RE-ASSUME

A Decision Maker's Guide to Evaluating Energy Scenarios, Modeling, and Assumptions

Implementing Body: National Renewable Energy Laboratory

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Acronyms and Abbreviations

ACES – Achieving Climate and Energy Security scenario (IEA-RETD)

ADAGE – Applied Dynamic Analysis of the Global Economy

AEO – Annual Energy Outlook

CCS – Carbon capture and sequestration

CPS – Current Policies Scenario (used in the World Energy Outlook)

DOE – U.S. Department of Energy

EC – European Commission

EIA – Energy Information Administration (affiliated with U.S. Department of Energy)

EFOM – Energy Flow Optimization Model

EMF – Energy Modeling Forum

EPPA – Emissions Prediction and Policy Analysis model

ERI – Energy Research Institute (affiliated with China National Development and Reform Commission)

ETP – Energy Technology Perspectives (scenarios published by IEA)

ETSAP – Energy Technology Systems Analysis Program, an Implementing Agreement organization at the IEA

EU – European Union

GEA – Global Energy Assessment (scenarios published by IIASA)

IAM – Integrated Assessment Model

IEA – International Energy Agency

IIASA – International Institute for Applied Systems Analysis

IPAC-SGM –Integrated Policy Assessment for China – Second Generation Model

IPCC – Intergovernmental Panel on Climate Change

LEAP – Long range Energy Alternatives Planning model

MARKAL – Market Allocation model

MERGE – Model for Estimating the Regional and Global Effects of greenhouse gas reduction

MESAP/PlaNet – Modular Energy System Analysis and Planning Environment, and Planning Network models

NEMS – National Energy Modeling System model (DOE)

NPS – New Policies Scenario (used in the World Energy Outlook)

NREL – National Renewable Energy Laboratory

PNNL – Pacific Northwest National Laboratory

PPP – Purchasing power parity

PSG – Project Steering Group

PRIMES – Partial equilibrium energy model for the European Union

PV - photovoltaic

RE – Renewable energy

ReEDS – Regional Energy Deployment System model (NREL)

RETD – Renewable Energy Technology Deployment, an Implementing Agreement organization at the IEA

TIMES – The Integrated MARKAL-EFOM System model

WEM – World Energy Model (IEA WEO)

WEO – World Energy Outlook

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Executive Summary

The desire for a "crystal ball" to peer into the future has perhaps never been stronger among energy and environmental planners. While the future has always been uncertain, the interconnectedness of modern economic systems serves to enhance the ripple effect of our energy actions. Today's decisions also seem to be made under heightened uncertainty, as demonstrated by the number of recent unexpected events, such as: a prolonged economic recession, an unfolding shale energy revolution, the Fukushima disaster, the Arab Spring, and a notable reduction in photovoltaic costs. Policymakers have historically relied on energy scenarios and modeling to help inform decision making. **While there exists a wealth of advanced model, data, and energy scenario options, important questions remain about how to effectively apply these tools to help plan for an uncertain future.**

Energy scenarios use varying techniques and approaches to consider alternative energy futures. They help prepare for decision making under uncertainty and inform policy options that society may desire. Most energy scenarios rely on quantitative models—often highly complex—to compare tradeoffs and quantify specific outcomes of different courses of action. Energy models are abstractions of reality that simplify the world into "bite sized" pieces in order to fit within certain sets of mathematic methodologies. They range in scale from the local to global, in sector from electricity- or transportation-only to economy-wide. They simulate, optimize, or equilibrate; forecast; and help plan. Some are used for academic purposes, others for policy, regulatory, or investment planning. All models rely on imperfect inputs, parameters, assumptions, and interpretation. They all contain structural compromises, simplifications, and omissions. **One must maintain a spirit of humility about predictions, particularly when asked to look decades into the future.**

Knowledge and cultural gaps that exist among policymakers, scenario developers, and energy modelers can also result in misunderstanding of modeling results. **This study attempts to help bridge some of those gaps so that stakeholders can use energy scenario results more effectively.** It also functions as a support guide for preparing or commissioning energy scenario analyses.

The "Top 10" key findings from this study are summarized here.

1. **Do not expect a model or energy scenario to predict the future.**

   No model can predict the future, but this is often forgotten. The further an energy scenario looks into the future, the more uncertainty is introduced. Single scenarios are rarely helpful, but must be combined with, and compared against, diverse alternatives as part of a larger strategic exercise.

2. **Match the model to the problem.**

   There are almost as many types of energy models as there are questions about our energy future. Make sure the question you want to answer is well-formed, and then pick the right type of model to best address it. For the simplest example, an electricity sector-only model should not be chosen to address an economy-wide greenhouse gas mitigation question.

3. **Make assumptions and accounting frameworks transparent.**

   Models require thousands, and often millions, of pieces of input data. The meaning of these data needs to be clearly understood by all. What type of energy accounting methodology is used? How do technology cost and performance assumptions change over time? Are the economic data measured in current or real values? Is traditional biomass included or only modern biomass? To address these and other potential misinterpretations, all assumptions should be clearly and transparently articulated. Without transparency, credibility is sacrificed and results can misinform.

4. **Understand the limitations of how human behavior is represented.**

   A typical energy model finds a solution based on the overall system's equilibrium (matching of supply and demand) or least-cost point. However, real-world producers and consumers often find themselves out of equilibrium, and agreement on a system-wide optimal point is rare. Institutional, jurisdictional, supply chain bottlenecks, or social barriers such as "not in my backyard" attitudes can prevent the system from reaching these ideal points. The potential for humans to change their behavior in unexpected ways is also commonly not factored into models. Energy models are typically better at characterizing supply-side options than they are those on the demand-side, particularly related to energy efficiency behavior.

5. **Use diverse tools and approaches to address uncertainty.**

   Uncertainty about the future comes in different forms. Some is “characterizable” while others are not (known unknowns and unknown unknowns). New analytic approaches are available to help address some classes of risk and uncertainty. Modelers can use a variety of techniques, often borrowed from the financial literature—Monte Carlo simulations, real options and portfolio theory, for example—to better characterize uncertainty. For “uncharacterizable” uncertainty, scenarios should be designed to consider the potential impacts of certain families of unexpected events or “black swans” (e.g., a disruptive technology innovation).

6. **Consider how unique traits of renewable energy are modeled.**

   Higher resolution is required to model the site-specificity, and variable and uncertain nature of many renewables. Constrained by computational limits, modelers are forced into trade-offs between increasing their geographic and time resolution, or simplifying other aspects of the energy economy. Because of the unique traits of renewables, transparency in their assumptions and model treatment is necessary to better understand if they are treated appropriately and whether the playing field is level. In particular, renewable technologies should be viewed within the larger energy system and not be forced to fit within the confines of the status quo technologies or operational practices, (e.g. some models erroneously use a one-to-one "back-up" requirement for each variable renewable power generation technology).

7. **Communicate effectively and appropriately.**

   Energy modeling is a highly specialized endeavor. What modelers consider "results" and what decision makers deem useful information may not overlap. The communication of results is inherently difficult. The two communities would benefit by better understanding the challenges and opportunities that exist for each other. Modelers should put themselves in the shoes of policymakers when communicating results and synthesize findings at an "appropriate" level of detail. Defining vocabulary in simple terms can help this "translation" from one world to another.

8. **Expect bias and learn to identify its traits.**

   All modeling approaches incorporate bias, either accidentally or purposefully. Consumers of energy scenarios can learn to identify scenario, data, and model subjectivity, and take steps to ensure appropriate interpretation. Commissioners of energy scenarios should use diverse networks of expert reviewers to address real and perceived bias before results are finalized.

9. **Consider energy scenarios with limited or no modeling.**

   Commissioners of energy scenarios should consider broad stakeholder engagements that focus on "upstream" discussion of assumptions and desired outcomes as a first step before modeling. Focusing limited resources on these discussions with "back of the envelope" calculations can provide unique value. Modeling can be a subsequent step after the stakeholder dialogues to provide additional useful insights.

10. **Conduct retrospective analysis to better understand energy scenario misses and hits.**

    Too often, energy stakeholders do not go back to revisit why certain energy scenarios were so far off the mark or why they provided unexpectedly valuable information. There is value "left on the table" by not returning more often to previous energy scenarios to analyze why they did or didn't work well.

These findings are principles—they are not comprehensive, nor do they apply in all cases. We hope this document will help catalyze and inform discussion and debate among stakeholders on how to improve the value of energy scenarios.

1 Overview of Energy Scenarios and Models

> "… The purpose of scenario planning is not to pinpoint future events but to highlight large-scale forces that push the future in different directions. It's about making these forces visible, so that if they do happen, the planner will at least recognize them. It's about helping make better decisions today."
>
> --Lawrence Wilkinson[1], co-founder of Global Business Network

1.1 Why Use Energy Scenarios?

The global energy system is highly complex and interwoven, and impacts the lives of billions of people every day through its diverse pathways of extraction, transportation, transformation, and services. We have developed a clearer understanding in recent decades of how the global energy system has the potential to disrupt ecological systems through land-use change, pollution, and the greenhouse effect. It also holds the possibility to positively transform economies by catalyzing wealth creation and social development. In response to the importance of the energy system on climate change, *inter alia,* a large number of analytical models and scenario techniques have been developed to help us understand the economic and social impacts of different energy system choices, as well as to inform policy and investment decisions.

Energy scenarios include a wide variety of techniques, often relying on complex computer models, to help prepare for future uncertainty and desired change. Historically, they often rested heavily on the idea that the future will be similar to the past, but the world has become far too dynamic to allow that practice to continue as the sole avenue for exploration. Many new techniques are now used to help address uncertainty and risk in energy scenarios and planning (Bazilian and Roques 2008).

Robust energy scenarios are not meant to be "predictions" of the future because these, by definition, almost always fail. Instead, they serve as points of comparison to evaluate sensitivities and alternative outcomes. Single scenarios are thus rarely helpful, but should rather be combined with, and compared against, diverse alternatives as part of a larger strategic exercise. Consumers of energy scenario results should be wary of any single-point estimates of future conditions (e.g., oil prices, total demand) unless accompanied by an analysis or discussion of uncertainty.

Figure 1.1 illustrates some ways of thinking about energy futures. All are highly simplified, and most energy scenarios include a combination of these approaches.

[1] Wilkinson, L. (2009). "How to Build Scenarios." *Wired.* Available at http://www.wired.com/wired/scenarios/build.html

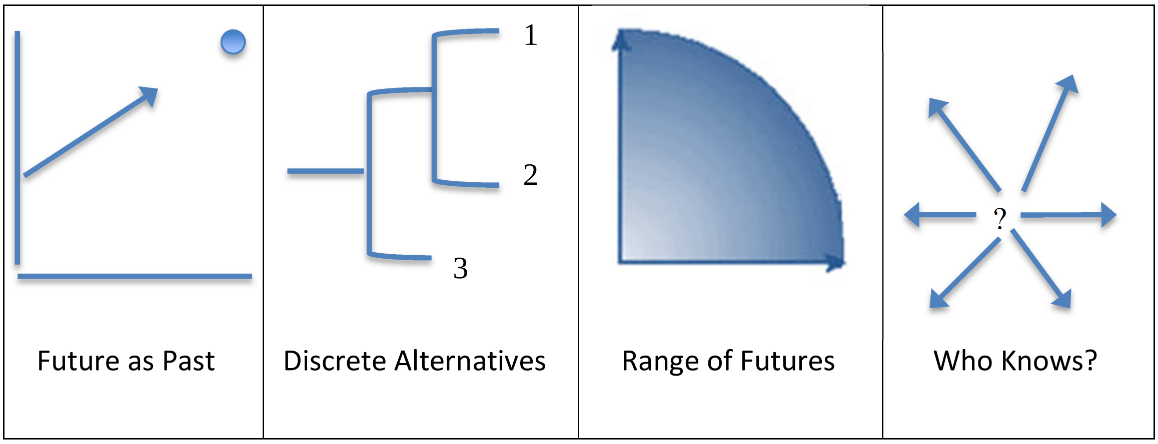

Figure 1.1 – Selected Approaches to Energy Scenarios

Adopted from WEC 2010

A rigid definition of energy scenario might include only one type ("classic"), but other methods are now routinely considered in practice:

- Classic energy scenarios ("storylines"), made popular by Shell, are usually normative (idealized) visions of how an energy system might develop under coherent, internally consistent sets of economic, social, and political assumptions.
- Forecasts, or baselines, are usually an attempt to predict the "most likely" future under a "business as usual" or modified set of assumptions.
- Policy, or alternative, scenarios are driven by a different set of assumptions than those used in the baseline, and aim to illustrate comparative differences in achieving a policy-driven future distinctly different from the baseline.

Energy scenarios do not necessarily require computer models to provide value, although nearly all scenarios today rely on them. A model usually employs a mathematically consistent framework to evaluate a set of inter-dependent equations that cannot be (easily) solved without a computer. Models operationalize the assumptions used in a scenario to simulate how an energy system might evolve over time. Energy models can complete their calculations in under a second or take days depending on the level of complexity. Many energy scenario modeling exercises can take weeks or months to prepare as data is gathered and verified, calibrations are performed, sensitivities evaluated and probabilistic analysis completed. Many factors – discussed in the following chapters – introduce uncertainty into modeling results. As a consequence, modeling results can be abused or misrepresented if not carefully understood or communicated.

Energy scenarios are used to inform both public and private sector decisions. Multilateral, regional, national and subnational governments commission energy scenarios that are used to help steer hundreds of billions of dollars of investment each year. **These scenarios will ultimately impact the quality of life for billions of people, and impact public perception of energy decision makers.** These agencies are also consumers of energy scenario results to help inform other policy making. Likewise, private companies are directly impacted by energy policymaking; they can both produce their own energy scenarios and consume information from others to inform investments and planning. Yet there remain clear misunderstandings in the process of commissioning and digesting information found in energy scenarios. **This report attempts to better equip both those who commission energy scenarios and those who directly use information in scenarios to make decisions.**

1.2 Evolution of Energy Scenarios

Using analytic methods to envision potential energy futures is not new. Since at least the late 1790s, for example, individuals have been estimating how long England's coal supplies might last (Williams 1810), and very sophisticated forecasts had already been developed by the mid-1860s (Jevons 1865). The modern era of energy scenarios—and associated detailed data collection—began to emerge in the 1950s and 1960s with the advent of more powerful computer models and the need for robust energy planning (Krammer 2012). **Today, the art and science of envisioning energy futures has grown increasingly complex, and can utilize sophisticated modeling tools that sometimes communicate overconfidence in the results, or are misaligned with the nature of the questions.** We often seem no better at "predicting" what the price of oil will be next year, or in a decade, despite these powerful tools and analytic approaches. While modeling techniques have improved tremendously, they have scarcely kept up with the speed of change in today's world and the uncertainties of tomorrow.

Numerous studies have evaluated the accuracy and usefulness of past energy scenarios (Bezdeck and Wendling 2002; Nielsen and Karlsson 2007; Craig et al. 2002). **There is no shortage of "missed" forecasts** pertaining to energy prices, energy demand, penetration of nuclear or renewable energy[2] technologies, and carbon dioxide emissions. Energy scenarios conducted during the 1970s for the year 2000, for example, almost uniformly overestimated how much energy major economies like the United States would be using then, mainly because they failed to envision the flexibility of human behavior in the face of rising energy prices (Craig et al. 2002). Attempts to predict oil prices have erred wildly on both sides of actual trends over the past 40 years. And while renewable energy may have been assumed to grow too optimistically in the 1970s and early 1980s, many of the most widely-read energy scenarios today seem to be scrambling to catch up with the recent rapid growth in its deployment (IEA 2012; see Chapter 8). On the other hand, decision makers may not acknowledge and appreciate the value that energy scenarios can provide when they are used constructively. Choosing not to use energy scenario modeling can leave decision makers completely unprepared for the future.

[2] This report follows the IPCC Special Report on Renewable Energy Sources and Climate Change Mitigation convention and define renewable energy as any form of energy from solar, geophysical or biological sources that is replenished by natural processes at a rate that equals or exceeds its rate of use.

Dramatic change has occurred in global and national energy markets over the past five years, compounding the difficulty of producing meaningful energy scenarios. Some of the major upheavals that have occurred recently include:

- Economic recession that began in late 2007 and still affects much of the globe
- Signals that global climate change is increasingly impacting our weather, human-built infrastructure, and ecosystems
- The Fukushima nuclear accident in Japan and the BP oil spill in the Gulf of Mexico
- Political awakening and instability in many Middle East and North Africa countries
- Dramatic reductions in the cost to manufacture solar PV modules
- China's emergence as a low-cost PV and wind manufacturing powerhouse
- Apparent "revolutions" in shale gas and tight oil production that are, so far, largely confined to North America.

These changes have also helped catalyze a **widely divergent set of recent energy scenarios that paint fundamentally different pictures of energy, environmental and social futures** (Martinot 2013; IEA-RETD 2010; BP 2013). A select group of these scenarios is presented in Table 1.1. The majority are global in nature, but examples at the regional and national level are also provided. The table highlights some differences in the assumptions that contribute to the metric of interest highlighted here: the percentage of renewable energy that is envisioned in the future. These percentages range from 12% in 2030 (BP) to 82% in 2050 (Greenpeace 2012) – even on this seemingly simple metric, definitions play a fundamental role in understanding their results. **The motivations and drivers behind the scenarios help explain much of the differences,** but the types of models used, data assumptions made, and measurement metrics chosen also play a role in the different outcomes.

