Technological Forecasting & Social Change 86 (2014) 177–187

Contents lists available at ScienceDirect

Technological Forecasting & Social Change

Energy technology expert elicitations: An application to natural gas turbine efficiencies

John E. Bistline *

Stanford University, Management Science and Engineering, Huang Engineering Center 253I, Stanford, CA 94305, USA

ARTICLE INFO

Article history:
Received 30 July 2013
Received in revised form 1 November 2013
Accepted 7 November 2013
Available online 2 December 2013

Keywords:
Expert elicitations
Natural gas
Technology R&D
Uncertainty

ABSTRACT

Expert elicitations are critical tools for characterizing technological uncertainty, since historical data on technical progress may not provide a sufficient basis for forecasting future advances. The objectives of this paper are to describe the protocol and results for an expert elicitation on the future performance of gas-turbine-based technologies in the electric power sector and to discuss how these insights relate to the current elicitation literature in energy modeling. Elicitation results suggest that prospective efficiency gains are likely to be slower than historical trends; however, the assessed values are still appreciably higher than the efficiencies used in many energy models. The results also indicate that conducting face-to-face elicitations may be important for minimizing overconfidence and for critically examining reported values, especially when assessing non-central probabilities in the tails of a distribution.

1. Introduction

Uncertainty analysis has played an increasingly prominent role in energy modeling in recent years [1], particularly in regard to technological change. This focus comes as no surprise given that assumptions about how technologies evolve over time are leading determinants of modeling results [2]. Despite considerable unknowns about the dynamics of technological change, it is necessary to quantify this uncertainty about cost and performance metrics in a range of modeling settings. Obtaining a set of potential outcomes and some idea of their relative likelihoods is required no matter if uncertainty analysis is conducted implicitly (e.g., using sensitivity analysis or propagating uncertainty through deterministic models) or explicitly (e.g., through sequential decision-making frameworks like stochastic programming). The interest in characterizing technological uncertainty has grown in the presence of proposed energy and climate policies to manage technical change through research and development (R&D).

Although there are many formal methods of quantifying uncertainty, expert elicitations are uniquely suited for characterizing technological uncertainty. Statistical approaches that rely primarily on historical data may not contain sufficient information to form conjectures about the future progress or returns on research investments for specific technologies. Since technological breakthroughs are fundamentally unique, planners often cannot extrapolate past trends into the future or use relative historical frequencies to generate probability distributions. Thus, when past data are unavailable or of limited use, one of the only remaining options is to ask individuals with expertise for their best professional judgments, which often take the form of expert elicitations [3].

An expert elicitation is a structured, formal process for collecting and assessing probabilistic estimates about uncertain quantities [4]. These elicitations allow expert knowledge about specific technologies to be embedded in models instead of relying on stylized, ad-hoc distributions over parameters of interest, which may be selected with limited consultation about the current state of knowledge in a technical domain.

The objectives of this paper are to describe the protocol and results for an expert elicitation on the future performance of gas-turbine-based technologies in the electric power sector and to discuss how insights from this work relate to the current elicitation literature in energy modeling. Section 2 briefly surveys the existing literature on energy

* Tel.: +1 814 935 0810.
E-mail address: bistline@stanford.edu.

0040-1625/$ – see front matter © 2013 Elsevier Inc. All rights reserved.
http://dx.doi.org/10.1016/j.techfore.2013.11.003

technology expert elicitations and highlights the best practices and unresolved questions. Section 3 demonstrates these elicitation techniques in the context of an overlooked technology that merits greater attention—namely, natural gas turbine architectures for stationary power generation. Section 4 presents the results of these elicitations, and Section 5 discusses possible implications for modelers and decision-makers.

2. Energy technology expert elicitations

Considerable uncertainty about future states of energy technologies suggests that it is important to collect expert judgments about a range of possible outcomes instead of focusing only on central tendencies. In this setting, analysts cannot reliably assume that statistical analyses of historical trends[1] or technological analogs [8] will provide accurate forecasts for the future evolution of energy technologies. However, despite considerable uncertainty, probabilistic estimates from a diverse set of experts, encoded through a structured elicitation process, can offer valuable insights into technological developments.

2.1. Existing work

Elicitations have been used for many decades to encode the knowledge, judgment, and experience of experts in fields where uncertainty and risk are critical components of decision-making [9,3,10]. Since work by Tversky and Kahneman [11], protocols for elicitations have been carefully designed using insights from psychology, decision analysis, risk analysis, economics, and statistics to reduce distortions from cognitive biases and heuristics. Many researchers have investigated the strengths and shortcomings of various elicitation methods, and comprehensive overviews of the literature on the psychology of probability assessment and on elicitation approaches have been published [12,9,13–15,3,16].

This paper focuses on elicitation methods and applications for quantifying future cost and performance characteristics of energy technologies. The emphasis reflects the objectives of surveying current practices and unresolved questions in this policy-relevant area and also of applying these insights to investigate the future performance of gas-turbine-based technologies in the power sector. Although probabilistic elicitations have been applied across a range of industries and research domains [12,17–20], the application of elicitations to energy technologies began in earnest only recently.[2] The limited research attention may come as a surprise given the pervasiveness of uncertainty in this domain and early interest in such analysis.[3]

For energy modeling, existing research uses elicitations to explore the future of several specific supply- and demand-side technologies. The most common objective is to inform questions of energy R&D policy, which has tremendous uncertainty about ex-ante returns on investments. The product of these elicitations is a rich set of data that encodes experts' best probabilistic judgments about future cost and performance characteristics for specific technologies conditioned on R&D effort and outcomes.

Table 1 shows a non-exhaustive list of major energy technology elicitations in recent years. The five institutions conducting widespread elicitation research across multiple energy technologies are Carnegie Mellon University, the US Department of Energy's Office of Energy Efficiency and Renewable Energy (EERE), Fondazione Eni Enrico Mattei (FEEM), Harvard University, and the University of Massachusetts Amherst.

- *Carnegie Mellon University*: Researchers from the Department of Engineering and Public Policy conducted elicitations in a range of decentralized studies for amine-based carbon capture [27], photovoltaic solar [28], and small modular reactors [29].
- *Office of Efficiency and Renewable Energy* (*EERE*): Researchers conducted elicitations for 40 renewable energy and efficiency technologies to support R&D portfolio management decisions using the Stochastic Energy Deployment System (SEDS) model, which has a Monte Carlo simulation framework. Affiliated researchers include Sam Baldwin (EERE), Max Henrion (Lumina), Thomas Jenkin (NREL), and Jim McVeigh (NREL).
- *Fondazione Eni Enrico Mattei*: Valentina Bosetti and colleagues conducted elicitations for many energy technologies within a European context as part of the ICARUS project with a focus on the impacts of R&D [30,31].
- *Harvard University*: Laura Diaz Anadon and colleagues from the Energy Technology Innovation Policy Research Group within the Belfer Center for Science and International Affairs at Harvard's Kennedy School conducted elicitations in support of the research and publication of their *Transforming US Energy Innovation* report [32].
- *University of Massachusetts Amherst*: Erin Baker and colleagues conducted elicitations for a variety of energy technologies, including nuclear [33], CCS [34], solar [35], battery technologies for vehicles [36], cellulosic biofuels [37], and CCS energy penalties [38].

