# *Study of advanced modelling for network planning under uncertainty*

*Part 2: Review of power transfer capability assessment and investment flexibility in transmission network planning*

## Report prepared for National Grid Electricity System Operator

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## Acronyms

| | |
|---|---|
| AC | alternating current |
| AEMO | Australia Energy Market Operator |
| AI | artificial intelligence |
| BCE | boundary congested energy |
| BCP | boundary congestion probability |
| BM | balancing mechanism |
| CBA | cost-benefit analysis |
| CDF | cumulative distribution function |
| COLF | component over-loading frequency |
| COLP | component over-loading probability |
| CPF | chronological power flow |
| CPPF | constrained probabilistic power flow |
| C&R | challenge and review |
| CRE | composite reliability evaluation |
| CVaR | conditional value-at-risk |
| DC | direct current |
| DER | distributed energy resource |
| DNN | deep neural network |
| ECON team | Economic team |
| ED | economic dispatch |
| EENS | expected energy not served |
| EISD | earliest in-service date |
| ETYS | Electricity Ten Year Statement |
| FACT | flexible alternating current transmission |
| FES | Future Energy Scenarios |

| | |
|---|---|
| GB | Great Britain |
| HVDC | high voltage direct current |
| LOLP | loss of load probability |
| LP | linear programming |
| LWR | Least Worst Regret |
| ML | machine learning |
| NETS | National Electricity Transmission System |
| NGESO | National Grid Electricity System Operator |
| NOA | Network Options Assessment |
| OPF | optimal power flow |
| PDF | probability density function |
| POUYA | **PO**wer system **U**ncertainty **Y**ear-round **A**nalyser |
| PPF | probabilistic power flow |
| RES | renewable energy sources |
| RFI | request for information |
| SC team | System Capability team |
| SEW | social economic welfare |
| SOF | system operability framework |
| SQSS | Security and Quality of Supply Standard |
| TEP | transmission expansion planning |
| TO | transmission owner |
| UC | unit commitment |
| VaR | value at risk |

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# Executive summary

There are significant and growing uncertainties associated with the planning process of Great Britain's transmission network. These are driven by fast-changing generation portfolios with more and more renewables and distributed energy resources, electrification of the heating and transport sectors. National Grid Electricity System Operator (NGESO) strives to strike a delicate balance between (i) benefits from reinforcements in terms of constraint cost reduction and increased system reliability, and (ii) risk of network over-investment and of stranded asset.

This *project* aims at providing a comprehensive review of the current investment planning methodology adopted by National Grid ESO in the context of the Network Options Assessment (NOA) process and with reference to the Electricity Ten Year Statement (ETYS), compare it with other methodologies used by other system operators and from the research literature, and recommend suitable improvements. In the first part of the project we have provided a comprehensive overview of the NOA methodology, discussed different planning methodologies adopted by other system operators worldwide, and assessed the suitability and proposed potential improvements of the current investment planning methodology that is based on least worst regret analysis.

In this *report* we aim at addressing two further fundamental questions to improve the NOA process:

- *How could network modelling be improved for operational constraint cost evaluation*; and
- *How could the current planning methodology be improved to enhance investment flexibility*.

### *Representation of network modelling in operation*

After a review of methodologies for deterministic and probabilistic operational analysis, we present an in-depth discussion on the meaning of the concept and potential definitions of *boundary capability* and introduce a simple case study to demonstrate the probabilistic distribution of boundary capability and system dispatch profiles under different conditions. We then propose a few options to improve the current methodology of NOA and ETYS from different perspectives.

Our recommendations for potential improvements of the system operational modelling include:

- Adopt K-means and stratified sampling algorithms to derive different boundary capability setpoints;
- Introduce a set of reliability indices and risk metrics to improve the confidence in applying a specific value for boundary capability in NOA's cost-benefit analysis (CBA);
- Integrate optimal power flow and redispatch algorithms into NOA's CBA, so that the accuracy of constraint cost evaluation could be improved by (i) replacing boundary flow constraints with a more complete set of network constraints, and (ii) including potential cost-effective redispatch options;
- Establish a unified framework for consistent and comprehensive evaluation of (operational) commercial solutions and network-based reinforcement options in NOA;
- Apply machine learning techniques to (i) accelerate and enhance the power flow analysis for security screening of the dispatch profiles, and (ii) automate the "Challenge and Review" process of NOA.

### *Enhancement of flexibility in investment planning*

Planning flexibility is associated with the capability of the current NOA CBA methodology to identify investment options that allow the system to adapt to changing future conditions (that are represented through the Future Energy Scenarios (FES)). An investment option or a group of investment options that can "help" the system *across* scenarios are referred to as *flexible investment options* or "*compromise solutions"*.

The identification of flexible investment portfolios is a challenging but essential task to avoid excessive and undesired investment and operation costs in the presence of uncertainty. It is challenging because it requires studying the operation of the system over multiple years under various conditions, as determined by the scenarios, and for different potential combinations of investments. To adequately value flexibility there are *three* key aspects that should be thoroughly assessed: (i) the decision structure behind each investment option (decisions that can be made at each stage of the development of the options); (ii) the representation of how the future can unfold and how decisions can be modified in time; and (iii) the representation of the operation of the system.

This report discusses these elements in general terms as well as with reference to the characteristics of the current CBA methodology. In the context of the current NOA methodology, what we have identified is that while the structure of decisions associated with each investment option is relatively complex, only two of these decisions (proceed/delay) become available at the time of evaluating investment flexibility (logic phase). This inherently limits the capability of the methodology to identify (more) flexible strategies. Also, potential futures are assumed to unfold in linear and independent patterns (following the scenarios). This reduces the ability of the methodology to identify compromise investment solutions that could adapt better to an unfolding future if the conditions anticipated by the specific scenarios were not to materialise.

Potential options that NGESO could pursue to address these limitations include:

- The determination of the optimal *deterministic* paths should be automated as much as possible, through: (i) an intelligent search of the optimal investment path given the pre-calculated operation costs for each option (short term), via relatively straightforward integer or dynamic programming approaches; or (ii) algorithms capable of performing an integrated assessment of investment and operation costs to determine the optimal path for each scenario (mid to long term).
- In order to capture more investment flexibility, in the *short-term* new heuristic approaches should be considered that are capable to identify "compromise solutions" among the global set of reinforcements that are being considered. This requires exploring options that the current methodology may not be able to identify due to the approach used to select the reinforcements that are subject to the single-year LWR decisions. In order to achieve this systematically, the *long-term* aim should be to build an integrated operation-investment *multistage* model that could consistently assess the role of network and non-network options. Formally, the underlying mathematical modelling could be based on stochastic programming with risk considerations, whose rationale and outcomes would be similar to and enhance the current least worst regret philosophy.
- Determining the right degree of details in the representation of system operation could reduce substantially the computational burden associated to the optimal investment path determination in the CBA analysis. This could be achieved by comparing the current optimal deterministic investment strategies with those obtained by progressively reducing the number of operational periods represented for each year (the selection of representative operation periods can be conducted by appropriate clustering methods). In fact, as all recommendations to improve the NOA CBA are strictly connected to the representation of operation, any gain in this regard could greatly improve the overall performance of the methodology.

As a last “umbrella” recommendation that refers to the overall NOA process, NGESO should seek to assess the optimal frequency at which the NOA process should be run, as changes in this regard would impact the time available to conduct *every* task in the methodology. Understanding the optimal trade-offs between running the process every year versus making it less recurrent (e.g., every two years) would affect substantially the need for implementation of various recommendations and eventually their overall impact.

# 1 Introduction

## 1.1 Context

Ensuring a secure and reliable electricity supply has always been the priority of power system operators across the world. Traditionally, power system expansion is used to satisfy the peak demand of the system, such as average cold spell (ACS) in the Great Britain (GB), which is annually measured by NG system operator and published in its Winter Outlook [1]. Transmission expansion planning (TEP) determines the requirement of additional transmission capacity to accommodate the increase of generation (to meet demand) and avoid network congestion in certain regions. Nowadays, the change of generation portfolio is not only bounded by meeting system peaks but also influenced by government policies, especially the decarbonisation of the energy sector, typically through integrating more renewable energy sources (RES). With increasing penetration of RES, which has a variable output, the challenge for system operation may no longer reside in peak demands, while the periods of high renewable output can also stress the network and consequently cause high voltage and stability issues. Therefore, the economic value of transmission network assets can also be enhanced by reducing renewable energy curtailment in addition to meeting electricity demand.

This transition of modern power system into a low-carbon and low-inertia one brings some imminent requirements, including the modification of current industrial practices in determining optimal network investments.

- First of all, the temporal and spatial considerations in transmission planning need to be expanded. From the temporal perspective, the system security analysis needs to be performed on the periods other than the peak snapshot to reflect the volatility of renewable energy output across a year. Regarding the spatial consideration, the reinforcement options are traditionally assessed on a boundary[1] or zone basis by splitting the whole system into a number of parts in order to improve computational efficiency. However, it is unclear whether this simplification can still hold in the future and the reasons are twofold: 1) Power plants are less geographically concentrated due to increasing penetration of distributed energy sources and this creates difficulty in defining boundaries and zones; 2) The reinforcement options are no longer limited to network-based assets, since there are more flexible resources (e.g. battery, electric vehicle) on demand side, which are spread across different regions and can provide network support as commercial solutions through demand response mechanisms.
- Secondly, electrification of energy demand and decarbonisation of the generation portfolio may lead to change of generation location and demand level in a relatively

[1] Boundary is a unique concept used by NGESO to split the GB power system to different parts to reduce the complexity of network assessment with minimum impact on the accuracy of power flow. This boundary concept is comparable to “zonal areas” applied by other system operators across the world. More information of Boundary can be found in ETYS [2].

short timeframe (e.g., 5-10 years) in comparison with the lifetime of network (e.g., more than 40 years), which creates investment uncertainties. The traditional "fit and forget" practice is no longer held in this case, and network planners need to make multi-stage decisions through a scenarios-based approach to quantify the impact of uncertainties in the future, so that a delicate balance can be struck between the risks (e.g., over-spending, stranded asset) and benefits (e.g., constraint costs[2] reduction) of a specific investment decision.

National Grid Electricity System Operator (NGESO) has been continuously upgrading the methodologies of relevant assessments in meeting its GB grid operator obligations so that the challenges mentioned above can be tackled. NGESO publishes two network related reports annually, which are the Electricity Ten Year Statement (ETYS) [2] and the Network Options Assessment (NOA) [3]. ETYS is used to determine the power flow across boundaries and identify the potential locations with the necessity of network upgrade. Then, NOA assesses the social economic welfare (SEW) brought by the reinforcement options that are proposed by transmission owners (TOs) and developed in response to the information given in ETYS. In the latest development of ETYS methodology, NGESO has begun to test probabilistic approach in assessing boundary transfers capability [4]. Also non-network solutions have been identified and considered in various Pathfinder projects to manage thermal, voltage and stability issues of the network in short or medium terms (i.e., 5-10 years) [5]. Regarding the methodology of NOA [6], a Least Worst Regret (LWR) approach has been adopted to identify the risk and benefits of reinforcement options across four Future Energy Scenarios (FES).

In order to consolidate its current methodology used in network planning, NGESO is collaborating with the Melbourne Energy Institute to perform reviews and studies of different network planning approaches under various uncertainties. In the first report of this project [7], a general overview of the NOA and ETYS processes was presented. In addition, the network planning practices of different grid operators across the world were reviewed, also discussing the available frameworks for decision-making. In this second report, we will put more focus on the technical aspect of the ETYS and NOA and elaborate on potential modelling of investment flexibility in network planning.

## 1.2 Aims and objectives

In this report, we focus on addressing the questions which are related to technical and economic perspectives of ETYS and NOA, specifically:

- What probabilistic power flow approaches are available and how to transit from a deterministic boundary transfer capability assessment to a probabilistic one in ETYS?
- How can the boundary capability assessed with the probabilistic approach in ETYS be better integrated with cost-benefit analysis (CBA) in NOA?

