Decision Maker Summary

All analysis is uncertain. Whether we are looking at statistics about the past, measurements of the present, or forecasts of the future, there will always be a degree of uncertainty in the outputs.

This uncertainty can be critically important to any decisions based on the analysis, as 'best estimates' are generally not enough to make an informed decision. For example, Option A may appear better than Option B when looking at the most likely outcome of each, but if the uncertainty in A is greater than in B then it might carry an unacceptable chance of much worse outcomes.

Making decisions using uncertain information can be uncomfortable – decisions would be far easier if we knew for sure what the consequences of each choice would be – but this is an unavoidable position, so analysts aspire to provide honest and practical advice on uncertainty.

The presence of uncertainty in analysis may not always inspire confidence, but the absence of uncertainty is even worse. Since uncertainty is ever-present, omitting it from analysis leaves it unacknowledged and unassessed. It could be of any size, leaving the true range of possible outcomes entirely unknown. A proper assessment of analytical uncertainty should reassure you that the analysts have considered the limitations in their data and methodology, as well as the inherent randomness in the world, in order to provide an honest assessment of the range of possible outcomes – rather than presenting misplaced confidence in an impossibly accurate estimate.

This toolkit has been written for analysts to help them understand and assess the uncertainty in their work, and then to communicate that to the users of their analysis in an effective and helpful way. Feedback from those users – those who commission the work and make decisions informed by it – is crucial to helping refine and improve this guidance.

Key points:

- Consider the full range of possible outcomes when using analysis to inform decisions, not just the 'best estimate'.
- Challenge analysts where information on uncertainty is absent or inadequate.
- Ask questions about how to interpret the uncertainty and its implications.
- Provide feedback to analysts on the usefulness and effectiveness of how they communicate uncertainty.

Agreeing how uncertainty should be used to help answer the question

Understanding the problem

How will outputs be used?

What information do we need from the decision maker to include uncertainty analysis at the right points?

1.

1. Agreeing how uncertainty should be used to help answer the question

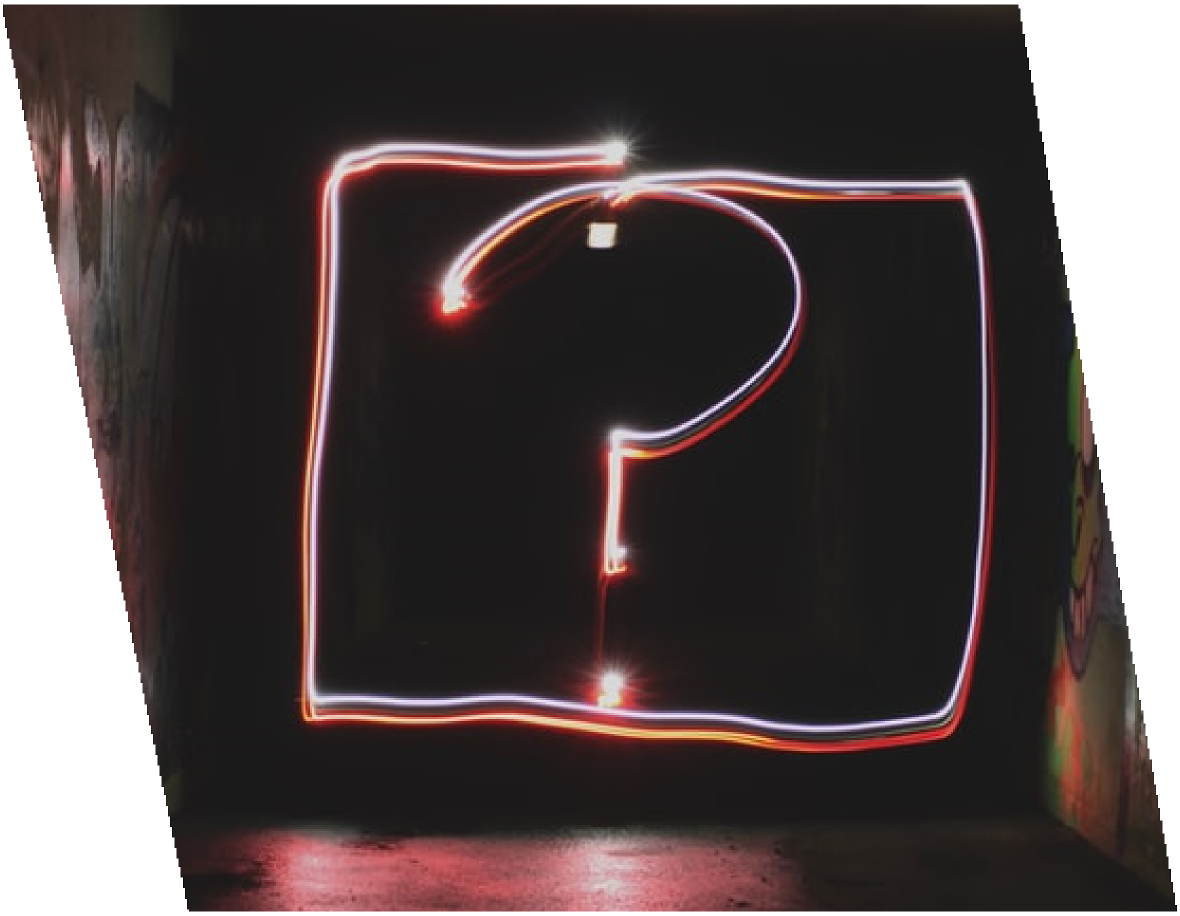
Decision-makers need information about uncertainty in the impacts of their decisions. This section looks at the steps to ensure that analysts and decision-makers agree on the question being asked, how analytical outputs will be used in the decision-making process, and how to appropriately incorporate uncertainty into the analysis.

1.1. Understanding the problem

Clarify what the real question is	It is important to ensure that the question is correctly framed to address the problem. For example, are we really interested in 'how much money is this new policy likely to save?', or should we be asking 'how certain can we that this policy would save more than £x?'.
Identify the important details	As well as clearly defining the question, we should also ensure that any important detailed questions to support the analysis are appropriately thought through. For example, are we interested in uncertainty on a calendar year or financial year basis?

Once the key questions have been agreed, analysts and decision-makers should discuss how the outputs will be used. Understanding the role of the analysis in the decision-making process will help to inform which uncertainty techniques are appropriate and proportionate.

It is also important to jointly identify sources of uncertainty that are so deep that little or nothing can be said quantitatively about their impact on the policy outcome. An example might be the impact of a natural disaster on a particular policy. Deep uncertainties can have major implications for decision-making, and may call for a descriptive approach to the analysis and presentation of options.



1.2. How will outputs be used?

Discuss the role for the analysis	Will the policy decision be based purely on the results of the analysis, or is it just one of a wider set of considerations informing the decision? The more influential the analysis is, the more important it is to build in robust uncertainty analysis.
Are there dependent models drawing on the analysis?	If the output is to be fed into 'downstream' models, then it is important to understand the requirements of those models. For example, if *scenarios* are used to illustrate uncertainty in your model, then these may not be suitable inputs for a Monte Carlo simulation in a dependent model.

Now that we know what the question is and the context in which the analysis will be used, we should agree how to build appropriate uncertainty into the analysis. It is a good idea to ask the decision maker what it is conceptually that they *would like* to be able to say. This is important as it frames how the uncertainty analysis will be conducted.

1.3. What information do we need from the decision maker to include uncertainty analysis at the right points?

Explain how the uncertainty can be used to better inform decisions

We can help the decision-maker to understand how information about the uncertainty present in the analysis supports a better informed and more robust decision. It's important to make it clear that not all sources of uncertainty will be quantifiable and/or supported by robust evidence, and we should jointly prioritise the key sources of uncertainty that need to be included in the model.

Avoid misleading results or spurious accuracy by choosing the appropriate presentation

We can assess the impact of uncertainty using many different techniques. Not all will be appropriate for a given piece of analysis. A poor choice of technique may even give misleading results. For example, if there are many sources of uncertainty, the use of 95% confidence intervals to describe just one limited part of this uncertainty may be misleading, and modelling a range of described scenarios may be more appropriate. Appropriate presentation, such as rounding, is equally important to avoid spurious accuracy (covered further in the Presenting and communicating uncertainty (https://rosiea1.github.io/UncertaintyWeb/chapter_4.html) section).

Discuss how the uncertainty will inform the decision-maker's judgement	Discuss with the decision-maker what level of uncertainty is acceptable. Do they want to know how wrong the forecast would need to be in order to change or rethink the policy? Or are they simply interested in an output "range"? If so, what does that "range" actually mean? Examples can be very helpful when discussing the analysis with the decision maker. An answer to the question of the net benefits of a policy may be £3m, with uncertainty analysis giving a broad range of £0.5-5.5m. You could discuss with the decision maker how they want to be able to frame the analysis, for example: *"A range of £0.5-5.5m";* *"The estimated benefits are £3m, with analysis showing a 90% likelihood that benefits will be between £1-5m";* *"Analysis shows that there is an 80% likelihood that the net benefits will be greater than £2m";* *"The policy needs to have X amount of takeup in order to break even"* Operational decision makers may not want to see a range of results, but instead want to plan to a certain level of confidence, such as 65% or 95% rather than 50%. For example, when planning the number of schools, prison places or GPs we'll need over the next 5 years, it may be more appropriate to plan to a higher level of confidence than 50%. Financial decision makers may be interested in understanding the likelihood of receiving a certain level of income, or that risks and opportunities will materialise. For example, HMRC might want to know the likelihood of receiving a certain level from tax receipts. Here, the analysis would need to go hand in hand with financial risk management to mitigate the risks materialising or crystallise the opportunities.

Defining and Identifying Uncertainty

Defining uncertainty

Sources of analytical uncertainty - Data

Sources of analytical uncertainty - Assumptions

Sources of analytical uncertainty - Analysis

Describing and Presenting analytical uncertainty

2.

