Study of advanced modelling for network planning under uncertainty

Part 1: Review of frameworks and industrial practices for decision-making in transmission network planning

Report prepared for National Grid Electricity System Operator

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Acronyms

AEMO	Australia Electricity Market Operator
CAPEX	capital expenditure
CBA	cost-benefit analysis
C&R	challenge and review
CR	Community Renewables
CVaR	conditional value-at-risk
DC	direct current
DCF	discounted cash flow
DER	distributed energy resource
DSM	demand side management
ECON team	Economic Assessment team
EENS	expected energy not served
EISD	earliest in-service date
ETYS	Electricity Ten Year Statement
FES	Future Energy Scenarios
GB	Great Britain
GDP	Gross Domestic Product
HVDC	high-voltage direct current
IC	interconnectors
LOLE	loss of load expectation
LOLP	loss of load probability
LWR	least worst regret
LWWR	least worst weighted regret
MMC	min-max cost
MMR	min-max regret
MMWC	min-max weighted cost
NEM	National Electricity Market
NGESO	National Grid Electricity System Operator
ND	Network Development
NOA	Network Options Assessment
NPC	net present cost
NPV	net present value
Ofgem	Office of Gas and Electricity Markets
RES	renewable energy source
RoCoF	rate of change of frequency
SC team	System capability team
SEW	social economic welfare

SQSS	Security and Quality of Supply Standard
SRF	System Requirement Forms
TD	Two Degrees
TEA team	Technical economic assessment team
TEP	transmission expansion planning
TO	transmission owner
VaR	value at risk

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Executive summary

In this report we address a number of fundamental questions of interest to NGESO for its NOA process, namely:

- What decision-making methodologies are available and which ones are practically adopted in different countries for electricity system planning under uncertainty?
- How could different decision-making methodologies be compared in a systematic way?
- What is the potential role of probability weights assigned to scenarios?
- Is LWR an adequate decision-making tool within the NOA scope?
- How could the current NOA decision-making process be improved?

To address these questions, we have performed a thorough literature review of technical and academic literature and current industry practices on transmission planning worldwide, as well as of methodologies for decision making under uncertainty.

The results of our study suggest that National Grid's current NOA methodology is at the forefront of the state of the art, particularly with regards to the use of a rolling-horizon Least Worst Regret (LWR) approach which accounts for considering the impact of the suggested investment option across multiple scenarios as well as for some degree of decision flexibility. Furthermore, none of the surveyed system operators around the world seems to adopt probability weights for their scenarios, and it is not even clear how integrated decisions across multiple scenarios are made.

To assess potential implications of a "more probabilistic" analysis, in case including scenario weights, and the use of different methodologies for planning across uncertain future, we have developed a new framework that views the planning problem across multiple (in case probability-weighted) scenarios as a multi-objective optimization problem. We then demonstrate how apparently different methodologies such as probabilistic planning (expected value analysis), min-max cost, LWR, etc., do essentially solve the *same* distance-minimization problem but only using different metrics in a vector space that describes probability-weighted attributes (e.g., costs, regrets) for several scenarios.

One of the consequences of looking at the NOA problem through the lenses of such a framework is that the current LWR approach *does* already include (implicit and equal) probability weights. In the same vein, comparing a probabilistic assessment approach, which aims to minimise expected costs (or, equivalently, expected regrets, as we show) across scenarios using specific weights, and a LWR approach with no weights (that is, with *implicitly* equiprobable scenarios) might be inconsistent, as the problems that they would be solving would effectively be different. A more consistent comparison could be carried out, as we discuss in our proposal, by adopting a more general Least Worst Weighted Regret (LWWR) approach, for which the current NOA methodology could readily and seamlessly be adapted in order to incorporate scenario probability weights.

In general terms, in comparison with a probabilistic assessment, we show how LWR (or the more general LWWR) is intrinsically "less risky" and allows exploring more investment solutions. Therefore, irrespectively of the use of scenario weights, LWR may be considered superior from the point of view of a decision maker that is *risk-averse*, and appears to be an adequate methodology to perform transmission investment analysis in a highly uncertain environment.

As potential NOA methodological developments, while we are aware that the selection of probability weights to assign to scenarios may be difficult and controversial, we believe that our proposed unified framework could at least provide a consistent and comprehensive approach to seamlessly compare and assess the outcomes of (apparently) different methodologies (i.e., stochastic/probabilistic, LWWR and min-max weighted cost), with scenario weights being considered as a *natural* component of the analysis. This could introduce, with negligible changes required in the NOA process, more transparency and robustness to the investment analysis and the selected options, thus resulting in reduced risk of spurious solutions and reduced risk of decisions being driven more by scenarios than by the methodologies themselves, and in general in enhanced hedge against planning uncertainty. As exemplified in a synthetic network case study application, such analysis could also be supported by visual tools that could identify *decision-stability* regions with win-win recommendations from different methodologies, suggest what solutions might require further analysis, and provide a systematic way to perform sensitivities to assess costs, benefits, risks and robustness of alternative investment options in the presence of uncertain scenarios.

1. Introduction

1.1. Context

With increasing renewable penetration level and electrification of different end-use sectors, electrical networks around the world are experiencing a drastic change of power flows at both distribution and transmission levels. The need for reinforcing existing networks is thus becoming more urgent and frequent. At the same time, there is increasing uncertainty as to what new network users will connect to the system, and when and where. Planners are thus required to strike a delicate balance between security and cost while facing significant long-term uncertainty. In the technical analysis of system planning, the planner needs to develop sophisticated models to mimic the operation of future power systems which are expected to be characterised by lower inertia and substantial volumes of non-dispatchable renewables and distributed energy sources. As for the economic analysis, due to the inherent nature of investment in large infrastructures, with large capital expenditures and long payback periods, the planner is required to thoroughly assess all reasonable reinforcement options and maximise consumers' benefits while hedging the risk of stepping into different potential futures. Solving all these challenges proves to be a daunting task, especially if the planner wants to proceed in a consistent and traceable way.

As the operator of the Great Britain (GB)'s power system, National Grid Electricity System Operator (NGESO) is in charge of carrying out several studies to inform stakeholders and provide recommendations about the development of the GB system in both the short and long terms. Among these studies, the Network Options Assessment (NOA) aims to assess the network reinforcement requirements across the GB system for the next 20 years, and to produce recommendations as to what assets to build or services to procure to meet those system requirements. The NOA involves both technical and economic evaluations that are performed for different scenarios. The technical analysis is currently carried out considering a deterministic approach based on a winter snapshot of operation of the system; the 'Electricity Ten Year Statement (ETYS)' process then evaluates network 'boundaries' based on scaled generation and demand. Based on this technical evaluation and the potential reinforcement options put forward by the Transmission Owners, the NOA cost-benefit analysis (CBA) then identifies the optimal path of network reinforcements by applying a single year Least Worst Regret (LWR) approach that takes into account the need for asset investment considering the multiple scenarios.

1.2. Aims and objectives

In this report, we aim at addressing a number of fundamental questions of interest to NGESO for its NOA process, namely:

- What decision-making methodologies are available and which ones are practically adopted in different countries for electricity system planning under uncertainty?
- How could different decision-making methodologies be compared in a systematic way?
- What is the potential role of probability weights assigned to scenarios?
- Is LWR an adequate decision-making tool within the NOA scope?
- How could the current NOA decision-making process be improved?

To address these questions, first we will perform a review of technical and academic literature and current industry practices on transmission planning worldwide. Additionally, we will review the academic and industry literature on decision making under uncertainty, focusing on different techniques (e.g., probabilistic approach, LWR, min-max cost, etc.), risk management approaches, and practical applications in different countries. We will then introduce a new, unified view of different methodologies for planning under uncertainty – most noticeably probabilistic planning and LWR. The proposed framework allows a consistent approach to decision making across several scenarios and potentially considering probability weights for each scenario, clear analysis of expected benefits and risks from different methodologies and scenario weights, and more transparent and robust insights into the reinforcement options recommended. Based on both the knowledge gained in the review and original research inputs, we will finally provide feedback on the current methodology and propose initial recommendations to potentially improve NGESO's planning process to deal with uncertainty.

1.3. Report structure

- Section 2 sets out to describe our understanding of the NOA process as an approach to make investment decisions in transmission expansion planning, not only for the boundaries within GB system but also for the interconnectors between GB and neighbour European countries.
- Section 3 presents a literature review on decision making under uncertainty and international best practices for transmission expansion planning (TEP), so as to compare the NOA's assumptions, principles, and attributes to the international experiences in the subject, identify relevant differences, and explore potential theoretical and practical improvements.
- Section 4 introduces a new view of planning across multiple (probability-weighted) scenarios as a multi-objective optimization problem, which allows us to develop a consistent representation of different methodologies for decision making under uncertainty – including probabilistic approach, min-max cost, and LWR – as a geometric distance problem applied to different value attributes (e.g., cost, regret) for different candidate solutions. Relevant case studies also illustrate the benefits of the proposed approach and some powerful tools that can enhance transparency and robustness of transmission planning under uncertainty.
- Section 5 provides overall feedback on the current NOA methodology based on the studies performed and puts forwards initial recommendations on potential improvements in terms of both the theoretical framework that supports the NOA process and the mechanics of the process itself.

2. The Network Options Assessment process

This section provides a general description of the NOA process. The description is based on official documentation published by NGESO [1], [2] and a series of interviews with different people involved in the NOA process. An adequate understanding of the process, as per steps, people involved, timing, supporting theory, working assumptions, etc. is of essence to provide recommendations that fit both the structure of process and the resources available.

The NOA process is run on a yearly basis with the objective to provide recommendations to the transmission operators on what projects to execute. The recommendations fall within 5 different categories that are described in Section 2.3.4. As presented in Figure 1, the NOA process is based on a rolling horizon strategy, in which each year a set of candidate transmission reinforcements is proposed by the transmission owners (TOs) in the context of scenarios describing the system's future (Future Energy Scenarios (FES) [3]).

The window of time used to assess the different reinforcement options varies between 20 and 60 years in different stages of the process in order to cope with the lifespan of transmission projects (40 years) and the window to make the investment decision (20 years).

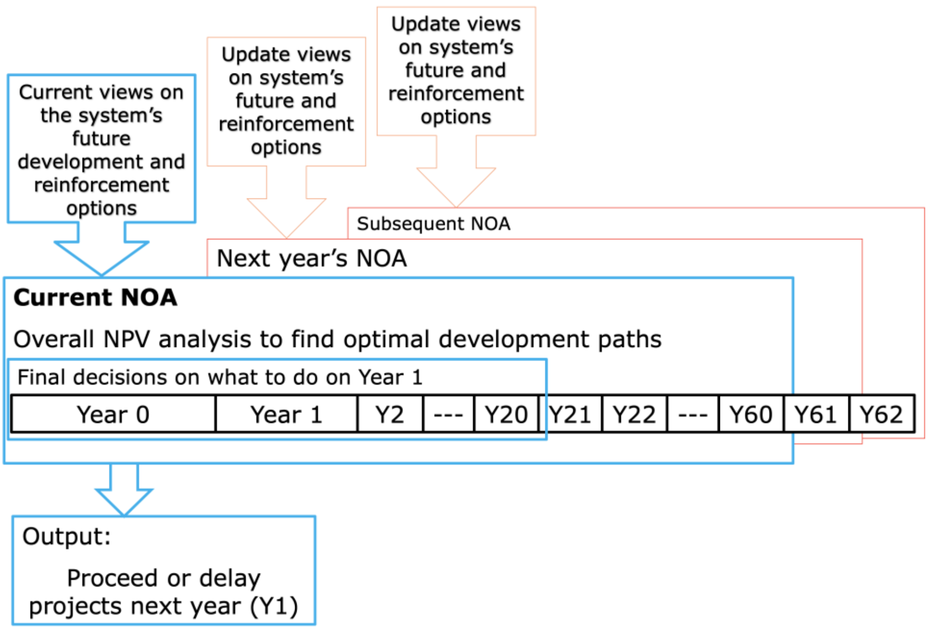


Figure 1. Inputs, output and rolling window structure of the NOA process

The NOA process is run by the Network Development (ND) Team within NGESO. The ND Team interacts mainly with the TOs, both to inform them about system requirements (determined within ETYS [4]) and to get the different reinforcement options to be considered in the NOA.

The following sections describe specific aspects of the process, including the timeline, modelling aspects of the process, and technical and economic assessments.

2.1. Team structure and timeline

The Network Development Team is a group of over 20 people that performs the different tasks associated with the technical and economic assessment of the process. The assessment spans over several months and it is repeated on a yearly basis.

The **Technical Economic Assessment Team** (TEA team) owns the NOA report and coordinates the entire process. It acts as the layer of communication with stakeholders, in particular the Office of Gas and Electricity Markets (Ofgem) and the TOs. Also, it helps the Economic Assessment Team and System Capability Team with heavy processes, like the cost-benefit analysis (CBA) and the challenge and review (C&R) process of the information provided by the TOs. It is in charge of assessing the pathfinding projects, which correspond to the evaluation of novel approaches to meet system needs.

The **System Capability Team** (SC team) owns the ETYS report which presents the boundary requirements and capabilities for the GB System. It also runs a C&R process of the information provided by the TOs about boundary capabilities. The general description of the SC team tasks is presented in section 2.2

The **Economic Assessment Team** (ECON team) owns the CBA and determines the investment decisions based on LWR. The process involves modelling the future conditions of the system and the economic impact of different transmission reinforcements under different system scenarios. The steps involved in CBA are described in section 2.3.

The activities conducted by each team are interdependent and also, they are affected by external inputs and interactions with other stakeholders, as presented in Figure 2.

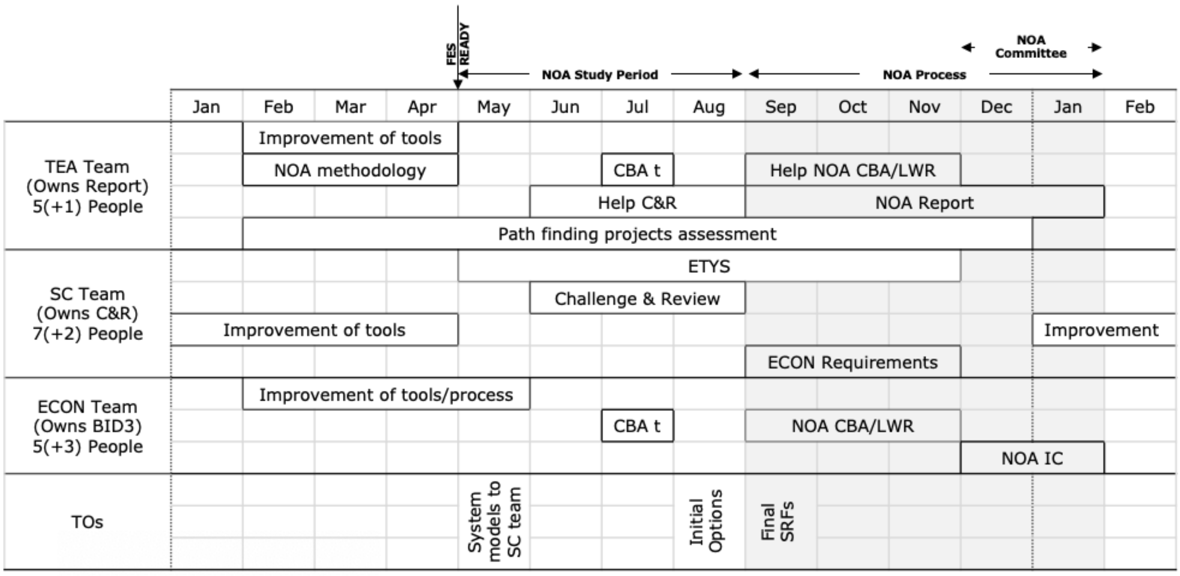


Figure 2. Simplified chart presenting main and timing of the NOA related activities conducted by the ND teams

The tasks can be grouped in three categories: improvements of processes, study period (including training for the CBA, or "CBA t") and NOA process. The report is published during January and before presenting the recommendations resulting from the analysis, these undergo the scrutiny of a group of experts, the NOA committee, to check that the recommendations are sound.

