Expert Systems with Applications, Volume 39, Issue 10, August 2012, Pages 8604-8610

Evidence and belief in regulatory decisions – incorporating expected utility into decision modelling

J. Li[1], G.J. Davies[2], G. Kendall[1], E. Soane[3], R. Bai[4], S.A. Rocks[2*] and S.J.T Pollard[2]

[1]*University of Nottingham, School of Computer Science, Jubilee Campus, Wollaton Road, Nottingham, NG8 1BB, UK*

[2]*Cranfield University, Collaborative Centre of Excellence in Understanding and Managing Natural and Environmental Risks, School of Applied Sciences, Bedfordshire, MK43 0AL, UK*

[3]*London School of Economics, Department of Management, London, WC2A 2AE, UK*

[4]*University of Nottingham Ningbo, Division of Computer Science, 315100, China*

Corresponding author:

Dr Sophie Rocks
Building 42, Cranfield University, Cranfield, Bedfordshire, MK42 0AL
Email s.rocks@cranfield.ac.uk
Tel: +44 1234 750111 (ext 2370); fax: +44 1234 751671

Abstract

Recent changes in the assessment and management of risks has had the effect that greater importance has been placed on relationships between individuals and within groups to inform decision making. In this paper, we provide the theoretical underpinning for an expected utility approach to decision-making. The approach, which is presented using established evidence support logic (TESLA™), integrating the expected utilities in the forming of group decisions. The rationale and basis are described and illustrated through a hypothetical decision context of options for the disposal of animal carcasses that accumulate during disease outbreaks. The approach forms the basis for exploring the richness of risk-based decisions, and representing individual beliefs about the sufficiency of evidence they may advance in support of hypotheses.

Keywords: decision support, uncertainty, risk, group decision making, evidence support logic, expected utility, TESLA™

1. Introduction

Regulatory decision-making is undergoing a revolution in the UK. Proposals for modernising regulation within Government in the 1990s (Cabinet Office, 1999) are being delivered through programmes that focus on ‘better’ and ‘risk-based’ regulation (Pollard et al., 2002; Hutter, 2005). The premise is that a step change can be delivered, with the regulation of risks to occupational and public safety, to the safety of the food chain and to the environment becoming smarter, more focused on high risks, and decisions being more open to external scrutiny and challenge (Davies et al., 2010). In addition, we observe a renewed emphasis on the use of scientific evidence in government decision-making. These initiatives test our understanding of the technical, political and psychological features of decision-making on risk, particularly in the regulatory and policy development contexts.

Previously, UK Government departments and their agencies have published risk frameworks that set out the technocratic processes of risk management and options appraisal (see Strategy Unit 2002). These spell out how sufficient, dependent and necessary a number of sources of evidence are for providing a solid basis for decision making. However, such decisions involve the consideration of factors well beyond the nature of adverse consequences, their probabilities, and the uncertainties in these conventional dimensions. Risk managers need to consider the costs of risk management, associated social issues, performance of technology (where it plays a part), and governance arrangements critical to ensuring that risks are actively managed by organisations (Pollard *et al.*, 2002). These attributes are reflected in the risk management 'frameworks' promoted by governments, regulators, business sectors and individual organisations. Yet in practice decisions are made by individuals within organisational contexts. For risk-based regulation, these are complex decisions requiring:

(i) clear problem definition (scoping) that identifies the risk under study within the context of the legal statute;

(ii) the gathering of evidence by multiple parties (professional advisors, researchers, the general public, operators, front line regulatory staff, regulatory policy staff);

(iii) the structuring of arguments in support of a case, including the assembly of individual lines of evidence with their discrete strengths, and the overall weight of evidence;

(iv) the ‘brokering’ of evidence and risk assessments between parties, including between consultants and their clients, internally within organisations, between the regulated and the regulator, and between regulators and policy officials with individuals valuing the benefit and cost in addition to the reputation, trustworthiness and persuasiveness of the provider (Chiu *et al*., 2009); and

(v) peer review of risk assessments and the supporting evidence in conjunction with defensible, robust decisions to be made on risk management, together with the defence of these decisions in the courts, if necessary (Defra, 2011).