2. Defining and Identifying Uncertainty

Analytical uncertainty can feed through into analysis and subsequent decision making from many different sources. Each step in data collection, data processing and modelling is likely to bring added uncertainty.

We encounter uncertainty throughout the decision making process and in the analysis which supports it. In addition to uncertainties around the analytical question, we will also find uncertainty in the context of the decision being made, the data and assumptions feeding into the analysis and in the analysis itself. As analysts we need to understand and describe contextual uncertainties to ensure our analysis has impact; and we need to describe and quantify analytical uncertainties to ensure decision makers are clear about how far analytical results can be used to support their conclusions.

Try to identify and record all the potential sources of uncertainty in your analysis at an early stage. Early identification of uncertainty is important; if you overlook a potential source of uncertainty this could reduce the usefulness and impact of your subsequent analysis.

This section sets out a range of techniques to help you understand and assess the sources of uncertainty in your analysis.

2.1. Defining uncertainty

Understanding the characteristics of different classifications of uncertainty can help you to identify sources of uncertainty in your own analysis. Further, categorising the types of uncertainty provides a framework for the next steps of analysis.

A common classification divides uncertainty into known knowns, known unknowns, and unknown unknowns. We explain these in Table 2.1.

Table 2.1: Classifications of Uncertainty

Classification	Known knowns - Aleatory uncertainty	Known unknowns - Epistemic uncertainty	Unknown unknowns - Ontological uncertainty
Definition	Known knowns are **things we know that we know**. This refers to the inherent uncertainty that is always present due to underlying probabilistic variability.	Known unknowns are **things that we know we don't know**. This type of uncertainty comes from a lack of knowledge about the (complex) system we are trying to model. Assumptions are used to plug these gaps in the absence of information.	Unknown unknowns are **things that we don't know we don't know** . It usually comes from factors or situations that we have not previously experienced and therefore cannot consider because we simply don't know where to look in the first instance.
Can it be quantified?	**Yes** it can be quantified. We usually characterise it using a probability distribution function (PDF). A PDF gives all the possible values that a variable can have and assigns a probability of occurrence to each. As analysts, the challenge for us is to derive the PDF. If you find that you can't then you may instead have a known unknown.	**Yes** it can be quantified (but isn't always) – e.g. through sensitivity analysis. These techniques try to quantify the uncertainty by altering assumptions and observing the impact on modelling outputs. They will work if the range of assumptions tested covers the range of unknown variables.	**No** it cannot be quantified. We cannot identify unknowable unknowns, so there are no actions we can take to quantify them. What we can do is be clear about the sources of uncertainty we have included, so that any others subsequently identified would likely add to that uncertainty.
Can it be reduced?	This type of uncertainty cannot be completely removed. We can sometimes reduce it through data smoothing or increasing the size of a sample, but there will always be some random variability.	Known unknowns are reducible by gathering information to lessen the gaps in our knowledge. Using new data sources, expanding our data collection or conducting research can remove the need for assumptions or refine their ranges.	This type of uncertainty is not reducible. However, this type of uncertainty can usually be separated into "unknowable unknowns" and "knowable unknowns". Horizon scanning can help identify knowable unknowns. Once they are identified they become known unknowns.
Example	Tossing a coin is an example of a known known. We can observe the possible outcomes (heads or tails) and the probability of each occurring (50:50), therefore create the PDF. However, prior to the coin being tossed we cannot reduce the uncertainty in outcome.	Taking our coin toss example, we don't know whether the coin is fair in the first instance. We may assume the coin is fair and will give a 50% probability of each outcome. Once we start to toss the coin, we start to gather information on its fairness. The longer we toss the coin the better our information gets and the greater the reduction in the known unknown.	Unknown unknowns are often future events or circumstances that we cannot predict, for example, somebody swaps the coin to a weighted one without our knowing, or steals the coin altogether! Previous analysis is no longer reliable as it didn't account for this change.

2.2. Sources of analytical uncertainty - Data

The data that feeds into your analysis project will have been previously specified, defined, and collected. In some cases, you will do this yourself, but you may also draw on data sources collected by others. Having chosen your data sources for your project you will need to think about how well your data describes the reality of the situation you are modelling or analysing.

To gain a full picture of the impact of data uncertainty on your analysis you should think through what you know about where your data has come from. The sorts of things you should think about include:

- **How your data source compares with your analysis objective:** How well do the definitions and concepts in the data chosen fit with what you are trying to measure? Differences between the data and your target group can mean that a dataset captured for one purpose is inappropriate for another. For example, you might want to analyse London & South East but only have data for the whole of the UK.
- **Where the data come from and how they have been collected:** How rigorous was the data collection process? Was the data owner’s quality assurance sufficiently robust? For survey data, would respondents have fully understood the question intent? Some datasets are subject to regulation and compliance with standards or other codes of practice. In such cases, quality should be well documented and assured like in National Statistics
- **What period the data covers:** More uncertainty will occur if either the data don’t match the time period of interest and/or if the data are volatile.
- **Whether your data has been subjected to any pre-processing:** For data obtained in a processed state from others you may need to explore what processing steps were taken to determine how that may affect the data you are using. For example, missing values may have been imputed,

survey data may have been weighted to make survey results representative of a wider population, extreme values and outliers may have been removed, data sets may have been combined (possibly resulting in false positive or false negative matches), disclosure controls may have been applied (potentially biasing the data set)

2.3. Sources of analytical uncertainty - Assumptions

Considering the assumptions you're making in your analysis is critical to any uncertainty analysis

Consider where you have used assumptions	Assumptions are used when we have incomplete knowledge. All models will require some assumptions, so you need to ensure that assumptions are robust and consistently understood. There should be an assumptions log. Where did the assumptions come from? How were they generated and why? What is the impact if they are wrong, and how often are they reviewed?
What assumptions are outside the scope of the model?	There are often parameters outside of the scope of the model that have been implicitly assumed. For example, models may assume no substantial policy changes in related areas and there may be deliberate limits in the coverage or timelines of your analysis – deliberate modelling exclusions that allow timely and effective analysis. These assumptions and limitations provide the context in which the modelling results are appropriate. You need to be aware of the restrictions that these assumptions impose on the interpretation of analytical results and take care to explain where modelling results can (and cannot) be used.
Assess the quality of each assumption	Assumptions should be based on robust evidence. The less evidence to support an assumption the more uncertain it will be. High quality assumptions will be underpinned by robust data, while low quality assumptions may simply be an opinion or may be supported by a poor data source.
Assess the impact of each assumption	The importance of an assumption is measured by its effect on the on the analytical output. The higher the impact of an assumption the more uncertain results will be. Critical assumptions will drastically affect the results, while less importance assumptions

	may only have a marginal effect on results. More weight should be given to gathering evidence to improve the quality of critical assumptions.
What don't you know?	Some uncertainties can't be captured in an assumption as we don't have perfect insight. However, effort should be made to identify all possible uncertainties and capture these as assumptions. The assumptions log will convey the boundary of what has been included.

2.4. Sources of analytical uncertainty - Analysis

An additional, but important source of analytical uncertainty is in the analysis itself. Good AQA practices can help identify the restricted uses of analytical ouputs and help minimise the possibility of errors. However, mistakes can still be made, so being clear with decision makers about the extent to which analysis has been quality assured can help them understand how far they may rely on analytical results in support of their decision making.

2.5. Describing and Presenting analytical uncertainty

It is important to understand sources of uncertainty in your analysis. In the following sections we think about how to quantify that uncertainty and how we present it. However, it is also important to understand the context your analysis feeds into when deciding the extent to which analytical uncertainty needs to be assessed and thinking about how it should be presented. In a highly uncertain context, detailed assessment of data-driven uncertainty may not be worthwhile. This is an analytical judgement to be made in light of the full consideration of sources of uncertainty.

Understanding and Measuring Uncertainty
General approaches for quantifying uncertainty in an input parameter
Common techniques for assessing uncertainty in analytical outputs
Monte Carlo Techniques
Convolution
Summing Uncorrelated Uncertainties in Quadrature
Focussing on the Dominant Uncertainty
Scenario Analysis
Using Past Variance to Estimate Future Uncertainty
Judgement
Quality assuring uncertainty analysis and accounting for wider uncertainties

3.

3. Understanding and Measuring Uncertainty

At this stage you should have considered where the uncertainties lie. You will now need to consider whether it is possible to quantify this uncertainty.

This section presents some approaches at a high level then in more detail for quantifying and measuring the uncertainty in your analysis.

3.1. General approaches for quantifying uncertainty in an input parameter

We have highlighted ways to think about the uncertainty coming from specific sources. We now bring this together into approaches that can be applied to understand the size and distribution of these uncertainties and how you might include this information in your analysis. In most cases, the approach to uncertainty quantification is limited by the data and time available to you, though you should also consider where the major sources of uncertainty are in your analysis and pay most attention to these.

When considering uncertainty in input data, you should think about whether the data being used was gathered for an alternative purpose and if it has been maipulated and how you can adjust or account for this. Accompanying data descriptions (or a quick exploration of the source data if these don't exist) can be helpful in understanding data limitations of the data and whether any adjustments made could conflict with or bias your analysis. Statistical sources often come with supporting information about accuracy and reliability. You can sometimes find information on variance (or standard errors, confidence intervals, coefficients of variation) and you may find indications of likely bias, from special studies comparing or linking sources. These direct measures of quality, together with indirect measures such as response and coverage rates can tell you a lot about the uncertainty.

In addition, the following approaches can be useful in understanding the size and distribution of the uncertainties in your analytical inputs.

Consider discrete and continuous distributions

A probability distribution describes the probability of occurrences of different outcomes. Generally, there are two types of probability distribution; discrete distributions and continuous distributions.

