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CSNP: Economic Decision-Making Under Uncertainty

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NESO
National Energy System Operator

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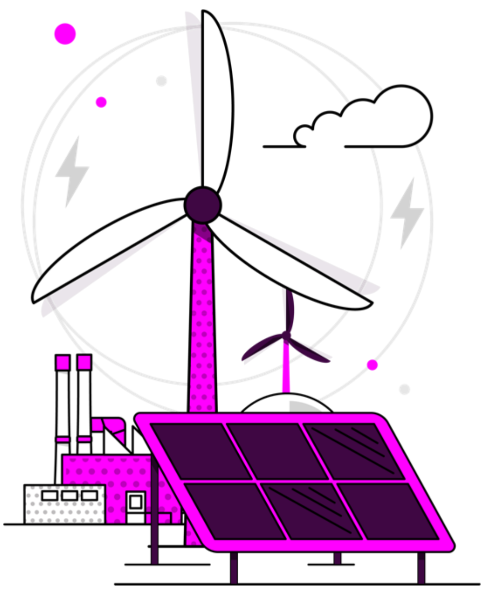
Glossary

Acronym	Definition
CSNP	Centralised Strategic Network Plan
LWR	Least Worst Regret
LWWR	Least Worst Weighted Regret
NESO	National Energy System Operator
NOA	Network Options Assessment
SSEP	Strategic Spatial Energy Plan
SWOT	Strengths, Weaknesses, Opportunities, and Threats



1. Introduction

Overview

Overview

In the future, the National Energy System Operator (NESO) will become responsible for developing the Centralised Strategic Network Plan (CSNP). A key requirement of the CSNP is for an analytical framework to support network investment decisions. This framework should account for future uncertainties when performing economic assessment of network design options, while also maintaining transparency and clarity for decision-makers. Currently, the tool used for economic decision-making is Least Worst Regret (LWR), but this may not be fit for the proposed purpose. This project has assessed the suitability of LWR and proposes an alternative tool, based on robust Bayesian analysis, that will improve the insights, transparency and value-for-money of network investment decisions.

The transition to net zero will require significant and rapid change to our already complex energy system. Achieving this at lowest cost while maintaining security of supply is a huge challenge. To address this, the Energy Act 2023 established the new role of NESO, with greater responsibility for whole system planning and operation than its predecessor, National Grid ESO. NESO will be responsible for energy system planning and strategic investment decision-making to maximise the chance of a successful, efficient, and co-ordinated transition.

NESO will achieve this via a series of interdependent plans, each with a different focus. The Strategic Spatial Energy Plan (SSEP) will define optimal locations for generation and demand infrastructure, while the CSNP focuses on the transmission infrastructure required to connect the elements of the SSEP. The combination of these plans will address the energy transition's requirement for holistic planning, which accounts for cross-vector integration and broader economic considerations, rather than the current purely load-related focus. This approach is intended to incentivise more proactive investment and drive cost-effectiveness, ultimately reducing the cost to consumers.

The Network Options Assessment (NOA) is a key component of the current transmission network planning process. NOA relies on LWR for economic assessment of network options. Within the LWR methodology, the outcomes often depend in a non-intuitive way on the precise future energy scenarios chosen for the analysis, making its outputs highly subjective. Furthermore, while 'regret' is a useful concept in some cases, it may not be the ideal decision-making objective to achieve the CSNP requirements—LWR is inflexible to different objectives such as expected utility or cost. LWR is also inherently risk averse and therefore may not be suited to making the transformational, anticipatory investment decisions required to deliver the energy transition.

The CSNP aims to optimise electricity and wider energy system planning and investment decisions by identifying the most valuable network expansion projects, whilst accounting for the environmental and consumer impacts of such decisions. It requires a less risk averse analytical framework that can deliver the required anticipatory investment and transformation, while balancing delivery of the transition with affordability for consumers. The process should be transparent, able to account for uncertainty across a range of scenarios and must interface with a decision-making process that evolves through time.

Project Aims and Objectives

To identify the most appropriate analytical framework, Frazer-Nash Consultancy and the University of Edinburgh have undertaken a project to:

- **Define** requirements for the CSNP analytical decision support tool.
- **Review** the potential tools and analytical frameworks.
- **Recommend** the most appropriate option based on identified benefits and limitations.
- **Assess** practicality of that recommendation based on worked examples.

DEFINE Tool's user requirements → **REVIEW** Many decision support tools → **RECOMMEND** An alternative tool → **ASSESS** Implementation and practicality

Following a thorough research project, an assessment framework based on Robust Bayesian Analysis has been identified as the most appropriate alternative economic assessment framework for robust, defensible decisions.

The key challenges that were explored in this research were:

- **Alternative tools**: assessment of a range of economic decision-making frameworks against a set of predefined criteria, such as transparency, resolution, usability, and explainability.
- **Dealing with uncertainty**: large investment decisions for complex future systems are inherently uncertain as, in addition to the uncertainties in the systems themselves, future conditions are relatively unknown. Currently, GB energy system investment decisions are evaluated against four different future scenarios that do not have probabilities assigned to them, making it difficult to capture a picture of future uncertainties. The benefits and trade-offs between the different potential tools were explored, including whether, and to what extent, expert judgement should, or could, be explicitly incorporated to improve confidence in uncertain outputs.
- **Economic considerations**: the existing process for network expansion decisions is load-driven and therefore influenced mostly by capital expenditure and constraint costs. The CSNP aims to generate an optimum technical solution with additional consideration of non-load drivers. The project focussed on characterising traditional economic indicators, whilst being aware of the future need to consider community, environmental and deliverability factors.
- **Practicalities**: the recommended tool must fit with NESO's needs and become a reliable aid for both short- and long-term decision-making. This requires an understanding of how its use will be implemented, and its outputs interpreted and

communicated to stakeholders. Worked examples to test and demonstrate how the new tool could be implemented and interpretated are included in this report.

NESO are interested in selecting an economic decision-making tool that is:

- **Capable of identifying the preferred investment options based on economic factors.**
- **An alternative to the currently used LWR approach.**
- **Draws on academic and cross-industry methods.**
- **Robust to sensitivity analysis and able to incorporate uncertainty around a range of future generation and demand scenarios.**
- **Transparent and easy-to-understand outputs for the industry.**

2. Review

User Requirements

Method Landscape

SWOT Analysis

Review: Economic Assessment Tools

A review of available decision support tools currently used across industry was undertaken against a set of elicited user requirements. Human judgement, deterministic and probabilistic approaches were assessed using a SWOT (Strengths, Weaknesses, Opportunities and Threats) analysis, resulting in the down-selection of four proposed tools that progressed to more detailed assessment: Least Worst Regret (counterfactual), Info-gap Decision Theory, Robust Bayesian Analysis and Stochastic Optimisation.

User Requirements

A requirements captured workshop was held with a range of stakeholders from NESO to understand the user requirements for the CSNP economic decision-making tool. In total, 51 requirements were elicited and scored based on their level of priority. The key themes that were captured included:

- **Explainability**: The tool should provide information that can be used to explanation decision-making outputs.
- **Uncertainty**: The tool should be able to handle uncertainty and provide additional confidence in the decision-making process.
- **Integration**: The tool should fit into the wider CSNP process, without requiring further enhancement of other steps.
- **Resolution**: The tool should be able to assess different combinations of future energy system and network reinforcement options.

Method Landscape

The range of decision support tools explored across human judgement, deterministic, and probabilistic techniques are highlighted in Figure 1.