In practice, the conventional manner of establishing a risk-management framework is likely to take too long to gather sufficient information to inform decisions for the growing number of new imminent risks. As such, expert-elicitation panels have become a common route to produce an evidence-based framework. This approach can achieve results with relative speed and has become invaluable for practitioners of modern risk-based regulation. Expert-elicitation and the interpretation of information are subject to value judgements (regarding the sufficiency of supporting evidence), which are rarely transparent to the end user. As such, there remains a view that these frameworks fail to fully capture the nuances and complexities of decision-making (Oxera, 2000; Petts *et al*., 2003). For example, the influence that individual preferences (or expected utilities) will have on judgments made regarding the sufficiency, dependency and necessity of supporting evidence. This influence is difficult to identify and indeed to measure, however the impact of such influences are unclear and a model can help to determine how important these influences are in decision making. Previously, Chiu and colleagues (2009) have presented a formal quantitative model for recommendations within a customer/supplier relationship, demonstrating the impact of trust and reputation;

however, this model does not specifically consider the belief and uncertainty that an individual may have in recommendations.

TESLA™ (Quintessa, UK), a commercial platform for evidence support logic, is a decision-support tool that addresses issues of transparency within expert elicitation panel decisions, thereby providing unique insights that are not normally included in conventional decision-support tools. TESLA™ can be used to describe and simulate complex systems. Environmental decision contexts, complex by their very nature, have been previously tackled by authors who have used evidence-support logic to negotiate, optimise the effectiveness of, and recently, model decisions.

In this paper, we propose the theoretical basis for a model that integrates: (a) the structuring of evidence that supports a group decision (represented here by the adoption of evidence-support logic); (b) the benefits of a decision outcome (represented by expected utility theory); and (c) that demonstrates the relevance of other influences in group decision making to practitioners, providing a model that increases the transparency of decision making influences. Representation of the combined approach is made here using TESLA™.

2. Methods

2.1 Selection of a model platform

TESLA™ offers the user a means of improving the transparency of regulatory decisions, by recording the structure and sufficiency of the evidence that supports a risk decision. It has been successfully used in the context of safety cases for nuclear waste management (Seo *et al*., 2004; Egan & Bowden, 2004) and is also proposed for building stakeholder confidence in the long term geological storage of carbon dioxide (Benbow *et al.*, 2006; Egan, undated). Lines of evidence are represented by a structured cascade of logical ‘parent’ and ‘child’ hypotheses, each with its own supporting evidence. User inputs are combined to determine how ‘sufficient’, ‘dependent’ and ‘necessary’ each child hypotheses is for supporting its corresponding parent. TESLA™ does not account for the influence that personal preferences have on value judgements.

2.2 Integrating expected utility theory in evidence-support logic

Expected Utility Theory (EUT) can be incorporated within evidence-support logic to explore the integrity of TELSA™. This provides an indication of how subjective value-judgements bias the sufficiency of supporting evidence and the structure of the resulting framework.

The evidence-support logic, embodied within TESLA™, is an information propagation approach developed from Interval Probability Theory (IPT) (Feller, 1971; Cui & Blockley, 1990; Hall *et al.*, 1998a). It has been applied in several fields of risk-based decision-making to allow experts to characterise lines of evidence by expressing what they believe with regard to child hypotheses actively supporting, overlapping, or conflicting when considering a corresponding parent hypothesis (for examples, see Foley *et al*., 1997; Hall *et al*., 1998b).

Expert belief is expressed by a triple (p, u, q), where p denotes the probability that an individual child hypothesis supports a corresponding parent hypothesis, q denotes the probability that it refutes the hypothesis, and u denotes the residual uncertainty attached to this belief. These values range between $0 \le p, q \le 1$ and $-1 \le u \le 1$; where $u = 1$ would denote a state of absolute ignorance, and $u < 0$ would denote a state of conflicting beliefs within the evidence.

