UKERC Energy Strategy Under Uncertainties

Identifying techniques for managing uncertainty in the energy sector

Working Paper

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UKERC is undertaking two flagship projects to draw together research undertaken during Phase II of the programme. This working paper is an output of the Energy Strategy under Uncertainty flagship project which aims:

- To generate, synthesise and communicate evidence about the range and nature of the risks and uncertainties facing UK energy policy and the achievement of its goals relating to climate change, energy security and affordability.
- To identify, using rigorous methods, strategies for mitigating risks and managing uncertainties for both public policymakers and private sector strategists.

The project includes five work streams: i) Conceptual framing, modelling and communication, ii) Energy supply and network infrastructure, iii) Energy demand, iv) Environment and resources and v) Empirical synthesis. This working paper is part of the output from the Environment and resources work stream.

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Introduction

The ‘energy system’ can refer to both the physical assets (i.e. the physical grid that connects power plants, power-stations, distribution centres, residential homes and industrial plants together) and also non-physical lines of communication that exist between the system actors (e.g. operators, regulators, consultants, academics, policy makers and ministers). The focus of this research is the latter and the development of a conceptual model to help practitioners transparently show, which techniques they use (and why) to assess risk and uncertainty in their decision-making.

Due to the increasing demand for energy, national targets to reduce carbon emissions and the nature of the industry, actors within the energy system have to make complex decisions using risk-based techniques. For strategic decisions, such as “*What type of energy policy should the UK implement in 2014 to meet national targets set for 2030?”*, there are various lines and levels of supporting evidence to support a defensible response, or set of responses. The availability and interconnectedness of this evidence can make it a challenge for decision makers to arrive at a conclusion. Nonetheless, practitioners must make decisions about energy futures under conditions of uncertainty and so pragmatic decision frameworks that allow the assembly and analysis of the available evidence are required.

Extensive work has been carried out on the characterisation of uncertainty to improve the transparency of decision processes. For example, scholars have shown the use of hierarchical models such as decision trees to illustrate how decisions collectively string together. Others have used techniques such as evidence-support logic to allow decision makers to represent how sufficient and dependent responses(s) to a supporting decision(s) are given the evidence base to support these decisions. Attempts have also been made to use agent-based simulations to represent the influence that personal and organisational features have on these measures of sufficiency and dependency for evidence. However, gaps still exist in the knowledge with regards to how practitioners account transparently for the techniques they use to assess risk and uncertainty when answering a decision. The conceptual model presented in this working paper addresses this by: 1) showing transparently what type of knowledge practitioners believe they require to answer their decisions; and 2) justifying which technique(s) they might use given the type of knowledge they believe exists to support their decision.

The remainder of this report: 1) describes the aim, objectives and methods used; 2) outlines a conceptual model, developed originally by Funtowicz and Ravetz (1990), to maps uncertainty techniques to an appropriate decision context; 3) provides a summary of the techniques used to assess uncertainty in the energy sector; 4) discusses the results from a workshop attended by policy-makers, industry experts and academics to assess and validate the model; and 5) explains why we believe this conceptual model could be used to promote decision makers' understanding of the complexity of uncertainty and the limitations (and benefits) of techniques when applied to decisions across the energy sector.

Research aim and objectives

The aim of this research was to develop a conceptual model that classified techniques for managing uncertainty in the energy sector. To achieve this aim the research objectives were:

1. to undertake a comprehensive review of approaches for assessing uncertainties (conceptual and methodological), relevant to the energy sector;
2. to develop a conceptual model able to help decision makers understand which techniques are most appropriate for addressing uncertainty within the context of their decision; and

3. to validate, via expert workshop, the basis of the conceptual model and the positioning of the uncertainty techniques, as well as gather practitioners' insight regarding the use of uncertainty techniques within the energy sector.

The following section provides a critique of the existing literature to explain: 1) why practitioners must account for uncertainties when making decisions on risk; 2) how risk and uncertainty associated with a single decision are actually statements about a) the 'presence of' and b) the 'lack of' the same type of knowledge, respectively. Based on this, and building on the work of Funtowicz and Ravetz (1994), we assume that all decisions can be assigned a specific technique (or set of techniques) to assess the existence of a particular type of knowledge. We also assume that 'compound' decisions comprise a number of 'single' decisions that must be addressed in succession before a final answer can be deduced. Finally, we believe that these techniques are useful for determining the presence (or not) of knowledge that then allows a user to assign a measure of risk or make a statement about the type of uncertainty (i.e. lack of knowledge) associated with the decision.

Accounting for uncertainties in decision-making

At both the national and international levels, government bodies understand the importance of acknowledging and dealing with uncertainty (Fairman et al., 1998; USEPA, 1998; Defra, 2011). Decision makers are beginning to acknowledge this uncertainty, which is leading to a shift away from the conventional definition of risk (i.e. likelihood x consequence) to a more encompassing acceptance of uncertainty and the role it plays in the decision process (Andrews et al., 2004). However, when confronted with uncertainty there is sometimes a tendency to take no action at all (inaction inertia: Tykocinski & Pittman, 1998) and this may become the preferred or default response for decision makers (Skinner et al., 2013). Regardless of whether or not an action is taken, decisions must be made and therefore, at the very least, assessment of the significance of risk and uncertainty should be completed to inform a response.

For governments, the implementation of long-term strategic policies (e.g. climate change policy goals) presents a challenged due to the inherently uncertain nature of the subject (Beck et al., 2009:16). Decisions makers must be conscious that their decisions (e.g. not to act or to adopt a precautionary approach) will have implications. For example, implementing the precautionary principle may place a regulatory burden on industry, thus impairing their competitiveness, their ability to innovate, and their ability to attract foreign investors. Precaution, as a response, needs to be informed by an assessment of risk, uncertainty and their significance, rather than being promoted as an alternative philosophy to risk-informed decision-making. As a result, governments have moved towards more decentralized regulation where risk-based decision-making informs the allocation of limited resources in a manner proportionate to the risks. This shift has led to the desire (and need) to acknowledge risk and uncertainty comparatively. However decision-support tools for comparative risk assessment are not easily achieved because of the difficulty of finding a common scale on which to compare inherently incommensurate issues. Moreover, comparison is largely limited by the reduction of risk and it's attending uncertainty to a single numeric value (e.g. a score or rank), rather than a description of different measures that reflect the full character of the risk. Participatory techniques, that include multiple stakeholders, have the potential to address these limitations by capturing the variability of subjective value judgements. However questions remain about the ability of these models to capture all of the complexity that a policy maker requires to inform their decisions.

The challenge for risk-based decision-making is to make well-reasoned decisions whilst acknowledging uncertainties and avoiding false confidence and complacency (e.g. by ignoring unidentified risks, which left unmanaged could surface to cause serious harm, Schneider, 1979). Uncertainty typologies have been developed to help decision makers characterise uncertainty (e.g. Skinner 2013) and understand that which is resolvable through active management and that which is not. These are useful for characterising system uncertainty and can be used alongside conventional techniques, such as statistical tests, to support understanding. Uncertainty analysis should not become an end in itself. Decision-makers must have in mind the level of confidence required to make their decision such that valuable resources are targeted towards those aspects that improve decision power and quality. There is little to be gained by attempts to resolve intractable uncertainties or by relentless focus on minor features of a problem that, even if resolved, are likely to have little influence on decision outcome. The character of the uncertainty is therefore critical. By understanding the character of uncertainty, decision makers can apply the appropriate qualitative or quantitative techniques for its management. Techniques for managing uncertainty depend upon the level of the organisation at which it is being applied. Typologies are not always explicit in providing this type of organisational guidance and as a result decision makers may misunderstand or misinterpret their uncertainty and the outputs of an applied assessment technique.