The Decision Support Tool Landscape

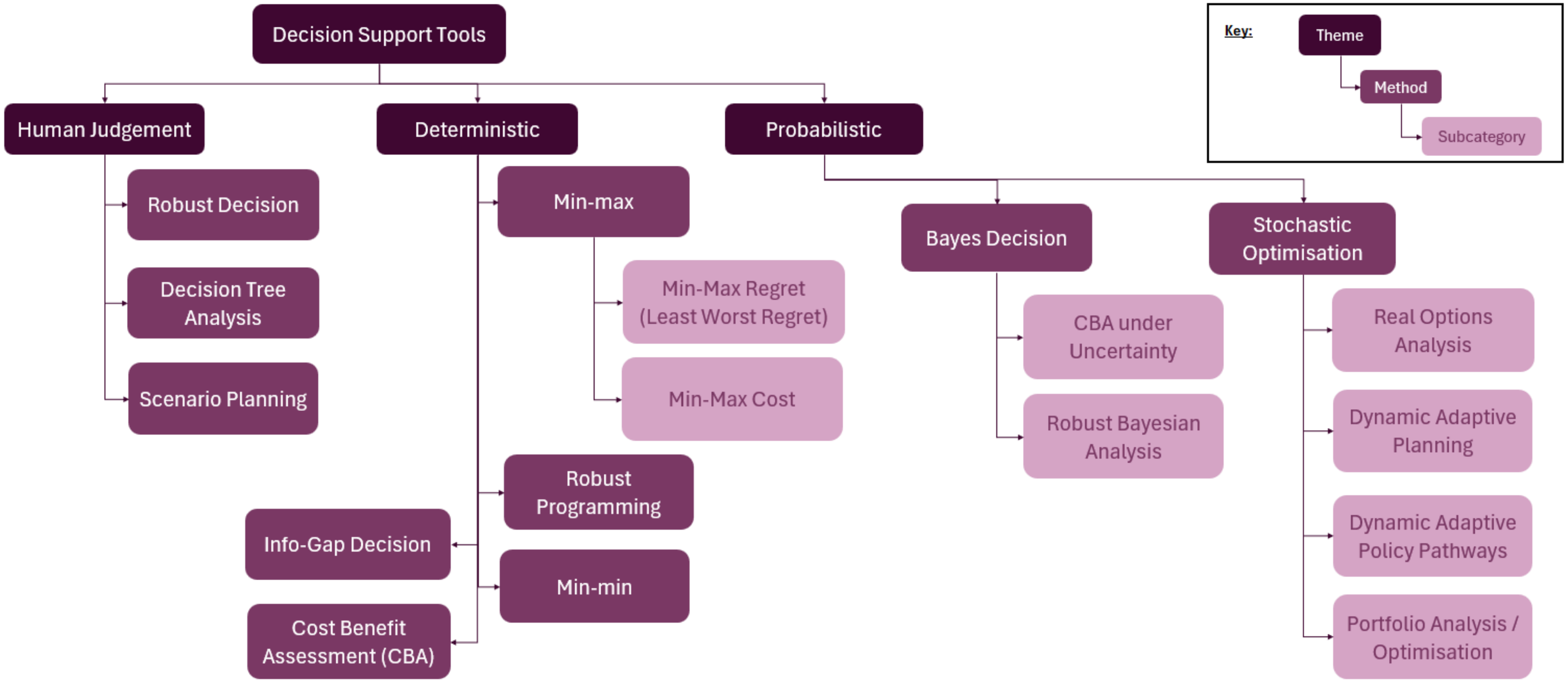


Figure 1. Listing themes, key methods, and subcategories of decision support tools used across industry.

SWOT Analysis

A review of the decision support tools was undertaken to identify relevant SWOT in each case. This was used to qualitatively assign each tool with a Red, Amber, or Green (RAG) status, with the following criteria:

Status	Description
R	Methods not suitable for the CSNP, with weaknesses and threats including limited or **no uncertainty handling and high resource** (computational or human) demand.
A	Methods that may have value based on ability to consider uncertainty, but their **complexity in implementation and/or communication** would prove challenging and need more thought.
G	Methods that warrant further assessment, with strengths including **handling of uncertainty** and breadth of applications.

The tools that were assigned 'green' status, and progresses for more detailed assessment, are outlined below (full SWOT Analysis included in Appendix A):

Least Worst Regret (Counterfactual)

LWR is an optimisation algorithm that focuses on minimising the maximum regret of decisions across a range of scenarios. In this context, regret is the net benefit difference between an investment strategy and the best strategy for a scenario.

- **Strengths**:
  - Focuses on minimising potential regret.
- **Weaknesses**:
  - Does not guarantee the best outcome and can be overly cautious, since it cannot consider difference in likelihood between different outcomes.
  - May lead to overly conservative decisions.
- **Opportunities**:
  - May help in making more cautious decisions in uncertain environments such as the CSNP.
- **Threats**:
  - Can be difficult to explain reason for result to stakeholders due to mechanistic approach.

Info-Gap Decision Theory

A method for making decisions under severe uncertainty by focusing on robustness to failure. It is regularly applied in Engineering and Conservation decision-making.

- **Strengths**:
  - Handles severe and deep uncertainty well.
  - Does not rely on probabilistic information.
- **Weaknesses**:
  - Can be overly conservative
  - May not always lead to optimal decisions.
- **Opportunities**:

    - Applicable to the CSNP process as it is used in engineering, environmental management, and economic decision-making.
- **Threats**:
    - Could lead to poor decisions if inaccurate data is used. A complex CSNP process may have uncertainties in the data.

Robust Bayesian Analysis

A probabilistic approach to decision-making that allows for subjectivity to be incorporated into the analysis through definition of prior probabilities.

- **Strengths**:
    - Allows for subjectivity to be considered where measurements cannot be used.
    - Provides a rational framework.
- **Weaknesses**:
    - Can require accurate probability estimates.
    - Can be computationally intensive.
- **Opportunities**:
    - Useful in uncertain environments and long-term planning such as the CSNP and SSEP processes.
- **Threats**:
    - Additional information to be gained in outputs is limited by the information used in defining ranges of the inputs.

Stochastic Optimisation

An optimisation method that accounts for uncertainty by incorporating random variables into the model. It is more commonly used in Finance, Supply Chain, and Energy.

- **Strengths**:
    - Provides robust solutions under uncertainty.
    - Widely applicable.
- **Weaknesses**:
    - Can be computationally intensive to achieve 'measured probabilities'.
    - Requires probabilistic information.
- **Opportunities**:
    - Opportunity to learn from successes and challenges of how this is implemented in other industries
- **Threats**:
    - May require significant computational resources in future if the CSNP decision space becomes highly complex.

3. Recommend

Comparative Assessment

Recommend: Alternative to LWR

To recommend a suitable alternative to LWR, the four tools that were progressed from the SWOT analysis were examined in more detail against specified criteria to generate a recommendation. This comparative assessment was undertaken by Frazer-Nash Consultancy, with an independent review being completed by University of Edinburgh for the purpose of verification, described in the additional note*. Both assessments concluded that a Robust Bayesian Analysis should be the preferred technique.

The present project is concerned with possible replacements for LWR analysis, which is a single-point-in-time decision-making technique. Nevertheless, in applying LWR or any other technique, account needs to be taken of possible future decision-making opportunities, both in evaluating possible future paths and in determining their associated costs.

Comparative Assessment

To compare the four approaches being assessed, a multi-criteria decision analysis (MCDA) was used, with weightings populated based on NESO survey responses asking about the importance of each criterion (seven were completed) and outcomes of the requirements workshop (based on number of requirements linked to different criteria and the requirement's priority status). The weightings demonstrate the importance of explainability, but also the ability to manage uncertainty and traceability. The criterion-weightings are shown in Table 2.