Table 1.1 – Selected Recent Energy Scenarios and Their Major Characteristics

Scenario Name	Organization	Outlook Period	Model Name (Characteristic)	Drivers	Energy Accounting	RE % at End of Outlook Period
Global Scenarios						
WEO Current Policies (2012)	IEA	2035	World Energy Model (WEM) (Hybrid)	Current policies and measures	Physical	14
WEO New Policies (2012)	IEA	2035	WEM (Hybrid)	Current and announced policies	Physical	18
WEO 450 (2012)	IEA	2035	WEM (Hybrid)	2 degrees stabilization	Physical	27
WEO EWS (2012)	IEA	2035	WEM (Hybrid)	All viable efficiency measures	Physical	19
BP Energy Outlook (2013)	BP	2030	Unknown	“Most likely future”	Substitution	12
Shell Oceans (2013)	Shell	2060	Unknown	Classic scenario analysis	Unknown	60 (solar only)
EM Energy Outlook (2013)	Exxon Mobil	2040	Unknown	“Most likely future”	Physical	15
ACES (2010)	IEA RETD	2060	TIMES (tech)	2 degrees stabilization	Substitution	62
ETP 4DS (2012)	IEA	2050	MARKAL (tech)	4 degrees stabilization	Physical	24
ETP 2DS (2012)	IEA	2050	MARKAL/ (tech)	2 degrees stabilization	Physical	41
GEA-Mix (2012)	IIASA	2050	MESSAGE/IMAGE (hybrid/integrated)	2 degrees plus other social goals	Substitution	37
MiniCAM EMF22 (2009)	PNNL	2100	GCAM (integrated)	~2 degrees stabilization	Direct equivalent	31 (2050)
Energy Revolution (2012)	Greenpeace	2050	MESAP/PlaNet (tech)	Revolutionary change	Direct equivalent	82
Regional Scenarios						
EU Energy Trends (2009)	European Commission	2030	PRIMES/Prometheus (hybrid)	Baseline	Physical	18
Rethinking 2050	European RE Council	2050	Unknown	100% renewable goal	Unknown	96
National Scenarios						
China LBNL (2011)	LBNL	2050	LEAP (tech)	Current policies and modest projected improvements	Physical	8
China ERI LC	China Energy Research Institute	2050	IPAC-SGM (hybrid)	Low carbon	Direct equivalent	32 (includes nuclear)
U.S. AEO Ref (2013)	U.S. DOE EIA	2040	NEMS (hybrid)	Current policies and measures	Substitution	14
U.S. REF 80% (2012)	NREL	2050	ReEDS (tech/spatial)	80% RE Generation	Direct equivalent	80 (power sector only)
Hybrid = emphasizes both economic linkages and technology detail; tech = emphasizes technology richness; integrated = integrated assessment model; spatial = emphasizes geospatial and temporal richness						

1.3 What Differentiates Energy Scenarios?

We note here three major characteristics of energy scenarios that are critical to anyone who commissions scenarios, or uses results. There are many other characteristics to consider, but these three will help to frame and inform the information provided in the chapters that follow.

- **What drives the scenario?** Is it an attempt to predict a "likely" future or is it a normative (prescriptive) description of a desired future end state?
- **What type of model is it?** No model can perfectly represent either economic or technical aspects of what it is trying to simulate, so how does it address the tradeoffs? For example, does the model represent economic relationships in more detail while sacrificing technological detail or vice-versa? Does it try to abstract the entire economic system, or focus just on one market segment?
- **What does the underlying data really mean?** Providers of energy and economic data often use different measurement metrics and a failure to understanding these nuanced differences can lead to misinterpretation of results. How is economic activity measured? Is renewable energy generation measured using the *substitution* method or the *direct equivalent* method[3]? The difference can vary by a factor of three, and has major implications when renewable energy accounts for a significant role in future energy systems.

1.4 Scenario Drivers

Table 1.1 characterizes energy scenarios by their primary driver. In reality, scenarios have an enormous number of drivers that are dependent on underlying assumptions (motivation, economic activity, population, fuel prices) and model characteristics (technology richness, economic feedbacks, spatial detail). Many recent scenarios, however, are policy-driven or normative descriptions of a future we may want to move toward. They attempt to determine, for example, the best pathway to achieving carbon mitigation that would limit the increase in average global temperatures to two degrees Celsius. Or they inform options that can be used to help achieve universal energy access by a certain date, or energy security as defined by a certain metric. Some remain relatively narrow baselines of how the current system might behave without significant policy, economic, or technology dynamics.

1.5 Types of Models

There are many different types of models used for energy scenarios, and they can give different results even when inputs are harmonized. Models have been classified as either **top-down** (focusing on economic relationships) or **bottom-up** (focusing on technology detail), although this labeling dichotomy is losing relevance as many energy

[3] The three main energy accounting methods (substitution, direct equivalent, and physical) treat primary and final energy measurement differently as discussed in Section 1.6.1.

models are now actually **hybrid** in structure. Choosing the best model(s) to use for scenario analysis involves trade-offs: no single model is ideal in representing the complex economic, technical, social and behavioral uncertainties associated with future conditions. We have simplified the summary in Table 1.1 to classify models as primarily those with at least some balance between economic relationships and technology detail (hybrid), those with rich technology detail (tech), those that provide an integrated vision of how economic and physical systems interact with one another (integrated assessment), and those with rich spatial and temporal detail (spatial). Chapter 2 provides more detailed information on model differences and how they can be best chosen for scenario analysis.

1.6 Underlying Data

Important differences exist in the way key organizations collect and disseminate global energy and economic statistics.[4] These differences can be magnified when used in energy scenarios that project far into the future, especially when non-fossil fuels play a significant role. We describe here some of the fundamental differences in accounting frameworks used in typical energy scenarios and what to look for so that the numbers are properly interpreted. Chapter 3 explores data issues in more depth.

1.6.1 How Primary and Final Energy are Measured Can Result in Large Differences

There are three common methods of reporting primary energy statistics: the substitution method, the direct equivalent method, and the physical method (Macknick 2009; IPCC 2011; IIASA 2012). The differences arise largely from the way conversion losses from primary forms of energy (upstream) to final forms (downstream) are treated. It is important to know which method is being used in energy scenarios because the **differences in certain renewable energy portions can appear to be three times as large upstream even though they are measuring the exact same number of kilowatt-hours produced downstream**.

The **substitution method** treats most forms of renewable energy *as if* they have similar conversion losses as coal (i.e., roughly 2/3rds of the energy is lost in converting coal into electricity) or other specified fossil reference source. It substitutes these assumed losses back into to the conversion calculation from downstream to upstream form. Generally, BP, the EIA and the World Energy Council use the substitution method.

The **direct equivalent method** takes each downstream kilowatt-hour of renewable and nuclear generation as the same kilowatt-hour when reporting its contribution upstream (no conversion losses are assumed). This method is typically seen in UN and IPCC publications. The physical method is often similar to the direct equivalent method but uses different conversion factors for “heat producing” sources.

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[4] These organizations include the International Energy Agency, the United Nations, the U.S. Energy Information Administration, and BP Group, among others.

The **physical method** is generally used in all OECD, IEA, and Eurostat publications. Text Box 1 below clarifies the importance of understanding the differences in primary energy accounting methods.

Text Box 1: Different Energy Measurement Metrics Matter

This example clarifies the importance of understanding the differences between the substitution method and the direct equivalent method in energy scenarios, especially when present and future energy contributions are noted as percentages of the total energy mix. In the WEO 2012, global hydropower generation in 2010 is reported as 3,431 terawatt-hours (TWh) while nuclear is reported at 2,756 TWh. When measured in primary form, the share of nuclear in the total global energy mix is reported as 6% while hydro comes in at only 2%. This is due to the differences in conversion process between the two otherwise similar sources. **The direct equivalent method (and sometimes the physical method) makes the contribution from renewable energy appear smaller than does the substitution method, especially when relatively large portions are part of the energy system.**

As noted in Macknick (2009), the main reporting agencies typically use the following energy accounting factors as shown in Table 1.2 when converting between final and primary energy measures.

Table 1.2 – Selected Energy Conversion Factors Typically Used by Data Providers

	IEA	EIA	BP	UN
Nuclear	33%	29-35%	38%	100%
Hydro	100%	34.4%	28%	100%
Wind and PV	100%	34.4%	N/A	100%
Geothermal	10%	16%	N/A	100%

The importance of the different ways in measuring and tracking energy is highlighted in the current *Sustainable Energy for All* discussions at the United Nations[5]. One of the objectives of this initiative is to double the share of renewable energy in the global energy mix by 2030. Without a clear and common understanding of what the current mix is, it may be difficult to declare the objective realized (IRENA 2013).

1.6.2 How Economic Activity is Measured Varies Substantially

How the value of economic goods and standards of living are measured in different countries can vary substantially, especially in developing countries. When measured in **purchasing power parity** (PPP), for example, China's annual per capita gross domestic product is estimated at approximately $8,400 while on the **exchange rate** scale it is closer to $5,400 (IMF 2012). Knowing which accounting method to use is essential for commissioning an energy scenario that helps inform objectives; for consumers of energy

[5] http://www.sustainableenergyforall.org/

scenario information, knowing which is used is also essential to properly interpret the results. This difference in measures can have an impact, for example, on properly interpreting a country's energy intensity level, or how much energy is needed to drive economic growth.

A second common misunderstanding occurs between **current-year and constant (or real) currency values**. The difference between these measures grows over time. A model that uses a capital cost for utility-scale PV of €2000/kilowatt in current currency might be considered a worthy pursuit now, but if it was intended to represent the inflation-adjusted real value of the currency in 2030, it would probably be considered expensive. For 2050, it would likely be considered unrealistically high.

1.6.3 Energy System Boundaries Vary Significantly

Modelers or scenario makers may make qualitative distinctions between different types of energy. Is traditional biomass included in the energy statistics? The IEA and UN statistics usually include detailed estimates of both modern and traditional (non-commercial) biomass use (Macknick 2009; IPCC 2011). Excluding them makes the contribution from renewable energy appear to be half as large when measured as a percentage of total energy mix. This is obviously an important metric to be aware of. In fact, together with the differences in how to measure primary and final energy, **measures of the global renewable energy mix can vary from a low of roughly 4% (direct equivalent method and no traditional biomass included) to a high of over 16% (substitution method and traditional biomass included)** (Martinot et al. 2007).

What about hydropower? Are distinctions made between large versus small, reservoir versus run-of-the-river plants, or perceived level of "sustainability"?

As a final example, international bunker fuels (petroleum products consumed at airports, in ports, and during international transport of goods) may or may not be included in global energy statistics. Yet, they account for over 6% of all petroleum product use according to one set of statistics (EIA 2012).

1.6.4 What Other Conversion Factors Are Important?

Is the higher or lower heating value assumed when determining final energy use (Macknick 2009; IPCC 2011)? What heating value and greenhouse gas conversions are assumed in the scenario? Proper interpretation of energy scenario results can be impacted by the conversion used.

To help address the communication barriers between energy modelers and decision makers, as noted by Munson (2004), scenario authors should be responsible for clearly identifying all assumptions used in their energy scenarios. **A concise summary for key stakeholders should be included in most energy scenarios, as well as a pre-publication review by diverse experts and decision makers.**

1.7 Overview of Remainder of the Report

Chapter 2 of this report describes the **types of models** that are typically used to conduct scenario analyses. It focuses on characteristics, and relative strengths and weaknesses of different classes of models. It illustrates how a particular family of model may be better for answering one series of questions than another.

Chapter 3 focuses on understanding **key inputs and drivers** of scenario models. Technology cost and performance assumptions are often considered to be the core of energy scenario assumptions, but many other variables also play an important role, including resource characterization and constraints, financing assumptions, and outlooks on incentives.

Chapter 4 illuminates the role that **non-technical drivers** play in energy scenarios. These include both involuntary and voluntary biases on the part of the commissioning agency or modeling team, social issues including, but not limited to, "not in my backyard (NIMBY)", siting issues associated with different jurisdictional authorities, supply chain issues that may be stretched or broken under certain types of scenario outcomes, and the unpredictable nature of human behavior on the likelihood of achieving certain outcomes in energy scenarios.

Chapter 5 delves into issues surrounding robust **design of scenarios** and how to maximize the likelihood of achieving valuable results.

Chapter 6 focuses on **boundary conditions** associated with proper scenario design.

Chapter 7 looks at issues specifically related to **modeling renewable energy** in scenarios, including variability, integration, and resource characterization.

Chapter 8 reviews some of the classic "**misses**" in energy scenario results and highlights previously ignored examples. It notes impacts of the misses, how they may have been avoided, and the role that **retrospective analysis** can play in learning more from past scenario mistakes.

Finally, Chapter 9 provides conclusions including a list of guidelines that consumers of energy scenario results should consider, and commissioners of new energy scenarios should discuss before choosing a scenario team.

2 Understanding Model Types and Classifications

There are many different types of models used for energy scenarios, and they can behave very differently and give vastly divergent results even when inputs and assumptions are aligned. There are numerous ways to classify models—for instance: top-down vs. bottom-up, equilibrium vs. optimization vs. simulation, and intertemporal vs. sequential. The complexity of the ecosystem of models is both a source of confusion and a boon for analysts. On one hand, the complexity means that results often diverge across models and that there is always one more model or scenario to consider; on the other hand, the range of available models generally span the space of possible models and can serve to balance each others' weaknesses and biases.

Many reports have surveyed classifications of model types, including van Beeck (1999) who described nine ways of categorizing models. Here we restrict ourselves to three classification dimensions:

1. Analytical approach (engineering or economic, to abuse both terms)
2. Methodology or "solve structure"
3. Level of foresight.

Other categories van Beeck uses—geographic coverage, sectoral coverage—are also useful for describing and classifying models, which we consider in Chapter 6, our discussion of model scope and boundary conditions. In addition, while we do not address these considerations in this document, the ownership and licensing of models varies dramatically: some can be very expensive, others are now offered in open source format. Some offer well-developed user-interfaces, others do not, creating barriers to new users.

2.1 The Analytical Approach: Top-down vs. Bottom-up

Two contrasting modeling approaches have developed for answering questions of the future of the energy system under technological, policy, or economic scenarios. The two approaches, called "bottom-up" and "top-down," emphasize different aspects of energy and economic decision making and, because of their different approaches are more-or-less suited to different types of questions. Increased understanding of the strengths and weaknesses of the two approaches over the past couple of decades has resulted in development of hybrid models that combine the two approaches in a single model or single integrated framework.

2.1.1 Bottom-up Models Capture Technical Detail

Bottom-up models are technologically specific representations of, in this context, the energy sector. They represent specific products and technologies to describe end-user goods and technological options in detail. These models, in keeping with an engineering/economic approach, are able to capture competition among technologies, and monitor or allow technological progress. The tight sectoral scope of these models makes them blind to macro-economic feedbacks: depending on the construction of the model a carbon cap will change the technology mix, induce fuel switching, perhaps influence vehicle choice or energy consumption; but a bottom-up model will not provide information about how the carbon cap affects economic growth, or how the cost of the cap is distributed across parties.

The ETP model, used for the Energy Technology Perspectives scenarios highlighted in Table 1.1, is a linked arrangement of four bottom-up models describing energy conversion, industry, transport, and buildings. Together, they provide a technology-rich description of energy supply and demand to develop global energy scenarios to 2075. The ETP analysis “provides important insights into the cost of CO_2 reductions for consumers and for the global economy” (IEA 2012a) but self-admittedly does not assess macroeconomic impacts of CO_2-mitigation scenarios: distribution across geography or demographics of economic growth impacts. Instead the ETP references similar scenarios created by top-down models to estimate GDP impacts of its scenarios.

2.1.2 Top-down Models Capture Economic Relationships

Top-down models describe market behavior and economic preferences to specify the economic system instead of focusing on technologies. The top-down approach allows wide coverage of interactions across sectors and regions, and it models economic interactions, including aspects of market distortions, through calibration to historical behavior in real economies.[6] The historical calibration gives top-down models the capacity to imply some non-economic decision-making (e.g., public acceptance restrictions on siting). On the other hand, because they are calibrated to historical behavior and often remain constant over time within the model, top-down models generally imply that the technologies, preferences, and behavioral patterns wrapped up in the model coefficients are fixed, or at least exogenously defined. Technological advancement, public policy, and shifts in attitudes or behavior have limited ability to change market dynamics.

Another limitation of top-down models is that they do not respect physical constraints. For example, transitioning from a coal-based electricity system to a natural gas-based system—unlike in a bottom-up model—is not governed by the physical replacement of a coal fleet with gas turbines. While the model is theoretically tuned to reflect the “stiffness” of the physical system, the calibration is necessarily generalized and coarse, and can sometimes lead to unrealistic behavior, especially for physically “sticky” or bulky, capital-intensive sectors like energy.

The differences between top-down and bottom-up models have prompted substantial debate over the years. Grubb (1993) comes close to calling the top-down approach

[6] In particular, industries and energy conversion are represented by the set of inputs required to produce the final product (production functions), and the ability to rearrange those inputs is characterized by elasticities of substitution. The production functions and elasticities of substitution are the calibrated quantities that define model behavior.

"pessimistic" and the bottom-up approach "optimistic" when discussing the "persistent gap" between the approaches. Top-down models are faulted for their failure to reflect physical realities and their inability to allow for substantial change. Bottom-up models take criticism for assuming economic rationality—finding and capturing improvements to current infrastructure that are, for various reasons, not appropriated in reality.