Evidence-support logic has a simple algorithm to aggregate multiple beliefs about evidence. For example, if n beliefs about n child hypotheses are aggregated to form a belief about a single parent hypothesis, each belief for each child hypothesis will be expressed as (p_i, u_i, q_i), $i = 1, \ldots, n$. Each child hypothesis would then have p_i and q_i values from 0 to 1 and u_i value of -1 to 1 assigned to denote how much belief 'for' (p_i) and 'against' (q_i) and how much uncertainty (u_i) is related to the corresponding parent hypothesis' belief. Greater values of sufficiency will result in evidence being more influential, whilst greater values of dependency result in pertinent child hypotheses having a shared influence. The presence of a necessary child hypothesis determines whether beliefs assigned to child hypotheses can be aggregated to form a belief for the corresponding parent hypothesis.

If (p_A, u_A, q_A) denotes the aggregated belief for child hypothesis A. Then p_{A} can be computed as follows:

$$p_A = \sum_{i=1}^{n} w_i p_i - \sum_{\substack{i,j=1 \\ i<j}}^{n} \rho_{ij} \min(w_i p_i, w_j p_j) + \sum_{\substack{i,j,k=1 \\ i<j<k}}^{n} \rho_{ijk} \min(w_i p_i, w_j p_j, w_k p_k)$$

$$+ \ldots + (-1)^{n-1} \rho_{1,\ldots,n} \min(w_1 p_1, \ldots, w_n p_n) \tag{1}$$

Therefore, if $S = \{i, j, \ldots\}$,

$$\rho_S = \frac{(1-D)\prod_{a \in S} w_a p_a}{\min_{a \in S}(w_a p_a)} + D$$

Where w_i is the weighting of the i^{th} line of evidence and D is the dependency between the evidence $p_i, p_j, \ldots, p_n$. Then q_A can be computed similar to (1).

$$q_A = \sum_{i=1}^{n} w_i q_i - \sum_{\substack{i,j=1 \\ i<j}}^{n} \rho_{ij} \min(w_i q_i, w_j q_j) + \sum_{\substack{i,j,k=1 \\ i<j<k}}^{n} \rho_{ijk} \min(w_i q_i, w_j q_j, w_k q_k)$$

$$+ \ldots + (-1)^{n-1} \rho_{1,\ldots,n} \min(w_1 q_1, \ldots, w_n q_n) \tag{2}$$

Where,

$$\rho_S = \frac{(1-D)\prod_{a\in S} w_a q_a}{\min_{a\in S}(w_a q_a)} + D.$$

Once we have the values of p_A and q_A, u_A can be determined by means of $p_A + q_A + u_A = 1$ For example, when $n = 2$ and beliefs 1 and 2 are independent, we have,

$$\begin{cases} p_A = w_1 p_1 + w_2 p_2 - \max(w_1 p_1, w_2 p_2)\min(w_1 p_1, w_2 p_2) \\ q_A = w_1 q_1 + w_2 q_2 - \max(w_1 q_1, w_2 q_2)\min(w_1 q_1, w_2 q_2) \end{cases} \quad (3)$$

2.3. Incorporating expected utility

Expected utility theory is widely adopted for addressing risk and uncertainty in economics (Hey & Orme, 1994; Starmer, 2000) and has applications in regulatory decision-making (Li et al. 2009). It can be traced back to the work of Daniel Bernoulli (1738) and has been further promoted through the 'theory of games and economic behaviour' (Von Neumann & Morgenstern, 1944). The underlying principle is that the decision-maker has prior knowledge of the probabilities of all activities occurring and can assign a value representing a sum of money or similar against each alternative. This assumes that the decision-maker has a complete, reflexive, transitive, and continuous evaluation over monetary outcomes, or in other words, s/he possesses a von Neumann-Morgenstern utility function.

Expected utility over a set of outcomes can be expressed as,

$$U(X) = \sum_{i=1}^{n} u(x_i) p(x_i) \quad (4)$$

Where *X* is the utility of all the set of possible outcomes; *x* is the utility of an outcome; *p* is the probability of *X* as $p = (p(x_1), p(x_2), \cdots, p(x_n))$; $p(x_i)$ is the probabilities of outcome $x_i \in X$ ($i = 1, \cdots, n$) occurring with finite elements $x \in X$ for which $p(x) > 0$, and that $p(x_i) \geq 0$ for all $i = 1, \cdots, n$ and $\sum_{i=1}^{n} p(x_i) = 1$ (all probabilities must add up to 1).