Data sources may include confidence intervals	Consider whether you have information about the underlying distribution of the parameter. Often data from other sources will be provided with confidence intervals (or standard errors, etc) that can be used to quantify uncertainty. Where such information is not provided, you may be able to approximate these with knowledge of the sample size and design.
Analyse past model performance to create distribution	Distributions can also be created using what you know about error from previous models. Consider the performance of previous forecasts against outturn results. The distribution of previous errors can provide the uncertainty distribution for the current forecast. Additionally, you might be able to use one source to validate another or to help estimate the uncertainty in the original source.
Without quantitative data, use expert judgement	If no quantitative data on the underlying population is available, you may be able to elicit this information from experts . For example, the Delphi Method (a structured facilitation method, which relies on a panel of experts to build a combined judgement, for example, about a particular number) can be used to ask a panel of experts to estimate the range of uncertainty and use the aggregated responses to produce a distribution.
Ranges can work in absence of distributions	A range is similar to a probability distribution, in that it considers the possible outcomes but does not consider the probability of each outcome occurring. If there are data or resource limitations a range can be a simple way to illustrate the uncertainty in a parameter.
Historical data can inform the range	Historical data can be used to quantify a range. Consider how the parameter has changed over a suitable time period. The maximum and minimum values could provide a sensible range. When using historical data be aware that you will only be able to assess ‘business as usual’ uncertainty. If there are future shocks to the system this may fall outside your historic range.
You can also use a literature review	For parameters that have been the subject of academic studies a literature review can be used to create a range. Consider why different studies may result in different outcomes, and which studies are the most suitable for what you are trying to measure.
Expert steers can inform the range	If no quantitative data is available, consider whether there are relevant policy constraints that will limit your range. Judgement from experts can be also be used to create sensible ranges.
	In some situations, it is not possible to create a probability distribution or a range. In such cases, make a qualitative assessment of uncertainty. This is still useful to analysts and customers to consider the magnitude of uncertainty.
RAG rate your parameters	You can make qualitative assessments yourself, and by using expert judgement. A simple approach is to Red Amber Green (RAG) rate the likelihood and impact of uncertainty in your parameters. This qualitative assessment should be considered when thinking about the analytical results. If data is categorised as highly uncertain and having a large impact on results, then final outputs will be subject to large uncertainty. Care in presentation is needed when using these more qualitative methods, however, as it’s potentially easier for decision makers to misunderstand the relevance of qualitative assessments of uncertainty for their decision as compared to quantitative assessments. It is particularly important to explain the impact of uncertainty on the analytical result and the decision to be made when using these types of qualitative assessment.
Break-even analysis can help re-frame the question	A further option to support decision makes is to use break-even analysis. This is useful to understand at which point a saving becomes a cost or possibly at which point you would take a different decision.
	Some decision makers will be used to seeing a range around a central estimate. Break-even analysis works backwards – if we were to break-even what would the input be? This could help bring the policy alive and help assumption owners to really consider how realistic the assumption is.
	Break-even analysis helps people understand how much the input has to change before you reach a break-even point so they can consider the probability of this occurring.

3.2. Common techniques for assessing uncertainty in analytical outputs

Now that we have explored how to assess uncertainties in individual analytical inputs, we turn to commonly used techniques for analysing overall uncertainty in analytical outputs, moving from approaches to use when we have a good numerical understanding of input uncertainties, though to approaches which can be used when we know less about how input uncertainties are quantified.

3.3. Monte Carlo Techniques

If all significant sources of uncertainty can be quantified, along with the correlations between them, then probabilistic methods can provide a picture of the range of possible outcomes and the likelihood of each.

Outline:

The basic process for a Monte Carlo simulation is to:

1. Define a distribution for each input showing the uncertainty in each. These can be simple distributions based on estimation (e.g. uniform, triangular) or more complex distributions based on data (e.g. normal, beta).
2. Define the correlations between these inputs
3. Randomly generate a value from each input distribution (accounting for correlations)
4. Calculate the outputs of the model deterministically
5. Repeat steps 3) and 4) many (i.e. thousands of) times
6. Analyse the distribution of the resulting outputs

This should be repeated until the key outputs are stable and reproducible at the level of rounding that will be used when communicating the results

Advantages:

- Produces a full probability profile of the range of possible outcomes and the likelihood of each – the gold standard in uncertainty analysis
- Enables analysis of complex interactions between uncertainties within a model
- Produces a visual representation of the range of possible outcomes, that may aid customer understanding
- Can be used to assess the impact of removing or reducing a source of uncertainty

Disadvantages:

- Highly dependent on the accuracy of the distributions used
- May require more resource than other techniques to build
- Correlations can be difficult to define mathematically, and can give misleading results if not properly accounted for
- Can be computationally expensive
- Outputs may not be reproducible if insufficient iterations are used (effectively introducing further uncertainty to the model)

Example:

- Can help assess overall uncertainty when you have uncertainty around many aspects of your model
- Assess uncertainty around a fund forecast
- Estimate the uncertainty around assumptions used in policy costings
- An example of how MoJ use Monte Carlo analysis to assess uncertainty is provided here (https://github.com/RosieA1/UncertaintyWeb/tree/master/Monte%20Carlo%20template)

3.4. Convolution

If there are a small number of uncertainty sources, then it may be possible to combine them mathematically, which can be quicker than using probabilistic methods

Outline:

In principle uncertainty distributions can be combined to give an exact distribution for the resulting overall uncertainty (known as convolution).

Consider rolling two dice - the value of each follows a discrete uniform distribution from 1 to 6. If we wanted to know the sum of the two dice, we can combine these uniform distributions to show that the resulting probability profile follows a triangular distribution from 2 to 12.

This avoids the randomness of probabilistic approaches. However this method tends to get very complicated once more than a few uncertainties are involved, and probabilistic methods may be easier.

Advantages:

- Deterministic, so outputs are reproducible and quick to generate
- Works with any input probability distributions (don't need to assume normality)

Disadvantages:

- Can be difficult to do with more than 2 or 3 sources of uncertainty
- Generally only feasible if the distributions are combined using simple mathematical operations (addition, subtraction, multiplication)
- Assumes that each uncertainty is independent (or correlations must be accounted for)

Example:

Any situation where you're combining two probability distributions using simple mathematical operations (addition, subtraction, multiplication)

3.5. Summing Uncorrelated Uncertainties in Quadrature

If multiple components need to be summed, and the uncertainty in each can be assumed to be normal and uncorrelated, then summing in quadrature is a useful shortcut for estimating the total uncertainty

Outline:

If the model is simply summing a number of output components (e.g. a number of different funding forecasts), and the uncertainty is known in each, then the uncertainty in the sum of those values can be given by the square root of the sum of the individual uncertainties squared (assuming that all errors are independent and normally distributed).

Advantages:

- Very simple to calculate
- Can include uncertainties from all sources

Disadvantages:

- Only applicable for models where uncertainties can simply be summed - more complex interactions will need to use other techniques
- Only valid if the individual uncertainty distributions are independent and normally distributed

Example:

Useful for financial forecasting, where individual budgets and their uncertainty has been assessed, and these must be summed to give the overall budget. In this situation assuming independence between budget over/underspends is often reasonable.

Also useful for quickly estimating the uncertainty when changing the timeframe of a forecast e.g. if you have a forecast by month (with quantified uncertainty), then this is quick way of estimating the uncertainty in the annual totals – assuming there is no correlation between the uncertainty from one month to the next.

3.6. Focussing on the Dominant Uncertainty

If one source of uncertainty has a much greater impact than all the others, then the uncertainty due to this one factor might be a reasonable proxy for the overall uncertainty

Outline:

Consider all the sources of uncertainty affecting the analysis and quantify the impact that each has on the overall uncertainty (even if this is approximate or subjective – see section on 'Defining and Identifying Uncertainty'). If one source has substantially more impact that the others, then simply looking at the uncertainty in this one factor might be a pragmatic approximation for the overall uncertainty measure, ignoring other sources.

This is not a robust way of estimating overall uncertainty, as it ignores all but one source. It should only be used if previous techniques are inappropriate, and there is genuinely one source of uncertainty that has an impact that is an order of magnitude larger than the others. However, when time is tight this may be a pragmatic way of estimating uncertainty.

Advantages:

- Relatively simple and quick
- No need to combine uncertainties
- Focusses attention on the key driver of uncertainty, avoiding unnecessary discussion of relatively minor elements

Disadvantages:

- Will always underestimate the overall uncertainty as most sources of uncertainty are excluded
- Can dramatically underestimate uncertainty if the source of uncertainty assumed to be dominant isn't as dominant as believed

Example:

The Accuracy Tracking Tool **link to DfE Accuracy tracking tool** can be used to estimate the residual uncertainty once the dominant uncertainty has been modelled. This tool assesses the accuracy of different forecast elements and allows you to see the percentage which both the dominant and residual uncertainty contribute to the total error.

3.7. Scenario Analysis

If there are many sources of uncertainty with complex correlations between them, then it may be more sensible to use a set of scenarios to illustrate the range of plausible outcomes.

Outline:

- Identify the individual sources of uncertainty, and the range of possible values for each.
- Create a set of coherent scenarios, setting each source of uncertainty to a value that could realistically occur in parallel with the others (e.g. a crimewave is unlikely to occur if the economy is booming).
- Try to ensure that the chosen scenarios cover the full range of possible outcomes, from highly optimistic to highly pessimistic, with equal attention given to each to avoid bias in presenting the results.
- Then quantify the overall uncertainty in each scenario, combining uncertainties using other methods in this section (the benefit is that this combining can be done manually for a small number of specific cases, rather than having to formulate the combinations mathematically for all possible inputs).

Advantages:

- Don't need to mathematically define the correlations between sources of uncertainty.
- Gives 'real-world' explanations to the range of possible outcomes, which may increase buy-in from the customers.
- Can include low-probability, high-impact events (i.e. system shocks) without needing to define their probability.

