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An expert elicitation of climate, energy and economic uncertainties ☆

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HIGHLIGHTS

- We conduct an expert elicitation of 25 UK energy experts from academia, industry and government.
- We obtained expert beliefs for six national and international drivers of energy demand.
- A linear pool of expert beliefs on oil price in 2030 is insensitive to correlation between the experts.
- Experts agree on dependence structure of energy uncertainties, but individual assessments of future values exhibit variation.

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ABSTRACT

Critical energy policy decisions rely on expert assessments of key future uncertainties. But existing modelling techniques that help form these expert assessments often ignore the existence of uncertainty. Consequently, techniques to measure these uncertainties are of increasing importance. We use one technique, expert elicitation, to assess six key uncertain parameters with 25 UK energy experts across academia, government and industry. We obtain qualitative descriptions of the uncertain parameters and a novel data set of probability distributions describing individual expert beliefs. We conduct a sensitivity analysis on weights for a linear opinion pool and show that aggregated median beliefs in 2030 are: for oil price \$120/barrel (90% CI: 51, 272); for greenhouse gas price \$34/tCO_2e (90% CI: 5, 256) and for levelised cost of low-carbon electricity 17.1 US cents/kWh (90% CI: 8.3, 31.0). The quantitative results could inform model validation, help benchmark policy makers' beliefs or provide probabilistic inputs to models.

1. Introduction

Investment and policy decisions made now have a substantial effect upon the composition of the future energy system due to the long lifetimes of energy plant and infrastructure and the consequent effects of path dependency and technology lock-in. Conversely, the current beliefs of decision makers regarding the value of key future parameters effect the decisions they make today. For example, Strachan et al. (2008) and Usher and Strachan (2012) have shown that energy transition pathways are sensitive to a range of uncertainties. Clearly, while it would be useful to have perfect knowledge regarding the future so that one could make perfect decisions, an approach which takes into account the range of possible future values is more realistic. Such decision theoretic approaches that allow a full range of possible futures to inform current decisions readily exist, such as stochastic programming (Keppo and Zwaan, 2011), real-options (Siddiqui et al., 2007) and uncertainty analysis (Morgan et al., 1992). However, while empirical data sources exist for the values of some key uncertainties, such as forward markets for oil (which could reflect traders' collective beliefs about the future oil price), for other important uncertainties there exist no sources of data. Furthermore, just as caution is required when extrapolating findings from a sample to a population, statistical data about the past is not necessarily indicative of the future. So, even when empirical data does exist, it may not be suitable for decision support. In such cases, a formal expert elicitation can provide quantified subjective beliefs for parameters with no alternative data sources.

To provide evidence for decision makers in the energy field, computer models are commonly used to support and codify expert knowledge of the integrated energy and climate change system (Rotmans and van Asselt, 2001b). In the process of constructing models, researchers make judgements about the structure of these models, the selection of parameters and the values of inputs. Commonly, the inputs to one model are derived from outputs of other models. For example, Integrated Assessment Models use formulae that emulate the relationships between energy technologies, the macro-economy and GHG emissions (Rotmans and van

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Asselt, 2001a). Researchers can incorporate estimates of uncertainties for these model inputs only if such data exists, or if they have the specific expertise to make sound scientific judgements as to the range and likelihood that represent these uncertainties. Consequently, the knowledge obtained from the outputs of models is inherently conditional on the assumptions made by the modeller (Stirling, 2010).

We propose that expert elicitation is an improvement upon the current situation. Firstly, an expert elicitation is a formal process that can produce high quality, traceable, transparent and explicitly subjective data on parameters for which there is no empirical alternative. Secondly, data from an expert elicitation can displace existing informal approaches to gathering data for uncertain parameters in models.

We claim that the formal approach provided through expert elicitation can enhance the policy making process through improved transparency and through the provision of more representative data.[1] We offer caution here, because there is potential for misuse and because there are some troubling aspects of the elicitation approach that undermine the benefits unless handled correctly. One important aspect is that expert elicitation does not provide an objective data set *de jure*, but the subjective beliefs of individual or a group of experts. Thus decisions based on this data are explicitly linked to the subjective beliefs held within the data. The integrity of the subsequent decisions rely both on the accuracy of the expert's beliefs and that of the process by which those beliefs were quantified. However, the former is the inherent nature of relying upon subjective judgements to make decisions, be they explicit or implicit and encoded within a model. Expert elicitation is rightly concerned with minimising the error in the latter through accounting for the influence of bias and heuristics upon an expert's judgement.

This work captures a snapshot of the beliefs of 25 UK energy experts in late 2011 about the value of six key uncertain parameters in 2030. We collected data on both the range of plausible values and the associated likelihoods for each parameter, through a formal one-to-one interview process. This study shows how expert elicitation can be used to produce data for use in energy-economic modelling. These results show the subjective beliefs of UK energy experts for parameters of national and international importance. The resulting probability distributions are of interest to a wide range of international and national stakeholders including those in academia, decision makers in the public and private sectors, governments and investors. The included data set can be used both to verify and validate existing scenario studies, to benchmark policy maker's beliefs or to inform model inputs.

1.1. Literature review

Bayesian probability theory stipulates that subjective beliefs about a well defined parameter can be described using a probability distribution (De Finetti, 1974). Expert elicitation is the process by which expert beliefs are encoded (Garthwaite et al., 2005) using methods that mitigate the detrimental effects of heuristics and biases (Kahneman et al., 1982).

O'Hagan (2006) provides a review of a number of heuristics and biases, first explored by Kahneman et al. (1982). Heuristics are tools or shortcuts used by individuals to replace reasoned decision making. Bias is a systemic distortion introduced into data through an unaccounted factor. Key biases and heuristics include anchoring and adjusting—respondents to not adjust their judgement sufficiently from an anchor value; availability bias—ideas that come more easily to mind are deemed more probable than those difficult to recall; representativeness—respondents are incoherent in their probability assessment (probabilities do not sum to one).

Elicitation methodologies received considerable attention between the 60s and 80s, predominantly at the junction of statistics and psychology. As such, there are a wide selection of methodologies from which to choose. Potential candidates include the fixed and variable interval methods for direct elicitation of continuous parameters. Alternatively, the elicitation can focus on statistical summaries of parameters, such as mean and variance. However, individuals are often poor estimators of statistical summaries, and the elicitation of intervals gives better results (see Garthwaite et al., 2005, for a detailed discussion).

Expert elicitation has been used in energy and climate policy to derive quantitative probabilistic judgements on key climate variables and their impact on climate sensitivity from sixteen USA-based climate experts (Morgan and Keith, 1995). There have been a range of subsequent elicitation studies on climate change impacts and adaptation uncertainties (Zickfeld et al., 2007; Granger Morgan et al., 2001; Hagerman et al., 2010). In terms of mitigation and energy pathway uncertainties, there have been fewer formal elicitation studies. Indeed these have largely been limited to assessments of individual key technologies (Baker et al., 2010; Baker and Keisler, 2011; Bosetti et al., 2012; Zubaryeva et al., 2012) and single policy measures (Baker et al., 2009), exploring the relationship between research and development funding and technological learning. Also, elicitation has been used to obtain data on uncertain input parameters, for which there is no other data source, such as the permeability of rock beneath proposed nuclear waste repositories (Bonano et al., 1990; O'Hagan, 1998). When data is unlikely to be readily forthcoming, for example through analysis of forward market prices, a formal elicitation process forms one of the only ways in which the subjective beliefs of experts can be captured.