There have also been efforts to make elicitation results more accessible and to compare and aggregate their insights. Megajoule.org is a website spearheaded by Max Henrion for sharing and reviewing elicitation results. The Technology Elicitations and Modeling Project (TEaM) is developing an integrated framework for analyzing and communicating the results from energy technology elicitation efforts. A related collaboration between Harvard and FEEM researchers compares US and EU elicitations for the future of nuclear power [39].

2.2. Discussion of unresolved questions

Given the costly and time-consuming nature of elicitations, it is important to identify and understand the factors that enhance their quality and usefulness. This section highlights unresolved questions from the literature on energy technology

[1] Frequently employed methods for projecting unit cost or performance characteristics using historical trends include regression analysis [5], decomposition [6], and monitoring for precursors [7].

[2] Multi-criteria decision analysis methods have used expert judgments to analyze energy technology decisions for many years [21–24], though such elicitations do not typically focus on probabilistic assessments for a small number of attributes.

[3] The Rasmussen report [25] on nuclear reactor safety is a prominent early example and the first to use quantitative expert judgments in a large risk analysis [26].

Table 1
Existing literature on energy technology expert elicitations.

	Carnegie Mellon	EERE	FEEM	Harvard	UMass Amherst
Supply–side technologies					
Nuclear			30	25	4
Coal with CCS	10			13	4
Gas with CCS				13	
Bioenergy and biofuels			15	8	6
Solar	18		16	11	3
Wind					
Grid–scale storage				25	
Demand–side technologies					
Vehicles				9	7
Energy efficiency				9	
Policy and/or R&D scenarios	Yes	Yes	Yes	Yes	Yes
Elicited years	2015 (CCS) 2030, 2050 (solar)	2015, 2020, 2025	2010, 2030	2010, 2030	2020, 2050
Year(s) conducted/published	2006–2012	2008–2010	2011–2012	2011	2008–2012
Protocol method	Mail (CCS); combined mail/online, and face–to–face (solar)	Unknown	Combined online and group (nuclear); face–to–face (biofuels, solar)	Mail	Mail/online (nuclear, solar, vehicles), combined mail/online, face–to–face, and phone (CCS, biofuels)
Context	US	US	EU	US	US
Associated model(s)	N/A	SEDS	WITCH	MARKAL	MiniCAM/GCAM

NOTE: Colored cells indicate, for a given research group, whether elicitations for a particular technology were not conducted (white), conducted (light orange), or conducted with published data (light blue). The values inside of technology cells indicate the number of experts included in the study (where available).

expert elicitations and discusses the implications of these issues for modeling results based on such elicitations.

2.2.1. In-person elicitations, conditioning, and tail events

Perhaps the most significant discrepancy between elicitation protocols is the method of administering elicitations and whether it is preferable to conduct them in person or at a distance.[4] Although at-a-distance methods are more economical and may allow greater participation, face-to-face elicitations have typically been preferred in the broader elicitation community due to a belief that such protocols yield higher-quality outputs [40,28,41]. Face-to-face elicitations allow interviewers to recognize and resolve sources of ambiguity or inconsistencies in responses, to challenge the expert with disconfirming evidence from the literature to have greater confidence that a complete range of possibilities is taken into account, to establish greater rapport, and to ensure that the expert is giving his or her full attention to the assessment task [40].

One of the largest concerns about at-a-distance elicitations is that experts may be conditioning their responses on unspecified events. For instance, results of a recent elicitation for nuclear technologies [39] demonstrate how experts believe that capital costs for Generation III/III+ reactors in 2030 would be higher than at present. However, questions remain about whether this increase is due to forgetting curve effects, commodity price escalations, regulatory costs, or another random variable. Aggregate elicited values like price changes are causally overdetermined. It is impossible to decompose an expert's response to assess their beliefs about which factors influenced their response most without the ability to ask follow-up questions to determine what is implicitly being conditioned upon (e.g., depreciation of knowledge capital, increasing steel prices, inflation). Experts' mental models play central roles in the elicitation process [42], but such models are inaccessible without the "interactive and iterative" [38] feedback between the elicitor and the expert. Although feedback steps can mitigate some of these challenges for mail or digital elicitations, it is considerably easier to request feedback in an in-person setting and to reassess values immediately if it is discovered that the expert is conditioning on something that the interviewer does not intend.

One method of avoiding these omitted variable biases while retaining the convenience and cost reductions of at-a-distance elicitations is to make more use of innovative electronic techniques for conducting elicitations. Web-based interactive interfaces for authoring and hosting elicitations like those used by Near Zero allow for more feedback from an expert conditional on their responses. In general, experimenting with newer elicitation techniques, particularly in ways that utilize digital tools and combine well-documented best practices from different methods, can improve the quality of elicitations over time. For instance, Anadon et al. [39] use a novel, two-phase approach for conducting nuclear elicitations that begins with interactive online elicitations and a group meeting afterward.

A related issue surrounds the most effective means of assessing non-central probability estimates like the 10th and 90th percentiles. In the domain of energy technologies, the probabilities of extreme upside events (e.g., low capital costs resulting from technological breakthroughs, which may lead to wide deployment of a particular technology) and improbable downside events (e.g., unexpectedly large costs that result from an inability to surmount engineering hurdles) are important to

[4] Although there is disagreement about how to conduct individual elicitations, there is broad agreement among energy technology research groups that individual elicitations are preferable to group methods. This sentiment aligns with recommendations in the elicitation literature, which caution against biases associated with group dynamics that can inhibit dissenting options [14].

assess properly. However, assessing extreme tail values can be problematic owing to a host of cognitive biases, which impede careful consideration of low-probability events [11]. The most common bias is the overconfidence effect, which leads to systematic underestimations of tail events. A failure to identify or correct overconfidence can result from not having an interviewer interact with and question an expert in real time (e.g., not giving feedback about egregiously narrow distributions). Debiasing is particularly challenging for the overconfidence effect. Probability estimates may still exhibit this bias even when assessors are knowledgeable about its existence, which means that simply providing an information packet before elicitations may not be enough to safeguard against excessively narrow distributions.

2.2.2. Selection of experts

The identification and selection of experts may be nearly as important as the design of the protocol itself. Although many technological elicitations are conducted to gain probabilistic information about future costs and performance characteristics, requesting cost and performance values from the same experts can be problematic. The Catch 22 of cost-related technological elicitations is that experts must be able to assess the probability of meeting specific cost targets, which requires a detailed understanding of the technology; however, technical experts may be less familiar with the factors that influence costs. The task of predicting costs is as complex as forecasting technological breakthroughs, because a technology's cost depends on many interrelated factors like prices of commodities, specific manufacturing processes that are used to produce the technology, the technology's design, learning effects, and economies of scale.

Since scientists and engineers may not be the most appropriate candidates to assess these economic values, it is important to elicit additional values from economic or industry specialists who have a familiarity with specific technologies. This aligns with the general best practice of encouraging elicitations with experts from a wide range of backgrounds and viewpoints to avoid bias [14,43]. Another method of overcoming this limitation is to elicit only cost values from cost experts and technology performance values from technology experts. Although this would reduce the efficiency of the elicitation process, it would likely provide better quality results. Currently, there has been a tendency to elicit many values at once instead of concentrating on a few parameters, which may be negatively impacting elicitations.