Disadvantages:

- The choice of scenarios is subjective, and may not cover the full range of plausible outcomes.
- Risk of optimism/pessimism bias, with scenarios not evenly distributed around the most likely outcome.
- Provides no information about the likelihood of each scenario occurring
- Needs input from a range of knowledgeable people

Example:

Forecasting where a range of policy options are being considered, particularly where the likelihood of an event occurring is unknown, for example early analysis on Brexit scenarios

3.8. Using Past Variance to Estimate Future Uncertainty

If a forecast has been produced repeatedly over many years, it may be possible to use the accuracy of all the previous forecasts to estimate the uncertainty in the new forecast

Outline:

Start by looking at the variance of all of the previous forecasts after one time period, and create a distribution of these variances. This distribution can be used to estimate the uncertainty of the new forecast after one time period.

Repeat for the variance at each subsequent time period to produce e.g. a fan forecast (smoothing if needed).

Advantages:

- Captures all sources of uncertainty
- Avoids the need to identify, quantify and combine individual sources of uncertainty
- Based on real-world performance, so avoids optimism/pessimism bias (the estimated uncertainty may be asymmetric as a result)

Disadvantages:

- Needs the system to be stable over time (i.e. there's no reason to think that the system is more/less predictable than in past years).
- Needs the approach to forecasting to have been consistent over the years (i.e. there's no

reason to think that our forecasts will be more/less accurate than in previous years).
- The forecasts must have been produced for a sufficiently long time so that we have enough historical data on the variance to capture the full range of plausible variances

Example:

MoJ prison population forecasting (https://rosiea1.github.io/UncertaintyWeb/case_studies.html#estimating_uncertainty_in_prison_population_projections)

3.9. Judgement

If the previous methods are unfeasible then you could make a subjective estimate of the overall uncertainty using expert elicitation techniques.

Outline:

If the previous methods are unfeasible, then adding a subjective estimate of the overall of uncertainty is an option. Where there is too little information or time to do a quantified analysis, it may be better to provide a judgement on the uncertainty than nothing at all.

Ideally this should be a group decision, using formal expert elicitation methods (e.g. Delphi) to avoid group-think and arrive at a consensus, agreement, or an average (depending on the technique used). If formal expert elicitation isn't possible, then the judgement of an individual is better than nothing, though less rigorous.

However the uncertainty is estimated, make sure that it is clear that it is a subjective opinion rather than results of analysis to prevent it being misused.

Advantages:

- May be able to be produced quickly, though can take time if using formal elicitation methods with large groups
- Requires little to no data
- Based on real-world performance, so avoids optimism/pessimism bias (the estimated uncertainty may be asymmetric as a result)
- Do not need to consider all sources of uncertainty individually

Disadvantages:

- Highly subjective
- Needs a group of knowledgeable experts, who can reasonably be expected to have a grasp of the range of possible outcomes

- Do not need to mathematically combine uncertainties

Example:

Providing context around a high priority figure that needs to be submitted quickly.

Analysis based on a data source of unknown reliability

Analysis where the expected range of results would lead to the same outcome

3.10. Quality assuring uncertainty analysis and accounting for wider uncertainties

It is best practice to test the outputs of the uncertainty analysis before using/presenting

After modelling uncertainty, you should always test the outputs of the analysis before sharing the results. This minimises the risk of errors in your analysis and helps you to understand the detailed outputs fully, including the level of the extreme or the most likely values.

	Uncertainty analysis may produce ‘extreme outcomes’, so that implausible results or scenarios are given. These can be identified through having a sensible checklist of validation rules (e.g. no negative values allowed) and aided with visualisation and filtering. These implausible outcomes could indicate an issue with the setup conditions of your analysis.
Unusual results may indicate a weakness in the use of the technique	Unusual results in uncertainty analysis may also indicate a weakness in how you have used your chosen technique. For example, if using the Monte Carlo technique, there may be unknown correlation which hasn’t been accounted for, or you might have used an inappropriate distribution for a parameter.
Accounting for uncertainties that analysis cannot capture	One element you may not be able to test in your analysis is the effect of unknown system shocks, such as a recession. It is not always useful or practical to investigate and analyse these types of epistemic or ontological uncertainty, but they should be accounted for in presenting your analysis, for example by highlighting the risks associated with the analysis and the decision it will inform.

Presenting and communicating uncertainty
Deciding what to communicate
Uncertainty improves the quality of the analytical communication
What is the key message?
Understanding the audience
Deciding how to communicate uncertainty
Communication Basics
Graphs and visualisation
Error bars
Box plots
Probability density functions (PDFs)
Cumulative density functions (CDFs)
Fan Charts
Multiple Line Charts
Tornado Diagrams
Infographics
Interactive Tools

4.

4. Presenting and communicating uncertainty

We now consider how to choose *what* messages about uncertainty we should communicate to decision makers and give advice on *how* to communicate those messages effectively. A wealth of additional information can be found on the Government Statistical Service website (https://gss.civilservice.gov.uk/wp-content/uploads/2018/12/Communicating_Quality_Uncertainty_and_Change_for_publication.pdf)

4.1. Deciding what to communicate

The analysis of uncertainty is often complex. We need to choose carefully which messages about uncertainty to communicate to decision makers – ensuring they receive enough information to understand the key points, without receiving so much that it clouds the central issue.

You should also consider the onward communication of your message to ensure that when your work is passed on to others its core message and integrity are maintained.

4.2. Uncertainty improves the quality of the analytical communication

Don't let uncertainty undermine confidence in the analysis

Decision makers are usually more comfortable with certain messages. This can make communicating uncertainty a difficult task. Decision makers can react adversely when faced with uncertainty, leading them to lose confidence in analysis. When uncertainty is large, decision makers may feel that the analysis is of no use.

A handy phrase to remember is "all models are wrong, but some are useful". All analysis will be uncertain because every model is a simplification of reality. However, that does not stop them from being useful. Models allow us to better understand a system and uncertain results can help identify important features of that system.

If uncertainty means that a straightforward conclusion is not possible, focus your communication on what the uncertainty analysis *can* tell you. This may be the key factor that drives overall uncertainty or a greater understanding of how features of a system interact.

4.3. What is the key message?

If most uncertainty is quantified, then present this prominently

If most of the overall uncertainty has been quantified, and you are confident that there are no unknowns which are likely to have a major impact on the results then this should be the most prominent message. Discussion of the unquantified uncertainties and risks should be included but should be positioned so that it doesn't reduce confidence in the main results when this is not appropriate.

If little is quantified, then it may be better to present no quantification at all

If there are substantial unquantified uncertainties, then presenting the uncertainty that has been quantified without this important context will give a misleading impression of precision and underestimate the uncertainty. Do not present a range with incomplete coverage if you know that there are substantial uncertainties that are not accounted for in that range.

If the largest source of uncertainty is the potential for a risk outside of the analysis to be realised, then this should be the most prominently displayed message.

Front load the important caveats and explain why they matter.

Think about how caveats are presented. A long list is unhelpful, but two or three upfront that have the most impact on the results are likely to be more helpful and easily understood. You should explain what the caveats mean for decision makers who want to use the analysis, rather than simply setting out what they are.

4.4. Understanding the audience

Consider the audience when choosing appropriate communication methods

People respond differently to different communication methods. We need to assess the intended audience to understand the best way to share information with them. The audience might be:

- Analytical - may respond better to a technical explanation of the uncertainty
- Non-analytical - may respond better to non-technical language
- Mixed - a combination of both

If it is a group or individual you have worked with before tailor the method to what has worked well in the past (or ask them or see how they respond to different formats).

Build relationships with decision makers

A good relationship with your decision maker will help you to choose the right communication approach for them. It will also help you to understand their motivations and the implications of uncertainty for their decisions.

Be conscious of how your analysis may be used in future communication

No matter how carefully you communicate the uncertainty to your immediate client, there is a risk that uncertainty will not be communicated upwards and that only the central numbers will persist, and important caveats will be excluded. This can also occur when writing part of a larger document – you need to ensure the key messages about uncertainty survive the drafting process.

A good relationship with colleagues will minimise this risk. Work collaboratively to ensure that colleagues understand why central numbers could be misleading and in which situations it would be inappropriate for them to be communicated on their own. Always ensure that wherever possible you have sight of further communication before it is sent.

4.5. Deciding how to communicate uncertainty

Now you have determined what the message is you need to consider how to communicate with your decision makers. Firstly, think about how you will be communicating your results. Will this be via a written report, presentation, or an oral briefing with or without visuals? Any constraints on format may steer you to an approach.

This section considers a range of approaches based on your understanding of the audience and the type of message you need to deliver.

4.6. Communication Basics

Assess whether to describe uncertainty in words or attach figures

How something is written has a major impact on how people perceive the uncertainty. Research shows (https://www.tandfonline.com/doi/abs/10.1080/17457289.2018.1465061) that analysis is seen as less reliable if the outputs are conveyed only in words. Numbers should be presented within a sentence if possible as this helps give context, making them easier to read and understand.

Be careful when using descriptive terms and adhere to an established system if possible

Descriptive terms such as ‘low risk’ or ‘very likely’ can be interpreted very differently by different people (https://www.tandfonline.com/doi/full/10.1080/02684527.2014.994955). If possible, it is best to attach a numerical probability and use these words in support.

An exception to this is where there is an established system that your audience is used to for attaching terminology to probabilities, one that can be assumed to be well-understood by the intended audience.