1.2. Layout

We first discuss the selection of parameters and experts and how we conducted one-to-one interviews with 25 energy experts from academia, government and industry to elicit uncertainties for six parameters that influence decision making in the energy sector. We then present results for five of the six parameters, and show the implications of two different approaches to pooling beliefs using expert beliefs for oil price in 2030 as a case study. We conclude with implications for policy makers and energy modellers, and suggestions for further work.

2. Methods

2.1. Selection of uncertain parameters

The selection of the six uncertain parameters (see Table 1) explored in this paper followed experience of modelling uncertainty in the energy system (Usher and Strachan, 2010, 2012) and interaction with policy makers. We selected a range of international and national drivers of energy demand including those parameters to which the structure of the future energy system is most sensitive. The parameters chosen are important drivers of energy demand, energy system structure, or energy system cost. Population is a strong scaling factor of energy demand, as is the change in GDP or relative affluence (Rosa and Dietz, 2012). Behavioural aspects of energy, such as the temperature to which individual homes are heated are important when multiplied over a population (Beugin and Jaccard, 2011). Prices of GHG and oil result in very different technology pathways in energy system modelling studies (Usher and Strachan, 2012). Consequently, expectations of

[1] i.e. representative of the actual beliefs of experts.

Table 1
Selected uncertain parameters.

Key input	Units
UK population in 2030[a]	Million
Average annual change in UK GDP 2010–2030[b]	Average annual % change
International GHG price in 2030[c]	(2010) $/tCO_2e$
Long-term oil price in 2030[c]	(2010) $/barrel
Average levelised cost of UK low carbon electricity system in 2030[b]	(2010) US cents/kWh
Average main room temperature during heating season in UK domestic dwellings[a]	°C

[a] National parameter.
[b] National parameter, but indicative of international situation.
[c] International parameter.

Table 2
Expert affiliation.

Expert affiliation	Experts contacted	Experts interviewed
Academia	26	16
Industry	5	5
Government	6	4
Total	37	25

different GHG and oil prices result in different investment decisions today. The levelised cost of electricity influence investment in different portfolios of technologies.

Following a trial elicitation conducted with staff researchers in the UCL Energy Institute, we determined that it was difficult to elicit more than six to eight univariate distributions per two hour interview. We therefore restricted the project to just six uncertainties. The trial elicitation also enabled us to establish a consistent interview structure and identify problematic wording in the definition of uncertain variables. For example, we first asked for an absolute value for UK GDP in 2030, but quickly found that participants thought more easily in terms of annual percentage change. This question was amended for the actual elicitation.

2.2. Selection of experts

We contacted 37 experts across industry, academia and government in the UK. Of these, 25 responded positively to a request for interview (Table 2). Although the proportion of experts from each sector is uneven, which may influence the findings, there is no indication from the results that affiliation is a significant explanatory factor. Even so, sample sizes are small, so we are not able to claim that we have captured a representative sample of all UK energy experts (as far as that would be possible). Clemen and Winkler (1999) note that there are decreasing marginal returns to adding experts and recommend using between three and five due to the trade-off between time required and results. Furthermore, experts similar in modelling style, philosophy and access to data tend to provide redundant information, and so heterogeneity is a preferential feature of the sample of experts. It is difficult to judge heterogeneity before making the interviews, and so we interviewed as many individuals as possible, particularly so as to provide even coverage across all the parameters. We collected data regarding experts' access to data for each parameter (see Table 3), as well as their research style, such as interpretation of secondary data, modelling from first principles. This data is used to weight the expert judgements, the results of which can be found in Section 4.

2.3. Overview of the elicitation process

We interviewed experts individually in sessions lasting one to two hours. The interviews consisted of an introduction, brief training in uncertainty, probability and the expert elicitation process followed by the actual elicitation. A script was used to ensure consistency between interviews.

We adopted a variable interval approach assessing the median and quartiles (also known as the bisection approach), where the following series of questions were asked:

> "Please could you give your lowest plausible bound for *x*, where you would be happy assigning a very low (as close to 0 as possible) probability that the value could be lower than this".
>
> "Please could you give your highest plausible bound for *x*, where you would be happy assigning a very low (as close to 0 as possible) probability that the value could be higher than this".
>
> "Please could you give your median estimate for *x*, where you consider it equally likely that the value could be above or below your median?"
>
> "Please could you give me your lower quartile for *x*, where you consider it equally likely that the value could be above or below your lower quartile?"
>
> "Please could you give me your upper quartile for *x*, where you consider it equally likely that the value could be above or below your upper quartile?"

The order of questions within each parameter elicitation was structured so as to avoid the inclusion of biases and heuristics into the process. For example, by first asking for an upper and lower plausible bound, the interviewee is anchored equally to both ends of the range when thinking about their median belief. The advantage of this approach is that only judgements of equal-likelihood are required. Individuals tend to be quite good at assessing probabilities using variable intervals, although there is a tendency for over-confidence. However over-confidence can be mediated to some extent through a calibration process. We therefore integrated a calibration step into the training stage, giving feedback to respondents regarding their performance in the practice elicitation.

While eliciting the quartiles, the participant was shown a visual representation of their upper and lower bounds when choosing the median, the lower bound and median when choosing the lower quartile and median and upper bound when choosing their upper quartile. The interviewee was then shown a plot of the equally likely values represented by their summaries, where each of four ranges is assigned a probability of 25%. In some cases, if the interviewee was not happy with the values shown, the summaries were again elicited or adjusted, following the order above. Once happy with the elicited values, the interviewee was guided by the facilitator to choose one of six distributions. These include either a normal, scaled beta, student-T, log normal, log student-T or gamma distribution. Distributions were initially fitted to the

Table 3
Data sources used by experts during elicitation.