The elicitation literature also suggests that it is important to have a cross-section of experts from industry, government laboratories, and academia.[5] This insight has largely been incorporated in all elicitations, though little work has been done to determine which types of experts provide the most reliable elicitation values. Preliminary research [39] suggests that experts from industry are more pessimistic about future costs than experts in public institutions (with academics being the most optimistic).[6] There is also recognition that expert opinions may differ by country and that it is important to conduct elicitations with global experts.[7]

3. Natural gas turbine elicitations

3.1. Motivations

Recent advances in technologies like horizontal drilling and hydraulic fracturing have caused rapid increases in production from unconventional natural gas resources like shale formations. However, the same technologies that have facilitated this growth have also raised important questions about their environmental impacts. Natural gas is broadly considered a more environmentally benign alternative to coal due to its lower CO_2 emissions from combustion and its avoidance of pollutants like sulfur, particulate matter, and mercury. These environmental benefits, combined with abundant reserves, suggest that unconventional gas can play an important role in national and international energy policy—bridging a transition to a lower-carbon economy, reshaping energy security, and altering investment decisions in the electric power sector [44,45].

Although abundant gas resources suggest expanded use in the electricity sector, uncertainty about the environmental impacts of production and long-run production costs makes the extent of this growth unclear [46,47,45,48,49]. Additionally, natural gas price uncertainty will be influenced by the unknown policy environment, public acceptance of hydraulic fracturing [50], and uncertainty surrounding life-cycle emissions [51,52].

Another relevant uncertainty that will shape the role of natural gas in the electric power sector is the future performance of gas-turbine-based technologies. In particular, first-law efficiencies of these technologies (both with and without carbon capture) may determine the diffusion of new capacity and market share of generation from natural gas. Such characteristics are especially important for a technology subject to large fuel price volatility and to similar levelized electricity costs as other technological substitutes, which mean that even small efficiency changes may have modest impacts on future diffusion and utilization of these technologies.

The goal of this elicitation is to investigate the best practices described above through a case study of a policy-relevant technology that has been hitherto neglected in the energy technology elicitation literature. In particular, the aim of this work is to represent the current state of knowledge regarding the future of gas turbine systems for new central station electricity generation. As Table 1 suggests, most elicitations for fossil-based electricity generation technologies have focused on coal with CCS, and when research groups look at gas with CCS, it is typically to encode uncertainty about capital costs. Here, expert judgments about the first-law efficiencies of

[5] As Morgan et al. [40] note, selecting experts differ from the process of estimating an underlying true value through random sampling. For expert elicitations, “it is entirely possible that one expert, perhaps even one whose views are an outlier, may be correctly reflecting the underlying physical reality, and all the others may be wrong.”

[6] This effect may potentially be due to a range of factors, including industry experts being most familiar with market barriers or academics' first-hand knowledge of cutting-edge technologies that are only on the brink of commercialization.

[7] The first paper to explore this issue [39] indicates that there are significant differences between expert opinions in the US and EU.

commercially viable natural-gas-fired power plants are elicited.[8]

In the absence of this approach, most energy-economic models simply assume that future plant efficiencies will remain constant at current levels (with combined cycle efficiencies between 50 and 60%) or will marginally increase between now and 2050, as shown in Fig. 1. Even slight deviations from these efficiency values can have significant impacts on the development and deployment of gas-turbine-based systems, particularly when natural gas prices and climate policy are uncertain and there are many substitute technologies and fuels.

3.2. Protocol summary

The elicitation protocol for this study was designed by drawing on the literature on techniques to minimize bias in probabilistic assessments [9,14,43,3,10] while addressing the issues raised in Section 2.2. The protocol emphasized robust suggestions for best practices like conducting in-person elicitations, carefully defining all terms and metrics, informing experts about common biases and strategies to avoid them (along with warm-up exercises and reminders during the elicitation discussion), and using visualization tools to facilitate quantification.

The elicitation focused on commercially viable natural-gas-fired power plants with the highest available first-law efficiency in 2025. This gas-turbine system should be scalable to a plant size of 500 MW and must be compliant with Clean Air Act regulations. Although the stochastic model in which this information is used contains fossil units with and without carbon capture, the elicitations considered only systems without carbon capture. These efficiency values are for commercially viable gas turbine technologies only, which is defined as having a total overnight capital cost of the system being less than or equal to $1000 per kilowatt.[9]

The description of this plant was intentionally general to allow for the possibility that future gas-fired systems may be very different from the most commonly implemented baseload plants today, which are typically combined cycle Brayton-architecture gas turbines with bottoming steam engines. For instance, next-generation combined cycle architectures may use a gas turbine as a bottoming engine in a solid oxide fuel cell, gas turbine combination. The decision to elicit values for a single technical parameter allowed the technological experts to focus on areas within their primary domain of expertise. Restricting attention to a single value also allowed for a more in-depth discussion of how the expert viewed the history and future status of the field, which can take many hours.[10]

The second portion of the elicitation aimed to understand how enhanced public and/or private R&D programs in the US may impact the efficiencies of these technologies. There are many ways to conceptualize the success of R&D projects [53]. Success can be viewed as the increased (binary) likelihood of success in reaching fixed technical or cost metrics [35] or as an acceleration in the number of years required to reach such metrics [54]. The research framework here conceptualizes R&D success as adjusting the range of expected cost and performance metrics. The versatility of this probabilistic framework allows for a diverse range of representations within a stochastic programming setting, including shifting the mean of a distribution over a target R&D parameter (e.g., capital costs), changing the variance, or eliminating fat tails (e.g., eliminating the possibility that a technology is always too expensive for deployment).

Since the selection of experts is nearly as important as the protocol itself, experts were recruited from a range of backgrounds in industry, national laboratories, and academia. Following a literature review, experts were contacted who had technological familiarity with gas-turbine architectures for stationary power generation with a preference for experts who could meet for in-person elicitations, who had strong technical expertise (since the focus was a technical parameter), and who are in the US. Quality control to ensure expertise was managed on the front end as assessors were being selected so that combining distributions later would not entail subjective weights. Table 2 lists participants in the elicitations in alphabetical order.

Each expert received a packet in advance of the interview, which clearly defined the quantity of interest, discussed common biases, and provided a general overview of the elicitation process. The design of the elicitation protocol was based on the Stanford/SRI Assessment Protocol[11] with modifications from the literature:

1. *Motivating and Briefing*: Each session began by discussing the structure of the elicitation, by providing background about the research and how the results will be used, and by answering the expert's questions about the elicitation process. The briefing helped experts understand the elicitation approach, to establish a sense of rapport, and to demonstrate that the elicitation was useful and worthy of serious effort.
2. *Structuring*: The next stage began by arriving at an unambiguous definition of the quantity of interest (expressed in manner that was conducive to the expert providing accurate judgments) and by determining if there were any conditioning factors that may influence the value of the quantity. This stage led into an extended technical discussion to understand how the expert saw the past, present, and future of the field. Also, this discussion allowed the experts to convey which evidence seemed most compelling and which factors and functional relationships were important for understanding the future of gas-turbine systems for power generation. This

[8] Results from these expert elicitations are used as inputs to a stochastic modeling framework, which assists decision-makers in the US electric power sector with capacity planning and energy technology R&D portfolio optimization under a range of technological, economic, and policy-related uncertainties.