Definition of uncertainty

In general terms uncertainty is defined as a 'lack of knowledge'. More specifically, uncertainty may be referred to as having "incomplete information about a particular subject" (Ascough et al. 2008) or of having a "lack of confidence in knowledge related to a specific question" (Sigel et al. 2010). For the purpose of this research we have adopted the definition of Walker et al. (2003) who refer to uncertainty as "any deviation from the unachievable ideal of completely deterministic knowledge of the relevant system". We believe this definition captures the aspiration of uncertainty management at all levels of decision-making, which is to strive to obtain perfect deterministic knowledge about the system.

Typologies of uncertainty

Obtaining deterministic knowledge requires an understanding of the character of the uncertainty. To this end there has been a shift (in practice) from simply acknowledging and understanding uncertainty (Van der Sluijs et al, 2005; Ascough et al., 2008) to a desire for understanding the varying 'types of uncertainty' (e.g. Regan et al., 2002; Raman, 2003). This shift is based on research by Knight, 1921; Kaplin & Garrick, 1981 and Wynne, 1992 and can be observed across a number of different domains. Typologies are useful tools for "...providing comprehensive, relevant, and reliable categorisations (complete with definitions) of all potential types of uncertainty that may be encountered (van Asselt and Rotmans 2002; Knol et al. 2009)." As a result, typologies form the basis for informing uncertainty management (Morgan et al. 1990).

Uncertainty management requires that specific techniques be applied to the most relevant types of uncertainty (van der Sluijs et al. 2004; Refsgaard et al. 2007). An excellent example is reported by Stirling (1999; 2003) who assessed uncertainty according to different degrees of knowledge that one may have about the probability and consequence of a risk. A high degree of knowledge about the probability and consequence of a risk may be referred to as 'stochastic uncertainty' and this can be addressed via conventional risk assessment techniques. A low degree of knowledge about the probability and consequence of a risk infers a state of ignorance where uncertainty needs to be managed using scenario development or expert elicitation. The value of this approach is that by characterising their uncertainty, decision makers can identify, with confidence, that the techniques they are using are appropriate to the decision at hand.

Typologies are common in the environmental domain where they are used for qualifying risk and stating the significance of risk estimates (Skinner et al., 2013). These typologies comprise different aspects or dimensions (Janssen et al. 2003; Walker et al.

2003; Knol et al. 2009) that relate to the nature, severity and location of the uncertainty. The nature of uncertainty describes the type of knowledge available. This information may be epistemic (limitations in our knowledge) or aleatory (the randomness of natural systems and their components). The level of uncertainty describes the severity or degree of uncertainty and is measured on a scale that ranges between deterministic to indeterminate. The location of the uncertainty describes where the uncertainty is manifest within the decision. Other typologies apply similar dimensions (Walker et al. 2003).

Typologies are largely overlapping, contradictory and subjective, based on small-scale literature reviews, or amalgamations of existing frameworks or researcher opinion (Skinner et al., 2013). These limitations may prevent transfer to other research domains and may impact the reliability of the content (Walker et al. 2003; Ascough II et al. 2008; Knol et al. 2009; Troldborg 2010). These issues lead to methodological inconsistency and a lack of consensus on the terminology and typology of uncertainty (Walker et al. 2010). Efforts to overcome these limitations have resulted in development of complex solutions that may not be appropriate for decision-makers (Skinner et al. 2013).

The magnitude and diversity of uncertainty generally increases as we move toward less deterministic policy level decisions (e.g. Walker et al., 2003), making the task of assigning confidence to the likelihood that an event will occur and the severity of potential outcomes difficult (e.g. Wynne 1992; Stirling, 1999). The type and level of uncertainty characterising decisions made at the different levels will differ by the extent to which the uncertainty can be characterised as being aleatory (randomness) and epistemic (lack of knowledge about something that in principle is knowledge).

Decisions about international policy, for example, are often characterised by deep uncertainty because of their complexity and the multitude of actors involved, and with a stake in, the decision process. These decisions are often characterised by a range of uncertainties that may encompass elements of ignorance as well as more deterministic aspects yet near always involve a "profound lack of understanding and predictability" (Kandlikar et al., 2005). Under these conditions, decision makers are challenged to identify and apply the appropriate uncertainty tools for the job.

Application of typologies in the energy domain

Decisions made within the energy sector are informed by lines of supporting evidence that stretch between the operational, tactical and strategic levels. Each level of the system is characterised by different types of uncertainty. Poorly defined uncertainty undermines the effectiveness of a decision or may delay the decision altogether. Possessing an understanding of the character of uncertainty and where it may become manifest within the operational levels of the organisation is integral for identifying the appropriate techniques for managing uncertainty.

Uncertainty characterisation requires the decision maker to distinguish between the different locations that the uncertainty may manifest and the nature/level of the uncertainty. To do so, requires decision makers to acknowledge that uncertainty is much richer than simply an assessment of a lack of knowledge. Funtowicz and Ravetz (1990) state: "*uncertainty is not simply the absence of knowledge; uncertainty has quantifiable and non-quantifiable components; components of uncertainty include 'fact' and 'linguistic' components*". In other words, uncertainties are also associated with the robustness of the data and facts on which knowledge is constructed and the way in which knowledge is formulated (i.e., the terms used to express knowledge, results, and assumptions).

Uncertainty is value-laden and sensitive to differences in subjective interpretations. The more interpretations (or stakes) involved in the decision process the greater the uncertainty. The value of Funtowicz and Ravetz's framework is that it explicitly includes uncertainty alongside the definition of risk, vulnerability and resilience (Aven, 2013). Funtowicz and Ravetz (1990) account for the influence of values into decision uncertainty by integrating technical uncertainty and assessment reliability using scales relating to decision stakes and system uncertainties.

Characterising uncertainty with respect to knowledge

This section charts the evolution of our decision support tool, which has been adapted from Funtowicz and Ravetz's (1990) model. This model characterises decisions with respect to criteria that describe 'decision stakes' and 'system uncertainties'. Within this characterisation the authors describe three areas, or classes, of problems: applied science, professional consultancy and post-normal science problems. Figure 1 illustrates how changes to the level of knowledge (system uncertainty) and complexity of values (decision stakes) relate to different classes of problems. The Funtowicz and Ravetz model refer to uncertainties as "*the complexity of the system within which the decision is made, including aspects that are technical, scientific, administrative and managerial while the uncertainties relate to a range of possible outcomes corresponding to each set of plausible inputs and decisions (ibid.)*". Decision stakes are referred to as "*the costs and benefits to the parties with an interest in the outcome of the decision, including regulators and representatives of various interests corresponding to each decision.*"