ID	Affiliation	Pop	GDP	GHG	Oil	Elec	Temp	Notes
1	Acad.	T	T	T	T	TPA	IHM, IHR	
2	Acad.	IHM		T, IHM	IEA	MM	Carb	
3	Ind.	UN	IHM		IHM, IEA, DEM	IHM	A (IHM)	
4	Ind.	A	OBS	CPF	A	IHM, MM		GHG bi-modal
5	Ind.	T		Scenarios			Carb	GHG bi-modal
6	Acad.	ONS, SRES	SRES	IHM	IHM	IHM		
7	Acad.	ONS, IHM, OPP						
8	Acad.	ONS, oms	IHR	IHR	GOD, IHR	IHM, IHR	IHR	
9	Ind.	ONS	ONS	IHM (EU)	IEA	IHM	A, T	
10	Acad.	ONS	ONS, T	CPF	DEM	TPA	A	
11	Acad.	A	A	A		MM	A	
12	Acad.	ONS, IHR	IHR, OMR	IHM	DEM		T	
13	Acad.	ONS, T	FS	IHR	GOD, IHR	IHM	IHR	
14	Acad.	ONS, FS	T, ONS	DECC	IHR	IHR	T	
15	Acad.	ONS, UKERC	IHR	IHR			T	
16	Acad.	T	NR	NR	NR	NR	IHR	
17	Gov.	ONS	IHM	IHM	DEM		T	
18	Acad.	IHM	IHM		DEM	IHM	A	
19	Gov.	ONS, GAD	HMT	E, T	DEM, IEA	MM, IHM	IHR, IHM	
20	Gov.	ONS,	IHM, OBR	IHM	IHR, DEM, IEA	NR	IHM	
21	Gov.	ONS, T	OBR, HMT, T	IHR, A	IEA, T, IHR	A, MM	A	
22	Ind.	ONS	T	IHM, IHR	BP, DEM, IHM			
23	Acad.	A	A, T	T	BP, GOD	E	A	
24	Acad.	ONS	WB, ONS	DCPF, NG, MM, CE	IEA, DEM, EAI	MM, oms, PB	E	
25	Acad.	IHR, A	T	IHR	T	MM, DECC	A	

A – anecdotal evidence, Carb – CARB heat project, CE – Cambridge econometrics, CPF – carbon price floor, DCPF – DECC carbon price forecasts, DEM – DECC energy model (Department of Energy and Climate Change, 2010), E – empirical data, EIA – Energy Information Administration (USA), FS – foresight scenarios, GAD – Government Actuaries Department, GOD – Sorrell et al. (2010), IEA – international energy agency, IHM – in-house modelling, IHR – in-house research (non-modelling), IPCC – international panel on climate change, MM – Mott MacDonald (2010), NG – national grid, NR – nonresponse, OBR – office of budget responsibility, oms – other modelling studies, ONS – office of national statistics, OPP – office of population projections, PB – PB power, SRES – Nakićenović and Swart (2000), T – knowledge of historical trends, TPA – Greenacre et al. (2010), UN – United Nations (population projections), WB – World Bank.

values given by the interviewee by minimising the sum-of-squares. After assessing, amending or confirming the fitted distribution, the interview progressed to the next uncertain parameter. During the interview, experts were encouraged to discuss the reasoning behind their beliefs, declare any interests they may have that could influence their answers, give a summary of their relevant expertise and a list of key evidence to which they referred. This process was repeated for each of the six parameters. Finally, feedback was provided to each expert for each parameter after fitting the final distribution.

To assist the elicitation we used the SHELF 2.0 software (Oakley and O'Hagan, 2010) a package for the R open-source statistical package (R Development Core Team, 2011) and saved the data in a Microsoft Access database.

2.4. Assessing the expert judgements

Elicitation is an inherently imprecise process. Even experts are unlikely to represent their beliefs exactly using the process of eliciting summaries, so we were careful to adopt a method that integrated validation of experts' claims and the method itself throughout the project.

Firstly, we assessed the degree to which the expert is calibrated, that is whether they are under- or over- confident (their distributions are too narrow or too wide) using a practice elicitation trivia question at the beginning of the interview:

> “What is the length of the Moscow Underground Network in km?”

An energy expert's uncertainty for this practice elicitation is epistemic, i.e. related to their lack of knowledge about the true value of the length of the Moscow underground. The uncertainty surrounding a future parameter is also epistemic, although unlike the practice question, unknowable at the present time. The results give an indication of expert performance, and an experts confidence can be checked by comparing the probability distribution they offer as a representation of their belief, with the true answer (known in this case to be 301.2 km).

Secondly, at the beginning of the interview we provided training on biases, heuristics and probability, as well as eliciting summaries in such a way as to avoid introducing further biases and use of heuristics. We provided two forms of feedback to the expert; equally probable ranges implied by the elicited summaries, and the distribution that best fit the elicited summaries.

Finally, we collected qualitative data from the experts during the interview on the data to which they referred when thinking about the uncertainty. This can be used as a proxy for determining correlation between experts. Table 3 shows the sources of data declared by experts. For example, expert 1 is an academic, knowledgable of the historical trends for GHG price, oil price and so on, but conducted in-house research and modelling for the average main room temperature. In contrast, expect 9 is in the industrial sector, conducts modelling in GHG price and for levelised cost of electricity, and draws upon ONS projections for population and GDP. The sharing of data sources indicates that for some parameters, the beliefs of the experts could be strongly correlated. For example 15 of the 25 experts cite the ONS population projections for the population parameter, while 5 of the 25 conduct in-house research or modelling on population or demographics. We address the consequences of this in the discussion section, through weighted aggregation techniques.

2.5. Aggregation of expert beliefs

The aggregation of expert beliefs can take two forms, either behavioural aggregation or mathematical aggregation. Behavioural aggregation requires the interview of a group of experts and requires careful management to avoid the biases inherent in group dynamics. O'Hagan (2006) recommends behavioural aggregation, and prefer to elicit expert judgements in small groups. In this study, due to organisational constraints, we interviewed experts individually and therefore mathematical aggregation is the only method available to us. There are a number of mathematical aggregation techniques, some of which are reviewed in Cooke (1991). A larger review (Clemen and Winkler, 1999), concludes that a simple average, or linear pool, is often the best performing aggregation method, as it is less sensitive to the input assumptions than some of the more powerful Bayesian aggregation techniques such as that suggested in Morris (1977). While an equally weighted linear pool (i.e. average) is simple, several rather strong assumptions are implicit in the process, chiefly that the experts' beliefs are independent of one another and that experts are equally expert. It is likely that experts draw upon similar data sources (experts are correlated), or perhaps are anchored to a particular value (experts are biased). If we correct for these, we are likely to arrive at a more precise description of the collective beliefs of the experts.

We recognise that mathematical aggregation can be controversial. For example Stirling (2010) remarks that representing the diversity of opinion is invaluable if the aim is to inform policy, while others entirely reject the rationale for aggregation (Keith, 1996), claiming that it is impossible to correctly rationalise the fundamentally different mental models experts have for describing complex systems. Morgan et al. (1992) note that checking the sensitivity of a particular aggregation technique should be part of the selection process.

While taking the above concerns into account, we have followed the guidance in Clemen and Winkler (1999) and O'Hagan (2006) and use a simple weighted linear pool to represent the aggregated expert belief, shown in Eq. (1),

$$p(\theta) = \sum_{i=1}^{n} w_i p_i(\theta) \tag{1}$$

where

- n is the number of experts
- $p_i(\theta)$ represents i's probabilities for unknown θ
- $p(\theta)$ represents the combined probability distribution
- w_i signifies the weights assigned to experts to reflect the combination of expert bias, correlation or expertise

As described later in Section 4.1, we carefully assessed the sensitivity of the linear pool to the weights applied to experts, and determined that our findings are robust to changes in whether experts are weighted according to their

(i) judgement of probabilities and
(ii) selection of data sources, or
(iii) both.

