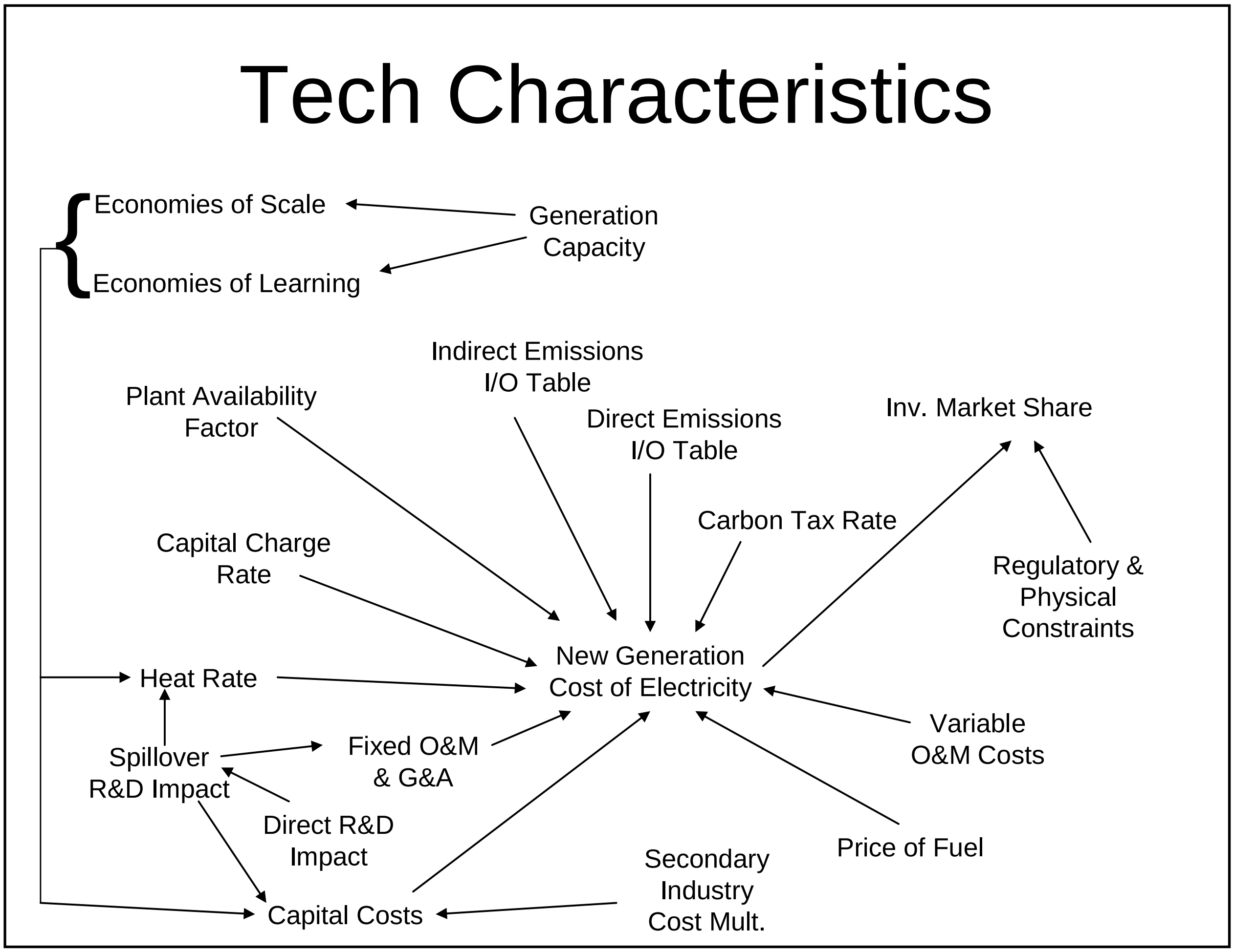

Figure 6: Technology Characterization and Choice Diagram

Goal-oriented R&D efforts can reduce the cost or improve the efficiency (heat rate) of new technologies. Improvement in, for example, biomass-generation ash-handling also benefits coal and municipal waste technologies. These spill-over effects can significantly alter the outcome of R&D away from the intended consequence for a new technology.

Additionally, early technologies are often conservatively specified or contain limitations not obvious until after adequate operations uncover the problem and the solution. As experience grows, costs and reliability improve. These phenomena are collectively called economics of learning or simply “the learning curve’ (NRC 2010).

Moreover, technologies depend on specially manufactured items requiring large front-end capital investments. As the demand for the technology grows, the fixed costs of development or fabrication are spread across a large number of deliveries. The large market allows for larger, more cost effective, facilities for manufacture that can also reduce costs. This phenomenon is called “economies of scale.” Several existing models document algorithms and data to simulate these three impacts on costs and efficiency noted above (EIA 2009, AQB 2010)

If the demand for the materials that form the facility are in short supply (due possibly to excess demand), then the capital costs can increase. This cost increase is captured in the secondary industry cost multiplier that is also a component of Figure 4. The price of fuel, the efficiency, and O&M costs affect the total expected costs of producing energy from a technology. The estimated impact of capital costs on the expected cost of pricing energy depends on the capital charge rates discussed earlier. The capital charge rate is very sensitive to interest rates (and perceived financial risk). For full capital recovery, the capital (investment) costs must be spread over the expected generation over the life of the plant. (See Appendix D for an overview of the capital charge rate.) If the technology can only serve peak load or can not tolerate many grid distortions, then its availability is low, which proportionally increases the capital cost component of the energy delivered from that technology. Lastly, under a carbon-policy regime, the direct and, in principle, the indirect emissions of GHGs add to the cost of producing energy with the technology.

Regulatory constraints (such as siting limitations) and physical constraints (such as changing water availability and wind intensity over the life of the facility due to climate change) will further modify the final choice of technologies to serve new load. With an estimate of the cost for producing energy with each specific technology, the utility (industry) can determine the portfolio of technologies to include in its investments with for that year. This sector establishes the market response to change regulatory and technology policy. The impacts of these “rule of the game” changes on market behaviors can be quite complex but the methods to simulate them have been developed in other studies. (Nabors 2002, Backus 2005,)

Data on technology costs and characteristics are available form many sources (ICF 2008, AQB 2010, EIA 2009).

Section 7: Analysis and Model Results

The model described above could determine the (time dependent) portfolio of technologies that best balances carbon emission goals with economic impacts. The choice of R&D priorities and direct carbon policy (e.g. carbon taxes) must reflect the control process to meet the desired ends and not idealized assessments of optimal prices. Uncertainty in costs, technology characterization, fossil resource availability, economic/consumer responses, climate itself, and many other phenomena affect the robustness of the policy choice. The model can define that sensitivity to determine robust policy – or it can simply establish a basis for risk-informed decision-making.

The equations needed to develop the model are publicly available within the documentation of other existing energy models. The data to parameterize the model appears to be equally available except for data assimilation efforts associated with indirect emissions.

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Appendix A: Example of Sector Equations (Economy Sector)

All α, β, λ, and "k" variables are date derived constants, as are response times (time constants). A subscripted "0" is an initial value. All other variables are defined in other sectors.

