M2D
Models to Decisions

M2D: Research Agenda on Decision Making Under Uncertainty

Introduction and Methodology

The **Models to Decisions (M2D)** Network focuses on decision making that is informed by evidence obtained from mathematical and numerical models and is led by Professor Peter Challenor (University of Exeter), Dr Catherine Powell (University of Manchester) and Dr Emma Clarke (University of Exeter), the Project Manager. The focus of the M2D Network is different from, but complementary to, that of our sister Network CRUISSE, which focuses on radical uncertainty.

The Management Team (Challenor, Powell, Clarke) take care of the day-to-day running of the Network but are assisted by an Expert Panel (EP) in making all important decisions (e.g., evaluating applications for feasibility funding, and running the annual conference[1][2]). The EP members:

- Professor Richard Bradley (London School of Economics)
- Professor Richard Clayton (University of Sheffield)
- Dr Alejandro Diaz (University of Liverpool)
- Dr Julie Gore (University of Bath)
- Dr James Lyons (University of Exeter)
- Professor David Woods (University of Southampton)

have very broad expertise, spanning applied mathematics, statistics, philosophy, psychology, engineering, cardiac modelling and film studies. Strategic oversight is also provided by the Advisory Board (AB):

- Matt Butchers (Knowledge Transfer Manager)
- Professor Mark Girolami (Imperial College London)
- Dr Ron Bates (Rolls-Royce)
- Professor Simon Maskell (University of Liverpool)

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[1] http://blogs.exeter.ac.uk/models2decisions/events/m2d-2017-annual-conference/

[2] http://blogs.exeter.ac.uk/models2decisions/events/m2d-2018-annual-conference/

- Hetan Shah (The Royal Statistical Society)
- Professor Tony O'Hagan (University of Sheffield)
- Professor Veronica Bowman (Defence Science and Technology Laboratory).

Over the lifetime of the Network, the Management Team, EP and AB have been eliciting the views of the UK scientific community on research challenges associated with decision making under uncertainty (in the context of model-informed decisions). In particular, our 300+ M2D Network members have provided feedback through online questionnaires and during Roundtable discussion sessions held at the 2018 M2D conference. Alexandra Freeman from the Winton Centre for Risk and Evidence Communication at the University of Cambridge has also made a major contribution to this document and we would like to acknowledge her contribution. These views have been distilled to produce this document, which is in two parts.

In **Part A**, we present a high-level summary of the main findings which can be read quickly and is available separately. In **Part B**, we provide a more detailed description of the research challenges that have been identified for each of the three core themes of the Network.

- **T1: Uncertainty Quantification** – developing novel mathematical and statistical methodologies for quantifying uncertainties associated with outputs of mathematical and numerical models.
- **T2: Models to Decisions** – considering how outputs/evidence obtained from models is used by decision makers to inform their decisions.
- **T3: Communicating Uncertainty** – considering how uncertainty associated with outputs obtained from models is best communicated and visualized to aid decision makers.

Part A: Executive Summary

We believe that there is a requirement for significant funding for research in the area of decision making using the output from uncertain numerical models. We have broken the problem into three parallel streams: uncertainty quantification, models to decisions and communicating uncertainty. We are agnostic on whether three interlinked programmes or a single large research programme is needed. However we do believe that significant research funds are needed in all three areas.

Key Research Challenges:

- How can we develop a rigorous mathematical framework for treating model error?
- How can we quantify and manage uncertainty well when we have chains/ensembles/networks of models?
- How can we reconcile probabilistic statements about uncertainty with deterministic bounds for numerical error? Can we combine them in meaningful ways?
- How can we design surrogate models that (i) have guaranteed error control, (ii) satisfy important physical constraints?
- What are the implications of the uncertainty around model outputs for decision making?
- How can model development and the assessment of uncertainties associated with model outputs be shaped by the needs of the decision maker?
- What level of confidence should decision makers have in model outputs and how should this affect their decisions
- How effective are different decision rules and procedures at managing different kinds of uncertainties?
- For the types of uncertainty relevant to decision-makers, what is the effect of different methods of presenting them? Which best support the relevant decision-makers?
- How best can such uncertainties be communicated in such a way that it is robust to being removed or misunderstood along the chain of communication?
- How best can uncertainty be communicated in person, during a meeting?

Key Recommendations

- A co-ordinated programme, at least for uncertainty communication, would be more effective than an un-coordinated one since there needs to be generalisation and comparison across types of communication and area of decision making.
- Some form of continuing networking would be extremely helpful to continue to build the community and to involve decision makers more with the research community. Whether this needs to be funded through the Research Councils or via some other mechanism needs further discussion.
- Education and training in this area is important. Not only for mathematical scientists but also for social scientists and decision makers themselves. The

former may be achieved via a CDT or similar (across institutions) while the latter may need different approaches such as short training courses or on-line material.