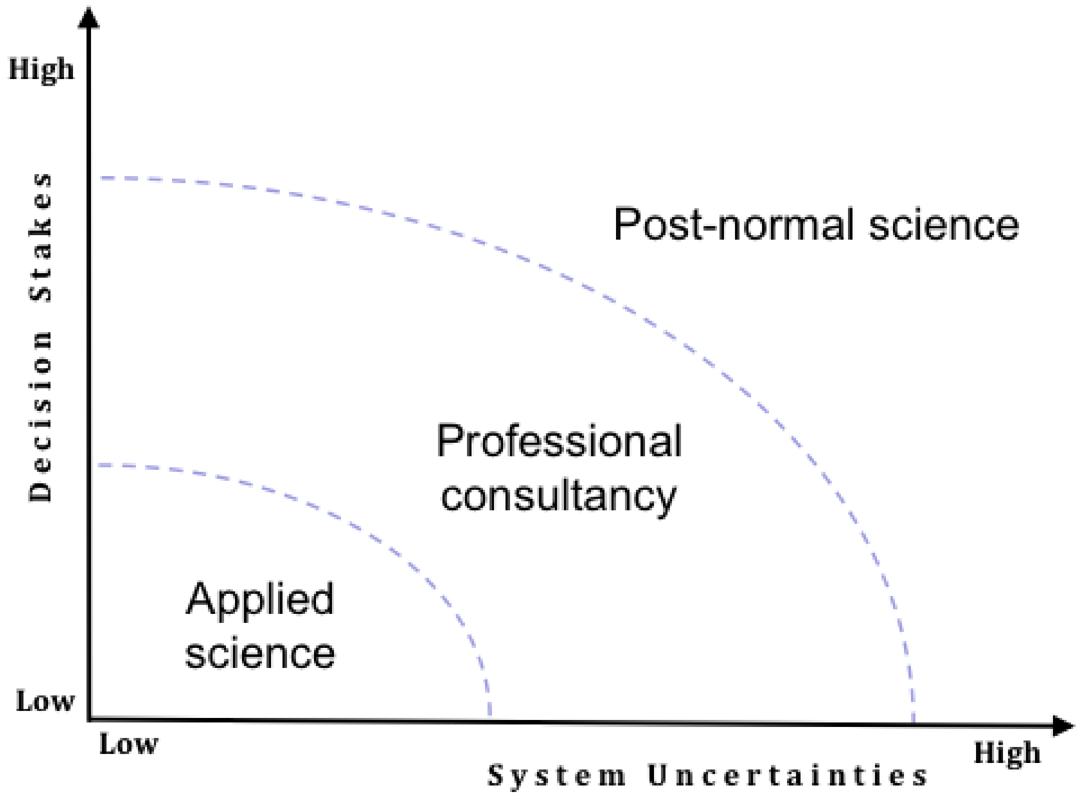

Figure 1. Taken from Funtowicz and Ravetz (1990). This schematic illustrates their conceptual model that classifies knowledge relative to the level of decision stakes and systems uncertainties inherent to the problem.

Differentiating between types of knowledge

Funtowicz and Ravetz categorise the knowledge used to make a decision into three distinct classes. Applied science typifies knowledge characterised by low levels of decision stakes and system uncertainties. Decisions within this class are curiosity driven where research outcomes provide a straightforward and focussed function. At this level there is minimal concern with how results may be used by the larger enterprise and most problems can be addressed by means of routines and procedures (Funtowicz & Ravetz, 1990). In most instances it is the decision maker's task to work out what the optimal strategy is by searching for maximum utility among a number of options (Maintzberg, 1994). Results are often not made public and instead form the 'corporate know-how' of intellectual property of private business or agencies that sponsor the research. (Hence not contested and considered to be characterized by low decision stakes) An example in the energy sector is the design and implementation of solar panels on a residential home, which represents a decision process that involves few stakeholders, a limited number of values and minimal system uncertainty.

Professional consultancy represents those decisions characterised by knowledge that has medium levels of decision stakes and system uncertainties. Decisions within this class require a greater measure of expert judgement or subject specialism in order to interpret, synthesise or assess the sufficiency or validity of evidence. At this level, both natural systems and stakeholder values are considered to be raising overall decision complexity. The extended stakeholder community may include investigative journalists, lawyers, pressure groups, which requires more complex problem-solving strategies and techniques for managing uncertainties (Funtowicz & Ravetz, 1990). The benefit of professional consultancy is the ability for it to manage system uncertainties that are not fully testable or reproducible through the use of techniques such as expert judgment.

Post-normal science represents decisions characterised by knowledge with high levels of system uncertainty, characterised by conditions of ambiguity, uncertainty and ignorance and high decision stakes (Rayner, 2012). At the extreme end of the scale decision makers need to manage irreducible uncertainty of knowledge and ethics, consider a plurality of different legislative perspectives and integrate all those with stakes in the issue. Problems like these can no longer be managed through a single perspective, instead needing to accommodate an increasing number of non-equivalent observers and observations (Giuseppe, 2008). Under these conditions decision-makers must appreciate the limits of uncertainty management and resign to the fact that a decision will be made under conditions of unresolved uncertainty.

Table 1. Description of the difference between low, medium and high levels of decision stakes and system uncertainties.

	Decision stakes	System uncertainties
Low	Low decision stakes describes knowledge that is usually only directly applicable to a single stakeholder. No obvious external interests are at stake so there is little concern about how the outcome will affect the wider community. Knowledge is not usually public knowledge but corporate knowhow, the intellectual property of private business or agency sponsoring the decision.	Low system uncertainties describe a situation where quality assurance is sought through the process used to collect and analyse data. Problems are puzzle-solving exercises dealing with objective knowledge, independent of values and perceptions. The task in had is to maximise the utility of the decision outcome because the existence of best solution is assumed.
Medium	Medium decision stakes describes e.g. knowledge required by a regulator or chief engineer acting as a consultant to an internal or external client. Controversial evidence may result in high decision stakes by extension of the peer community to investigative journalists, lawyers, pressure groups etc.	Medium system uncertainties, decision makers carry a heavier burden of proof and must be willing to grapple with new and unexpected situations. System uncertainty is commonly assessed using probabilistic methods potentially allowing the decision maker to predict the behaviour of the system under different future conditions.
High	High decision stakes are characterised by multiple non-equivalent observers and observations increasing the reflexivity and complexity of the decision. Power is shared between conventional decision makers and the breadth of the extended peer community (typically politicians, press, client, operators, public, investigative journalists, lawyers, and pressure groups)	High system uncertainties describe knowledge characterised by human commitment and values; value judgements in the form of extended facts and lived experiences (e.g. expert/local knowledge) offered by the extended peer community. The existing knowledge is characterised by ignorance and incompatible value commitments and the need to cope with irreducible uncertainty.

The following section is a presentation of the conceptual model we are proposing energy system practitioners use to help them choose a suitable technique and justify the techniques they may currently be using. We argue that this will provide a helpful tool to increase the transparency between different actors in the energy system and the reasons why they are choosing to focus on the use of different techniques to help them know how to make their decisions.

Developing the conceptual model

The Funtowicz and Ravetz model (1990) is a useful tool for understanding different types of knowledge that characterise complex problems; where decisions are urgent and values disputed. The model provides a rough guide whereby decision makers can make distinctions about the type of knowledge needing to be accounted for to manage different levels (and dimensions) of uncertainty. The model and distinctions can be applied to any complex problem, and therefore provides a generic basis for informing management of system uncertainty. Users benefit from the consistency of language and visual comparability (by plotting all techniques on a single diagram), which helps support the communication and assessment of uncertainty.

The character of complex problems will differ and so too will the response needed to manage system uncertainties. To accommodate this issue, the framework is flexible, or sensitive to the scale and context of a decision. The changing character of complex problems is a reflection of the different types of knowledge contained within a decision. In reclassifying the categories, or knowledge classes, set out by Funtowicz and Ravetz (1990), we refer to different types of knowledge: objective (applied science), semi-objective (professional consultancy) and subjective (post-normal science) knowledge. These classifications more clearly reflect the type of knowledge available within each decision landscape and enable a smooth transition to an energy context.

Objective knowledge

Decisions characterised by objective knowledge are analogous to problems in the applied science domain due to their character of being 'pure' or 'basic' research driven by curiosity and fact. Problems that are objective state existing information independently of external values and perceptions where the existence of one best solution is assumed and the task of the analyst is to identify the strategy that provides optimal utility among a number of options (Mintzberg, 1994). Processes used for quality assurance are similar to those applied in the core science (Funtowicz & Ravetz, 1990). In general, objective knowledge is used to inform decisions by means of standard routines and procedures, for example through risk analysis, which is a highly objective technique.

Semi-objective knowledge

Decisions characterised by semi-objective knowledge are analogous to the knowledge used in the professional consultancy domain and require techniques that have some capacity to draw on theory and experience. These decisions often require input from questions characterised by objective knowledge given the relatively new and unexpected nature of the problems. As a result, techniques designed to process semi-objective knowledge can be informed, but cannot be solved, by the result of techniques designed to process objective knowledge. Decisions characterised by semi-objective knowledge are similar to professional consultancy decisions in that they explore the impacts of unique situations and require input and validation from experts' opinion.

Expert opinion is an important element of the decision process characterised by semi-objective knowledge because techniques only designed to process objective knowledge are unable to address the complexity of uncertainty. As decision stakes increase the decision-makers must consider the clients' interests alongside technical expertise. Hence, decisions processes become an aggregation of information from multiple stakeholder and natural systems inputs. An example of a decision characterised by semi-objective knowledge may be agreeing upon the finite number of wind turbines on a particular wind farm. This decision involves multiple values (e.g. investment portfolio, number of wind turbines, regulation) and a variety of uncertainties (e.g. future profit margins, availability of wind, presence of subsidies). However, the issue can be addressed through techniques designed to process semi-objective knowledge that one would typically find within the professional community.