Gross National Product ($/Yr)
$GDP=GDP_0*A*(Capital/Capital_0)^\alpha * (Labor/Labor_0)^\beta$
Technological Advance ($/$)
$A=A_0*\exp(\lambda*time)$
Labor (Population is exogenous - Persons)
Labor=k0*Population
National Productive Capital ($)
Capital=Integral(Nat_Investment-Retirement)
Capital Retirement ($/Yr)
Retirement=Capital/Capital_Lifetime
National Investment ($/Yr)
Nat._Investment=GDP-Consumption
National Consumption ($/Yr)
Consumption=k1*GDP*PFCM*PECM

Indicated Price-of-Fuel Consumption Multiplier ($/$)
$IPFCM=(PF/PF_0)^{k2}$
Price-of-Fuel Consumption Multiplier ($/$)
PFCM=Integral)(IPFCM-PFCM)/Price_Response_Time)
Indicated Price-of-Electricity Consumption Multiplier ($/$)
$IPECM=(PE/PE_0)^{k3}$
Price-of-Electricity Consumption Multiplier ($/$)
PECM=Integral((IPECM-PECM)/Price_Response_Time)

Indicated Price-of-Fuel Demand Multiplier (BTU/BTU)
$IPFDM=(PF/PF_0)^{k4}$
Price-of-Fuel Demand Multiplier (BTU/BTU)
PFDM=Integral((PFDM-IPFDM)/Price_Response_Time)
Indicated Price-of-Electricity Demand Multiplier (BTU/BTU)
$IPEDM=(PE/PE_0)^{k5}$
Price-of-Electricity Demand Multiplier (BTU/BTU)
PEDM=Integral((IPEDM-PEDM)/ Price_Response_Time)
Economic Activity Fuel-Demand Multiplier ((BTU/BTU)/($/$))
$EAFDM=(GDP/GDP_0)^{k6}$
Economic Activity Electricity-Demand Multiplier ((BTU/BTU)/($/$))
$EAEDM=(GDP/GDP_0)^{k7}$
Demand for Electricity (BTU/Yr)
DE=DE0*PEDM*EAEDM

Demand for Fuel (BTU/Yr)
DH=DH0*PFDM*EAFDM
Demand for Fuel (BTU/Yr)
DF=DH+Generation_Demand_for_Fuel

Appendix B: Model Considerations

These notes describe issues the model could include. The conventional use of Marginal Avoidance Cost (MAC) curves for carbon only include direct carbon emissions under an assumption of a marginal investment within a static environment (i.e., ceteris paribus). This view is very limited and may misguide both policy and R&D priorities (NRC 2010). Below are several of the more obvious and some of the more controversial "corrections" a model design might consider. The first section of the main text of this report extracts a small subset the issues having the greatest potential impact on analysis conclusions and act as the basis for the initial model design.

Because this effort combines economics with engineering, it needs to establish the approach that most self-consistently presents an advance over current practice. The discussion below assumes the one-dimensional approach of the McKinsey study (Enkvist 2007) and notes issues or extensions in the context of that foundation. The McKinsey-type effort is a bottom up, technology-by-technology approach. A parallel top-down approach uses econometric-type efforts where technology choice and characterization is treated largely as a fluid, continuous, aggregate process (e.g. MIT's EPPA work, Paltsev 2005). For discussion purposes, the effort here is assumed to contain an underlying technology-by-technology approach. However, because that analysis may need to assume the technology evolves, the concept of a "technology-family" is probably more valid characterization of specific technologies. This quasi-specific, quasi-aggregated technology classification of economic processes would require econometric formulations be part of the model construct.

The information below is meant to simply introduce the concept – with its further implications left to later discussions. In most instances, the concepts below emphasize the importance of portraying technologies as existing in an integrated market rather than in isolation to one another. It is these interactions among technologies that define their potential success. In this context, the current practice of ordering technologies by direct cost and carbon intensity are misguiding and useless for policy assessment. Below is a brief discussion of several considerations neglected in current MAC efforts.

1. Indirect and Embodied Carbon

Forty to sixty percent of the capital cost for synthetic fuels, nuclear power, and wind-power, for example, is energy. Much of this "cost" is tied up in the use of concrete and steel. When the price of energy increases, the required price for these technologies to become competitive rises. Minimally, changing energy prices shifts the allocation of choices across technologies. A Leontief approach to the economics can capture these impacts in a static sense. The use of substitution elasticities (Manne 2004) or Induced-Technological Improvement (Ruttan 2002) can capture components of this change in a dynamic sense. For any modeling effort, it appears that most of the technology-specific embodied-energy data are now lost or obsolete. Thus, there is the need to use (existing) aggregated sectoral data to approximate and capture this phenomenon.

1.1 Energy payback times

Having embodied energy means that as the penetration of a technology in the market place grows, there is a real growth limit whereby the secondary energy demands for construction (or possibly for the fuel cycle in the case nuclear power) overwhelm the energy savings that the *operation* of the technology was supposed to provide (Kenny 2010). A dynamic simulation would capture these phenomena.

1.2 Indirect CO2 changes

Equally important are the systems-wide impacts of carbon-use during construction and in the use of the technology for converting one energy form to that variety needed by the marketplace. The previous item 1.1 implied a whole range of secondary phenomena that generated carbon emissions during construction. A common example on the production side is the hydrogen fuel-cell that produces only water as a direct emission – while the energy to produce the hydrogen could have come from coal-generated electricity. A centralized hydrogen infrastructure would entail the massive energy-intensive construction of pipelines. As another example, uranium mining, processing and enrichment also include energy-intensive processes that generate immense amounts of carbon, despite the "zero" GHG emissions for a nuclear power plant. For the purposes of the modeling proposed here, the absence of this accounting is a fatal flaw in the current (static, ceteris paribus) MAC analyses. A modified I/O table can capture this accounting (White & Kulcinski 1998,2000, Kenny 2010, Norris 20078, Rebitzer 2004, Pennington 2004).

1.3 Land-use CO2 change

Whether based on food products or not, the use of biomass drives food production to more marginal land thereby requiring more energy-intensive factor-inputs, such as fertilizer. Additionally, it can cause land substitutions as in the case of the deforestation of the Amazon Basin. Further, wind-turbine farms can disrupt local wind patterns. These can reduce the land productivity downwind – leading to the replacement of agriculture by urbanization, thereby causing reduced land absorption of carbon, increased energy usage, and disruption of larger hydrological cycles. The rapid growth in the use of biomass fuels for electrical generation will clearly cause a net increase in atmospheric carbon levels until decades after the growth in technology deployment ceases – when new sylviculture can mature/expand to where it more than matches the existing carbon flow into the atmosphere from its burning and harvesting. In the same vein as the bio-fuel discussion above, the change in land use would affect food and demographics with a net impact toward greater energy intensity. The CCSM model's biome and land-use components have data useable for these assessments (Blackmon 2001, Dickinson 2006).