[9] Expressed in terms of 2010 US dollars. This value reflects the approximate future cost of a natural gas combined cycle unit according to the Energy Information Administration's 2012 Annual Energy Outlook. The phrase "commercially viable" is used to indicate that the technology is cost-competitive with other forms of baseload electricity generation.

[10] The average elicitation session took three hours with the shortest lasting about two hours.

[11] This section summarizes the primary steps and draws attention to modifications of the standard Stanford/SRI Assessment Protocol. Other authors [10,3] provide extensive information about the standard SRI Protocol.

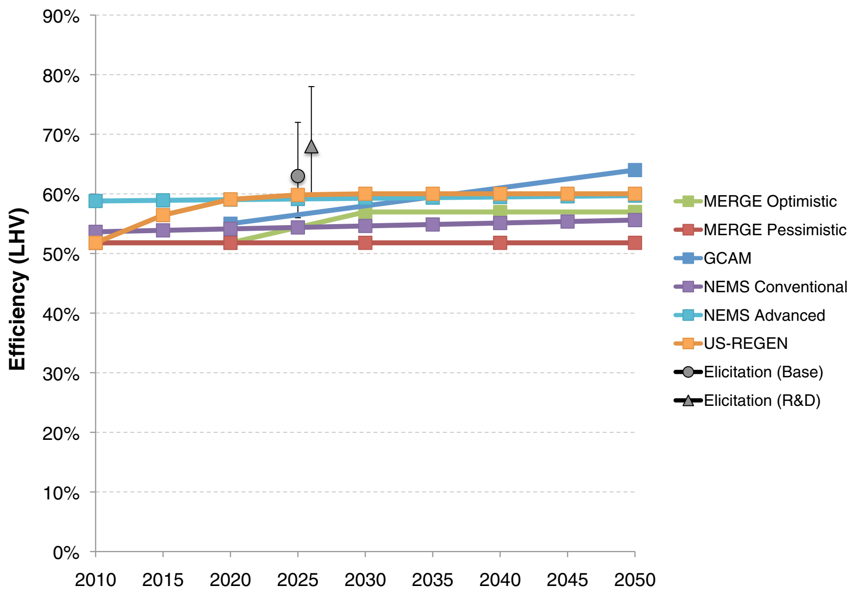

Fig. 1. First-law efficiency values (2010–2050) on a lower heating value (LHV) basis for a range of energy–economic models along with assessed range of 2025 efficiencies from this elicitation.

stage of the pre-encoding process was often the longest in the elicitation process [10].

3. *Conditioning*: The objective of this step was to condition the expert to think deeply about his or her judgment and to avoid the cognitive biases discussed in the information packet. This stage incorporated a series of warm-up questions to familiarize the expert with the concepts, structure, and techniques of the elicitation process and to get them thinking in terms of probabilities. This portion of the elicitation began with "almanac questions" for unrelated quantities and then moved to more domain-specific questions related to gas turbines.
4. *Encoding*: This stage involved the actual probability encoding process for the quantities of interest. The step began by establishing maximum and minimum credible values and by probing the expert to think carefully about these extreme values (e.g., asking for backcasts through bounding cases, where experts had to invent plausible explanations for why the true value could be lower or higher than their initial range). Once this range was chosen, cumulative probability values were elicited largely using fixed-value methods with consistency checks using fixed-probability questions. During this process, carefully articulated justifications and reasons for and against their judgments were requested.

Table 2
List of experts and affiliations from the gas turbine elicitations.

Name	Affiliation
Leonard Angello	Electric Power Research Institute
Chris Edwards	Stanford University
Dale Grace	Electric Power Research Institute
Sankaran Ramakrishnan	Stanford University

5. *Verifying*: The objective of this final step was to test the quantitative judgments that the expert provided to ensure that the values accurately reflected their beliefs. The values given by the expert were recorded in a spreadsheet so that the results could be instantaneously plotted as both probability density functions (PDFs) and cumulative distribution functions (CDFs). Any remaining inconsistencies were resolved through conversation and iteration.

The elicited values from individual experts were later combined to summarize the current state of expert opinion in an aggregated manner. Although there are many diverse mathematical combinations and justifications for these methods [55], the linear opinion pool method was used with equal weights attached to each expert's input. There are many convenient axiomatic justifications for this approach [55] and evidence that simple combination procedures produce combined probability distributions that perform as well as those from more complicated Bayesian aggregation methods [56]. As mentioned before, instead of using complex calibration procedures or differential weighting, the experts in Table 2 were selected with great care before requesting their participation and then treated all experts equally (i.e., weighting was performed up front when choosing experts instead of post-processing individual elicitation results).

Combined percentile values were later fitted to shifted log-logistic distributions. These three-parameter distributions are versatile enough to represent a range of different shapes of distributions while offering a convenient way of using the 10th, 50th, and 90th percentiles to parametrize the distributions and a quantile function that is easy to use for Monte Carlo experiments. For this work, the shifted log-logistic distributions were used only as tools to visualize the PDFs and CDFs for the elicited values.

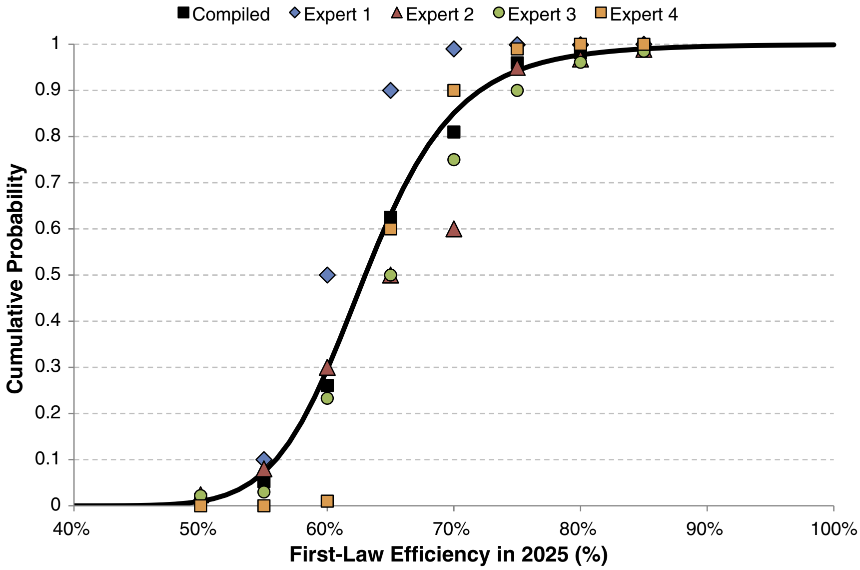

Fig. 2. Elicited values for first-law efficiencies (lower heating value basis) of gas-turbine-based electricity generators in 2025.

All elicitations were conducted between September and October 2012.