Each of the down-selected tools was given a score of 1-5 for the different criteria, based on findings from a literature review and the SWOT analysis. The results of the MCDA are presented below, showing that Robust Bayesian Analysis ranked highest, with LWR ranking second highest (Table 1).

Table 1 – Results of MCDA.

Characterstic / Technique	Cost effectiveness	Adaptability	Customisability	Data security	Explainability	Integration capability	Interopability	Licensability	Real-time analysis	High resolution	Ease of scenario definition	Scalability	Support and training	Traceability	Uncertainty management	User friendliness	Score	Rank
Weighting	**3%**	**5%**	**6%**	**5%**	**19%**	**7%**	**1%**	**3%**	**4%**	**5%**	**8%**	**1%**	**9%**	**9%**	**9%**	**7%**		
Least Worst Regret	4	2	3	3	4	4	2	5	3	4	4	5	4	2	3	4	3.50	2
Info-Gap Decision Theory	4	3	3	3	4	3	3	5	3	3	2	4	4	4	4	3	3.47	3
Robust Bayesian Analysis	3	4	4	3	5	4	3	5	4	3	3	5	3	5	5	3	4.03	1
Stochastic Optimisation	3	3	4	3	3	3	3	5	3	4	3	3	3	3	4	3	3.26	4

* C. Dent,. A. Wilson and S. Zachary "CSNP - Economic Decision-Making Under Uncertainty - University Team Note" University of Edinburgh

Table 2 – Criterion-Weightings after combining survey results and requirements.

Criteria	Survey Results		Requirements		Weighting
	Mean	Median	No. Linked	Priorities	
Cost effectiveness	6.3	6.5	1	1	3%
Adaptability	7.0	7	6	11	5%
Customisability	7.0	8	3	6	6%
Data security	6.9	8	2	4	5%
Explainability	8.3	9	4	12	19%
Integration capability	7.0	8	8	19	7%
Interoperability	5.0	5	1	1	1%
Licensability	4.2	4	1	1	3%
Real-time analysis	3.6	4	2	4	4%
High resolution	6.2	6.5	13	36	5%
Ease of scenario definition	7.4	8	4	11	8%
Scalability	6.4	7	1	1	1%
Support and training	7.5	8.5	1	2	9%
Traceability	8.2	8	2	5	9%
Uncertainty management	7.3	8	3	11	9%
User friendliness	7.3	7	1	3	7%

4. Assess

Methodology Overview

Worked Example

Alternative Worked Example

Assess: Comparison with LWR

To demonstrate the use of the proposed alternative approach, Robust Bayesian Analysis, a well-defined worked example was undertaken. The worked example uses data produced from a historic NOA to confirm whether the proposed alternative tool was sufficiently beneficial compared to LWR to warrant internal changes to the CSNP process.

Methodology Overview

Least Worst Regret

LWR is a decision-making methodology that focuses on minimising the potential regret associated with a decision, often called *minimax* regret. A full description of the LWR approach used in the historic NOA can be found here[†]. A schematic of LWR is shown in Figure 2, and a summary is as follows:

1. Define the decision space: the total number of combinations of reinforcement options being considered. In this explanation, a decision is notated as d_i .
2. For each of the various possible evolutions of the future - here referred to as scenarios - calculate a cost associated with the reinforcement option (c_{ij} where i is the reinforcement option, and j is the scenario). In this assessment, the cost is a combination of Capex and constraint costs.
3. For each scenario, calculate a regret (r_{ij}) associated with the reinforcement option. The regret is the cost of the reinforcement option for a given scenario minus the minimum cost of reinforcement across all the scenarios for that reinforcement option:
$$r_{ij}=c_{ij} - \min_{i'} c_{i'j}$$
4. For each reinforcement option, find the maximum regret value. These values are the “worst-case” for each reinforcement option.
5. For the entire decision space, find the minimum “worst-case” decision. This is the reinforcement option that minimises the potential “worst-case” regret.

[†] https://www.neso.energy/document/90851/download

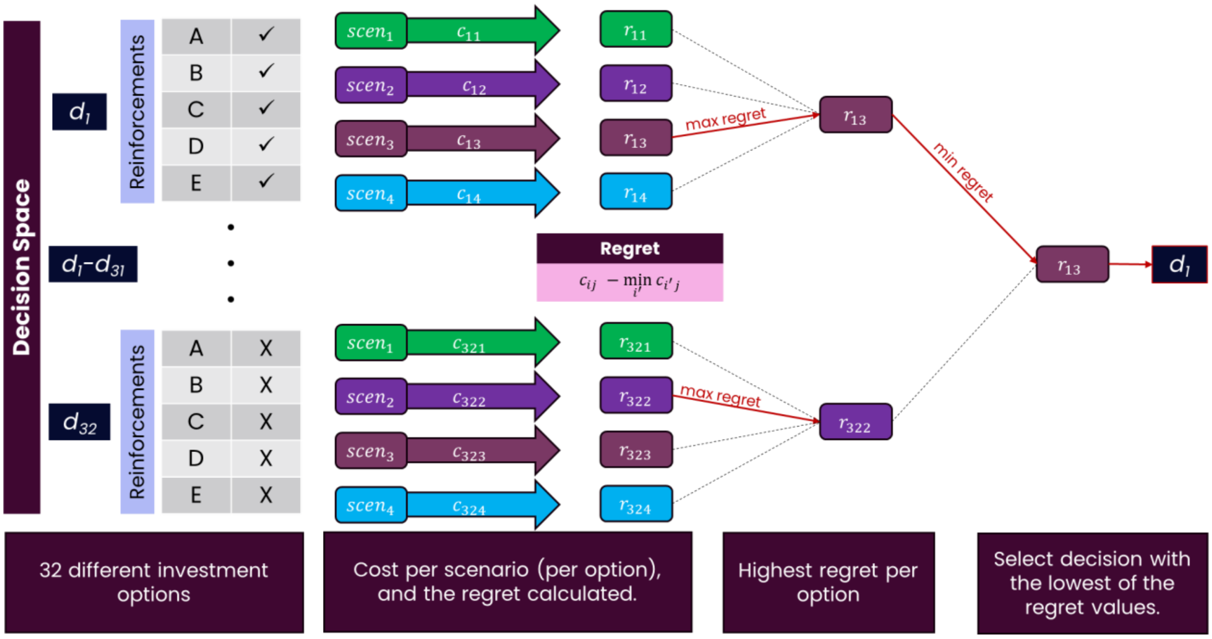


Figure 2 – Least Worst Regret schematic.

Least Worst Weighted Regret

Least Worst Weighted Regret (LWWR) is currently being proposed as an approach for NESO to use‡. Whilst the scope of the current project is to compare with LWR, a summary of LWWR is given for context.

LWWR is an extended decision-making methodology that aims to minimise the worst-case regret while also considering the relative importance of different scenarios. A summary of the LWWR approach is as follows:

1. Define the decision space: the total number of combinations of reinforcement options being considered.
2. Assign a weight to each scenario or pathway to reflect their relative importance.
3. For each scenario, determine the cost associated with each reinforcement option for every scenario.
4. For each scenario, calculate the regret for each reinforcement option by subtracting the minimum cost for that reinforcement option from the cost in the given scenario.
5. For each reinforcement option, calculate the weighted maximum regret for each reinforcement option by considering the weights assigned to each scenario.
6. For the entire decision space, choose the reinforcement option with the lowest worst-case regret when the weighted scenario values are applied.

Robust Bayesian Analysis

Robust Bayesian Analysis is a decision-making methodology that combines Bayesian principles with robustness techniques to account for uncertainty. Under this methodology, a decision is considered 'robust' if it is either optimal, or remains close to optimal, under all plausible assumption combinations. Robust Bayesian Analysis aims to provide

‡ https://www.neso.energy/document/185066/download

decision-making guidance while considering possible variations in the underlying assumptions. A schematic of this approach is shown in Figure 3, and a summary of it is as follows.