3. Results

We present results for following international and national parameters; the UK population in 2030, average growth in UK GDP between 2010 and 2030, oil price in 2030, GHG price in 2030 and levelised cost of low-carbon electricity in 2030. Due to the dominance of anecdotal evidence referred to by the experts for average main room temperature in 2030, we have excluded the results from this study. All prices are deflated to US$2010.

3.1. UK population in 2030

Fig. 1(a) shows the range of expert beliefs for UK population in 2030. The experts stated that the key determinants of UK population in 2030 are birth rate, death rate, and net migration. Each of these factors are related to one or other of the uncertain parameters included in this study as well as with a complex web of other uncertainties. For example, birth rates typically decrease as GDP increases, depending on the overall development phase within which the country sits. Birth rate often increases with positive net migration, the subjects of whom are often of a younger, working and family raising age. Net migration depends upon the relative economic prosperity of the UK compared to other countries to which its borders are open, while border permeability is dependent on country policy. The current Conservative Government has a low-migration policy, limiting the entrance of non-EU migrants to the UK, but this will have limited effect on the flow of EU citizens, especially if Turkey were to join the EU. Death rate is declining, and the population is ageing, a result of increasing improvements in health, again correlated with positive GDP growth. A number of respondents declared that the natural components of population, birth and death rate, are relatively certain while the quantity of net migration is more uncertain; the significantly uncertain component of the latter being the UK Government sentiment and policy towards immigration. A few respondents mentioned that high impact but improbable events could have a significant positive or negative effect on UK population such as the migratory effects of climate change (i.e. an influx of refugees), or a significant disaster such as nuclear meltdown or war.

When discussing population, most experts referred to historical trends and the population forecasts published by Office of National Statistics. These forecasts are developed by the Office of Population Projections, a source mentioned by just one respondent. Just three interviewees (2, 7 and 18) maintained some form of population or demographic model. Most experts were therefore users of forecasts developed by one central Government source.

UK population reached 62 million in 2010, having grown from 57 million in 1990. All median expert beliefs show that UK population will continue to grow out to 2030, although the ranges given by many of the experts cover the possibility of a contraction in population.

3.2. Average annual change in UK GDP: 2010–2030

The expert beliefs of UK GDP were less consistently similar than those of population and the dynamics are arguably more complex. Beliefs coalesced around the principle of the UK in global markets, with recession and recovery a significant determinant of growth over the next two decades. Even if the UK were able to radically restructure its economy to become a market leader in new technologies and services, it is likely that a global recession would significantly dampen GDP growth. There were some suggestions that UK could play a leading role in low carbon technologies, and a few experts emphasised the existing strength of the UK's financial sector. Across the range of possibilities expressed, the lower end (near-zero) growth could only be possible in the case of a very weak recovery following a lengthy and drawn out recession.

Fig. 1(b) shows the range of expert beliefs for the average annual growth in UK GDP between 2010 and 2030. Most respondents were strongly anchored to the historical average of 2%, despite detailed discussions that considered the ongoing economic crisis, and the potentially deleterious effect this may have over the next two decades. Experts 4, 6 and 23 gave very pessimistic forecasts, with a median belief less than 1% average annual growth between 2010 and 2030. No expert interviewed believed that

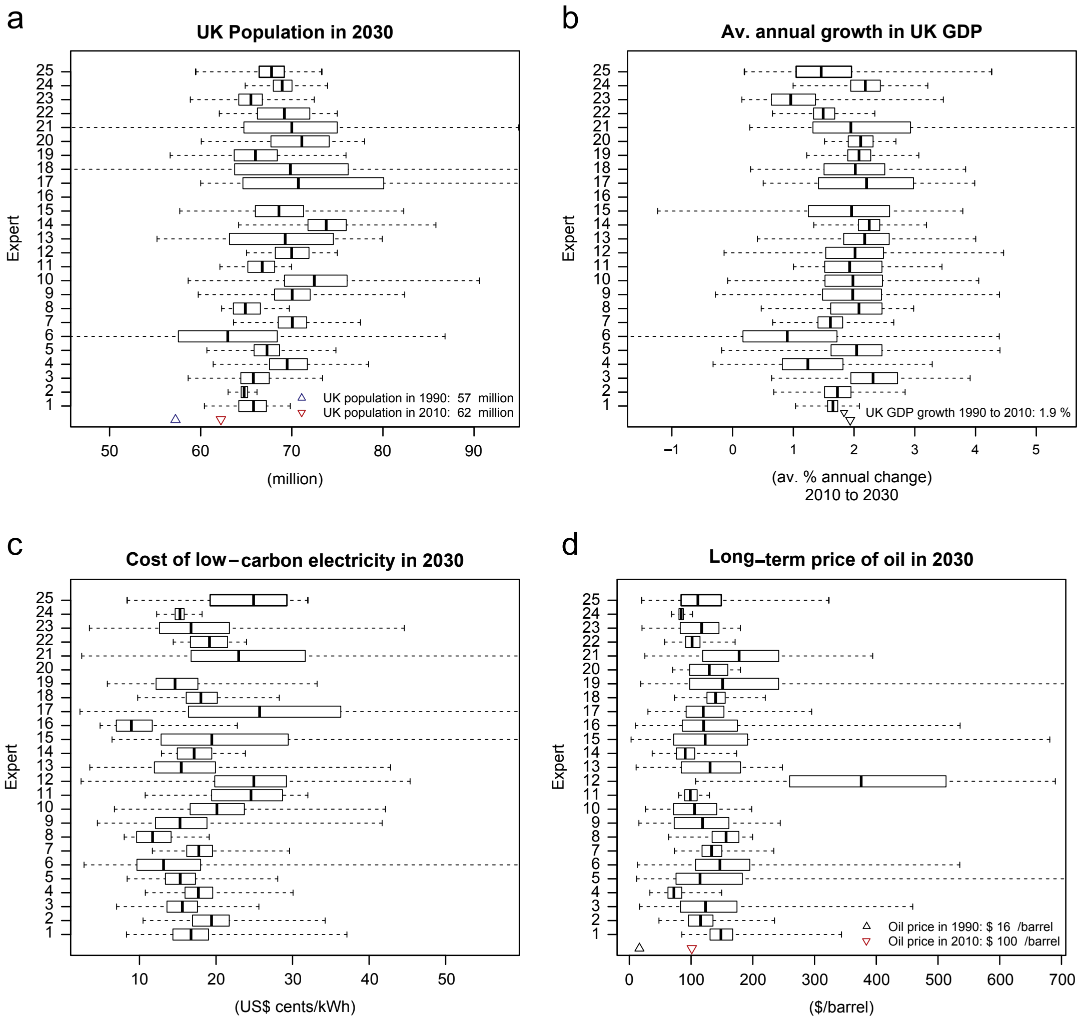

Fig. 1. (a) shows UK population in 2030, (b) shows average annual change in UK GDP: 2010–2030, (c) shows Levelised cost of low-carbon electricity in 2030 and (d) shows long-term price of oil in 2030.

an average growth rate over 2.3% is more than 25% likely. Many of those interviewed practised some form of modelling capability.