[2] In the following context, the term "constraint costs" is used to refer to the additional system operating cost when the natural energy flow is above the thermal and voltage constraints of network, which requires some of the generators to be redispatched from their optimal levels and/or the activation of commercial solutions (e.g. demand response and generation de-loading).

- How could Machine Learning (ML) techniques potentially be used to improve the workflow of NGESO's network planning?
- What is investment flexibility and how can investment flexibility be defined and better captured in both the current NOA framework and then looking forward?
- How to improve the workflows of ETYS and NOA in the short term and long term?

In order to achieve the aims mentioned above, we have set the following objectives:

1) Elaborate on the current methodology of ETYS, which deals with the boundary capability assessment and the identification of commercial solutions.
2) Review the probabilistic power flow approaches (e.g., analytical, sampling) available in the literature.
3) Propose feasible improvements on probabilistic sampling and new technical indices to increase NGESO's confidence in applying probabilistic boundary capability.
4) Establish a methodology which can ultimately avoid the inaccuracy of constraint cost evaluation brought by boundary flow constraints.
5) Identify potential applications of machine learning and artificial intelligence (AI) in ETYS and NOA.
6) Review the definition of investment flexibility to facilitate the understanding of a framework that can capture this type of flexibility in a TEP process.
7) Provide feedback and recommend potential improvements, which enable more interactions between the technical analysis in ETYS and CBA in NOA, so the network planning methodology can be better-prepared for the challenges in the forthcoming lower-carbon power system.

## 1.3 Report structure

- Section 2 gives a review of ETYS's workflow, deterministic/probabilistic power flow methodology and the current methods of identifying commercial solutions.
- Section 3 presents a literature review of probabilistic power flow models in academia and discusses the fundamental definition of boundary transfer capability. Then, several approaches are introduced to potentially enhance NGESO's current methodology, especially in selecting the capability value based on some customised reliability indices and risk metrics. Furthermore, a method of achieving the full integration of network assessment and economic dispatch in NOA's CBA is proposed. Finally, two potential applications of machine learning techniques are elaborated on, which have the potential to improve the efficiency of NOA and ETYS's workflow.
- Section 4 sets out to discuss the methodological aspects of the NOA CBA with a special focus on seeking more investment flexibility from the reinforcement options under analysis.
- Section 5 provides a summary of our feedback based on the review work carried out in this project and presents a potential roadmap for implementation of the recommendations made in this report.

# 2 The Electricity Ten Year Statement process

The Electricity Ten Year Statement (ETYS) is a part of several documents published by National Grid Electricity System Operator (NGESO) to identify the potential developments which would be required to safeguard a secure, affordable and sustainable GB power system. The focus of ETYS is to indicate the aggregated power transfer at different boundaries in both current and future GB power systems based on the projections given in Future Energy Scenarios (FES). This information of power transfer requirement will be used by stakeholders (i.e., NGESO, Transmission network owners (TOs)) to propose relevant network-based or commercial solutions to expand the capability of current GB network.

In this section, the workflow in the preparation of Electricity Ten Year Statement is presented. The description is based on publications [2], [4], [8], [9] which can be found on National Grid's website, while several rounds of interviews with system capability (SC) team has also been carried out to identify and verify the relevant details.

## 2.1 Tasks structure and timeline

The publication frequency of ETYS is the same as NOA, which is on an annual basis. The preparation of ETYS is immediately initiated following the publication of the latest NOA in January. The timeline of relevant tasks in the ETYS preparation is summarised in Figure 2.1.

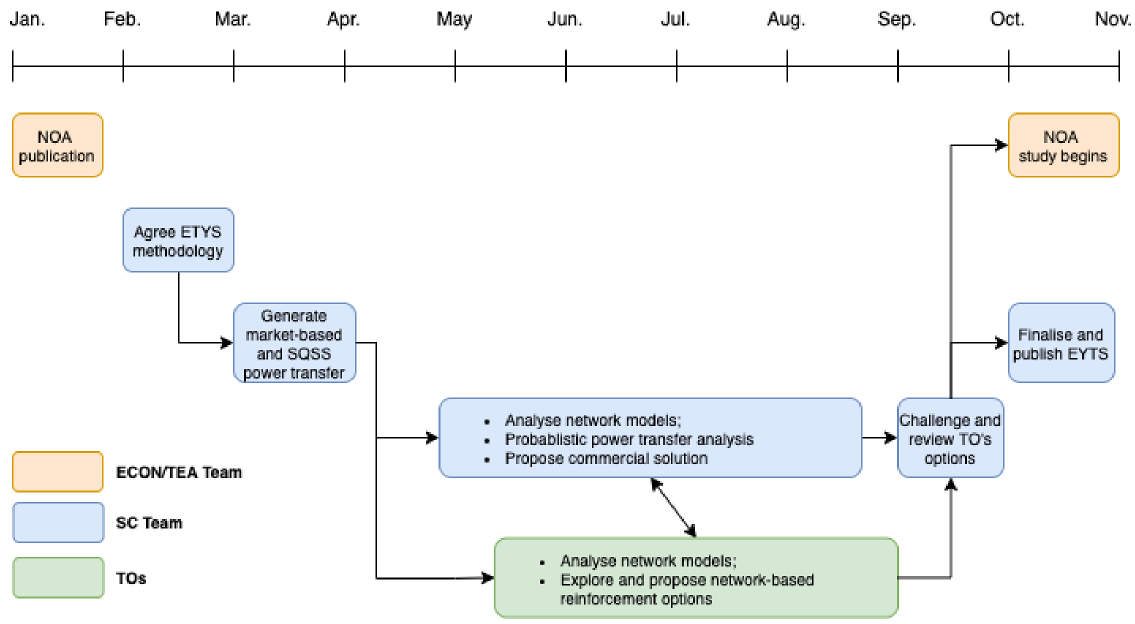



*Figure 2.1. ETYS preparation timeline*

The details of each task are explained as the following:

- In February, SC team meets with stakeholders of ETYS (i.e., TOs in GB power system) and reach an agreement of the methodology in preparation of the forthcoming ETYS, such as the full guideline and case studies, etc.
- In March and April, SC team consults FES team and determine the input data to model the evolution of GB power system in next 20 years. The input data includes generators

capacity and corresponding locations, generators ranking order in economic dispatch, annual demand profile and winter peak. The analysis is carried out in two parts:
  - Determine the economy and security transfer in winter peak condition based on the procedure listed in [9].
  - Determine unconstrained year-round market-based power transfer at each boundary. This profile is simulated by running GB system economic dispatch without considering transmission network constraints.
- Around May, SC team firstly passes the unconstrained power transfers, and security and economy transfers based on SQSS to TOs. Then, Data and Modelling team begins to construct the network model in Power Factory in collaboration with all stakeholders, such as TOs, so that a consistent network model can be used by different parties.
- From the beginning of June to the end of August, Data and Modelling team and TOs separately construct and update network models in Power Factory, which represent the potential GB power network in Year-1, Year-2, Year-3, Year-4, Year-5, Year-7 and Year-10[3]. Generally speaking, no network reinforcement options will be proposed with a planning horizon longer than 10 years due to the high level of uncertainty faced by GB power system. However, considering the complexity and lead time of some projects proposed by TOs, NGESO recognised that there is potentially a requirement to assess the options beyond this timeframe of 10 years.
  - **SC team**:
    1. The team tests network-based reinforcement solutions (proposed in the last NOA) on the network models with security constraints, such as thermal, voltage compliance, voltage collapse and stability.
    2. For the reinforcement options which satisfied the security constraint, the team will perform both deterministic and probabilistic analysis to assess the increment of boundary transfer capability with the reinforcements. The methodology of determining boundary transfer capability is further elaborated in section 2.2.
    3. In parallel, commercial solutions (e.g., deloading and intertrip of generators) are explored by the team, which can reduce constraint costs like network-based reinforcement options. More information of commercial solutions is given in section 2.3.
  - **TOs**: By examining the unconstrained boundary transfer profiles and economy and security transfers, TOs will propose network-based reinforcement solutions and test them on the latest network models. TOs also have the obligation to calculate the additional boundary transfer capability brought by individual reinforcement options.
- In September, the TOs need to submit all the network reinforcement options with the corresponding technical and financial information to the Network Development team. Subsequently, the Network Development team facilitates the Challenge and Review (C&R) process to selectively examine the validity of technical performance of a portion

[3] The number following "Year" represents the number of years following the current time. For example, for 2020 ETYS publication, Year-3 model represents GB power network with confirmed and proposed reinforcement options in 2022.

of options submitted by the TOs. By the end of September, all valid options will be passed to Economic Assessment (ECON) and Technical Economic Assessment (TEA) teams to prepare cost-benefit analysis in NOA, while SC team will prepare for the publication of ETYS.

## 2.2 Boundary capability assessment

"Boundary" is a unique concept used by NGESO in assessing the aggregated power transfer capability between different regions of GB power system. Defining boundaries takes a lot of experience in system operation and planning. Before deciding boundary locations, NGESO has firstly split the system into different zones in ETYS, which are interchangeably called "Minor zones" or "FLOP zones". Each FLOP zone is formed based on the criteria that it has a strong internal network connection but a relatively weaker connection to adjacent areas. Then, 17 Major zones are defined as the sum of some FLOP zones [2]. A boundary may also be drawn across some FLOP zones, which have major generation sources. Boundaries may also sit across important power transfer corridors [2], such as the corridor between England and Scotland. The illustration of boundaries in GB power system can be found in Appendix A.

Boundary transfer capability is usually calculated as the maximum power transfer across a specific boundary without violating any security criteria (i.e., voltage, thermal and stability) and its value can be different considering the power flow directions (i.e., from North to South in comparison with from South to North). Traditionally, a deterministic approach outlined in National Electricity Transmission System (NETS) Security and Quality of Supply Standard (SQSS) [9] is applied in assessing the capability. The assessment is firstly carried out as a snapshot at winter peak conditions with given initial dispatching level of generators. In addition, sensitivity studies are run at off-peak conditions. In this regard, NGESO has also introduced seasonal boundary capabilities to represent the year-round conditions of the NETS and then used in the economic dispatch model for the CBA analysis. These capabilities are assessed as the scaled winter-peak boundary capabilities or under specific sensitivities. However, NGESO has recognised that the winter peak may no longer represent the most stressful situation faced by NETS and it is necessary to consider the uncertainty embedded in both generation and demand sides, especially with increasing penetration of renewable energy sources, such as wind and solar plants. Therefore, NGESO has introduced the probabilistic analysis to retrieve the potential boundary transfer profiles and test them with security constraints. The following two subsections explain the methodology of the deterministic and probabilistic assessments.