1.4 LCA and full system impacts over time

The previous points indicate a need for a full life-cycle analysis (LCA) that recognizes the dynamic feedback interactions with (possibly global) socio-economic and geo-physical systems. Many organizations (Norris 20078, Rebitzer 2004, Pennington 2004) has data and techniques (as used with the US EPA - Beaver 2000) for these evaluations.

2. Secondary industry (growth multiplier) cost dynamics
As groups of new technologies enter the market place, they impose short-term constraints on the capacity for support industries. These capacity or resource constraints can dramatically increase construction (or operating) costs, often by a factor of three or more. Such situations can delay or invert investment decisions across technologies, while also convoluting energy price dynamics. The old FOSSIL2 (Naill 1992) and SRI-Gulf (Nesbitt 1984) models have these algorithms.

3. R&D spillover
Efforts to improve the cost or efficiency of one technology to make it competitive can often improve the same characteristics for competitors (e.g. better ash removal and heat exchangers help both biomass and coal generation plants). Further, if a new technology threatens an incumbent technology, the suppliers of the incumbent technology act to make the "old" technology better or to encumber the new technology (e.g., the Wankel engine lost out to improved internal-combustion engine improvements; and municipal-waste power-plant ash was deemed hazardous waste). Cambridge Econometrics Ltd (UK) has methods for modeling this (unconventional) type of spillover (Barker 2010).

4. Unintended Consequences of Rapid Deployment
The rapid deployment of corn-ethanol caused global food impacts; the rapid deployment of nuclear power or wind would dramatically affect grid stability. Electric or hydrogen vehicles would dramatically affect electrical infrastructure and possibly urban infrastructure. The dynamics of a technology deployment can create cascading constraints that effectively prevent the future it was supposed to create. The SNL NISAC group (http://www.sandia.gov/mission/homeland/programs/critical/nisac.html) would have some experience useful to this analysis.

5. Strategic materials and elemental extinction.
Fuel cells currently require rare-earth catalysts whose global abundance is far below that needed for the technology to have game-changing impacts. The demand for alloy elements needed in high performance steels (or for long-term nuclear-waste storage) exceed the conceivable supply and marks are dominated by overseas suppliers (DOE 2010b).

6. Need to consider impact of other economic usage on need for particular products
As the model structure decides the selection of new technologies (assumed for electrical generation in this modeling effort), it may result in the demand for a significantly increased use of oil and coal for the supply of construction materials. This may generate higher energy prices, greater pollution, land-use, and water-use caused dislocations, and natural gas shortages. With climate change, water will become a (dynamically) diminishing commodity, and thus represent a severe constraint for new generation capacity. The shifting water situation may also dramatically shift load centers and thus affect the applicability of new technologies. There can clearly be situations where the early choice of one technology preempts the choices for later technologies. This new area could be captured using a variant on the secondary industry logic above by incorporating hard resource constraints rather than just transient capacity constraints.

7. Supply versus demand components of the carbon balance

Historically, the number one error in planning and technological forecasting has been the neglect of supply and demand feedback interactions (Nelson 1985, Ford 1997, 1982). The excess development of supply can suppress prices and stimulate demand. The delayed development of supply can increase prices, reduce demand, and recast the further need for supply. Energy is not a good onto itself. Energy is a derived demand contingent on the service demand, such as for heat or light. Demand needs to be part of a supply model and markets (prices) need to drive supply. (A Economist article reinforces the view that subsidies are counterproductive in the dynamic market sense - Economist 2009). The ENERGY2020 model has all algorithms needed for the demand side and combining it to the supply side to establish (disequilibrium) price dynamics (ICF 2008, AQB 2010, Backus & Amlin 2005).

7.1 Process versus device efficiency

Devices convert primary energy to a secondary energy service, and they are limited by Carnot efficiencies. In a static (no economic growth, no population growth) world, carbon emissions need to drop by 80% or more just to bring emissions and natural absorption into balance. Process efficiencies define the $ of output per unit of energy (or carbon in this context of the proposed work). Zoning laws to have commercial, industrial, and residential activities all in one building (as is common in Sao Paulo) reduce heating, lighting, and transportation energy usage by orders of magnitude. Telecommuting is another obvious example of a non-Carnot-limited process efficiency improvement. Decentralized versus centralized manufacturing (consistent with economies of scale) reduces energy use and becomes viable when carbon costs are explicit. For this work, demand behaviors must include process responses. Decentralized energy supply (local, combined heat and electricity) is also subject to process-side dynamics.

7.2 Economic/market choices versus costs/engineering

Not everyone buys the same, least expensive automobile. Tastes and preferences, as well as local needs and conditions affect the choices made. More importantly, at an enterprise level, the choice is a portfolio (or mix) that is dominated by uncertainty and risk mitigation. While firms and individuals all seek to maximize the utility of their choices, idealized, discrete, optimal decisions based on simple engineering costs do not reflect the actual marketplace dynamics (Jaffe 1994, Sutherland 1991). Because this effort is to actually help solve climate change problems, assumed optimal selections of ranked technologies based on perfect foresight cannot be the modus operandi for analyses. Qualitative choice theory (QCT) as partial embodied in the SGM (Edmonds 2004) and fully embodied ENERGY2020 (ICF 2008, AQB 2010, Backus 1995) models can realistically simulate technology selection.

7.3 Learning curve (power versus exponential)

New technologies initially have high costs until experience allows improved designs and operations. Typically, models assume a learning curve based on a constant return to experience (NRC 2010, NEMS 2009). Under the massive transformation needed to combat climate change, exponential functions with better-defined asymptotic behaviors are more realistic. Over time, many technologies have experienced cost reductions of 80% over prototype costs, in real-dollar terms. Conversely, some technologies (such as nuclear power) have experienced large cost increases due to added required (safety) complexity. These time dynamics can create bifurcations in the market trajectories relative to technology lock-in. The DOE NEMS (NEMS 2009) model uses a documented power-law curve to capture learning, whose parameters could define an exponential-learning model.

7.3 Economies of scale (power versus exponential)

In the same vein, the increased flow of technology deployment spreads fixed and hurdle costs over a large number of units, thereby (often dramatically) reducing delivered costs (NRC 2010). Several models (including FOSSIL2 - Naill 1992) have attempted to capture economies of scale dynamics.

7.4 Financial/Legal Constraints

Classical optimization assumes perfect DCF/NPV[1] results. In reality, companies who own technologies are at the mercy of markets. Prices and operating costs vary. Companies may not be able to maintain investment paths while accommodating financial downturns. Interest payments cause real cash-flows and inflation can quickly make some technology decisions non-starters. Legal constraints can limit the prices companies can offer, the financing they can obtain, the designs they can use, and the places where they can to build. A dynamic simulation approach readily captures changing market conditions and bifurcations.

7.5 Carbon mitigation and adaptation constraints

In addition, already conceived carbon mitigation and adaptation programs will stretch capital markets. International economic growth itself can strain financial market conditions. Anticipated global government spending on social security and medical-costs already represents daunting challenges. These financial demands will produce investment constraints with cyclical, transiently high interest rates that can dominate the viability of capital-intensive technologies. Algorithms can determine the risk associated with these impacts.