- Success breeds success, it is important that any research programme has mechanisms (and funding) for demonstrating impact. This will improve the take up of uncertainty quantification and its use in decision making, particularly in areas where the current take up is low, such as finance and life sciences.

Part B: Research Challenges by Theme

Below we present an overview of research challenges that have been identified for each of the themes T1 (Uncertainty Quantification), T2 (Models to Decisions) and T3 (Communication of Uncertainty). For T1, discussions were held not only with M2D Network members, but also with mathematical scientists from the international uncertainty quantification community who participated in the six-month research programme[3] on Uncertainty Quantification for Complex Systems at the Isaac Newton Institute for Mathematical Sciences (INI) in Cambridge from January to June 2018. To make the document accessible, technical details have been kept to a minimum.

T1: Uncertainty Quantification (UQ)

UQ is a broad phrase used by mathematical scientists to describe methodologies for taking account of uncertainties when mathematical and computer models are used to describe real-world phenomena. When we use models to simulate real-world processes (e.g., the weather, the temperature in a jet engine), the quantities we compute have uncertainty in them due to features such as: (i) model error/discrepancy; (ii) uncertainty in inputs/parameters for the model(s); (iii) errors associated with the use of numerical algorithms (computer models); (iv) measurement errors. The language of probability is used by mathematical scientists to express beliefs about many of these types of uncertainty. However, this is not universal, and there are fundamental differences between mathematical disciplines which often impede collaborations. For example, numerical error, unlike model error, often has an identifiable source and can be controlled. Traditional numerical analysis and engineering approaches lead to deterministic statements about numerical errors, but require model-specific knowledge. Statistical approaches often do not exploit such knowledge but, because of this, can be used where the model is a ‘black-box’, for example is a commercial proprietary code or a complex legacy code.

UQ is fundamental to model-based science and associated decision making. Ignoring uncertainty can lead to overly confident (and potentially incorrect) decisions due to the under-estimation of risk. At the same time, being too cautious when faced with uncertainty can also lead to bad decisions, or to indecision, which may be worse. Modern science is challenging UQ with the scale and complexity of the models required to solve real-world problems. UQ involves far more than simply implementing Monte Carlo methods to propagate uncertainty from model inputs to outputs. Experiments need to be carefully designed to collect numerical and physical data, surrogate models need to be constructed to ameliorate computational expense but at the same time be accurate,

[3] https://www.newton.ac.uk/event/unq

inverse problems need to be solved efficiently and accurately to estimate unknown model inputs, and discrepancy needs to be identified to bias-correct predictions and parameter estimates.

Research Challenges

1. *How can we develop a rigorous mathematical framework for treating model error?*

   No model is a perfect description of reality. The *discrepancy* between a model and the real-world process it represents is vitally important but often neglected. Indeed, if it was known in what way a model was deficient, steps could be taken to improve it. Instead, such discrepancies are often identified from data, which is linked to the *inverse problem* of parameter estimation. When the model cannot be solved exactly, and computer models are required, the total discrepancy involves numerical error. Currently, it is not clear how to systematically exploit knowledge about this.

2. *How can we quantify and manage uncertainty well when we have chains/ensembles/networks of models?*

   Modern decision making rarely relies on the results from a single model. Multiple models may be chained, with outputs (and uncertainties) from earlier models defining the (uncertain) inputs into later models. Multiple models may also operate in parallel, all feeding into a decision making process or providing alternative (perhaps competing) descriptions of the same process or a number of models may form a network with dynamical feedbacks between the various components. Even when there is a single preferred computer model, recent advances in numerical analysis and statistics (e.g. multilevel, multi-fidelity and multi-index methods) have shown that substantial computational savings can be achieved by combining hierarchies of different models in the right way.

3. *How can we reconcile probabilistic statements about uncertainty with deterministic bounds for numerical error? Can we combine them in meaningful ways?*

   Different mathematical communities approach the quantification of numerical error in different ways. Numerical analysis exploits the structure of models and their numerical implementations to produce deterministic bounds for, and computable estimates of such errors. Statistical approaches more commonly treat models as black-boxes and model the input to output relationship using stochastic processes. What are the limitations of both approaches, and when is one approach more appropriate than another?