2.2. Boundary capability assessment

This step of the process is responsibility of the system capability (SC) team. The purpose is to determine the capability requirements of the GB system and assess the boundary capability provided by combinations of reinforcements.

The process starts with the development of the ETYS report, which processes the Future Energy Scenarios and determines the requirements of the network for the next 10 years for each scenario. The process includes running the scenarios with an unconstrained transmission network in BID3[1] to determine the boundary requirements; also, the SC team runs specific studies described in the Security and Quality of Supply Standard (SQSS) [5] for each boundary to generate information that is made publicly available and also sent to the TOs so that they can propose options for reinforcement.

The concepts of boundaries, boundary capability and reinforcements interact in the process of determining the required transmission infrastructure in GB. Boundaries correspond to virtual frontiers of interest; they allow to quantify the capacity of the system to transfer power across it. Reinforcements, on the other hand, are physical assets that can be deployed in the system[2]. They affect the capacity to transfer power across one or more boundaries (also known as boundary capability). A given set of reinforcements can unlock additional boundary capability when they are deployed in the system. The interaction between reinforcements and boundaries is depicted in Figure 3. In this example, there are three reinforcement options (D, E, F) and three boundaries (B1, B2, B3); each combination of reinforcements may impact the boundary capability (BC) of the boundaries under consideration (for example, BC_{EF_B3}, corresponds to the boundary capability of boundary B3 when the set of reinforcements "EF" is in place). Some reinforcement combinations may not be possible because of rules governing their interactions (for instance, rule "F must follow E" makes reinforcement sets "F" and "DF" infeasible). The information that the TOs are required to provide and the SC team is required to review is similar to the table shown within Figure 3: for various combinations of reinforcements (not all of them, as the set of combinations grows exponentially with the total number of reinforcements) various boundaries are analysed to determine the resulting boundary capabilities that are unlocked. This process is conducted for selected years.

[1] BID3 is a proprietary power market dispatch tool developed by AFRY.
[2] NGESO can propose no-build or reduced build options that can also bring network benefit.

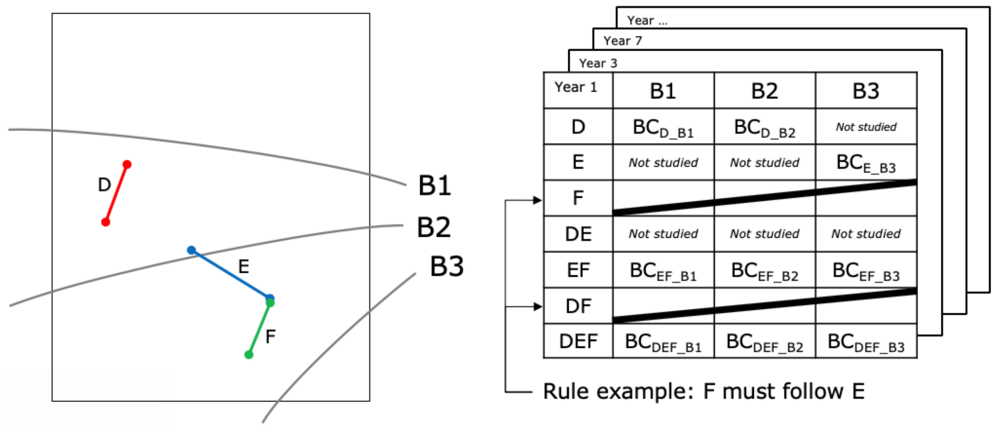


Figure 3. Boundaries, reinforcements and boundary capabilities

With the aim of including a probabilistic assessment of the boundary capabilities, the SC team has also developed a tool based on direct current (DC) load flow and Monte Carlo analysis to calculate the resulting distribution of boundary flows for input distributions of loading and generation conditions of the whole system, which is used at the stage to provide information of boundary requirements year round.

Considering the reinforcement options that the TOs propose in response to the requirements reported in the ETYS, the SC team runs studies described in the SQSS to confirm the capability reported for each combination of options under consideration. The information produced by the SC team is used for a process of C&R of the capabilities that the TOs inform for each option and combinations of options based on the boundary studies they perform annually; the information provided by the TOs and reviewed by the SC team is then used to run the NOA CBA. The base network models and study guidelines are annually agreed among all parties involved in the assessment.

The main elements in the SC team tasks are presented in Figure 4.

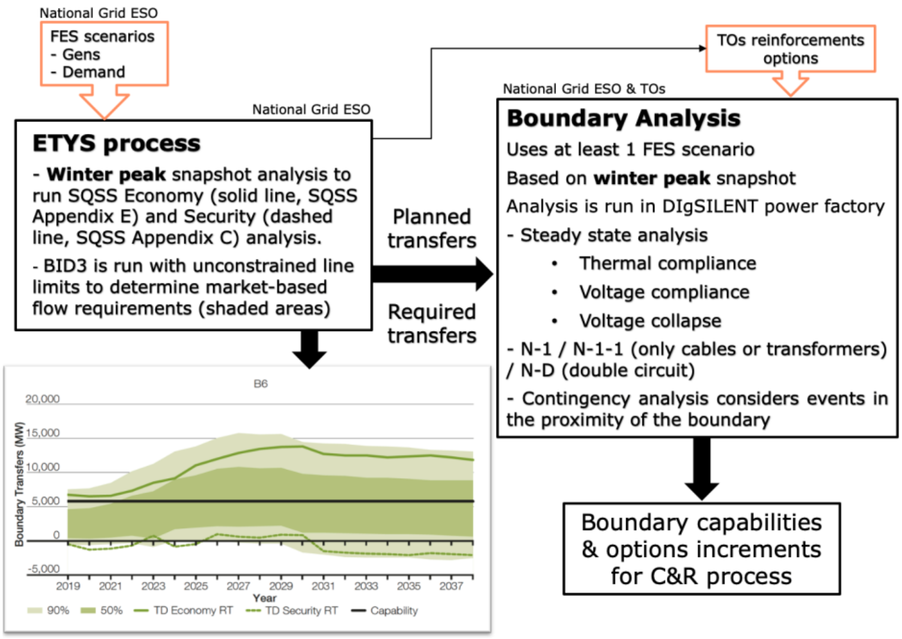


Figure 4. System Capability team process

It is important to highlight some of the aspects of the procedure to calculate the boundary capabilities for the C&R process. The SC team in principle uses only one scenario of the FES, which is selected on the grounds of the level of stress the scenario imposes to the boundaries so they can find robust capability limits (the scenario is selected in agreement with the TOs). The target is to find the scenario which, on average across all boundaries, stresses the network the most. In the last three years the selected scenario has been the one labelled as two degrees (TD), which drives very high north to south power flows due to all the northern wind generation observed in Scotland. In the current NOA process, the community renewables (CR) scenario came very close to the network loading of the TD scenario; however, TD was selected under the consideration that using the same scenario as before generates consistency with previous year's results. If available resources allow, the SC team would run sensitivities against other scenarios and other relevant parameters (e.g. interconnector flows) to report the difference in the boundary capabilities for different system conditions.

2.3. Cost-benefit analysis

NGESO has to produce recommendations that fall within the range of "proceeding" or "not proceeding" the next years' actions to secure that the projects that are critical will be in place at the right time.

To complete this task the NOA process starts by finding the optimal set of reinforcements in the system (from a cost-benefit point of view) for each of the four FES scenarios which describe four different future conditions for the system. The set of optimal reinforcements for each scenario is a subset of a total of near 200 projects (for the 2019-2020 NOA process) presented by the transmission operators. Each project has an "Earliest In-Service Date" (EISD) which corresponds to the earliest year the project could be in place, but the cost-benefit assessment will determine if it is better to build the reinforcement by EISD or later on.

The deployment of a subset of projects is governed by interaction rules. Some projects:

- *can be mutually exclusive*,
- *must follow* other project(s), or
- *must happen together with other project(s)*.

On top of these 3 interaction rules, some projects might not be feasible to build simultaneously because of conflicting outages in the network that are required to deploy the new infrastructure.

It is also important to highlight that not all the combinations of projects have a corresponding boundary capability evaluation, as it was described in the previous section. Also, the impact of some combinations of projects on capability is available for some boundaries and not for others. If no information is available for a specific boundary given a set of reinforcements, the base case value for the boundary is considered.

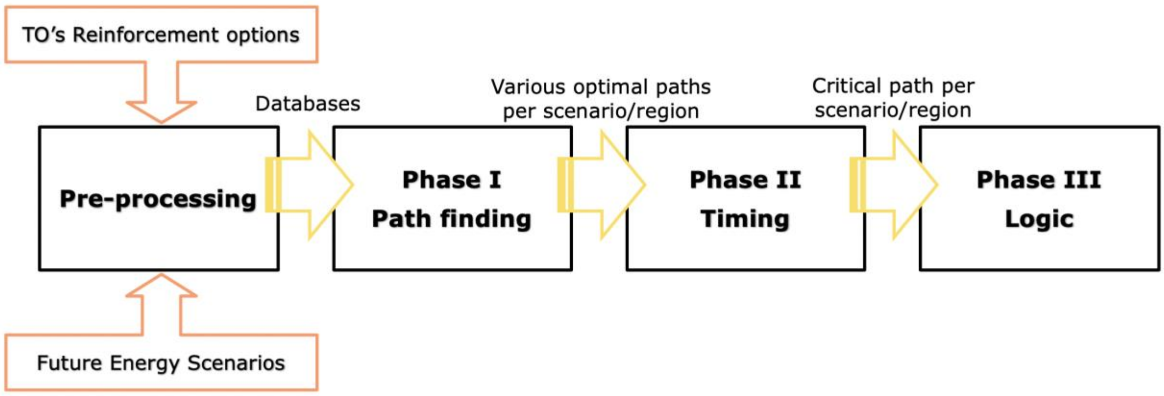


Figure 5. Cost-benefit analysis process

The previous rules and the considerations about information availability reduce the search space of combinations of reinforcements in each scenario to impact the boundary capabilities of the system. The search is conducted in two phases, phase I and II, also known as path finding and timing phases, respectively. As depicted in Figure 5, these two phases yield an optimal path of reinforcements for each scenario; the resulting paths enter phase III or logic phase, to calculate the permutations necessary to run the LWR process.

The following sections describe the actions conducted within the phases of the CBA, highlighting duration, assumptions, inputs and results.

2.3.1. Pre-processing and power system modelling

The CBA analysis relies on the techno-economic modelling of the system to assess the trade-off between additional investment in transmission and the corresponding benefits associated to the reduction of the transmission constraints costs. NGESO uses BID3, which needs to be fed with information about the structure of the GB's power system to describe current and future conditions.

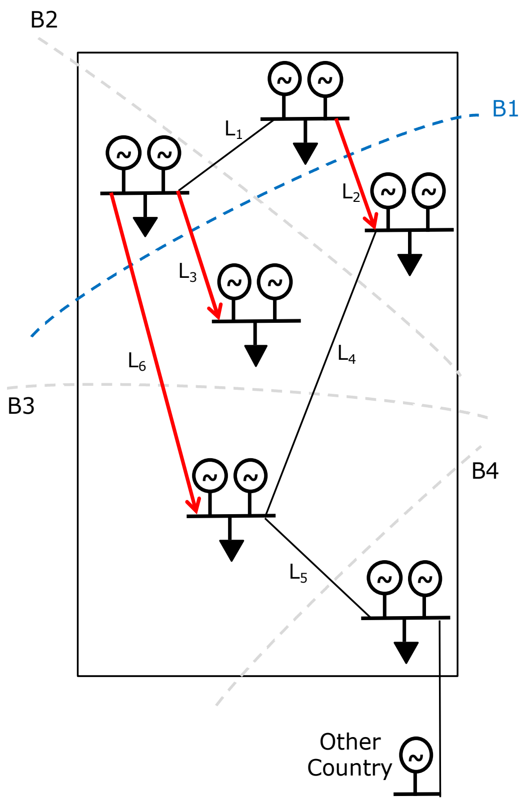


Figure 6. Boundary modelling

The boundaries that represent the GB system are defined in the ETYS. These boundaries interact, as illustratively depicted in Figure 6, defining areas that are then used to determine the generation technologies and aggregated load that represent each of them. Each area is represented as a balancing node, and then they are interconnected through fictitious transmission lines without transfer limits. The constraints that matter to limit flows between areas are those associated to the boundaries, which are imposed by determining all the transfers between areas that cross the boundary. For instance, for boundary B1, the flows through lines 2, 3 and 6 (F_{L2}, F_{L3} and

F_{L6}) respectively are constrained by the boundary capabilities of B1 (BC_{B1},BC_{B1}^{rev}) as follows:

$$-BC_{B1}^{rev} \leq F_{L2} + F_{L3} + F_{L6} \leq BC_{B1}$$

A given set of transmission reinforcements may affect the value of BC_{B1} and other boundaries. To assess the effect of a set of reinforcements on constraint costs, the boundary capabilities are changed in BID3 when the reinforcement is considered. The associated benefits are balanced out by the investment costs of the corresponding reinforcements.

To get to this point, first it is necessary to determine the **base network** for GB, which is based on current system conditions and projects under construction.

The interaction with neighbouring countries is assessed a priori, through a simplified description of the GB system and its neighbours. BID3 is run considering the conditions for each of the scenarios. This allows creation of bidding price functions for every time step for all neighbour countries. These price functions are later used to determine interconnector flows when assessing the detailed operation of GB.

There is an additional consideration in regard to the general approach to model the system. The system displays a high degree of decoupling between the south region (England and Wales) and the north region (Scotland); reinforcements in one region show a relatively low impact on the distribution of the flows in the other region. By assuming that reinforcements in one region have low impact on the opposite region it is possible to limit the combinations of reinforcements that need to be studied to derive the capabilities of the boundaries contained in the incumbent region. The base networks used to analyse each region are reinforced on the opposite region to avoid systematic bottlenecks that can degrade the quality of the result in the target region.

BID3 models a linear economic dispatch of generators, based on a rolling horizon approach within each year under consideration. Years are assumed to be independent, which means that results are not transferred from one year to the next. The model is run based on 3 or 6 hour steps, where the representing values for load and variable renewables in a given step are selected by choosing a random representative hour within each 3 or 6 hour period (e.g. for step 7-12, the operation could be represented by hour 9 for all the time series involved). Variable renewable units, load and other input parameters are arranged in a database for all the hourly periods and all scenarios in the planning horizon.

Another important aspect of the pre-processing stage is the consolidation of the so-called System Requirement Forms (SRF) into data ready to be used in the BID3 simulations. These forms are provided by the TOs and they contain the information about the different reinforcement options, including EISD, capital expenditure (CAPEX), outages, rules, boundary capabilities (thermal, voltage, stability), etc.

When all the information required to run the CBA is ready, the ECON team executes the path finding phase.

2.3.2. Phase I: Path finding

The objective of this phase is to determine potential development paths for the network in each scenario and each region. All the analysis is run in Microsoft Excel in a purpose-specific arrangement of spreadsheets and macros (the tool is known as COMP) to prepare BID3 input files and read results. This phase spans for around 4 weeks and 8 people are directly involved in the task (one for each scenario and each region).

The process is broadly trial and error. By running the base network, the cost of each boundary constraint is determined for each year (and for each scenario). This signalises the boundaries that require capability expansion, hinting what reinforcements should be considered for the system. The boundary capabilities associated to the sets of candidate reinforcements to address the previous constraint costs are included in BID3; a new case study is run in order to determine the cost of constraints associated to the new boundary capacities.

The results of the BID3 runs are arranged in the form of a matrix displaying boundaries on the rows and years on the columns. By exploring different entry years (after EISD) it is possible to visually recognize (heatmap) the changes in the constraint costs in each boundary to identify further reinforcement requirements.

After quantifying the benefits of deploying different combinations of reinforcements, this information is used to determine the optimal entry year of each reinforcement. There are reinforcements that clearly dominate the pool of options; hence the resulting paths have common combinations that branch out.

The resulting paths are compliant with the rules mutually exclusive, must follow, and must happen together.

2.3.3. Phase II: Timing

The most important aim of this stage is to check that outages associated to the construction of different reinforcements do not produce clashes that can make the path infeasible. The clashes strictly happen during lead-time because they are related to operation issues while building the reinforcements. If the clashes were not lead-time related, they would be part of the mutually exclusive rule.