Expected utility theory may also be applied for considering costs and benefits in risk-based regulation, where the public (or environmental) health is a benefit arising from preventative risk management decisions. If we consider a scenario of decision making under risk (for example, the disposal of nuclear waste; Pape, 1997) where there is a risk of an environmental hazard being realised, the hazard may lead to a loss of utility (e.g. wealth, ecosystem function, environmental quality), $w_N - w_A$ (expressed for illustrative purposes by a monetary value); where w_N denotes the value of the hazard not being realised and w_A the reduced value of the hazard being realised. In the case where the utility is purely financial, the decision maker can quantify the cost (loss of utility) of a hazard being realised ($w_N - w_A$) and envisage the value of making an investment to manage the risk. The challenge that practitioners face, however, is the ability to optimise the amount of money (C) that they invest along with the extent to which they are able to minimise the risk of the hazard being realised (often referred to in regulatory circles as ‘optimisation’). For this, let γ denote the possibility of a hazard being realised. We assume the existence of a state-independent utility function of the regulator $u(w)$ defined over payoffs, thus:

$$U(\gamma, C) = \gamma\, u(w_A - C) + (1 - \gamma) u(w_N - C) \qquad (5)$$

Notice that $U(\gamma, C)$ represents the expected utility of the regulator and that γ is a function of C. For illustrative purposes, we assume that when the decision maker is risk-neutral, the condition of optimal expenditure against risk is:

$$\gamma' = 1/(w_N - w_A) \tag{6}$$

Under (6), a risk is reduced to the extent that further investment would be disproportionate to the benefits received. Note that the optimal expenditure is independent of individual utility in (6). If the parameters of w_N, w_A and $\gamma(C)$ are from unique sources and remain the same among all stakeholders, (6) then holds for different risk-neutral decision makers. Arrow and Lind (1970) indicated that decision makers should behave in a risk-neutral fashion when public welfare is concerned. For this, it is possible for the decision to be unanimous within a group of stakeholders. However, if the stakeholders are not all risk-neutral or cost and benefit are not evenly shared, (6) will not hold.

By incorporating expected-utility theory within evidence-support logic we provide a greater level of transparency that facilitates optimisation being achieved. The output from TESLA™ provides a decision maker with an informed, evidence-based, decision that they can use to decide the level of resource to invest in managing the risk. However, before this can happen, experts (or a group of experts) must come together to map out the cascades of parent and child hypotheses that form different lines of supporting evidence. Then experts must determine how sufficient, dependent and necessary each child hypothesis is for answering its corresponding parent. Sufficiency, in this context, becomes the expert's best guess and is, of course, a value-based judgement. However, in group decisions, risk and benefit may be unevenly shared and the decision makers may have their own utilities towards risk and uncertainty.

2.4 Application to group decision-making

When multiple agents are involved in group decision making, there is also a need to determine the group decision based on individual utilities and evidence-support logic. If there are m agents faced with n alternatives $\{x_1, x_2, \cdots, x_n\}$ each agent will have a von Neumann-Morgenstern utility and a monetary cost-benefit estimation for all alternatives. Here, the von Neumann-Morgenstern utility is not necessarily the evaluation of his/her own individual benefit; rather the value of the decision expressed in terms of public health or environmental benefit (though monetised here for illustrative purposes). If $U_i(x_j)$ denotes agent i's expected utility of an alternative x_j where $i = \{1, \cdots, m\}$ and $j = \{1, \cdots, n\}$, for each agent we are able to establish a set of beliefs, each of which denotes the comparison between two different alternatives. Therefore agent i's belief can be represented by the triple ($p^i_{jk}, u^i_{jk}, q^i_{jk}$) which denotes the belief where $j, k = 1, \cdots n$ and $j \neq k$. For all n alternatives, every agent has a complete set of beliefs that contains $\frac{1}{2}n(n-1)$ items, each of which denotes a comparison between two different alternatives. For example, when n = 2, there is only one belief with respect to the hypothesis that 'alternative x_j is preferred to alternative x_k'. When n = 3, each agent has three beliefs. Each agent assigns a set of values (between 0 and 1) to each belief, which denotes how much sufficiency the agent assigns each belief. The relationship between individual beliefs and their utilities of alternatives can be expressed as:

$$p^i_{jk} - q^i_{jk} = \frac{U_i(x_j) - U_i(x_k)}{D_i}$$

where $D_i = Max\{U_i(x_1), \cdots, U_i(x_n)\} - Min\{U_i(x_1), \cdots, U_i(x_n)\}$.