Subjective knowledge

Decisions characterised by subjective knowledge exist where facts and value-based arguments are discussed alongside an extended peer review process. These decisions are characterised by a lack of quantitative data, multi-causality, unknown impacts, long timescales, uncertain facts and disrupted values. Outcomes are the result of complex cause-effect relationships that lead to multi-directional impacts (Fredrichs, 2011), which often go beyond the “given state of affairs” (Ariza-Montobbio and Farrell, 2012). Decision makers have to accept that political power is shared between conventional decision making agents and extended peer communities (DeMarchi and Ravetz, 1999; Healy, 1999).

The complexity of decisions characterised by subjective knowledge is also a catalyst for promoting democratic thinking in long-term energy planning. The ability to consider different stakeholder inputs is valuable when exploring policy level trade-offs. For example, decisions about where to build a wind farm may require input from local authorities, regulators, environmentalists, representatives of institutions of energy, environmental consultants, members of parliament, industry and the public.

At this level decisions are made with the aim of reaching a desirable future. The knowledge behind these decisions are characterised by ignorance and there exists conflict between values and knowledge (Pielke, 2012). These conflicts arise between different views in the social, economic, technological and political domains. For action to be taken ignorance must be managed and practitioners will apply participatory methods to engage stakeholders and explore uncertainty.

Proposed decision classifications

We propose that subjective, semi-objective and objective knowledge map directly across onto Funtowicz and Ravetz's categories of post-normal science, professional consultancy and applied science respectively. We can take this reclassification a step further by adopting terminology from the management sciences. Categories describing strategic, tactical and operational decisions have been defined previously (Ackoff, 1974) and may be used to replace the categories described by Funtowicz and Ravetz. In the context of management, strategic decisions are made at the highest level, set the objectives of the organisation as a whole and set direction over longer periods. Tactical decisions are more localised focussing on a part of the organisation, have shorter-term objectives and focus on efficiency gains or improvements. Operational decisions deal with day-to-day decisions and are concerned with the immediate, or very short term.

The divisions between decision categories are not explicit but rather vague, or 'grey' and therefore one must acknowledge that the schematic offers only guidance. We must also note that the decision categories may be applied to decisions at all levels, for example, Government, industry or consumers. By way of example:

- Government: Considering the evolution of energy feed in tariffs, let's assume that Governmental decision makers begin the decision process at a high-level; the strategic level. Here decision makers consider what objective they intend to pursue, for example, how to meet renewable targets. Gathering knowledge at this stage would have required considerable stakeholder input and would involve exploratory techniques to test a range of hypothetical options. Once a decision has been made (assuming this decision was to achieve renewable targets) a direction is set, and the next step would consider how Government may achieve these targets over the shorter-term. Here Government focuses on tactical measures that could be taken to deliver on an objective (e.g. investigation of price incentives such as feed-in tariffs). These tasks will often be left to small teams and the outcome of their work is unlikely to impact the strategic direction of the Government. The final phase of this decision process puts into operation, the previously developed plan. Or more specifically, what type of feed-in tariff is appropriate for incentivising different technologies. Knowledge for these decisions is highly objective and quantifiable, leaving little in the way of expert input and subjectivity, and the impact of decisions will be realised over the short-term.

- Industry: Similar to the above, the decisions that are made by industry may be classified as being strategic (e.g. does an energy company pursue natural gas or oil?), tactical (e.g. if we pursue gas, do we enter a joint agreement with a government to ensure a market?) and operational (e.g. can we technically produce the gas to make this venture economically feasible?).
- Individual: Finally, the decisions of the individual may also be categorised using our classification. For example, determining an individual's best mode of transport (e.g. car, public transit, walk) is a strategic decision that requires one to consult a range of friends and expert to assess options. Assuming one chooses to drive a car, tactical decisions must be made as to whether or not the individual purchases, rents, or joins a car share. Finally, at the operational level the individual must assess whether or not their chosen option matches their expectations or fits within the requirements of practical day-to-day use.

As these examples demonstrate, our classification can be applied to decisions across vastly different contexts within the energy sector and though the decision scale may change (e.g. government, industry, individual) the classifications and the type of knowledge required remains similar. The examples also show that decision processes or classifications are rarely clear and therefore, decision makers must maintain flexibility and remain open to using multiple techniques for gathering knowledge to address uncertainty.

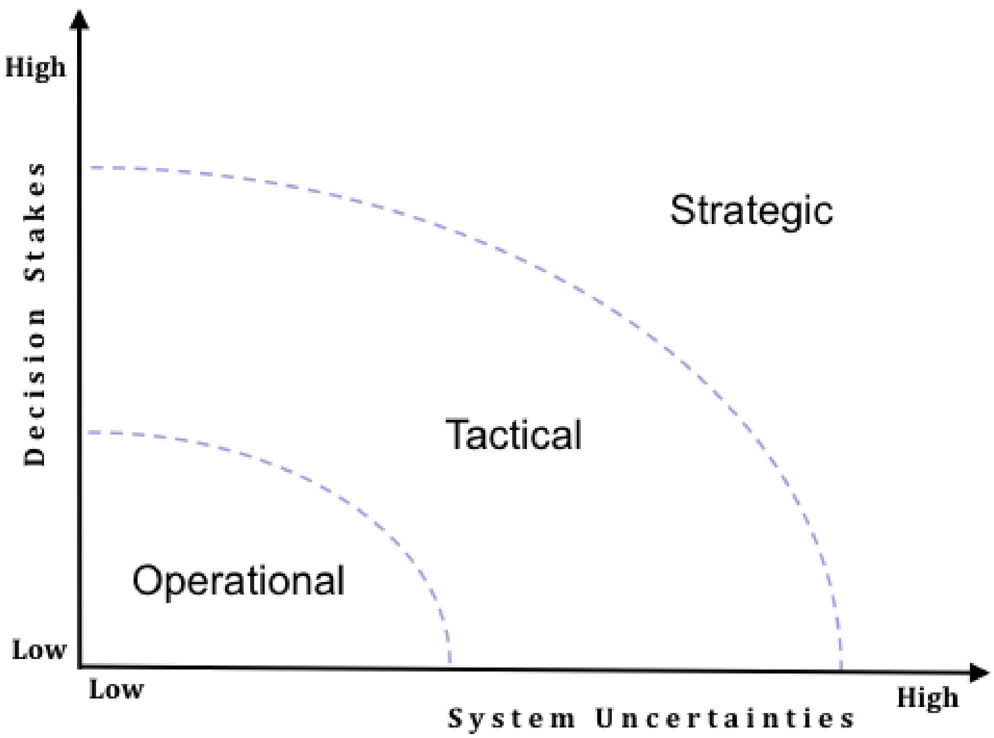

Figure 2. Illustrating the use of the Funtowicz and Ravetz (1990) model to classify techniques used to measure uncertainty (or lack of knowledge) of decisions across the energy system characterised by objective, semi-objective and subjective knowledge and labelled using management science terminology.

Positioning the techniques

Lacking a meaningful scale on either axis, positioning uncertainty techniques on the Funtowicz and Ravetz model poses some challenge. Most importantly, without a common metric or scale, reproducibility of any positioning would come into question, regardless of the fact that the nature of the assessment is largely subjective. Therefore, to provide structure and consistency to the assessment we adopted the metrics of uncertainty as described in the uncertainty typology of Skinner et al. (2013). Table 2 describes the level (or severity), the location of and the nature of the knowledge that the techniques assess.

Table 2. Summary of the different characteristics of uncertainty adapted from insights contained in Skinner et al., 2013.