3.3. *Levelised cost of low-carbon electricity in 2030*

Experts identified a limited portfolio of low-carbon technologies each of which they believed capable of achieving a 20% share of the UK electricity market (in energy rather than capacity terms), given build, infrastructure and other constraints. However, the mix of technologies identified changed substantially across the range of costs. The technologies identified included: on-shore and off-shore wind, nuclear and gas or coal with carbon capture and storage (CCS). One individual mentioned that solar could technically contribute this quantity of electricity in the UK. Many experts were sceptical of CCS, noting that while the technology has great promise, it is still unproven on a commercial scale. Many experts indicated that the range of costs depended on a function of (i) the mix of technologies employed which in turn depended on the domestic policy support extended to renewable generation in the interim decades to 2030; (ii) the degree to which cost reductions occur for the identified technologies due to domestic and international learning effects, correlated with the likelihood of a global deal; (iii) the effect of the Fukushima disaster upon the nuclear sector, specifically the public perception of nuclear safety; (iv) the ability of the UK to successfully deploy nuclear power at the required scale; and (v) the technical success or failure of any one or group of the low-carbon technologies. High costs were associated with a number of scenarios, ranging from perverse policies that subsidise expensive low-carbon technologies that do not undergo learning cost-reductions, to a failure of any one of CCS, nuclear or wind. Low costs were generally technically optimistic, associated with international cooperation, large scale roll out of low-carbon technologies, targeted policies delivering renewable generation at least-cost, coupled with large expansion of nuclear. Opinions on nuclear were divided across experts. These ranged from the pessimistic—the true costs of nuclear are unknown, to the optimistic—wide scale roll-out will result in least-cost electricity. However, most experts were cognisant of the limited time in which there is to build nuclear power stations and as such, the optimism was moderated by acknowledgement of the mix of technologies likely to comprise the 2030 electricity system.

Fig. 1(c) shows the range of expert beliefs for the cost of low-carbon electricity in 2030. Median estimates ranged between 8.8 and 25.3 US cents/kWh, with a much larger range of estimates for upper and lower quartiles of 6.9–37.3 US cents/kWh. These costs are largely similar to estimates of the levelised cost of generating electricity in Heptonstall (2007). The majority of experts interviewed conducted independent modelling or research into the levelised cost of low-carbon electricity.

3.4. Long-term price of oil in 2030

The discussion of oil prices focused on the classic dynamics of supply and demand and the role of substitution for alternative energy carriers due to concern surrounding the environment or energy security. Supply focused on geopolitics, the technical availability of oil and at what price, the marginal price of extraction, the degree to which exploration would remain financially viable given alternative competing fuels and advances in extraction technology. Dramatically increasing demand, particularly from transition economies and the potential for lock-in to Western style consumption patterns (e.g. very large road construction projects in China), could counter increasing pressure to reduce oil consumption in the more economically developed regions such as Europe, due to concerns surrounding energy security and climate change. The substitution of alternative fuels for oil provides an upper limit on the long-term oil price, given the increasing range of technologies available, but this is also dependent on the support for the development of these technologies in the periods up to 2030, thus critical dependency on mid-term environmental or energy security policies. As oil prices are determined on the global market, increases in the long-term oil price are likely to be correlated with positive global economic growth and therefore positive UK GDP growth. However, an increase in GHG prices may suppress demand for oil in participating countries which could in turn depress the global price of oil.

Fig. 1(d) shows the range of expert beliefs for the long-term price of oil in 2030

Compared to the 20 year period between 1990 and 2010, when oil prices rose to reach an historic high of $100/barrel, the pooled beliefs show an expectation that oil prices will increase yet further. The pooled beliefs indicate that there is a 90% likelihood of the oil price in 2030 lying between $51/barrel and $270/barrel, with just a 25% likelihood of the price falling below $88/barrel.

3.5. Price of GHG credits available to the UK in 2030

Of the uncertain parameters discussed in the interviews, GHG price provoked the most diverse range of beliefs from experts. A key driver was determined to be ‘political will’, the determination of politicians, and by extension civilians, to affect change. The majority of experts declared their hope for a carbon price by 2030, with an agnostic minority. However, the majority of respondents expressed pessimistic beliefs relative to their hopes. The major dependent parent uncertainty was the likelihood of achieving a global deal. Political will is loosely inversely correlated with global GDP growth, with many respondents declaring that a prolonged recession would be likely to distract citizens and policy makers from environmental concerns. As such, a number of experts (e.g. 4 and 5) identified the distribution for their beliefs of price of GHG credits to be bimodal. Thus, if political will were strong enough to secure a deal, the carbon price would be greater than $0/tCO_2e$. While our software was not able to explicitly represent a bimodal distribution, we separately elicited the non-zero part of the elicitation. Most experts also noted that the UK ambition would likely falter in the absence of a global deal, and thus the carbon price would fall to $0/tCO_2e$. One individual noted that if the UK was isolated internationally yet continued with an ambitious policy, it would be exposed to extremely high GHG prices due to the need for entirely domestic mitigation measures.

Fig. 2 shows the cost of GHG credits available to the UK in 2030. The majority of median beliefs are below $160/tCO_2e$ and only two experts give a 25% likelihood to the value being greater than $150/tCO_2e$.

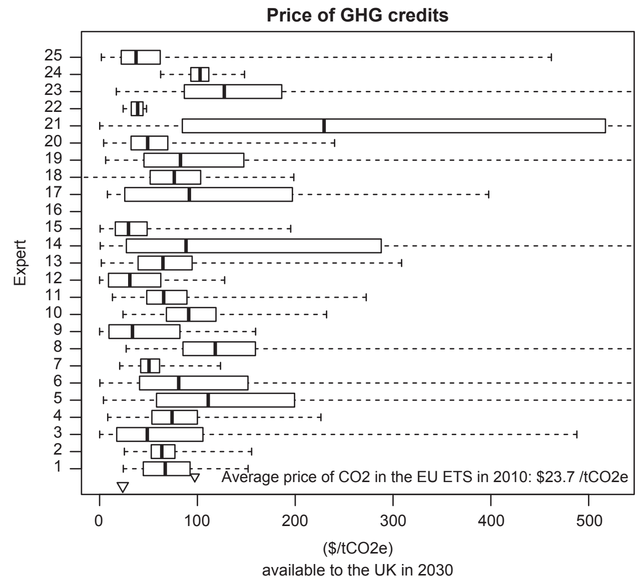

Fig. 2. Shows price of GHG credits available to the UK in 2030.

4. Discussion

While the spread of beliefs represented by the elicited distributions across the cohort of experts is interesting in their diversity, an individual distribution that represents the collective belief of all the experts is more practical to incorporate into the decision making process.