If a clash is found, the entry date of the reinforcements creating the problem is changed until the lead-time clash is resolved. If further clashes are created, the process continues until the deployment of the reinforcements is clash-free.

After solving all the clashes by displacing reinforcements, one of the paths found in the previous stage will yield the largest benefits. This path is considered optimal (one for each scenario for each region). All the reinforcements that are critical in one or more of the scenarios associated to these paths enter the final stage (logic phase) to conduct the LWR.

Phase II takes around 1 week to be completed using 8 people.

2.3.4. Phase III: Logic

Each of the paths found in phase II is a collection of reinforcements and entry dates. Those reinforcements whose optimal entry date is the same as its EISD in any of the scenarios, are classified as critical. The logic phase looks to determine the LWR strategy among all the possible permutations produced by proceeding with or delaying each of the critical options.

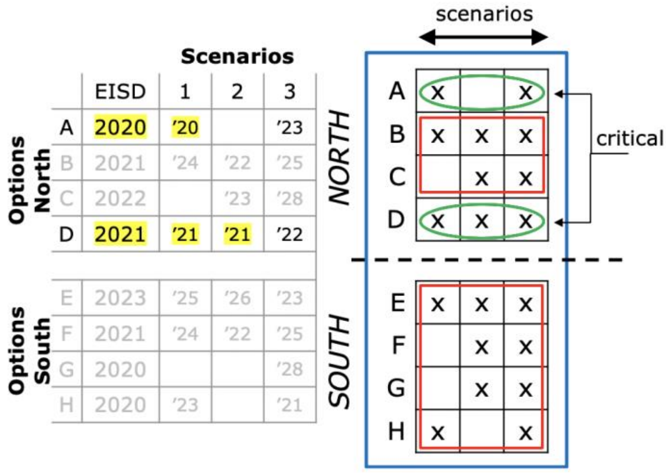


Figure 7. Example for a system with 2 regions and 8 reinforcements

Figure 7 presents an example to depict the concept of critical reinforcements. Let us consider there are three scenarios and four options in each region of the system. After running phases I and II, the results will look as presented on the left-hand side table in Figure 7. All reinforcements in the north region appear active in the paths found in phase II for one or more scenarios. In particular, reinforcements A and D become optimal on their EISD, which means that they are labelled critical.

Let us now assume that there are no critical options in the south region. Then, as depicted in the right-hand side diagram in Figure 7, all non-critical reinforcements optimal entry dates (red boxes) for each scenario are fixed to the value found in the previous phase. The critical options entry dates are permuted between the optimal entry date (EISD for some scenarios) and delaying it one year, thus creating new deployment paths that may require running further studies in BID3 to determine their operational costs.

It is relevant to highlight that those reinforcements that need to be deployed by EISD are critical because any delay in the decision about proceeding would prevent the reinforcement to become available when the system needs it (according to the optimal paths found in the previous phases).

The process of permuting all the critical options between the states “proceed” or “delay by one year” gives form to the so-called “single year LWR”. Considering the example presented in Figure 7, the results for the permutations of the two critical options would look as presented in Figure 8. The four permutations produce 12 different cases, considering that the entry year for the reinforcements vary depending on the scenario. Each case will have a different net present value (NPV), which will allow to compare the four strategies (permutations), calculate the regrets and in turn determine the minimum (among strategies) maximum (among scenarios) regret. In Figure 8, the strategy that yields the LWR is permutation 3, which considers proceeding with both options. This yields the ***Proceed*** recommendation for reinforcements A and D, that is, over the following year the work on those reinforcements should continue, or start, to maintain the EISD.

The ***Delay*** recommendation is given when an option is optimal and critical but delaying it by one year results in lower regrets. This means that phases I and II show that the optimal time to deploy the expansion is EISD for at least one of the scenarios, but when permutating and running the LWR, delaying its deployment by 1 year is optimal from the point of view of the LWR metric. Another recommendation that can be deduced from this process is to ***Hold.*** For those reinforcements whose optimal in-service year is later than EISD there is no pressing need to continue developing that option. Delivery of this reinforcement should be delayed by at least one year.

Permutation	Recommen-dation	Scenario	In Service Date	NPV [m£]	Regret [m£]	Worst Regret [m£]
1	Proceed Option A & Delay Option D	S1	A: 2020 D: 2022	149	51	51
		S2	A: ------ D: 2022	100	0	
		S3	A: 2023 D: 2022	145	5	
2	Delay Option A & Proceed Option D	S1	A: 2021 D: 2021	98	102	102
		S2	A: ------ D: 2021	65	35	
		S3	A: 2023 D: 2022	140	10	
3	Proceed Option A & Proceed Option D	S1	A: 2020 D: 2021	200	0	15
		S2	A: ------ D: 2021	98	2	
		S3	A: 2023 D: 2022	135	15	
4	Delay Option A & Delay Option D	S1	A: 2021 D: 2022	47	153	153
		S2	A: ------ D: 2022	68	32	
		S3	A: 2023 D: 2022	150	0	

Figure 8. Permutations and calculation of regrets

The process can also result in the ***Stop*** recommendation. A reinforcement that is already being built or procured, which does not appear in the optimal paths stemming from phases I and II in the current NOA, should not continue. In a similar fashion, an option that was not being built and does not appear in the optimal paths, gets the recommendation ***Do not start***.

2.4. Network Option Assessment for Interconnectors

NOA for Interconnectors (NOA IC) aims to provide a quantified assessment of the potential benefits of increased interconnection with neighbouring countries. The NOA IC and the NOA are not interdependent; the results found in the NOA are used as the input information for the NOA IC, but the results of the NOA IC are not fed back into the current NOA process, they are used as an input in the next year's FES process, hence influencing also next year's NOA process.

The NOA IC methodology is a techno-economic assessment of the optimal level of interconnection capacity for GB. It evaluates the social economic welfare (SEW), that is, the overall benefit to society of a particular course of action, which includes pondering constraint costs and capital expenditure costs of both the interconnection capacity and network reinforcements necessary to increase the transfer capabilities between GB and selected countries in Europe. The NOA IC does not assess the viability of real projects, it only indicates the amount of interconnector capacity and the countries to interconnect that create the most SEW. Currently, the path for expansion of interconnection is produced for each scenario independently.

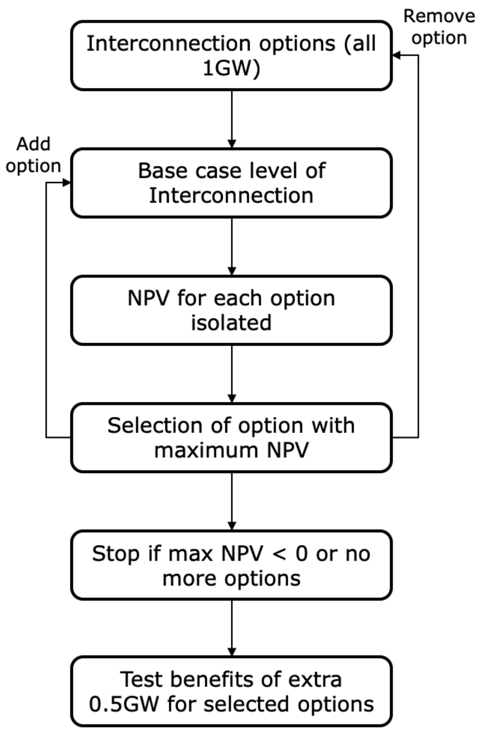


Figure 9. NOA IC steps

Figure 9 presents a diagram of the general steps taken to run the assessment. Firstly, the list of interconnection location options is determined, and each of them is assigned an interconnection capacity of 1GW. Second, in the context of a base network (results of current NOA and current interconnection levels) each individual alternative is added at a time, to assess its SEW. After running the analysis for all the options, the one with the most SEW is added to the base network. The process continues until all interconnections have been added or if none of the remaining options generates positive SEW. After defining the set of 1GW expansions that result in positive SEW, an additional step of adding 0.5GW to the subset of selected expansions is conducted to determine if more SEW can be captured from additional interconnection levels. The optimal deployment path is presented for each of the scenarios under consideration.

3. Literature review and international best practices

3.1. Uncertainty in electrical power system Transmission Expansion Planning (TEP)

3.1.1. Uncertainty sources

Power systems are currently heavily influenced by development of energy policy, growth of new technologies and evolution of new business models. All these lead to high and growing uncertainty. This section reviews the main uncertainty sources influencing transmission expansion planning (TEP). CIGRE's review on uncertainty in optimal power system planning [6] is the starting point of this analysis.

1. **Load growth:** Uncertainty in demand development has been traditionally one of the system planner's main concerns. In fact, most planning methodologies already include some level of uncertainty in demand. Currently, demand patterns are expected to change due to electrification of end-uses (e.g. cooking, heating) and the appearance of new technologies (i.e., electric vehicles, electric heat pumps). Furthermore, these new technologies can potentially be responsive to system conditions through demand side management (DSM), distributed storage, etc. In this context, there are high levels of both short-term (e.g., higher variability and uncertainty, price-responsive demand) and long-term (e.g., levels of electrification of other sectors, energy efficiency measures) uncertainties associated with the demand side.
2. **RES growth**: The penetration level of renewable energy sources is increasing in the system due to energy policies and cost reduction, especially in the case of Distributed Energy Resources (DERs), which has changed the traditional view of the distribution network as a passive network. These new elements need to be included in both network operation, considering the increase in variable and partly unpredictable and non-dispatchable generation, and therefore increasing operational uncertainty, as well as network planning, considering the uncertainty in volume, location and timing of renewable energy sources (RES) connection.
3. **Commercial technologies**: Traditionally, power systems have required high investments and considerable lead times to implement network changes. Nevertheless, new technologies (i.e., DSM, battery storage, etc.), can result in lower investment costs and shorter lead times compared to traditional infrastructures. However, they are characterised by cost functions that are largely based on operational cost (which are typically uncertain) rather than investment costs as for traditional asset. This creates issues in how to compare these two types of assets (traditional investment-heavy infrastructure with relatively small operational costs and low-investment asset with considerable operation costs), also considering that, depending on the regulatory framework, new technologies may not belong to or be operated by the system operator.
4. **Regulatory and energy policy environment**: Energy policy and regulation are currently under continuous revision in most countries, being a great source of long-term uncertainty. A few of the most remarkable ways in which regulation and policy might affect power systems are the following:
    a. Influence the cost of certain technologies by directly supporting their development using subsidies or by taxing other technologies. For instance, subsidies to promote residential PV are a common practice in many regions of the world.

b. Introduce new schemes which affect the paradigm of the sector. For instance, enforcing the consideration of environmental issues, promoting the development of certain regions, or considering interconnection objectives with other countries.

5. **Electricity markets and regulation**: Closely related to energy policy, in regions with high decarbonization targets there is an ongoing revision of power market structures and mechanisms that can have crucial effects on economic dispatch and power flows. Furthermore, new technologies have triggered the appearance of new markets, which are currently under study. For instance, the increase of renewable penetration level and the full retirement of coal plants by 2025 is challenging NGESO to fulfil its role of reliably operating the GB power system. However, the GB electricity wholesale market does not offer enough incentive to build relatively low-carbon conventional generators, e.g., combined cycle gas turbines and biomass plants, which are required to enable adequate reserve margin in winter peak periods. Therefore, a capacity market mechanism has been introduced to give extra financial support to peak capacity contributor since 2014 [7]. Similar challenges are being faced in other jurisdictions worldwide, for example in Australia
6. **Generation mix**: Changes in the generation mix are a source of long-term uncertainty as well. As has been mentioned throughout this section, new technologies have emerged and are being introduced with high penetration in power systems worldwide, changing the generation mix in most regions. This change may be driven by policies (e.g., subsidies for renewables), extreme events (e.g., catastrophic events leading to closure of nuclear generation), new ancillary services requirements in the presence of renewables and asynchronously connected resources (e.g., requirements for faster frequency response and minimum system inertia), etc.
7. **Investment cost**: The uncertainty in (reduction of) investment costs of new technologies increases the uncertainty of the planning problem, as it might change the optimal investment option (both in resources portfolios as well as in asset to facilitate the development of new resources) in a few years. For instance, the cost reduction of new technologies such as high-voltage direct current (HVDC) might lead to a totally different optimal design of reinforcement. The substantial cost reduction of renewable generation and batteries could also substantially impact the planning exercise.

Hence, in this rapidly evolving and highly uncertain context there are a number of new opportunities but also risks. Planning the electricity network using modelling that is able to consider rightfully all these uncertainty elements is therefore key to provide cost-effective solutions.

3.1.2. Uncertainty factors in TEP

As mentioned above, there are seven key uncertainty factors that have been identified in the TEP process. Based on the documents ([1]–[3], [6], [8]–[13]), which describe the current TEP practices of six countries across four continents, Table 1 summarises the uncertainty factors currently being considered or which are material but are not considered by corresponding network planner.

It can be noticed that **load growth and RES uncertainty** is being considered in all countries, although State Grid considers the increasing penetration of RES in a deterministic way, as the planning of renewable energy in China is under the jurisdiction of the National Energy Agency.

As for **generation mix**, this uncertainty factor has been widely acknowledged by all six network planners that have been reviewed, but only the Australian Electricity Market Operator (AEMO) and EirGrid have made relevant considerations on the impact of evolving generation mix, e.g., by setting new frequency response requirements and inertia constraints, limiting the maximum output of single generator to reduce contingency size, etc. NGESO has also begun to assess the impact of increasing renewable penetration by including rate of change of frequency (RoCoF) in its economic dispatch modelling.

With regards to **new technologies and commercial solutions**, which can range from direct controls of existing assets (i.e., generators intertrip and de-loading, demand response) or investing non-network based assets (i.e., batteries), although there are relevant technology deployments in France, UK, Australia and Ireland, these alternative options have not been systematically considered in transmission network planning to defer or avoid investments of traditional infrastructures (i.e., power lines, substations, etc.). It is worth to highlight that NGESO has considered using commercial services as part of its network reinforcement recommendations.

As for **new technology's investment cost** uncertainty, this factor may directly influence the planning decision of holding or proceeding with specific reinforcement options. However, most network planners do not thoroughly consider economic risks and benefits of holding investment decisions, as for example carried out in the NOA process. It is worth mentioning, however, that State Grid in China has a department which focuses on monitoring and predicting costs of equipment, and this information is used in technology selections for reinforcement.

The uncertainty of **regulatory and policy environment** is commonly embedded *within* the scenario design process. For example, governments' policies on decarbonisation target can be interpreted as various expected futures, such as high renewable energy penetration level, electrification of different sectors, widespread retirement of coal plants, etc. These actions determine key projections in different scenarios, as in the case of National Grid's Two Degrees scenario.

With regards to the uncertainty embedded in **energy markets and regulation**, National Grid, AEMO and EirGrid simulate wholesale and balancing services market operation by implementing, with different levels of approximation, dispatch and redispatch processes and bidding behaviour in their operational model, which gives their network planning process the capability to capture the potential impact of market changes.

Table 1. Uncertainty factors of TEP considered by different transmission network planners ([1]–[3], [6], [8]–[13])

"✓": exist and considered; "⊕": exist but not considered;

Country	Uncertainty factor						
	Load growth	RES growth	Generation mix	New commercial solutions	Technology Investment cost	Regulatory environment	Energy market and regulation
France (RTE)	✓	✓	⊕	⊕	⊕	✓	⊕
China (State Grid)	✓	⊕	⊕		✓		
UK (NGESO)	✓	✓	⊕	✓	⊕	✓	✓
Chile (CEN)	✓	✓	⊕		⊕	⊕	⊕
Australia (AEMO)	✓	✓	✓	⊕	⊕	✓	✓
Ireland (EirGrid)	✓	✓	✓	⊕	⊕	✓	✓

3.1.3. Modelling Uncertainty through Scenarios

Scenarios allow planners to model different evolution of uncertain variables as well as their correlations. This strategy is preferred in most decision-making problems that tackle planning, as it provides a balance between analysing a broad range of futures and (technical) detail in such analysis. Furthermore, they can be applied to some of the most common methodologies used in decision making, including, potentially, methodologies based on probabilistic approaches (in which scenarios have specific associated weights). Scenario analysis or "scenario-based" approach is currently used by most system planners around the world to model the uncertain future [6].