2.1.3 Hybrid or Linked Models Try to Capture the Best of Both Approaches

The persistent gap between and the clear shortcomings of each of the two approaches prompted a movement toward **hybrid models that link top-down and bottom-up approaches in a single integrated framework**. The hybrid models created from these linkages emphasize the strengths of each of the component models: the technological specificity and physical underpinnings of the bottom up models with the more-realistic microeconomic decision making and macroeconomic feedback associated with top-down models (Hourcade et al. 2006).

Böhringer and Rutherford (2008) discuss three methods of linking top-down and bottom-up methodologies. 1) Linking two independently developed, full-featured models. 2) Emphasizing one of the two approaches in a combined system (e.g., a full-featured, top-down model with a reduced-form, bottom-up energy sector model). Both still capable of being run independently, but the secondary model highly simplified compared to its stand-alone equivalent of the first type. 3) Building a single completely integrated framework with the two approaches within it. Many of the models presently used for energy/economy/environment analysis circa 2013 are hybrid models: examples include MESSAGE-MACRO and WITCH[7].

2.2 The Methodology: Equilibrium, Optimization, and Simulation

This classification dimension refers to the solve methodology of the model. **Equilibrium models balance the flow of goods and services in an economy, optimization models are structured to minimize or maximize a quantity** (e.g., minimize cost) while meeting stated requirements, and **simulations describe a process according to a set of rules**. Other model formulations are used as well, and the population of hybrid models generally links a top-down general equilibrium model with a bottom-up model of another type.

2.2.1 Computable General Equilibrium to Balance Supply and Demand

General equilibrium, or computable general equilibrium (CGE) models are representations of the **full economy that relate producers and consumers through supply of and demand** for goods and services (see Figure 2.1). Consumers, generally

[7] MESSAGE-MACRO is an example of the first hybrid model type, a bottom-up energy model (MESSAGE) nested inside a top-down, full-economy model (MACRO), each of which can be run independently (Messner and Schrattenholzer 2000). WITCH is an example of the third type: a framework includes both the top-down economy-wide model and the detailed energy sector (Bosetti et al 2011).

considered as households, supply labor and capital to production sectors, which in turn convert those inputs to goods and services for consumption by the consumers.

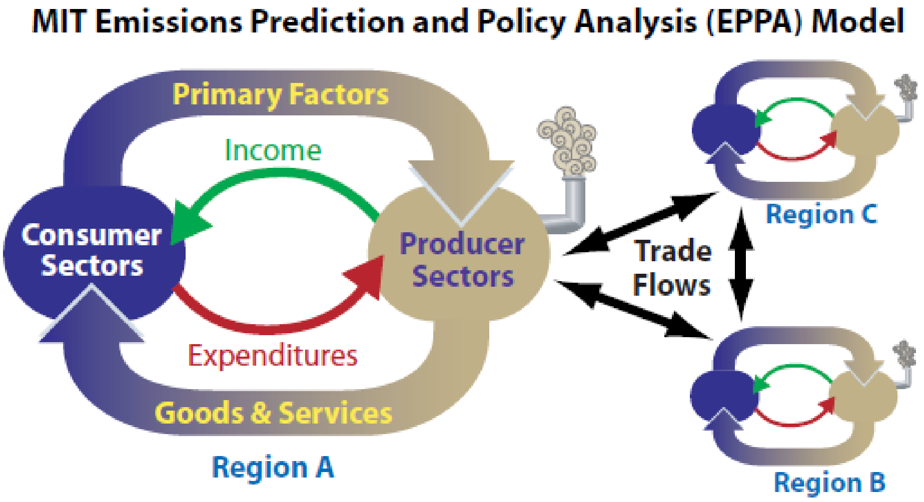

Figure 2.1 – A Visualization of the Consumer/Producer Relationship and Flow of Goods in the EPPA CGE Model

Source: Paltsev et al. (2005)

CGE models find a set of prices that balance supply and demand across the set of commodities, and balance the households' expenditures on goods and services with their income from their contributions to production. Partial equilibrium models similarly balance supply and demand but for a smaller set of commodities and within a limited set of economic sectors rather than the entire economy. All other commodities are assumed to have fixed or exogenously defined prices.

How consumers value goods relative to each other are described by elasticities of substitution that are calibrated from historical economic data. The production functions that describe how capital, labor, energy, and material inputs are used to produce outputs are similarly defined. The interrelationship of consumers and producers across multiple sectors of the economy allows these models to estimate how economies evolve in different technology, economic, or policy scenarios.

Global CGE models often include multiple independent consumer/producer loops linked by international trade flows.

2.2.2 Optimization to Select the Best Pathway

An optimization model **minimizes or maximizes a stated quantity**. In the context of energy models, the optimization is usually over investments in energy infrastructure. Optimization models are constructed with an objective function (e.g., minimize cost, maximize welfare, maximize the sum of producer and consumer surplus) and a set of constraints that reflect requirements or physical realities (e.g., serve load, any fuel used must both be paid for and exist in the available resource).

These models are driven by their cost assumptions. How much does it cost to build this, operate that? What is the cost of fuel? Tracking physical stocks and resource allotments are important, but decisions are made based on costs. Optimizations are known to be "knife-edgy": if option A is even a penny cheaper than option B, the model will choose all option A and none of B. As a result, conscientious modelers will build mechanisms to encourage distribution into their models to mitigate the concern.

Optimization models can also include a partial equilibrium component.

2.2.3 Simulation

Simulations do not seek to balance or optimize, but instead **follow rules set forth by the modeler**. Like a billiard ball bouncing around the table in accordance with the laws of physics, a simulation makes incremental advances, generally through time, from its initial condition to some other (later) state.

Constructed as a series of computations, simulations make their investments (for example) not as decisions or choices as in optimizations or equilibrium models, but based on formulae. To induce diversification, simulations generally rely on market share algorithms like logit functions to allocate investment dollars across competing technologies—a simulation's analog to reducing knife-edge behavior in optimizations. The WEO model (WEM) and the demand modules of ETP model are stock-accounting simulation models (stock-accounting describing that the models explicitly keep track of infrastructure stocks through time). The ETP energy supply module is an optimization of the sort discussed above.

Like equilibrium models, simulations require careful calibration (e.g., of the logit coefficients) to produce realistic behavior. As with CGE models, however, such coefficients are exogenously selected and often static, which may inhibit models from reflecting changes in consumer/producer behavior over time. When properly balanced, however, such models can be excellent tools for scenario-building: they are inherently parallelizable—the math can be distributed to a large number of computer processors and solved simultaneously—rendering them better able to leverage the trend of high-performance computing than equilibrium or optimization models; and they lend well to stochasticity—introduction of randomness or probability—and Monte Carlo analysis.

2.3 Foresight: Intertemporal vs. Myopic

Classification based on foresight differentiates models based on how much "knowledge" of the future a model has when it makes decisions. **Intertemporal models make all decisions across the time horizon simultaneously**. Because all decisions are made simultaneously, the model has perfect foresight and can act strategically by, for instance, making investments in early years that will yield dividends much later.

That foresight is in contrast to myopic models that make decisions in stages, with limited information about future conditions. These models generally employ a sequential framework where fixed time windows are solved seriatim. Because the model is considering only a short time interval (e.g., a handful of years out of a decades-long total timeframe), **it makes investments without knowledge of their performance beyond that window**. Thus, decisions can be, in retrospect, shortsighted. Because some information is, in fact, known in advance, most developers of myopic models imbue their agents or central planner with specific future information that one would be expected to know ahead of time. A GHG mitigation scenario, for instance, would make the pending regulation common knowledge before the model year that the regulation takes effect (similarly, the model would be told about the trajectory of a ratcheting-down carbon cap). That information will prevent the model from investing unwisely in fossil fuel technologies that would be stranded or underutilized shortly, if built. On the other hand, political and other uncertainties, can prevent "future knowledge" from being acted upon.

A notable side-effect of intertemporal or sequential structure is that (if there were such otherwise-equivalent models) an intertemporal model is solved via a single, large computation process (a single "solve") whereas a sequential model is solved through a series of smaller solves.

There are a few models, notably the EIA's NEMS, which blend sequential and intertemporal construction to take advantage of the strengths of both[8]. Decisions are made based not only on current conditions but also on projections for conditions in the mid-term—some of which may turn out to be wrong. **This approach is closest to matching real-world decision making**. In comparison, intertemporal models with perfect foresight provide more-optimistic scenario assessments, always making perfect long-term decisions; and myopic models, which only have information about current conditions, are pessimistic, more likely to make ill-considered investments, thus increasing costs and risking stranding assets. The drawback of sliding-window models is the heavy computational burden.

2.4 Scenario Taxonomy: Descriptive vs. Prescriptive Scenarios

Along with models taking different forms, analysis projects have different aims and objectives. The different types of studies can be classified in various ways, as by McDowall and Eames (2006). We first describe two broad categories of scenarios: descriptive and prescriptive. **Descriptive scenarios extrapolate from current or stated conditions based on current or implied trends**. **Prescriptive** (McDowall and Eames call this category "normative") **scenarios impose a desired future state and describe that state or pathways to achieve that state**.

[8] NEMS has a sequential sliding-window formulation, with a set of several years solved iteratively to convergence so that there is perfect foresight within the cycle. Within each cycle, there are opportunities to make strategic investments based on mid/long-term information. NEMS then slides the cycle forward by less than the length of the cycle and repeats the process. Only the investments from early in the cycle are saved, and assumptions and projections are updated to prepare for the next solve (EIA 2012a).

Descriptive analyses explore. Depending on the project, they might explore implications of potential policies, technological changes, or—for an economy-wide model—population growth and economic development. Such scenarios do not have a predetermined end state, instead choosing their own path into the future, perhaps steered by externally defined conditions (e.g., the prospective policy).

Under the "descriptive" umbrella, McDowall and Eames differentiate between "forecasts," "exploratory scenarios," and "technical scenarios" where forecasts predict likely futures based on current conditions and projections while exploratory and technical scenarios survey futures with alternative projections (e.g., of technological development or energy policies).

In prescriptive analyses, the future is known, and the model's purpose is to describe that future or how to reach that future. Names for sub-types of prescriptive analysis—"visions," "storylines," "roadmaps"—allude to how the scenarios are used. Visions emphasize the future state: what it looks like, how it behaves. The model contributes an internally consistent framework to flesh-out the raw vision. Storylines and roadmaps are about the path to that future, where "storylines" refers to an emphasis on external conditions (demographics, economic growth, general technological progress) and "roadmaps" refers—loosely—to actions that may be undertaken (policies, targeted technological development) to steer along or reduce barriers on that path.

2.5 Summary

While it is important to pair models and analysis questions appropriately, the categories of models and different styles of scenarios discussed here unfortunately do not provide a recipe for such pairings. Some model types are better-suited to certain of these analysis types than others, but even within each model classification bin, individual models can have vastly different strengths and weaknesses. Nevertheless, the classifications can provide some guidance:

- Descriptive, "exploratory" scenarios call out for bottom-up models, especially if they involve transformational technology changes because of the ability of bottom-up models to adapt behavior to changing circumstances.
- Myopic models are useful for "forecasts" and "visions" where limited knowledge of future conditions is preferred, while "storylines" and "roadmaps" often benefit from foresight.
- Top-down, CGE models are most useful for analysis taking an economy-wide perspective, e.g., concerned with economic growth and distribution impacts of policies. Not having explicit technological representations, they would be less useful for an exploration of the mitigation potential of renewable technology development.

But knowing the individual character and quirks of the models is more important. As discussed in Chapter 5, analyses often benefit from using multiple models that complement each other: multiple models of different scope (Chapter 6) with aligned inputs to look at scenarios at different scales; including both top-down and bottom-up architectures, whether in an integrated framework or separately. Robust results come from asking the right questions of the right set of models.

3 Finding Key Knobs and Levers in Models

In this chapter, we provide insights into the **key model inputs that drive scenario results**. We do not attempt to comprehensively evaluate input parameters across all models or even for a single model. Detailed sensitivity analyses[9] (see Chapter 5) can help identify drivers for a particular study and we recommend such analyses to accompany all studies. Our goal is to highlight key considerations on input data for the critical consumer of scenario results.

3.1 Business-as-Usual Assumptions Lead to Business-as-Usual-Results

Energy models are driven by a large set of interacting data inputs and their relative importance can vary depending on model and analysis. The primary driver in many energy scenarios is the assumed future policy landscape and its design within the modeling framework. This is particularly true for scenarios with greater deployment of low-carbon technologies. Martinot et al (2013) shares this sentiment and states, "indeed, policy is one of the main drivers in moderate and high-renewables scenarios."

Figure 3.1 provides an example of the business-as-usual static view through primary energy use projections from the Energy Modeling Forum (EMF) 22 reference scenarios (Fawcett et al, 2009). Five different models were used to produce future reference and carbon-constrained scenarios in the EMF 22 study. The reference scenario did not include any new carbon policies, and largely relied on business-as-usual assumptions. As a result, **all five models projected similar futures** with continued reliance on existing fossil fuel technologies (black dashed lines), and limited growth of renewable, carbon capture and storage (CCS), or nuclear technologies. The fractional mixes of the different fossil energy sources (oil, coal, gas) are even similar in 2050 across most of the models and are similar to the historical fractions.[10]

[9] Generally speaking, sensitivity analyses include systematic perturbations of data inputs to understand their influence on scenario results. For example, a core scenario may use a single fuel price trajectory, while multiple sensitivity scenarios can cover a spectrum of prices. This enables the modeler (and reader) to bound possible results and weight the importance of one lever over another. In short, the additional runs can identify how "sensitive" results are to certain key inputs.

[10] The MERGE result provides an exception in that oil consumption declines dramatically by 2050 and is largely replaced by coal.

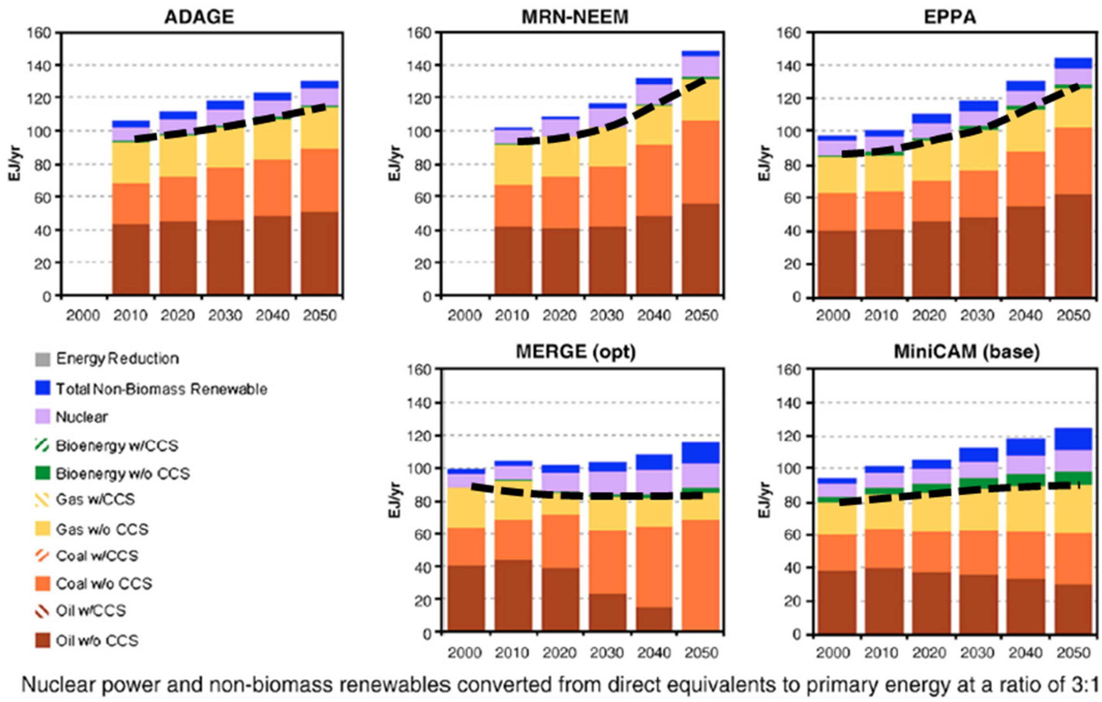

Figure 3.1 – Global Primary Energy Consumption from EMF 22 Reference Scenarios (dashed lines added to indicate fossil energy shares)

Source: Fawcett et al. (2009)

Without any new policies, model results are largely insensitive to other assumptions and generally project a smooth incremental change into a future that largely retains the characteristics of the present system. In fact, this business-as-usual projection often does not even closely resemble the past, which may be jagged with multiple political, economic, and technological shocks. Figure 3.2 demonstrates the booms and busts of various generation technologies in the U.S. power sector, while Chapter 8 provides other prominent examples of shocks and scenario misses.