	For example: • According to the IPCC (Intergovernmental Panel on Climate Change) (https://wg1.ipcc.ch/SR/documents/ar5_uncertainty-guidance-note.pdf), “very likely” means 90-100% probability. • According to NICE (National Institute for Health and Care Excellence) (https://bnf.nice.org.uk/guidance/adverse-reactions-to-drugs.html), probabilities of between 1 in 100 and 1 in 10 are referred to as “common”.
Use positive and negative framing	Presenting the likelihood of success may be perceived differently (https://www.uzh.ch/cmsssl/suz/dam/jcr:00000000-64a0-5b1c-0000-00003b7ec704/10.05-kahneman-tversky-79.pdf) to presenting the corresponding likelihood of failure. Present the information both ways to avoid bias (e.g. “there is an 80% chance of success and a 20% chance of failure”). By adding in the chance of failure, you remind the reader that it exists and how large it is, which may otherwise be overlooked. Visual part-to-whole comparisons can help with this. See infographics section (https://rosiea1.github.io/UncertaintyWeb/chapter_4.html#infographics) for more details.
Decide how to present your numbers	There is no clear preference for choosing between probabilities and fractions (e.g. 10% probability, or 1 out of 10). Given this, the usual preferences of the audience or the ‘norm’ within the organisation should be followed (https://www.annualreviews.org/doi/pdf/10.1146/annurev-statistics-010814-020148). If using fractions, keep the denominator constant (https://www.ncbi.nlm.nih.gov/pubmed/24625237) (e.g. “1 in 100 vs. 2 in 100”, rather than “1 in 100 vs. 1 in 50”) and as small as possible while keeping to integers (e.g. “1 in 100” rather than “10 in 1,000”), rounding if appropriate.
Be clear on the specifics and applicability	Saying a ‘10% chance of rain’ is meaningless unless you also state the time period – e.g. in the next hour, or at some point tomorrow – and location. If the outputs are only intended for use within a specific frame (for example, a specific area or to a particular group of the population), then make sure this is clearly stated alongside the outputs.
Use an appropriate level of precision	Consider the overall uncertainty in the numbers you have calculated. Round them appropriately to avoid spurious accuracy (e.g. perhaps 40% rather than 38.7% if the overall uncertainty is greater than one percentage point).
Use ranges wherever possible	Presenting a single figure is best avoided as it can give a misleading impression of precision (e.g. “between 1,200 and 1,800”, rather than “1,500”). Commissioners may request a ‘best estimate’ for ease of onward use, but you must consider the risks in providing this. Try to understand how they intend to use the analysis, so you can provide something that meets their needs while also acknowledging the uncertainty.
Consider whether to include a ‘best estimate’ within the range	Stating a range may be perceived as a uniform distribution across the range. Conversely, stating a range around a best estimate may be perceived as a triangular distribution (or Normal with analytical audiences). The output distribution could of course also be asymmetric or bi-modal. Consider which of these best reflects the actual uncertainty when deciding what to present.
Choose appropriate confidence/prediction intervals and be clear	Don’t simply use 95% confidence intervals by default. Think about what the outputs are going to be used for (see Agreeing how uncertainty should be used to help answer the question (https://rosiea1.github.io/UncertaintyWeb/chapter_1.html) section), and discuss the level of risk and uncertainty that the decision maker wants to plan for – this might not be 5%. Be clear what confidence level you are using and ensure your audience understands what this means (avoiding precise statistical definitions if it will increase comprehension).

4.7. Graphs and visualisation

Graphs can be an excellent way of communicating the quantified elements of uncertainty	Graphs and visualisations are an excellent way of communicating the outputs of analysis, and many graph types allow you to communicate uncertainty within the graphic (provided the uncertainty has been quantified). Unquantified uncertainties cannot generally be included in graphs, so will need to be communicated through other means (e.g. a risk log and/or assumptions log).
Some graph types cannot be used to show uncertainty clearly	Some types of graphs are not particularly well suited to displaying quantified uncertainty, though this does not preclude their use if they are the most useful way to communicate a core message. You would need to find other ways to communicate uncertainty if using these chart types. Some simple graphs *Pie charts, donut charts, stacked charts* These charts may not always be useful when presenting uncertain analysis as they only show a single value for each data point. People can also find it difficult to compare angles or sizes of different sections.

More complex graphs
Heat and Choropleth maps, Treemaps, Sankey diagrams

As a general rule, it can be difficult to communicate uncertainty in very information dense visualisations such as those above. There is not space to include the necessary extra information among the colours of heatmaps, the densely packed rectangles of Treemaps or the detailed flow lines of Sankey diagram.

Decide what level of detail to include on uncertainty

You may have the full understanding of the underlying probability distribution, or just a range within which we expect the result to fall. You may choose to only include the uncertainty due to a single dominant uncertainty, or the outputs from a range of scenarios.

For representing numerical uncertainty, scatter plots with 2d error bars, line graphs with a range, bar or line graphs with error bars and single point graphs with error bars can be useful when representing an uncertain range. Box plots or box plot series can be useful when representing summary statistics. Probability (or Cumulative) Distribution functions are helpful if you have full knowledge of the distribution around a result.

For representing uncertainty due to alternative scenarios, multiple line graphs and descriptions in prose may be most helpful

For representing uncertainty due to alternative scenarios, multiple line graphs and descriptions in prose may be most helpful.

4.8. Error bars

Error bars are a simple way to illustrate a range around a data point

Error bars can be added to bar graphs, line graphs and scatter graphs to illustrate a range around a central estimate, within which we expect the value to lie with a given probability.

Choose an appropriate probability level based on the context

As referred to previously, consider the situation and decide on an appropriate level to display. E.g., don't apply 95% confidence/prediction intervals by default.

Be clear about what the error bars represent

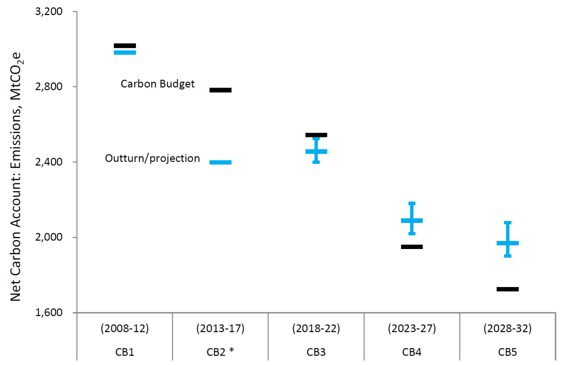
State what probability the error bars represent, and describe in prose how the viewer should 'read' the error bar.

Error bars can be applied to series of data points

Error bars can be added easily to a data series or time series. However, if the data are continuous (e.g. a time series) then consider whether showing multiple line graphs would be clearer than a single line graph with error bars.

2-dimensional error bars can be used where necessary

If the output data are 2-dimensional, then you can apply error bars in 2 dimensions. Be careful to ensure that the resulting graph does not become illegible due to clutter.



Example: ***Actual and projected performance against carbon budgets, BEIS (https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/794590/u energy-and-emissions-projections-2018.pdf)*** *For future emissions, vertical bars show uncertainty in the projections and indicate 95% confidence intervals for the uncertainties that have been modelled.*

4.9. Box plots

Box plots can convey more information about possible outcomes than a range alone

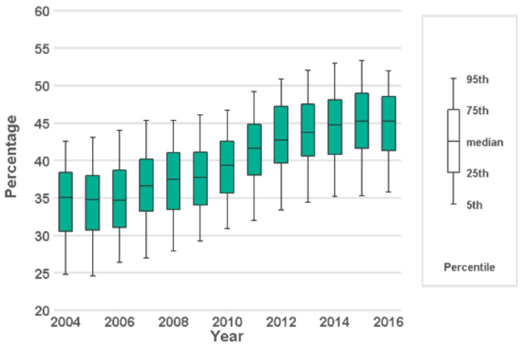
Box plots can help the audience understand the underlying distribution of possible outcomes in more detail than just a range. Typically they show the median, interquartile range, maximum and minimum values for the range of possible outcomes. This can be particularly useful when the underlying distribution is skewed or non-normal.

A series of box plots can be used to compare distributions

Box plots can be arranged in parallel to show the distributions for a range of measures, and can help compare the different shapes.

Think about whether the audience will be familiar with the format

Box plots may not be widely understood by non-analysts, so think carefully about whether the added information will be effective, or whether a simple range would be sufficient. A labelled example can be used to help the audience interpret the format.



Example: ***Deaths in the usual place of residence, Public Health England (https://www.gov.uk/government/publications/end-of-life-care-profiles-july-2018-data-update/statistical-commentary-end-of-life-care-profiles-july-2018-update)*** *The graph depicts the percentage of individual that die in their usual place of residence. Box plots are used to show the variation between different Clinical Commissioning Groups, and district and local authorities. A labelled box plot is presented to explain what the ranges mean.*

4.10. Probability density functions (PDFs)

PDFs show complete information on the quantified uncertainty

A probability density function can be used to give complete information on the range of possible outcomes, and the likelihood of each for a given estimate.

Think about whether the audience needs this much information

While presenting complete information may seem ideal, it may be more information than the audience actually needs. Would a prose description of the mean and range be sufficient?

PDFs can be useful when the distribution of outcomes is multimodal, or otherwise complex

If the PDF is approximately normal, then there may be little value in displaying it, as the essential features can be described in a few words.

The distribution could be multimodal – for example the marks for students passing a university module may have a peak for a number who don't study very hard, and a peak for those who worked really hard. In this case it could be misleading to present the mean, so a graphical illustration of the distribution may be more effective.

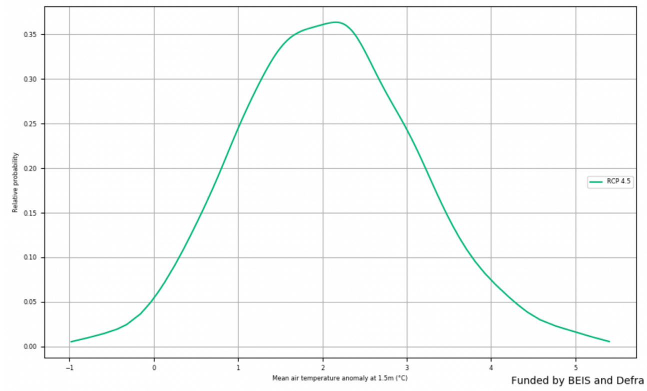
Labelling can be used to highlight the key features

It may aid clarity to draw the reader's attention to important features, such as the mode.