7.6 Political realities/constraints

In an earlier time, nuclear power was seen as an environmentally, economically, and socially problematic technology. Now in varying ways and in different settings, all technologies are seen to have political baggage. Uncertainty in the acceptance of new technologies, or the continue acceptance of technologies once their impacts are recognized, may totally determine the technological outcome decades hence. Scenarios that attempt to illuminate the implications of political dynamics could constructively add to the climate change decision-making.

[1] DCF=Discounted Cash Flow, NPV=Net Present Value

8. Transient (oscillatory) energy prices
Despite economic "laws" to the contrary, oil prices do not follow a monotonic trajectory nor do prices contain perfect-foresight. Investments (consumer and supplier) are necessarily based on imperfect expectations about the future (Hotelling 1931). Over-building or under-building capacity causes price oscillations which add to consumer and supplier decision uncertainty. Changes in usage decisions cause changes in commodity demands, and input-fuel prices can vary even more dramatically. Only simulation modeling can capture these dynamics (Sterman 2000).

8.1 Cap & Trade versus Carbon taxes
In the above context, cap & trade and carbon-tax approaches to carbon mitigation have very different impacts (despite orthodox claims to the contrary). Carbon taxes are a fixed market signal that allocates resources with an added sense of certainty –albeit with market dictated winners and losers. The tax level is the control mechanism to ensure market responses. Cap & Trade schemes distort markets with a priori allocations of permits whose value is determined by the vagaries of unverifiable, uncertain future needs for permits. As already experienced, carbon prices in a cap & trade scheme can vary dramatically over time, thereby increasing the perceived risk and preventing the proper timing of investment decisions (Green 2007, Nordhaus 2009, Reuven 2009, Economist 2009).

9. Dynamic versus static implications
All the above indicates the need for a realistic dynamic rather than a static approach to the analysis. Real decision-makers do operate in an environment of uncertainty. The analysis cannot assume that all parties have prefect knowledge about the future and make perfect decisions (Kahneman 2003).

9.1 Growth scenarios
Population and economic growth will determine the required intensity of and constraints on the technologies that collectively must lead to sustainable carbon emissions. Economic and population growth could be specified within co-dependent scenarios (to simplify the analysis) to illustrate this crucial link between solutions and the drivers that create/exacerbate the problems. Different growth rates will require different food and economic investment regimes, and thus create conditions requiring very different carbon-management programs.

9.2 Economic feedbacks
Energy is a production factor for all economic activity. The price of energy affects economic growth. Relatively unsophisticated "production function" approaches to economic growth can drive energy demand needs at a US and Rest of world (ROW) level (Paltsev 2005).

9.3 Global versus US view
Although much of the analysis can focus on the U.S. as an isolated entity moving to reduce its carbon footprint, global impacts on prices and material flow will in turn affect the ability for the U.S. to meet its goals. In addition, U.S. policy (for example bio-fuel

subsidies, and Canadian tar-sand imports) can have large impacts on energy needs, carbon emissions, and economic conditions at a global level.

9.4 Impact of boundary choice on conclusion

As such, the choice of the analysis boundary -- geographically, economically, and technologically – can affect the conclusions derived. Again, it would seem that a detailed U.S representation linked to an elementary aggregate ROW representation is required for legitimacy and self-consistency.

9.5 Security premium

Legislation and programs to promote specific technologies (special interests) often have to justify the energy balance or cost-effectiveness problems by invoking a security premium value that somehow justifies these efforts. Because the proposed analysis is strictly meant to inform the debate, it would seem that the proposed analysis should remain agnostic (blind) to "security premium" arguments (and other national security rationalizations).

9.6 Control feedback theory process w/uncertainty

Because the problem is dynamic with large uncertainty, the actual derived path of technology implementation is secondary to the control scheme that generates it. The control space represents the policy options (indeed, constrains the flexibility) in robustly pursuing carbon emission goals. Because of the non-linearities and uncertainties in the system, heuristic approaches or the leveraging of Darwinian processes (that allow failure and correction within an ecology) may be the hallmarks of viable policy options.

9.7 Picking the winning technology

Many a career has come to an abrupt end through the hubris of picking a "winning" technology. The current approach to MAC would seem to imply such a selection is possible. History continues to argue otherwise (Jaffe 1994). The proposed effort is to capture the market dynamics that lead to a desired outcome. This outcome will obviously entail technologies, but the good policy merely provides for the maximal potential for a beneficial outcome. The model simulates technologies to understand the impact of market interventions on market choices such that a societal goal (reduced carbon) is effectively (economically) achieved.

9.8 Verification and Validation

Given the enormity of system interactions and unknowns, sensitivity analyses are critical to developing defendable conclusions. Additionally, providing confidence intervals on solutions that emanate from varying input technology characterizations, behavioral parameters, and delay times is required for defining the real decision-space for policy makers. SNL has several computer applications that can facilitate this component of any analysis (Eldred 2006).

10. Interaction of electric generation with other energy services

Electric cars affect both transportation and electric generation choices. They change the load shape and infrastructure requirements for the grid. Fuel-cell vehicles complicate the situation by allowing two-way transactions. The net impact on carbon emission could be quite complex, especially if the link between transportation and electrical generation makes both less efficient. Additional electricity is a competing fuel for process heat. Other heating fuels also compete for transportation needs. The model design needs to recognize and describe this problem, but its resolution goes far beyond the proposed scope of this effort and is best explicitly noted as a limitation of the analyses.

11. Sequestering dynamics and the non-linear supply curve

Sequestering dramatically changes the perspective on coal (and all fossil-fuel) generation. Sequestering entails significant infrastructure creation and geographical constraints on technology choices. It is also a finite resource with non-linear, uncertain, cost curves. Its effectiveness, reliability, and extent remain ill-defined. The adequate portrayal of sequestering in a dynamic model is a major undertaking. Although it would cause a large amount of controversy, analyses with the proposed model could generate scenarios that vary the summary cost and magnitude of sequestering. These values, in turn, strictly limit the amount of coal generation in essentially a GIGO sense of the modeling. This approach to sequestering is troubling however, and further research may discover some creative alternative approaches.

12. Hybrid solutions

New estimates indicate that biomass can never serve more than 20% of global energy needs – under the proviso that the globe also gives up food production. Tar sands currently produce over 2 tons of CO_2 for every ton of oil. Coal definitionally produces over three tons of CO_2 for every ton of coal. Adding water in gasification to produce lighter hydrogenated compounds may make the problem worse. If carbon is simply considered a backbone upon which to place hydrogen, biomass could serve all energy needs, tar sands emissions would be zero in Alberta, and net oil-sand-derived fuels and coal-derived oil emissions could be 30% of present value – all without the need to use coal as more than a benign feedstock. The problem is in the production of hydrogen and process heat. Several small nuclear reactor designs can provide both. Further, metal-fuel, fast reactor designs can eliminates essentially all the CO_2 emissions from the nuclear fuel cycle. Using intermittent renewable sources to make liquid fuels also appears to have the greatest system-wide benefits – compared, for example, to electricity generation on a brittle grid system. The current focus is on electric generation limits the ability to address this perspective. An exploration of hybrid solutions could be the basis of a much easier to achieve efforts than that proposed.