4. *How can we design surrogate models that (i) have guaranteed error control, (ii) satisfy important physical constraints?*

   The construction of surrogate models (also known as emulators or meta-models) is a key step in the solution of UQ problems involving computationally expensive (high-fidelity) computer models. A surrogate model is a cheaper computer model that can be run more quickly than the original high-fidelity one, usually resulting in loss of accuracy. While many approaches to building surrogates exist, it is often difficult to make statements about the errors between the high-fidelity model output and the surrogate model output, and about the impact of these errors on quantities of interest that are computed using surrogate models. When the computer model simulates physical processes, important characteristics/constraints (conservation of mass, positivity, monotonicity, etc) are often not satisfied by solutions of surrogate models. Moreover, it is often not clear how to incorporate available data (observations), into the construction of surrogate models.

Other important questions include:

- *How can we better fuse data (which is becoming increasingly available) and models in UQ studies, and provide rigorous underpinning mathematics?*
- *How can we deal with high-dimensional, time-varying and heteroscedastic uncertain processes?*
- *While UQ is well established in applications like engineering, how can we advance UQ methodology in newer applications in areas such as biology, healthcare and finance?*
- *Can we use causality inferred from data to validate the form of the model? This may be particularly important in the biological and social sciences where there are no physical laws to guide model building.*
- *The use of UQ methods with data-based Machine Learning/Artificial Intelligence models (and the wider use of ML/AI in UQ)*

Supporting Structures

In addition to the above research challenges, there is a need for resources to support (i) community building; (ii) pathways to impact and (iii) training people and developing UQ support tools.

Community Building: How do we foster a stronger sense of community (and a critical mass) among UQ researchers and practitioners in the UK, with more regular interactions across subdomain boundaries? How do we extend interactions between modellers, UQ researchers and decision-makers?

Demonstrating Impact: How do we better promote success stories of UQ, e.g., via exemplars and demonstrators, so that UQ is adopted in all modelling disciplines?

People pipeline, training & software: Who should be trained in UQ (mathematicians, statisticians, modellers, decision makers)? How should the training take place (CDTs, degree programmes, short-courses)? What should be included in a training programme? How can we ensure that UQ software becomes more widely available (i) to disseminate the latest advances to experts and (ii) to empower non-experts (with appropriate checks and caveats)?

Summary

A programme providing resources to address the above UQ research challenges and supporting structures would solve outstanding methodological problems, identify new research challenges, bridge gaps between researchers, practitioners and decision makers (and universities, industry and government), and develop the UK research base through the training of the next generation of researchers and application-area scientists.

Properly implemented, it will build on the UK's core strengths in Applied Mathematics and Statistics to produce world-leading research and practically implementable methods.

T2: From Models to Decisions

Mathematical models are increasingly used to support decisions made under uncertainty in a wide range of fields. These models bring predictive and explanatory benefits by allowing decision makers (DMs) to understand and predict the consequences of their decisions to a much greater accuracy. However, many models are so complex that they are not fully understood by the decision makers that make use of the information they provide. Moreover, since models and their computer implementations are imperfect representations of the real-world systems they represent, there is always a degree of uncertainty about the outputs. Although there has been much recent progress on UQ methodology within the mathematical and statistics communities, DMs are often unsure how to respond to statements about uncertainty. There is both an appetite amongst users of model outputs for more guidance as to how to do so and a need to map a course that avoids both (i) the Scylla of ignoring model uncertainty (and hence making decisions on the assumption that the model's projections are completely accurate) and (ii) the Charybdis of failing to use the projections in decision making simply because they are uncertain (thereby foregoing the useful information they contain).

Mathematical and numerical models are vital tools for informing decisions under uncertainty. This is not because they deliver certainty (they don't) but because they enable a systematic exploration and quantification of possible outcomes of decisions. Recognition of uncertainty around model projections should not blind us to this potential. But equally, failure to recognise all the uncertainties associated with model results can give users a false sense of confidence. Research in this area should aim to provide decision makers with the level of confidence in model outputs that is justified by the state of scientific understanding and empower them to make use of these outputs in their decision making in a manner appropriate to this level of confidence.

Research Challenges

We propose a research agenda on the use of scientific models to support decision making which has both a descriptive and a normative/prescriptive dimension. The former is directed at the question of how models are currently used by decision makers and the latter at the (perhaps more important) question of how they can and should be used. The primary aim will be to improve the use of models in decision making under uncertainty by 'bridging the gap' between (i) the scientific understanding of the systems being modelled and (ii) the decision making that draws on that understanding.

We propose four main challenge questions as a foundation for a programme of research. The first concerns the passage from models to the decisions they support (M2D) while the second concerns the manner in which decision requirements should shape models (D2M). The third and fourth questions concern the scientific assessment of uncertainty associated with the use of models and the design of decision rules to manage it.