1. Define the decision space: the total number of combinations of reinforcement options being considered (d_i is a decision).
2. Assign a probability to each scenario which reflects a weighting of how likely a scenario is to occur, relative to the others (p_j).
3. For each scenario, calculate the probabilistically-weighted cost associated with the reinforcement option and the probability of that scenario (EC_i).
4. For each reinforcement option, calculate a sum of the weighted costs. This is the total cost of this reinforcement option for the assigned probabilities:
$$EC_i = \sum_j p_j c_{ij}$$
5. The subjective nature of assigning probabilities (step 2) can be addressed through the robust element of the proposed approach. This involves testing the robustness of the decision by exploring the decision space.
6. The **robust decision** is the reinforcement option that is optimal, or nearly optimal, for all plausible probability combinations. By iterating through the entire probability space, we are considering *all* possible combinations of reinforcement costs.

In this worked example, the robustness is tested by exploring the probability combinations from a range of likelihoods (between 0 and 1).

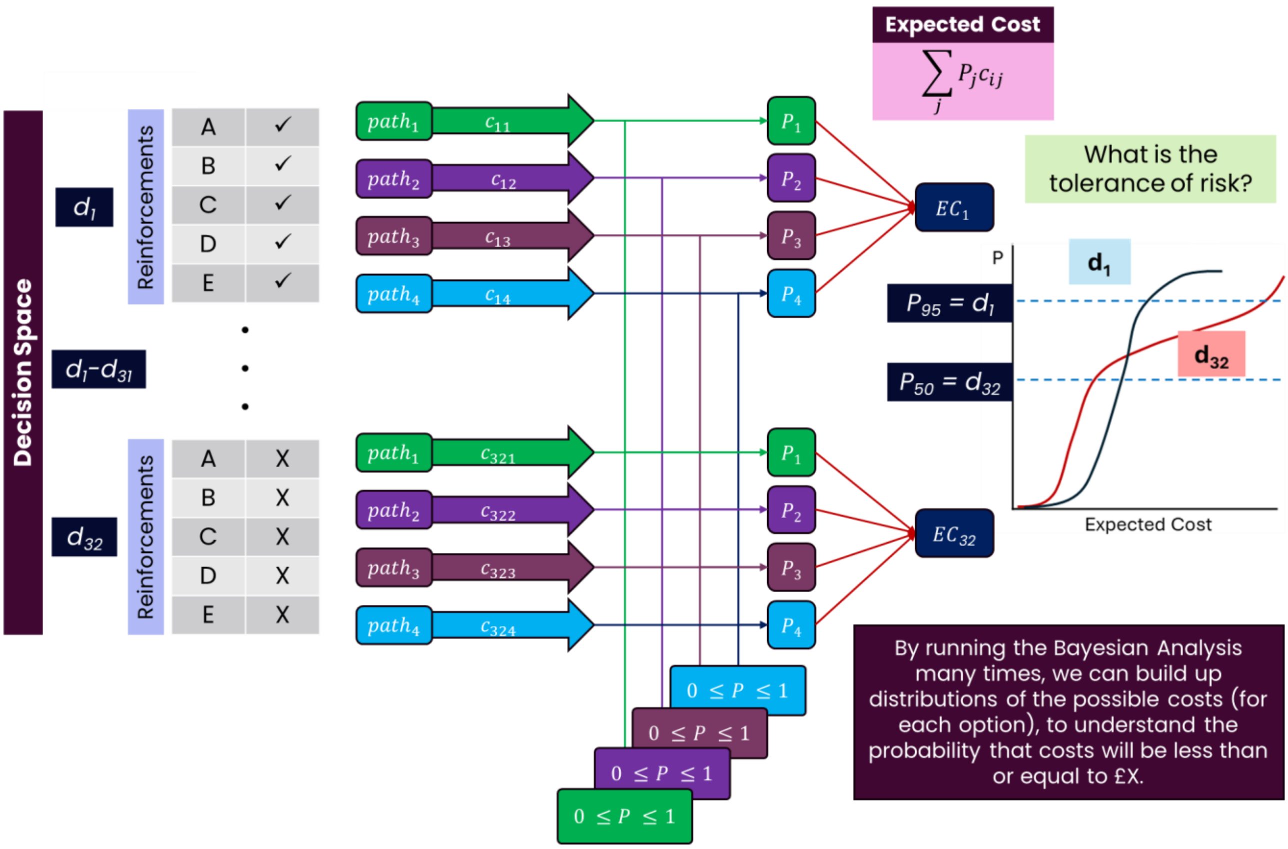


Figure 3 - Robust Bayesian Analysis schematic.

The benefit to using a Robust Bayesian Analysis is that it is economically rational, and it explicitly acknowledges and incorporates subjectivity/expert judgement regarding relative likelihood. There is no *one-size-fits-all* approach with a Robust Bayesian Analysis. The range and distribution of probabilities must be explicitly outlined before analysis begins. As all decision-making requires human judgement, a Robust Bayesian Analysis makes this subjectivity transparent and defensible.

Worked Example

Data

The data used in the worked example is representative of a previously analysed NOA. Figure 4 shows the total reinforcement costs associated with each combination of reinforcements across four scenarios (LW, ST, CT, and FS). The reinforcement costs are a combination of capital cost (i.e., the cost of a reinforcement/infrastructure) and the constraint cost (i.e., the cost arising from limitations on the network). For this worked example, there are five reinforcements (A, B, C, D, E). Therefore, there are 32 combinations of these reinforcements that are considered in the LWR and Robust Bayesian Analysis.

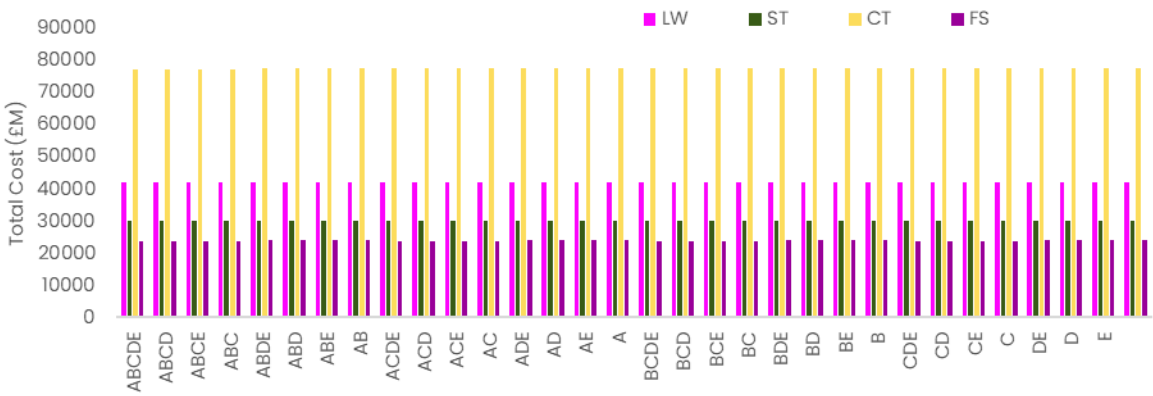


Figure 4 - Reinforcement costs for NOA-like example. Data provided by NESO.

Least Worst Regret

The result of the LWR is that reinforcement option **ABCDE** is the least worst regret option. That is, **ABCDE** is the reinforcement option that minimises the maximum regret possible.