Level	Deterministic	Confidence about the likelihood and outcomes.
	Statistical	Confident in assigning probabilities to an event but little understanding of the ramifications.
	Scenario	Confident about the outcomes but not confident about the likelihood of the event.
	Recognised ignorance	Not possible to define the probabilities or a complete set of outcomes.
	Total ignorance	Inverse of determinism; when nothing is known about the uncertainty.
Location	Data (Availability)	The incomplete, scarcity or absence of data.
	Data (Precision)	The lack of accuracy.
	Data (Reliability)	The trustworthiness, stemming from errors in processing, statistical analysis or presentation of data.
	Language (Ambiguity)	Present in the face of multiple meanings.
	Language (Underspecificity)	When meaning are not clear.
	Language (Vagueness)	When meanings are not clear or understandable.
	System	Tallies with the scientific understanding of a system – particularly pertinent to a field such as nanotechnology that experienced rapid growth, raising questions about unknown effects. Uncertainty of a system can be characterised by focusing on the existence of sources, pathways and the receptors in a system.
	Variability	The inherent unpredictability of a human or natural system. Human variability can stem from intentional bias and subjective action e.g. because there is something to gain or the importance of evidence is weighed differently. Natural variability forms the characteristic traits of a system primarily associated with extrapolation when faced with limited data or process understanding.
	Extrapolation (Intraspecies)	When members of a species are used to represent members of the same species.
	Extrapolation	When members of a species are used to represent the

	(Interspecies)	members of a different species.
	Extrapolation (Laboratory)	When data from the laboratory are used to represent real-world phenomena.
	Extrapolation (Quantity)	When information specific to one quantity is used to represent a different quantity.
	Extrapolation (Temporal)	When information specific to one timescale is used to represent a different timescale.
	Model (Structural)	The structure chosen to represent the real world.
	Model (Output)	Reflects the level of confidence assigned to results.
	Decision	Doubts about the optimal course of action in the face of differing stakeholder perspectives and objectives.
Nature	Epistemic	Refers to the imperfect knowledge of a system that with understanding can be quantified, reduced and potentially eliminated. However, additional research can reveal the true depths of ignorance increasing the level of uncertainty.
	Aleatory	The inherent randomness characterising the natural and human system. By definition aleatory uncertainty cannot be reduced but additional research can reveal that a system thought of as random is instead found to be chaotic and therefore in principal resolvable.

The uncertainty typology described in Skinner et al. (2013) provides a list of fundamental characteristics to help understand and thus assess uncertainty. We believe these characteristics of uncertainty can be used as surrogate measures for assessing decision stakes and system uncertainty. For example, under high decision stakes Funtowicz and Ravetz (1990) state "*decisions are characterised by multiple non-equivalent observers and observations increasing the reflexivity and complexity of the decision.*" This maps well with Skinner et al. (2013)'s reference to the location of uncertainty, whereby there are "doubts about the optimal course of action in the face of differing stakeholder perspectives and objectives". We can see that both descriptions represent high complexity, multiple stakeholders' objectives and a plurality of values.

Similarly, system uncertainty can be described using Skinner et al. (2013) metrics for level of uncertainty. Other studies that aim to assess the severity of uncertainty also apply a continuum similar that used by Skinner (i.e. ignorance through to determinacy) though few works afford the specificity that Skinner's scale and divisions provide. The nature of uncertainty is a unique classification that, on this schematic (Figure 3) becomes an expression of location and level and provides insight about the character of the uncertainty. Using this logic we can classify uncertainty techniques taken from the literature.

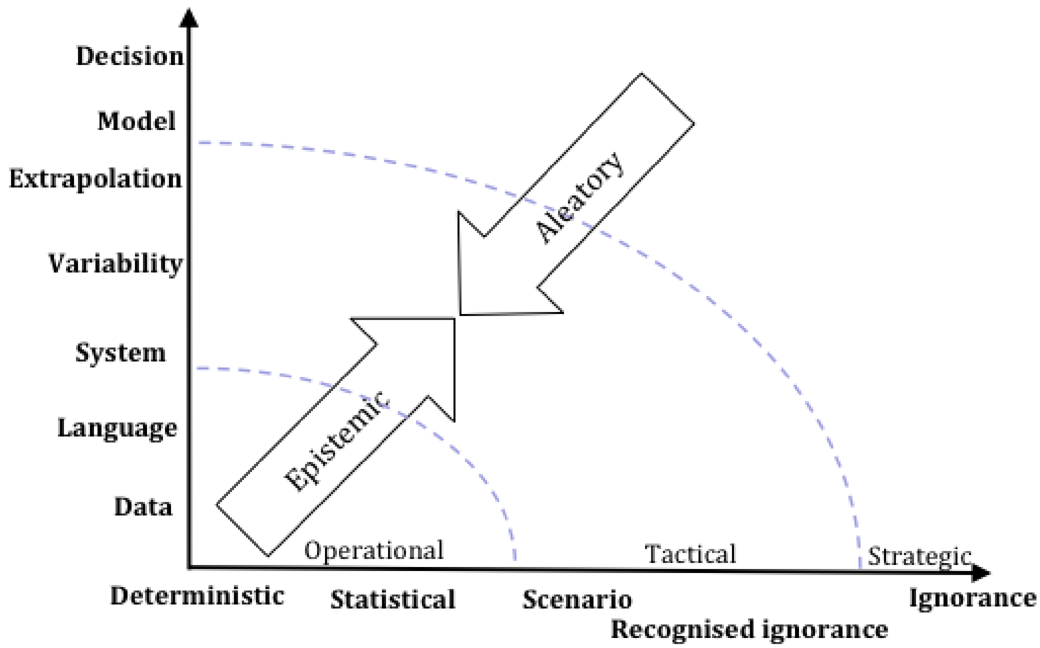

Figure 3. Schematic showing the metrics used for analysing uncertainty techniques. The metrics were taken from Skinner et al, 2013 and describe location (x-axis), level (y-axis) and nature (z-axis) of uncertainty. These metrics are implied in Figure 2 and used to categorise techniques in Table 3.

Positioning uncertainty management techniques

To gain an understanding for the range of techniques that have been used to assess uncertainty across the energy sector, search terms 'uncertainty' & 'energy system' (or 'energy sector') were used to gather articles and reports using Scopus, Web of Science and Google Scholar. After creating a list of techniques, a search was carried out for papers that included the use of the 'name' of each technique in the abstract and the words 'energy system' (or 'energy sector/domain) and 'uncertainty' anywhere in the paper. This allowed us to answer the following questions:

- *What techniques are currently being used to assess uncertainty in the energy system?*
- *What is the nature, location and level of uncertainty characterising the type of knowledge that each is used to assess?*

The assessment was guided by the characterisation of uncertainty (Table 2) and the results were captured in Table 3. This data was then used to position the techniques within the model (Figure 4), guided by the characterisation scales and an assessment of the type of decision being addressed. A workshop hosting 40 energy experts was used to validate the conceptual positioning of the techniques. During the workshop experts were asked to comment on the general position of the techniques, identify missing techniques and provide insight with respect to the applicability of the model to their sector.

Assessment of the techniques used for investigating uncertainty

The results of the assessment are shown in Table 3 and provide a comprehensive list of techniques and relevant examples from literature. The techniques were mapped on to our model (Figure 4), illustrating our initial, conceptual effort. Few techniques were identified as strictly belonging to the operational decision category (i.e. low location of uncertainty and low level of system uncertainty) and this may be due to the multi-use appeal of these tools or may suggest a genuine lack of appropriate techniques within this domain. In either case, this suggests that multiple mitigation techniques may be required to address and manage uncertainty.