Note that $p^i_{jk} + u^i_{jk} + q^i_{jk} = 1$ and $0 \le p^i_{jk}, q^i_{jk} \le 1$, p^i_{jk} and q^i_{jk} can be uniquely determined by the following, when:

$$-(1-u^i_{jk}) \le \frac{U_i(x_j) - U_i(x_k)}{D_i} \le 1 - u^i_{jk},$$

$$\begin{cases} p^i_{jk} = \dfrac{1-u^i_{jk}}{2} + \dfrac{U_i(x_j) - U_i(x_k)}{2D_i} \\ q^i_{jk} = \dfrac{1-u^i_{jk}}{2} - \dfrac{U_i(x_j) - U_i(x_k)}{2D_i} \end{cases} \tag{7}$$

When,

$$\frac{U_i(x_j) - U_i(x_k)}{D_i} < -(1-u^i_{jk}),$$

$$\begin{cases} p^i_{jk} = 0 \\ q^i_{jk} = 1 - u^i_{jk} \end{cases} \tag{8}$$

When,

$$\frac{U_i(x_j) - U_i(x_k)}{D_i} > (1-u^i_{jk}),$$

$$\begin{cases} p^i_{jk} = 1 - u^i_{jk} \\ q^i_{jk} = 0 \end{cases} \tag{9}$$

Equations 7 to 9 are conditional functions; the value of the belief, p_j and q_k are dependent on where the utility functions, $\frac{U_i(x_j) - U_i(x_k)}{D_i}$, lie, in relation to the uncertainty, u_j $\frac{U_i(x_j) - U_i(x_k)}{D_i}$.

Each agent can be assigned a weight (w_i) range from 0 to 1 that denotes her/his power in the group decision. This acts as the sufficiency of belief in the process of aggregation of multiple beliefs. Multiple agents' beliefs can then be aggregated. The aggregated beliefs denote a group preference over all alternatives. This can be illustrated using a hypothetical example, in this case the decision over disposal options of animal carcasses produced during exotic disease outbreaks, which we have previously described the international policy context and implications of these types of decision and the benefits of having an established hierarchy of options for carcass disposal (Delgado *et al*., 2010).

3. Results and discussion

With exotic animal disease, the policy officials (in any country) must consider the differential merits of various carcass disposal options and the ensuing implications for public health, animal health and welfare and environmental protection. Consider a grossly simplified and hypothetical case whereby policy advice is informed by a stakeholder group on whether to restrict (or not) certain disposal methods. We assume that five agent representatives are involved: (1) a policy official; (2) a government regulator; (3) an environmental expert; (4) an industrial representative; and (5) a public interest representative. For ease of illustration, 3 alternatives (A1, A2, A3) are considered: A1, the on-farm burial of carcasses; A2, burial in permitted, constructed landfills; and A3, controlled incineration. A1 poses hazards to animal and human health and a high potential for groundwater contamination from pathogens and nutrients. A2 reduces this risk but retains a long term risk to groundwater and poses a significant odour nuisance, especially during the operational phase. A3 reduces animal health, public health and environmental risks to the minimum, but has the disadvantages of higher construction and maintenance costs. The benefit each agent perceives from each of the options in this illustrative example can be represented by either expected utilities (not shown here) or monetised values (Table 1).

Table 1 Benefits of the agents

There are three hypothesises: H_1: Alternative A_1 is preferred to A_2; H_2: Alternative A_1 is preferred to A_3; H_3: Alternative A_2 is preferred to A_3. With respect to these hypothesises, each agent i has three beliefs ($p_{12}^{i}, u_{12}^{i}, q_{12}^{i}$), ($p_{13}^{i}, u_{13}^{i}, q_{13}^{i}$) and (p_{23}^{i}, u_{23}^{i}, q_{23}^{i}). According to (7), the values of the beliefs can be calculated for each hypothesis (Tables 2 to 4).