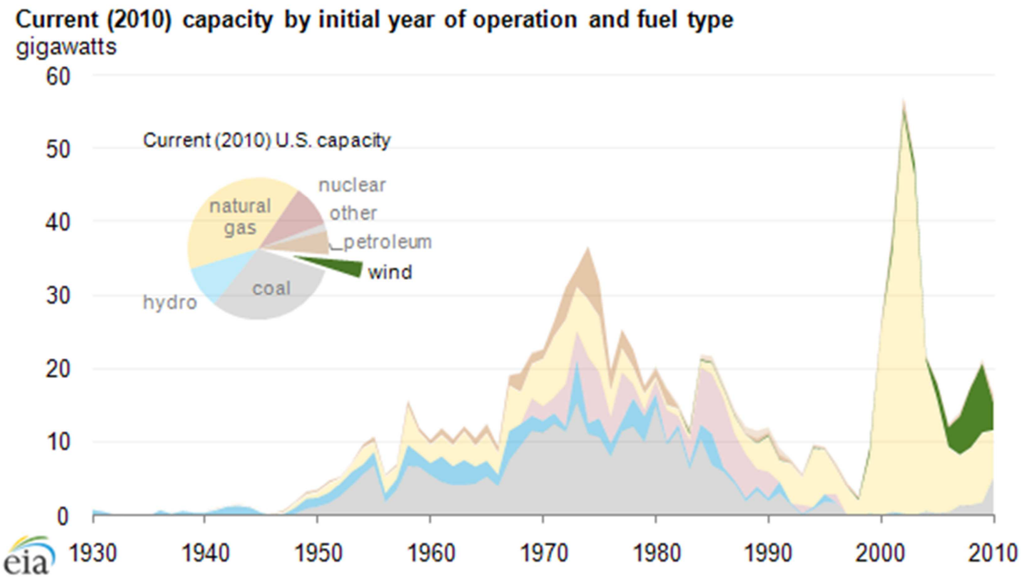

Figure 3.2 – Installed Capacity by Year in the U.S. Power Sector

Source: EIA (http://www.eia.gov/todayinenergy/detail.cfm?id=2070)

3.2 Winners (and Losers) in Transformational Scenarios Are Highly Sensitive to Policy Assumptions

While variations in business-as-usual scenarios are generally minor, scenarios with transformational changes in the energy system vary significantly and are highly sensitive to model assumptions. Transformational scenarios are commonly the result of a strong policy driver or implied policy and they, by definition, do not resemble the present. These scenarios typically represent a shift from today's conventional technology-based system into one consisting of low-carbon technologies. However, there exists a portfolio of clean energy technologies and the technology outcomes depend on modelers' assumptions and their modeling framework. **Sometimes the options live on a knife's edge and the winners and losers are determined by minor perturbations**, some of which are not explored fully by modelers.

The EMF 22 scenarios are again used to illustrate this point. Figure 3.3 shows scenario results for a carbon-constrained scenario (203GtCO_2e) from the same models as in Figure 3.1 (Fawcett et al., 2009). In contrast to Figure 3.1, the 2050 energy mix in Figure 3.3 varies dramatically across models. There is no consensus between the choices of energy efficiency, renewable, nuclear, and carbon capture and sequestration (CCS) technologies to mitigate carbon emissions. Even within the CCS category of technologies, there is significant variation in the relative deployment of coal with CCS, gas with CCS, or bioenergy with CCS between the models. This example highlights that **assumptions become much more critical under transformational scenarios** and that assumptions need more careful examination under such scenarios.

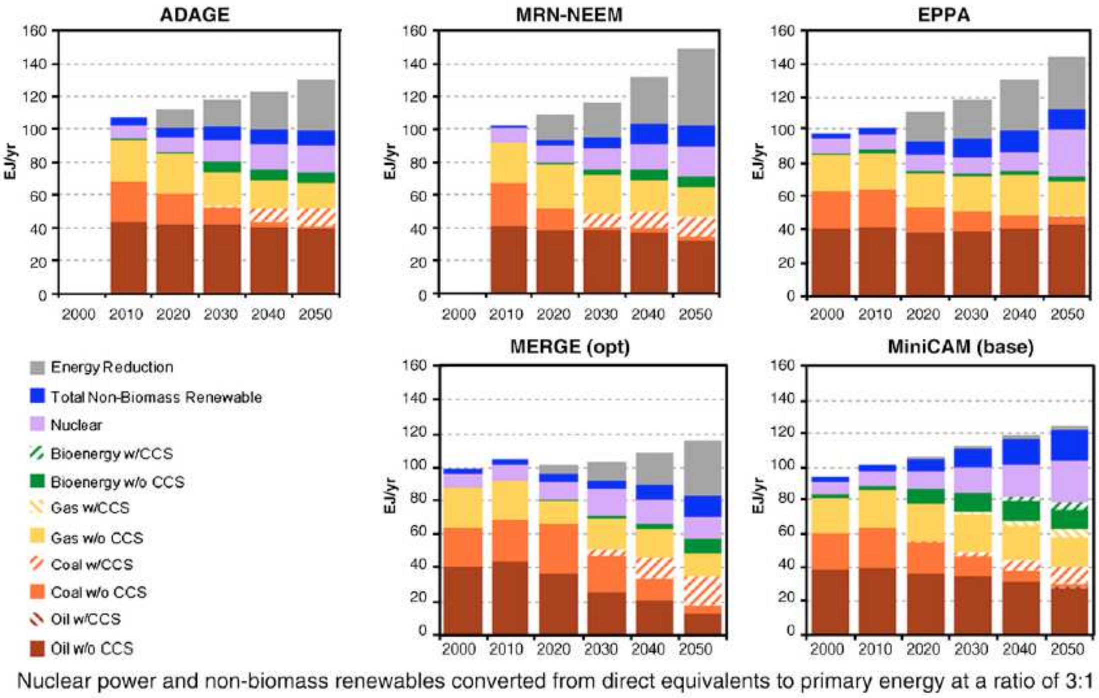

Figure 3.3 – Primary Energy Consumption from EMF 22 Carbon Constrained (203GtCO$_2$e) Scenarios

Source: Fawcett et al. (2009)

3.3 Costs Are Principle Drivers of Model Results

Energy models are driven by costs, which move the economically-rational (model) world. Many input data must be monetized in order to inform the model to find the least-cost solution or balanced equilibrium point. Though there are many factors in each model, **technology and fuel costs are typically principle drivers of model results**. However, cost figures are both difficult to ascertain precisely, and vary dramatically, by country and region, see Figure 3.4

How technology costs are applied in models should also be carefully explored. Technology costs cover a wide range due to region-specific conditions, resource quality, subsidies, and labor costs. As shown in Figure 3.4, the lower end of the ranges of levelized cost of energy (LCOE)[11] for most renewable technologies overlap those of non-renewable technologies. To understand how this fuller picture is represented in models, one might ask the following questions: Is the full spectrum of options available? Is a single value chosen to represent the entire span of costs? If so, what is the value and how was it chosen? In addition, the LCOE is a simple metric and does not fully represent all factors, including relative value and system-wide impacts. **It is more transparent and**

[11] The comparison of technologies is further complicated by the fact that costs are oftentimes compared with prices, while they are different economic quantities. For example, Feldman et al. (2012) surveys differences between PV *pricing* trends and *cost* trends in the U.S. over recent years.

credible when all relevant data, such as capital costs, O&M costs, heat rates, capacity factors, outages, discount rates, are provided instead of the more-aggregated, but less-informative, LCOE.

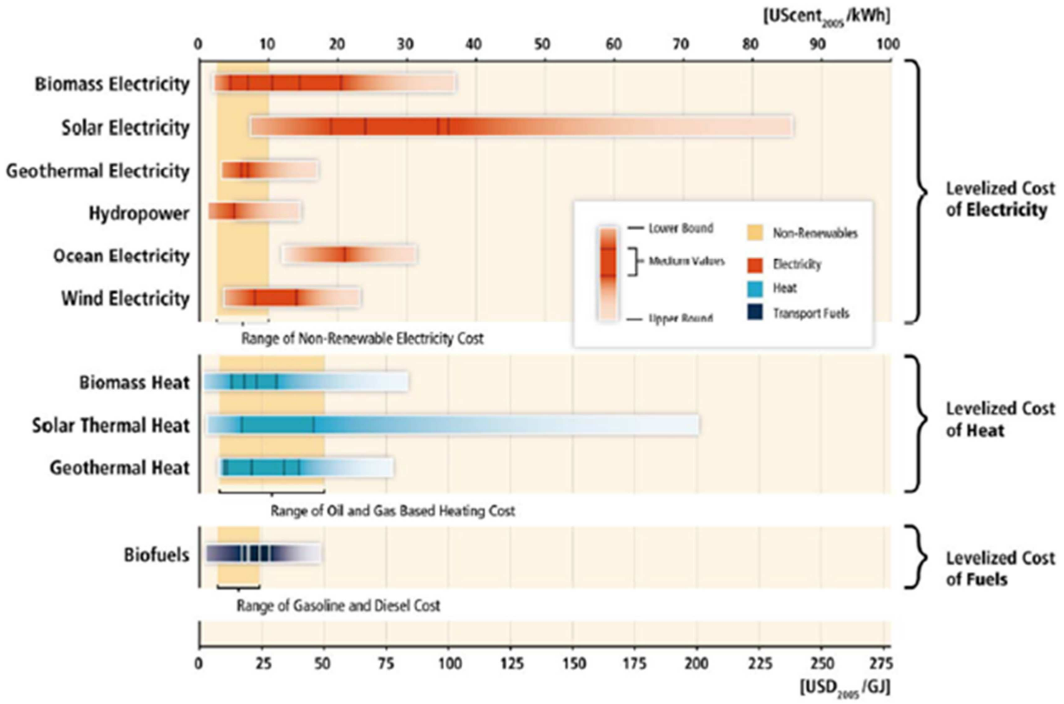

Figure 3.4 – Range in Levelized Cost of Energy for Renewable Technologies

Source: IPCC (2011)

Technology and fuel costs are often presented in reports and one can make reasonable expectations of outcomes simply from this data. However, it would be a mistake to focus on cost trajectories of individual technologies as deployment results are primarily driven by *relative* costs. Absolute costs, including fuel prices, play an important role in economic implications of scenarios (or of energy policies being modeled), but do not pick winners like relative costs do. For example, if low-carbon technologies are assumed to achieve little improvement, a carbon policy may be estimated to have high incremental costs (e.g., higher prices, lower GDP, or higher marginal carbon abatement costs) and the specific winning low-carbon technology will be determined in large part by the lowest cost technology.

The treatment of technology learning can also drive results. Learning curves (or "endogenous learning" within models) are often used to understand past trends and to forecast future cost reductions.[12] They operate under the premise that cumulative production of a technology leads to a reduction in costs and are often applied in models to endogenously simulate the influence of deployment on the underlying costs of the

[12] This paragraph summarizes the discussion from Text Box A-1 in NREL (2012).

technology. However, there are numerous potential pitfalls with the use of learning curves. The first is that learning curves imply that learning-by-doing explains all cost decreases, whereas, in actuality, cost decreases (or increases) are driven by R&D, supply-demand imbalances, material costs, economies of scale, etc. When technology improvement is strictly represented by learning curves, the modeler potentially misses other opportunities for cost reductions, and therefore, can shortchange improvement potentials of emerging technologies. Secondly, learning curves are complicated by system boundaries. Renewable energy markets are international, and if global renewable energy installations are outside the scope of the model, learning curves are not directly applicable within that model. Finally, technology maturity changes the shape of learning curves, such as through diminishing returns at the latter stages of technology advancement. The assumption of persistent improvement at the same rate could result in continued growth of the incumbent technologies (e.g., fossil) at the expense of newer technologies (e.g., renewables) with potentially greater room for improvement. Through their inherent feedback characteristic, learning curves can amplify these effects and, thus, how learning is applied in models should be critically reviewed.

The algorithms in many models are designed to represent central-planning decision making and least-cost options are prioritized. Though technology and fuel costs are certainly important drivers, the changing energy landscape calls this central-planning point of view into question. The growing deployment of rooftop PV systems provides a glaring counter-example to the least-cost perspective. Non-economic energy systems, including those in transportation decisions, demand-side behavior, and distributed generation, are deployed despite their higher costs relative to large central-scale systems. **With liberalizing markets growing consumer options, it is unclear how long the central decision-maker perspective of many energy models will remain pertinent**. Even in centralized model objective functions, individual investor's risk tolerance and specific revenue-maximization within his portfolio is not captured. As such, one must be keenly aware of the modeling framework (Chapter 2) to understand the potential influence of certain model drivers.

3.4 Missing or Hidden Factors Also Drive Model Results

Technology costs, fuel costs, and policies are all important data inputs to energy models. However, often the inputs that are *not* included in energy models can also play a role in a model's evaluation of technology competitiveness. Martinot et al (2013) points out three "key deficiencies of the conventional approach" to evaluating the competitiveness of renewable energy: **environmental costs, existing fossil fuel and technology subsidies, and fossil fuel price risk**.

The environmental cost of emissions and other pollutants are often not "internalized" by energy models. There is a large and growing literature on the cost of these externalities (e.g., EC 2003, NRC 2010, IWGSCC 2010, IPCC 2011), however, their application in energy models (or in actual policy) has been limited. Figure 3.5 shows estimated externality costs from a range of electricity generation technologies. Of particular note are the high estimates for fossil-based systems. The relatively higher externality costs for fossil generation compared with renewable generation are often not embedded in energy models. In fact, including these costs in Figure 3.5 with LCOEs from Figure 3.4 would bring parity between many of the renewable electricity technologies with coal (note the log scale on Figure 3.5). However, there is certainly a tremendous amount of uncertainty in externality cost estimates (IWGSCC 2010) and their applicability in energy models depends on the questions that are being answered.

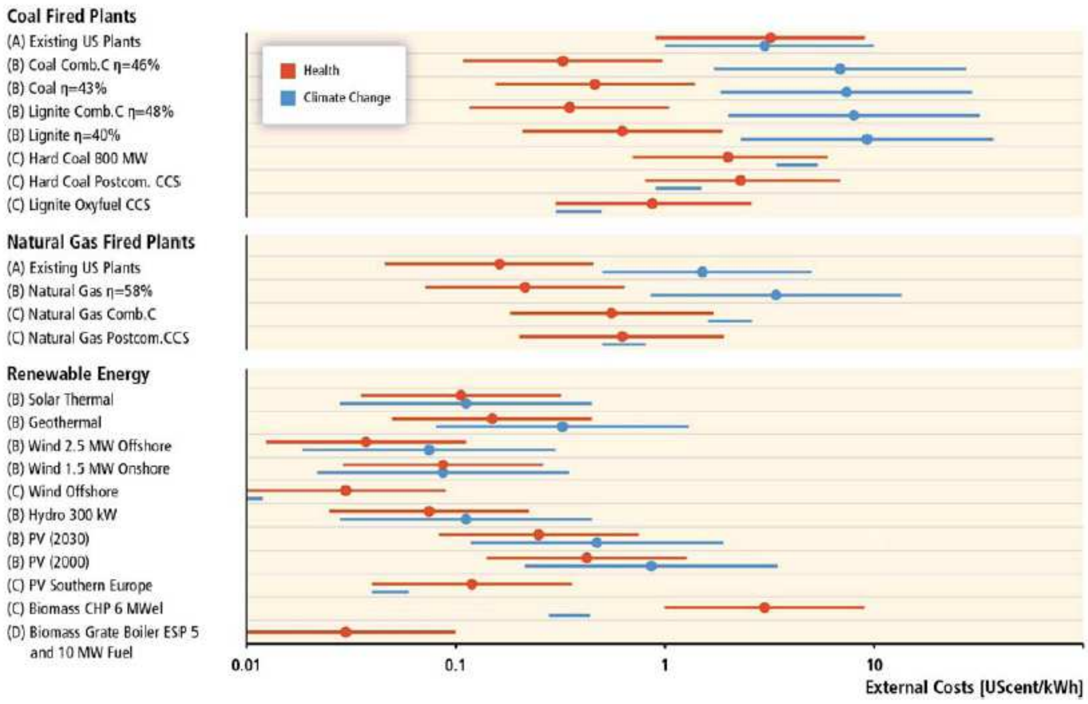

Figure 3.5 – External Life-cycle Costs of Electricity Generation Technologies

Source: IPCC (2011)

In addition, fossil subsidies and fuel price volatility are often not fully considered in many scenarios. Fossil subsidies may "tilt the playing field" toward fossil fuels, but the cost of the subsidies may not be factored in by energy models. In addition, although there is considerable effort to quantify the risk of fossil fuel price volatility, "hedging premiums" are often not included in models. This is true despite existing hedging practices by the utility industry, particularly in their integrated resource planning efforts. These are some common examples where the absence of real drivers, including externality costs, fossil subsidies, and fuel price volatility, can skew scenario results.

3.5 How Much Should the Future be Discounted?

One important assumption is the discount rate used in long-term energy models. The discount rate determines how much to weight costs incurred in the future relative to the present, i.e. it determines the net present value cost. Its influence on model results can depend on the model structure. For example, in an intertemporal model[13] the choice of discount rate can drastically affect model results. There is certainly a time value of money, however, figuring out what discount rate to use can be highly speculative and can depend on the context. Investors use discount rates, which can differ tremendously between individual investors, to inform debt payback and expected revenue return. Meanwhile, social discount rates are used to estimate social cost and benefits, and can also vary significantly. **Energy models rely on both types of discount rates and one must be clear what discount rate is applied for what purpose**.

A discount rate that is too high can lead to heavy reliance on future technologies to meet policy goals, even though future conditions have greater uncertainty. Conversely, a low discount rate can lead to misses for future opportunities and lead to erroneous (likely high) cost estimates to achieve clean energy policies. Finally, discount rates can determine the balance between competing technologies, especially when capital-intensive technologies are competed with fuel-intensive ones.