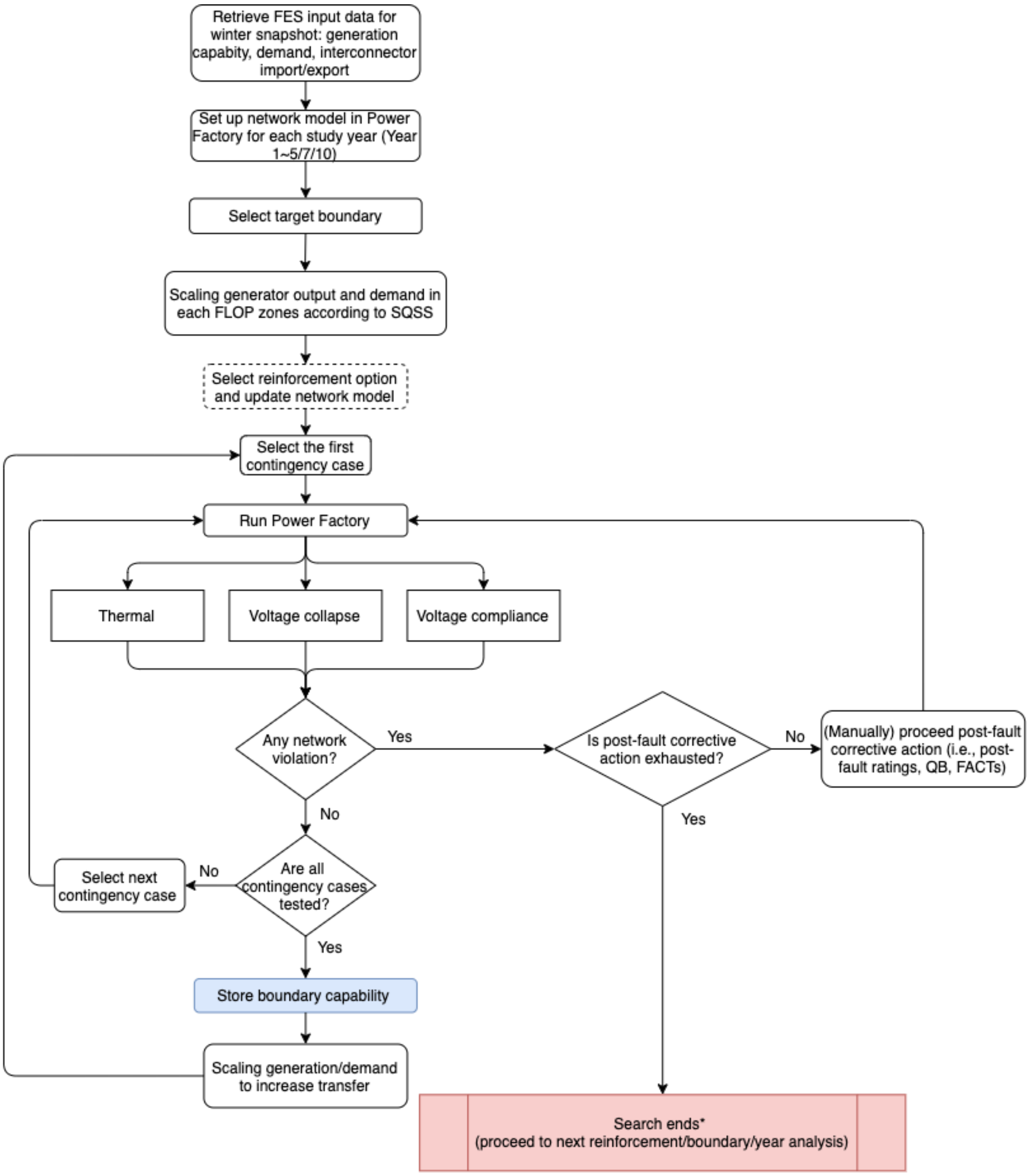
### 2.2.1 Deterministic method (based on SQSS)

As mentioned above, a deterministic approach is used in the assessment of boundary capability. It is considered to be part of system operator's obligation that NGESO accurately defines the boundary capability following the guidance listed in SQSS. There are two types of planned transfer conditions defined in SQSS, which are called "security transfer" and "economy transfer". The main difference between the two transfers is the scaling factors that are used to determine the output level of different generator types. The workflow of determining the value of a specific boundary transfer capability is shown in Figure 2.2, which is explained below:

1) First of all, the input profiles of the winter snapshot are retrieved from Future Energy Scenarios. These inputs include generation capacity, demand, generator ranking order, interconnectors' import/export capacity and levels.
2) Then, the base network model is set up in Power Factory, which represents the current NETS network and the model can perform alternating current (AC) power flow analysis and contingency analysis.
3) Furthermore, the target year and boundary are selected with a range of reinforcement options proposed by TOs. An initial scaling factor is given to individual generators based on its fuel type and the transfer type (i.e., security or economy) in the analysis. For example, in the security transfer assessment, the scaling factors[4] for wind plants, solar plants and interconnectors are set to 0, while the scaling factor of conventional generators is set to 1. However, in the economy transfer, the initial scaling factor for wind plants is set to 0.7, while the scaling factors of coal and nuclear plants are set to 0.85.
4) Subsequently, for every network model, which is reconfigured from the Year-1 model by adding FES corresponding generation and demand and also a combination of reinforcement options modelled to be evaluated, SC team runs several contingency case studies and make sure the whole network is operating in compliance with its thermal and voltage constraints. It is worth mentioning that the contingency is only considered for the network assets, such as branches and direct current (DC) links. Before storing the final value of boundary transfer capability, there are several loops to be executed, which are elaborated as following:
   - Step 1: After selecting the first contingency case, the network model is altered by removing corresponding outage components, and then the operation is simulated in Power Factory.
   - Step 2: If any of the thermal, voltage compliance and voltage collapse constraints are violated, post-fault actions are taken to alleviate the network congestion. The post-fault actions include post-fault ratings of lines, QB transformer, flexible alternating current transmission (FACT) networks. All these actions are executed manually in the network simulation based on advice from the experts in SC team. It needs to be highlighted that post-fault actions in the planning stage don't include market-based solutions, such as re-dispatching generators.
   - Step 3: If all contingency cases have been simulated and results don't have any constraint violation, the scaling factor of generators on the boundary side with net generation is increased at a specific interval (i.e., 10%), while the generators output level on the opposite side would decrease to avoid over-generation and keep the balance of demand and generation in the system. In this case, the feasibility of a case with higher boundary transfer can be tested.
   - Step 4: The highest value of feasible transfer capability is stored for the selected boundary. It needs to be mentioned that if the generation portfolio with initial scaling factors had resulted in a violation of network constraints,

[4] All detail can be found in the Appendices C and E of SQSS [9] for the settings of security transfer and economy transfer respectively.

the scaling factors on the net generation side would be decreased to test the case with a smaller transfer volume.




** If the network cannot be securely operated with initial scaling factors defined in SQSS, generation/demand are scaled down to reduce the transfer in order to find valid boundary capability.*

*Figure 2.2. Workflow of evaluating boundary capability with a deterministic approach defined in SQSS*

Capability under both economy and security transfer requirements can be determined with this workflow by applying different scaling factors, as explained in point *3)* above. After determining both the security and economy transfer requirements of all the boundaries, the capability under the higher required transfer is used as the input for economic dispatch studies in CBA of NOA. The increment of boundary transfer capability due to reinforcement options is also passed to CBA, so that the reduction of system annual operating cost caused by reinforcement can be calculated to inform the least-worst regret (LWR) analysis in NOA.

### 2.2.2 Probabilistic method (all year-round)

As mentioned in [4], a probabilistic methodology in boundary capability assessment has been introduced in order to identify the likelihood of events other than winter peak which can stress the network. In comparison with the deterministic approach, the probabilistic one simulates the network behaviour with year-round generation output profiles, which is crucial for evaluating the impact of increasing penetration of renewable generation and interconnectors.

Figure 2.3 gives a summary of the probabilistic methodology in boundary transfer capability assessment. Firstly, year-round transfer profiles at hourly resolution are generated and examined in the network. The profiles would be divided into two groups and labelled as "acceptable" and "unacceptable", which represent the network operation condition with/without violating security constraints (i.e., thermal, voltage collapse, voltage compliance[5]). Then, the profiles would be converted to power segments at a specific interval (e.g., 100 MW) to indicate the period of relevant transfer levels. For example, if there are two snapshots of transfer volume, which are 1643 MW and 1670 MW, both of them would be categorised into the segment 1600 MW, if the segment interval is 100 MW and the cover range is from the segment setpoint to the setpoint plus the interval. Then the corresponding 1600 MW segment hours would increase by 2. After deriving the transfer volume segment profiles, further calculation is performed to determine the opportunities lost and energy at risk, which are consequently used to determine the boundary transfer capability. It needs to be mentioned that there are two sets of the opportunities lost, energy at risk and boundary capability for each boundary, which are separated as positive and negative values to represent the bi-directional energy transfers across the boundary. The following subsections 2.2.2.1-2.2.2.4 explain the tasks in each block of Figure 2.3.

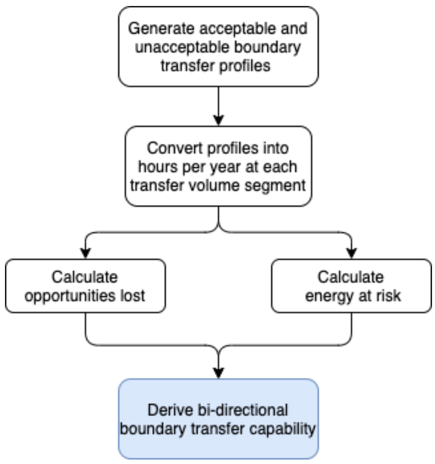



*Figure 2.3. Probabilistic methodology in determining boundary transfer capability*

[5] Currently, POUYA has only developed the capability to run DC power flow with network corrective actions included, and therefore voltage collapse and compliance cannot be examined in probabilistic analysis. SC team has planned to develop the AC power flow function in POUYA within the next couple of years.

#### 2.2.2.1 Probabilistic transfer profiles generation

Unlike the analysis of few peak and minimum snapshots, the year-round probabilistic analysis has many data points to be analysed. Therefore, it is necessary to develop a tool to simulate network operation and more importantly post-fault actions, which need to be executed automatically instead of manually to improve computational efficiency. SC team has been developing a tool to perform more efficient year-round analysis of the network, which is called **PO**wer system **U**ncertainty **Y**ear-round **A**nalyser i.e., "POUYA". Currently, POUYA only has the capability to perform DC power flow with network thermal constraints, while the capability of applying voltage constraints are under development. POUYA can also automatically apply some post-fault actions, such as post-fault ratings and QB tapping.

The workflow of generating and verifying year-round boundary transfer profiles is shown in Figure 2.4. The detail of each block is further explained below:

Step 1: First of all, the network model is to be set up in Power Factory based on the selected year (Year 1-5/7/10).

Step 2: Then, SC team uses a unit commitment (UC) model to generate time-series dispatch profiles of generators without imposing network constraints. The UC is simulated on a weekly basis with an hourly resolution in order to properly capture the charging/discharging behaviours of pumped hydro storages. The generation capacity and marginal cost is retrieved from FES and BID3. There is a Monte Carlo simulation to generate 10 scenarios for each year to cover the various output levels of renewable energy and system demand.

Step 3: Furthermore, the target boundary and a list of reinforcement options are selected to update the network model. Subsequently, POUYA uses its interface to extract network parameters from Power Factory, which makes POUYA ready for running DC power flow analysis.

Step 4: There are three loops nested for POUYA simulation in the case study of single network topology. These loops are contingency cases, scenarios, and hourly generation and demand profiles in each scenario. As mentioned above that, POUYA can only examine whether the thermal constraints are violated, while voltage constraints examined in the deterministic method are not applied here. An hourly dispatch profile is only labelled as "acceptable" if all contingency simulation succeeded without any constraint violations, otherwise this profile is labelled as "unacceptable". At this stage of the analysis, all profiles are considered as individual snapshots without any link. Consequently, 87,600[6] snapshots are examined with thermal network constraints based on the current methodology.

[6] Since the UC simulation has an hourly resolution, annual simulation generates 8760 time-steps. Moreover, 10 scenarios are considered in Monte Carlo simulation in profile generation, therefore the total number of snapshots is 87,600.