Table 2 Individual beliefs on H_1

Table 3 Individual beliefs on H_2

Table 4 Individual beliefs on H_3

By assigning each agent a weight of 0.2, the aggregated belief, can be computed by means of (1) and (2). TESLA™ provides a graphical interface on which to present these outcomes (Egan, undated; http://www.quintessa-online.com/TESLA/ESLGuide.pdf).

Figure 1 Interface of TESLA™.

The aggregated beliefs are computed as: (p_{12}^{A}, u_{12}^{A}, q_{12}^{A}) = (0.16, 0.22, 0.62); (p_{23}^{A}, u_{23}^{A}, q_{23}^{A}) = (0.39, 0.2, 0.41); and (p_{13}^{A}, u_{13}^{A}, q_{13}^{A}) = (0.18, 0.14, 0.68). These beliefs infer that alternatives A2 and A3 are preferred to alternative A1, and alternative A3 is slightly preferred to alternative A2. Ratio plots, in which both individual beliefs and the aggregated beliefs are illustrated, can be produced for each hypothesis (Figures 2 to 4), where the horizontal axis indicates the percentage uncertainty in the evidence, and the vertical axis indicates the ratio of “evidence for” to the “evidence against”. In Figure 2, all beliefs lie below the horizontal axis, which shows a consensus that ‘A2 is better than A1’.

Figure 2 Ratio plot with respect to H_1**.**

Figure 3 Ratio plot with respect to H_2.

Figure 4 Ratio plot with respect to H_3.

In these examples, an equal weight was given to all agents to reflect their power to decide. Note that the scale of individual payoff or monetary values does not affect the group decision. Individual agents cannot manipulate the final decision by scaling up (or down) their benefits. This ensures that each agent cannot influence the group decision by more than his/her assigned weight, which provides a greater level of transparency to the model.

This work establishes the basis for integrating evidence support logic and utility for regulatory decisions on risk. It allows, albeit mechanistically and in practice probably for presentational and illustrative purposes alone, an exploration of the role experts value judgements might have on regulatory decision outcomes. Nevertheless, as Monticino and colleagues (2007) also illustrate for forest ecosystem decisions affected by various stakeholder interests, 'unpacking' the flow of information between the contributors to decisions has merit in communicating the evidential basis for complex environmental decisions. A further contribution of this work, which we seek to further explore in later work, will be in understanding the role of personality traits on decision outcomes as well as the affect that different amounts of power will have on a group decision.

4. Conclusions

We have attempted to develop the theoretical basis for a model that seeks to represent expert judgements and the impact this has on the impact of supporting evidence within regulatory decisions. What emerges is a rudimentary proof of concept, which we have illustrated, which has application to authentic regulatory decision contexts. We have proposed a new decision support approach that can be used to make group decisions when risk, uncertainty, and conflicts of interest among stakeholders are involved. While this study makes a preliminary effort to link evidence-support logic and economic analysis, it should be recognised that it has been conducted using important simplifying assumptions; for example, individual utilities with respect to decision outcomes and the independency of individual beliefs. So far we deal with group decision making as a static process. However, it is of course a dynamic process where individual beliefs may change along with interactions between experts, and where uncertainty may be reduced through dialogue, negotiation and the introduction of new information. Intelligent computer agents can learn in this process and be adaptive to the dynamics. The benefit of this approach will be the ability it will provide Government bodies and organisations to explore the influence people in relative positions of power have on the weight assigned to different lines of evidence. Future research will focus on the dynamics of this group decision making process.

Acknowledgements

The authors acknowledge support from the Engineering and Physical Sciences Research Council (EPSRC) grant (EP/E017975/1) on which GJD was funded. The Collaborative Centre of Excellence in Understanding and Managing Natural and Environmental Risks (Risk Centre) is funded by Defra, EPSRC, NERC, ESRC and Cranfield University under EPSRC Grant EP/G022682/1. We are grateful for the discussions held with colleagues at Quintessa during the development of this approach. The views expressed herein are the authors' alone.

References

Arrow K & Lind R. 1970. Uncertainty and the Evaluation of Public Investment decisions. American Economic Review, 60, 364-378.

Beecham, J.A.; Engelhard, G.H. 2007. Ideal free distribution or dynamic game? An agent-based simulation study of trawling strategies with varying information. Physica A, 384, 628–646.