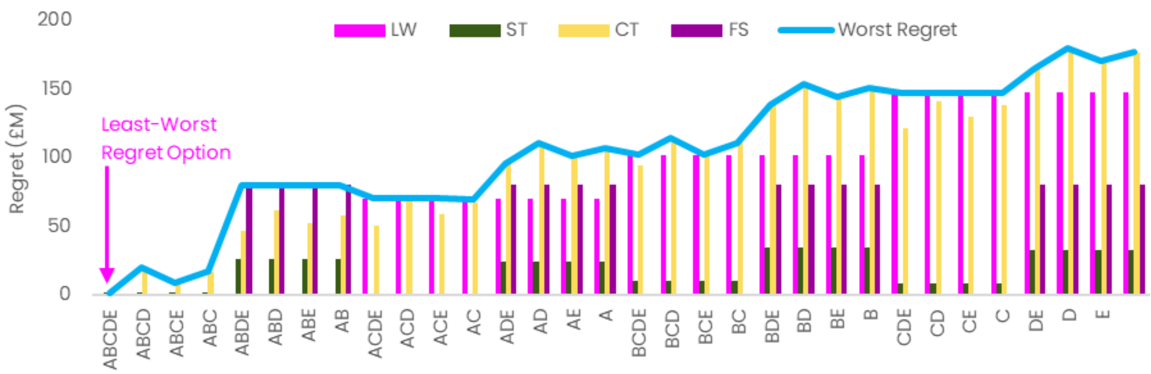


Figure 5 - LWR regret results for the worked example.

Figure 5 presents the regret associated with each reinforcement combination and the worst regret as a line across all combinations. The worst regret associated with **ABCDE** is £1.5M.

Robust Bayesian Analysis

With the data shown in Figure 5Figure 4, the Robust Bayesian Analysis approach was applied, using probabilities ranging from 0 to 1 for each of the four scenarios. This analysis found that in 99.4% of the probability space, reinforcement option **ABCDE** was optimal. In 0.6% of the probability space, reinforcement option **ABC** was optimal.

Figure 6 shows the cumulative likelihood functions of **ABCDE** and **ABC**. The cumulative likelihood function shows the evolution of likelihood that a cost of regret (£M) occurs.

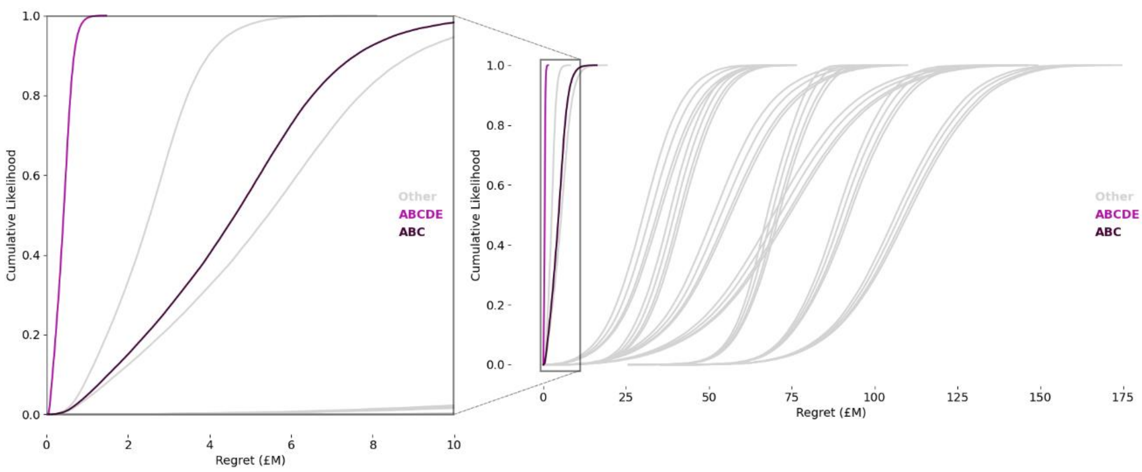


Figure 6 - Robust Bayesian Analysis cumulative likelihood functions for the worked example.

A benefit of Robust Bayesian Analysis is that, based on the entire space of future scenario likelihoods, you can gain confidence in the expected cost (or regret in this example). Depending on the stakeholder receiving outputs, the presentation and language used to portray results can be adapted for accessibility. Whilst analysts may be comfortable inferring results from cumulative likelihood functions, other stakeholders, such as the general public, may wish to receive justifications for decision in more familiar language, such as “in 99.4% of cases analysed, **ABCDE** was the reinforcement option that minimised the total cost to consumer”. The ranked decisions can also be tabulated, for example:

Rank	Decision	Lowest expected regret (£M)	Most likely expected regret (£M)	Highest expected regret (£M)	Confidence
1st	ABCDE	0.01	0.42	1.44	99.37%
2nd	ABC	0.04	4.46	16.54	0.61%
3rd	ACDE	0.37	30.26	67.08	0.01%

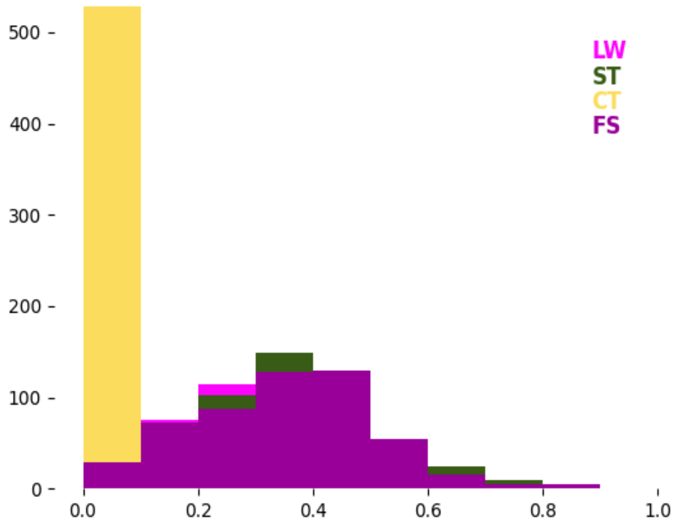


*Figure 7 - Histogram showing the frequency of scenario likelihood when ABCDE is **not** the optimal decision for the worked example.*

Additionally, should one wish to understand the factors driving the second-best decision, the probability ranges can be explored by subjectively altering the ranges of probability associated with each scenario and rerunning the analysis. This can inform discussions between decision-makers about how likely, or not, a scenario is to emerge and whether much attention should be given to alternative decisions.

For example, Figure 7 shows that when ABCDE is not the optimal, the CT scenario had a likelihood of 0-10%. Decision-makers can use this information to reflect on their beliefs about the true likelihood of CT occurring and understand the scenario trigger points where the best investment decision mix changes.

If we are confident that CT should have a higher probability, we can change its range of likelihoods to be 10-100% and re-run the analysis, which results in ABCDE being optimal in 100% of runs.

The performance of **ABCDE** can also be compared with the 'optimal solution' in these samples. In all cases, **ABCDE** was very close to the optimal value (<£0.05M regret), providing additional confidence that **ABCDE** should be progressed.

Based on the data provided, the final decision aligns with LWR and doesn't necessarily demonstrate the benefits of a Robust Bayesian Analysis. We have therefore explored the approach further using an alternative worked example.

Alternative Worked Example

To better demonstrate the value of a Robust Bayesian Analysis, the input cost for **ABCDE** in the FS scenario was increased by £10M (a 0.04% increase on the original cost).

Least Worst Regret

As a result of the relatively small alteration in the cost for a single scenario for **ABCDE**, LWR analysis now finds that **ABCE** is the reinforcement combination that is best, as seen in Figure 8.