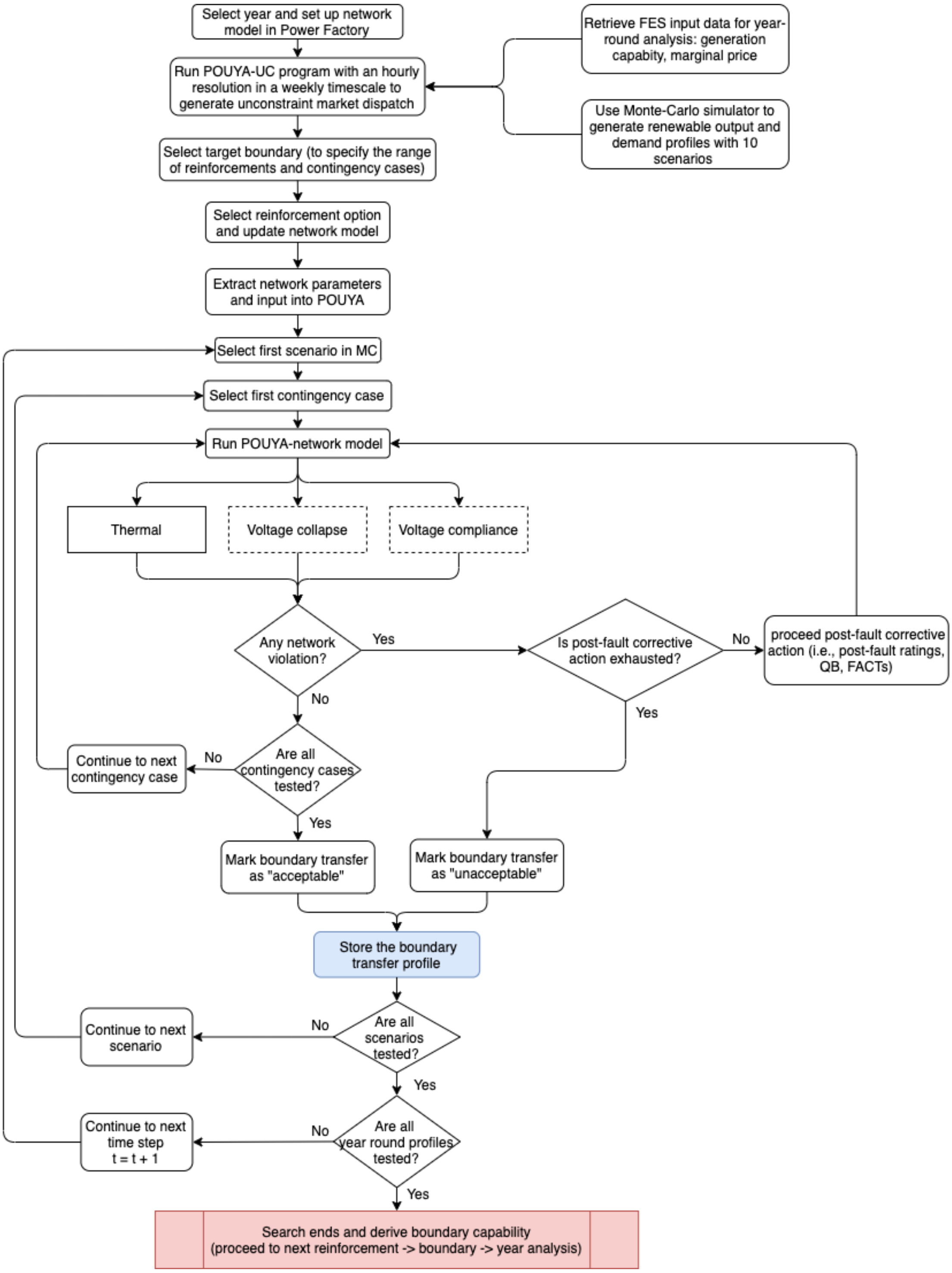



*Figure 2.4. Workflow of evaluating boundary transfer profiles with a probabilistic method*

After labelling all the snapshots, the corresponding transfer profiles need to be converted to the transfer frequency as mentioned in Figure 2.3, which is in the unit of hours per year or per season. The current practice of SC team is to distribute the profiles into segments with 100 MW interval. Since there are multiple scenarios in the Monte Carlo simulation, the value of the aggregated transfer frequency needs to be divided by the number of scenarios (i.e., 10). An example of boundary transfer frequency in one season is shown in Figure 2.5. It can be noticed that there is a range of segments which have both acceptable and unacceptable transfers. This phenomenon indicates different generation dispatch snapshots may result in the same boundary transfer requirement, while some of the snapshots can result in network constraint violation. This further highlights the importance of using probabilistic analysis to understand events other than winter peak which stress network operation.

Since there are overlap regions between acceptable and unacceptable transfer frequencies for both positive and negative power transfers in Figure 2.5, which are from -3800 to -900 MW and from 4500 to 5700 MW, further calculation is carried out in order to draw a single value of positive/negative boundary transfer capability. In this case, SC team has introduced the concept of opportunities lost and energy at risk, which will be elaborated in the following sections.

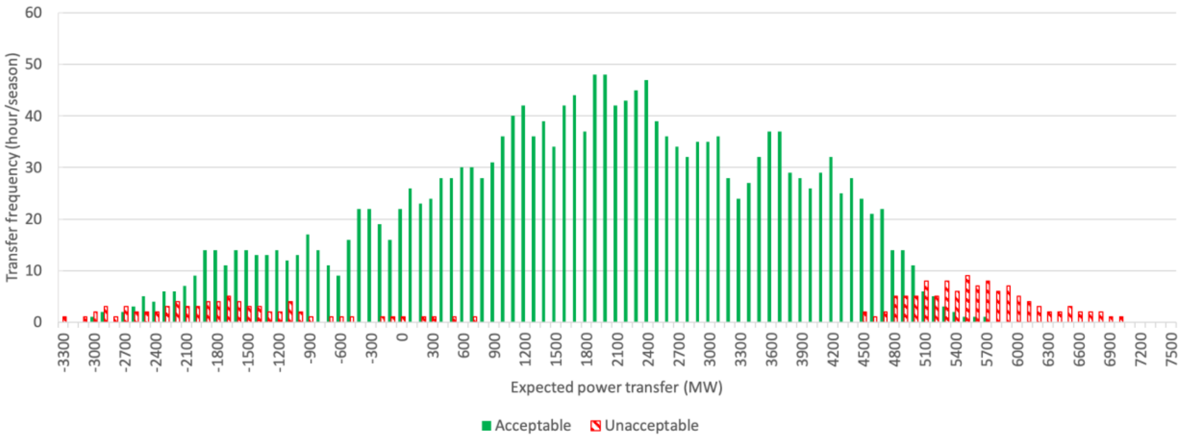



*Figure 2.5. Transfer frequency example of a specific boundary in one season*

### *2.2.2.2 Opportunities lost*

The opportunities lost is used to indicate the volume of energy which *could* be transferred through the boundary in the acceptable dispatch profiles, but won't be if the capability setpoint is lower than the selected transfer segment in a boundary flow-constrained economic dispatch model. The procedure of determining opportunities lost is shown in Figure 2.6, which is elaborated below:

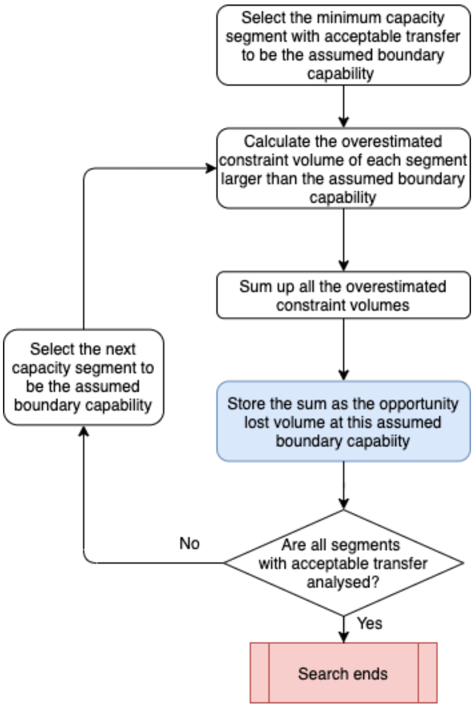



*Figure 2.6. Flowchart of opportunities lost calculation*

Step 1: First of all, the initial value of the transfer capability setpoint is the smallest segment with a positive acceptable transfer frequency. Taking the example shown in Figure 2.5, the initial capability setpoints for negative and positive transfers are both 0 MW respectively, since that's the smallest segment which has a valid acceptable transfer frequency.

Step 2: Then, the overestimated constraint volume at each segment being larger[7] than the setpoint can be calculated. The numerical example shown in Figure 2.5 for negative segments would be:

- Transfer capability setpoint (MW): $0$
- Valid transfer segments (MW): $-100/-200/-300/\ldots/-2900/-3000$
- Transfer frequency (hr/season): $16/19/22/\ldots/2/1$
- Overestimated volume at -100 MW: $[0-(-100)]\cdot 16 = 1600\ MWh$
- Overestimated volume at -200 MW: $[0-(-200)]\cdot 19 = 3800\ MWh$
- …
- Overestimated volume at -3000 MW: $[0-(-3000)]\cdot 1 = 3000\ MWh$

Step 3: The opportunities lost at 0 MW can be calculated as the sum of all overestimated volume:

$$1600 + 3800 + 6600 + \cdots + 3000 \ = \ 364200\ MWh/season$$

Step 4: The next segment (i.e., -100 MW) is selected as the setpoint and Steps 2 and 3 are repeated to calculate the corresponding opportunities lost, which is 331900 MWh/season. The overestimated constraint volumes at each segment with a capability setpoint of 0/-100 MW are shown in Figure 2.7.

[7] The comparison is carried out based on the absolute values of the setpoint and segments, which means for a setpoint of 0 MW, the segments ranging from -100 to -3000 MW (which is the largest negative transfer segment with a valid power transfer) should be considered in overestimated volume calculation.

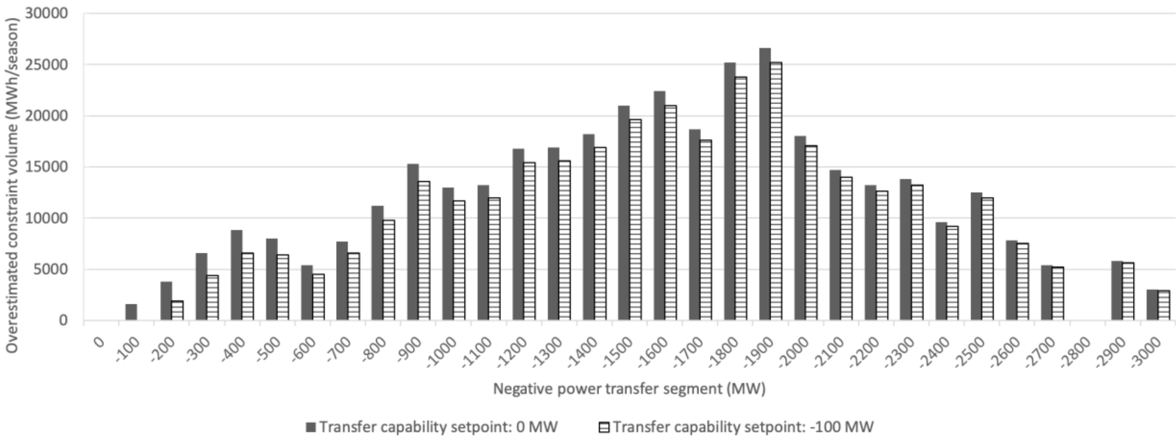



*Figure 2.7. Overestimated volumes with 0 MW and -100 MW boundary transfer capability setpoints respectively*

Step 5: The last setpoint would be the last negative segment with a valid acceptable transfer, which is -3000 MW as seen in Figure 2.5. The opportunities lost at this setpoint is 0 MWh/season by repeating Steps 2 and 3. The quantity of opportunities lost at the all valid negative transfer capability setpoints is shown in Figure 2.8.