The number of characteristics of scenarios used in twelve selected countries are listed in Table 2. It can be noticed that most planners prefer to use less than five scenarios to represent plausible futures, e.g., envisaging nuclear or coal plants retirement, increase of DER penetration, electrification of heating and transport, etc.

In some cases, the system planner builds scenarios or performs further studies to represent (technical and economic) sensitivities around core scenarios. For example, AEMO has developed two additional scenarios "Increased role of gas" and "Early exit of coal-fired generation" around its Neutral scenario to represent two possible important opportunities/risks in the future [10]. Terna (Italian grid operator) also uses two extra scenarios to represent sensitivity of potential futures rather than the expected future [14]. Spanish transmission network planning uses three scenarios (central, superior and inferior) to represent various assumption of the relationship between electricity consumption and growth domestic product (GDP) growth [15]. NGESO is currently using a Monte-Carlo approach in the network assessment of the "Two Degrees" scenario, to add robustness in the analysis of the boundary transfer capability with/without proposed reinforcements, as this scenario is considered to be the one with highest network stress among all four scenarios. In Swissgrid's Strategic Grid 2025 proposal [16], two marginal scenarios, "Sun" and "Stagnancy", are built to check the long-term robustness of reinforcement options proposed in the two core scenarios, whilst the two marginal scenarios are not used to identify any additional network reinforcement requirement. France, Belgium and Germany considered 3-4 scenarios to consider the impact of phasing out nuclear and coal plants with increasing penetration renewable penetration level [17]–[19]. In the cases of PJM and China, only single demand and generation portfolio projections are applied in market efficiency (economic) and reliability studies. PJM also emphasised that they also performed studies with different scenarios considering the potential impact of Clean Power Plan imposed by the American government; however, no detail information regarding the scenarios and relevant case studies were given in its planning report [20].

Given the complexity of both technical and economic analysis associated with scenario-based planning, as well as the unfolding of uncertainty, some system operators have also envisaged to reduce the number of scenarios that are considered in the process. For example, the Chilean SO has decided to decrease the number of scenarios from five to three from 2020, while EirGrid has removed the "Slow-Progress" scenario from its Tomorrow's Energy Scenarios 2019 [11].

As an important point to note, none of the countries listed in Table 2 explicitly considers weighting scenarios in their CBA process, as there is no explicit probability assigned to the scenarios used in the planning.

Table 2. Number of scenarios used in transmission planning in ten selected countries ([1], [3], [20], [6], [9], [11], [13], [14], [16]–[18]*)*

Australia	UK	Italy	Spain	Switzerland	France	Belgium	Germany	China	PJM(US)	Chile	Ireland
5+2[3]	4 (1[4])	1+2[5]	3	2(4)[6]	4	3	3	1	1[7]	5	3

3.1.4. Technical characteristics of models used in TEP

Other than identifying existing uncertainty factors and scenarios in several countries, the technical details of the TEP models used by the seven selected countries already discussed above are listed in Table 3. The table is divided into four sections, which follow the methodology of TEP explained for the NOA process in Figure 4 and Figure 5, which is considered to be common practice worldwide. More specifically, the four sections are completed in a sequential way in the transmission network planning process:

1) **Economy zonal flow assessment**: This analysis is aimed at mapping the variation of the power flow between zones without imposing line limit constraints, which reflects the flow requirement of an efficient electricity market in the future. NGESO uses the concept of boundaries instead of zones in the identification of transfer requirement.
2) **Network zonal flow assessment (current network)**: The security constrained analysis is used to identify the transfers at peak demand period and other snapshots which not necessarily reflect system peak demand but can seriously stress the transmission network between specific zones.

[3] Two additional scenarios are built to represent the sensitivity of policy and risks faced by the Australian National Electricity Market (NEM).

[4] Only the "Two Degrees" scenario is used in the network transfer capability assessment of NOA.

[5] Two scenarios are built to represent the sensitivity of the core scenario instead of reflecting the expected future.

[6] Two marginal scenarios are constructed to test the robustness of reinforcement options, but the scenarios are not used to determine additional reinforcement requirements.

[7] PJM only explicitly uses one demand forecast scenario in its market planning, but it also mentioned in [22] that it would consider the impact of government policy (i.e., clean power plan) on generation, but no detail information of relevant approaches is given.

3) **Network reinforcement options assessment**: The reinforcement options have been identified at this stage, but their additional contribution to zonal transfer capability needs to be assessed with network constraints such as based on steady-state thermal, voltage and stability analysis, in both the intact system and the system with contingencies. This quantification is carried out in this assessment.
4) **System operating cost assessment:** After retrieving the transfer capability with various reinforcement options, these options are applied in the operational model to generate system operational cost in the relevant scenarios, whose results are then fed into the CBA process determining the best option for reinforcement.

The **cycling period** of the transmission network planning studies and the relevant reports are in the range of 1 to 10 years. For instance, NGESO and EirGrid carry out the transmission planning for the whole system every year, while Swissgrid only carries out the planning every ten years considering moderate changes of demand and generation mix.

As shown in Table 3, the **planning horizon** is generally in the range of 15 to 20 years, except for Swissgrid which only defines a transmission expansion plan for the next 10 years. However, Swissgrid would then perform technical analysis against the robustness of its reinforcement options for a 20 years horizon. For PJM, the planning activity is split into two parts: 1) the near-term planning with 5 years forward period to address reliability issues; 2) long-term planning with up to 15 years forward period to reduce network congestion cost and provide other economic benefits.

For the **economy transfer capability analysis**, the time resolution of simulation varies from 15 minutes to few hours across different countries. One practice to be highlighted is that both Chile and Australia use *load-block techniques* which can reduce simulation time steps by clustering several time periods, but only for the periods with similar demand level rather than adopting it with a fixed time length. This action can increase computational efficiency while only marginally affecting the accuracy of the results compared to fixed-time clustering. At the same time, China and Chile perform simulations only with *typical day(s)* of each month and then scale them up to represent transfer volumes variation or annual operational cost.

For the **network assessment of zonal transfer capability**, there are countries which perform more than a winter peak snapshot analysis. For example, Chile does not only perform Winter/Summer peak snapshots, but also analyses specific snapshots that are likely to be associated with maximum levels of power transfer across relevant zones. As mentioned above, NGESO use the concept of boundaries instead of zones to reflect a wider range of transfer capability requirements in combination of several zones.

With regards to the **network assessment with a combination of reinforcement options** shown in Table 3, most countries prefer to perform the analysis at various demand levels to mimic different system operating condition besides the peak snapshot. Furthermore, it seems that most countries under consideration perform thermal, voltage and stability tests. This is done for the network under different types of contingencies, such as N-1 and N-1-1. On the other hand, other SOs perform extra tests such as reactive power management and frequency stability assessment, like in the case of AEMO.

For the **operating cost assessment of reinforcement options**, which is used in CBA process, different countries use different sampling period varying from 1 year by NGESO up to 10 years by State Grid and Swissgrid. Additionally, with regards to the modelling of system operation, some countries use simple economic dispatch, while other countries adopt unit commitment analysis to better capture the technical characteristics of conventional generators (minimum up- and down-time, start-up/shut-down activities, etc.). The technical constraints of system operation also vary in the simulation performed by different planners. In terms of *modelling of the network*, the maximum flows of individual transmission lines are typically calculated according to thermal, voltage and fault-clearing standards, then the results are mapped as numerical constraints in economic-dispatch/unit-commitment. However, the transfer capability between zones applied in the economic dispatch model SPER (which is used by State Grid) is more strictly constrained by monthly energy exchange allowances between zones or energy export allowances of specific generators, while the sum of capacity of lines is used as the upper limit for the transfer capability [21]. With regards to *ancillary services*, most countries model these as "lumped" spinning reserve through derating online plant capacity, while AEMO also models the requirement of minimum inertia level due to RoCoF, which can be crucial for low-inertia system operation. PJM emphasises that a security constrained unit commitment model is applied for market efficiency analysis which is used to produce input for CBA.

Most importantly, for investment decision-making tools, only NGESO and AEMO appears to use LWR[8], while other countries use deterministic approach to obtain the best reinforcement option that brings NPV maximisation in each scenario. However, from the review conducted it is unclear how a final, integrated decision across scenarios would be made. It is also worth mentioning that PJM also uses a benefit-to-cost threshold (currently 1.25) to screen individual transmission enhancement proposals. The benefit-to-cost ratio is calculated by using the present value of project's annual benefits over the first 15 years divided by the present value of the revenues required over the same period [22].

In the following section we will focus on assessing the implication of using different decision-making tools.

[8] AEMO are also considering adopting a LWR approach in their Integrated System Plan (ISP).

Table 3. International practice of technical modelling characteristics in TEP process ([1], [2], [14], [16]–[18], [23]–[26], [3], [6], [8]–[13]*)*

Simulation Stage	features	Countries								
		UK (NG ESO)	**France (RTE)**	**China (State Grid)**	**Chile (CEN)**	**Australia (AEMO)**	**Ireland (EirGrid)**	**Switzerland (Swissgrid)**	**US (PJM)**	**Spain (REE)**
Study rolling period		Every year	Every 2 years	Every 5 years	Every year	Every 2 years	Every year	Every 10 years	Every 1-2 years[9]	Every 6 years
Planning and CBA horizon		20 years	15 years	15 years	20 years	20+ years	20 years	10(20[10]) years	5/15[11] years	10-20 years
Zonal flow assessment (Economy)	**Software**	BID3	ANTARES	SPER	OSE2000	PLEXOS	*Not available*	N/A[12]	*Not available*	*Not available*
	Simulation resolution	3-6h (up to 1 hour)	Hourly	15 mins to hourly	8 load blocks[13]	Few load blocks	Hourly		Hourly	Hourly
	Simulation timescale	Whole year	Whole year	Typical day in each month	Typical weekday/ weekend in each month	From snapshot to whole year[14]	Whole year		Whole year	Whole year
Zonal flow assessment (Network)	**Software**	DIgSILENT/POUYA	CONVERGENCE	PSD-BPA	DIgSILENT	N/A	PSS/E, DSA		*Not available*	*Not available*
	Simulation timescale	Winter peak snapshot and year-round	Snapshots	Typical snapshots	Winter/summer and transfer peak snapshots		Peak and other demand snapshots		Winter and summer peak, and light load [15]snapshots	Winter and summer peaks
	System condition	N-1/N-D	N-1	N-1	Intact/N-1[16]		N-1		N-1/N-1-1	N-1
Reinforcement options	**Software**	DIgSILENT/POUYA	CONVERGENCE	PSD-BPA	DIgSILENT	PSS/E	PSS/E, DSA	*Not available*	*Not available*	*Not available*
	Sampling frequency	Every year[17]	*Not available*	Every typical year[18]	Every year	Every year	*Not available*	Every 10 years	Every 2-3 years	Every year

[9] PJM carries a 24 months cycle for long-term and long lead-time projects and a 12 months cycle for near-term projects to address reliability criteria violations.

[10] Scenarios for 2035 in “Strategic Grid 2025” [16] are only used for robustness evaluation of reinforcement options.

[11] Near-term planning only carried out on year 1 and year 5 models, while long-term planning has a 15 years planning horizon.

[12] Swissgrid directly tests different reinforcement options instead of building up boundaries.

[13] Using load-block methods to aggregate similar demand periods into one time-step in the simulation.

[14] Using snapshot simulation to determine which reinforcement options appear to be economic options and then including them in whole year analysis.

[15] Light load conditions are referred to the demand level as low as 30 percent of summer peak to address high voltage issue in network [22].

[16] N-1 compliance is checked at peak transfer condition, while the transfer during summer and winter peak periods are examined in an intact system condition.

[17] Network assessment is performed every year with the corresponding demand and generation profiles, while the corresponding network configuration of each year is selected from four potential settings, which are the networks in 3, 5, 7 and 10 years (counting from the current year) respectively.

[18] One typical year is chosen from next 5-10 years range and another one is chosen from next 10-15 years range.

assessment (Network)	**Simulation timescale**	Winter peak snapshot and year-round	Snapshots	Typical snapshots	Peak demand snapshots	Peak/low demand snapshots	Peak and other demand level snapshots	Peak congestion snapshots	Winter and summer peak snapshots	Winter and summer peaks
	Constraints	Thermal; Voltage; Stability; Contingency analysis								
Reinforcement options assessment (Economy)	**Software**	BID3	ANTARES	SPER	OSE2000	PLEXOS	*Not available*	*Not available*	*Not available*	*Not available*
	Sampling frequency	Every year	*Not available*	Every typical year	Every year	Every 5-7 years	Every 5 years	Every 10 years	Every 4 years	Every year
	Simulation resolution	3-6h (up to 1 hour)	Hourly	15 mins to hourly	8 load blocks	Daily energy limit to hourly power balance	Half hourly	Hourly	Hourly	Hourly
	Simulation timescale	Whole year	Whole year	Typical day in each month	Typical weekday/ weekend in each month	Whole year	Whole year	Whole year	Whole year	Whole year
	Operational model	Economic dispatch	Unit commitment	Economic dispatch	Economic dispatch	Simplified[19] unit commitment	Economic dispatch	Economic dispatch	Security constrained unit commitment	Economic dispatch
	Constraints	• Network constraints (thermal, voltage, stability) • Lumped spinning reserves	• Network constraints (thermal, voltage and stability) • Lumped spinning reserves	• Static network constraints • Lumped spinning reserves	• Network constraints (thermal, voltage and stability) • Lumped spinning reserves • System inertia constraint	• Network constraints (thermal, voltage and stability) • Lumped spinning reserves • System inertia constraint	*Not available*	*Not available*	*Not available*	• Network constraints (thermal, voltage and stability) • Lumped spinning reserves • System inertia constraint
	Reliability index	LOLE	LOLE/LOLP/EENS	EENS	EENS[20]	EENS	*Not available*	*Not available*	LOLE	LOLE and LORE
Decision making tools		LWR	*Not available*	NPV maximisation	NPV maximisation	LWR	*Not available*	*Not available*	NPV maximisation and benefit/cost ratio	NPV maximisation

[19] Only some generators have active start-up/shut-down constraints. Each simulation time horizon is two days, with one-day results retrieved.

[20] EENS is used as a penalised variable in the ED optimisation rather than as a compulsory standard to meet.

3.1.5. Considerations on international best practices for TEP

Based on the review performed, there are few key points that it is possible to highlight:

- Planning uncertainty is typically dealt with by scenario-based approaches.
- Most countries adopt a (very) limited number of scenarios in their planning methodologies, often building sensitivities around main scenario(s) rather than new, very different scenarios *per se*.
- No probability weight is associated with the considered scenarios, possibly again also based on the fact that many scenarios are only sensitivities.
- Scenarios seem to be typically analysed independently and then planning options are chosen based on specific rules to make an integrated decision across several scenarios, while only NGESO performs an integrated analysis across multiple scenarios via LWR.

Based on our review and to the best of our knowledge, NGESO's NOA methodology to plan and reinforce the transmission network seems to be at the forefront of the state of the art of planning under uncertainty. This is essentially because: 1) there is a clear and publicly available methodology that describes how an investment decision is performed *across* multiple possible and uncertain scenarios that are all simultaneously accounted for in the decision making process; and 2) the methodology allows consideration for the potential negative consequences of an investment decision (basically via using the regrets as risk measure – see further below), rather than, for example, just going for onerous investments that might be driven by the most extreme case (this would correspond to a minmax cost approach – see again further below). However, before providing further methodological considerations and explanations for planning under uncertainty, we should also point out a clear opportunity for improvement in the NOA process which has emerged from our studies. This is the inclusion of additional operational snapshots in the technical analysis besides the current winter peak assessment, which could be considered in light of increasing operational complexity and uncertainty that might drive worst case flows across boundaries at different times of the year. Similarly, inclusion of new operational characteristics and constraints, such as associated with low-inertia conditions, could be desirable.

3.2. Decision making under uncertainty

The previous section has focused on uncertainty, the uncertainty sources and their inclusion in the transmission expansion planning in different countries, as well as modelling those uncertainties through scenarios. When a system planner faces different scenarios to model uncertain future conditions, the TEP problem effectively becomes a decision-making problem. However, as shown in 3.1.4, most countries do not include advanced methodologies to model decision-making problems. In most cases, the planner only assesses the NPV for individual scenarios, without combining scenarios in any (at least publicly clear) way. Different rules, often based on practical experience, are then likely to be used to select the reinforcement options that may perform best *across* multiple scenarios. In fact, the international survey from section 3.1.4 shows that only NGESO is considering the TEP problem including uncertainty as a decision-making problem in the sense of combining scenarios (via LWR).