Because the discount factor grows exponentially over time, discount rates can be even more influential for scenarios that span multiple decades. As such, it is important to understand how models use the discount rate within their differing frameworks. Ideally, multiple models and a set of sensitivity scenarios that span a range of discount rates should be compared. Finally, **as with other key input drivers, transparency is essential for credibility**.

3.6 The Persistence of the Incumbent System Influences the Viability of New Technologies

Models are effective at weighing the economic value of competing technology options to meet new energy demands. However, **divestment or retirement decisions are not easily characterized and, thus, are poorly represented in most energy models**. In reality, the lifetime of energy assets vary significantly and can extend well beyond the design lifetime.[14] In models, the treatment of the incumbent system, particularly with respect to asset lifetimes, can have significant impact on scenario results. We find this class of assumptions to be critical, yet often under-stated in scenario reports.

One of the largest effects that technology lock-in assumptions have is on the implied costs of energy policies. When the incumbent system is assumed to have long lifetimes, the incremental cost of transforming the system can be overestimated. The incremental cost of replacing existing capacity with new renewable capacity would be much larger than the relative difference between new renewable capacity and new conventional options. These higher costs would be borne out in the estimated costs to transform and replace the existing fleet with new clean technologies. The converse situation may also

[13] An intertemporal model is one that considers all time periods within the model simultaneously, whereas a sequential model steps forward in time in defined increments (see Chapter 2).
[14] Figure 3.2 shows coal and hydropower units that have operated for nearly 80 years in the U.S.

be true: modelers may underestimate asset lifetimes and, thus, underestimate the incremental cost of one scenario over a business-as-usual one.

While the treatment of existing infrastructure can critically change scenario results, we also point out that **the treatment of emerging technologies, such as hydrogen, CCS, ocean technologies, or advanced vehicles can fundamentally alter scenario outcomes**. The technical and commercial viability of these technologies is highly uncertain, yet they can and do appear in many scenario results as major contributors. For example, four of the five scenarios shown in Figure 3.3 rely heavily on CCS technologies, whereas CCS has yet to realize large-scale deployment. This report does not imply that emerging technologies will not or could not play a major role in future energy supplies. Certainly, all technologies were considered "emerging" at some point and there are recent examples where technological innovation has revolutionized the energy sector.[15]

3.7 Other Major Data Input Considerations

We identify four other major considerations related to model "levers and knobs."

- Uncertainty: **All data inputs have uncertainties, most are difficult to quantify, and often none of the uncertainties are modeled**. For example, while investors internalize risks and hedge against price volatility, energy models typically do not consider these factors.[16] Oil and natural gas prices have proven to be highly volatile, while modeled fuel prices tend to follow smooth trajectories.
- System Boundaries: One must also understand system boundaries (Chapter 6) and the influence of exogenous assumptions on scenario results. Regional models often use exogenously defined imports or exports of energy and sector-specific models rely on reduced formed assumptions on price/demand elasticities. Under globalized energy economies, national or regional models have become increasingly reliant on exogenous assumptions.
- Renewable Technologies: Renewable resources can be resource-constrained, location-dependent, and can have unique output characteristics for power generation (e.g., variability). To handle these traits of renewables, models rely on renewable-specific assumptions, such as resource supply curves, transmission costs and limits, and integration costs. These assumptions can take the form of soft caps (cost adders) or hard caps (strict limits on deployment) and can erroneously limit renewable uptake. Their absence can lead to overly optimistic results for renewables. The issue of renewable representation in energy models is discussed in Chapter 7.

[15] For example, hydraulic fracturing and horizontal drilling have revolutionized the unconventional gas and oil industries in North America.

[16] There are certainly approaches to quantifying the value of hedging against fuel price volatility (e.g., Bazilian and Roques 2008, Wiser and Bolinger 2006), however, these approaches have not been widely adapted to the decision-making algorithms of large energy models.

- Energy Efficiency and Demand: **Many energy models are designed to capture the economics of supply-side technologies, but not the decision-making process of demand-side consumers**. As such, energy demand is either exogenously-defined or modeled using simplified financial and economic parameters. One consequence of this is that the significance of energy efficiency spans a very wide range across models and scenarios (see Figure 3.3 and scenarios listed in Table 1.1). In addition, the interplay between efficiency and renewable energy can be complicated in that under certain conditions efficiency helps reduce the integration barriers for renewables (e.g., by increasing the availability of conventional plants to provide reserve services), while under other conditions, reduced energy demand leaves less room for growth in new renewable technologies.

3.8 Summary

We have identified key considerations related to model levers and drivers in this chapter. We observe that without a significant policy driver, the future will likely look similar to the present. While an assumed energy policy can transform the energy scenario, the path that the model takes is highly sensitive to other key assumptions, such as technology and fuel cost, technology learning, discount rates, and the longevity of the incumbent system. The relative importance of these factors is not universal and depends on modeling framework. Sometimes the drivers that are missing from the model can be as important as the ones that are included. One should acknowledge that all input data have uncertainties, most models do not capture these uncertainties, and the uncertainties will certainly trickle through to the model results. No one can evaluate the impact of all major model assumptions, however, we believe that the publication of assumptions is required so that such an evaluation can be done. **Craig et al. (2002) state that "the importance of transparency of models cannot be overestimated" and we would add transparency of *assumptions* also cannot be overestimated.**

4 Understanding Non-Technical Drivers

The previous chapter described how technical and economic assumptions drive energy scenario results. This chapter focuses on how other, less quantifiable issues affect the commissioning and undertaking of energy scenarios. Two examples of these non-technical drivers include the motivation of the organization commissioning the energy scenario and the unpredictable nature of human behavior. These factors can significantly impact energy scenario results. Many of these issues are difficult to model quantitatively and therefore scenarios need to help determine the effects of these drivers as well as to mitigate any bias introduced by them. These drivers can also be transient—important today—but perhaps not in the future.

4.1 Commissioners of Energy Scenarios Have Real, Perceived or Inadvertent Bias

One of the obvious, but often overlooked, non-technical drivers, is the motivation of the commissioning agent and the modeling team. **Purposefully or not, modeling results are often biased in some way** (Keepin and Wynne 1984; Halladay 2012). Users of energy scenarios may have difficulty identifying and understanding these biases. Conversely, it can also be difficult for a modeling team to achieve public acceptance for its results if there is a perceived bias. Lack of data (particularly with regards to future technology improvement), for example, can lead to assumptions (expert opinion) that skew final results significantly. Similarly, agencies with a certain type of institutional focus might inadvertently influence results in a direction that aligns with their world-view. In the most general simplification, an environmental organization that commissions an energy scenario might be assumed to favor low-carbon or renewable energy in its assumptions while an oil company might behave similarly toward status-quo fossil fuels. But these generalizations do not always hold up in reality, as illustrated by the renewable energy deployment achieved in the Shell Oceans scenario illustrated in Table 1.1.

How can a decision maker address this issue? Questioning the assumptions and motivations about the key drivers as noted in Chapter 3 is a key element. If the data used are not reported or sourced, that could indicate a bias. Additionally, if the results are not comprehensively reported, that can be another sign of bias. Bias can also take the form of a modified system boundary or optimism (or pessimism) on cost or technology development. The main defense against this bias is to be broadly familiar with the literature and therefore able to understand how a particular analysis product differs from others. **Peer review from diverse networks of experts** (both formal and informal) **is often an important step to help identify potential bias and project objectivity**.

4.2 NIMBY Issues Are Dynamic and Can be Difficult to Simulate

All energy options face public opposition at times. Nuclear power is widely cited, as are carbon capture and storage and renewables. Increased negative perception of nuclear power in Japan after the recent Fukushima disaster is well documented (IEA 2012;

Fesharaki 2011). Renewable technologies, while generally perceived to have a more positive effect on the environment, are not immune from local development concerns (Akella et al. 2009; Logan and Kaplan 2008). Not-in-my-back-yard (NIMBY) issues range from fears about impacts on real estate values and personal health to fears about impacts on local ecological systems. Among renewables to date, these effects have been felt most strongly by the wind industry as their development pace and system size has increased significantly. Throughout the world, the visual impact of wind turbines has raised objections even among groups that would generally support renewables.

From a modeling perspective, these NIMBY issues can be difficult to simulate. Typically, the modeling of these issues involves increasing construction cost estimates and time of development. However, the NIMBY effect is uneven, transient and often unexpected, making it difficult to uniformly represent. In the case of wind power, attempts are being made in some countries to refine the costs of these barriers and impacts to resource development. In a model, the two primary methods for handling this are to reduce the wind technical potential by removing regions with significant species habitat or proximity to urban areas from the resource that is modeled and by adding additional costs for wind development in certain areas.

The NIMBY effect can also strongly affect the energy infrastructure that is critical to optimum energy deployment in the future, specifically transmission and distribution lines. Therefore, **another method to examine the potential impact of objections to new transmission is to model several scenarios that limit future transmission development**. For example, if future major transmission line development is not an option, model results will favor technologies that can be deployed close to load centers (such as PV or offshore wind in some cases) when those technologies might not be deployed as significantly if lower cost sources could be effectively transmitted from better resource areas. Other examples related to siting of nuclear or CCS plants, and shale gas and oil drilling rigs, provide similar examples from the non-renewable energy sectors.

4.3 Jurisdictional Siting and Permitting Issues

Closely tied to the issue of local opposition, infrastructure approval in many regions often involves negotiation among overlapping jurisdictional authorities. A rejection by any one authority can halt the entire development. Figure 4.1 shows the variation in construction time of PV systems in selected EU member countries. Delays in construction time – sometimes due to permitting delays – adds a hidden cost to these projects and increase the risk that projects will not be complete.

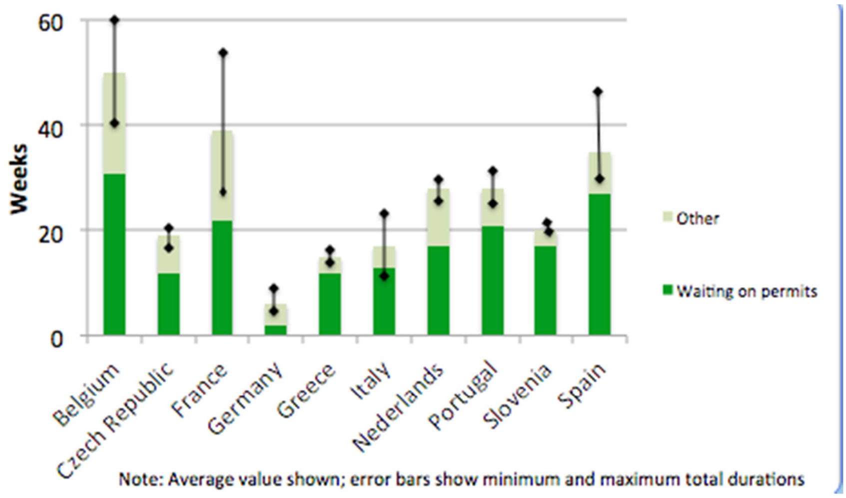

Figure 4.1 – Time Needed to Develop Small-scale Rooftop PV Systems in EU Countries

Source: Adapted from IEA (2012a)

As with the NIMBY effect, if data exists to suggest variation in costs based on land ownership or jurisdictional authority, those costs can be included in the resource supply curves. In rare instances, those areas where it is difficult to develop new projects can be eliminated from the (developable/economic) resource potential completely. These assumptions should be detailed in the model or report documentation.

There also needs to be an assumption made about the longevity of these issues. Stakeholders need to review the model and scenario assumptions to confirm that these assumptions are deemed to be appropriate. Will these issues continue into the future or will the regulatory landscape change to facilitate the development of plants and infrastructure?

4.4 Market Supply Chain Issues Can Influence Deployment

Under certain carbon mitigation scenarios, market supply chains may not be able to function as simulated in models. If carbon legislation leads to strong growth in wind deployment or CCS, for example, manufacturers might not be able to produce and deploy them at the rate the model envisions, especially if incentives remain uncertain. This uncertainty can limit the growth of the underlying wind turbine or CCS supply chain from growing into a sustainable business. This causes variation in wind turbine and CCS capital costs. These cost variations combine with the subsidy uncertainty to create modeling uncertainty well into the future. These types of uncertainties occur throughout the world as governments attempt to stimulate clean energy deployment at minimal cost. Therefore, **model results should indicate what assumptions are made about future incentives or other policy drivers and the reader needs to reflect on whether that is a historically appropriate assumption**.

Another place that supply chain issues can occur is special materials (such as rare earth magnets within wind turbines, or certain materials for photovoltaics) that are generally unique to that technology and do not have other large markets (IEA-RETD 2012a). Often, these basic components can constrain growth in the rest of the industry either due to technical availability (i.e., this material can only be mined in a particular country) or that the supplier isn't compelled to grow just because demand has increased (prices can go up instead) and there is a large burden of entry for other companies to develop this supply component. The converse can be true also if the price of a commodity shoots upwards due to the demands of other supply chains. Demand for steel in China has driven up the cost of steel for wind turbines and other technologies even without growth in the wind industry. Another critical link can occur in specially trained labor markets, where lack of availability of skilled personnel can constrain deployment (IEA-RETD 2012b).

Therefore, supply chain issues associated with both renewable options and non-renewables might be ignored in models that use "business as usual" scenarios, but shouldn't be ignored in transformational scenarios where there is very dramatic deployment growth or periodic deployment. In these cases, the scenario team should conduct specific analysis to better understand supply chain issues.

4.5 Human Behavior Is Not Always Rational

Human behavior is enormously complex to model. **It may be the most uncertain aspect of our energy future, especially when transformative futures are envisioned**. To date, modelers have not done an adequate job of dealing with the uncertainty of human behavior (Laitner 2007).

As discussed above, many energy models assume that the actors within the energy system make economically optimum decisions. However, in reality, that isn't always the case, especially when individuals or homeowners make the decisions. For example, many energy efficiency technologies, while having a positive net present value or positive payback, are not deployed to the scale that a model would otherwise indicate. This is because building owners either are un-informed or have barriers to action beyond the "slightly positive NPV." In other words, a great and immediate bargain is required for them to invest their energy as well as their money. When considering larger organizations such as utilities or large businesses, the decision they make will likely be closer to the economic optimum but that is not always the case.

How should a modeler determine the impact of "real deciders" like the building owners above? From a modeling perspective, it is generally assumed that decision makers will select the optimum solution. However, as above, if the choice is a relatively easy decision (or more "attractive" financially), this is a good assumption. When the decision is barely break-even, these decision makers might pass due to the effort involved. In a model, this can be examined via a parametric analysis by varying the technology costs and financial assumptions while reviewing the net present value of the choices. For example, as the discount rate is raised, the implication is that renewable energy technologies or energy efficiency technologies become significantly less attractive as future energy value is depreciated. If the amount of distributed photovoltaic deployed is very strongly impacted by small changes in the discount rate for the purchasers in the model, then additional research into the likely decision-making criteria of those actors should be undertaken.

4.6 Summary

There are many non-economic drivers that impact investment decision making, and are very difficult for the typical energy system to model. These tools are generally focused on economic decisions. Non-economic drivers include the bias of the modeling team or commissioning agent, NIMBY attitudes, non-economically rational human behavior or the ability of humans to be far more flexible than expected, jurisdictional approval issues and market supply chain issues. All of these issues can be at least partially addressed by understanding the structure, data and limitations and by using models and tools objectively to help inform decision making. Additional breakthroughs and advances are needed, however, to lower the uncertainty around non-economic factors.

5 Understanding the Value of Scenarios

Good modeling practice is conducted within an appropriate scenario framework designed to answer a specific question and provide context. Comparing scenarios is most easily done comparing the "business as usual" scenarios and one or more policy (or implied policy) scenario. **Oftentimes the differences in scenario results are more informative than the absolute values.** One of the compelling aspects of models is the consistent framework they provide to help answer complicated questions. As such, a comparative analysis of multiple scenarios using multiple models can help to reduce some of the biases from models.

This chapter describes various aspects of scenario construction and the value of combined approaches, models, and scenarios. The scenario framework should seek to refine the answer to the question it is designed for and provide a range of results that add insight rather than just additional data points.

5.1 Bracket Possibilities through Multiple Scenarios

The ability to accurately capture all future effects is impossible. However, to inform a decision today, **the scenario framework needs to effectively bracket the potential outcomes of that decision**. While the analysis of future solutions may not be sufficient to inform a decision, the differences in outcomes due to changes in input values may be much more insightful. For example, while it would have been difficult to predict the global slowdown in energy demand with the recent global recession, a set of scenarios bounding energy growth potential would have helped to bracket the growth in generation needed to meet the range of possible demand levels. With such bounding scenarios, one might be prepared to understand the conditions in which new investments would be hampered.

As discussed in Chapter 1, there are several definitions of scenarios. Bracketing results with a wide range of possible data inputs would inform all types of scenarios, but would be particularly useful under the policy-driven scenario type. There are situations where a specific forecast is necessary, but those situations are rare and generally do not preclude a bracketing approach. In all cases, the modeling outputs should explicitly indicate if the scenarios are meant to bracket anticipated reality, represent a precise forecast, or are visionary by nature.

The Renewable Electricity Futures Study (NREL 2012), which relied on 27 separate future scenarios, provides an example. It found a large number of scenarios to be necessary to bound the impacts of the numerous and diverse drivers, which included RE penetration level, future electricity demand, fuel prices, technology costs, and constraints to building new transmission, the ability to manage variability and resource accessibility. The range of scenarios also enabled the study to simultaneously evaluate multiple dimensions of renewable deployment under a single consistent modeling framework. However, a large number and diversity of scenarios can be difficult to follow.