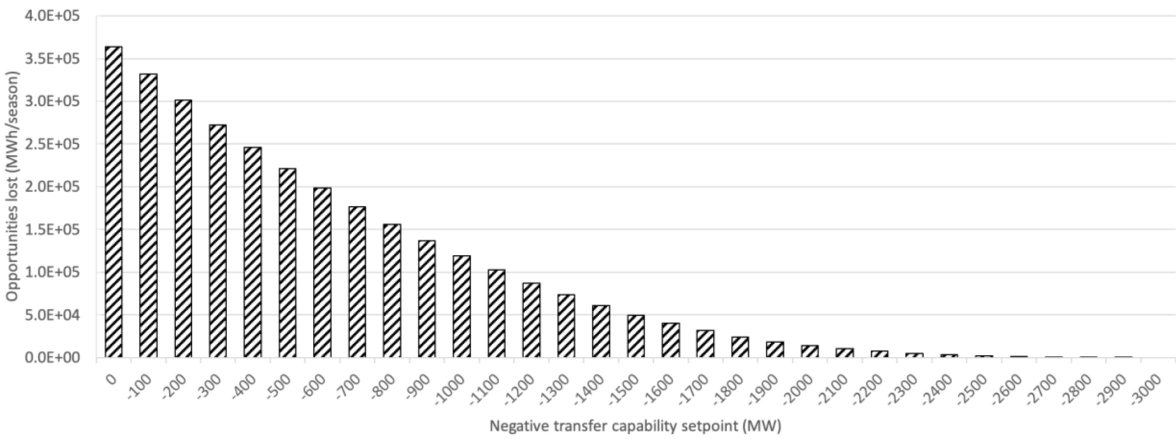



*Figure 2.8. Opportunities lost of all negative capability setpoints*

Step 6: After the calculation of opportunities lost of all capability setpoints in negative transfer, Step 2-5 are carried for all positive power transfer segments. The opportunities lost in these segments are shown in Figure 2.9.

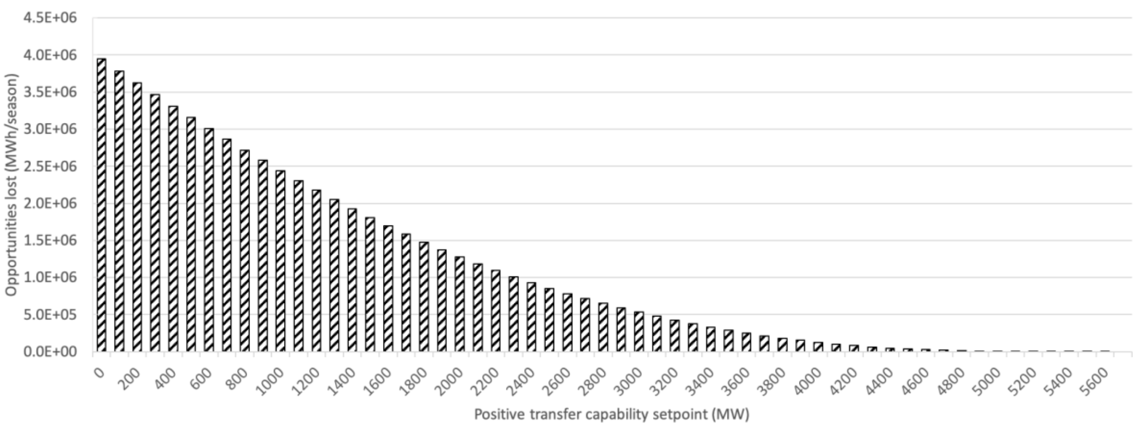



*Figure 2.9. Opportunities lost of all positive capability setpoints*

In summary, we will see a gradual decline of opportunities lost value from the segment of lowest transfer capability to the highest one.

#### 2.2.2.3 Energy at risk

The concept of energy at risk is used to indicate that the volume of unacceptable transfers which cannot be transferred, when the capability setpoint is lower than the segments of unacceptable transfers. The procedure of determining energy at risk is shown in Figure 2.10, which is further explained below:

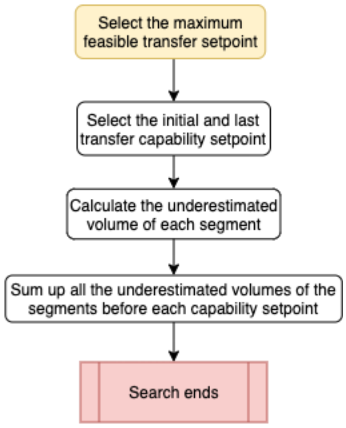



*Figure 2.10. Flowchart of energy at risk calculation*

Step 1: First of all, the maximum feasible transfer setpoint needs to be selected. This is the last segment without any unacceptable transfer. According to the profiles shown in Figure 2.5, it can be seen that the maximum segment without unacceptable transfer is 100 MW for positive transfer, which is used as the feasible transfer setpoint in this case. For the negative transfer, since there has already been 1 hour/season of unacceptable transfer at 0 MW segment, the maximum feasible transfer setpoint should be set to 0 MW for the evaluation in the negative transfer capability.

Step 2: Then, the initial and last values of the transfer capability setpoint are selected, which represent the lowest and highest segments based on transfer power with a valid unacceptable transfer frequency. Taking the example shown in Figure 2.5, the initial transfer capability setpoints are 200 MW for positive power transfer and -100 MW for negative power transfer. Regarding the last transfer capability setpoint, it would be 7000 MW and -3300 MW for positive and negative power transfer respectively.

Step 3: Then, the overestimated constraint volumes at each segment from initial to last feasible transfer setpoints can be calculated. Figure 2.11 depicts the overestimated constraint volumes of the positive power transfer segments based on the profiles given in Figure 2.5. The detail of the calculation is listed at below:

- Underestimated volume at 200 MW: $[100 - 200] \cdot 1 = -100\ MWh$
- Underestimated volume at 300 MW: $[100 - 300] \cdot 1 = -200\ MWh$
- Underestimated volume at 400/…/6900 MW
- Underestimated volume at 7000 MW: $[100 - 7000] \cdot 1 = -6900\ MWh$

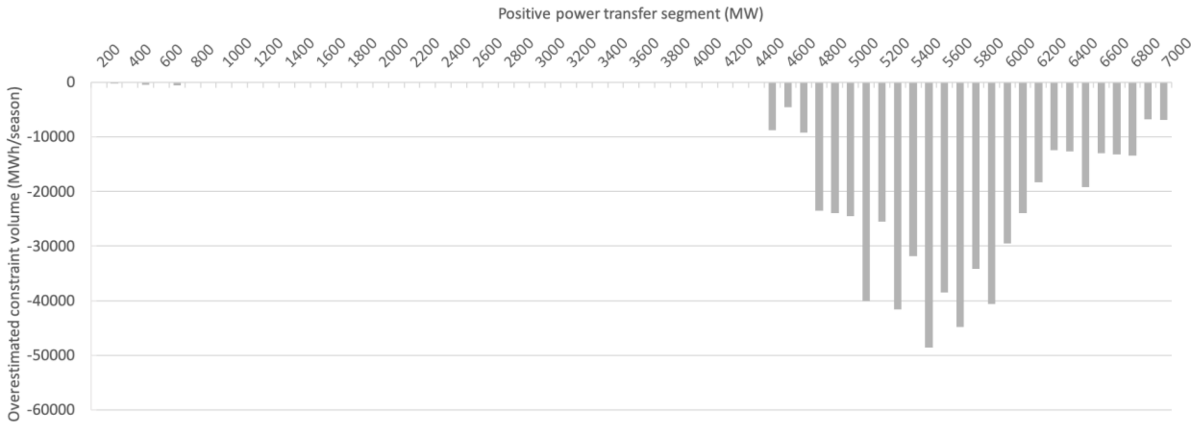



*Figure 2.11. Overestimated constraint volumes of positive power transfer segments*

Step 4: Calculate the energy at risk at each capability setpoint. Based on the profile given in Figure 2.5, the energy at risk for negative and positive power transfer are separately shown in Figure 2.12 and Figure 2.13. For the calculation detail, the energy at risk in the case of 7000 MW capability setpoint can be calculated as the sum of overestimated constraint volumes between 200 and 7000 MW:

$$(-100) + (-200) + \cdots + (-6900) = -610700\ MWh/season$$

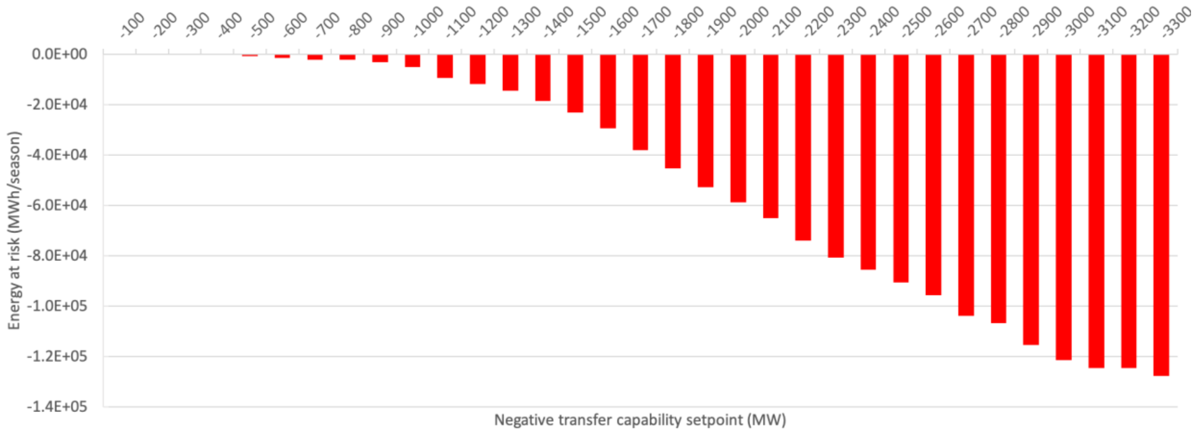



*Figure 2.12. Energy at risk of negative power transfer segments*

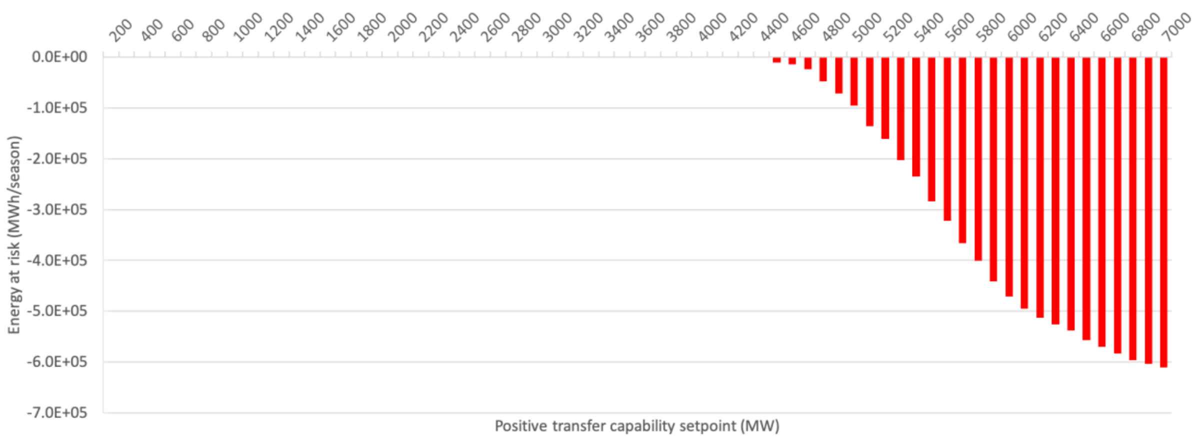



*Figure 2.13. Energy at risk of positive power transfer segments*

In summary, the absolute value of energy at risk will gradually increase from the first segment of unacceptable transfer to the last segment, as seen in Figure 2.12 and Figure 2.13.