4.1. Pooling expert judgements

We explore the implications of imposing a linear opinion pool on the expert judgements for long-term oil price in 2030. Fig. 3 shows two iterations of the linear opinion pool, as described by Eq. (1). In the unweighted pool all experts are treated as independent and no compensation is made for bias or correlation. In the weighted pool, weights are assigned to experts based on combination of expert bias and correlations between experts due to shared data.

Weights were assigned to experts corresponding to their performance in the practice elicitation (a proxy for bias), with higher weights assigned to those whose interquartile range enclosed the actual value, medium weights assigned to those whose 90% confidence interval enclosed the actual value, and lowest weights assigned to those for whom the actual value was outside their 90% confidence interval. We experimented with different ranges of ratios of weights, e.g. from 1:10:100 to 1:2:3 (low:medium:high). Weightings were also adjusted according to the correlation of expert data sources. The effect of data correlation is that if the value expressed in the data source were to change, all correlated experts would update their beliefs in the same direction. It follows that correlated beliefs should be given less weight than independent beliefs.

Each combination of the weightings resulted in only very small changes to the shape of the pooled distribution, and negligible movement in the median. The correlation weighting has a very small effect on the linear pool for oil, due to the fact that the most correlated individuals are close the median of the sample. A lower weighting for these experts results in a slightly flatter distribution, thus the pool slightly under-estimates the degree of uncertainty surrounding future oil price, but again, the median remains relatively close to the value given above.

Both the weighted and unweighted linear opinion pools give a median oil price of \$120/barrel (90% CI: 51, 272) for 2030. Our results agree with Clemen and Winkler (1999), results from the linear pool are insensitive to the input assumptions.

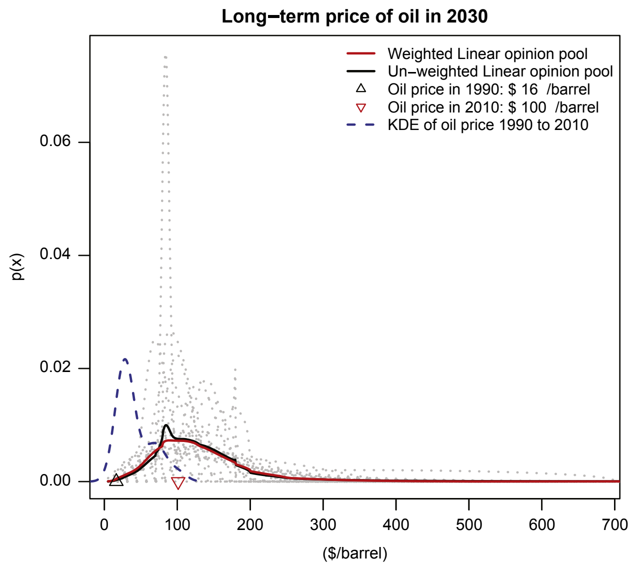

Fig. 3. The weighted and un-weighted linear opinion pool for oil price, and a kernel density estimate showing historical oil prices, all inflated to 2010\$.

Table 4
Summary of linear pooled beliefs for uncertainties in 2030.

Parameter	5th perc.	Lower quartile	Median	Upper quartile	95th perc.
Pop (millions)	60.80	65.20	68.00	71.20	76.90
GDP (av. ann. %)	0.59	1.43	1.86	2.30	2.96
Elec (US cents/kWh)	8.32	13.98	17.12	21.28	31.04
Oil (\$/barrel)	51.50	88.10	120.00	161.00	272.00
GHG (\$/tCO_2e)	4.83	19.40	33.90	109.00	256.00

Given the relative insensitivity of the linear pool to expert weighting, we now present a summary of unweighted linear pooled beliefs for each of the parameters in Table 4.

For UK population, the pooled 90% confidence interval gives a range between 60.8 and 76.9 million, with a median belief of 68.0 million. This median value represents an average annual increase of around 0.5%, which is somewhat lower than the historical average annual increase of almost 1% between 1990 and 2010.

Fig. 3 shows a kernel density estimate with the distribution of (real) oil prices between 1990 and 2010, compared with the pooled results from the elicitation. The results show a median expectation (equal odds) that average oil price will be \$120 in 2030, significantly higher than historical prices.

Pooled beliefs for GHG prices are such that the median value will be \$34/tCO_2e, which is very low compared with that needed to maintain an average global surface temperature of 2 °C or below, according to existing modelling studies (e.g. Edenhofer et al., 2006, 2010; Hanson and Laitner, 2006; Vaillancourt et al., 2008; Weyant et al., 2006).

4.2. *The uncertain parameters in a wider context*

In the introduction, we described the use of models as a means to understand and describe the complex energy-economic system, and the importance of beliefs about the future for decisions made today. The interviews provoked the experts to describe the complex relationships between those uncertain variables for which we elicited distributions, and those for which we did not. Each expert therefore described their 'mental model' for each parameter. It quickly became clear that the structure of uncertainties are highly dependent, in that the values for, and indeed uncertainties surrounding, each parameter are dependent on one another. The sketch in Fig. 4 collates this information from the expert interviews. The signs in Fig. 4 indicate the direction of change influenced by the independent (parent) variable on the dependent (child) variable. Dependence follows the direction of the arrows. The consensus achieved regarding the 'mental models' held by experts for the structure of the uncertain parameters is

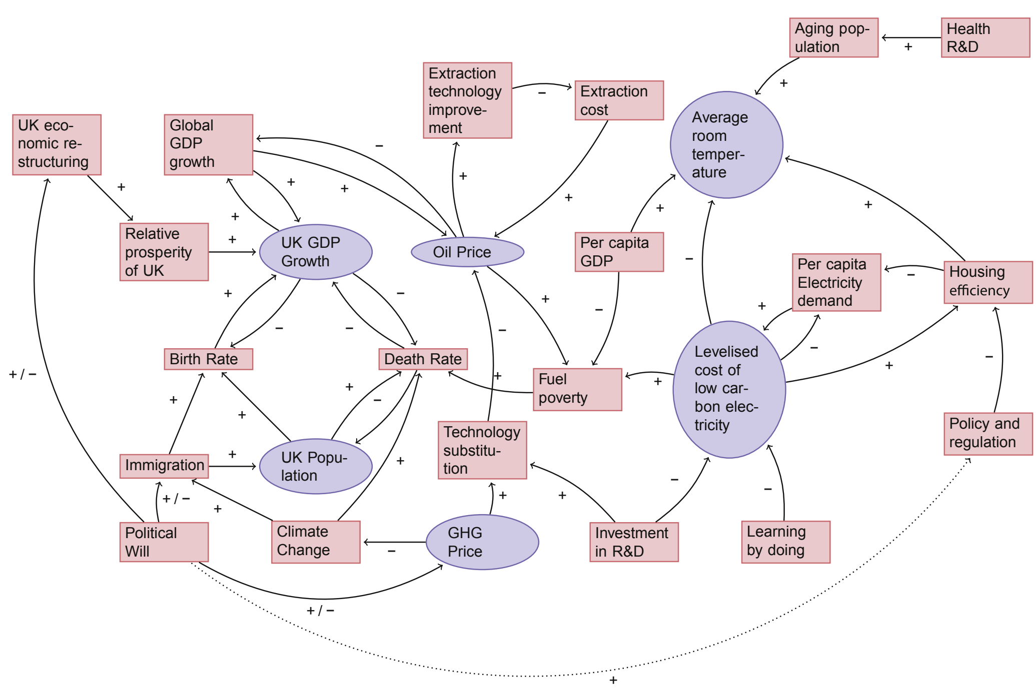

Fig. 4. The six uncertainties' relationship to other non-elicited parameters as described by the experts. The + or − sign shows the relative effect on the dependent parameter given an increase in the independent parameter.

surprising given the diversity of beliefs shown by the quantitative results.