5.2 Use Sensitivity Analysis

Even when scenarios capture the non-economic drivers (see Chapter 4), there still remains a definitive need for sensitivity analyses around basic inputs such as cost and performance. Sensitivity analyses include systematic perturbations of data inputs to understand their influence on scenario results. They are classified differently than the core scenario, in that they result from simply exercising the model across a range of values for one input (or a few linked inputs such as technology performance and cost). This type of analysis can effectively help find where the “break point” or “inflection point” is in the results. For example, Figure 5.1 demonstrates the non-linear impact different energy scenarios of the World Energy Outlook have on the renewable energy generation level. In another example, a core scenario may utilize a single fuel price or price trajectory, while multiple sensitivity scenarios can cover a spectrum of prices. Sensitivities are important because the values of many model drivers will likely evolve. **A robust sensitivity analysis can help assess the impact of updated inputs**.

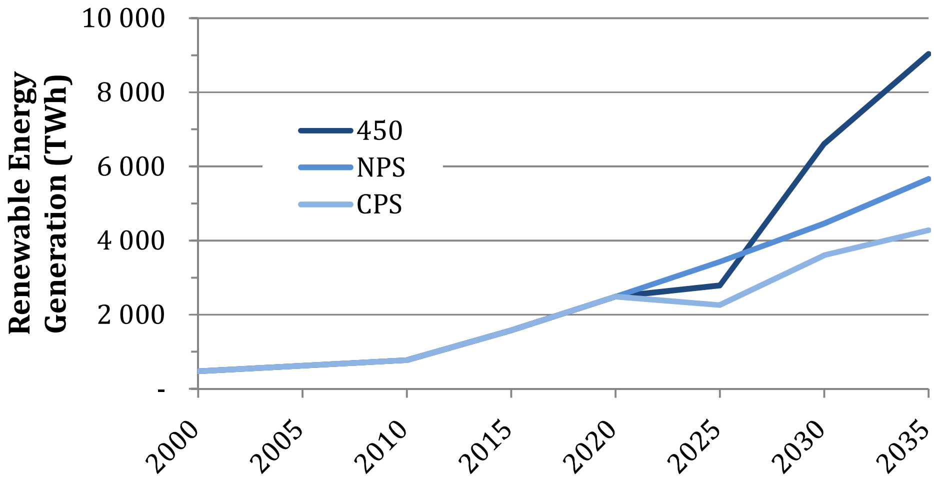

Figure 5.1 – Comparison of Total Global Renewable Energy Generation Under Different Scenarios in the WEO

Data Source: IEA (2012)

5.3 Seek to Pair Models with Appropriate Analysis Questions

Two of the often-asked questions about the future of energy development and deployment are **where will resources be developed and where will generation deployment occur**? Some models are better than others in providing provincial- and state-level insights. This information can be important in gaining stakeholder buy-in on regional or national legislative proposals.

It is important to select a model that integrates the relationships between the primary drivers of interest. For example, integrated assessment models (IAM) provide estimates of the global climate impact of energy decisions, but are not appropriate for evaluating grid, system, or market integration questions. The grid integration question occurs at the local “balancing area” or area at which the grid is operated. Only a very short time-step model at that geographical focus can provide answers to the questions of grid integration. Similarly, system integration questions that focus on balancing or back-up generation issues also need finer resolution than IAM's can often provide. Finally, market integration models should be able to reflect the way that regulations in one country affect operations in another.

As a commissioning agent, it is important to review the modeling literature to identify the ones with a "sweet spot" that are capable of answering the posed question. This statement does not mean that the model cannot be used for new purposes but that there would be higher likelihood of errors and inappropriate results. For example, it is likely inappropriate to use a model normally used to analyze global trends to look at a specific region of the world or even a specific technology. If the model doesn't have a robust temporal representation of a renewable technology, it would not make sense to consider the value of a variable resource like solar or wind with a more baseload resource like geothermal, coal, biomass or nuclear.

5.4 Use Combined Approaches

When possible, modeling the same scenarios with various types of models (as described above) and multiple models within the same family of models is preferred. This serves as a platform for stakeholders to discuss why results differ and what the impact of different assumptions are. Because of the unique training of the analysis team and resource availability, this is not often done. Model comparisons with aligned or partially aligned inputs can further bound results.

In 2008, NREL worked with other modeling teams, including the U.S. EIA, to compare the results of various models with both aligned and unaligned assumptions. This is documented by the REMAP team (Blair et al 2009). Various models were subjected to the typical assumptions that the modeling teams use for their analyses. Then, the modeling inputs were aligned and the models were re-run over the same scenarios. The outputs for the case with aligned inputs agreed much more closely. However, even in the case where the input assumptions are aligned, the range of carbon reduction is still significantly variable (see Figure 5.2).

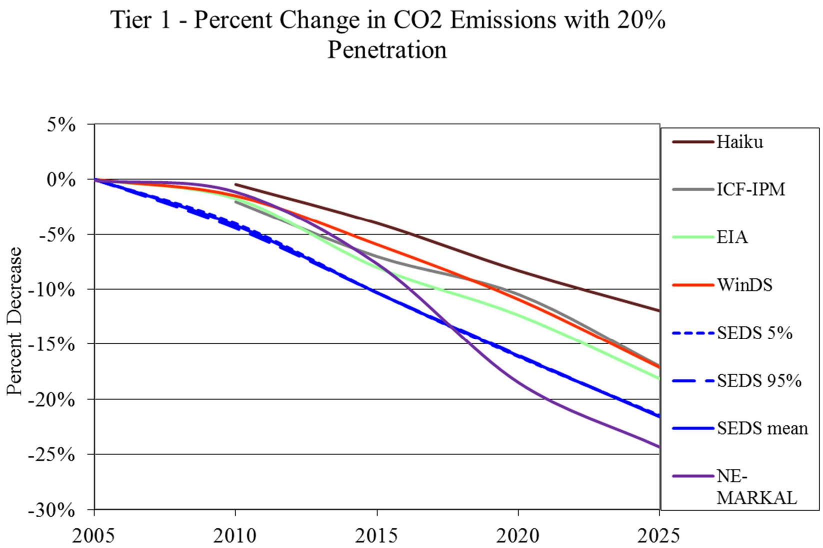

Figure 5.2 – Variation in CO_2 Emission Reductions With 20% Renewable Penetration With Aligned Input Values

Source: Blair et al. (2009)

In addition to using various models and modeling teams, **stakeholders should also review other non-modeling inputs including expert opinion and non-modeling industry market predictions.** Another resource would be basic technical potential values for renewables that would set the upper bound of potential deployment.

5.5 Summary

There are various reasons to pursue scenario analyses – from mitigating uncertainty to being able to focus results specifically on the question being asked in the analysis. Within scenario analyses, using sensitivity analyses to examine the impact (often non-linear) of a single variable can also address issues of uncertainty and increase the durability of the analysis under varying future values.

It is important to pair the analysis question with the proper model. That will provide the best answer at the lowest level of uncertainty. Finally, it is important to use all sources of data and information and hopefully even several models in a combined approach.

6 Understanding Boundary Conditions

Another set of choices that need to be made by modelers and analysts is how to define the scope of the model (or, by customers of analysis, the appropriate model scope for the project). There are a host of dimensions in which scope can play a role, and we will discuss two of the important ones: **geography and sector**. Understanding where and how the system boundaries are drawn in the model is important for both modelers and consumers of analysis to understand because the scope of the model is a strong determinant the type of questions it is best qualified to engage.

6.1 Geographic Scope

Models can be global, regional, national, or local, where regional and local are loose terms that generally mean groups of countries—the PRIMES model of Europe (Capros 2004) or the AIM model of Asia/Pacific region[17] (Kainuma and Matsuoka 2003)—or sub-national—e.g., NE-MARKAL, a version of MARKAL covering the northeast United States (Goldstein et al. 2008)—respectively. Depending on country size, the scope order is not necessarily monotonic; large countries can dwarf some multi-country groups.

Geographic scope determines not only the area the model represents, but also what economic interactions the model includes. Global models can describe the world economy, complete with international trade, competition, and leakage. International trade is important for many energy questions, because of the ubiquity of global markets for energy commodities like oil and gas. The GCAM model, for instance trades a number of commodities across its fourteen geopolitical regions: fossil fuels, bioenergy, agricultural products, and emissions permits (PNNL 2003).

Global scope is not sufficient to guarantee the inclusion of the full spectrum of international relationships. Along with trading commodities on international markets, countries compete with each other, and they have transfers of population and information. Global models do not automatically account for such interactions— e.g., some utilize a trade assumption in which all regions supply to or demand from a global pool—but some can and do: game theoretic models allow countries to act strategically in relation to other countries, and some models allow international technology spillovers: if one country invests in a technology, others can reap some of the benefits (Bosetti, et al. 2009). International markets for such goods as greenhouse gas (GHG) emissions allowances may, in contrast, need to be consciously restricted in global models to represent rules and friction in trading, or modified to represent GHG emissions embodied in imported goods.

Models with smaller geographic scope necessarily sacrifice some of the above capabilities. National models restrict their economic outlook to a single national entity, so they do not represent international trade directly, but that does not mean they ignore international concerns. In fact, they have several means of recourse, including:

[17] There also exists a global variant of AIM, AIM [Global].

- An external description of the behavior of the rest-of-world
- Flexible boundaries where the rest-of-world's baseline behavior is adjustable based on model behavior
- Explicit, reduced-form representation of other countries.

Fixed system boundaries, an exogenously specified rest-of-world, require a storyline to describe its system boundaries appropriately. The storyline is not always complex or detailed, but there needs to be some default consideration for certain goods (e.g., oil supply and price). That storyline may be embodied simply by an assumption of national oil prices, but both modelers and consumers of analysis should be aware that the exogenously defined oil price is not, in fact, produced from a vacuum, but rather is based on a narrative of external conditions. Of course, most model teams do not define their system boundaries by hand. Most use, instead, results from scenarios of larger-scope models. Fossil fuel prices in PRIMES, for instance, a model of the European region, come from POLES, a global model that selects global market-clearing prices for fossil fuels (E3MLab 2011). Through that relationship, PRIMES obtains much of the information about global supply and demand of fossil fuels with a single number. It is important that the global model and scenario match the scenario being run on the national model: if the national scenario represents a low-carbon future, the boundary conditions should be consistent with such.

Flexible system boundaries offer a slightly more complex relationship between the model region and the rest-of-world. As with fixed boundaries, there is an exogenous specification of external behavior but with parameterized information at the system edges: the boundaries flex based on internal behavior. The USREP model, for instance, a top-down general equilibrium model of the United States, allows import and export of goods, governed by elastic supply functions (Rausch et al. 2009). Compared with fixed boundaries, this allows the United States to increase quantity of imports if it is willing to pay higher prices.

Models with permeable system boundaries include other countries (or groups of countries) directly, but at reduced resolution. External entities (neighbors, major trading partners) are represented with limited degrees of freedom. To continue the oil price example, other major oil purchasers can be described simply as price-sensitive demands for oil, eliding most aspects of the countries' internal behavior. Describing the external nodes requires assumptions of their behavior in the same way that the flexible boundaries do.

While sub-global models clearly sacrifice information about global trends and interactions, smaller-scope models can have significant advantages in a range of analysis situations. At a fixed level of model complexity, a geographically smaller model can have greater resolution within its boundaries: more sectors, more goods, higher-resolution spatial considerations. Compare, for instance, EPPA and USREP, similarly constructed CGE models, both built at MIT, global and US-based respectively. Both are full-economy models with multiple non-energy sectors complementing the emphasis on energy, but USREP has 12 regions within the United States to EPPA's one and differentiates among nine household income classes to better assess distributional effects of policies. (Rausch et al. 2009; Paltsev et al. 2005)

Alternatively, a national model can be smaller, faster to solve, and therefore more nimble: able to run more scenarios faster. Data requirements are also generally lower for smaller models.

6.2 Sectoral Scope

The other major scope/boundary dimension is sectoral. **Energy sector models describe supply and demand of energy, but dramatically simplify the interactions of the energy sector with the rest of the economy.** In the same way that national models interact with the rest-of-world, energy sector models can have fixed or flexible transactions with, or reduced-form representation of, other sectors of the economy. Larger-scope models can represent multiple sectors or the entire economy. The ETP model has four component models, one for energy supply that balances with the three major energy demand sectors: industry, buildings, and transport (Figure 6.1) but remains distinct from true full-economy models that account for macro-economic linkages across sectors.

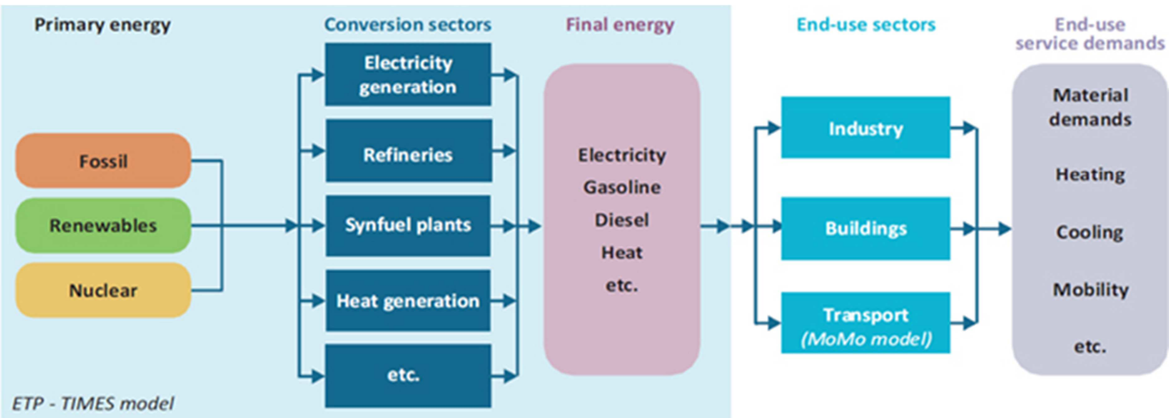

Figure 6.1 – Sketch of Sectoral Interactions in the ETP Model

Source: ETP (IEA 2012a)

The sectoral scope dimension is independent of geographic scope: there are global energy models and national full-economy models. Van Beeck (1999) asserts that bottom-up models are generally sectoral rather than full-economy. Top-down models can be either.

The class of models known as integrated assessment models (IAMs) expand beyond economic sectors either internally or by linking with other models to complement the economic model with handling of concerns like demographics, environmental impacts, land use change, and climate. In GCAM 3.0, for instance, an agriculture-land-use model is fully integrated with the GCAM energy and economy modules (Wise and Calvin 2011).

Demand for bioenergy (transport, electricity, or cooking) interacts with the availability and cost of land for agriculture (and competition among different crops) to determine the availability and cost of that biomass.

As with geography, some modelers choose decreased sectoral scope in exchange for smaller models or increased resolution within the sector(s) they do cover. NREL's ReEDS model (Short et al. 2011), used in examples elsewhere in this paper, is an electric sector model of the continental United States, focused on the provision of electricity supply[18]. While ReEDS does not have sufficient scope to perform national or certainly global energy and climate analysis like NEMS and GCAM, the increased fidelity within its chosen realm makes the model well suited to perform analysis of U.S. electric system with a focus on the contributions of geographically specific renewable technologies.

6.3 Summary

System boundaries are where a model stakes its claim about the types of scenarios and types of analyses it is equipped to undertake. Modelers make choices about what to include when designing a model, weighing data availability, computational appetite, and expected or desired scope of analysis questions. They emphasize those features they believe important and draw a box around the model's sphere of influence. As discussed, the box can be porous, allowing some information to be transferred across system boundaries, but a reduced scope model is meant to focus on its reduced area.

Accordingly, analysis questions should be matched to models of appropriate scope: energy-sector transformation analysis can be done by sectoral models, but analysis of climate policy on economic growth obliges the use of an economy-wide model. Similarly, global models are worthwhile for exploring comprehensive, global energy pathways and international interactions; but for more parochial analysis, a national or regional model can, in general, provide more detailed treatment over the relevant area.

This chapter did not discuss emphasis on certain features or phenomena within the chosen scope of the model, but it should be noted that such detail is also a design choice meant to signal the model's target analysis. Study commissioners should discuss with model development teams the focus and intent of the tools when selecting models for an analysis project. This leads into the next chapter, which discusses characteristics and representation of renewable energy technologies in energy models, one possible focus area that can be of particular importance in technology-based energy scenario analysis.

[18] Not even a full energy sector model, ReEDS lacks explicit competition for biomass between transport and electricity (a U.S. model, it also omits traditional biomass for heat and cooking). On the other hand, it can manage a dramatically more complex representation of the electric grid than full energy sector models: the ReEDS electricity transmission network has 134 nodes across the continental United States compared to 22 electricity market regions in NEMS (EIA 2012a).

7 Issues with Renewable Energy Modeling

In this chapter, we will describe some of the **characteristics of renewable energy technologies and how they are represented or misrepresented in energy models**. This discussion is not intended to be a critique of any model or class of models. As such, this report minimizes the referencing of specific models. In fact, some of the issues described below are not solely directed at models, but may be applicable to the general conventional wisdom on renewable technologies. This discussion is primarily intended for readers of scenario analyses when presented with scenario results that appear to be overly pessimistic or optimistic about future renewable deployment. The issues presented are not exclusive to renewables and may also be applicable to certain non-renewable technologies.