4. Results

4.1. Efficiency elicitations

Fig. 2 shows the CDF of elicited values for first-law efficiencies[12] in 2025 under the business-as-usual R&D scenario. Individual values for all four experts are given along with the combined and fitted CDF. Although the figure shows some disagreement among the experts particularly for higher efficiencies, it is notable that all experts agree that the median efficiency value for 2025 will be at least 60%. Recall that Fig. 1 showed that only one existing energy-economic model has an efficiency value that exceeds 60% through 2050.[13] Thus, existing models significantly underestimate performance characteristics for future natural gas systems for electricity generation.

The median first-law efficiency of the combined distribution is about 63%, as shown in Fig. 3. This figure compares the compiled CDFs for the business-as-usual R&D case and enhanced R&D case. These fitted values are shown as PDFs in Fig. 4. Experts believe that targeted R&D programs can increase the median efficiency from 63 to 68% and can increase the variance of the distribution. The increased variance suggests that the impact of research and production experience could be that new knowledge begets more uncertainty and/or opens up new possibilities for more dramatic efficiency improvements, as discussed in the next section.

[12] All efficiencies for the remainder of the paper are expressed on a lower heating value basis.

[13] The Siemens SGT5-8000H gas turbine achieved a world-record 60.75 percent efficiency in a combined-cycle configuration at the Irsching Power Station in Bavaria, Germany in May 2011.

4.2. Discussion

The experts agree that efficiency improvements in the coming decades will likely result from implementing existing research ideas by taking them from the laboratory, lowering costs, and implementing them at larger scales. Technological advances in gas turbine design have historically come from three sources: materials science and engineering advances, cooling improvements, and new architectures [57]. The lengthy technical discussions during the elicitations suggest that these factors will continue to play some part in future efficiency increases, though likely for different reasons than historical gains. When asked about prominent uncertainties that could influence the development of higher-efficiency turbine-based generators, the consensus view among the elicitations is that natural gas prices and environmental policies will play significant roles. Higher (lower) gas prices are thought to increase (lower) firms' motivation to make efficiency improvements. Experts view environmental policies (e.g., a potential federal climate policy) and regulations for emissions from existing assets (e.g., particulate matter and mercury) as important drivers for technical progress.

Progress in materials science has allowed turbine blade materials to move from conventional cast alloys in the 1960s to more highly-specialized, single-crystal alloys today [57]. These metallurgical advances have made high temperatures possible in combustors and turbine components. Many experts view the prospect of increasing turbine inlet temperatures and operating at higher pressure ratios as promising methods of raising efficiency values in the near term, even though efficiencies exhibit diminishing marginal returns for higher temperatures. Turbine inlet temperatures are one of the largest sources of competition between big gas turbine original equipment manufacturers (OEMs). The top priority areas for future materials research are reducing the cost of single-crystal alloys that already exist in the near term and then developing and commercializing ceramic and metal matrix composites in

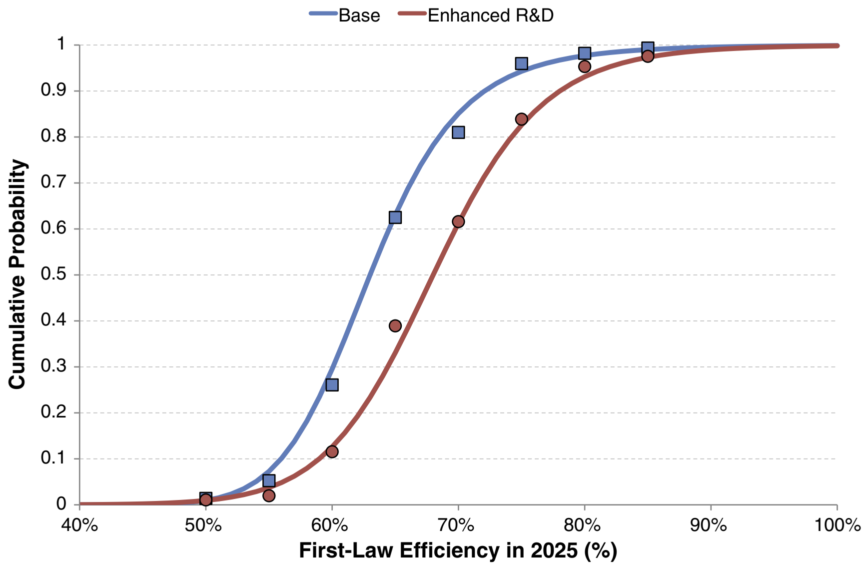

Fig. 3. Cumulative distribution functions of compiled elicitation values for the base and enhanced R&D cases.

the longer term.[14] However, although they agree about the potential importance of ceramics, the experts disagree about the prospects for the widespread use of ceramics over the next decade.

Cooling techniques for gas turbines typically involve circulating air or steam through hot turbine components. Technological progress for cooling cascaded as a series of spillovers from military turbojet engines (where such techniques were developed in the 1960s) to civilian aircraft two to three years later, followed by diffusion to stationary power generation in approximately five years [57]. Many experts agree that spillovers from aerospace applications are unlikely to continue at their historical rates, as the operating profiles are very different between heavy-duty stationary gas turbines and those used for aviation (e.g., different standards for monitoring and reliability, material needs, environmental conditions, and weight restrictions). Additionally, cooling techniques advanced along with improvements in computer codes and models for finite element analysis, heat transfer, and fluid dynamics, which were useful in modeling intricate cooling pathways, tunnels, and holes to facilitate heat transfer to the cooling fluid. The experts acknowledge that blade cooling will be an important source of temperature increases, particularly if materials science progress slows, but did not mention improved computational tools as a means of achieving these improvements.

Individual experts also suggest that first-law efficiency improvements could arise from improving auxiliary loads of the cycles themselves, from implementing more advanced architectures (e.g., intercooling, reheating, wet cycles), and from developing better heat exchangers.

The greatest disagreement between experts came in elicitations and discussions surrounding longer-term trends for gas-based architectures, especially for systems that incorporated fuel cells. Experts agree that the high end of the achievable and economic efficiency range is between 65 and 70% in the absence of dramatically new architectures. Efficiencies in this range are viewed as technically feasible but economically unlikely without enhanced R&D, which would be unlikely to come from major OEMs due to a lack of incentives for innovation or competition (outside of merely increasing inlet temperatures). The prospect of an integrated solid oxide fuel cell and gas turbine system is a highly uncertain one, though a couple of experts suggest that industry research might move toward this architecture in 10–20 years. On one hand, these systems may offer a promising route to decarbonization, since fuel cells provide an inherently high-efficiency approach to chemical separations with very high separation rates. On the other hand, such systems are currently only demonstrable at a laboratory level and would face numerous hurdles to commercialization due to concerns about the overall economics of the system, the longevity of the fuel cell, the stability of the membranes, and the ability to increase the packing density and decreasing size by a factor of ten. Experts disagree about the likelihood of achieving the required performance and cost targets for this fuel cell system even with targeted R&D. This sense of uncertainty about advanced turbine-based architectures and technical progress in the mid- to long-term future accounts for the large variance for the enhanced R&D distribution in Fig. 3.