Nevertheless, in the research literature there are several examples of applications where transmission (and distribution) expansion planning under uncertainty could be treated as a decision-making problem. The most relevant and well-known methodologies are probabilistic assessment (which may be seen as a relatively simple version of the more general field of stochastic programming) and min-max (or minimax), applied to both costs (min-max-cost, MMC) and regrets (min-max-regret, MMR, also often indicated as least worst regret, LWR). Robust programming, min-min cost, and real options are other methodologies potentially available to solve transmission expansion planning problems with uncertainty, while certain applications of these methodologies also include specific risk measures that may be relevant for TEP. We will briefly review these methodologies in the following subsections.

3.2.1. Probabilistic assessment/stochastic programming

Probabilistic assessment (also referred to as "probabilistic choice") falls within the more general stochastic programming/stochastic optimization framework, which may also include multi-stage decisions. This is the somehow intuitive development of a deterministic approach whereby uncertainty is introduced through scenario analysis. It has a flexible formulation that has drawn much attention, including efforts to develop a canonical framework, equivalent to the one found in deterministic optimization [27], [28].

The simplest formulation of probabilistic assessment problems is based on the use of probabilities applied to different scenarios to enable the selection of the "statistically" best solution. In fact, it originated from assessing the uncertain outcome of a significant number of experiments, in which the frequency of occurrence is close to the probability value assigned. These experiments would typically be carried out in fixed conditions, under the same set of laws. The formulation of a probabilistic approach can be readily adapted to the transmission expansion planning problem, in which a limited number of scenarios are assigned (probability) weights and the best investment strategy is selected to optimise (e.g., minimise, in the case of cost) a given attribute (e.g., net present cost) across scenarios through a linear composition of its values weighted with the respective scenario probabilities [29], [30].

3.2.2. Min-Max

This general methodology, much used in the field of *game theory*, uses two nested optimisations (*min*{*max*{}}) to model the decision-making problem under uncertainty. It requires a more complex formulation than stochastic programming, but in principle does not require the *explicit* assignment of weights for each scenario, which is considered as an advantage by system planners. However, adequate scenario definition may then become of critical importance, because there might be "no compensation" among scenarios, as generally implied in stochastic programming. In a TEP problem, these two nested optimisations are most commonly used with two attributes, namely, cost (min-max cost) and regret (min-max regret).

3.2.2.1. Min-max cost (MMC)

In min-max cost (MMC), the two nested optimizations use cost as the value attribute. This is intuitively a very conservative approach that would be undertaken by a (most) risk-averse decision maker, whereby a high-cost scenario, and the desire to hedge against its consequences, will eventually define the selection of the optimal investment strategy.

3.2.2.2. Min-max regret

Min-max regret (also referred as LWR in NOA) is a version of the general nested min-max optimization where the value attribute is now a *regret*. Regrets are based on an *ex-post* evaluation of the decision maker's perception regarding its decisions, usually expressed in monetary terms. The selected option is the one that minimizes the regret felt by a decision maker after verifying that the decision he had made was not optimal given the future that would have eventually actually occurred [22].

Regret functions can be built with different levels of risk-aversions, including non-linear functions to model unacceptable outcomes for the decision makers (e.g., "vetoes" and "absolute preferences").

It has been pointed out that by shifting the focus on the *decisions* rather than the solutions (as in the probabilistic approach), LWR may reflect better the real decision making process [29], [30]. Furthermore, when regret is used rather than cost (as in min-max cost), a high-cost scenario does not necessarily trigger the strategy selection, because regret compares the relative performance of strategies within each scenario. This is a considerable drawback of min-max cost when compared to LWR. On the other hand, it has been discussed within previous NOA methodology reviews [31] that the use of LWR may also have drawbacks. For example, while LWR may not be directly sensitive to the highest-cost scenario, it may still be sensitive to the relationship between "worst" and "best" scenarios, so that it is again possible that extreme (and particularly high-cost) scenarios may somehow drive the results. Furthermore, the methodology may not be robust to the inclusion of "irrelevant" investment options, which may lead to "spurious" decisions. In contrast, a min-max cost approach does not suffer from the latter issue[21].

It is also important to notice that, as discussed by Arroyo et al [32], and as in classical literature on decision making under uncertainty [33], [34], regrets can be used as a measure of risk (see also below for other risk measures). A methodology such as LWR that aims to minimise regrets (and therefore risk) is therefore intrinsically risk-averse.

3.2.3. Robust programming

In robust programming or robust optimization, the decision maker imposes feasibility for all possible scenarios, even if not all the scenarios but only the boundary ones are explicitly modelled. Since the worst-case scenario must be feasible too, it effectively becomes the scenario driving the decision. Therefore, the risk aversion of this methodology is again highly dependent on the scenario definition. Robust optimization can implicitly account for all scenarios within the uncertainty set through efficient search algorithms, an advantage when dealing with large sets of scenarios compared to the previous methodologies[35].

3.2.4. Min-min cost

Min-min cost has a similar formulation to min-max cost, that is, a *min*{*min*{}} nested optimization that does not require the explicit assignment of weights. Conceptually, it is opposite to min-max cost, since it aims to obtain the highest benefits by minimizing the cost

[21] However, with regards to NOA, as all the proposed options are plausible, technically valid and checked beforehand, the risk of including "irrelevant" options in the LWR analysis should be fairly limited.

in the lowest-cost scenario. In the context of a decision-making problem, it is used when a risk-seeking decision maker is willing to obtain the maximum benefits from uncertain scenarios, essentially regardless of risk.

3.2.5. Real options

Real options analysis is a methodology coming from financial options theory. Its application comes from the belief that evaluating investment options using the *traditional indicators* such as NPV, net present cost (NPC) or the discounted cash flow (DCF) is not adequate in a number of investment problems, including for TEP. This belief mainly comes from the assumptions regarding the irreversibility of investments that these metrics make, which cannot capture realistically the flexibility of the decision-making process. In this light, the framework proposed by Real Options Analysis allows a better quantification of the benefits of flexible investments [36].

However, most proposed real options models are not adequate for transmission expansion planning problems. For example, analytical models using the likes of Black-Scholes formulas only account for two correlated uncertainties, modelled assuming certain distributions and making a number of other questionable assumptions. On the other hand, lattice models cannot consider multiple interactions between options. Furthermore, concepts such as volatility or the effect of competition need to be carefully considered in real options, as the original settings the field of finance are inherently very different. Schachter and Mancarella thus concluded that rather than real options models from financial mathematics it is more adequate to introduce a “real options framework” or "real options thinking" to deal with electricity system investment decision making, which can indeed deploy methodologies such as multi-stage stochastic programming or LWR [37].

3.2.6. Measuring risk in decision making: VaR and CVaR

The previously presented methodologies are used for making decision according to a value attribute (e.g., cost) in an uncertain environment. Regardless of the methodology used, decisions will eventually have associated a distribution of expected consequences (e.g. costs). The decision will lead to a different outcome in each scenario, and it may be the case that for a given scenario the outcome is not acceptable for the decision maker. Therefore, when uncertainty is involved, any such problem is intrinsically related to a decision’s risk. Approaches from risk management may therefore be incorporated in the decision-making process to avoid unacceptable decisions.

The most common way to handle risk when making decisions is to include a *risk measure*. For example, Conejo *et al.* review different risk measures in their book about Decision Making Under Uncertainty in Electricity Markets [38], namely, variance, shortfall probability, expected shortage, Value-at-Risk (VaR) and Conditional Value-at-Risk (CVaR). In particular, our view is that VaR and CVaR may be most suitable for applications that include risk management in transmission expansion planning problems.

Given a loss function (i.e. a cost function) for an $\alpha \in (0,1)$ the **VaR** answers the question: "Given an investment decision, what is the highest cost I might experience with a probability of α x 100%[22]?" Other interpretations of VaR can be found in [39]:

- The maximum costs that will not be exceeded with a given probability α x 100%;
- The α-quantile of the cost distribution;
- The smallest cost in the $(1-\alpha)$x100% of worst cases;
- The highest cost in the α x100% of best cases.

On the other hand, the **CVaR**, answers the question of "Given an investment decision, what will be the average value of costs in the $(1-\alpha)$x100% worst cases?" This risk measure is also known as mean excess loss or average value-at-risk [38]. Other interpretation is:

- The average cost in the $(1-\alpha)$x100% of worst cases.

CVaR is often the preferred risk measure to manage risk in decisions. From the previous interpretations of both measures, VaR informs about the cost when the worst cases start (worst cases are defined by the selection of α) while CVaR informs what is the average cost of those worst cases, providing information about their distribution. Therefore, CVaR is able to better recognise scenarios with low probability incurring in very high costs (which will substantially increase the average cost of the worst scenarios). This is an attractive attribute for a risk measure in transmission expansion planning problems, where these low probability and high cost scenarios can take place. Figure 10 illustrates in a cost distribution function the definitions of VaR and CVaR for an $\alpha = 0.95$:

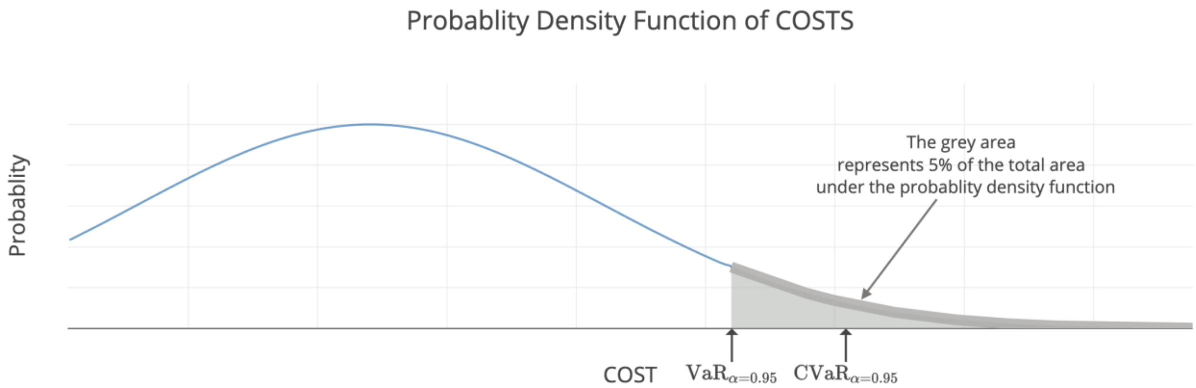


Figure 10. Example of cost distribution function showing VaR and CVaR for α=0.95

CVaR mathematical properties are also more attractive than for VaR. For example, reference [40] defines certain properties that are desirable for any risk measure, namely, monotonicity, translation equivariance, subadditivity and positive homogeneity, so that it is possible to talk about *coherent risk measures.* VaR does not meet the subadditivity characteristic, while CVaR meets all criteria of a coherent risk measure.

The previous reasons make CVaR an interesting candidate to measure and manage risk in transmission expansion planning problems with uncertainty. For example, it may be used as an *ex-post* analysis of the result distribution of a decision-making problem, or included in the problem formulation [38]. For instance, a decision-making problem may be modelled by using stochastic programming, whose aim is to maximize expected profits, and CVaR may then also

[22] Also referred to as α confidence level, with α=0.95 (95%) and α=0.99 (99%) common values used to define VaR and CVaR.

be included in the formulation of the objective function. In this case, weights between the expected value and CVaR are applied to represent the decision maker's attitude towards risk. A more risk-averse decision maker will increase the relative weight of the CVaR in the objective function, while a risk-seeking decision maker will use a higher relative weight for the maximization of expected profits.

4. A unified framework for decision making under uncertainty

4.1. Scenario planning under uncertainty as a multiple-criteria decision-making problem

In the previous section, different methodologies to model decision making under uncertainty have been described. While there is a significant number of applications that use these methodologies to solve different decision-making problems related to electrical power systems, there is a general lack of research that aims to systematically assess and compare the implications of selecting one methodology over another. For instance, [29], [30] are some of the few studies that compare methodologies (i.e., probabilistic assessment and LWR) and draw relevant conclusions, while most publications on methodology comparison do not reach any relevant and general conclusions (see for instance [41]).

One of the main reasons is the absence of a unified framework that enables such methodology comparison. In particular, most works consider probabilistic assessment, LWR and min-max cost (which are the most common methodologies used in decision making) as different frameworks, which hinders the possibility of carrying out a systematic comparison.

However, below we will develop an idea that these three "most common" methodologies (namely stochastic programming, LWR and MMC) do actually belong within a same, unified framework. Our framework development is supported by concepts from multi-objective decision making and is inspired by Starr and Zeleny's work in [42] and follows closely the work of Miranda and Proenca in [29], [30].

It is also worth mentioning that in our analysis below we will focus on probabilistic assessment, LWR and MMC for a few reasons:

- They are well-known and common methodologies for decision making;
- As it will be clearer from our discussion below, they can be applied in a straightforward way to the current NOA methodology with only minimal changes in the very last stages, i.e., when investment decisions need to be made based on strategy cost/regret tables;
- Although robust programming and min-max cost are formally and theoretically different, in practice if they were applied to the current NOA methodology they would coincide [23];
- Min-min cost has not been included since it does not seem to be a suitable decision-making tool to plan critical infrastructure due to its intrinsic risk-seeking nature;
- Real options modelling and similar approaches are primarily concerned with investment flexibility and they might require more substantial changes to the current NOA methodology: this is ongoing work that we are performing and the results will be reported at a later stage of the project;
- Likewise, use of risk measures such as VaR and CVaR is also part of ongoing work.

The first step to build this unified framework is to realise that non-trivial decision making takes place when facing multiple attributes or objectives that may be in conflict with each

[23] As previously mentioned, robust programming's main attribute is in fact to optimize by ensuring feasibility in all scenarios (including, and in particular, the worst-case one). However, when used in the NOA process, all available investment options have already been screened for (technical) feasibility. Hence, the decision proposed by robust programming would effectively be driven by the highest-cost solutions as in MMC, thus the equivalency between the two methodologies in this specific case.

other. As presented in [42], when facing a decision typically the decision maker has a view on the relative importance of each of the objectives. Therefore, each objective or attribute can be assigned a weight, and be referred as *weighted criterion*. In a decision-making problem with a set X of $n = 1, \ldots, N$ weighted criteria, each objective or attribute x_j has an assigned weight λ_j:

$$X = (\lambda_1 \, x_1, \ldots., \lambda_j \, x_j, \ldots, \lambda_N x_N) \tag{1}$$

The analogy with a planning-under-uncertainty problem across multiple scenarios characterised by an attribute x_j (for example cost or regret) and probability weight λ_j in the scenario *j*, which we will explore further below, should have by now become evident.

For each of the weighted criteria (or weighted scenario, in our case), there is at least one value preferred to all the remaining ones. A solution that has the preferred value for all the weighted criteria is referred to as the *Ideal Solution*. The Ideal Solution is intrinsically a virtually infeasible solution in any non-trivial problem, firstly introduced as a technical artefact in decision-making problems in [43]. If it was feasible, the problem would be trivial and ideal solution would be the obvious choice for the decision maker and there would be no decision-making problem.

Evolving from the concept of Ideal Solution, Zeleny defined compromise solutions as the set of feasible solutions to a decision-making problem which are closest to the ideal one. These compromise solutions cannot be improved in any objective without losing in another objective. Intuitively, this is the set of solutions that the decision maker shall explore to select the final decision (best compromise solution). This set is also referred to as Pareto-Optimal and a more detailed analysis regarding their role in planning problems can be found in [44].

4.1.1. Multi-criteria decisions as a distance minimization problem

Using the previous concepts, it is intuitive that a multi-criteria decision-making problem's objective will be looking for which of these feasible compromise solutions are closest to the ideal solution. A more formal definition of that intuitive decision-making objective is to *minimize the distance* from the ideal solution. Therefore, the formulation of the decision making becomes a distance minimization problem.