13. Utility generation modeling

This effort focuses on electrical generation technologies. There are many, many utility planning and regulatory models in existence. To avoid unnecessary controversy, this effort should not compete with any of them. While the models do have to capture the realities (constraints) to technological change in the utility industry, the objective here is solely to describe the technology choice process and its impacts such that analyses can discover robust policy interventions to minimize (global) carbon with the greatest ***realizable*** economic efficiency.

13.1 Sacredness of property and contracts

Utilities have special franchise rights and contractual agreements. Thus, customer generated or third party generated power remains illegal in most franchise contracts. Further, existing generation counts as property, and as such, governmental rights to extort ownership or abrogate contracts for generation usage are only negotiable in relation to monetary compensation.

13.2 Electricity Demand

It is the expectation of future demand that drives capacity additions in regulated utility markets. It is the expectation for future prices that drives capacity expansion of deregulated utility markets. Demand is price responsive, differently over the short and long term. More importantly, the demand varies with the time of day and season. Peak power is dear. Peak power is not only expensive but challenges the load following capabilities of even gas-turbines under the constraints of the brittle U.S. transmission system. As climate change evolves, extreme weather will dramatically increase the share of the load that corresponds to peak power. Intermediate power represents the load between base-load and highly variable peak loads. Oil and small-unit coal generation must accommodate this load. Base load represents that load that is nearly constant over periods of time consistent with the time constants of large thermally-inertial power plants. Even a simplified demand construct needs to capture the load curve dynamics because it so constrains the viable technology options – by unfortunately making required near term choices obsolete before the plant is old enough to retire.

13.3 Plant replacement and growth

Given a constant demand, a large percentage of facilities, in principle, need to be replaced over the next decade. However, the first choice is to austerely extend the life of existing facilities. With growth there is new construction and multiple companies can (incorrectly) plan to serve the same load – or have the market (i.e., other utilities) serve it. This process creates financial risk and (usually) capacity levels that are out of sync with realized demand. The extreme weather of climate change (driving highly-uncertain, weather-related, real-time demands) may defeat the best efforts of regulators and utility planners. This modeling can readily capture the planning function and response, but the response (or lack thereof) to financial risk will require scenario methods.

13.4 Intermittent power of renewable energy

When wind becomes a substantial fraction of a regional grid's power supply, the grid can no longer maintain stability. Redundant new (often coal) capacity must compensate for the variability in renewable generation or the renewable source must be taken off-line when its operation threatens the grid. Spinning condensers can partially compensate for long transmission runs, but this is outside the scope of the proposed study. The analyses could possibly include a simple (off line) probabilistic (illustrative) analysis of renewable generation as it affects the grid and the dispatch of other generation – up to an estimated maximum constraint. Despite talk of Smart Grids (a 30-year-old concept), regulatory constraints on new grid construction would seem to make this a non-solution for realistic policy analysis. Nonetheless, scenarios could include "what-if" runs to indicate its potential value. This leaves energy storage as the (controversial) required "solution" for allowing unlimited renewable capacity. This effort does to consider the storage technologies "married" to renewable energy in the model. Flow batteries, compressed air, and fuel-production (hydrogen or carbonaceous) are just a few of the possibilities.

13.5 Geography
The grid topology, load centers, pipelines, rail lines, and water make electric demand and generation subservient to regional geography. Given time and funding limitations, in all cases, the proposed modeling must neglect this reality.

13.6 Grid dynamics
While the modeling must subsume most of the grid away, other than its constraints, there are concepts that use the grid to take advantage of the fact the sun shines and the wind blows somewhere on the globe at all times (Meisen 1976 and http://www.geni.org/). The analyses probably do not want to include this logic or directly address any of the grid stability or constraint issues, but by making sure the design-thinking stays "in-the-box," the design ensures that what the model produces may be irrelevant to what will actually transpire. Does the design process need to step back a bit and consider tech-surprise or black-swan scenarios instead of embellishing the single evolutionary branch the world thinks it is now technologically on?

13.7 Cycle of build and bust
Just like commercial real-estate, utilities are routine victims of build and bust cycles (As intimated above and studied in Ford 2002). The capacity expansion choice, in monotonically growing (in demand and price) scenarios, is far different from those that include cyclical phenomena. It may be very insightful to include the cyclical behaviors (endogenously generated in a simulation model) as the basis for analyses rather than the conventional wisdom.

13.8 Utility choice process
Utilities have to make choice under uncertainty. They seldom "put all their eggs in one basket," and they are risk adverse. Optimization models can describe what should be done, but empirical data shows that the board of directors maintains a strong tie to human nature and produces decisions consistent with the qualitative choice theory (QCT) noted earlier (Sterman 1988). Perceived consumer needs plus regulation drive decisions to select and finance new capacity. The model can capture these phenomena, as noted above. A key point is that although utilities are the actual consumers of technology, their choice is the end of a cascading sequence of constraining conditions. That is, utilities make the choice the immediate situation requires, not the choice they would make if only perfect economic foresight entered into the equation.

13.9 Marginal investment vs. production costs
Marginal investments costs are typically used to simulate utility capacity expansion decisions. These calculations assume a fixed utilization of the capacity. Operationally, plants are dispatched based on variable (production) costs and plant availability. In a regulated market, idle capacity is still allowed to recover its capital (fixed) costs in the price. The capital component of the price dilutes the price signal because only the

variable costs fluctuate. The price becomes an average price and demand responses (only efficient with marginal cost pricing) leads to further market distortions in technology choice -- and in the value of those choice to society (in terms of economic efficiency or in terms of cost-effectively meeting climate change goals). Analyses may want to consider experiments that apply marginal cost pricing versus those that do not. Because of the feedback response on demand and capacity additions, the two results should be significantly different.

13.10 Regulated vs. Deregulated markets

There are many issues concerning the differing conclusions that would come from deregulated versus regulated markets that go beyond the scope of the proposed efforts (Backus 2005). Just characterizing the deregulated market definition would raise such controversy that no reviewer would ever even make it to the analysis part of the proposed work. Nonetheless, the model must resolve the fact that self-generation and (non-utility) third party generation violates the regulatory franchise. Many of the technologies the model might include could fall in these categories. (Is co-generation a represented technology in the model?) A potential way to get around this conundrum could be through assuming the utility is paid (i.e., made whole and risk free) if it accepts generation from alternative sources. Note that the new technology then only becomes economically viable under conditions of capacity expansion where the alternative choice is less costly (from a risk-adjusted perspective) than any choice the utility could implement of its own means.

13.11 Climate Impacts on Generation Lifetimes

Climate induced changes in precipitation cannot only reduce the available output from conventional capacity, but changes in the timing of precipitation can dramatically reduce the capability of hydropower. More importantly, change weather patterns due to climate can reduce solar-facility output and nullify wind capacity. Weather changes cause also cause biomass-energy plantations to be abandoned with the (competitive) loss of the local biomass generation capacity. Whenever a renewable facility is dependent on the local weather, future climate change might eliminate the required local conditions needed for it use.

The above only scratches the surface and covers a fraction of all possible considerations, but it raises enough of the key issues to allow a triage for the purpose of deciding a workable route for modeling as described in the main text.