Multiple PDFs can be used to show uncertainty across different measures

If we need to communicate a series of PDFs, then multiple functions can be shown to compare the range of possible outcomes across the series.

If there are only 2 or 3 these can be overlaid to make it easy to compare. With more, 'small multiples' are likely to be clearer.



Example: ***Change in Air Temperature for 2080-2099, Met Office (https://www.metoffice.gov.uk/binaries/content/assets/metofficegovuk/pdf/research/ukcp/ukcp18-guidance---how-to-use-the-cdf-and-pdf-plots.pdf)*** *The graph shows the expected change in air temperature in 2080-99 compared to 1981-2000 for a medium emission scenario.*

4.11. Cumulative density functions (CDFs)

A CDF may be more helpful than a PDF if there is a specific threshold of interest to the customer

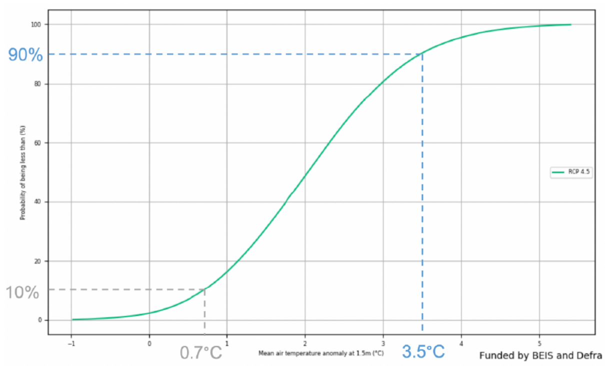
A cumulative density function essentially shows the same information as a probability density function. However a CDF may be more helpful when the audience is primarily concerned with how likely it is that the value will be below (or above) a particular point (rather than the range within which we expect the value to fall). For example, how likely is it that our costs exceed our budget? (rather than what are our costs going to be?

The most likely value is less clear on a CDF

However, features such as the mode are less clear on a CDF (shown by the steepest part of the graph), as they are harder to read by eye.

Labelling can be used to highlight the key features

Drawing gridlines intersecting at key points of the function can help the viewer understand how to 'read' the graph.



Example: ***Change in Air Temperature for 2080-2099, Met Office (https://www.metoffice.gov.uk/binaries/content/assets/metofficegovuk/pdf/research/ukcp/ukcp18-guidance---how-to-use-the-cdf-and-pdf-plots.pdf)*** *The graph shows the same information as the PDF example above. The grey dotted lines indicated there is a 10% probability of a mean temperature change of less that 0.7C. The blue dotted line indicated that there is a 90% probability of a mean temperature change being less than 3.5C.*

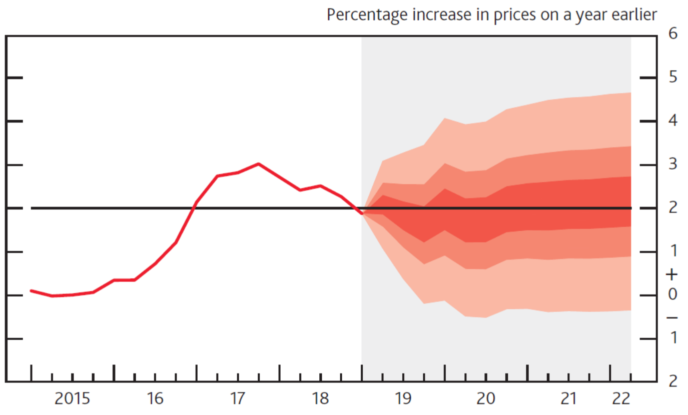
4.12. Fan Charts

Fan charts can show how uncertainty changes over time

Fan charts can be used to show a series of different prediction intervals for time-series projections (e.g. 30%, 60% and 90% at the same time). This is essentially plotting selected points from a time-dependent PDF.

Avoid including the mode

Often a central 'best estimate' is not included, to avoid the viewer focussing on a single estimate and undermining the importance of the uncertainty



Example: ***CPI inflation projection, Bank of England (https://www.bankofengland.co.uk/-/media/boe/files/inflation-report/2019/may/inflation-report-may-2019.pdf?la=en&hash=D4985F6D513BF04EB81A28C53F6DB0CFB8CC09FB)*** *The graph depicts probability of various outcomes for CPI inflation in the future. The fan charts are constructed so that outturns of inflation are also expected to lie within darkest central band and each pair of the lighter red areas on 30 occasions. In any particular quarter of the forecast period, inflation is therefore expected to lie somewhere within the fans on 90 out of 100 occasions. And on the remaining 10 out of 100 occasions inflation can fall anywhere outside the red area of the fan chart (grey area).*

4.13. Multiple Line Charts

Multiple line charts can be clearer than a series of error bars

Multiple line charts with time series data to show a quantified range around a 'most likely' projection (essentially a series of error bars).

Alternative scenarios can be illustrated with multiple line graphs

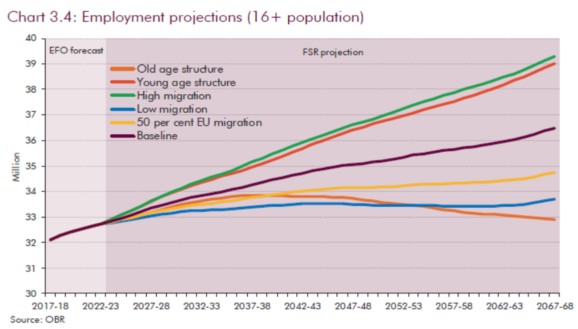
With scenario analysis, a series of line charts can be used to show the projections from each scenario.

Give equal prominence to each scenario

Generally with scenario analysis each scenario should be presented with equal prominence, to avoid suggesting that one is more likely than another (unless analysis has been carried out to quantify the likelihoods of each).

Try to have an even number of scenarios

Try to include an even number of scenarios, to avoid having a middle option that may be misinterpreted as the 'most likely' scenario.



Example: ***Employment Projections, OBR (http://cdn.obr.uk/FSR-July-2018.pdf).*** *The graph presents future employment levels for different demographic scenarios. Each scenario is represented by a separate line plot. The graph does not attempt to show the probability of each scenario occurring.*

4.14. Tornado Diagrams

Tornado diagrams can be used to show the *sources* of uncertainty

Tornado diagrams are different to most other graphs discussed here. They are not used to show the outputs of the analysis, but to show how different sources of uncertainty contribute to the overall uncertainty.

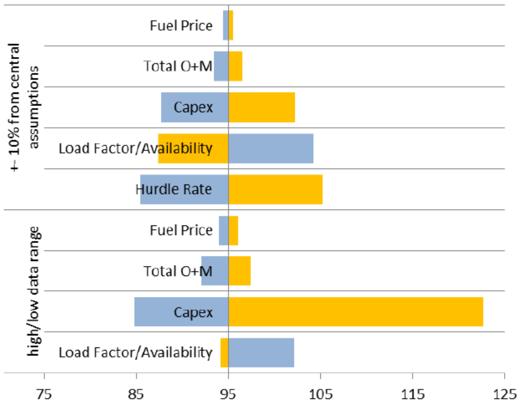
Tornado diagrams depict sensitivity of a result to changes in selected variables. They show the effect on the output of varying each variable at a time, keeping other input variables at their assumed values.

Can help communicate the reasons for uncertainty, and identify further need for analysis

If the level of uncertainty is unpalatable to the customers, then this format can be useful to help focus work on reducing the level of uncertainty in key parameters. Tornado diagrams also help you to focus on the inputs which are most important to focus on getting as "right" as is possible.

Tornado diagrams can be misleading in complex models

One limitation of the format is that only one parameter is changed at a time. There are some situations where the uncertainty due to one variable may appear small initially but becomes much more prominent if a second variable takes on a slightly different value (e.g. think of a workflow model with a bottleneck. A tornado diagram might show the bottleneck parameter to be the overwhelming uncertainty. However, if this parameter is increased slightly then the bottleneck may move elsewhere, completely changing the picture)



Example: ***Nuclear Levelized Cost of Electricity, BEIS (https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/566567/B*** ***.*** *The graph presents the change in the levelized cost of nuclear electricity (£/MWh) that would result from changes in input parameters. Impacts are shown from both 10% upward or downward movement in central estimates and from predetermined parameters ranges (high/low data range). Yellow bars represent an increase in the parameter, blue bar represent a decrease in the parameter.*

4.15. Infographics

Infographics can be useful for public facing communications

Infographics are graphic visual representations of information, data or knowledge intended to present information quickly and clearly. They can improve people's understanding (http://ptgmedia.pearsoncmg.com/images/9780789749499/samplepages/0789749491.pdf) by using graphics to enhance peoples' ability to see patterns and trends.

Graphics can grab attention and make messages more accessible

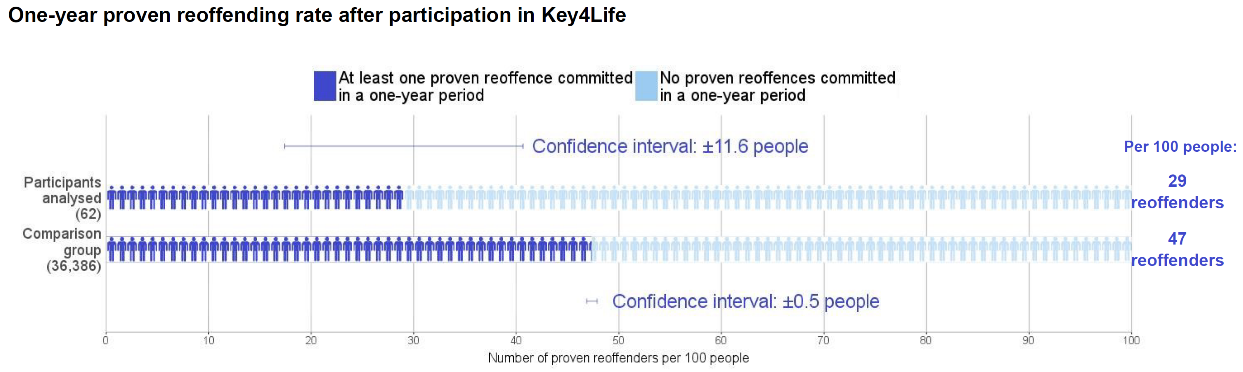
When done well they will grab the reader's attention from become a very powerful way of communicating key messages. Designing a good infographic may be worthwhile if your audience is less confident with data and analysis.