7.1 Renewable Energy Technologies Require Special Attention

Renewable energy technologies are diverse with wide-ranging characteristics. We focus on certain traits of major renewable technologies used for power generation. These traits include **geographic constraints, variability, and uncertainty**.

With few exceptions, renewable energy resources are location-restricted and cannot be easily stored or transported.[19] For example, one cannot alter where the sun shines or where the wind blows. As such, power plants or refineries that rely on renewable fuel must be installed at or near sites where the resource is located. Inconveniently, regions with high quality resources are often remotely located from large load centers, where the energy is most needed. The location-dependence of renewable energy and their relatively diffuse nature introduces siting challenges and can severely constrain the deployable resource in a region. For power generation, electrical transmission lines spanning long distances may be required to access high quality renewable resources. The transmission lines themselves may introduce additional siting challenges, as well as market and institutional challenges.[20]

Another characteristic of many renewable electricity technologies is their intrinsic variability. Natural variations in weather patterns cause the output of renewable power plants to vary at all timescales. For example, water availability and stream flow fluctuations may constrain hydroelectric plant output differently between years and seasons. Perhaps most consequential are the annual, seasonal, diurnal, and sub-hourly variability of wind and solar power plants due to changing weather conditions and clouds. There also exists variability in load and conventional power plant outages. Power systems, markets, and rules in developed countries have traditionally evolved to handle

[19] Pelletization of biomass offers an opportunity to conveniently store and transport one type of renewable fuel, and electrical or energy storage options are available. However, these options have yet to be widely adopted and there remain cost and market barriers to their deployment.

[20] Siting constraints exist for non-renewable technologies as well. For example, new large nuclear and coal plants often have site restrictions to be away from populations or environmentally-sensitive areas. Cooling water restrictions present another siting challenge to all thermal generators. CCS technologies are restricted to viable locations where carbon storage is possible.

these sources of variability, however, the additional variability of renewable energy may cause additional challenges in power system operation.

In addition to output variability, some renewable resources introduce uncertainty for power system scheduling and operation. Forecast errors for wind and solar output can make the job of maintaining a reliable grid more difficult. In an industry where reliability is expected, the variability and uncertainty of renewable energy can introduce real and perceived obstacles in the scheduling and operation of the power system. The electric industry in a developed nation is required to "keep the lights on" at all times in the most cost-effective manner.

Figure 7.1 graphically demonstrates the impact of net load from increased use of wind from Denholm et al. (2010). The impact of increased solar has a qualitatively similar effect. [21]

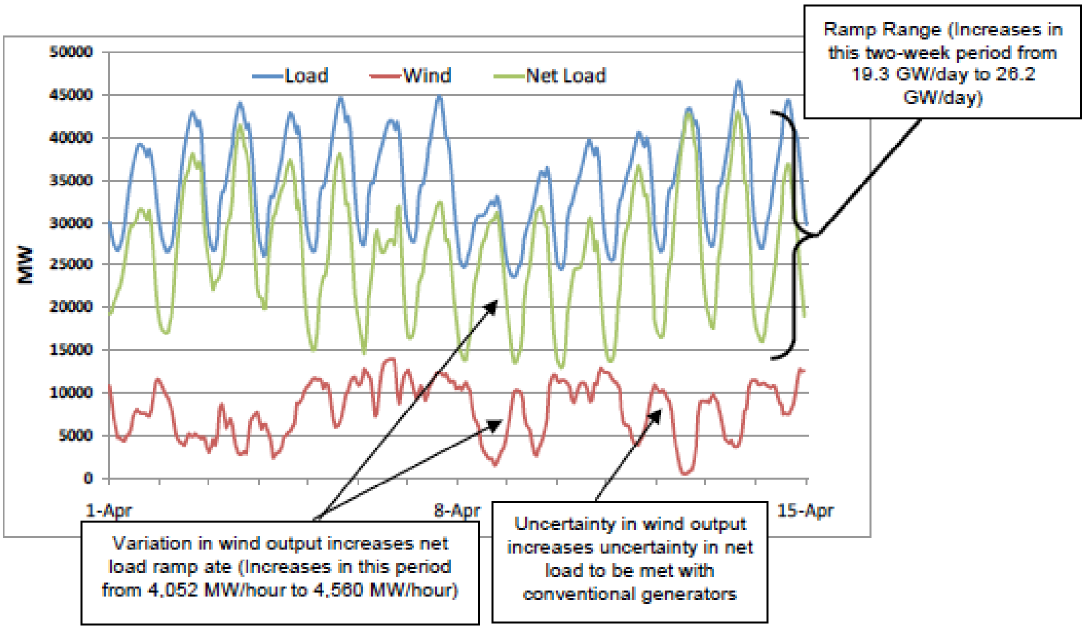

Figure 7.1 – Impact of Net Load from Increased Use of Renewable Energy

Source: Denholm et al. (2010)

Although this paper has focused primarily on renewable power generation, there are certainly unique characteristics of renewable technologies across all sectors. Some of these are related to competition for land (e.g., bioenergy crops versus food crops), market adoption behavior (e.g., compatibility of biofuel vehicles), and infrastructure and

[21] It should be noted that non-renewable technologies can also introduce challenges to grid integration (Milligan et al, 2011). For example, inflexible "baseload" generators are less responsive to variations in demand. In addition, the large size of nuclear and some coal plants require additional costly reserves to be held and can cause more catastrophic events when they experience outages.

technology lock-in (e.g., natural gas infrastructure for heating and industry). We introduce these issues to demonstrate the complexities with renewable energy and the difficulty in modeling these complexities.

7.2 Models Need High Spatial and Temporal Resolution for RE

For all scenario analyses, the scale and scope of the models introduce computational limits that prevent models from fully representing all of the characteristics of renewable energy technologies. Simplifications are certainly necessary, particularly in global or large regional models. In this section, we illustrate some of the techniques that have been used to represent the above-described traits of renewable energy technologies.

To directly address the site-specificity and resource limits of renewable energy would require models to have high spatial resolution or statistical techniques to handle this spatial variability. However, most global long-term energy models have very low resolution and the computational cost of increasing spatial resolution is often prohibitive. One common method is to rely on supply curves that represent resource constraints and resource quality variations for each low-resolution region. However, calculated supply curves often do not capture other regionally varying aspects such as profile differences and transmission requirements. The treatment of transmission in large energy models may also indirectly influence renewable technologies. For example, renewable deployment may be underestimated when long and expensive lines are required to connect large model regions. Biases in the other direction also exist such as when the full cost to interconnect remote renewable power plants is ignored completely.[22]

To directly address variability and uncertainty in renewable power plant output would require models to have high temporal resolution or other sophisticated techniques. Similar to spatial resolution, most long-term energy models have very low temporal resolution and the computational cost of increasing temporal resolution to explicitly capture the effects of variability is prohibitive. Effective simplifications to capture variability and uncertainty, however, are at early stages of development. Some models attempt to fit renewable technologies within the same framework as other energy technologies by requiring "back-up" dispatchable plants (typically natural gas-fired plants or energy storage) to be deployed alongside wind or solar plants. Others impose exogenously defined adders to the cost of renewable energy to represent "integration costs." These cost adders provide a "soft" cap to renewable deployment and are often not grounded on rigorous analysis. They also often do not dynamically vary with the system configuration. In certain models, more restrictive "hard" caps are applied by simply arbitrarily limiting renewable penetration levels.

[22] As described previously, non-renewable plants, such as large nuclear or coal-fired plants, often also have significant transmission needs.

The examples above illustrate the challenges with modeling renewable energy technologies and some simplifying methods used by large-scale energy models. These methods generally view renewable power plants in isolation instead of the more appropriate system-wide perspective. For example, the requirement for dedicated "back-up" for wind plants is a myth as the variability of wind (and load and other energy sources) is managed at the system level and not for individual plants (Milligan et al, 2009).[23] In another example, the renewable output profile at high penetration levels is often simply estimated by scaling-up the profile from a small number of renewable power plants. In actuality, variability can be much lower due to geospatial diverse; correlations in renewable power output between separate plants are typically reduced with distance, which would mitigate some of the variability and uncertainty (Milligan et al. 2010).

We have provided examples of how modeling simplifications can be overly restrictive of renewable (and non-renewable) energy technologies. However, simplistic models may also ignore all of the challenges with renewable energy and, thereby, be overly *optimistic* of renewable deployment. To avoid biases more sophisticated modeling methods are required.

7.3 Is It Feasible to Achieve High Renewable Levels?

As renewable technology deployment increases globally, the need for more sophisticated modeling techniques has grown, as has our understanding of how renewable technologies interact with the rest of the energy system. Recently, **real world experiences have shown that renewable energy can provide a substantial share of the energy demand**. For example, during a week in May 2012, 18% of total German electricity demand was met by solar energy, while instantaneous penetration levels exceeded 50%. In another example, Xcel Energy, a large utility in the U.S., met over 50% of its electricity demand through wind power during a fall morning hour in 2011. On an *annual* basis, Denmark has led all countries with nearly 26% wind share of total electricity consumption (EWEA 2012).

Model scenarios allow us to extrapolate beyond these real world experiences and explore the potential for renewable energy well beyond their current levels. In fact, over recent years, numerous studies have found that very high (>70%) renewable energy or electricity penetration levels are technically possible. These include studies of Germany (German Advisory Council on the Environment 2011), Denmark (Lund and Mathiesen 2009), Ireland (Connolly et al. 2011), Great Britain (Kemp and Wexler 2010), Portugal (Krajacic et al. 2011), Europe (ECF 2010), Australia (Elliston et al. 2012), New Zealand (Mason et al. 2010), United States (NREL 2012), and the world (WWF 2011; Greenpeace

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[23] This is analogous to the fact that plants are not designed to "back-up" variations of different demand-side electricity consumers, but the fleet of power plants are installed and operated to handle the variability of the aggregate load. For example, not all factories require back-up generators, nor is there a battery for every home, appliance, and light bulb.

2012; IIASA 2012).[24] These studies rely on a diverse range of models, all of which have some level of simplification in their treatment of renewables and the rest of the energy system.[25] However, the studies demonstrate the evolving and improving treatment of renewable energy. Nonetheless, gaps in the treatment of renewable energy certainly exist and continued development of models and techniques are needed. Readers of scenarios would benefit from understanding these gaps in energy models.

7.4 Summary

In terms of representing renewable energy, large models have fallen behind the real world. Many energy model structures and algorithms were formulated in an era where renewables were simply niche players, and, therefore, their cursory treatments of renewable technologies were justified. However, the rapid growth of renewable penetration levels, particularly in Europe, and the new visions of much greater penetration levels throughout the world have demanded a revisit of these old paradigms.

Renewable energy technologies are certainly unique and can be difficult to model. They are site-specific. They can be variable and uncertain. They use fuels that do not deplete over time. They can have very low marginal costs. These traits require models to have high spatial and temporal resolution or advanced methods to accurately reflect their impact on investment and operation. Renewables are growing contributors to the world energy supply and energy models need to catch up or they may find themselves irrelevant.

[24] Table 1.1 from Chapter 1 lists other examples.

[25] In particular, the NREL (2012) study relied on models that were specifically designed to address the location-restrictions and variable nature of wind and solar technologies. The high spatial resolution of the model enabled it to capture resource constraints, transmission need, and the impact of geospatially varying technology characteristics for many renewable technologies. In addition, the study also used a high temporal resolution (hourly) production cost model to represent grid operations and plant dispatch with high levels of solar and wind generation.

8 Evaluating Historical Modeling "Misses"

This chapter evaluates three energy scenario "misses" from the literature. There is no shortage of examples to choose from. Our goal is to both **illustrate the difficulty of "predicting" the future and to identify, to the extent possible, why the results were not better anticipated and what we can learn from past "misses."** We do not acknowledge here any of the energy scenario "hits" that are often achieved and the constructive insights they can provide.

Energy scenario misses can result for a variety of voluntary and involuntary reasons. We evaluate three examples below and highlight why, if known, scenarios missed the mark by so much. In cases where there is lack of consensus on why scenarios missed badly, we argue that stakeholders should conduct retrospective analysis to prioritize lessons learned for the future.

8.1 China's Energy Intensive Growth Spurt

One of the most significant recent examples of an energy scenario miss is seen in China's energy intensive growth spurt that lasted from roughly 2002 to 2006. As recently as 2004, the IEA's World Energy Outlook (and others, including the U.S. Energy Information Administration's International Energy Outlook and some of China's own forecasts) had expected Chinese energy demand to finally surpass that of the United States only after the year 2030. In fact, China became the world's largest energy consumer by 2010 after only 5 or 6 years of unusually energy intensive economic expansion (Figure 8.1). This was an **enormously important miss and had major implications around the globe for energy pricing, energy security, and greenhouse gas emissions**.

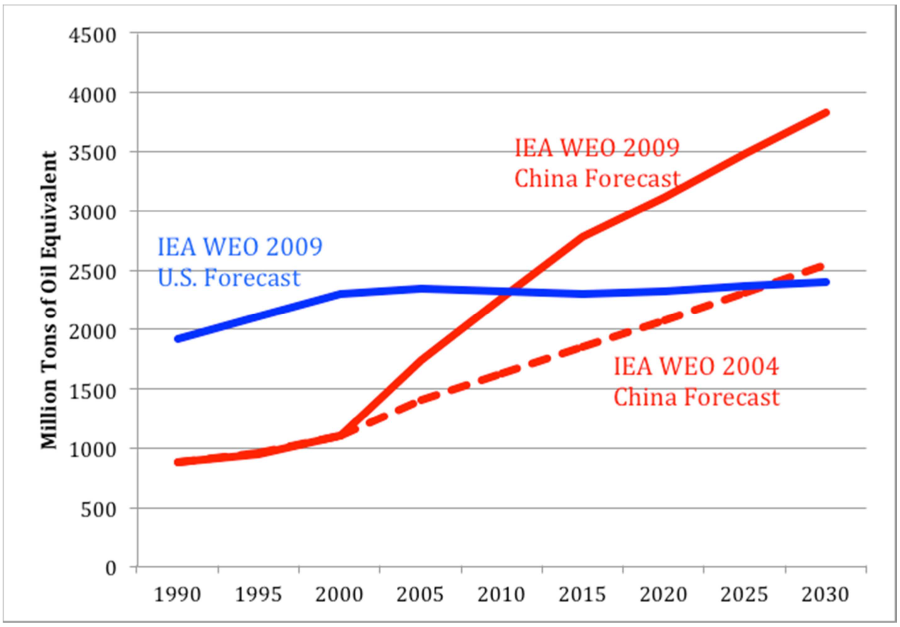

Figure 8.1 – Comparison of WEO 2004 and WEO 2009 Energy Demand for China and the United States

Source: IEA World Energy Outlook, 2004 and 2009.

Some of the immediate impacts that resulted from the failure to anticipate such change in China include:

- Shortages in domestic Chinese electricity supply that led to lost economic opportunity and temporary deployment of dirty, inefficient oil-fired back-up generation
- Uncertainty and instability in petroleum markets as Chinese imports grew much faster than had been anticipated
- Increased uncertainty and hesitancy in global climate change negotiations
- Pursuit by China of an aggressive alternative energy strategy, including renewable and nuclear energy.

Energy forecasters should not be blamed for missing the brief, but rapid, structural change in the Chinese economy. They can, however, be criticized for not tracking the unfolding process more closely and, to this day, not working more earnestly to understand how it happened and what lessons could be gained.[26] The Chinese energy surge may have been an acceleration of the inevitable: energy-intensive build-out of urban infrastructure would have probably occurred eventually. It is therefore difficult to pinpoint the actual long-term impacts of the Chinese energy surge.

Some of the reasons that many global forecasters missed the Chinese energy surge include:

- Lack of real-time "on the ground" knowledge about investment drivers, market evolution, and policy debates
- Lack of flexibility in anticipating that the future would be significantly different from the past
- Lack of transparent and accurate data.

The shortcomings associated with the failure to anticipate, or better track, China's energy surge were difficult to address since it occurred over a brief period of time. Perhaps the most important lesson to take away from this experience is **the importance of conducting retrospective analysis to better understand why it happened and what signals might be evident to anticipate similar outcomes in the future**. Other conclusions are that accurate and timely data are important to everyone and that China should be encouraged to provide more such transparent data for the global public good.

[26] One of the few analyses presented to describe the shift in China's energy behavior is found in Rosen and Houser (2007).

Finally, China's energy surge should instill a deep sense of humility within the modeling community.

8.2 Global Oil Price Forecasts Caught Off Guard

> "On the other hand, if you're still operating under the assumption that the earth's petroleum--or at least the cheap stuff--is about to run out, you're not going to thrive in the new oil era. Technology is making it possible to find, produce, and refine oil so efficiently that its supply, at least for practical purposes, is basically unlimited."
>
> --Businessweek, 1998

The quote above, written when global oil prices had fallen to $11/barrel (in then-current dollars), was just before oil prices began an historic and unprecedented rise. Within a decade, they would far exceed $100 per barrel.