Appendix C: Qualitative Choice Theory

Qualitative Choice Theory (QCT) has a long history in psychology. It has only been fully developed for economic use through the work of Daniel McFadden (who won the Nobel Prize for the effort in 2000).[2] Independent of whether an individual is rational, irrational, profit maximizing, or satisficing, qualitative choice theory applies to the decision making process. It simply says that individuals make a choice based on their perception of utility in regard to those choices. QCT causes any and all information (preferences, tastes, price, time to delivery, "little voices," etc.) utilized by the individual to define a valid (or at least functional) representation of choice behavior. QCT analyses starts with the data reflecting the conditional probability of a choice given possibly interacting, conflicting, and limited information.

Theoretically, any form of the probability distribution can be assumed. In practice, the Weibul distribution has the greatest numerical ease-of-use and has shown itself to be empirically the most likely shape of the actual distribution. The Weibul distribution is skewed to the left with a broad tail to the right. This implies that while individuals consider high "cost" options, they tend to focus on the lower "cost" (higher value) options. People do not have perfect information. A sampling of the population shows different perceptions of actual costs and personal preferences. The choice made is called Random Utility Maximization or RUM.[3] Figure 1 below shows the illustrative distribution of perceived price for three technologies (choices). While the QCT formulation can include any concept of culture, ideology, tastes, or preferences, etc, only the classical economic example is discussed here.

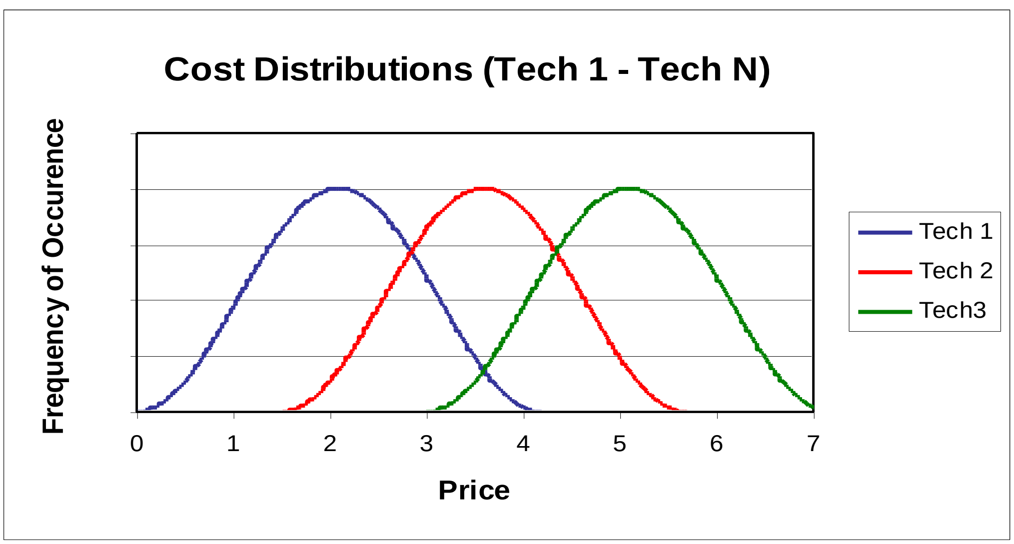

Figure 1: Illustrative Choice Distribution

[2] McFadden, D., "Qualitative Response Models," in Advances in Econometrics, Ed. Werner Hildenbrand, Cambridge University Press, New York, 1982

[3] McFadden, D., (1986), "Econometric Model of Probabilistic Choice," in Structural Analysis of Discrete data with Econometric Applications, ed. C.F. Manski and D. McFadden, Cambridge, MA, MIT Press.

Maximum-likelihood estimation (MLE) methods determine the shape of the distribution as a function of costs and preferences in the model.[4] The actual market share is determined by mathematical integration over the distributions.[5] Nonetheless, the physical process can be understood intuitively. The fraction of the time Technology 1 would be picked would be the region to the left of the red line and half the region between the left red and left green line under the blue distribution. (The half comes from the price having a 50% chance that the cost of Technology 1 is perceived as lower than Technology 2.)

Technology 2 would be selected by the fractional amount equaling one-half the area between the left red line and right of the blue line. Technology 3 would be selected by the fractional amount equaling one-half of the area between the left green line and the right blue line under the blue curve. This is the fraction of the instances that Technology 3 is perceived as having a lower cost than Technologies 1 or 2. The width (standard deviation) of the distribution can be shown to be the uncertainty in the perceived information about the technology.

The market share of Technology 1 would be as shown in Figure 2, as its price varied relative to the price of the other choices. As the price of Technology 1 becomes small compared to the other choices, its market share would go to unity. If the uncertainly is large (as in a residential decision), the slope is gradual. If there is significant effort to reduce costs (have less uncertainty), the curve is steeper as shown for industrial choices. If there is perfect information, as assumed in an unconstrained linear programming (L-P) framework, then the market share would jump from 0.0 to 1.0 with the smallest of price differentials.

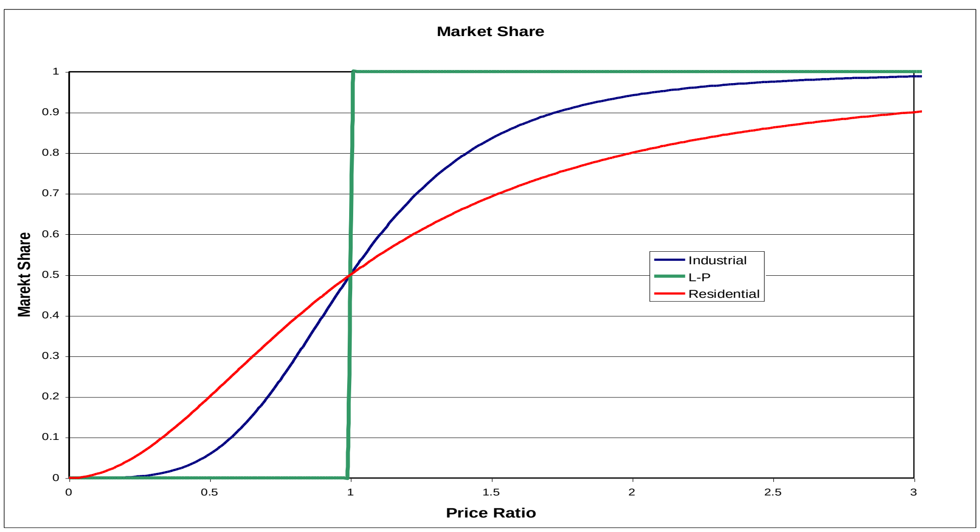

Figure 2: Illustrative Market Share Response

[4] Ben-Akiva, M., Discrete Choice Analysis: Theory and Applications, MIT Press, Cambridge, MA, 1985.

[5] McFadden, D., "Conditional Logit Analysis of Qualitative Choice Behavior," in Frontiers in Econometrics, Ed. P. Zarembka, New York, Academic Press, 1974.