Table 3 – Uncertainty assessment

Uncertainty technique	Nature of uncertainty	Location of uncertainty	Level of uncertainty	Example in literature
Social surveys investigating public perception	Epistemic	Data	Ignorance	Reise et al., 2012; Laes et al., 2011; Gram-Hanssen et al., 2012; Sirin, 2011
Social surveys willingness to pay	Epistemic	Data	Recognised ignorance	Hanemann et al., 2011; Kraeusel and Most, 2012)
UK MARKAL	Epistemic	Model	Statistical	Strachan and Usher, 2011; Usher and Strachan, 2012
Bayesian Methods	Epistemic	Decision	Recognised ignorance	Armstrong et al.
Scenario analysis	Epistemic	Model	Scenario	Morlet and Keirstead, 2013; Amiri et al., 2013; Karvetski and Lambert, 2011
Sensitivity analysis	Aleatory	Data	Statistical	Jain et al., 2012
Discourse analysis	Epistemic	Decision	Recognised ignorance	Ariza-Momtobobbio and Farrell, 2012; Mander, 2008
Real options	Epistemic	Data/model/ variability	Recognised ignorance/ statistical/ scenario	Fernandes et al., 2011; Zavodov, 2012; Bredin et al., 2011; Chronopoulos et al., 2013
Tree method	Aleatory	Availability	Scenario	Xu and Guan, 2012
MCDA	Aleatory	Variability	Scenario	Loken et al., 2006; Wang et al., 2009
Case study	Epistemic	Data/ language	Recognised ignorance	Luo et al., 2009; Trygg and Amiri, 2007; Laurikka and Koljonen, 2006
Monte Carlo simulation	Aleatory	Model	Statistical	Chaudry et al., 2013
Mixed integer multi-objective optimisation	Aleatory	Model	Recognised ignorance	Abedi et al., 2012
Discourse analysis	Epistemic	Decision	Ignorance	Ariza-Montobbio and Farrell, 2012
Discrete event	Aleatory	Model	Scenario	Azcarate et al., 2012

simulation				
Logic programming	Epistemic	Language/ ambiguity	Recognised ignorance	Baldwin, 1987
Optimisation methods	Aleatory	Model/ output	Scenario	Bano et al., 2011
Interviews	Epistemic	Decision	Recognised ignorance	Beers et al., 2003
Combined qualitative/quantitative models	Epistemic	Decision	Recognised ignorance	Stephens et al., 2008
Agent based models	Epistemic	Decision	Recognised ignorance	Berger et al., 2010; Downing et al., 2001
Delphi method	Epistemic	Decision	Recognised ignorance	Cam et al., 2002
Analytical hierarchy process	Epistemic	Decision	Recognised ignorance	Chinese et al., 2011; Ascough et al., 2008; Awudu and Zhang, 2012; Li et al., 2007; Wang et al., 2009
Fuzzy logic	Aleatory	Data	Statistical	Eltamalay and Farh, 2013
Heuristic models	Epistemic	Decision		Banos et al., 2011; Berger et al., 2010
Linear programming	Epistemic	Data	Statistical	Garcia and Weisser, 2006; Amiri et al., 2013 Zhang and Rong, 2008
Non-linear programming	Epistemic	Data	Statistical	Perez-Diaz et al., 2010
Swarm intelligence	Aleatory	Variability	Scenario	Kiran et al., 2012; Mitra et al., 2006
Stochastic modelling	Epistemic	Data	Statistical	Sun et al., 2006; Falcao, 2004; Huijbregts et al (2001)
Portfolio theory	Aleatory	model	Recognised ignorance	Favre-Perrod et al., 2009; Tisigkas, 2011; Wilson and Grubler, 2011

The results from the positioning exercise are shown in Figure 4, which presents a relative comparison for a range of uncertainty management techniques.

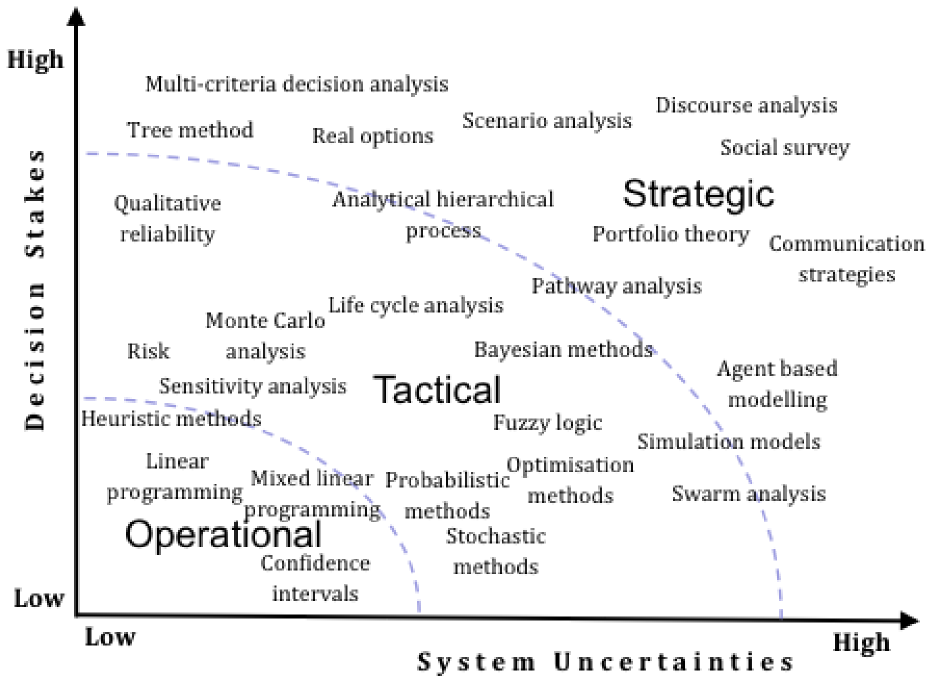

Figure 4. Initial positioning of techniques for assessing uncertainty.

In presenting these results we stress that this conceptual model is not a tool for measuring or assessing uncertainty per se. This approach provides a means for characterising the uncertainty within a decision and to identify suitable techniques for its investigation.

The following questions are intended to guide decision makers through the process of understanding their uncertainty and selecting the appropriate assessment techniques:

- Step 1: How extensive is the uncertainty associated with my decision – or what level of understanding do I have to support my decision?
- Step 2: What knowledge is required to address the uncertainty and where might I find it – or where is in the decision process it is required?
- Step 3: Given the above, which technique(s) are best suited to the handling of uncertainty?

Uncertainty workshops (23rd May 2013)

The workshop provided an opportunity for practitioners to engage with the concept and to comment upon the positioning of the techniques. The workshop consisted of a presentation of the concept followed by a breakout session whereby experts were divided into three groups and asked to: query the positioning of techniques, add or subtract techniques, and comment on the applicability of the concept. The workshop concluded with a group discussion to discuss how best the conceptual model may progress. Comments made during the group discussion by participants were summarised and are presented below.

General points and comments about the concept

- A useful way of thinking about dealing with uncertainty is to think of it as a funnel. When decision processes are initiated the boundaries are broad however, as a decision begins to form the process moves down into the funnel where the boundaries begin to tighten. At this point the decisions become increasingly tactical and then operational where the problem becomes quite well bounded.
- A point to consider when using this approach: 1) what answers are we looking for? i.e. what is it we are trying to maximise? 2) How do we want to get our answer? i.e. what are the techniques we will use to get this answer? 3) How do we combine our answers with other people's answers? Then once we have answered these questions, which essentially determine the direction we think we should go in, we could consider how do we design the framework so that when people go off and do their own thing they do it in the right way?
- Important to frame the question so it's clear if it's about a decision already made or about the process of decision making i.e. whether we are intending to use the techniques to understand the state of the world or take a specific decision.

- Framing the decision correctly will be key to selecting the appropriate combination of techniques to address an issue.
- Important to first make sure that the correct diversity of questions have been identified before focusing on the correct diversity of techniques.
- For ease of use it was generally agreed that it would make sense to cluster techniques that are closely related.

Choosing appropriate techniques

- It was clear that there was a diversity of perspectives with regards to the usefulness of different techniques and what was understood by the different techniques, which seemed to stem from the diversity of participant backgrounds. It was acknowledged, therefore, that participants' background will have biased their perspective of the value techniques had.
- There are two ways of thinking about what techniques should be used: 1) what quantities are targeted or 2) what prices should be set so people do the right thing.
- It was suggested that it might be possible to identify a cluster of techniques that are commonly used across the energy system (e.g. referring to Monte-Carlo Analysis, Cost Benefit Analysis, Decision Trees, Scenario Analysis, Optimisation Techniques and Simulation Methods).
- The variety of techniques that are used is very important to bring in the unexpected and the unintended consequences.