In Figure 11, we depict a simple example to illustrate the concepts discussed above. The figure represents a decision-making problem considering two weighted criteria ($x_1\lambda_1$ and $x_2\lambda_2$). In the problem presented, both weighted criteria can only take positive values, and the best possible, desired value for both is zero (the similarities between this generic problem and a cost minimization problem can again already be perceived and will be further discussed). However, such an ideal solution, as aforementioned, is generally not feasible, and the set of feasible solutions for the problem is explicitly shown in the figure. The figure also illustrates the "intuitive" distance between a feasible solution and the ideal in a two-dimensional space, referred to by using $L(y_i)$, where index $i \in \{1, \ldots, K\}$ denotes the i-th element in the feasible solution set. The distance between the feasible solution y_3 and the ideal solution is taken here as example.

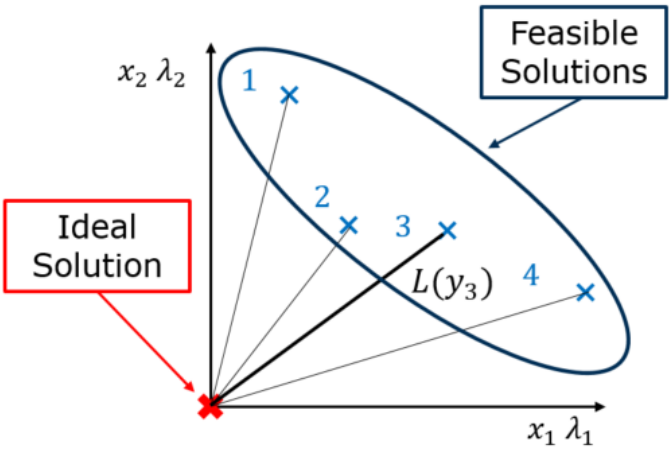


Figure 11. Multi-Criteria Decision Making as a Distance Minimization Problem

Finding the minimum distance in a two-dimensional space, as shown in Figure 11, would seem intuitive and straightforward. However, most decision-making problems are characterised by a set of weighted criteria typically larger than two. The problem is therefore to "measure the distance" of K candidate solutions to the ideal solution in an N-dimensional space and select the closest among them. Measuring distances in N dimensions is now less straightforward, and a suitable metric needs to be considered.

To formulate the problem in the most general way, we use the general Minkowski metric formulation to "measure distance" in an N-dimensional vector space, where y_{ij} now refers to the value of the feasible solution i in the weighted criteria j defined by $x_{ij}\lambda_j$:

$$L_p(y_i) = \sqrt[p]{\sum_{j}^{N} (|y_{ij}|)^p} \quad p \in \{1, \dots, \infty\} \tag{2}$$

where L refers to metric function, p is a parameter defining the metric, i is the index referring to a specific candidate solution and j is the index referring to the criteria (space dimensions). Using the general Minkowski metric formulation (2) thus allows us to formally define the objective function of a multi-criteria decision-making problem in a generic way, where y_{ij} represents the candidate solution i for the criterion j with its associated weight λ_j and the distance of a candidate solution to the ideal solution is to be minimized in N dimensions:

$$\min_i L_p(y_{ij}) \tag{3}$$

Once this general formulation has been presented, the following subsections will discuss the use of different specific metrics obtained when varying p from 1 to infinite.

4.1.2. Manhattan Metric

The Manhattan Metric measures the distance between two points by summing the length of all paths connecting those two points using only vertical and horizontal segments. Based on the example shown in Figure 11, the distance between the Ideal Solution and the feasible solution 3 using the Manhattan Metric is represented in Figure 12.

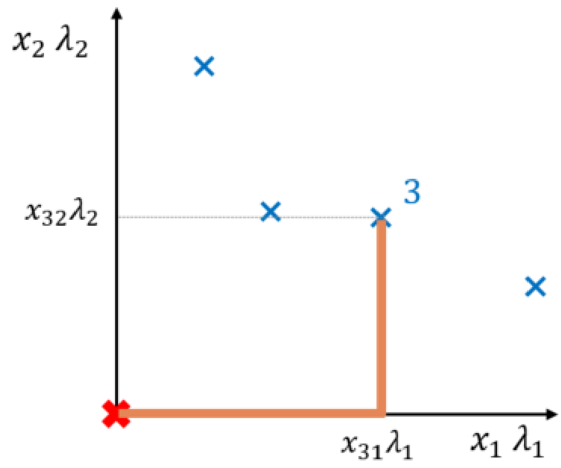


Figure 12. Example of Manhattan Metric to Measure the distance of Alternative 3

The previous definition of the Manhattan Metric corresponds to the General Minkowski formulation when $p = 1$. Therefore, the distance of a feasible solution i to the ideal is defined with the following expression and then applied to the example given for Solution 3.

$$L_1(y_i) = \sum_j^N |y_{ij}| \tag{4}$$

$$L_1(y_3) = y_{31} + y_{32} = x_{31}\lambda_1 + x_{32}\lambda_2 \text{ [24]} \tag{5}$$

[24] The symbol of absolute value is not included since the weighted criteria have been previously defined as positive. This is also the practical cases that we discuss here which always refer to positive costs and regrets.

4.1.3. Euclidean Metric

The Euclidean Metric is the "traditional" geometric distance between two points, as can be seen in Figure 13. In the Minkowski formulation the Euclidean Metric corresponds to $p = 2$, and the following general expression and its exemplificative application to Solution 3 are shown below.

$$L_2(y_i) = \sqrt[2]{\sum_{j}^{N} (y_{ij})^2} \tag{6}$$

$$L_2(y_3) = \sqrt[2]{(y_{31})^2 + (y_{32})^2} = \sqrt[2]{(x_{31}\lambda_1)^2 + (x_{32}\lambda_2)^2} \tag{7}$$

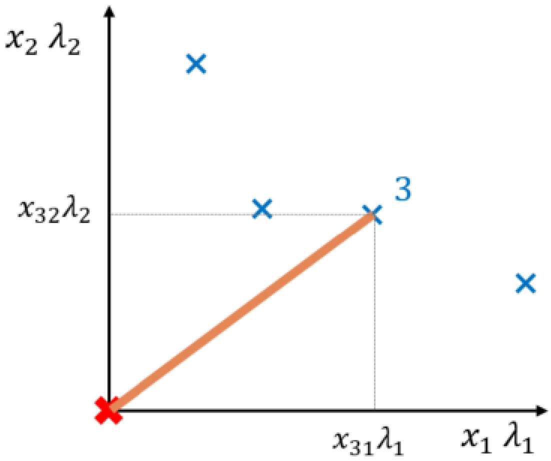


Figure 13 . Example of Euclidean Metric to Measure the distance of Alternative 3

This metric may somehow be considered as a "halfway" approach between the Manhattan Metric and the Chebyshev metric. The latter is explained in the following paragraph.

4.1.4. Chebyshev Metric

The Chebyshev Metric defines the distance between two points as the greatest of their differences along any of the dimensions. This metric corresponds to the formulation of the Minkowski metric when $p = \infty$. Its general formulation is:

$$L_\infty(y_i) = \max\left(\left|y_{ij}\right|\right) \quad j = 1, \dots, N \tag{8}$$

When applying this metric to measure the distance of Solution 3 to the ideal, L_∞ is equal to $x_{31}\lambda_1$, which is the largest value across both dimensions, as Figure 14 shows.

$$L_\infty(y_3) = \max(y_{31}, y_{32}) = \max(x_{31}\lambda_1, x_{32}\lambda_2) = x_{31}\lambda_1 \tag{9}$$

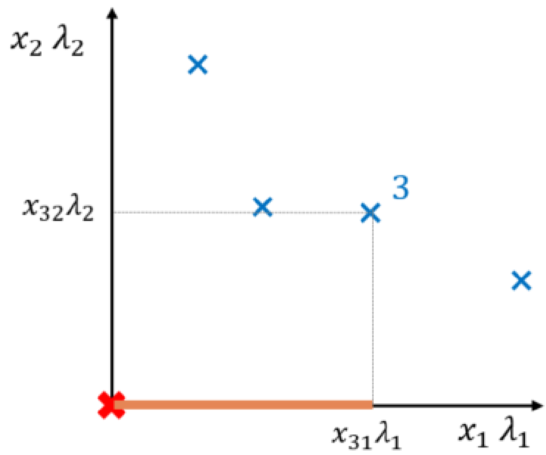


Figure 14 Example of Chebyshev Metric to Measure the distance of Alternative 3

4.2. Implications of using a unified framework for decision making under uncertainty

In the previous section we presented a framework to turn a multi-criteria decision-making problem into a distance minimization problem, also introducing the concepts of weighted criteria, ideal solution and compromise solutions. The objective was to find the feasible solution that is closest to the ideal (generally not feasible) solution for the decision maker. It was shown that there are different metrics available to measure a distance when dealing with a N-dimensional space.

As already anticipated earlier, these concepts intuitively resemble the concepts used in decision making under uncertainty, when uncertainty is modelled through scenarios. In fact, as demonstrated below, these problems are fully equivalent. Table 4 summarizes the details of such equivalency using the terminology of electrical power systems planning problems.

Table 4 Comparison of Multi-Criteria Decision Making and Scenario-Based Decision Making Under Uncertainty

Concept	Multi-Criteria Decision Making	Scenario-based Decision Making Under Uncertainty
$x_{ij}\lambda_j$	Weighted Criterion	Probability-Weighted Scenario
Ideal Solution	Best value in all criteria	Best value in all scenarios
Objective function	Minimize distance to ideal	Minimize distance to ideal = Minimize value attribute (e.g., cost, regret)
$L_1(y_i) = \sum_j^N \lvert y_{ij} \rvert$	Manhattan Metric	Probabilistic Assessment
$L_2(y_i) = \sqrt[2]{\sum_j^N \left(y_{ij}\right)^2}$	Euclidean Distance	Euclidean Distance
$L_\infty(y_i) = max(\lvert y_{ij} \rvert) \quad j = 1, \ldots, N$	Chebyshev Metric	Min-max cost and LWR

In a decision-making under uncertainty problem in power systems, where a value attribute such as cost or regret is minimized, the ideal solution will have a value equal to zero (e.g., zero costs or regrets) for all the weighted scenarios. However, different constraints make this ideal solution infeasible, and investment strategies that involve *some* costs and regrets must be pursued. Therefore, the objective is to find the investment strategy that satisfies such constraints minimizing the selected attribute. This is equivalent to finding the solution "closest" to the ideal. Different metrics have been introduced in order to find the closest solution in N-criteria problems.

Table 4 clearly demonstrates that as anticipated at the beginning of the section the most common methodologies used for planning under uncertainty through scenario analysis belong to the same framework as multi-criteria decision making based on distance minimization, where the aim is to find the solution closest to the ideal. It is thus possible to conclude that probabilistic assessment, min-max cost and LWR are not different approaches, but simply different metrics with the same purpose (distance minimization) to solve a geometric problem. Therefore, if these apparently different approaches are just different metrics to solve the same problem within the same unified framework, they can be systematically compared to discuss their suitability in terms of what is the *most suitable* metric to address the specific planning problem under consideration and, as mentioned earlier, with minimal changes having in mind the current NOA methodology.

The following section will address the implications of considering probabilistic assessment, LWR and min-max cost as different metrics in a unified framework. Since both min-max cost and LWR are applications of the Chebyshev metric only applied to different attributes, in the following discussion we will focus on LWR, as it is currently implemented in the NOA.

4.2.1. Implications of (not) assigning probabilities to scenarios

The NOA's Methodology Review Report [31] mentions several times the advantage of LWR, min-max cost and min-min cost in avoiding the use of "potentially miss-specified" probabilities, as opposed to probabilistic assessment and more in general stochastic programming approaches that require scenario probability weights. In fact, in stochastic programming the weights or probabilities assigned to each scenario must be explicitly stated, as the strategy selection is based on a probabilistic approach (for example, select the strategy that performs best when averaging scenario-specific costs or regrets by their relevant probability weights). This has led to a preference of approaches that avoid the explicit assignment of probabilities, like LWR, over probabilistic assessment, especially when assigning such probabilities may be considered controversial.

In the previous section, when defining our proposed unified framework, weights were embedded in the definition of scenarios and, accordingly, the Chebyshev metric was formulated with weights too. Now, in the LWR formulation there is no weight (at least explicitly), and as such it is considered a "weight-agnostic" approach, as discussed. However, not including weights does not mean that these are not *implicit* in the formulation and, in fact, we argue that when no weights are assigned LWR (and in general any min-max approach) is *implicitly* considering all scenarios *equiprobable*.

To demonstrate this, take the simple following example where the Chebyshev distance metric minimization problem is presented as an equivalent weighted version of LWR. The indexing is coherent with what previously presented.

$$\min_i \max_j \left(\lambda_j \text{regret}_{ij}\right) \tag{10}$$

If the general formulation is specified for a case of equiprobable scenarios with a probability (λ), that is:

$$\lambda_j = \lambda = \frac{1}{N} \quad \forall\, j \tag{11}$$

Then the common weight or probability associated to all scenarios becomes a common factor that can be brought outside the minimization function, where effectively "the decisions are made", yielding:

$$\min_i \max_j \left(\lambda \,\text{regret}_{ij}\right) = \lambda \cdot \min_i \max_j \left(\text{regret}_{ij}\right) \tag{12}$$

This simple example thus proves that a LWR weighted formulation including equiprobable scenarios is equivalent to a LWR formulation not considering probabilities. In this sense, based on the unified framework presented, there are a few key considerations that can be made, with relevant implications on the suitability of different approaches:

- A Least Worst Weighted Regret (LWWR) approach can be proposed as the generalised version of LWR with scenario weights corresponding to the Chebyshev metric applied to the generic unified framework for multi-criteria weighted assessment.
- Comparing a probabilistic assessment approach using different weights or probabilities for the scenarios and a LWR approach with no weights (which we demonstrated corresponds to having *implicit* equiprobable scenarios) become inconsistent, as the problems that are being solved are now different.
- For consistency, the decision maker would need to include weights in the approaches based on the Chebyshev metric too (LWR, MMC), since, when using scenarios, probabilities are *implicitly* involved in all methodologies. This would lead to adopting LWWR and min-max weighted cost (MMWC) approaches for generalised scenario-based planning under uncertainty. Weighted scenarios for such approaches are for example discussed in [29], [30], [32], [45], [46] .
- Different methodologies can now be consistently and seamlessly compared by assigning relevant probability weights, and the implications of adopting one approach/metric or another clearly assessed.

4.2.2. Expected costs and expected regrets provide the same results

When comparing probabilistic assessment with LWR, there are two distinct differences which can be highlighted. On the one hand, they are using a different metric to calculate the distance to the ideal solution, as previously explained (Manhattan and Chebyshev, respectively). On the other hand, they are using different indicators, namely, probabilistic assessment and more in general stochastic programming (typically) techniques use costs, while LWR uses regrets. However, within the considered unified framework where scenario probability weights are applied to all indicators, it is possible to show that the different behaviour of the two approaches clearly comes from using different metric formulations rather than different indicators. In fact, a stochastic programming approach (looking at scenario-weighted expected values) would yield the same optimal solution when applied to cost and regret. In other words, expected costs and expected regrets will provide the same results.

To demonstrate this, let us consider that for a given scenario j the regret felt by a decision maker's choice over a strategy i can be defined as the difference in cost between that strategy (c_{ij}) and the optimal strategy for that scenario (c_j^{opt}). Using this definition of weighted regrets in a stochastic formulation that minimizes the expected regrets can be written as:

$$\min_i \sum_j \lambda_j \left(c_{ij} - c_j^{opt}\right) \tag{13}$$

By rearranging the terms in the previous expression, we get:

$$\min_i \left(\sum_j \lambda_j \, c_{ij} - \sum_j \lambda_j c_j^{opt} \right) \tag{14}$$

Since c_j^{opt}, the best strategy for each scenario, is indeed a constant for each scenario, it can be taken out of the minimization function.

Therefore, the new minimization problem can be written as:

$$\min_i \left(\sum_j \lambda_j \, c_{ij} \right) - \sum_j \lambda_j c_j^{opt} \tag{15}$$

which correspond to minimising the expected costs.

As also discussed in [29], the previous expressions demonstrate that using (weighted) regrets and costs in a probabilistic assessment context provides the same solution. This also confirms the suitability and consistency of the proposed framework where probability weights are now *naturally* part of scenario-based planning.