Information on uncertainty can be included

Not all infographics communicate uncertainty, but uncertainty information can be included within the infographic. In the example below, confidence intervals are included as part of the infographic .

However, watch out for common pitfalls and follow best practice for the design

Like all graphs and visualisation you should ensure the information is presented clearly and truthfully. With infographics there is additional the risk that visual design elements detract from the key message. Consider the final audience for the information to determine if an infographic is the right choice and follow best practice (https://www.nngroup.com/articles/designing-effective-infographics/).



Example: ***Reoffending Behaviour After Receiving Treatment, MoJ (https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/747467/K***
The infographic uses people icons rather than a bar chart to show the number of reoffenders in a sample. An uncertainty in the form of confidence intervals is included in the infographic

4.16. Interactive Tools

Interactive tools can be used to immerse your reader on complex matters

An interactive tool can help make analysis more accessible to non-specialists. They can create an immersive experience that is easier for them to understand and is highly memorable.

Focus on specific messages

Consider the overall message and where the uncertainties lie. Which aspects will the audience be interested in and what do they need to know? Use this understanding to bring focus to which interactive elements to create.

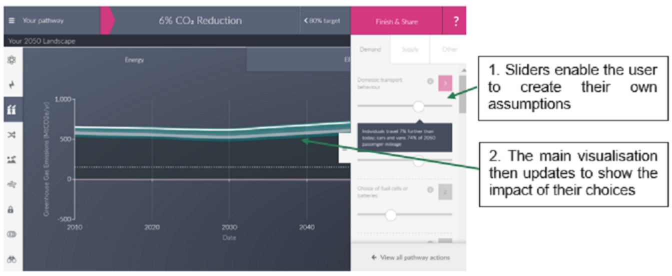
The interactivity will enable your users to manipulate and get a deeper understanding of the message.

Allow reader to adjust a key variable

If a key source of uncertainty is a single variable, then it may be possible to construct a display that can be changed as the user adjusts the value of this variable by moving a slider.

Or, if there are several key assumptions that impact the result a chart may be created that will change depending on the inputs that the user inserts.

Being able to see what would happen if an underlying assumption was to change is a powerful way to demonstrate the level of uncertainty we may have in a given result.



Example: The DECC 2050 Calculator (https://www.gov.uk/guidance/2050-pathways-analysis) is an award-winning, user-friendly tool that helps users to explore the choices available to meet the 2050 carbon target. Whilst it doesn't explicitly cover the uncertainty in the underlying data it does allow the user to create their own set of policies to try to reach the target. This engaging tool was helpful in demonstrating to users how difficult some of the options are and the relative impact of each choice.

Estimating the impact of evidence volumes in Legal Aid spend

Estimating uncertainty in prison population projections

Estimating changes to staff travel times following an office relocation

Predicting staff pay costs

Case Studies

Estimating the impact of evidence volumes in Legal Aid spend

The situation:

Prices in Crown Court Legal Aid work had been undergoing a sustained increase. Several drivers were identified that suggested that these increases would continue, such as:

- Increased electronic evidence
- Media focus on collapse of trials due to lack of evidence
- New guidance on the disclosure of data

However, there was no information to determine for how long these increases could continue. In addition, prices had risen particularly quickly in more recent months and may be an indication of an accelerating trend.

The analytical approach:

The existing model takes predicted court activity and calculates expected bill volumes, which a price forecast is then applied to.

Asking the right question:

- What should the price forecast be set at for Crown Court Legal Aid?
- What is the risk of over or underspending against this forecast?

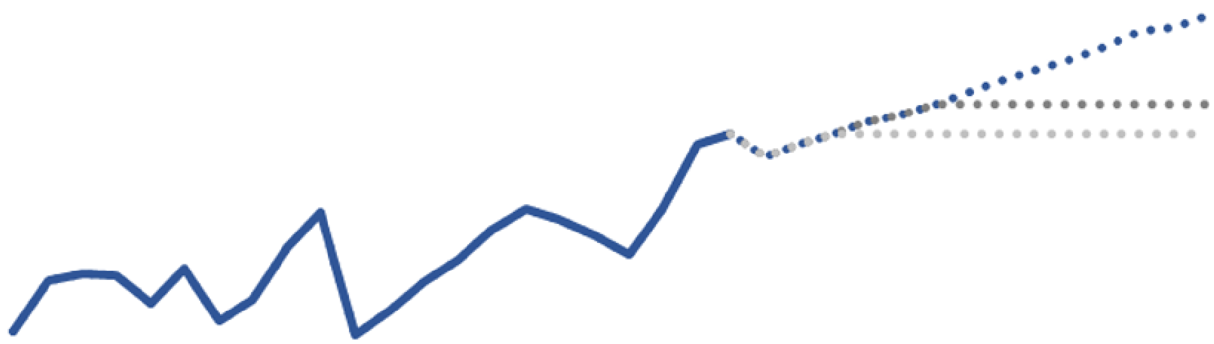
Defining and identifying uncertainty:

- The timing and value of upcoming bills

- Potential changes in underlying cases mix
- Case volumes

Understanding and measuring uncertainty:

- Uncertainty around case volumes was discounted (**Dominant Uncertainty**) as the impact was expected to be small.
- No information was available to determine the scale of future increases, so scenario analysis was used to assess the impact of certain assumptions.
- The impacts of 3 price scenarios, representing price increases continuing for 3, 6 or 12 months, were estimated.
- Although there was insufficient evidence to support it being considered for the main estimate, an additional scenario representing an increasing level of price rises was considered and logged in the risk register to highlight the potential variance.
- An additional scenario was considered for prices levelling out immediately in case the full impact had fed through. However, due to the volume and timing of identified drivers this was felt to be very unlikely, so including it could be misleading and contribute to an optimism bias to the decision making.



Presenting and communicating uncertainty analysis

- Decision makers were presented with the option of taking either the 3, 6 or 12 month assumption for the central projection, with the higher and flat scenarios being logged in the risk register.
- The options were presented to decision makers, stressing that there was no information that would allow us to tell which scenario was more likely.
- Decision makers agreed that the range of scenarios considered reflected the range of reasonable outcomes.
- As no information was available on the which scenario was mostly likely, discussion focused on the risks that were associated with taking each scenario through for planning purposes, such as over or underspending against the overall budget.
- Scenario analysis was used to provide a range of values to illustrate the large amounts of uncertainty around the forecast without giving the impression that any particular outcome was more likely, allowing a decision to be made with the understanding of the risks involved.

Estimating uncertainty in prison population projections

The situation:

Prison population projections are the end result of a number of criminal justice system interconnected models. The uncertainty around each of these models had not been estimated, but understanding the uncertainty of prison projections was essential for capacity planning.

The analytical approach:

Court demand and sentencing and forecasts were used within a prison population microsimulation model, with policy forecasts overlaid.

Asking the right question:

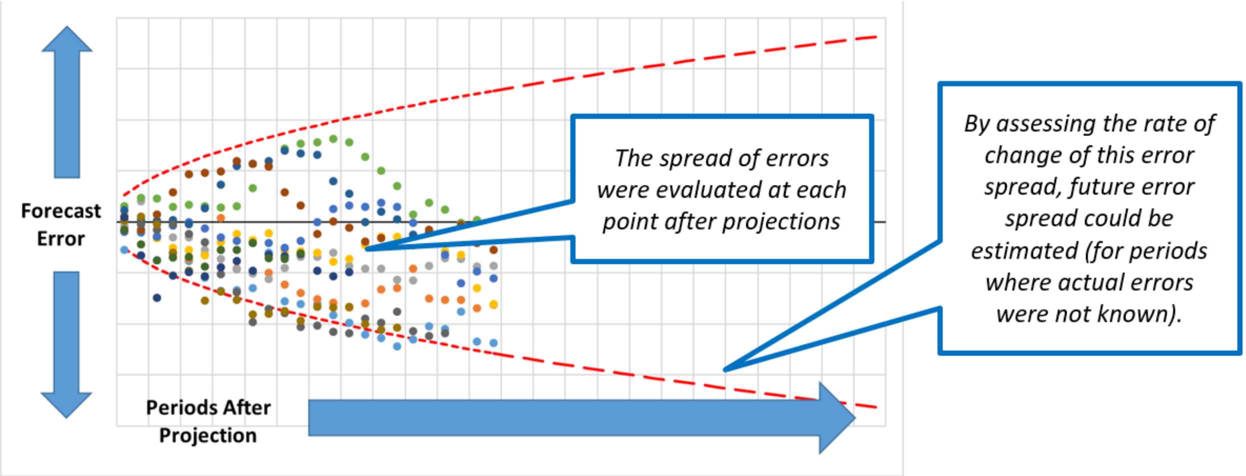
- How confident are we that the prison population will not exceed a particular threshold?
- Was there sufficient resource to estimate uncertainty using a traditional bottom-up approach (i.e. combining the uncertainty from all constituent models)?

Defining and identifying uncertainty:

- Court demand projections
- Sentencing assumptions (custody rate)
- Impact estimates of future policy changes
- Unknown impacts such as exogenous system shocks or policy changes not known at time of projection
- Estimation error (such as sampling bias) from simulation model

Understanding and measuring uncertainty:

- A top-down approach was chosen as the resource requirement for a traditional bottom-up approach would have been prohibitive.
- The variance of all the previous forecast errors after 1 time period were fitted to a chosen probability distribution (in this case a normal distribution was chosen). This distribution was used to estimate the uncertainty of the new forecast after 1 time period.
- This process was repeated for the variance at each subsequent time period.
- The rate of change of variance was used to extrapolate the variance for periods where no forecast error existed.