Issues to be aware of when choosing techniques

- Some techniques that are commonly used are often pushed to the limits of their capacity because those are the techniques that practitioners are most familiar with and are therefore more inclined to refer to.

- Some techniques will straddle between levels of decision making and as such how techniques might be used and their outputs interpreted may vary, e.g. Multi-Criteria Decision Analysis could be used to reach a specific answer or it could be used to map out different perspectives to help in a discursive decision-making process.
- Must not expect too much from these tools and techniques given the rapid rate of change we are seeing happen across Government.
- Need to look carefully at the uncertainty in the relationship between the model and the real system, which it is intended to represent. For example, in an extreme case if the relationship between the model and the real system is poor then the danger is that the practitioner will be using the output from the model thinking they are taking systematic decisions when in actual fact they will be taking arbitrary decisions.

Issues to be aware of when applying these techniques to the energy system

- Are the techniques appropriate? Are they being pushed beyond their limits? Are policy makers simply not listening, or are academics/R&D misinterpreting senior level requests?
- Policy makers tend to think a model is a perfect representation of reality until they know what is in it and at which point they think it's a ludicrous representation of reality.
- Techniques should not just be good for assessing uncertainty. They must also be able to provide a pragmatic way of moving forward within the context of the organisation.
- There is a political challenge caused by the fundamentally changing policy background.

- Choosing the correct techniques is as much about good governance and about establishing an evidence base that adheres to principles such as transparency to facilitate public and private sector engagement, otherwise we run the risk of developing policy-based evidence making as opposed to evidence-based policy making.
- In government departments the focus is more on taking one step forward each day. Rather than starting with a clean sheet and letting the process of analysis determine the direction – results from different studies are used to make any progress in any direction at all.
- Many tools exist but only a few are every used. Often these are unsophisticated techniques including rules of thumb, so there is a need to ask not just what the best technique is but what technique is realistic given the organisations constraints.
- Many sophisticated mathematical techniques could in principle make a valuable contribution, but how can we move from their use in academia and R&D to being applied in the field, given the relatively small number of people who currently have the necessary high level modelling skills. Further, given the rate at which the energy policy landscape is changing, it is sometimes not possible to perform the R+D which would be necessary to take a decision in an ideal way – one must therefore consider the best pragmatic way of taking decisions in these circumstances. As a consequence it may be that in some cases verbal reasoning may be more appropriate than sophisticated mathematical modelling techniques if that latter cannot adequately represent the real system, or the relationship between the model and the real system cannot be assessed.
- It was suggested the quadrants of the graph could be separated out into regions of ‘guess’, ‘procrastinate’ and ‘copy what others are doing’, where the tendency to procrastinate was suggested to be what people do intuitively when they are

worrying about optionality. It was also said that there is a need to develop a systematic process that could help people think through this process.

- One participant suggested that the correct approach in making a decision under uncertainty is to specify the problem at hand and then decide on appropriate modelling techniques without any preconceptions as to what approach is required for a given type of decision.

Validating the positioning of uncertainty techniques

Participants had few comments regarding the relative positioning of the techniques and, in general, were comfortable with the categorisation. Participants noted that the number of techniques mapped was too great and that many of the techniques were too specific or unknown (outside academia) to provide practical benefit to decision makers. Instead, participants suggested that similar techniques be clustered, particularly those commonly used across the energy sector (e.g. referring to Monte-Carlo analysis, cost benefit analysis, decision trees, scenario analysis, optimisation techniques and simulation methods). The resulting schematic (Figure 5) was developed in response to this comment and provides a more accessible description of general techniques. A brief description of the technique clusters is provided below.

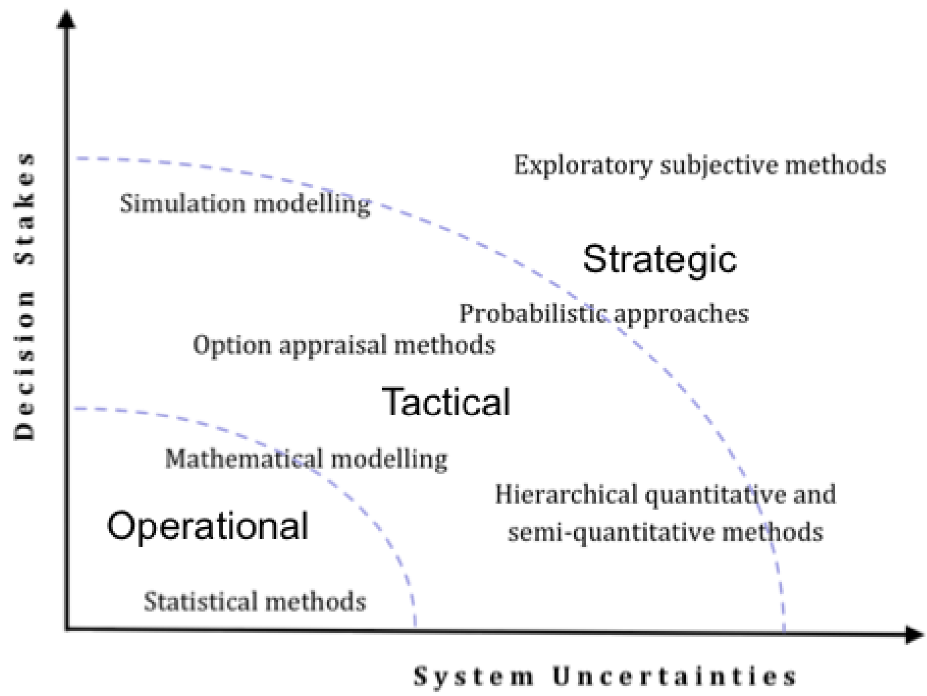

Figure 5. Final positioning of uncertainty management techniques after input from stakeholder workshop.

Exploratory subjective approaches

Exploratory subjective approaches refer to techniques such as: scenario analysis, participatory multi-criteria methods, discourse analysis, Delphi methods and social surveys. These have been used to assess uncertainty characterised by the subjective knowledge. The uncertainty is located in the decision (Cam et al., 2002) and the integrity of the structure of supporting models (e.g. Amiri et al., 2013). The severity of uncertainty typically ranges between scenario (e.g. Amiri et al., 2013; Morlet and Keirstead, 2013), recognised ignorance (e.g. Kraeusel and Most, 2012; Gram-Hanssen et al., 2012; Reise et al., 2012; Sirin, 2011; Laes et al., 2011; Hanemann et al., 2011) and total ignorance. Specifically, social surveys, scenario analysis and discourse analysis are useful techniques for assessing uncertainty with an epistemic nature (e.g. Morlet and Keirstead, 2013), whilst techniques such as participatory methods are useful for assessing uncertainties that are also aleatory in nature (e.g. Burger et al., 2010; Bryant and Lempert, 2010).

Simulation modelling

Simulation modelling refers to techniques such as: agent-based modelling, simulation models and swarm intelligence. These have been used to characterise semi-objective knowledge. The severity of uncertainty typically ranges between scenario (e.g. Amiri et al., 2013; Morlet and Keirstead, 2013), recognised ignorance (e.g. Kraeusel and Most, 2012; Gram-Hanssen et al., 2012; Reise et al., 2012; Sirin, 2011; Laes et al., 2011; Hanemann et al., 2011) and total ignorance. This uncertainty is located in the variability of the human system (Kiran et al., 2012); the decision (Berger et al., 2010; Dowing et al., 2001) and the supporting model output (Azcarate et al., 2012). Specifically, agent-based modelling can help account for the aleatory and the epistemic nature of uncertainty (Berger et al., 2010; Dowing et al., 2001), whereas techniques such as discrete event simulation (Azcarate et al., 2012) and swarm intelligence (Kiran et al., 2012) are better suited to help practitioners assess aleatory uncertainty.