#### *2.2.2.4 Boundary transfer capability derivation*

The intuition behind the calculation of *opportunities lost* and *energy at risk* is to quantitatively measure the potential impact of applying a nonoptimal value to limit boundary flow in NOA's CBA. An inadequate boundary transfer capability setpoint would consequently influence the accuracy of estimating constraint costs in the CBA. For instance, taking the example given in Figure 2.5, there are two circumstances when boundary capability on positive power transfer may be set to an inappropriate level:

- **Capability setpoint too low**: Let's set the boundary capability setpoint to 2000 MW for positive power transfer. In this case, it is much less likely that the simulation of boundary flow-constrained economic dispatch would give any dispatch profile with a network constraint violation. This is because only 4 hours per season with a unacceptable dispatch profile are presented before boundary transfer reaching 2000 MW, which accounts only 3.5% of all unacceptable transfer periods in positive transfer segments, as depicted in Figure 2.5. However, this 2000 MW setpoint may seriously limit the boundary transfer in some acceptable dispatch profiles, such as the ones with a transfer level in the range 2000 to 4400 MW, and consequently result in unrealistically high network constraint costs. Essentially, the network would be able to handle some dispatch profiles without constraint violation, but it is not allowed to do so in this simulation due to a "conservative" selection of setpoint.
- **Capability setpoint too high**: If we set the boundary capability to 6000 MW, although all positive acceptable dispatch profiles given in Figure 2.5 would be successfully simulated in CBA, there could also be a large number of unacceptable dispatch profiles which are "disguised" as acceptable ones in the boundary flow-constrained economic dispatch. In this case, the boundary flow constraints cannot mimic the function of network constraints and the CBA would underestimate the constraint costs.

Subsequently, it is convenient to adopt a method that can determine an appropriate boundary capability setpoint and "neutralise" the risk of using boundary flow constraints to represent network constraints in economic dispatch for CBA. The SC team has used an index called "constraint forecasting error" ($CFE(s)$) to find an appropriate boundary capability. This is calculated via opportunity lost ($OPL(s)$) and energy at risk ($EaR(s)$) at each transfer segment ($s$), as shown in (2.1). By subtracting energy at risk from the opportunity lost, a balance can be struck between overestimating and underestimating the boundary transfer capability.

$$CFE(s) = OPL(s) + EaR(s) \tag{2.1}$$

By processing the opportunities lost and energy at risk profiles given in Figure 2.8, Figure 2.9, Figure 2.12 and Figure 2.13, the constraint forecasting errors for  are displayed in Figure 2.14. It can be noticed that the value constraint forecasting error crosses the zero value when the transfer capability is at -1700 and 4700 MW for positive and negative transfer respectively. Therefore, the maximum transfer capability of this specific boundary in this season is set to -1700/4700 MW based on the probabilistic analysis.

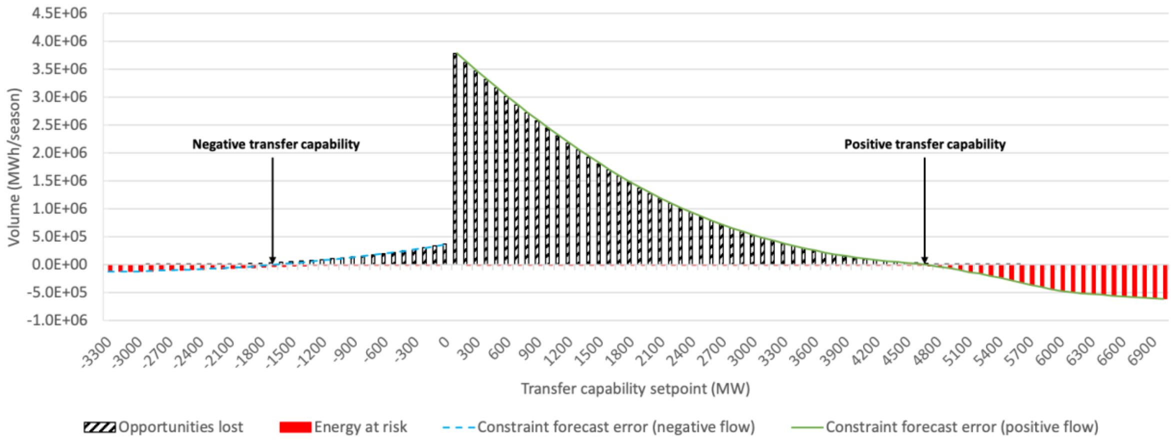



*Figure 2.14. Opportunities lost, energy at risk and constraint forecasting error of a specific boundary in one season*

## 2.3 NOA Pathfinder projects

As mentioned in section 2.2, ETYS does not include any market-based solutions in the assessment of boundary transfer capability. However, NGESO has envisaged the crucial role of non-asset-based solutions in provision of system services in the future. Also some issues like high voltage and stability issues not associated with bulk transfers cannot be captured through the annual ETYS analysis. Therefore, NGESO has set up several groups to explore different solutions and relevant contract arrangements, which are called "NOA pathfinder" projects. Since the introduction of NOA pathfinder projects are relatively new and still under exploration, these projects are quite flexible in terms of time plan and deliverables.

There are ongoing Pathfinder projects in NGESO:

i. High voltage management;
ii. Constraint management;
iii. Stability management.

The high voltage management project is used to address voltage issues in regions of the NETS. Traditionally, the voltage issue can be managed through installing assets, such as shunt reactors, shunt capacitors, synchronous compensators and static reactive compensators. However, NGESO considers the full range of solutions from assets to non-network market based commercial services. The first trial[8] of high voltage management Pathfinder projects was in the Mersey area to address the increasing need to absorb MVArs in recent years which has resulted in increased voltage management costs overall. In the project tender participants were required to have a dispatchable reactive power capacity of no less than 15 MVAr. The tenders were run separately for short term and long term contracts, for example for the long-term project, the contracts were successfully awarded for a period of 9 years starting in April 2022.

For the constraint management project, the concept is to reduce the constraining period and the corresponding cost of specific boundaries. The constraining cost is incurred when the transmission network assets are overloaded and require a redispatch of generators in order

[8] More information can be found in https://www.nationalgrideso.com/industry-information/balancing-services/transmission-constraint-management

to avoid constraint violation. The constraint management focuses on managing active power at only when a fault has occurred thus reducing network constraint costs of pre-fault constraining plant.

The constraint management pathfinder can also be utilised to deliver the commercial solutions options which are proposed by the ESO and included in the NOA together with assets-based reinforcement options from TOs. For example, there are four ESO-led commercial solutions proposed in 2019/20 NOA [3]. It needs to be pointed out that commercial solutions can be contracted with a flexible duration and usually require low initial investment (for control and communication devices).

The current workflow of constraint management projects can be summarised as shown in Figure 2.15. Other Pathfinder projects can basically follow a similar procedure. The actions involved in each block of Figure 2.15 are explained below:

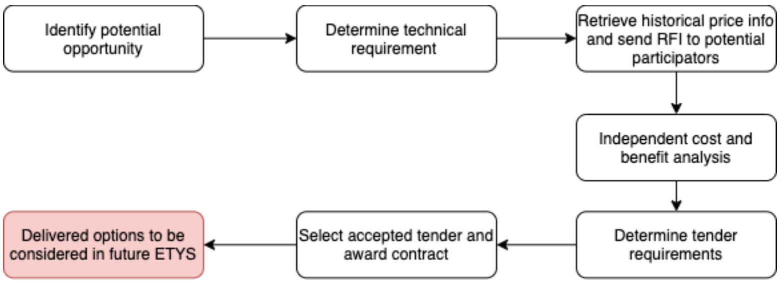



*Figure 2.15. Workflow of constraint management Pathfinder project*

Step 1: The procedure starts with identifying boundaries which have a potentially long constraining period. For instance, it was found that there are scenarios which indicate some constraint management opportunities on the North side of the boundary B6 were required for significant amount of time every year.

Step 2: Then, the simulation results of future system dispatch and historical dispatch data are analysed to identify the service's technical requirements, such as magnitude, activation frequency and duration.

Step 3: Constraint management are traditionally achieved through re-dispatching generators in the resource pool of the balancing mechanism (BM), and this redispatch will consequently incur relevant operational cost. This information of BM cost can be used to guide the price setting of the constraint management service. Constraints are also managed through intertripping generation by arming plant pre-fault to trip off post fault. As part of an innovative approach to managing constraints, NGESO proposed a service which can reduce the power flows across a boundary and sent a request for information (RFI) to the market to gauge intertest and understand the expected revenue of the market.

Step 4: After setting the expected cost of constraint management service, CBA is performed so that the benefit of constraint management service can be directly compared with resolving the constraint and balancing the system in the Balancing Mechanism.

Step 5: If the CBA shows that the service has a potential to bring significant reduction in the balancing costs, then the volume required to procure is determined.

Step 6: Through tendering process, NGESO contracts the service based on relevant criteria and awards annual contracts to the successful tenders.

Step 7: The steps are repeated to determine the volume required for the next year and the tender is re-run to ensure the cheapest volume is contracted to resolve the constraint.

With regard to stability management, it is related to operational options to enhance system security from stability and frequency perspectives. The stability pathfinder project has recently published the result of its Phase-1 inertia service tender. The result shows that 12.5 GW.s inertia has been contracted for six years from 2021 to 2026.

In conclusion, Pathfinder projects helped to bridge the gap between long-term planning and short-term operation in NETS as well as proposing a broader range of solutions to meet additional network needs. The mechanism of implementing Pathfinder projects is similar to the one of capacity market [9] to incentivise flexibility provision required in short-term operation. While Pathfinder projects focus on addressing the rising concerns of network congestion to meet electricity demand across the system, the capacity market is aimed at ensuring enough generation capacity is being procured to meet system peak demand. The generation portfolio of NETS has been quickly evolving, especially considering the increasing penetration level of renewable energy sources. Renewable generation usually has a lower capacity factor than base-load conventional generators. Subsequently, in order to keep the same average energy output of the system generation portfolio, the installed capacity of renewable generation can be higher than the replaced capacity of conventional generators, and consequently leads to a higher level of imbalance at different boundaries of NETS. However, the flexibility embedded in demand side and storage can be used to manage the network constraints instead of building assets-based reinforcements. More importantly, the Pathfinder projects provide a route to secure the service provision by utilising this flexibility in a medium term.

[9] Capacity market has been introduced in NETS at 2014 and it is used to ensure enough generation capacity is procured for the forthcoming winter peaks.

# 3 Probabilistic power flow analysis

In section 2, we have discussed the current workflow and methodology used in Electricity Ten Year Statement (ETYS), and it can be clearly seen that NGESO has recognised the essential value of applying a probabilistic approach in assessing boundary transfer capability across GB network. First of all, assessing boundary transfer capability is one of the NGESO's obligations as defined in SQSS. At the same time, an accurate estimation of this capability can improve the accuracy in NOA's CBA. The current methodology of integrating the boundary transfer capability approved by SC team and NOA's CBA is shown Figure 3.1.

In order to identify the benefits of different reinforcement options, especially the benefits of options on reducing constraint costs, it is necessary to perform year-round system economic dispatch or unit commitment, with network constraints. In the simulation of small power systems, this can be achieved by running optimal power flow (OPF). However, it may become time-consuming and difficult if non-linear features need to be captured. Therefore, NGESO decided to break down the AC OPF functionalities and use boundary transfer constraints in lieu of full AC power flow constraints in the generators' dispatch exercise, as depicted in Figure 3.1.