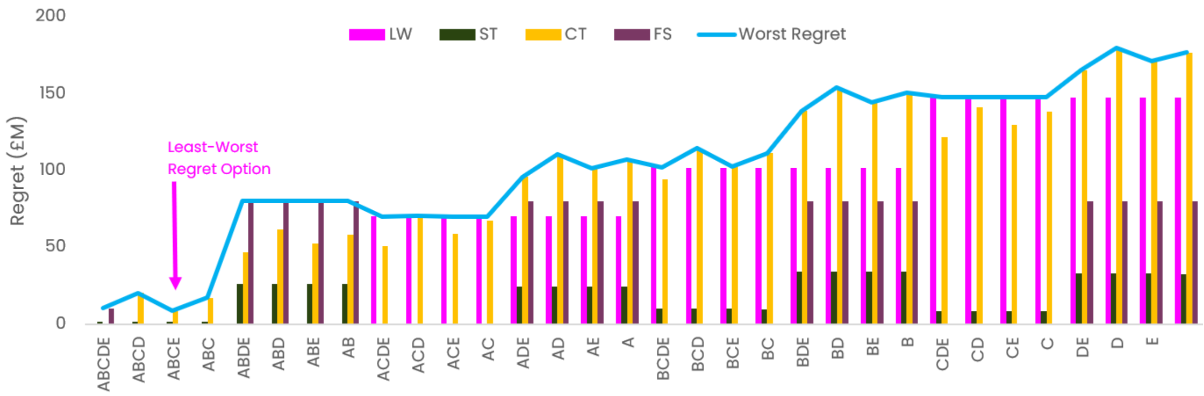


Figure 8 - LWR regret results for the alternative worked example.

Robust Bayesian Analysis

When this is run through the Robust Bayesian Analysis, the same option is identified as optimal most often (**ABCE**), as shown in Figure 9. However, this is only for 57% of the probability space, reducing our confidence in that decision, with **ABCDE** being identified as optimal in 43% of samples. For both approaches, the minor adjustment to costs - acknowledged to be inherently uncertain, demonstrates the sensitivity of the output recommendations to small changes in input parameters. However, Robust Bayesian Analysis provides context and information to drive subjective discussion post-analysis, which LWR is less capable of doing.

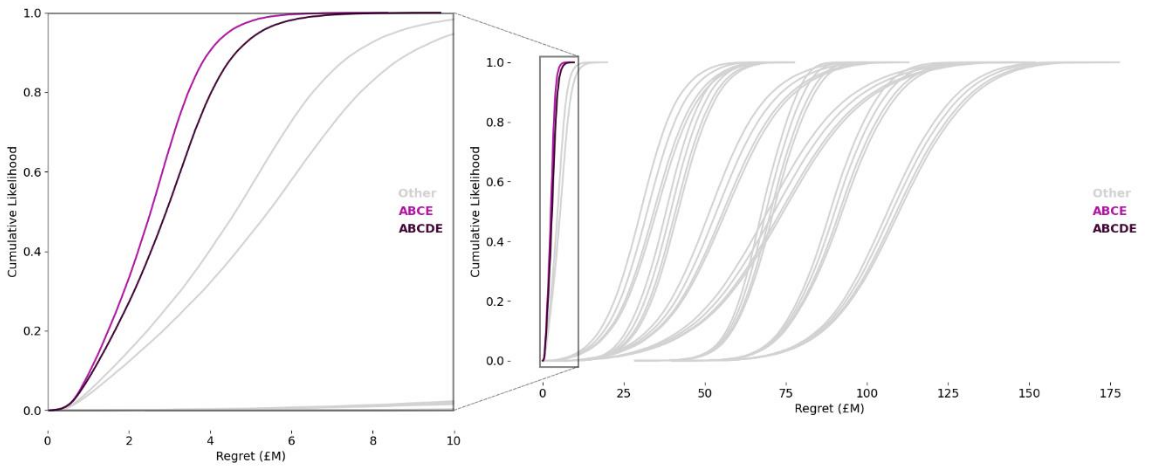


Figure 9 - Robust Bayesian Analysis cumulative likelihood functions for the alternative worked example.

Rank	Decision	Lowest expected regret (£M)	Most likely expected regret (£M)	Highest expected regret (£M)	Confidence
1st	**ABCE**	0.08	2.55	8.05	57%
2nd	**ABCDE**	0.04	2.93	9.76	42%
3rd	**ABC**	0.02	4.64	16.05	1%

As before, the histogram in Figure 10 shows the sampling instances where the most commonly optimal solution **ABCE** is in fact not optimal. While less stark than the original example, there is a trend that in the FS scenario solution **ABCE** has probabilities of being optimal of 40% and below. If we believe FS is more than 40% likely to be realised, the analysis should be re-run with a range of likelihoods on FS of 40–100%. This retains **ABCE** as the preferred option, but now across a more confident 84% of the probability space. Comparing the performance of **ABCE** with the 'optimal solution' in these samples shows more variation, with up to £5M regret difference from the optimal solution.

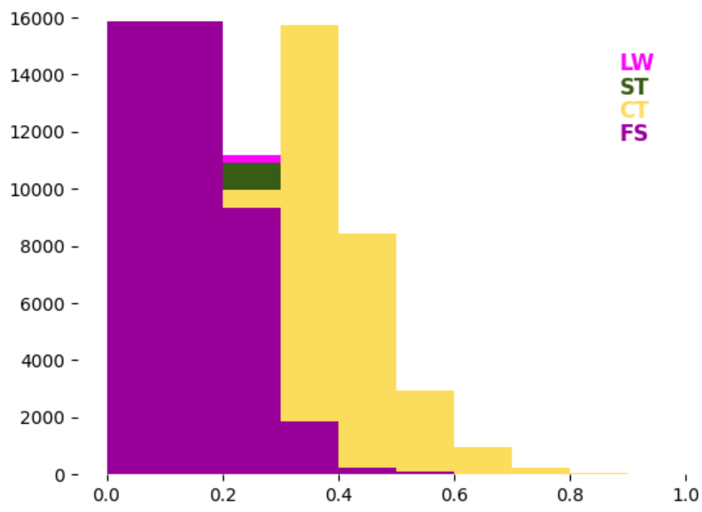


*Figure 10 - Histogram showing the frequency of scenario likelihood when **ABCE** is not the optimal decision for the alternative worked example.*

5. Conclusions

Conclusions

The project finds that the LWR tool for economic decision-making is sub-optimal for the significant infrastructure projects the CSNP will be assessing. Many times, LWR will provide a 'good' answer, however this is very much dependent on inputs, and it will not always provide the 'best' answer or an understanding of the sensitivity of the outcome to input assumptions. The proposed alternative solution is a Robust Bayesian Analysis, which is flexible to the changing needs of the CSNP and provides much greater insight and transparency as to the factors driving the decision.

The final recommendation is that NESO should implement a Robust Bayesian Analysis as the tool for making economic decisions. The proposed technique complies with the requirements elicited from the NESO teams, specifically with how it is:

Managing Uncertainty

Robust Bayesian Analysis accounts for uncertainty on inputs, through the assigning of probabilities. In the case of the CSNP, the uncertainties lie in what the future pathway of the UK energy system might be. To account for this, the costs associated with multiple scenarios can be estimated and considered for assessment, with probabilities assigned to each scenario and an associated regret calculated for that probability distribution.

Where there is high uncertainty in future scenarios, as there is here, and a reluctance to assigning probabilities (which could also risk application of present-day biases), Robust Bayesian Analysis allows for the informal exploration of the probability space. Exploring the probability space enables analysts and decision-makers to understand the sensitivity of reinforcement costs to changes in scenarios.

It is also acknowledged that the costs themselves are uncertain, particularly constraint costs, which are based on restrictive assumptions. An extremely valuable attribute of the Robust Bayesian Analysis is that it is flexible enough to handle uncertainty associated with the cost inputs. LWR would not be able to handle uncertainty in this manner.