Getting future oil prices wrong has been the norm since the late 1960s. Almost no one anticipated the first oil shock of the early 1970s, and after that occurred, energy modelers had almost routinely overestimated prices until they crashed in the 1980s (Lynch, 2002). The decline of global oil prices in the 1980s resulted in slower deployment of renewable and nuclear power technologies to say nothing of those focused on alternatives to conventional petroleum (e.g., oil shale). Then, just when analysts seemed prepared for low oil prices into the foreseeable future—as noted in the quote above—prices surged ten-fold over the following decade. Now, in 2013, even short-term price projections vary widely, with some expecting $120/barrel by 2014 and others calling for $60/barrel (Nelder 2012). The unfolding shale oil revolution in North America, together with the uncertain global economic recovery and instability in oil-producing nations, is contributing to this growing uncertainty.

While many examples of missed oil price scenarios can be cited, we focus here on projections from the European Commission that were conducted back in 2003 and then updated every two years thereafter (Capros et al. 2010; Capros et al. 2008; Mantzos and Capros 2006; Matzos et al. 2003). At first glance, the estimates don't seem as off-the-mark as they actually turned out to be. Figure 8.2 below shows 4 different forecasts for Brent oil going out to 2030. All price projections have been converted to 2008$US for comparability. In the first edition of the study, published in 2003, modelers anticipated that oil prices would fall and then slowly return to their year-2000 level by 2030. In fact, prices rose steadily, exceeding $140 per barrel in mid-2008. Each new biennial forecast continued to miss the magnitude of the rapidly rising global price.

Reasons for the increasing prices—growing instability in oil producing countries, fear that "peak oil" had been reached, rapidly growing demand—did not seem to penetrate into the outlook of energy modelers at the time. One of the primary causes here thus seems to be an **inflexibility to view tomorrow's world differently from that of today**. Even if some modelers wanted to believe that prices were rising much faster than they had projected, they face pressure and potential criticism for standing out from the pack. Furthermore, some energy scenario developers can be pressured by "status-quo" stakeholders who benefit from a future that is similar to the past. In particular, some energy modelers can be "captured" by stakeholders from industry and other political forces much in the same way that regulators might be captured. Some major global energy scenario developers are claimed to fall into this category of captured, or biased, forecasters, either intentionally or not (Clemente and Considine 2007; Rechsteiner 2008). Others believe, of course, that scenarios conducted with traditional models and mindsets are wrong for an entirely different set of reasons (Laitner 2007).

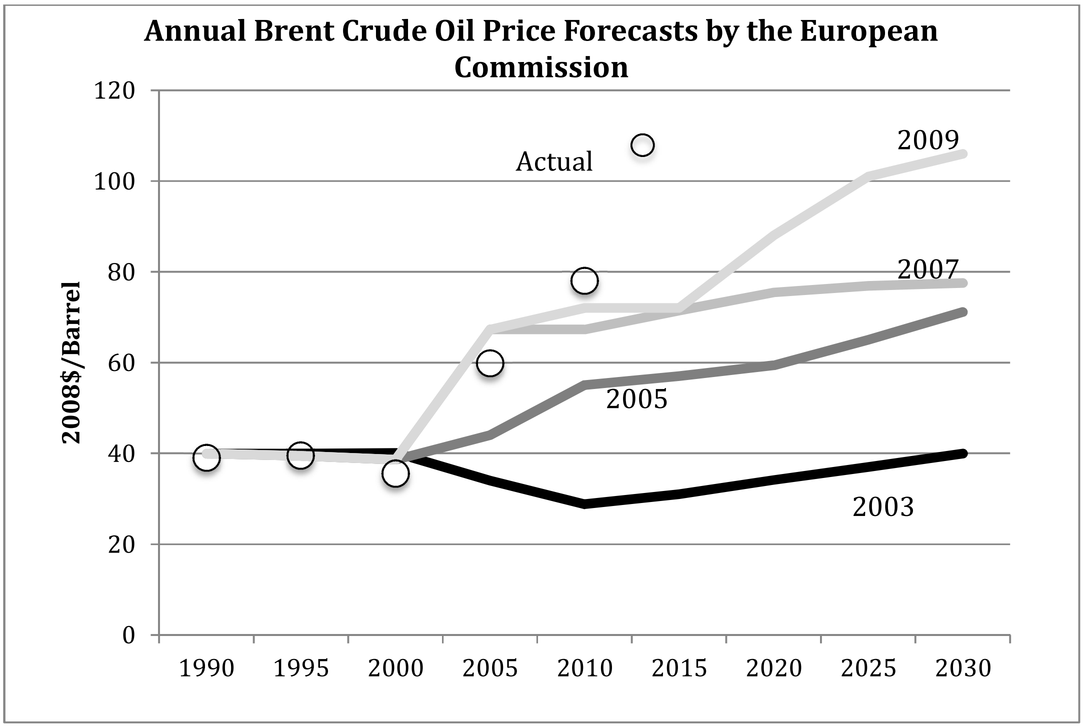

Figure 8.2 – Comparison of Global Oil Price Forecasts by the EU

Source: Capros and Capros et. al., various years.

8.3 U.S. Wind Deployment Forecasts Underestimate Reality

While some forecasts of future renewable energy deployment from the 1970s and 1980s may have been at least temporarily overly optimistic (NARUC 1991; Hourcade and Nadaud 2010), a recent example demonstrates the opposite impact. The U.S. Energy Information Administration presents its annual forecast in the Annual Energy Outlook (AEO) using the National Energy Modeling System (NEMS) model. Comparative analysis of wind forecasts from the past dozen years is particularly instructive, and highlights several limitations in the modeling approach.

Beginning in 2001, the AEO was anticipating very slow growth in wind deployment, with less than 10,000 cumulative megawatts installed by 2020. Each subsequent year showed a moderate increase in future-year deployments, although the forecasts were always horizontal lines and had to be updated upwards each year. By 2009, the baseline forecast was up to nearly 45,000 megawatts in 2030. As recently reported, cumulative capacity in the U.S. surpassed 60,000 megawatts at the end of 2012 (AWEA 2013).

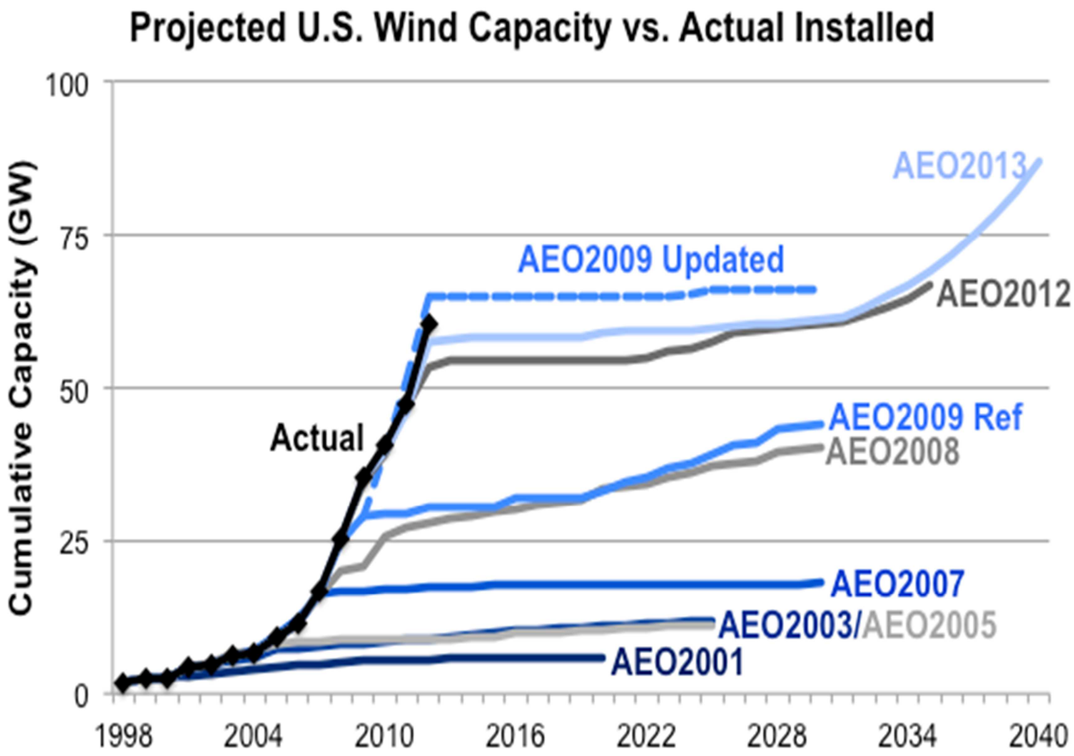

Figure 8.3 – Projected Wind Power Deployment from the Annual Energy Outlook

Source: EIA Annual Energy Outlook, various years.

One important limitation in the EIA modeling approach must be noted: all assumptions used in the organization's baseline modeling must reflect **current laws and regulations**, including the projected expiration of the Production Tax Credit (PTC) incentive. Because the EIA cannot assume that the PTC will be reapproved by the Congress, as it historically has been, it must assume the incentive will expire as defined by current law. The PTC has, in fact, expired briefly on 4 occasions[27], but has always been renewed retroactively for at least 1-2 year periods soon thereafter. The IEA also used to restrict itself to a Current Policies Scenario, but recently added more flexibility by using the New Policies Scenario as its central scenario. **Realistic baseline scenarios should be flexible enough to assume at least some probable dynamic change in the future beyond existing law and policy** (as these will inevitably change). The EIA does include alternative future

[27] Specifically, the expirations occurred in 1999, 2001, 2003 and 2013.

policy scenarios in the AEO that explore some issues such as permanent enactment of temporary incentives, but they play a minor role in informing the public compared to the reference scenario.

Despite the inability of AEO modelers to make assumptions about potential legal and policy changes in the reference scenarios, other limitations also affect their forecasts. One is structural: the NEMS model has limited geographical resolution. In other words, the model does not have a lot of detail about the specific locations of good wind resources and how wind farms might be integrated into the grid. It may also lack temporal resolution that captures when wind resources are available. The ultimate impact is that assumptions in NEMS may not accurately represent real wind resources. On the other hand, all models have strengths and limitations and where a strength exists in one model it often results in a tradeoff with another weakness. Spatial and temporal resolution can have a significant impact on the projected role that some forms of renewable energy are projected to play. Models with higher resolution generally are better at evaluating renewable energy opportunities, although they may lack a sophisticated representation of economic connections and feedback (see Chapter 7).

8.3 Summary

Niels Bohr, the great Danish physicist of the 20th Century, was fond of saying that "Prediction is difficult, especially about the future." No one can routinely predict the future. Energy forecasting should not be viewed as a prediction, but as a relative comparison or as a backcasting tool. A single energy scenario of the future probably provides little useful information. Combined with policy alternatives or sensitivity runs, however, it begins to provide meaningful information. Used as a tool to plan how to get from here to there it can be even more powerful.

A further important benefit of energy scenarios, especially ones that are far from proving themselves accurate, can be found by conducting retrospective analysis that attempts to determine and prioritize what went wrong and how decision makers can be better prepared based on lessons learned from weak predictions. "Discussion platforms" for stakeholders to challenge each other's' assumptions, desires, and biases are powerful opportunities to advance knowledge.

9 Conclusions

This report has explored various issues and techniques related to energy scenarios and modeling. Energy scenarios include a wide variety of techniques, often relying on complex computer models, to help prepare for future uncertainty and change. Robust energy scenarios are not simple predictions but rather frameworks that can help better inform decision making under uncertainty.

We have briefly reviewed the history of energy scenarios and how they have become increasingly sophisticated, but still often falling short of their potential. Recent events have seemingly made the ability to "forecast" the energy sector even more difficult. These factors mean that a deeper understanding of the potential for energy system evolution is critical for both decision makers and commissioning agents.

Additionally, we have reviewed the types of models used in energy scenarios, the key inputs and economic drivers, the non-economic drivers, the value of sensitivity analyses, specific issues for renewables, and addressing uncertainty.

A series of 10 key take away messages that decision makers may want to keep in mind while either commissioning or reviewing energy modeling results are presented below.

1. **Do not expect a model or energy scenario to predict the future.**

   Be wary of anyone who claims his or her energy scenario is a prediction of the future. No model can do that, but it is often forgotten amongst consumers. The further an energy scenario is projected into the future, the more uncertainty is introduced. Single scenarios are rarely helpful, but must be combined with, and compared against, diverse alternatives as part of a larger strategic exercise. Models are useful as "backcasting" tools (picking an idealized period in the future and considering the barriers to arriving at that point from today), and to weigh relative differences in outcomes when different policy, technology, and social assumptions are chosen.

2. **Match the model to the problem.**

   There are almost as many types of energy models as there are questions about our energy future. Make sure the question you want to answer is well-formed, and then pick the right type of model (or suite of models) to best address it. For the simplest example, an electricity sector-only model should not be chosen to address an economy-wide greenhouse gas mitigation scenario. Likewise, a model with perfect foresight (i.e., knowledge that certain things will occur in future years) may not provide a realistic way to think about real greenhouse gas mitigation options given political, social, and technological uncertainties.

3. **Make assumptions and accounting frameworks transparent.**

   Models require thousands, and often millions of pieces of input data. The meaning of these data needs to be clearly understood by all. What type of energy accounting methodology is used? The difference between the most commonly used methods, for example, can mean a three-fold difference in the apparent amount of renewable energy reported in results. Are the economic data measured in current or real values? Is traditional biomass included or only modern biomass? To address these and other potential misinterpretations, all assumptions should be clearly and transparently articulated. Similarly, policy and regulatory frameworks are not always clear. In these cases, what a national government claims to be its policy and what it does in practice can diverge markedly. Having on-the-ground, "insider" knowledge can help lead to proper interpretation of scenario results. Without transparency, credibility is sacrificed and results can misinform.

4. **Understand the limitations of how human behavior is represented.**

   A typical energy model finds a solution based on the overall system's equilibrium or least-cost point. However, real world producers and consumers often find themselves out of equilibrium and agreement on a system-wide optimal point is rare. Institutional, jurisdictional, supply chain bottlenecks, or social barriers such as "not in my backyard" attitudes can prevent the system from reaching these ideal points. While agent-based models are designed to capture some of these human aspects, they often do not capture and reflect the full range of human behavior, including economically irrational behavior. The potential for humans to change their behavior in unexpected ways is also commonly not factored into models. Energy models are typically better at characterizing supply-side options than they are those on the demand-side, particularly related to energy efficiency behavior.

5. **Use diverse tools and approaches to address uncertainty.**

   Uncertainty about the future comes in different forms. Some is "characterizable" while others are not (known unknowns and unknown unknowns). New analytic approaches are available to help address some classes of risk and uncertainty that have statistical histories. Monte Carlo simulations are perhaps one of the oldest such tools, but many other new techniques, often borrowed from the financial literature (real options and portfolio theory, for example) can be used by modelers to characterize uncertainty. For "uncharacterizable" uncertainty, scenarios should be designed to consider potential impacts of certain types of unexpected events. A few well-planned example "black swans" can help modelers understand the potential magnitude and direction of certain classes of shock.

6. **Consider how unique traits of renewable energy are modeled.**

   Higher resolution is required to model the site-specificity, and variable and uncertain nature of many renewables. Constrained by computational limits, modelers are forced into trade-offs between increasing their geographic and time resolution, or simplifying their representations of other aspects of the energy economy. Because of the unique traits of renewables, transparency in their assumptions (e.g., cost and performance) and model treatment (e.g., hard caps on deployment) is necessary to better understand if they are treated appropriately and whether the playing field is level. In particular, renewable technologies should be viewed within the larger energy system and not be forced to fit within the confines of the status quo technologies or operational practices, (e.g., some models erroneously use a one-to-one "back-up" requirement for variable renewable power generation).

7. **Communicate effectively and appropriately.**

   Energy modeling is a highly specialized endeavor. What modelers consider to be “results” and what decision makers deem useful information may not overlap. The communication of results is inherently difficult. The two communities would benefit by better understanding the challenges and opportunities that exist for each other. Modelers should try to put themselves in the shoes of decision makers when communicating results and synthesize findings at an “appropriate” level of detail. Defining vocabulary in simple terms can help this “translation” from one world to another. While modelers may be from Mars and decision makers from Venus, better communication can help bring both groups back down to Earth.

8. **Expect bias and learn to identify its traits.**

   All modeling approaches incorporate bias, either accidentally or purposefully. Consumers of energy scenarios can learn to identify scenario, data, or model subjectivity and take steps to ensure appropriate interpretation. Combined approaches and efforts from multiple organizations could help balance out biases and provide a more robust outcome. Commissioners of energy scenarios should use diverse networks of expert reviewers to address real and perceived bias before results are finalized.

9. **Consider energy scenarios with limited or no modeling.**

   Commissioners of energy scenarios should consider broad stakeholder engagements that focus on “upstream” discussion of assumptions and desired outcomes before modeling. Focusing limited resources on these discussions with “back of the envelope” calculations and sensitivities can provide useful insights in comparison to more costly and time consuming, complex modeling. Modeling can be a subsequent step after to provide additional insights.

10. **Conduct retrospective analysis to better understand energy scenario misses and hits.**

    Too often, energy modelers and decision makers do not go back to revisit why certain energy scenarios were so far off the mark or why they provided unexpectedly valuable information. There is value “left on the table” by not returning more often to previous energy scenarios to analyze why they did or didn't work well. Some organizations, like the U.S. EIA, do publish comparisons between the current energy scenario and previous ones, but they are often done mechanically. As an example, very few analyses have been conducted to understand why China's recent energy future turned out so differently than scenarios had expected.

We hope that energy scenario stakeholders will vigorously discuss and debate this list of findings, and use the information to improve the value of scenarios going forward.

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