1. *What are the implications of the uncertainty around model outputs for decision making?*

What use can DMs make of mathematical scientists' quantification of this uncertainty? What is the decision relevance of different types of uncertainty and measures of them?

2. *How can model development and the assessment of uncertainties associated with model outputs be shaped by the needs of the DM?*

   What is the relationship between the DM's uncertainty (about the consequences of their decisions) and mathematical UQ measures? How can the decision sensitivities to uncertainty be used in model development?

3. *What level of confidence should DMs have in model outputs and how should this affect their decisions?*

   What are the main factors driving confidence / trust in models? How should an assessment of the state of scientific understanding be linked to decision parameters? How might models with known limitations or which are designed to answer questions different from those confronting the DM, nonetheless be used to help inform a decision?

4. *How effective are different decision rules and procedures at managing different kinds of uncertainties?*

   What values should decision rules be sensitive to and, in particular, what is the normative status of aversion to uncertainty on the part of DMs? How should different decision desiderata (efficiency, safety, impact, flexibility, robustness) be reconciled/traded-off in managing uncertainty?

Summary

A research programme that addresses the above challenges will produce methods, tools, communication protocols and potentially even designs of institutions, that support (a) the decision-relevant assessment of models and the level of scientific understanding of systems, and (b) the use of model outputs and, more generally, of scientific knowledge, within decision making processes.

T3: Communicating Uncertainty

However well uncertainty has been quantified it is the way in which it is communicated that will determine how useful it is to decision makers. Despite this, there is very little research focussed on how best to communicate uncertainty.

Because of this paucity of research, it is not known how generalisable any research findings might be. We therefore propose a co-ordinated swathe of empirical research carried out to the highest methodological standards across a wide range of fields. This is facilitated by one of the great strengths of the M2D community: the variety of the fields in which it works: from intelligence to engineering; healthcare to climate change. An important aspect is the co-ordination of any future research programme; a set of unconnected research projects will be much less effective than a co-ordinated programme where the generalisation and comparison between the subjects and topics can be carried out effectively and lessons learned.

The empirical research should be carried out using an iterative, user-centred methodology. A varied range of projects are needed in which researchers can work closely with both the modellers and the specific decision-makers involved. By pulling together the results of all these individual research projects, it should be possible to determine where there are generalisable guidelines on the communication of uncertainty across fields, where guidelines might apply only within a field, and where specific user-centred work will always need to be done to tailor communication to specific circumstances.

From this well-selected swathe of projects, patterns of results should emerge, to create a sum total of knowledge bigger than its individual parts.

Research Challenges

1. *For the types of uncertainty relevant to decision makers, what is the effect of different methods of presenting them? Which best support the relevant decision makers?*

   This will encompass verbal, numerical and visual communication. Projects should be selected across a number of different fields (more than one from each), and across a range of types of uncertainty.

   The methods of communication need to be evaluated on how accurately decision-makers interpret their meaning, what effect they have on decision makers' emotions and trust, and what effect they have on decision makers' decision satisfaction, decision consistency and decision regret.

2. *How best can such uncertainties be communicated in such a way that it is robust to being removed or misunderstood along the chain of communication?*

   As well as being useful to decision makers in theory, it is important that methods of uncertainty communication are also efficient and robust in practice. The second part of the research agenda therefore concentrates on the practical delivery of uncertainty communication – ensuring that it reaches the decision maker in its optimum form, possibly having been through many hands. This research package requires careful analysis of lines of communication within decision making chains, and an in depth understanding of the practical and political barriers to uncertainty communication.

   Each project evaluating the effects of methods of communication (above) should also evaluate and refine the methods with this practical angle on ensuring that they retain their integrity in the real world.

3. *How best can uncertainty be communicated in person, during a meeting?*

   This final aspect of the research agenda aims to complete the vital process of uncertainty communication. In many situations final decision making relies on personal communication, not (simply) on written materials. How can people with expertise best communicate their uncertainty in person without losing the trust of decision-makers or finding their uncertainty communications ignored?

High quality empirical research is needed in this area, which can then be used to produce training materials for modellers and others with specific expertise who find themselves needing to communicate in person with decision makers.

Summary

This deeply practical research agenda will produce a well co-ordinated set of empirical results which should allow conclusions to be drawn and guidelines produced for the communication of uncertainty across a wide range of fields. By employing principles of user-centred design and carefully chosen outcome measures, it should ensure that future decision-makers are presented with uncertainty in a way that best supports their decisions, and that future modellers are enabled and supported to present their uncertainties confidently.