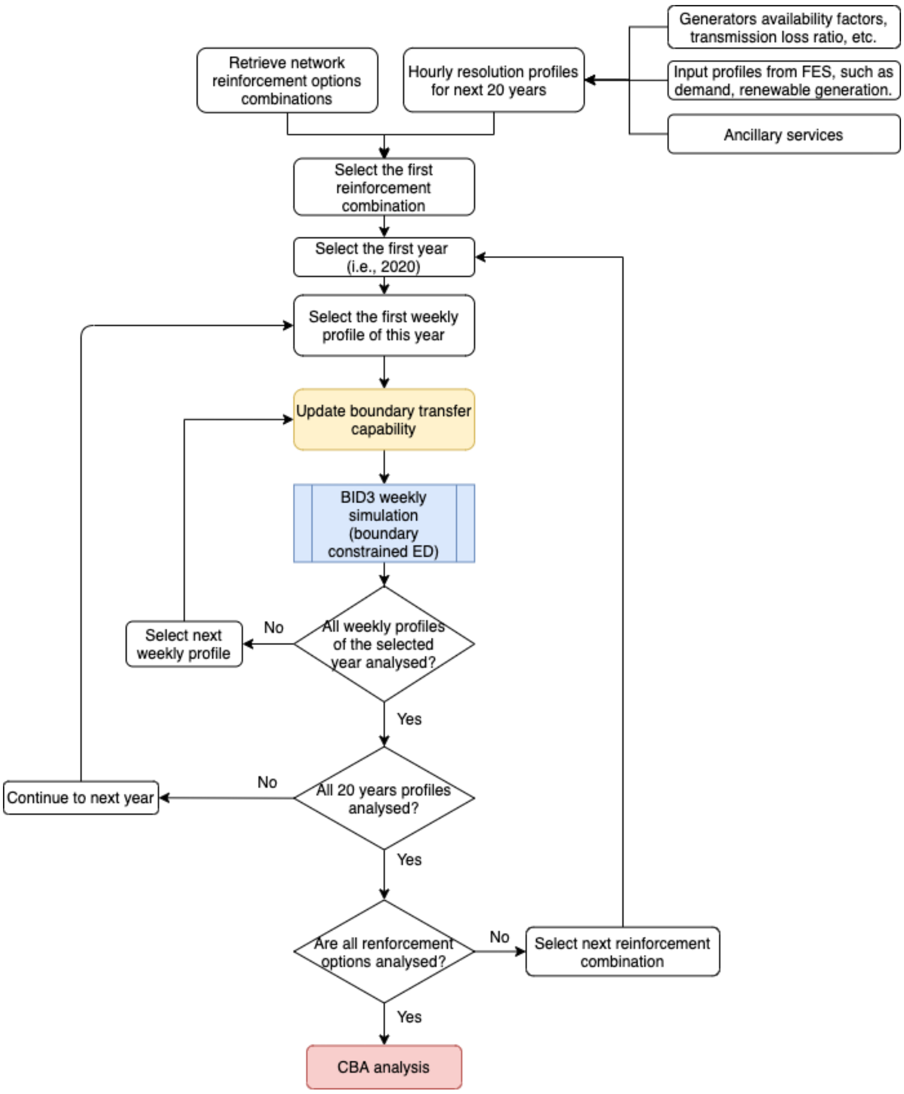



*Figure 3.1. System operational cost assessment process for NOA's CBA*

Traditionally, this boundary transfer constraint is set as a static value in each season of a year in NOA's CBA study, while these static values are derived by scaling the boundary transfer volume assessed at winter peak or based on specific sensitivity studies. This is because the uncertainty of system operation was mainly embedded in demand side, while the generation portfolio is composed of large conventional power plants, which are geographically concentrated and dispatchable, therefore the maximum transfer and the most stressful period of the network should ideally happen in winter peak.

However, the uncertainty and volatility of renewable energy brings the necessity of analysing multiple snapshots other than the peak. For instance, when there is high renewable generation and low demand in certain regions, boundaries may face voltage compliance issues. More importantly, the maximum transfer across a boundary may be induced by high output level of renewable generation on one side of the boundary which may not be coincident with the peak demand snapshot. In summary, it may be unclear, *ex ante*, under which system conditions and in which parts of the network thermal or voltage issues could arise. Therefore, as mentioned before, the SC team has introduced a probabilistic assessment method to generate hourly input profiles (i.e., wind, solar and demand) of a few year-round scenarios (currently 10) so that a probabilistic DC power flow[10] analysis can be performed to understand various network conditions in tens of thousands of snapshots.

In this section, we want to explore the answers of three questions in implementing probabilistic analysis for NGESO's network planning:

- **What are the alternative approaches in assessing boundary capability under the conditions defined in SQSS?**
- **Should the concept of "boundary" be kept in the cost-benefit analysis of NOA?**
- **How to improve the integration of the technical study performed in ETYS and the economic analysis in NOA?**

## 3.1 Boundary capability assessment

In this section, we would like to explore potential approaches that could complement current boundary capability assessment. Firstly, a literature review of probabilistic power flow research is performed. Then, we facilitate a discussion of the purpose of applying probabilistic power flow and what are the potential setpoints[11] for boundary capability. Furthermore, we propose different sampling methods based on the current methodology to derive the value of several boundary capability setpoints mentioned above.

### 3.1.1 Literature review of probabilistic power flow

Researchers in power system sector have begun to investigate the application of probabilistic power flow (PPF) since 1970s [10], [11]. Initially, PPF was used to calculate the probability

[10] "Power flow" and "load flow" are usually considered to be two interchangeable terms. The formally more correct "power flow" will be used in this report.

[11] "Setpoint" refers to the maximum power transfer across a specific boundary with the assumption of no network constraints (e.g., thermal, voltage and stability) violation. The value of the setpoint is applied to the boundary flow constraint in NOA's CBA [4].

distribution of power flows by assigning randomly generated load and generation profiles to each node of the network [11]. PPF has also been widely applied in power system planning [12], through the concept of composite reliability evaluation (CRE). The following gives a clear explanation of the difference between PPF and CRE [12]:

- **Probabilistic power flow**: Assessment is performed under the current system condition before any remedial action. The simulation results can be used to map the probability density functions (PDFs) or the cumulative distribution functions (CDFs) of power flows, which can then be used to derive the value of some indices, such as the probability of a component operating at overloading level and probability of a busbar voltage exceeding its limit [12].
- **Composite reliability evaluation (CRE)**: Assessment is executed after resolving the network problems through remedial actions. Typical Indices involve loss of load probability (LOLP), expected energy not supplied (EENS).

The remedial actions mentioned above include network assets-based solutions and market-based services, which may reflect operations such as active/reactive power output adjustment, load transfer or curtailment at bus level, tap changing and network reconfiguration, etc.

The PPF analysis performed by SC team is deemed to be the middle ground between PPF and CRE, because the analysis has only included the assets-based solutions while flexibility provided by uncontracted resources should not be considered, such as redispatching a group of generators without explicitly stating the cost of utilising this service. This type of research problem is called “constrained probabilistic power flow” (CPPF). The attempt of solving the CPPF problem dates back to 1982 [13], when a multiple piecewise linear transformation was implemented to represent the finite voltage adjustment capability of transformer tap changers and generator excitation systems. Furthermore, CPPF has been applied to short-term operational planning [14] and long-term network planning [15] by Hatziargyriou. In [14], [15], an iterative algorithm is proposed to adjust the control variables of the flexibility of network equipment so that the constrained variables (i.e., voltage and thermal level) fall back into the acceptable regions. This iterative algorithm is quite similar to the methodology considered in SC team’s probabilistic analysis, depicted in Figure 2.4.

The latest researches on the topic of PPF are composed of three aspects: component outage modelling, chronological features of profiles and algorithm acceleration. With regard to component outage modelling, the researchers were mainly focusing on the impact of probabilistic generation unit and branch outage, while the analyses are performed with DC [16] or AC power flow approximation [17]. For the chronological features of the variables and input profiles, the concept of chronological power flow (CPF) was introduced to capture the time-varying feature of load [18] and renewable energy [19]. Last but not least, there are many papers of PPF algorithm acceleration, which focus on the linearisation of power flow constraints [15], [20] and improve the sampling techniques used in Monte Carlo simulation [21], [22].

### 3.1.2 Static or dynamic boundary capability?

Before discussing further the current methodology for boundary capability assessment, we would like to ponder over the meaning of the term “boundary transfer capability”. First of all, let us clarify the purpose of applying probabilistic analysis, which can be summarised in the following two targets:

1) **Determine the boundary transfer capability (single value) to be used in NOA's cost-benefit analysis**

and/or

2) **Examine the network performance in handling boundary transfer snapshots (multiple cases) other than winter peak**

The methodology of probabilistic analysis needs to be dedicatedly customised in order to achieve the two targets in a unified way, and there is no need to say that *a single transfer capability value might not be representative of all dispatch profiles over a relatively long period (e.g., a year or a season) in a system with high renewable integration*. The rationale behind this argument is twofold:

- "Boundary" could somehow be treated as a *virtual* transmission line which is aggregated from numerous network components with different ratings and configurations. Consequently, it is highly unlikely that a boundary has a linear operating envelope against the active power flow crossing it, especially when congestions may arise in regions across the boundary which might limit the transfer in a nonlinear fashion. Therefore, although it may be feasible to analytically determine the boundary transfer capability in any given snapshot other than winter peak, the criteria in selecting these snapshots require extensive clarification on the same basis as the winter peak defined in SQSS. The most crucial question would be: *Does the network need to be absolutely secure in snapshots other than winter peak*? If it is, then what do these snapshots look like? There could be a large variance of regional supply-demand profiles and the setting of regional constraints.
- Comparing with conventional generators, the output of RES is highly variable, and their connection points can be geographically diversified. These characteristics may stress a wider range of network components and consequently leads to more frequent unacceptable transfer snapshots.

Based on the statement given above, it can be seen that there may be controversy in applying a boundary to represent network constraints. Therefore, a case study has been designed to use numerical examples to illustrate the drawback of boundary representation. A five bus system is depicted in Figure 3.2. In this system, G1/G2/G3/G4 represent conventional generators, while D1/D3/D4/D5 indicate connection points of electricity demand. C1 and C2 represent network components such as transmission lines. Bn indicates a hypothetical boundary, which splits the system to two parts. For the sake of simplicity, only one demand node is defined on the lower side of boundary Bn, which represents the net demand. Boundary capability is defined as the maximum power transfer across Bn without overloading C1 and C2 in this case study. Comparing with the boundary capability derivation method designed by NGESO (as explained in 2.2.1), the constraints considered in this case study is simplified for illustration purpose. More specifically, not all security constraints are considered at below, as voltage constraints and contingency consideration have been ignored. More importantly, the limits of components should not only be considered on the crossing ones, such as C1 and C2 in Figure 3.2, but also the components inside a boundary, which is omitted in this five bus system.

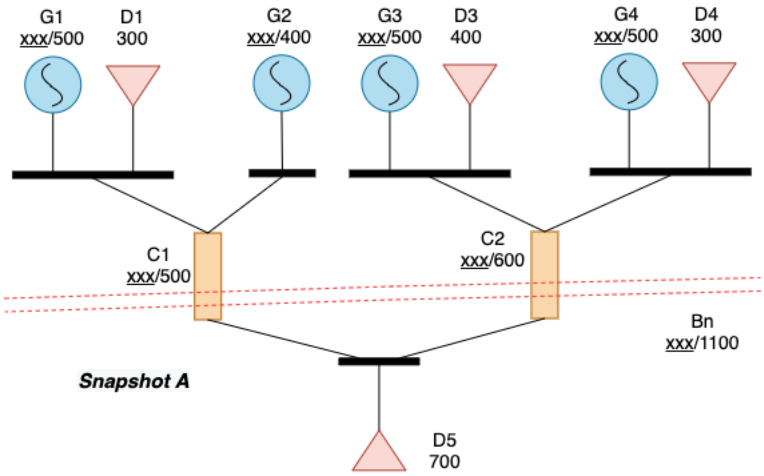



*Figure 3.2. Five bus system with boundary concept embedded*

The active power ratings of all components in this five bus system are shown in Figure 3.2, such as 500 MW for G1, 400 MW for G2 and 500 MW for C1, etc. A scenario "Snapshot(A)" is also designed with its demand profile shown in Figure 3.2, such as 300 MW in D1 and 400 MW in D3, etc. Depending on the marginal cost[12] of generators, there could be some different generation profiles simulated in economic dispatch and two of them are selected and displayed in Figure 3.3. Boundary validation is carried out by checking whether the boundary flow has exceeded the sum of crossing network components capacity[13], while network validation is carried out based on flow through individual components. In Figure 3.3, comparing with "Dispatch.1", "Dispatch.2" has a 200 MW output increase of G2 while the output level of G4 is decreased by 200 MW. The underlying assumption is that the marginal generation cost of G4 has increased to a level which is higher than G2. It can be noticed in the right subfigure of Figure 3.3 that "Dispatch.2" will experience a violation of network constraint. However, if we assume that the boundary capability is calculated as the sum of ratings of the components cross the boundary, it is still considered as feasible in the simulation of boundary flow-constrained economic dispatch, which is the same simulation performed by BID3 used in NOA's CBA.