4.2.3. Implications in finding compromise solutions

As previously presented, compromise solutions are formally defined as feasible strategies which cannot be improved in one scenario without losing somewhere else. As there is no feasible solution that does best in all scenarios (it would be the ideal solution), compromise solutions compose the natural set of candidates to consider for the final decision. These are also called the non-dominated set of solutions, or Pareto Optimal [42]. Effectively, in the NOA's context these are all the options or strategies that would have been pre-screened in the technical analysis, before the permutations are assessed.

Compromise solutions are close to the ideal and show relatively good performance in all scenarios, which is of course of great interest for decision makers. Therefore, the ability of each methodology/metric in "exploring" the feasible set and selecting one of the compromise solutions is critical.

As discussed in [29], [30], when a decision-making problem involves integer variables very likely we will have a non-convex set of compromise solutions. Furthermore, methodologies such as probabilistic assessment which are based on linear compositions across different scenarios are only able to explore the convex hull of the whole set of possible solutions, potentially missing some of those compromise solutions in the non-convex space which might potentially lead to overall "better" decisions. In contrast, non-linear approaches such as the Chebyshev metric are in principle able to "invade" the non-convex space of the compromise solution set. This feature may be of particular interest in the TEP problem in which investment variables are intrinsically discrete. Figure 15 shows a simple example which depicts compromise solutions, and how LWR can better explore the space of compromise solutions.

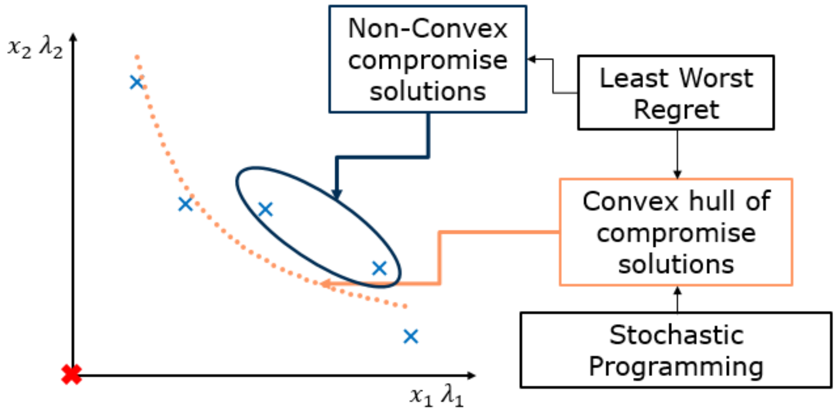


Figure 15 Example of Compromise Solutions and Probabilistic Assessment/Stochastic Programming and LWR's ability to explore non-convex solutions from this set

4.2.4. Performance of indicators and metrics with spurious investment options

There is concern that some decision-making approaches (and LWR in particular) might be less robust against quantitative errors in the reinforcement options, introduction of unsuitable reinforcement options, etc. These investment options are sometimes referred to as *spurious*.

From the definition of the Chebyshev metric, it is evident that when using the regret indicator adding a new reinforcement strategy may change the relative solution ranking, thus producing a new, different optimal decision. This is exemplified in the numerical case presented below (it assumes equal probabilities for the scenarios).

a)	STRAT	SCENARIO s_1 λ_1	x_1	$\lambda_1 x_1$	SCENARIO s_2 λ_2	x_2	$\lambda_2 x_2$	METRIC *Manhattan*	*Euclidean*	*Chebyshev*
COST	A	0.5	100	50	0.5	85	42.5	92.5	65.6	50
	B		110	55		80	40	95	68.0	55

b)	STRAT	SCENARIO s_1 λ_1	x_1	$\lambda_1 x_1$	SCENARIO s_2 λ_2	x_2	$\lambda_2 x_2$	METRIC *Manhattan*	*Euclidean*	*Chebyshev*
REGRET	A	0.5	0	0	0.5	5	2.5	2.5	2.5	2.5
	B		10	5		0	0	5	5.0	5

c)	STRAT	SCENARIO s_1 λ_1	x_1	$\lambda_1 x_1$	SCENARIO s_2 λ_2	x_2	$\lambda_2 x_2$	METRIC *Manhattan*	*Euclidean*	*Chebyshev*
	A		100	50		85	42.5	92.5	65.6	50
COST	B	0.5	110	55	0.5	80	40	95	68.0	55
	C		500	250		70	35	285	252.4	250

d)	STRAT	SCENARIO s_1 λ_1	x_1	$\lambda_1 x_1$	SCENARIO s_2 λ_2	x_2	$\lambda_2 x_2$	METRIC *Manhattan*	*Euclidean*	*Chebyshev*
	A		0	0		15	7.5	7.5	7.5	7.5
REGRET	B	0.5	10	5	0.5	10	5	10	7.1	5
	C		400	200		0	0	200	200	200

Figure 16. Numerical example to exemplify the effect of adding new strategies for different indicators and metrics.

As it can be seen in the example, the addition of strategy C modifies the optimal decision when using regret as the indicator and Chebyshev (or Euclidean) as the metric. In fact, when considering only strategies A and B (see table b in Figure 16), strategy A is selected. Then, if strategy C is added, the optimal decision switches to B. Hence, *if* strategy C were to be a spurious one, then the decision might have lost robustness.

In the context of the NOA, however, it should be highlighted that only *actual* engineering feasible and technically viable solutions are proposed as candidate strategies; hence, in principle no project should be labelled as spurious as such[25]. In this sense, the example

[25] In other words, while the concept of "spurious solution" may have its mathematical relevance, from an engineering perspective and in this specific context it may be less appropriate, given that each and every solution proposed into the NOA would have first been checked for technical feasibility.

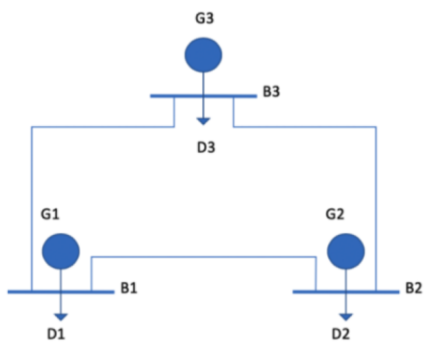
presented in Figure 16 should effectively be considered as two different planning exercises: in the first one (tables a and b) there are only two candidate options and in the second one (tables c and d) a new valid/feasible strategy has become available and it has to be considered in the context of the assessment. The moment that a new strategy is available, the regrets effectively change, because the decision maker is aware of a new option to face the uncertain future and they will be conscious of the potential regret associated to using strategy A or B in the presence of strategy C.

If there were concerns regarding the quality of some of the options included in the different strategies that are being assessed, for example because of various errors, it may not be the role of the decision-making metric/indicator to "isolate" the spurious solutions: the spuriousness of the different reinforcement options is something that would need to be assessed before starting the assessment process and based on specific considerations. Furthermore, if, notwithstanding the technical feasibility of a solution, for different reasons there were still doubts about its relevance, sensitivity analyses should be run, for example, assessing how the strategy ranking changes with and without consideration of this solution "suspected" to be spurious. The tools illustrated below may also support such analyses.

4.3. Illustrative case study application

4.3.1. Case study description

In order to illustrate some of the concepts presented in the previous sections and to expand further on the NOA's potential applications and implications of the proposed unified decision making framework and relevant weighted decision metrics, we consider here as illustrative example a simple TEP problem, namely, the 3-bus system (B1, B2, B3) whose topology and parameters[26] (in per unit, 1pu = 100MW) are presented in Figure 17.



Generator	Pmax (pu)	Cost ($/MWh)
G1	0.8	100
G2	0.8	60
G3	0.6	40

Line	Tmax (pu)
L12	0.1
L13	0.1
L32	0.1

Figure 17. 3-bus system and parameters of generators and lines.

The model to calculate the optimal investment simplistically considers the operation of one day only. The uncertain variable is the demand in each node (D1 in B1, D2 in B2 and D3 in B3), whose hourly time series for three scenarios (high, medium and low demand) are depicted in Figure 18.

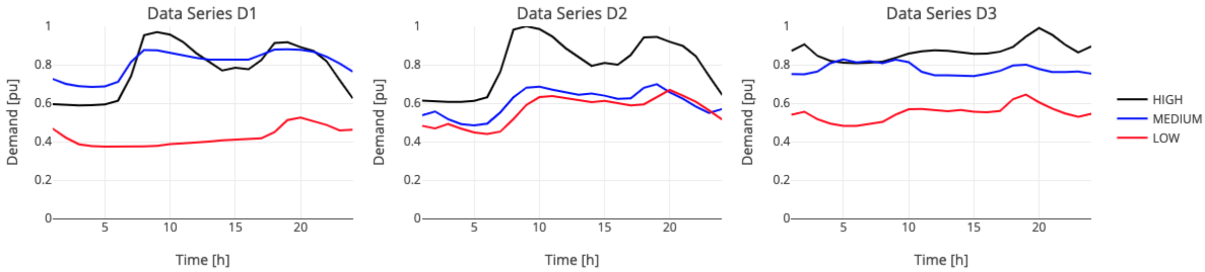


Figure 18. Hourly values of load for each demand in each of the three scenarios under consideration

For simplicity and given the illustrative nature of the example, the power flows in the transmission lines are not subject to Kirchhoff voltage law (transport model only). There are six investment strategies that we consider, as presented in Table 5. The investment cost INVC is the same for all the options (that is, 100% expansion costs INVC for each line and 50% expansion costs INVC/2 again for each line); the value for INVC was chosen aiming to create interesting numerical outcomes, resulting in a value of $1385 per line per day. The ID for each strategy is relevant to interpreting the results in Figure 19 since the colours are normalised to identify each strategy. Table 5 also shows the results for the deterministic assessment of costs[27] for each strategy for each scenario, highlighting in bold the least cost strategies for each scenario.

[26] The value of lost load is conventionally set to $300/MWh.

[27] The model corresponds to a linear problem minimising the costs of operation with nodal balances and generation and transmission limits for 24 time periods of 1 hour.

Table 6 presents the results for the regrets calculated based on the results presented in Table 5. It also shows the maximum regrets for each strategy and the LWR for the unweighted case is highlighted in bold.

Table 5. Investment strategies, investment costs and deterministic results

Strategy ID	Action	Investment Cost [$/Line/day]	Cost by scenario [$]		
			High	Medium	Low
0	Not to expand	0	610602.54	426307.07	247709.93
1	Expand Line 1 in 100%	INVC	611987.72	426089.73	**246452.39**
2	Expand Line 2 in 100%	INVC	**604949.16**	424769.84	249082.63
3	Expand Line 3 in 100%	INVC	**604949.16**	426752.31	246882.11
4	Expand Line 1 in 50%	INVC/2	611295.13	425793.43	246804.09
5	Expand Line 2 in 50%	INVC/2	606601.92	**424473.54**	248390.04
6	Expand Line 3 in 50%	INVC/2	606601.92	426059.72	246846.25

Table 6. Regrets calculated based on deterministic results

Strategy ID	Action	Regrets [$]			Max Regret [$]
		High	Medium	Low	
0	Not to expand	5653.39	1833.53	1257.54	5653.39
1	Expand Line 1 in 100%	7038.56	1616.2	0	7038.56
2	Expand Line 2 in 100%	0	296.31	2630.23	2630.23
3	Expand Line 3 in 100%	0	2278.77	429.71	2278.77
4	Expand Line 1 in 50%	6345.97	1319.89	351.69	6345.97
5	Expand Line 2 in 50%	1652.76	0	1937.65	1937.65
6	Expand Line 3 in 50%	1652.76	1586.19	393.85	**1652.76**

4.3.2. Decision making under different metrics and decision-stability regions

The next step involves using the previous results to determine the optimal strategy based on the weighted metrics presented in earlier sections of this document. In particular, in this case study we analyse the effect of using the following metrics:

- Manhattan metric (probabilistic assessment/stochastic programming): $L_1(y_i) = \sum_j^N |y_{ij}|$
- Euclidean distance: $L_2(y_i) = \sqrt[2]{\sum_j^N (y_{ij})^2}$
- Chebyshev metric (LWWR): $L_\infty(y_i) = max(|y_{ij}|) \quad j = 1, \dots, N$

Using the numerical results presented before it is possible to build these metrics for different weights λ_j for the scenarios. The resulting heatmaps presented in Figure 19 use the y-axis to represent the weight of scenario LOW (λ_L) and the x-axis for the weight of scenario HIGH (λ_H); considering that there are only three scenarios, the weight of scenario MEDIUM (λ_M) is implicit in each chart by considering that $\lambda_M = 1 - (\lambda_L + \lambda_H)$. By analyzing a range of weights, it is possible to determine the strategy that the different approaches would select for each weight combination, which then can be plotted by means of the associated ID. This graphical approach also results in a clear visualisation of the scenario weight ranges for which same decisions are recommended by different methodologies.

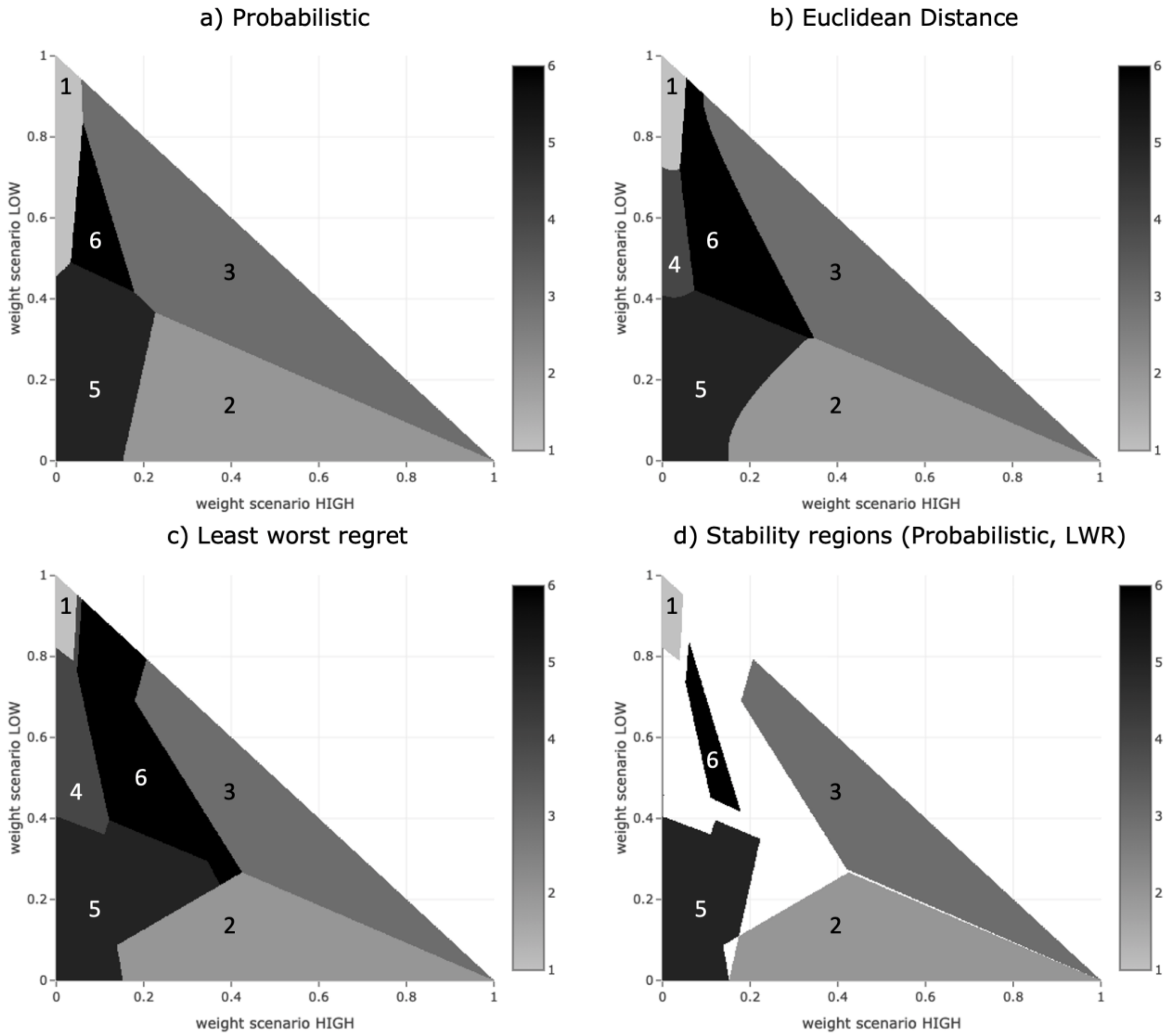


Figure 19. Optimal strategies for weighted scenarios and different metrics

As can be seen in Figure 19a, the probabilistic approach identifies only five out of six investment strategies; furthermore, the resulting areas are convex (the line formed by any two points in the area is contained in the area itself) and the transition from a strategy to another across scenario weights is smooth. As soon as a non-linear metric is used, strategy 4 appears too in the optimal solution set, as can be seen for the Euclidean distance (Figure 19b) and LWWR (Figure 19c). These findings are all in line with the theoretical considerations discussed above.