Probabilistic approaches

Probabilistic approaches refer to techniques such as: fuzzy logic and Bayesian methods. These have been used to assess uncertainty characterising both subjective and semi-objective knowledge in the energy system. The level of uncertainty typically ranges between recognised ignorance (e.g. Armstrong et al.) and statistical (Eltamalay and Farh, 2013) uncertainty. The uncertainty is generally located in the data (Eltamalay and Farh, 2013) and the decision (Armstrong et al.). Specifically, Bayesian methods are useful techniques for assessing uncertainty with an epistemic nature (Armstrong et al.), whilst techniques such as fuzzy logic are useful for assessing uncertainties that are aleatory in nature (Eltamalay and Farh, 2013).

Option appraisal methods

Option appraisal methods refer to techniques such as: portfolio theory, real options; pathway analysis; and risk analyses. These have been used to assess semi-objective knowledge in the energy system. The severity of uncertainty typically ranges between recognised ignorance, statistical and scenario level uncertainty (Fernandes et al., 2011; Zavodov, 2012; Bredin et al., 2011; Chronopoulos et al., 2013). The uncertainty is located in the variability of the data and model of the system (Favre-Perrod et al., 2009; Fernandes et al., 2011; Zavodov, 2012; Bredin et al., 2011; Chronopoulos et al., 2013). Specifically, portfolio theory and real options theory are useful techniques for assessing uncertainty with an aleatory nature (e.g. Gracevva, 2002), whilst techniques such as pathway analysis and risk analyses are better suited for assessing the epistemic nature of uncertainty.

Mathematical modelling

Mathematical modelling refers to techniques such as: life cycle analyses, mathematical reasoning, mixed linear programming, and linear programing. These have been used to assess objective and semi-objective knowledge in the energy system. The level of uncertainty typically exists at the statistical level (e.g. Venkatesh et al., 2013). The uncertainty is located in the knowledge of the system (Garcia and Weisser, 2006; Amiri et al., 2013 Zhang and Rong, 2008; Perez-Diaz et al., 2010) and extrapolation of data (Elia et al 2001; El-Shimy, 2009; Whittaker et al., 2009; Venkatesh et al., 2013). All of these techniques are designed to account for the epistemic nature of uncertainty.

Hierarchical quantitative and semi-quantitative methods

Hierarchical quantitative and semi-quantitative methods refer to techniques such as: multi-criteria decision-making, decision tree methods, and analytical hierarchical process. These techniques have been used to assess semi-objective knowledge in the energy system, where the decision is characterised by relatively low decision-stakes and high system uncertainties. The severity of uncertainty typically ranges between scenario (e.g. Loken et al., 2006; Xu and Guan, 2012) and recognised ignorance (e.g. Chinese et al., 2011; Ascough et al., 2008; Awudu and Zhang, 2012) levels of uncertainty. The uncertainty is located in the variability (Loken et al., 2006) and availability of data (Xu and Guan, 2012). Specifically, multi-criteria decision analyses and tree methods are useful for assessing uncertainty with an aleatory nature (e.g. Loken et al., 2006; Xu and Guan, 2012), whilst techniques such as analytical hierarchy process is more useful for assessing uncertainties that are epistemic in nature.

Statistical modelling methods

Statistical modelling refers to techniques such as: Monte-Carlo analysis, optimisation methods, probabilistic methods and sensitivity analysis. These have been used to assess semi-objective knowledge in the energy system. The level of uncertainty is typically statistical (Jain et al., 2012; Chaudry et al., 2013). The uncertainty is located in the data (Jain et al., 2012) and the structure and output of the model (Chaudry et al., 2013). Specifically, sensitivity analysis and Monte Carlo simulation are useful techniques for assessing uncertainty with an aleatory nature (e.g. Jain et al., 2012; Chaudry et al., 2013).

Discussion

The purpose of this research was to develop a conceptual model capable of categorising techniques used to assess uncertainty in the energy sector. Conventionally, this includes techniques ranging from scenario analysis, which explicitly acknowledges the presence of uncertainty, to techniques such as statistical analysis, which are designed to provide the user with information about the strength of relationships between variables in a system. In this research we considered all techniques used to assess uncertainty irrespective of its explicit reference to uncertainty because: 1) regardless of whether a technique refers explicitly (or not) to uncertainty, if the tool assesses a user's knowledge of a system then implicitly it assesses the user's lack of knowledge (i.e. uncertainty), and 2) our goal was not to suggest new techniques for assessing uncertainty but instead to reveal what techniques currently exist and are being applied to different types of decisions (e.g. operational, tactical or strategic decisions).

Decision processes can be divided into different categories depending upon their complexity and degree of uncertainty (Funtowicz and Ravetz, 1990). Complexity may refer to the quantity of values or variety of stakeholders involved in a decision process. Uncertainty relates to the level (or severity) of uncertainty in the process. Decisions can be further analysed by applying uncertainty typologies (Skinner et al., 2013), which are useful for characterising the level, location and nature of uncertainty. By using our framework it is possible to map uncertainty management techniques against decision categories, thus providing guidance on the use of the most appropriate techniques for different decision context. Though admittedly coarse, our approach is useful in guiding decision makers to select the most appropriate technique for their given problem.

Decision processes and the techniques used to manage them will differ greatly and it is important for users to ensure that their approach is commensurate with the context in which it is being applied. To this end, three types of knowledge were identified (Figure 1) – objective, semi-objective and subjective. These represent distinctly different problems (or decisions) and are characterised by varying levels and types of knowledge, stakeholders and values.

Our framework assumes that as decisions traverse the subjective (or post-normal science) domain, into the semi-objective, and then finally the objective (or analytical science) domain the decision becomes increasingly tractable. The decision boundaries become more clear, values begin to form, data begins to build and the number of involved stakeholders decreases. This implies that the location and level of uncertainty is also changing and therefore the tools required to assess the uncertainty must change as well. The decision environment is dynamic and as a decision evolves, so to must the techniques used to address uncertainty. For example, the uncertainty in highly complex decisions characterised by subjective knowledge requires methods able to account for multiple perspectives and values and do not require complete or robust data sets. These techniques include scenario analysis, surveys and multi-criteria decision analysis – techniques that help users to explore, frame and characterise issues. As the decision boundaries begin to substantiate and data emerges, users can apply techniques such as agent based simulation or Bayesian methods – techniques that combine quantitative and qualitative information. Finally, as the decision becomes focussed on to a single, tractable problem, likely supported by a high degree of data, quantitative methods, for example, statistical methods, can be applied. The challenge for decision makers is to understand the character of their uncertainty and the limitation or appropriateness of the tools and techniques being applied.

This framework is not without limitation and we acknowledge that the categories of knowledge types are not mutually exclusive. Similarly, we acknowledge (and recommend) that uncertainty techniques not be applied in isolation. Instead, uncertainty management requires that decision makers operate within a framework of multiple techniques combing complimentary techniques that are fit for purpose. As the decision context changes so will the techniques used, and decision makers may find themselves applying a series of techniques over time. Though some techniques for managing uncertainty will be better suited for a specific decision type than another this is not to say that some techniques are wrong for a given decision type, but simply that some techniques may provide a more useful answer than others.

It may seem intuitive that different decision categories (or types) require different uncertainty tools. However, our workshop revealed that most decision makers do not take the time to characterise their decisions and therefore may lack an appreciation for the level, location and nature of uncertainty they encounter. It is likely that decision makers will apply tools and techniques that are not well suited for the problem at hand. In fact, multiple attendees said that decision makers would use whatever techniques are available to them, rather than identify the most appropriate tool for the job. Moreover, under conditions of uncertainty, decision makers will often rely on doing what others have done before them, revert to guessing or, under considerable uncertainty, procrastinate and wait for more information to become available. Finally, the techniques used to assess uncertainty are all too often abstract and therefore, presentation of a family of suitable techniques (i.e. multiple options) may increase the end users comfort level for dealing with uncertainty.

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