As mentioned at the beginning of this section, it is not clear *prima facie* whether future performance and cost trends for turbine-based electricity generators will follow historical values. Although there are many promising developments on the horizon, there are also many reasons to doubt that historical sources of technological change (e.g., spillovers from the aerospace industry, rapid advances in computational fluid dynamics, or increasing turbine inlet temperatures) will continue to be primary drivers of efficiency gains in the future. Consequently, expert elicitations fill this void by providing a basis for forecasting future efficiency values for gas-based systems.

[14] Ceramic materials can withstand heat and corrosion and allow for higher inlet temperatures without cooling. In experimental applications as first-stage blades and combustor liners, ceramics have managed to achieve 37-degree Celsius temperature increases with associated efficiency gains of six percent [57].

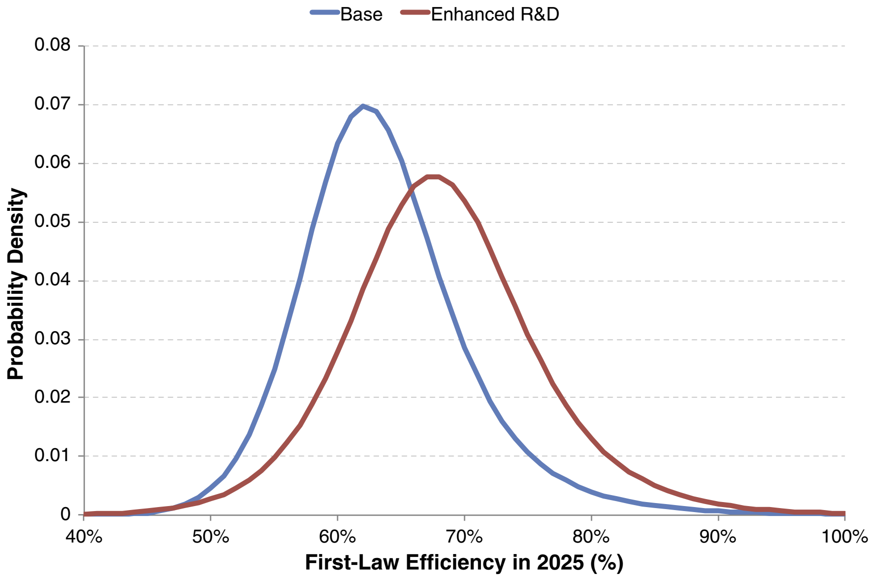

Fig. 4. Probability density functions of compiled elicitation values for the base and enhanced R&D cases.

Fig. 5 shows the historical values for combined-cycle efficiencies in the US electric power sector between 1968 and 2003 [57]. A simple linear trendline, when extrapolated to 2025, suggests that efficiencies would reach upward of 70%. Although this efficiency falls within the 10th and 90th percentiles of the elicitation values, the median estimates under business-as-usual and enhanced R&D conditions are notably lower than this trendline. Thus, the expert elicitations support the conclusion that prospective efficiency gains are unlikely to follow historical trends. However, these median values are still appreciably higher than the efficiencies used in many integrated assessment models from Fig. 1.

5. Takeaways and recommendations

In addition to the insights about the future of gas turbine systems discussed in the previous section, these elicitations illustrated many best practices for conducting expert elicitations.

The largest takeaway was that face-to-face elicitations are extremely useful in critically examining reported probability values, particularly for the tails of the distribution. Feedback questions for participants' responses make them think critically about the values they give and force them to brainstorm how extreme values may be lower or higher than their initial impressions suggest. In one elicitation, a question was reframed

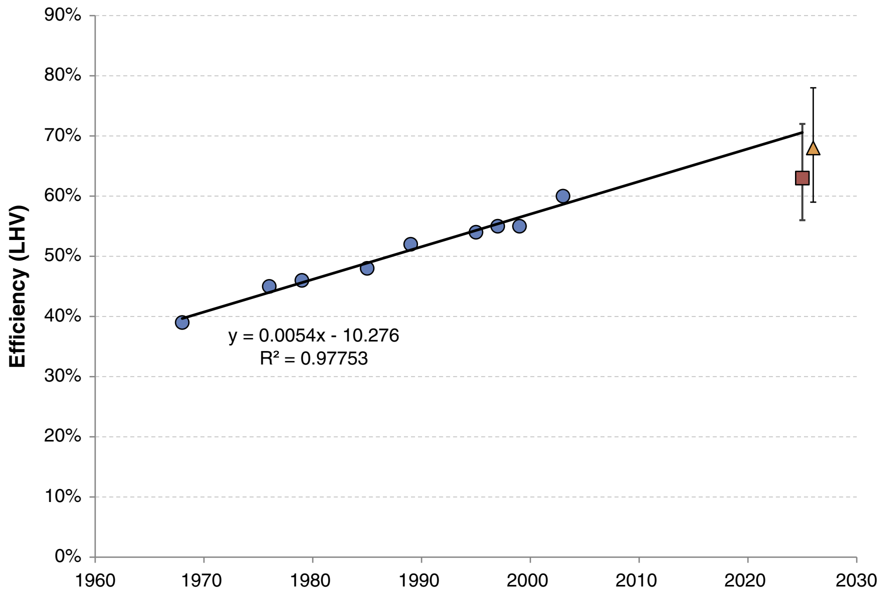

Fig. 5. Historical values of best-available combined-cycle efficiencies (1968–2003) with a linear trendline. The values at 2025 represent the median combined expert elicitation values for the base R&D (red square) and enhanced R&D (orange triangle) with the 10th and 90th percentiles shown with error bars.

in three different ways before the expert noted the possibility of using supercritical water injection in the combustor and revised the efficiency estimate upward. During the debriefing sessions, subjects reported discomfort in thinking about tail probabilities and suggested that, without the interviewer's intervention, they would have selected an anchor value and then extrapolated to select other values. Additionally, the warm-up exercises suggested that the experts were initially overconfident, as the actual number of "surprises" (i.e., values falling outside of the 10th and 90th percentiles) was over twice as high as the expected number of surprises in three of four cases. Thus, based on these observations, future research should examine to what degree at-a-distance elicitations exhibit greater overconfidence compared with in-person protocols and how interactive digital tools can bridge this gap if it exists.

Many other advantages of conducting in-person elicitations were observed:

- In-person elicitations allow the interviewer to clarify misconceptions that may not be noticed without asking probing questions. This technique was invoked to determine whether an expert was conditioning on events that were not discussed, to clarify specific instances of how experts can avoid biases during the actual elicitation, and to resolve a misunderstanding about the definition of cumulative probabilities, which was discovered when the interviewer noticed an inconsistency in the given values.
- Conducting an in-person elicitation indicates that the interviewer cares about the quality of the elicitations and the results of the assessment.
- Many subjects reported that they were more comfortable eliciting the values face-to-face due to the ability to ask the interviewer questions.