Presenting and communicating uncertainty analysis

- We presented our historical forecast errors, explaining their main drivers and how each contributes to our current uncertainty range. This helped our key customers to better understand the uncertainties inherent in the system we model, and therefore why we can't produce more precise forecasts.
- The other aspect was helping customers think about how they should use the uncertainty estimates. For example: for the prison estate, assessing the likelihood of prison population reaching different levels together with an assessment of risk appetite and contingency measures we could use. This allowed for an evidence based approach for how much capacity we should plan for, not simply planning to the central estimate.

Estimating changes to staff travel times following an office relocation

The situation:

Alternative government office locations were being considered and their on staff travel times.

The analytical approach:

Google maps API was used to estimate journey times from each home address to each potential location.

Asking the right question:

- 90 minutes was considered to be a 'reasonable' travel time.
- The distribution of journey times was an output of interest, but the key focus was "What proportion of staff will have a journey time of over 90 minutes?"

Defining and identifying uncertainty:

Missing Data:

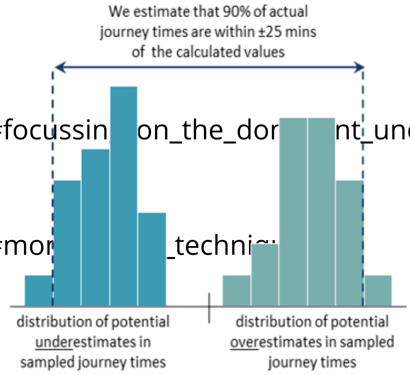
- Only first half of staff postcodes were available.
- Not known who could feasibly travel by car.

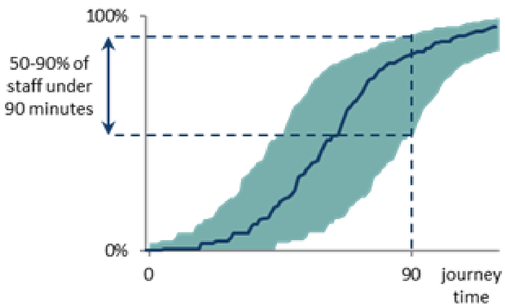
Assumptions:

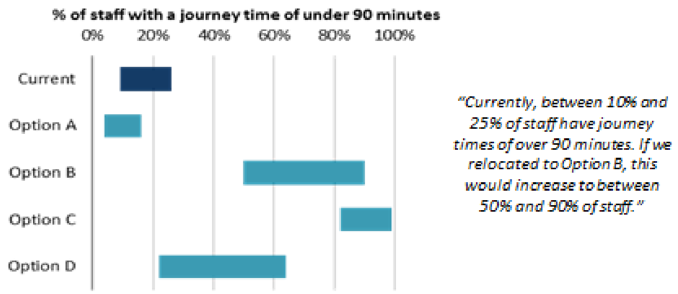
- Staff begin and end work at 9am and 5pm.
- Journey time assumes all transport is running to schedule.
- Assumptions for transfer times, walking speeds etc.

Understanding and measuring uncertainty:

- Through sensitivity analysis on each parameter, the use of partial postcodes was found to be the most significant source of uncertainty and so Dominant uncertainty (https://rosiea1.github.io/UncertaintyWeb/chapter_3.html#focussin on_the_dor nt_uncertainty) was chosen.
- A Monte Carlo (https://rosiea1.github.io/UncertaintyWeb/chapter_3.html#mor _techni approach would have been a more complete analysis but was not viable in the available time.
- A sample of postcode districts were reviewed to calculate: - The journey time from the centre of the postcode; - The shortest possible journey from within that postcode; - The longest possible journey from within that postcode.
- The differences in these times were analysed across the sample to form distributions.
- Producing an uncertainty estimate of 90% of journey times to be within ± 25 minutes of the calculated durations.







Presenting and communicating uncertainty analysis

- A cumulative distribution (https://rosiea1.github.io/UncertaintyWeb/chapter_4.html#cumulative_density_functions_(cdfs)) of journey times along with uncertainty bounds clearly presented how many journey times were estimated to be within the crucial threshold of 90 minutes.
- Bar graph ranges (https://rosiea1.github.io/UncertaintyWeb/chapter_4.html#error_bars) were presented to the senior move managers, to show how journey times compared between location – the central estimate wasn't plotted to avoid the reader putting too much significance on it.
- Prose sentences were used to clearly present the key results.

- Unquantified uncertainties were communicated e.g. the assumption of no delays.
- The communication of the uncertainty made clear the case for obtaining exact postcodes, allowing the analysis to be repeated with less postcode uncertainty.

Predicting staff pay costs

The situation:

Each department has to manage their pay costs to ensure they stay within their budget, making decisions to recruit (or not) in the face of uncertainty over staff turnover, pay rises, etc.

The analytical approach:

Use a microsimulation to model staff members over time, with departures, promotions, and new recruits modelled stochastically.

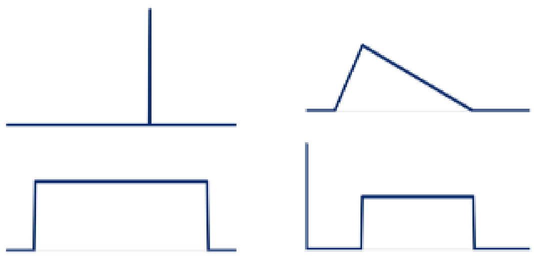
Asking the right question:

- Initially 'What will our pay costs be at the end of the year for a given recruit plan?'
- Redefined as 'how likely is it that our costs will exceed our budget?', allowing a risk-based approach to decision-making, and also allowing uncertainty in the budget to be incorporated.

Defining and identifying uncertainty:

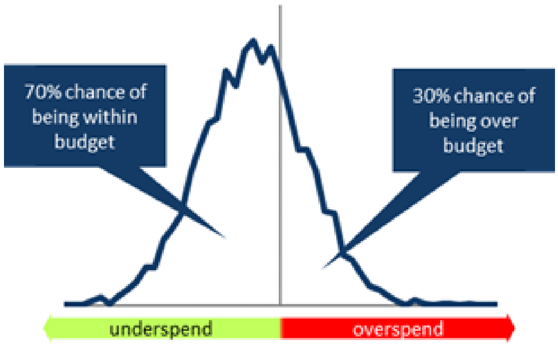
Unknowns:
- The pay budget including additional sources of funding not known until the start of the year

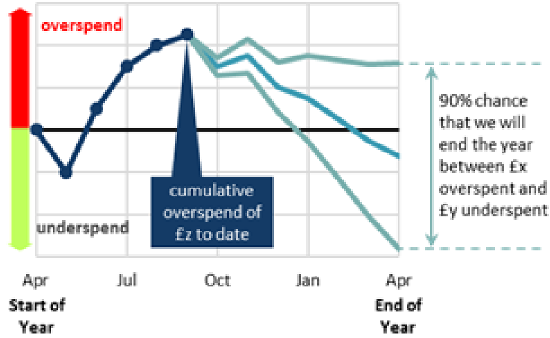
Assumptions:
- Number of staff who will join or leave the department in future months
- Variation in starting salaries, pension etc. for new staffs
- Variation in pay awards based on staff performance



Understanding and measuring uncertainty:

- A Monte Carlo (https://rosiea1.github.io/UncertaintyWeb/chapter_3.html#monte_carlo_techniques) approach was used due to the large number of sources of uncertainty, its suitability in microsimulation, the (assumed) lack of correlation between sources, and availability of time. Given that the model was likely to be reused many times, it was worth investing the time to build a full probabilistic uncertainty assessment into the model.
- Most numerical assumptions in the model (including dates) can be entered as a distribution (exact, uniform, or triangular, along with some bespoke distributions for specific purposes).
- This resulted in a full probability distribution of the range of possible outcomes.





Presenting and communicating uncertainty analysis

- All major uncertainties were quantified, and presented (with any unquantified sources noted elsewhere).
- The key output was simply the likelihood of remaining within budget, using positive and negative framing (e.g. "We have an 70% chance of staying within budget, and a 30% chance of exceeding our budget")
- As the budget holder was an analyst, we chose to present the full probability density profile (https://rosiea1.github.io/UncertaintyWeb/chapter_4.html#probability_density_functions_(pdfs)) to illustrate the range of possible over-/under-spends.
- Alongside, simple prose descriptions of the 90% prediction intervals to describe the likely range of the over-/under-spend
- A further graph was used to show how performance against budget was predicted to evolve over the year, using multiple line graphs (https://rosiea1.github.io/UncertaintyWeb/chapter_4.html#multiple_line_charts) to show the 90% prediction intervals.

Conclusion

This toolkit is designed to provide guidance to analysts on how to incorporate uncertainty analysis into their work, as well as setting out some high level advice to decision makers, so they know what to expect when commissioning analysis and interpreting analytical results. It sets out best practice, gives examples of situations where different techniques could be used, and highlights things to consider when conducting your analysis.

The toolkit is presented in the first instance as a suggested set of guidelines and we will be consulting with experts from Governnment, the academic community and other external bodies to develop thinking in line with the latest evidence on communicating uncertainty. We welcome feedback on the content. You can get in touch by emailing: **placeholder for email address**

It is not meant to give hard and fast rules, and there will be times where the work you are doing will necessarily bend or break some of the recommendations we have presented here.

Users of the toolkit should be aware that it is not designed to provide hard and fast rules and should also think about consulting other sources of guidance.

Additional papers that may be of interest are presented in the Further Reading tab. Your department may also have an uncertainty group who can advise on specific techniques and their implementation.