The integration of Figure 1 produces the probability of the choice, or in the aggregate, the market share, of the i'th choice (MS_i) per Figure 2. For a Weibul distribution, this integral has a closed-form solution:

$$MS_i = \frac{e^{U_i}}{\sum_{j=1}^{N} e^{U_j}} \qquad 16)$$

Where U_i is the utility of choice "i," and "e" is the base of the natural logarithm.

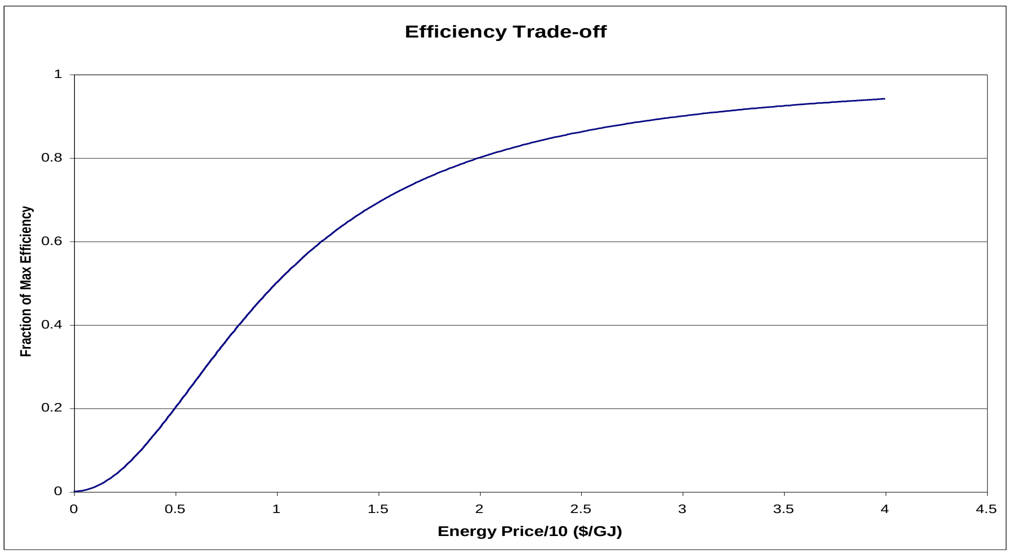

Figure 3: Aggregation of Choices.

If Technology 1 through 3 represents technology choices, then Figure 2 would represent the technology market shares on the margin. If there are many technologies, the shape of Figure 2 only changes quantitatively but not qualitatively. The sum of market shares is a market share. It is then possible to make a curve of an aggregate characteristic such as efficiency, where the choice goes from the lowest efficiency technology (when factor costs are low) to the highest efficiency (when factor costs are high). Preferences also play into this, but for simplicity, these can be thought of as added perceived costs, in this example. The curve in Figure 3 is the selected marginal efficiency at the current price and preferences for an infinite number of choices. The efficiency ratio (Efficiency/-Maximum-technological-efficiency) goes between 0.0 and the maximum (1.0). QCT allows the valid aggregation of individual choice to societal choice. This aggregation problem has haunted economics for centuries.[6]

[6] Keene, S. Debunking Economics, St. Martin's Press, New York, NY, 2001

The utility function is often written, for example, as a simple linear function of price (P_i) with the constant (non-price) term noted by Train.[7]

$$U_i = A_i + B^*P_i \qquad 17)$$

In this case, the "A" would be (assumed constant) non-price factors of taste and preference for the i'th choice. It can also capture the ability to make the choice (e.g. the limitation of physician selection in an insurance plan) or the availability of the choice (e.g. the winter availability of solar energy at the South Pole). Note again that the B does not have a subscript. The "B" is directly related to the uncertainty of the choice – how well the information of the choice *set* is known and understood. The uncertainty of the decision process is the same for all choices in a set because it is an ordinal and not a cardinal process that compares all options at once.

There can be a hierarchy of choice, like a binary tree, but called nesting. Each level is a choice among all the options of that level (e.g. choosing the flavor of ice cream to eat occurs, after choosing which place to go for the snack, after the decision to go for a snack.) Each decision level is self-contained but can be conditional on the level below it.

The derivation of the theory of QCT requires that all choices at any level are mutually exclusive (e.g., the decision to live in Boston or Austin). Empirically this limitation is non-binding. A classic example is the addition of travel choice by painting half of all the buses green and the remaining buses blue. There really has been no change in the choices -- taking the green bus is no different than taking the blue bus. The "A" of equation 17 can capture this fallacy by simply multiplying the blue-bus and green-bus choice, in this example, by 0.5. The same process can often allow the complicated nested equations to be reduced to a single layer called a "comb" that requires only the single use (and estimation) of Equation 16.

Reducing the uncertainty, increasing the understanding of the choices, and making better decisions (as contained in the "B" term), takes time and effort. The benefit may not be worth the effort. When buying a house, a purchaser may want to know the price within 1% or less. For a candy bar, a 200% uncertainty variance is tolerable.. The consequences of purchasing a house are much more momentous than purchasing a candy bar. The magnitude of the "B" appears to vary directly with the importance of the decision. That importance is the cost of the decision compared to the value of the entire output (a labor-year of income for a person and the revenue for a company).

If many choices are aggregated to produce the equivalent of Figure 5, the magnitude of "B" will be reduced. This reduction occurs because aggregation is like taking a weighted average. It "smoothes" the response intensity compared to a disaggregated either-or-situation.

Data indicates the linear function of Equation 17 works well for small variations of the input variables, but the actual underlying function is logarithmic. Equation 18 is a simple logarithmic enhancement of Equation 17.

[7]Train, K., *Qualitative Choice Analysis,* MIT Press, Cambridge, MA, 1986.

$U_i = A_i + B*\ln(P_i)$ 18)

This indicates that people can determine relative proportionality but not absolute differences in price (or other components of utility). This implication is consistent with the previous discussion that the B is proportional to the percentage impact it has on total outcome.

If Equation 18 is substituted into Equation 16 and "m" is defined as

$m_i = \exp(A_i)$ 19)

then Equation 16 becomes

$$MS(i) = \frac{m_i P_i^B}{\sum_{j=1}^{N} m_j P_j^B} \qquad 20)$$

This equation is consistent with the engineering assessment of options according to the distribution of (estimated) cost versus (estimated) performance. The uncertainty of the estimate (the "B") is also a function of the importance of accuracy. This is the only example the author knows, where engineering theory and economic theory agree.

While MLE is required for the unbiased estimation of Equation 20, within a feedback system, ordinary least-square estimation often produces adequate parameterization to generate accurate forecasts.

Note that because the decision process is always ordinal, there is no absolute concept of preference. Therefore, one of the "m_i" must be arbitrarily selected as the numaire and set to unity.

When used over a 50 year period to simulate, for example, energy demand, some limitations of Equation 18 start to appear. One obvious area is the impact of income on decisions. A cup of Starbuck's coffee is more expensive than one from home. The ability to afford luxury items affects demand. Changes in the disposable income (I), relative to the minimum (I_m) needed to maintain health, affects buying and other decision responses.