Ultimately, one of the largest benefits of the elicitation process is that it gives modelers more opportunities to consult technical experts who have the greatest experience and familiarity with technologies. These experts also have knowledge that energy-economic models may not capture but is important to the development and deployment of technologies. Since these insights typically come out in unstructured conversation, at-a-distance elicitations bypass (or do not take full advantage of) these deep interactions. This point also implies that elicitations have an important role in energy modeling even in a deterministic setting. For instance, exogenous technological progress in deterministic models is typically informed by engineering cost estimates, which should rely on elicitations to assess expert opinion and to structure sensitivities. No matter the model structure, elicitations can help modelers to identify and avoid potential blind spots in the planning process. This function is particularly salient for energy modeling in the context of climate change, which prominently features a few nascent technologies.[15]

Expert elicitations are as important for future modeling efforts as they are for those in the present. Probabilistic assessments preserve information about current beliefs for use in the future, which means that formally capturing such beliefs is necessary for hindcasting exercises. Therefore, elicitations play an integral part in constructing information management systems, improving models for decision support, and combating hindsight bias. These assessments are likewise necessary for evaluating the dynamics of learning [58,59] and for understanding why errant forecasts were wrong [60]. Modelers should compare forecasts with evolving observations to determine trends in estimation errors and to diagnose any systematic forecast biases.

A stochastic analysis is only as good as the probability encoding process behind it. The usefulness of models and elicitation processes would be enhanced if future research compared face-to-face, online, phone, and written elicitations. There are currently no empirical assessments of whether there is an upward or downward bias to moments of distributions based on whether elicitations are conducted in person or at a distance, though the experience here suggests that at-a-distance methods likely underestimate tail probabilities. These experiments could explore how interactive digital elicitation tools can bridge the gap between in-person elicitations (which are recommended by decision analysis practitioners) and at-a-distance paper elicitations (which are prevalent due to their cost-effectiveness and economies of scale). Answers to these questions are especially relevant given the need for more frequent elicitations involving rapidly changing technologies like solar, where it is important to use techniques that can save time and money while not compromising quality.

Acknowledgments

This research was supported by the William K. Bowes, Jr. Stanford Graduate Fellowship and by the Office of Science (BER), US Department of Energy. The author gratefully recognizes the participation of the technical experts Leonard Angello, Chris Edwards, Dale Grace, and Sankaran Ramakrishnan. The author also thanks Erin Baker, Ahren Lacy, Witi Sachchamarga, and Detlof von Winterfeldt for their useful suggestions in designing the protocol used for these elicitations and John Weyant for his constructive feedback on this paper. Any errors are solely the responsibility of the author.

References

[1] A. Kann, J.P. Weyant, Approaches to performing uncertainty analysis in large-scale energy/environmental policy models, Environ. Model. Assess. 5 (2000) 29–46.
[2] J.P. Weyant, Introduction and overview: EMF-19 alternative technology strategies for climate change policy, Energy Econ. 26 (2004) 501–515.
[3] M.G. Morgan, M. Henrion, Uncertainty: A Guide to Dealing with Uncertainty in Quantitative Risk and Policy Analysis, Cambridge University Press, Cambridge, UK, 1990.
[4] R.L. Keeney, D. von Winterfeldt, On the uses of expert judgment on complex technical problems, IEEE Trans. Eng. Manag. 36 (1989) 83–86.
[5] P. Söderholm, T. Sundqvist, Empirical challenges in the use of learning curves for assessing the economic prospects of renewable energy technologies, Renew. Energy 32 (2007) 2559–2578.
[6] G.F. Nemet, Beyond the learning curve: factors influencing cost reductions in photovoltaics, Energy Policy 34 (2006) 3218–3232.
[7] J.P. Martino, Using precursors as leading indicators of technological change, Technol. Forecast. Soc. Chang. 32 (1987) 341–360.
[8] V. Rai, D.G. Victor, M.C. Thurber, Carbon capture and storage at scale: lessons from the growth of analogous energy technologies, Energy Policy 38 (2010) 4089–4098.
[9] A. O'Hagan, C.E. Buck, A. Daneshkhah, J.R. Eiser, P.H. Garthwaite, D.J. Jenkinson, J.E. Oakley, T. Rakow, Uncertain Judgments: Eliciting Experts' Probabilities, John Wiley & Sons, Ltd, West Sussex, UK, 2006.

[15] For instance, elicitations in Baker et al. [34] suggest that the prospects of technical success for post-combustion carbon capture technologies are still controversial among experts in the area, even though many energy models take the availability of such technologies as given.