We did not attempt to elicit distributions to represent the dependencies between the parameters—indeed, we elicited univariate distributions only. The elicited distributions therefore represent a 'package' of dependent beliefs. The practice of eliciting bi- or multi-variate uncertainties or the covariances of the intertwined network of uncertain parameters, although possible, is complicated and time consuming. An alternative to eliciting joint distributions to provide a multivariate description of parameters is to structure the questions in such a way to avoid conditional dependence (O'Hagan, 2006). For example, structuring the elicitation so that 'UK GDP in 2030' is expressed as 'per capita GDP in 2030' would result in a much weaker dependency on population. Thus decomposition of uncertain parameters is recommended for future studies, but this approach was unsuitable for this paper, given our resource constraints and the broad scope. The results offer guidance to future work, for example the experts describe the logical components for decomposing their beliefs of UK population—birth rate, death rate, net migration.

5. Concluding remarks

While our approach to the problem of uncertainty is influenced by our background in energy system modelling, the problem of treating uncertainty is common to all studies of long-term energy transitions. We have shown that it is possible to quantify key uncertainties that fall outside the models for which expert elicitation is normally used. By careful definition of the uncertain parameters and interview approach, experts can communicate their mental models for the structure of the uncertainties (i.e. the relationships between parameters) as well as quantify the value of the uncertainties themselves. We found that while experts agreed on the structure of the uncertain parameters, the shape of the distributions representing their beliefs showed wide variation, reflecting the differing perspectives of the interviewees. Decomposing the structure of the parameters and exploring the influence of dependence on expert responses may help explain some of these differences. However, the pooled beliefs are insensitive to the weighting assumptions that compensate for bias and correlations within and between experts. This implies that the pooled median values in Table 4 are a robust representation of the beliefs of those experts interviewed, given our choice of a linear pool.

As decision makers seek to make strategic decisions on energy investments that account for uncertainty, obtaining probabilistic data to support these decisions will require increasingly sophisticated techniques. Obtaining probabilistic inputs is hindered by constraints on both supply and demand—a lack of data and the prevalence of deterministic models, especially in the field of energy modelling, that use expected values where probability distributions would be more appropriate. Expert elicitation is an effective technique to obtain values of uncertain parameters for which it is otherwise difficult or expensive to obtain data.

The quantitative results of this expert elicitation have a range of applications across the energy modelling community in academia, government and industry. Firstly expert elicitation could inform model validation (across various types of models), and the data set included in Appendix A can be used for input and output parameter validation. Secondly expert elicitation can help benchmark policy makers' beliefs and form a structured comparison across decision makers differentiated by country, income, political viewpoint, age or other criteria. Finally expert elicitation as described in this paper can provide probabilistic inputs to models; an especially important application as modellers now have greater software capacity to describe models probabilistically than underlying knowledge of what probability distributions to employ. Future work will conduct a systematic review and comparison of high-profile energy models with the results of an expert elicitation process.

In this paper, we have applied a method that can enable a transparent debate on uncertain parameters of key importance to a wide range of stakeholders involved in energy decisions. But, in the longer term, we recommend using expert elicitation with other uncertainty methods, such as the propagation of uncertainties through models, formal scenario analysis and sensitivity and uncertainty analysis.

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Appendix A. Data set

Note all distributions designated 'beta' in the data file are in fact scaled beta $f_\beta(x)$, calculated using the following formula, where a closed interval, the upper and lower bound, $[x_0, x_1]$ is specified:

$$f_\beta(x|\alpha,\beta,x_0,x_1) = \{[(x-x_0)/(x_1-x_0)]^{\alpha-1} [(x_1-x)/(x_1-x_0)]^{\beta-1}/[B(\alpha,\beta)(x_1-x_0)]$$

where $B(\alpha,\beta)$ is the beta function.

Expert Param Dist Lo Up A B
1 Pop Beta 60 70 2.74 2.09
2 Pop Gamma 63.5 65.5 17100 0.003787879
3 Pop Gamma 60 69 778 0.084745763
4 Pop Lognorm 65 74 4.24 0.0425
5 Pop Norm 64 72 67.2 2.2
6 Pop Norm 45 75 62.8 8.05
7 Pop Lognorm 66 76 4.25 0.0317
8 Pop Beta 62.3 70 1.23 2.04
9 Pop Norm 62.3 77 70 2.92
10 Pop Gamma 62.3 85 196 0.37037037
11 Pop Beta 62 70 1.92 1.42
12 Pop Beta 65 75 1.56 1.57
13 Pop Beta 55 80 1.37 1.18
14 Pop Lognorm 70 80 4.3 0.0429
15 Pop Lognorm 0 85 4.23 0.0553
17 Pop Beta 60 100 0.892 1.92
18 Pop Gamma 55 93 52.7 1.338688086