All goods provide a service. That service is "demanded" relative to the production of output, be that output a labor year as measured in annual income units or the revenue from an industrial widget. The market share is for a service. The price is the cost per unit. That unit is a factor input to production. (Food is required to produce a labor-year; iron is required to produce a power plant.) The units of price are $/factor-unit. For "B" to have a probabilistic meaning, the "P" term must be a proportion. The proportion is the comparison of the factor price to the price of output. That process requires a conversion term whose units are $ of output per factor unit, here defined as the economic intensity

EI. EI is the measure of efficiency in using the input factor. With the improved income and price concepts, equation 18 becomes:

$$U_i = A_i + B^*\ln(P_i/EI)+C_i^*(I/I_m) \qquad 21)$$

The term P/EI has the units of $-factor/Factor-Unit / $-Output/Factor-Unit. The factor-units cancel, but the dollars do not. The dollar units of measure have important adjectives. The rigorous use of QCT could lead to the claim that there is no such thing as a dimensionless number and that valuable interpretive/causal information is lost by attempting to use dimensionless numbers. (As another example, energy efficiency is not a canceling Btu/Btu ratio, but rather BTU-Service-out/Btu-Primary-in.)

The Income term of Equation 21 is adequate for simulating demand in industrialized countries, where I/I_m is significantly greater than unity. A more complicated formulation is needed for values below and near unity.

The "A" term can be divided into its separate components ($A_{i,k}$). One term will always have to contain "other" residual "A" components. For policy purposes, these components can represent advertising, availability, color, style characteristics, or anything else that might affect the choice. Care is needed during estimation to avoid spurious parameters due to too many degrees of freedom given the quality of the data. Equation 21 then becomes:

$$U_i = \sum_k A_{i,k} + B^*\ln(P_i/EI)+C_i^*(I/I_m) \qquad 23)$$

Note that because the "$A_{i,k}$" are use in the exponential context of Equation 16, they reflect relative, rather than absolute preferences, From a QCT sense, they are proportional just like all other terms.

Limitations of Qualitative Choice Theory

Non-price terms may be truly co-dependent. Peer pressure and the reduction of early-adopter risk may be both a function of knowledge of other users (i.e., the average existing market share). It can become difficult to break out the separate influences.[8] Naïvely defining decision components can lead to invalid conclusions.

Value of Qualitative Choice Theory to Technology Assessment Modeling

The use of QCT seems to force a rigor and a method for defining the implicit or explicit decisions associated with a rate formulation. Experience indicates that QCT forces a self-consistency of thought and theory that always has a causal description consistent with empirical data.

[8] Keeney, R. L. and Raiffa, H., Decisions with Multiple Objectives, John Wiley & Sons, New York NY, 1976.

Appendix D: Derivation of the Capital Charge Rate

The capital charge rate is the annualization of capital expenses to account for taxes, tax credits, return of principal, return on investment, and interest during construction. The "CCR" equation is:

CCR = (1+R)**(C/3)*(1-ITC/(1+NR)-TR*(TL/2)/(TL/2+NR))
*R/(1-(1+R)**(-BL))/(1-TR)

Where:

R = Real Return on Investment
NR = Nominal Return on Investment
C = Construction Time
ITC= Investment Tax Credit
TR = Tax Rate (Federal plus State income tax)
TL = Tax Life
BL = Book Life

NR=(1-TR)*(1-F)*ND+F*NE
R=(1+NR)/(1+INF)-1
ND=(1+D)*(1+INF)-1
NE=(1+E)*(1+INF)-1

Where:

F = Fraction Equity
INF= Inflation Rate
ND = Nominal Return on Debt (Interest Rate)
D = Real Interest Rate
NE = Nominal Return on Equity
E = Real Return on Equity

For small "INF" (less than 10%/yr), a simpler calculation can be used with acceptable error:

ND=D+INF
NE=E+INF
R=(1-TR)*(1-F)*D+F*E
NR=R+INF

Risk can be added to "R" to reflect uncertainty and a higher required return. The model can include financial risk concerns by increasing the required rate of return. Typically, a .02 to .05 risk (RISKN) is used for new technologies.[9]

Although the standard approach uses a constant risk adjustment, a dynamic risk adjustment can be easily calculated. As a first approximation, a technology is assumed

[9]Backus, G. A., *FOSSIL79 National Energy Policy Model*, Resource Policy Center, Thayer School of Engineering, Dartmouth College, Report No. DSD-165 through DSD-168, 1979.

to be mature when the demand (D) for it is 10% of the total market demand (MPD). The risk can be reduced over time to reflect this phenomenon:

RISK=RISKN*EXP(-D/MPD)
RR=R+RISK

where "RR" is the risk-adjusted "R" that can be used instead of "R" in all appropriate equations.

The "(1+R)**(C/3)" term in the "CCR" equation represents interest during construction which must be added to the final cost of the facility. During construction, costs accumulate faster near the end of the project than at the beginning. As a good approximation, it can be assumed that all the construction costs occurred two-thirds of the way through the construction program. That means interest charges (R) are accumulated for a time equaling “C/3".

The "R/(1-(1+R)**(-BL)" term is the classical capital recovery term.[10] The "(1-TR)" term at the end converts the after tax calculation into before tax dollars.

Investment tax credits reduce the cost of the plant by the tax credit after the first year of operation using "original" dollars. Therefore the value of the tax credit is "ITC/(1+NR)".

Depreciation is expensed for tax purposes during each year of the tax life of the plant. With the double-declining balance method (DDB) of computing depreciation, the depreciation (DEP) of the plant for each capital dollar spent in year "t" is:

DEP(t)=2/TL*(1-2/TL)**(t-1)

Depreciation, under existing laws, is a current dollar phenomena which does not account for inflation. Therefore the net present value of the energy is calculated with the nominal rate of return. If the depreciation life is adequately long to neglect end year effects, then the net present value of depreciation expenses is:

(2/TL)/(NR+2/TL)

Because depreciation is a benefit (negative cost) based on the total plant before investment tax credits, it shows up as an additional negative term in the capital cost modifiers of "CCR:"

(1-ITC/(1+NR)-TR*(TL/2)/(TL/2+NR))

The CCR calculation is naturally appropriate to business decisions but its use in the residential sector may appear artificial. When the CCR calculation is used for the residential sector, TL and C are set to zero because the residential sector can neither write off depreciation expenses nor make adjustments for extended construction times. This makes the calculation exactly correct for housing and any long-term investments.

Concerns can occur when the life of the loan is much shorter than the physical life assumed in the CCR calculation. When short-term loans (2-5 years) are used, the home owner still implicitly discounts the equity portion of equipment and depreciates the

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[10] Smith, Gerald W., *Engineering Economy: Analysis of Capital Expenditures*, Iowa University Press, Ames, Iowa 1973.

equipment over its expected life time. (Consumers do not expect a car or stove to fail as soon as the loan is paid-off; they write-off its value over its actual life time.) Therefore, the CCR calculation can only be incorrect for the debt portion of the investment. When a life cycle cost analysis of the actual cash flows is performed, which levelizes the short-term interest payments with the life of the equipment, the results are essentially identical to those obtained with the CCR calculation here.

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