Explainable and Transparent

Robust Bayesian Analysis is a well-established approach for generating explainable and transparent decision outputs. Whilst the probabilistic nature of the approach could deter stakeholders from engaging, the robust approach can be used to provide confidence that a decision has been tested against a wide range of uncertain futures.

The fundamental application of a Robust Bayesian Analysis allows for:

1. Calculation of confidence metrics for the most favourable decision.
2. Interrogation of the instances of 'tipping points' where a decision is no longer favourable.

3. Investigation into what the 'next best' decision might be, and whether there are similarities with the best.

Ability to Communicate Decisions

The proposed approach can be used to generate outputs with different extents of information based on both a stakeholder's appetite for detail and experience of using statistical methods. The table below describes how the outputs can be tailored to the audience, while giving confidence in the decision.

Stakeholder Group	Level of detail/ expertise	Communication Type	Type of information
Analysts Economic Assessment Teams	High	‣ Robust Bayesian Analysis tool (internal) ‣ Data Workbook (external)	Underlying datasets and distributions for interrogation.
TOs Ofgem	Medium	‣ Appendix of CSNP Publication	Examples of 'outliers' where a recommendation would not be the optimal solution. High-level metrics for the most frequently optimal options.
Directors Secretary of State General Public	Low	‣ CSNP Publication ‣ Community Consultation	Range of anticipated costs for the decision. Associated confidence in these costs, and in the decision being optimal (e.g., 90% confidence in this being the best option).

Robust to Future Energy Landscapes and Costs

A decision can be tested for robustness by running the analysis for many probability combinations, which allows for cases where the likelihood of each scenario is not known. Where there is more confidence in certain scenarios, the probabilities can be weighted in their favour. However, if there is little evidence favouring any scenario, and there are concerns around 'present-day biases', a full sweep of all probability combinations can be run.

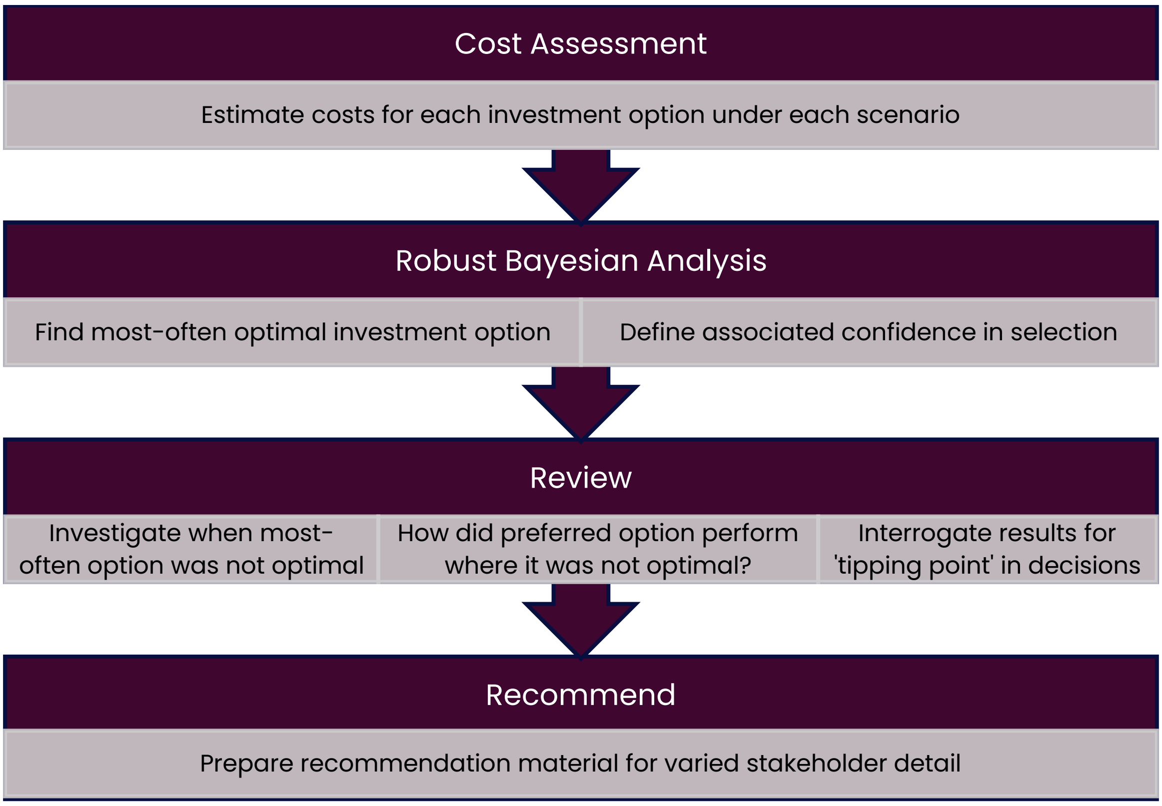
This approach also allows for additional uncertainties to be considered without changing the fundamental workflow. These uncertainties could include:

- Capital and constraint costs for each scenario.

- Wider, less traditional economic considerations such as societal and/or environmental impact.

Integrates with the CSNP Process

The Robust Bayesian Analysis approach can integrate within the CSNP process without impairing the current methods in place. The following diagram provides the key stages in the economic decision-making stage of the CSNP, and what considerations should be covered when applying the proposed approach.



While the practical steps to implement the process will be relatively straight-forward, it will require a change in mindset of the analysts and key stakeholders to familiarise themselves with the benefits of the benefits of the approach.

Instead of viewing Least Worst Regret as an approach that avoids subjectivity and delivers the single optimal option, stakeholders will instead be able to use Robust Bayesian Analysis ***to challenge implicit subjectivity*** *and* ***to explore the performance of other options*** *based on the wide range of probability options.*

Appendix A

Full SWOT Analysis

NESO
National Energy
System Operator

Human Judgement

Robust Decision-Making

A method for making decisions under deep uncertainty by evaluating multiple scenarios and identifying strategies that perform well across them.

- **Strengths**:
    - Handles deep uncertainty well.
    - Flexible and adaptive.
- **Weaknesses**:
    - Can be complex and resource intensive.
- **Opportunities**:
    - Can be useful in long-term planning and policymaking, making it applicable to the CSNP process.
- **Threats**:
    - Could be difficult to communicate and implement, making stakeholder engagement and buy-in difficult – a key aspect of the CSNP process.

SWOT RESULT: A

Decision Tree Analysis

A graphical representation of decisions and their possible consequences, including chance event outcomes, resource costs, and utility.

- **Strengths**:
    - Easy to understand and visualise.
    - Helps in making structured decisions.
- **Weaknesses**:
    - Can become very complex with many branches.
    - Relies on extensive expert engagement.
    - More focussed on qualitative decision-making.
- **Opportunities**:
    - Considered useful in project management and strategic planning, therefore applicable to the CSNP process.
- **Threats**:
    - Inaccurate design can lead to poor decisions, making it dependent on capturing the CSNP accurately.

SWOT RESULT: R

Scenario Planning

A strategic planning method that organisations use to make flexible long-term plans by considering various possible future scenarios.

- **Strengths**:
    - Encourages long-term thinking and flexibility.
- **Weaknesses**:
    - Time consuming.
    - More focussed on qualitative decision-making.
- **Opportunities**:

    - Can be helpful in identifying potential risks and opportunities and therefore give alternative ideas for the CSNP process.
- **Threats**:
    - Scenarios may be too broad or unrealistic and therefore difficult to map to the CSNP scenarios.

SWOT Result: R

Deterministic / Computational

Min-Max

A decision rule used in decision theory and game theory to minimise the possible loss for a worst-case scenario.