19 Pop Lognorm 60 75 4.19 0.0528
20 Pop Beta 60 78 2.07 1.39
21 Pop Norm 0 90 70.1 7.32
22 Pop Beta 62 75 1.24 0.997
23 Pop Lognorm 62.3 70 4.18 0.0308
24 Pop Normal 65 73 69 1.51
25 Pop Gamma 64 75 989 0.068493151
1 GDP Norm 1.4 1.9 1.65 0.144
2 GDP Norm 1.25 2.25 1.75 0.31
3 GDP Norm 1.2 3.2 2.31 0.556
4 GDP Beta −0.5 3.5 3.61 4.43
5 GDP Norm 0.85 3.2 2.02 0.643
6 GDP Norm −1 3 1 1.08
7 GDP Norm 0.8 2.5 1.6 0.295
8 GDP Beta 0.3 3 3.09 1.73
9 GDP Norm 0.5 3.5 2 0.71
10 GDP Norm 0.5 3.25 1.99 0.693
11 GDP Beta 1 3.5 1.36 2.01
12 GDP Norm 0.6 3.5 2 0.709
13 GDP Norm 1 3.5 2.18 0.562
14 GDP Norm 1.75 2.75 2.25 0.271
15 GDP Beta −3 4 7.19 3.12
17 GDP Beta 0.5 4 1.22 1.33
18 GDP Beta 0 4 3.76 3.76
19 GDP Norm 1.5 3 2.1 0.288
20 GDP Beta 1.5 2.7 2.17 2.09
21 GDP Lognorm 0 5 0.667 0.584
22 GDP Norm 1 2 1.5 0.264
23 GDP Gamma 0.1 2.5 3.86 0.27173913
24 GDP Norm 1 3 2.17 0.371
25 GDP Gamma 0.5 3 5.27 0.292397661
1 GHG Beta 15 100 1.21 2.46
2 GHG Lognorm 25 80 3.7 0.292
3 GHG Gamma 0 120 0.775 57.47126437
4 GHG Gamma 13.5 100 4.6 10.8577633
5 GHG Lognorm 0 300 4.23 0.929
6 GHG Gamma 2 200 1.35 50.50505051
7 GHG Lognorm 20 60 3.46 0.289
8 GHG Lognorm 0 275 4.28 0.451
9 GHG Beta 0 100 0.555 1.21
10 GHG Beta 10 200 3.32 9.41
11 GHG Lognorm 20 100 3.72 0.455
12 GHG Beta 0 80 0.63 1.53
13 GHG Gamma 0 100 2.65 17.48251748
14 GHG Lognorm 0 1000 3.92 1.78
15 GHG Beta 0 200 1.6 12.4
17 GHG Beta 5 250 0.525 1.32
18 GHG Norm 15 80 47.5 23.9
19 GHG Lognorm 10 300 3.97 0.846
20 GHG Gamma 0 70 3.1 10.89324619
21 GHG Gamma 0 1000 0.872 248.7562189
22 GHG Beta 15 30 1.1 0.759
23 GHG Lognorm 0 200 4.35 0.585
24 GHG Norm 50 80 64.4 8.36
25 GHG Lognorm 0 100 3.11 0.764
1 Oil Lognorm 100 200 5 0.185
2 Oil Gamma 50 175 15.3 7.575757576
3 Oil Gamma 40 250 3.48 39.5256917
4 Oil Lognorm 30 100 4.29 0.223
5 Oil Lognorm 25 300 4.77 0.695
6 Oil Gamma 40 300 4.79 32.78688525
7 Oil Lognorm 100 180 4.89 0.173
8 Oil Beta 60 200 2.65 1.35
9 Oil Beta 15 250 1.43 1.79
10 Oil Beta 25 200 1.44 1.57
11 Oil Beta 80 130 1.16 1.62
12 Oil Beta 100 700 1.31 1.43
13 Oil Beta 10 250 1.53 1.48
14 Oil Gamma 60 130 18.1 5.102040816
15 Oil Gamma 10 500 2.17 67.56756757
16 Oil Gamma 40 250 4 34.12969283
17 Oil Beta 20 400 3.76 10.1
18 Oil norm 80 200 140 22.2
19 Oil lognorm 20 500 5.03 0.651
20 Oil Beta 70 180 0.893 0.796
21 Oil Beta 25 400 1.78 2.39
22 Oil Lognorm 80 140 4.63 0.176
23 Oil Beta 15 180 2 1.4
24 Oil Gamma 75 100 258 0.326797386
25 Oil Gamma 30 200 6.18 19.53125
1 Elec Lognorm 7.5 15 2.33 0.212
2 Elec Gamma 8 16 29.1 0.420168067
3 Elec norm 6 12 9.68 1.83
4 Elec Lognorm 8 15 2.4 0.157
5 Elec Lognorm 7 13 2.25 0.187
6 Elec Lognorm 2.5 20 2.11 0.482
7 Elec Lognorm 9 15 2.41 0.144
8 Elec Beta 5 12 0.955 1.67
9 Elec Lognorm 5.5 17.5 2.25 0.328
10 Elec Gamma 6 20 13.2 0.980392157
11 Elec Beta 6.7 20 1.33 0.876
12 Elec Norm 6 25 15.4 4.44
13 Elec Gamma 3 15 7.53 1.342281879
14 Elec Beta 8 15 1.24 1.82
15 Elec Beta 4 50 1.2 4.5
16 Elec Beta 3 16.5 1.37 4.89
17 Elec Gamma 4 40 2.89 6.172839506
18 Elec Gamma 8 16 33.5 0.338983051
19 Elec Gamma 5 15 13.8 0.675675676
21 Elec Gamma 5 30 4.89 3.215434084
22 Elec Beta 9 15 1 1
23 Elec Gamma 5 20 6.82 1.623376623
24 Elec Normal 8.6 10.4 9.55 0.538
25 Elec Beta 5 20 1.72 0.869
1 Temp Norm 19 21.5 20.3 0.775
2 Temp Lognorm 20.5 21.5 3.04 0.0119
3 Temp Norm 18.5 21.5 20 0.83
4 Temp Beta 17 20 1.58 1.55
5 Temp Norm 20.4 22 21.2 0.43
6 Temp Norm 18 22 20 0.99
7 Temp Gamma 18 23 256 0.081967213
8 Temp Beta 12 17 1.72 1.2
9 Temp Beta 17 22.5 2.09 1.53
10 Temp Norm 17 21 19 0.797
11 Temp Beta 13.5 23 2.45 2.06
12 Temp Beta 16 24 1.82 1.81
13 Temp Beta 15 25 2.13 1.57
14 Temp Beta 19.5 21 1.19 1.91
15 Temp Norm 17.1 23 20 1.46
16 Temp Norm 19 23 21 1.24
17 Temp Norm 15 24 19.7 2.63
18 Temp Norm 16 21 18.5 0.943
19 Temp Norm 18 20 19.1 0.618
20 Temp Gamma 17 22 188 0.10460251
21 Temp Norm 15 25 20 2.67
22 Temp Gamma 19.5 22.5 948 0.021645022
23 Temp Lognorm 13 25 2.91 0.179
24 Temp Beta 18 22 3.09 2.04
25 Temp Beta 17 21 2.28 1.42
1 calib Norm 25 150 95.8 38.5
2 calib Beta 100 400 2.04 1.99
3 calib Norm 20 500 246 125

4 calib Gamma 0 2000 1.94 444.4444444
5 calib Lognorm 50 2000 5.99 0.95
6 calib Gamma 100 4000 1.7 917.4311927
7 calib Lognorm 100 300 5.23 0.22
8 calib Gamma 0 500 4.81 45.87155963
9 calib Lognorm 30 600 5.73 0.482
10 calib Beta 100 1000 0.78 0.827
11 calib Beta 650 1500 0.686 0.802
12 calib Beta 50 400 0.662 0.764
13 calib Beta 20 500 2.33 1.87
14 calib Beta 80 400 0.804 1.43
15 calib Lognorm 5 3000 5.57 0.896
16 calib Lognorm 200 10000 6.91 0.799
17 calib Beta 60 360 2.85 2.19
18 calib Beta 10 10000 1 1
19 calib Gamma 250 5000 3.19 704.2253521
20 calib Beta 0 600 1 1
21 calib Gamma 15 500 1.71 116.2790698
22 calib Beta 100 3000 1.07 0.907
23 calib Lognorm 100 400 5.28 0.357
24 calib Beta 100 300 0.985 0.551
25 calib Gamma 5 70 2.79 11.69590643

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