Benbow, S.; Metcalfe, R.; Egan, M. 2006. Handling uncertainty in safety assessments for long term geological storage of CO_2. In: N. Rokke, O. Bolland and J. Gale (eds.) *Proceedings of the Greenhouse Gas Control Technologies Conference (GHGT8)* Trondheim, Norway, June 2006.

Brown, D.G., Page, S.E., Riolo, R. & Rand, W. 2004. Agent-based and analytical modelling to evaluate the effectiveness of greenbelts, Environmental Modelling and Software, 19, 1097-1109.

Cabinet Office. 1999. Modernising Government. White Paper, available at:http://www.cabinet-office.gov.uk/moderngov/whtpaper/index.htm

Camerer, C. F. 2003. Behavioral game theory: experiments in strategic interaction. New York, Russel Sage Foundation.

Chaturvedi, A. R.; Gupta, M.; Raj Mehta, S.; Yue, W.T. 2000. Agent-based simulation approach to information warfare in the SEAS environment. Proceedings of the Hawaii International Conference on System Sciences 2000, Hawaii.

Chiu D.K.W.K.; Leung H.-F.; Lam K.-M. 2009. On the making of service recommendations: an action theory based on utility, reputation and risk attitude. Expert Systems with Applications, 36, 3293-3301.

Courdier, R.; Francois, G.; Andriamasinoro, F.H.; Paillat, J.-M. 2002. Agent-based simulation of complex systems: application to collective management of animal wastes. Journal of Artificial Societies and Social Simulation, 5, 1-26.

Cui W & Blockley D. 1990. Interval probability theory for evidential support, International Journal of Intelligence Systems, 5, 183-192.

Delgado, J., Longhurst, P., Hickman, G.A.W., Gauntlett, D.M., Howson, S.F., Irving, P., Hart, A., Pollard, S.J.T. 2010. Intervention strategies for carcass disposal: Pareto analysis of exposures for exotic disease outbreaks. Environmental Science and Technology, 44, 4416-4425.

Defra 2011. Guidelines for environmental risk assessment and management (3rd edition). Risk Centre/Defra, London, *in press*.

Egan, M.J., & Bowden, R.A. 2004. Application of evidence support logic to the role of palaeohydrogeology in long-term performance assessment. Quintessa report for UK Nirex Limited, Report QRS-1219A-1, October, 2004.

Feller W. 1971. An introduction to probability theory and its applications, Vol. 2, 2nd ed. Wiley New York.

Feuillette, S., Bousquet, F., & Le Goulven, P. L. 2003. SINUSE: a multi-agent model to negotiate water demand management on a free access water table. Environmental Modelling and Software, 18, 413-427.

Foley L., Ball L., Hurst A., Davis J., Blockley D. 1997. Fuzziness, incompleteness and randomness classification of uncertainty in reservoir appraisal, Petroleum Geoscience, 3, 203-209.

Hall J., Blockley D., & Davis J. 1998a. Uncertain inference using interval probability theory. International Journal of Approximate Reasoning, 19, 247-264.

Hall J., Blockley D., and Davis J. 1988b. A decision-support methodology for performance-based asset management, Civil Engineering and Environmental Systems, 21, 51-75.

Hey J. & Orme C. 1994. Investigating generalizations of expected utility theory using experimental data. Econometrica, 62, 1291-1326.

Hutter, B.M. 2005 The attractions of risk-based regulation: accounting for the emergence of risk ideas in regulation. CARR Discussion Paper Series, DP 33, Centre for Risk and Regulation. London School of Economics, London.

Kurahashi, S. & Terano, T. 2005 Analyzing norm emergence in communal sharing via agent-based simulation. Systems and Computers in Japan, 36. 102-112.

Li J., Pollard S., Kendall G., Soane E., & Davies G. 2009. Optimising risk reduction: an expected utility approach for marginal risk reduction during regulatory decision-making. Reliability Engineering and System Safety, 94, 1729-1734.

Macal, C.M. & North, M.J. 2006 Tutorial on agent-based modeling and simulation Part 2: How to model with agents. Proceedings of the 2006 Winter Simulation Conference. L. F. Perrone, F. P. Wieland, J. Liu, B. G. Lawson, D. M. Nicol, and R. M. Fujimoto (eds), Monterey, California.