- **Strengths**:
    - Provides a clear strategy for worst-case scenarios.
- **Weaknesses**:
    - Tends to be overly conservative.
    - Ignores potential gains.
- **Opportunities**:
    - Useful in competitive environments and risk management, which isn't applicable to the CSNP process.
- **Threats**:
    - Could lead to suboptimal decision-making if worst-case scenarios are unlikely.

SWOT Result: R

Min-Max Regret (Least Worst Regret)

LWR is an optimisation algorithm which focuses on minimising the maximum regret of decisions across a range of scenarios. In this context, regret is the net benefit difference between an investment strategy and the best strategy for a scenario.

- **Strengths**:
    - Focuses on minimising potential regret.
- **Weaknesses**:
    - Does not guarantee the best outcome and can be overly cautious, since cannot consider difference in likelihood between different outcomes.
- **Opportunities**:
    - May help in making more cautious decisions in uncertain environments such as the CSNP.
- **Threats**:
    - Can be difficult to explain reason for result to stakeholders due to mechanistic approach.

SWOT Result: G

Min-Max Cost

A decision-making approach that aims to minimise the maximum cost associated with a decision.

- **Strengths**:
  - Effective in cost-sensitive environments.
  - Clear focus on cost control.
- **Weaknesses**:
  - Tends to be overly conservative.
  - Ignores potential gains.
  - May ignore other important factors like quality or benefits.
- **Opportunities**:
  - Useful in budgeting and financial planning. For CSNP this could be used to highlight minimum cost risk options
- **Threats**:
  - For CSNP, this could lead to cost-cutting at the expense of quality.

SWOT RESULT: R

Robust Programming

A method in optimisation that ensures solutions remain feasible and effective under a range of possible scenarios.

- **Strengths**
  - Ensures solutions are resilient to uncertainty.
- **Weaknesses**
  - Can be computationally intensive.
  - Requires well-defined uncertainty sets.
  - Doesn't readily allow for subjectivity in potential inputs.
- **Opportunities**
  - For CSNP, this would compel investment analysis teams to explore a comprehensive list of feasible scenarios, potentially leading to further insights.
- **Threats**
  - May require significant computational resources.

SWOT RESULT: R

Info-Gap Decision Theory

Used in Engineering and Conservation, a method for making decisions under severe uncertainty by focusing on robustness to failure.

- **Strengths**
  - Handles severe and deep uncertainty well.
  - Does not rely on probabilistic information.
- **Weaknesses**
  - Can be overly conservative
  - May not always lead to optimal decisions.
- **Opportunities**
  - The CSNP approach could learn from implementations in engineering, environmental management, and economic decision-making.
- **Threats**

    - Could lead to poor decisions if inaccurate data is used. A complex CSNP process may have uncertainties in the data.

SWOT Result: G

Min-Min

A decision rule that aims to minimise the minimum possible loss.

- **Strengths**:
    - Simple and easy to understand.
    - Focuses on minimising losses.
- **Weaknesses**:
    - May ignore potential gains.
    - Can be overly conservative.
    - May ignore other important factors like quality or benefits.
- **Opportunities**:
    - For CSNP, this could highlight the lowest loss options to decision makers.
- **Threats**:
    - Can lead to suboptimal decisions if potential gains are significant.

SWOT Result: R

Cost-Benefit Assessment (CBA)

A systematic approach to estimating the strengths and weaknesses of alternatives by comparing costs and benefits.

- **Strengths**:
    - Provides a clear comparison of costs and benefits.
    - Widely used.
- **Weaknesses**:
    - Can be difficult to quantify all costs and benefits.
    - May require restrictive assumptions.
    - Does not allow for consideration of uncertainty in inputs.
- **Opportunities**:
    - For CSNP, this could form a useful input set to the decision making.
- **Threats**:

Does not help with the down-selection of option mixes on its own

SWOT Result: R

Probabilistic / Stochastic

Robust Bayesian Analysis

A probabilistic approach to decision-making that allows for subjectivity to be incorporated into the analysis through definition of prior probabilities.

- **Strengths**:
    - Allows for subjectivity to be considered where measurements cannot be used.
    - Provides a rational framework.
- **Weaknesses**:

    - Can require accurate probability estimates.
    - Can be computationally intensive.
- **Opportunities**:
    - Useful in uncertain environments and long-term planning such as the CSNP and SSEP processes.
- **Threats**:
    - Additional information to be gained in outputs is limited by the information used in defining ranges of the inputs.

SWOT RESULT: G

CBA under Uncertainty

A variation of CBA that incorporates uncertainty into the analysis.

- **Strengths**:
    - Provides a more realistic assessment of costs and benefits under uncertainty.
- **Weaknesses**:
    - More complex than standard CBA.
    - Requires additional data.
- **Opportunities**:
    - Applicable to a future CSNP process as it is used in decision-making for uncertain environments and long-term planning and will provide additional information for the decision makers to consider.
- **Threats**:
    - Technical complexity could make it difficult to implement and communicate in the CSNP process.

SWOT RESULT: A

Stochastic Optimisation

Used in Finance, Supply Chain, and Energy, this is an optimisation method that accounts for uncertainty by incorporating random variables into the model.

- **Strengths**:
    - Provides robust solutions under uncertainty.
    - Widely applicable.
- **Weaknesses**:
    - Can be computationally intensive to achieve ‘measured probabilities’.
    - Requires probabilistic information.
- **Opportunities**:
    - Opportunity to learn from successes and challenges of how this is implemented in other industries
- **Threats**:
    - May require significant computational resources in future if the CSNP decision space becomes highly complex.

SWOT RESULT: G

Real Options Analysis

A method for valuing the flexibility of making future decisions based on changing conditions.

- **Strengths**:
    - This is an approved Treasury Green book economic investment appraisal approach to addressing timing uncertainty in investment decisions.
- **Weaknesses**:
    - Can be complex and require advanced knowledge.
- **Opportunities**:
    - Opportunity to be incorporated into the CSNP decision making process as part of the timing decisions on investment options.
- **Threats**:
    - Complexity can make it difficult to implement and communicate in a future CSNP process.

SWOT RESULT: A

Dynamic Adaptive Planning

A planning approach that adapts to changing conditions over time by continuously updating plans.

- **Strengths**:
    - Highly flexible and adaptive.
    - Handles uncertainty well.
- **Weaknesses**:
    - Requires continuous monitoring and updating.
    - Can be resource intensive.
- **Opportunities**:
    - Useful in long-term planning and policy making, therefore this could be suitable for incorporating into a future, more complex, CSNP process.
- **Threats**:
    - Resource-intensive nature can be a barrier, making it difficult to implement within the CSNP decision-making process.

SWOT RESULT: A

Dynamic Adaptive Policy Pathways

A method for developing adaptive policies that can change over time in response to new information and changing conditions.

- **Strengths**:
    - Highly flexible and adaptive.
    - Handles deep uncertainty well.
- **Weaknesses**:
    - Requires continuous monitoring and updating.
    - Can be complex.
- **Opportunities**:
    - Opportunity to be incorporated into the CSNP long-term decision-making process as scenarios evolve.

- **Threats**:
  - Complexity and compute resource requirements can be barriers to implementation, making it hard to apply in a complex CSNP process.

SWOT RESULT: A

Portfolio Analysis

A method for evaluating and managing a portfolio of investments or projects to achieve specific objectives.

- **Strengths**:
  - Provides a comprehensive view of a portfolio.
  - Helps in diversification.
- **Weaknesses**:
  - Can be complex and require advanced analytical skills.
- **Opportunities**:
  - Applicable to the CSNP process as it has precedent in investment management and strategic planning decision making.
- **Threats**:
  - Technical complexity could make it difficult to implement for a future CSNP process that has many pathways.

SWOT RESULT: A