[10] C.S. Staël von Holstein, J.E. Matheson, A Manual for Encoding Probability Distributions, SRI International, Palo Alto, CA, 1979.
[11] A. Tversky, D. Kahneman, Judgment under uncertainty: heuristics and biases, in: D. Kahneman, P. Slovic, A. Tversky (Eds.), Judgment under Uncertainty: Heuristics and Biases, Cambridge University Press, Cambridge, UK, 1982.
[12] P.M. Kuhnert, T.G. Martin, S.P. Griffiths, A guide to eliciting and using expert knowledge in Bayesian ecological models, Ecol. Lett. 13 (2010) 900–914.
[13] P.H. Gathwaite, J.B. Kadane, O.A., Statistical methods for eliciting probability distributions, J. Am. Stat. Assoc. 100 (2005) 680–700.
[14] M.A. Meyer, J.M. Booker, Eliciting and Analyzing Expert Judgment: A Practical Guide, Society for Industrial and Applied Mathematics, Philadelphia, PA, 2001.
[15] R.R. Hoffman, N.R. Shadbolt, A.M. Burton, G. Klein, Eliciting knowledge from experts: a methodological analysis, Organ. Behav. Hum. Decis. Process. 62 (1995) 129–158.
[16] R.M. Hogarth, Cognitive processes and the assessment of subjective probability distributions, J. Am. Stat. Assoc. 70 (1975) 271–289.
[17] B.M. Ayyub, Elicitation of Expert Opinions for Uncertainty and Risks, CRC Press, Boca Raton, FL, 2001.
[18] A. O'Hagan, Eliciting expert beliefs in substantial practical applications, J. R. Stat. Soc. 47 (1998) 21–35.
[19] S.C. Hora, D. von Winterfeldt, Nuclear waste and future societies: a look into the deep future, Technol. Forecast. Soc. Chang. 56 (1997) 155–170.
[20] M.G. Morgan, D.W. Keith, Subjective judgments by climate experts, Environ. Sci. Technol. 29 (1995) 468A–476A.
[21] R. Abu Taha, T. Daim, Multi-criteria applications in renewable energy analysis, a literature review, in: T. Daim, T. Oliver, J. Kim (Eds.), Research and Technology Management in the Electricity Industry: Methods, Tools, and Case Studies, Springer, London, UK, 2013.
[22] J.-J. Wang, Y.-Y. Jing, C.-F. Zhang, J.-H. Zhao, Review on multi-criteria decision analysis aid in sustainable energy decision-making, Renew. Sust. Energ. Rev. 13 (2009) 2263–2278.
[23] A.H.I. Lee, H.H. Chen, H.-Y. Kang, Multi-criteria decision making on strategic selection of wind farms, Renew. Energy 34 (2009) 120–126.
[24] I. Linkov, F.K. Satterstrom, G. Kiker, C. Batchelor, T. Bridges, E. Ferguson, From comparative risk assessment to multi-criteria decision analysis and adaptive management: recent developments and applications, Environ. Int. 32 (2006) 1072–1093.
[25] NRC, Reactor safety study: an assessment of accident risks in US commercial nuclear power plants, Technical Report, US Nuclear Regulatory Commission, 2010.
[26] R.M. Cooke, Uncertainty analysis comes to integrated assessment models for climate change…and conversely, Clim. Chang. 117 (3) (2013) 467–479.
[27] A.B. Rao, E.S. Rubin, D.W. Keith, M.G. Morgan, Evaluation of potential cost reductions from improved amine-based CO_2 capture systems, Energy Policy 34 (2006) 3765–3772.
[28] A.E. Curtright, M.G. Morgan, D.W. Keith, Expert assessments of future photovoltaic technologies, Environ. Sci. Technol. 42 (2008) 9031–9038.
[29] A. Abdulla, I.L. Azevedo, M.G. Morgan, Expert elicitation of the cost of small modular nuclear reactors, Proc. Natl. Acad. Sci. (2013) (forthcoming).
[30] V. Bosetti, M. Catenacci, G. Fiorese, E. Verdolini, The future prospect of PV and CSP solar technologies: an expert elicitation survey, Technical Report, Fondazione Eni Enrico Mattei, 2012.
[31] G. Fiorese, M. Catenacci, E. Verdolini, V. Bosetti, Advanced biofuels: future perspectives from an expert elicitation survey, Technical Report, Fondazione Eni Enrico Mattei, 2012.
[32] L.D. Anadon, M. Bunn, G. Chan, M. Chan, C. Jones, R. Kempener, A. Lee, N. Logar, V. Narayanamurti, Transforming US energy innovation, Technical Report, Harvard Kennedy School, Belfer Center for Science and International Affairs, 2011.
[33] E. Baker, H. Chon, J. Keisler, Advanced Nuclear Power: Combining Economic Analysis with Expert Elicitations to Inform Climate Policy, Technical Report, University of Massachusetts Amherst, 2008.
[34] E. Baker, H. Chon, J. Keisler, Carbon capture and storage: combining economic analysis with expert elicitations to inform climate policy, Clim. Chang. 96 (2009) 379–408.
[35] E. Baker, H. Chon, J. Keisler, Advanced solar R&D: combining economic analysis with expert elicitations to inform climate policy, Energy Econ. 31 (2009) S37–S49.
[36] E. Baker, H. Chon, J. Keisler, Battery technology for electric and hybrid vehicles: combining expert views about prospects for advancement, Technol. Forecast. Soc. Chang. 77 (2010) 1139–1146.
[37] E. Baker, J. Keisler, Cellulosic biofuels: expert views on prospects for advancement, Energy 36 (2011) 595–605.
[38] K.E. Jenni, E.D. Baker, G.F. Nemet, Expert elicitations of energy penalties for carbon capture technologies, Int. J. Greenhouse Gas Control 12 (2013) 136–145.
[39] L.D. Anadon, V. Bosetti, M. Bunn, M. Catenacci, A. Lee, Expert judgments about RD&D and the future of nuclear energy, Environ. Sci. Technol. 46 (2012) 11497–11504.
[40] M.G. Morgan, H. Dowlatabadi, M. Henrion, D. Keith, R. Lempert, S. McBride, M. Small, T. Wilbanks, Best practice approaches for characterizing, communicating, and incorporating scientific uncertainty in climate decision making, Technical Report, US Climate Change Science Program and the Subcommittee on Global Change Research, National Oceanic and Atmospheric Administration, 2009.
[41] L.D. Phillips, Group elicitation of probability distributions: are many heads better than one? in: J. Shanteau, B. Mellors, D. Schum (Eds.), Decision Science and Technology: Reflections on the Contributions of Ward Edwards, Kluwer Academic Publishers, Norwell, MA, 1999.
[42] M.G. Morgan, B. Fischhoff, A. Bostrom, C.J. Atman, Risk Communication: A Mental Models Approach, Cambridge University Press, Cambridge, UK, 2002.
[43] R.L. Keeney, D. von Winterfeldt, Eliciting probabilities from experts in complex technical problems, IEEE Trans. Eng. Manag. 38 (1991) 191–201.
[44] S. Pacala, R. Socolow, Stabilization wedges: solving the climate problem for the next 50 years with current technologies, Science 305 (2004) 968–972.
[45] DOE/EIA, Annual energy outlook 2011, Technical Report DOE/EIA-0383(2011), US Department of Energy, Energy Information Administration, 2011.
[46] H. Huntington, EMF 26: changing the game? Emissions and market implications of new natural gas supplies, Technical Report EMF Report 26, Volume I, Energy Modeling Forum, 2013.
[47] J.E. Bistline, Electric sector capacity planning under uncertainty: Shale gas and climate policy in the US, in: 31st USAEE/IAEE North American Conference, Austin, TX, 2012.
[48] J.L. Coleman, R.C. Milici, T.A. Cook, R.R. Charpentier, M. Kirschbaum, T.R. Klett, R.M. Pollastro, C.J. Schenk, Assessment of undiscovered oil and gas resources of the Devonian Marcellus shale of the Appalachian basin province, Technical Report US Geological Survey Fact Sheet 20113092, US Geological Survey, 2011.
[49] E.J. Moniz, H.D. Jacoby, A.J.M. Meggs, The future of national gas: interim report, Technical Report, Massachusetts Institute of Technology, 2010.
[50] Infogroup/ORG, Fracking and clean water: a survey of Americans, Technical Report, Infogroup/ORG, 2010.
[51] R.W. Howarth, R. Santoro, A. Ingraffea, Methane and the greenhouse-gas footprint of natural gas from shale formations, Clim. Chang. 106 (2011) 679–690.
[52] M. Jiang, W.M. Griffin, C. Hendrickson, P. Jaramillo, J. VanBriesen, A. Venkatesh, Life cycle greenhouse gas emissions of Marcellus shale gas, Environ. Res. Lett. 6 (2011).
[53] G. Chan, L.D. Anadon, M. Chan, A. Lee, Expert elicitation of cost, performance, and RD&D budgets for coal power with CCS, Energy Procedia 4 (2011) 2685–2692.
[54] G.J. Blanford, R&D investment strategy for climate change, Energy Econ. 31 (2009) S27–S36.
[55] R.T. Clemen, R.L. Winkler, Combining probability distributions from experts in risk analysis, Risk Anal. 19 (1999) 187–203.
[56] D.A. Seaver, Assessing probability with multiple individuals: group interaction versus mathematical aggregation, Technical Report Report No. 78-3, Social Science Research Institute, 1978.
[57] D. Unger, H. Herzog, Comparative study on energy R&D performance: gas turbine case study, Technical Report, Central Research Institute of Electric Power Industry, 1998.
[58] A. Hannart, M. Ghil, J.-L. Dufresne, Disconcerting learning on climate sensitivity and the uncertain future of uncertainty, Clim. Chang. 119 (3–4) (2013) 585–601.
[59] M. Oppenheimer, B.C. O'Neill, M. Webster, Negative learning, Clim. Chang. 89 (2008) 155–172.
[60] P.P. Craig, A. Gadgil, J.G. Koomey, What can history teach us? A retrospective examination of long-term energy forecasts for the United States, Annu. Rev. Energy Environ. 27 (2002) 83–118.

John E. Bistline is a Ph.D. candidate in the Department of Management Science and Engineering at Stanford University. His research examines uncertainty analysis and technology dynamics in the contexts of energy modeling and environmental policy.