Monticino, M., Acevedo, M., Callicott, B., Cogdill, T. & Lindquist, C. 2007. Coupled human and natural systems: a multi-agent based approach. Environmental Modelling and Software, 22, 656-663.

Nute, D., Potter, W.D., Maier, F., Wang, J., Twery, M., Rauscher, H.M., Knopp, P., Thomasma, S., Dass, M., Uchiyama, H & Glende, A. 2004. NED-2: an agent-based decision support system for forest ecosystem management. Environmental Modelling and Software, 19, 831-843.

OXERA 2000 Policy, risk and science: securing and using scientific advice. Health and Safety Executive, HSE Books, Suffolk, UK.

Perez, L. & Dragicevic, S. 2010. Modelling mountain pine beetle infestation with an agent-based approach at two spatial scales. Environmental Modelling and Software, 25, 223-236.

Petts, J. Gray, A-J., Delbridge, P. & Pollard, S. 2003. Participatory risk assessment: characterising Environment Agency decisions on risk, Environment Agency, R&D publication E2-043/TR/02, Environment Agency, Bristol, UK.

Pollard, S.J.T., Yearsley, R., Reynard, N., Meadowcroft, I.C., Duarte-Davidson, R. & Duerden, S. 2002. Current Directions in the Practice of Environmental Risk Assessment in the United Kingdom, Environmental Science and Technology, 36, 530-538.

Pape R. 1997. Developments in the tolerability of risk (TOR) and the application of ALARA. Nuclear Energy, 36, 457-463.

Starmer C. 2000. Developments in non-expected utility theory: the hunt for a descriptive theory of choice under risk. Journal of Economic Literature, 38, 332-382.

Seo, T., Tsuchi, H., Metcalfe, R., Suyama, Y., Takase, H., Bowden, A., Toida, M., Furuichi, M., Matsumura, A., Yoshimura, M. & Horio, A. 2004. A decision making methodology taking into account uncertainties and its possible application for the selection of preliminary investigation areas. Proceedings of DisTec 2004, 26th - 28th April, Berlin, Germany.

Strategy Unit 2002. Risk: improving Government’s capability to handle risk and uncertainty. The Strategy Unit, London, available at www.number-10.gov.uk/SU/RISK/risk/home.html.

Egan, M.J. undated. TESLA. Decision support software. Evidence support logic. A guide for TESLA users. Vresion 2.1., Quintessa, Henley on Thames, UK, << accessed 5th January, 2010 at http://www.quintessa-online.com/TESLA/ESLGuide.pdf>>

Tversky, A. & D. Kahneman 1992. Advances in prospect theory: cumulative representation of uncertainty. Journal of Risk and Uncertainty, 5, 297-323.

Von Neumann J. & Morgenstern O. 1994. Theory of games and economic behavior. Princeton University Press, Princeton, NJ.

Table headings

Table 1. Table showing the perceived benefits for Agents 1 to 5 (monetarised) for three alternative scenarios for carcass disposal, where A_1 is the on-farm burial of carcasses; A_2 is the burial in permitted, constructed landfills; and A_3 is controlled incineration.

Table 2. Table showing the individual beliefs on H_1 (Alternative A_1 is preferred to A_2)

Table 3. Table showing the individual beliefs on H_2 (Alternative A_1 is preferred to A_3)

Table 4. Table showing the individual beliefs on H_3 (Alternative A_2 is preferred to A_3)

Figure legends

Figure 1. Graphic interface of TESLA demonstrating the aggregation of individual agent's belief in a hypothesis (illustrated here with respect to H_1) using a calcuated weight.

Figure 2. Ratio plot of evidence ratio against the percentage uncertainty in the evidence illustrating aggregated (1) and individual beliefs (2-6) with respect to H_1 .

Figure 3. Ratio plot of evidence ratio against the percentage uncertainty in the evidence illustrating aggregated (1) and individual beliefs (2-6) with respect to H_2.

Figure 4. Ratio plot of evidence ratio against the percentage uncertainty in the evidence illustrating aggregated (1) and individual beliefs (2-6) with respect to H_3.

484