There is a further relevant consideration that can be derived from Figure 19: by superposing the charts for the probabilistic approach (Figure 19a) and the one associated to LWWR (Figure 19c) it is possible to find what we could define as *decision-stability regions*, namely those regions characterised by a combination of weights within which the selection of the optimal strategy would be the same regardless of the metric used to calculate it.

As each decision-stability region is defined for a range of weights for each scenario, this allows us to potentially select a strategy from the stable regions which is independent of the metric used and can also cope with "uncertainty" in the determination of the probability of each scenario. For example, if the LOW and HIGH scenarios were to be considered low probability scenarios (~10% each), the strategy selected would be number 5 regardless of the metric used; this would be true even if the scenario HIGH would change its weight between 0 and 15%, scenario LOW in the 0 to 35% range and the scenario MEDIUM between 50 and 100%. Decision-stability regions can thus be a powerful tool to test the robustness of given solutions to uncertain scenario probability assignment or to the plausibility of given scenarios.

Another interesting aspect worth highlighting from the results presented in Figure 19 is that there exists a relationship between the location of the reinforcement and the geometry of the areas. In fact, strategies 1 and 4 correspond to the expansion of line 1, strategies 2 and 5 to line 2, and strategies 3 and 6 to line 3. It can be seen that lines 2 and 3 dominate the resulting strategies for all the metrics, and that the total corresponding area falls within clear triangular sections of the heatmaps (a), (b) and (c) in Figure 19. This hints that important physical insights could be gained by deploying such a tool.

It is also interesting to point out that, as discussed above, the "classical" (apparently "unweighted") LWR approach would correspond to an equal weight combination for the three scenarios, and such LWR (that is, a LWWR with equal probability weights) could be compared with the results from probabilistic assessment with the same 33.3%-33.3%-33.3% combination of weights. It is clear from visual inspection that in this specific case study the classical approach does not yield decision-stable solutions across different metrics, hinting that further analysis may be worthwhile. This is discussed further below.

It is important to highlight that for applications with more than three scenarios, for example the four scenarios considered in the NOA process, the same graphical representation could still be obtained by varying the probability weights of two scenarios, for example the ones that are expected to perform "worst" and "best", and by assuming that the other two (more "central") scenarios are equally probable. Also, a four-scenario case can be represented through a 3D heatmap with specific values assigned on each scenario probability.

4.3.3. Cost and regret analysis of the solutions from different metrics

Figure 20 illustrates the distribution of expected costs (a)-(b) and maximum regrets (c)-(d) within each of the areas for the selected strategies using the probabilistic and LWWR approaches. To understand how the regrets push the boundaries of the areas to become what they are in Figure 19c, Figure 20 shows that the optimal areas found by the LWWR metric naturally reduce the maximum regrets that can be experienced compared to the probabilistic case in Figure 20c. In fact, the probabilistic metric is applied to minimize the weighted average costs across scenarios, hence resulting in strategy spaces that have been optimised without considering the corresponding regrets. The differences in regrets between the probabilistic and LWR metrics can be seen in Figure 21a; the values presented there are the results of subtracting the values Figure 20d from the values Figure 20c. Furthermore, Figure 21b shows the differences resulting from subtracting the expected costs presented in Figure 20a from Figure 20b. It is clear from the positive differences seen within the LWWR decision boundaries in Figure 21b that they would change to match the probabilistic decision boundaries if the probabilistic metric was used to make the decisions.

In general, by performing this kind of expected costs and expected regrets analysis for different methodologies all the implications of using different approaches, risk-aversion degrees, and scenario weights may be clearly assessed, potentially leading to developing an enhanced decision-making framework where the performance of the proposed investment solutions are much more transparent in terms of including costs and risks and robust to different uncertainties.

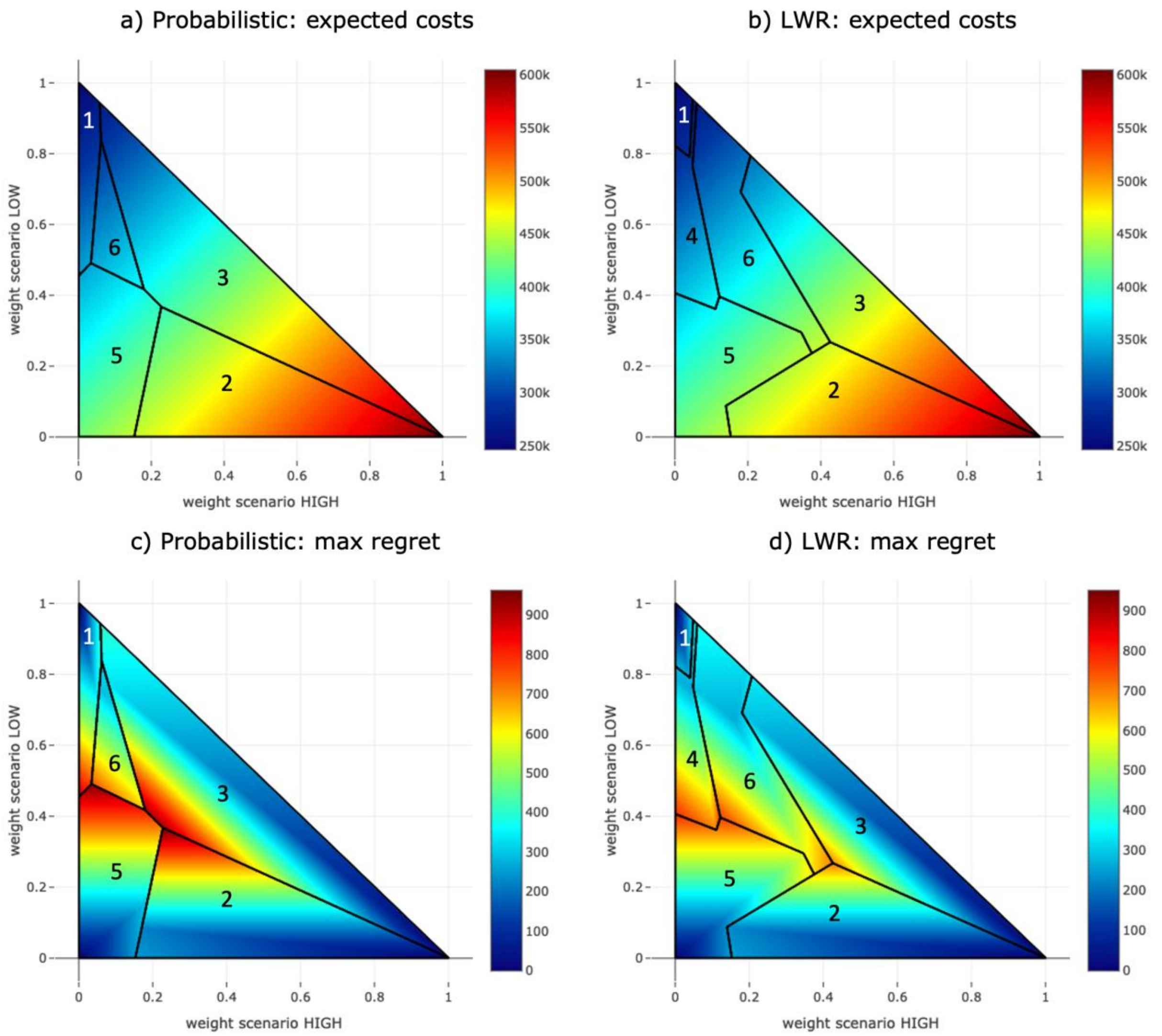


Figure 20. Expected cost and maximum weighted regret for the optimal decisions in the Probabilistic and LWWR cases

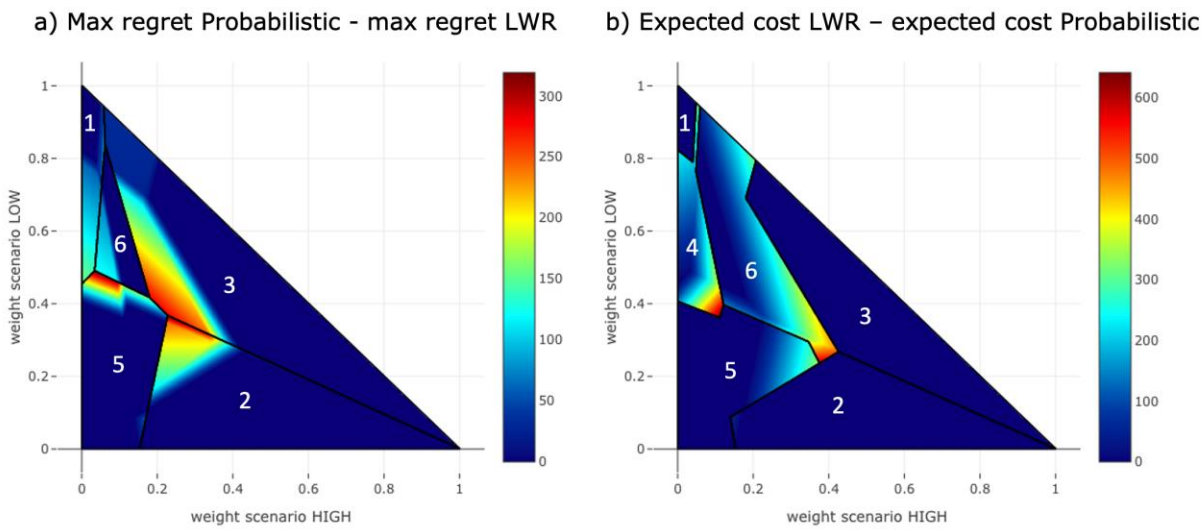


Figure 21. Differences between Probabilistic and LWWR solutions for maximum regrets and expected costs

5. General feedback on the NOA process and initial recommendations for improvement

5.1. General feedback

Based on the reviews and study performed, there are few key points that it is possible to highlight as feedback for the current NOA process and considerations for a more probabilistic approach:

- Planning under uncertainty is typically dealt with by scenario-based approaches in most countries. National Grid ESO's approach seems therefore in line with what is done elsewhere.
- Most countries adopt a (very) limited number of scenarios or sensitivities around central scenarios in their planning methodologies, with no probability weights explicitly associated with the considered scenarios. In fact, scenarios seem to be typically analysed independently and then planning options are chosen based on specific rules to make an overall decision. National Grid ESO's NOA methodology based on LWR that integrates decisions *across* several scenarios thus seems to represent the state of the art of planning under uncertainty.
- Based on our proposed unified view that brings together apparently different decision-making approaches, the current LWR approach *does* already have (implicit equal) probability weights and is therefore *not* probability-agnostic. The current NOA methodology could also readily and seamlessly be adapted to incorporate scenario probability weights, by adopting a more general Least Worst Weighted Regret (LWWR) approach.
- Comparing a probabilistic assessment approach, which aims to minimise expected costs (or, equivalently, expected regrets) across scenarios using specific weights or probabilities, and a LWR approach with no weights (that is, with *implicitly* equiprobable scenarios) may be inconsistent, as the problems that they would be solving would be effectively different.
- LWR and its weighted counterpart, LWWR, allow exploring more investment solutions than a probabilistic assessment, which is naturally more appealing.
- In comparison with a probabilistic assessment, LWR (or the more general LWWR) is intrinsically "less risky", as it explicitly adopts a risk measure (the regrets themselves) and minimises it. Effectively this means that LWWR tends to opt for investments that perform satisfactorily in all scenarios, reducing the potential economic impacts that an unfavourable scenario might generate once the decision has been made. Conversely, a probabilistic assessment, which does not take into account any risk measure (and is indeed risk-neutral), could lead to greater economic impacts if unfavourable scenarios were to take place.
- As an interesting feature in practical applications, including potentially in the NOA, by a suitable use of scenario probability weights LWWR effectively allows modulation of the decision maker's attitude to risk aversion. In fact, assigning relatively smaller weights to extreme scenarios that might tend to drive investment would correspond, in practical terms, to decreasing the risk-aversion level.
- Therefore, from a point of view of a decision maker that is risk-averse, due to their intrinsic approach to risk LWR and, if using probabilistic weights, LWWR may be

considered more adequate for investment analyses such as in the NOA. Furthermore, as aforementioned, the decision maker's risk attitude can also be potentially modulated by using weights in the LWWR approach.

5.2. Initial recommendations

In terms of possible improvements to the current NOA process and more in general aspects that might be worth exploring, we would like to recommend the following:

- Additional operational snapshots could be included in the technical analysis besides the current winter peak assessment. This is in light of increasing operational complexity and uncertainty that might drive worst case flows across boundaries at different times of the year. Similarly, inclusion of new operational characteristics and constraints, such as associated with low-inertia conditions, could be desirable.
- The use of LWR or similar approaches could be adopted to inform the optimality of interconnector assessment across scenarios too. This would allow a more consistent and integrated approach between selection of (internal) boundary reinforcement and optimal level of interconnectors.
- A Least Worst Weighted Regret (LWWR) approach, in which scenarios have explicitly assigned weights could be proposed as the generalised version of LWR (where equiprobable scenarios are implicitly assumed).
- The implicit equiprobable scenario representation of the current LWR approach can be interpreted as a special case of the more general LWWR whereby it is intrinsically believed that all current scenarios are similarly plausible and likely to happen[28]. However, if there are reasons to consider asymmetry in the likelihood of the considered scenarios, consideration might be given to a more detailed assessment that might explore different probability weights.
- While we are aware that the selection of probability weights to assign to scenarios may be difficult and controversial, our proposed unified framework provides a consistent and comprehensive view that could seamlessly compare and assess the outcomes of (apparently) different methodologies (i.e., probabilistic, LWWR and min-max weighted cost), with scenario weights being considered as a *natural* component. This could eventually provide more transparency and robustness to the investment process and the selected options, thus resulting in reduced risk of spurious solutions and reduced risk of decisions being driven more by specific scenarios than methodologies, and in general enhanced hedge against potential uncertainty. Furthermore, by modulating the value of the scenario weights, the impact of different degrees of risk-aversion may also be explored.
- Such analysis could also be supported by visual tools that could identify decision-stability regions with win-win solutions from different methodologies and suggest what solutions might require further analysis, for example in terms of expected costs and regrets.
- Irrespective of the formal use of probability weights, multi-parametric scenario sensitivity studies could be performed to provide insights into the benefits and risks of

[28] Equiprobability of scenarios corresponds to Laplace's "principle of insufficient reason". This, however, generally requires absence of lack of symmetry in the considered scenarios. Once again, if such symmetry may be present due to different views on future scenarios, the use probability weights is advocated in the classical theory.

different proposed solutions under different possible future occurrences, with for example expected costs and expected regrets (a measure of risk) analysis for different methodologies able to clearly assess all the implications of using different approaches, risk-aversion degrees, and scenario weights.

5.3. Next steps

Next steps in this study include: looking into techniques to embed more flexibility in the NOA methodology (e.g., more explicit approaches that resemble Real Options) starting from and possibly improving the current use of annual rolling horizon; looking into considering the use of different risk measures (for example, based on utility theory and CVaR); studying in more detail the role and impact of extreme scenarios and alternative solutions on the proposed decision making approaches, possibly with real case studies; and attempting to bring closer technical and economic aspects of the NOA and looking for overall improvement of the mechanics of the whole methodology in its interaction between technical and commercial studies.

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