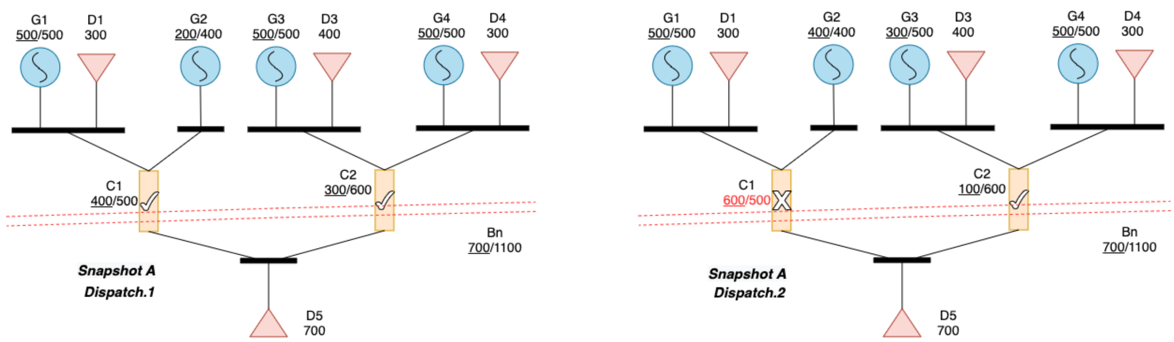



*Figure 3.3. Two potential dispatch profiles of five bus system in Snapshot A: Dispatch.1(left) and Dispatch.2 (right)*

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12 The generators' marginal cost is not displayed here to simplify the discussion.

13 This is an assumption to simplify the presentation of the concept. In many cases the boundary may be limited by a network component within the considered zones of the boundary but not a boundary crossing which results in a capability less than the sum of crossing components.

Based on the data shown in Figure 3.3, it can be insecure to dispatch the system with the boundary transfer capability derived from summing up the capacity of all network components. Therefore, the question to pose is**:** *is there a robust value for boundary transfer capability*? "Robust", in this case, means that there is no network violation in any system dispatch profile generated by the boundary flow-constrained economic dispatch model. In this case, the *static* boundary transfer capability can be derived from (3.1), which is determined by the smallest rating of network components embedded in this boundary before crossing circuits.

$$P_{B0} \leq \min(P_{C1}, P_{C2}) \tag{3.1}$$

This principle of determining this static boundary capability based on the smallest rating would ensure the network operation being "absolutely secure", but it could also seriously limit the energy transfer across the boundary. This would consequently result in higher constraint costs and even load shedding in the economic dispatch of CBA, which does not replicate the security constrained generation scheduling performed by system operators (i.e., NGESO) . For example, in the two dispatches shown in Figure 3.3, if the boundary transfer capability is set to 500 MW following this "smallest for all" principle, then the maximum transfer across this boundary would be limited to 500 MW and result a 200 MW supply shortage at D5, which would likely be covered by more expensive generators on the D5 side of the boundary (which is not drawn in this five bus system for simplicity).

Other than the static one, the boundary capability can also be calculated *dynamically* based on current system conditions, such as generators' marginal cost and output level and network components operating level, etc. For example, the dynamic boundary capability in "Dispatch.1" can be set to 800 MW, as G2 can still increase its output by 100 MW without overloading C1. In a new snapshot "Snapshot(B)", the demand in D3 is decreased from 400 MW to 300 MW comparing with "Snapshot(A)", and the new dispatch profiles is shown as "Dispatch.3" in Figure 3.4. Then, the dynamic boundary capability[14] can be increased from 800 MW in "Snapshot(A)" to 900 MW in "Snapshot(B)", because the generator output level of G2 can increase from 100 MW to 300 MW without overloading C1, if there is a demand increase in D5.

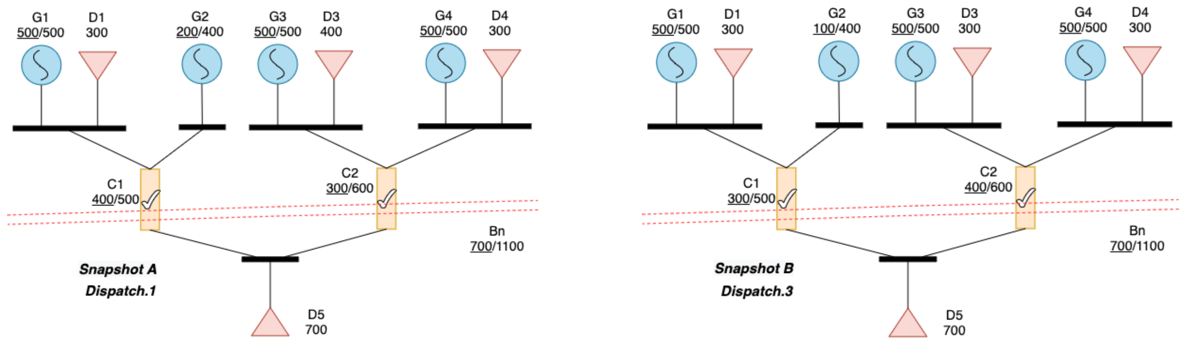



*Figure 3.4. Comparison of dispatch results between two snapshots: Dispatch.1 for Snapshot A(left) and Dispatch.3 for Snapshot B (right)*

[14] Once again, it needs to be pointed out that this boundary capability derivation has not considered all security constraints used by SC team in NOA and may overestimate the capability in practice.

In summary, the *dynamic* boundary transfer capability is highly dependent on the states of generators and demand. Therefore, it is difficult to build a model from typical predictive approaches (e.g. decision tree) to accurately calculate the boundary capability before running economic dispatch which determines the output levels of generators.

The increasing penetration of renewable energy sources and distributed energy resources (DERs) could also complicate the calculation of dynamic boundary capability. To illustrate this, the five bus system listed in Figure 3.2 has been modified to reflect integration of variable renewable energy. Comparing with the system configuration given in Figure 3.2, wind generation plants have replaced the conventional generators G3 and G4. Additionally, we have reduced the demand level in D3, D4 and D5 to construct snapshots with high renewable generation and low demand (for example due to embedded generation). "Snapshot(C)" is characterised by a sum of renewable generation being higher than the local demand as shown in the left subfigure of Figure 3.5. In this case, the dynamic boundary capability is 1092 MW, which allows the total output of G1 and G2 to increase from 308 MW to 900 MW. In "Snapshot(D)", the renewable generation G3 and G4 outputs are 360 MW and 9 MW as seen in the right subfigure of Figure 3.5. Consequently, D5 is heavily relied on G1 and G2 to supply its demand, and component C1 is overloaded which results network constraint violation in "Dispatch.5".

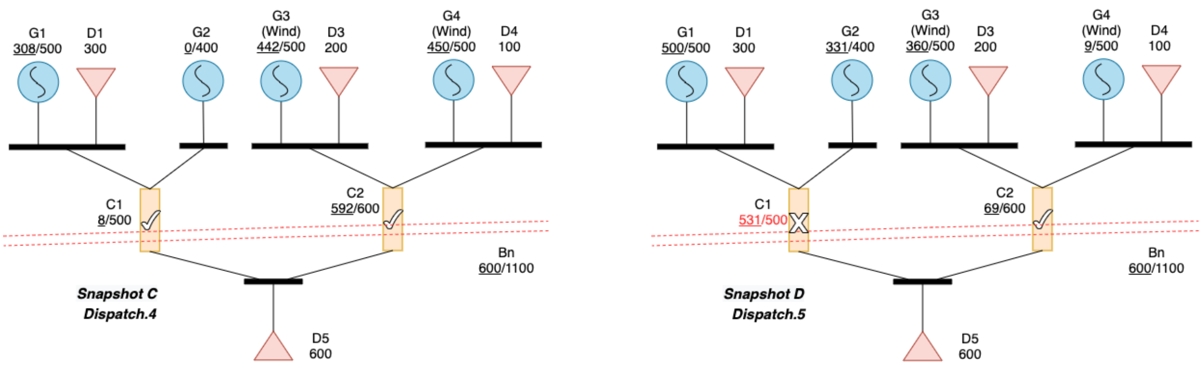



*Figure 3.5. Five bus system configuration and two potential dispatch profiles (dynamic boundary capability with renewable generation)*

Based on the discussion of renewable integration given above, we can notice that the introduction of variable energy can create much more diverse dispatch profiles and consequently highly variable power flows across the network. There are two underlying factors which lead to this high level of diversity:

- **Variability**: the output level of renewable generation varies much more than conventional generators and it is independent[15] of the demand level given in the scenario.
- **Dispatch priority**: The marginal generation cost of renewables is usually set to zero in the economic dispatch exercise, so that renewable energy is firstly dispatched

[15] Although it needs to be highlighted that SC team tries to capture some correlation of renewable output and demand in the scenario generation process of probabilistic analysis.

without any curtailment[16]. For conventional generators, unless it is the marginal online generator[17], the output level is usually set to either zero or maximum level in economic dispatch (without considering ancillary services provision – thus reducing the number of potential operating points and yielding less variable power flows.

Renewable energy integration could also affect the calculation of the *dynamic* boundary transfer capability. In fact, the unused capacity of network components with only RES connection at sub-level cannot be counted as part of boundary transfer capability. For example, according to "Dispatch.4" in Figure 3.5, C2 has 592 MW used in its 600 MW capacity. However, the remaining 8 MW capacity cannot be considered in dynamic boundary transfer capability of this snapshot, because renewable generation cannot ramp up its output in this case.

The calculation of boundary capability explained above is based on a simplified system with only five bus without taking contingencies into account. However, there could be tens or even hundreds of network components, generators and demand connections points for a power system in practice, as depicted in Figure 3.5, where a boundary is used to split the system and both sides of the boundary usually contain some generators, demands and network components. Therefore, an analytic method would be required to derive the dynamic boundary capability. Multi-parametric programming [23] could be used to derive a function of this boundary capability, which could use the marginal cost of generators, generator and network component capacity, dispatch profiles of generators, and component loading levels in order to dynamically determine the boundary transfer capability on a basis of snapshot by snapshot. This can be a potential improvement on boundary capability evaluation, which the SC team can pursue in the future.

However, without resorting to multi-parametric analysis, it may still be possible to determine the dynamic boundary transfer capability in some scenarios by using appropriate sampling techniques. The assumption is that a large database of demand and renewable generation profiles would contain at least a few snapshots in which all network components are almost operating at maximum loading level without any constraint violation. Then, we can possibly assume that the boundary transfer volumes in those snapshots would be "optimistically" considered as the boundary transfer capability without the need for deriving the capability analytically. However, this boundary capability may only be valid (means no security constraints violation) when there is an even distribution of loading levels across different components. While in other snapshots with an asymmetrically distributed power transfer within the boundary, the violation of security constraints may still incur before the aggregated boundary transfer hitting the assumed capability.

[16] The curtailment of renewable generation is not allowed in the technical study of ETYS since it is not straightforward to set the associated curtailment cost.

[17] The marginal generator represents the one with the highest accepted energy bid in the energy market at the given snapshot.

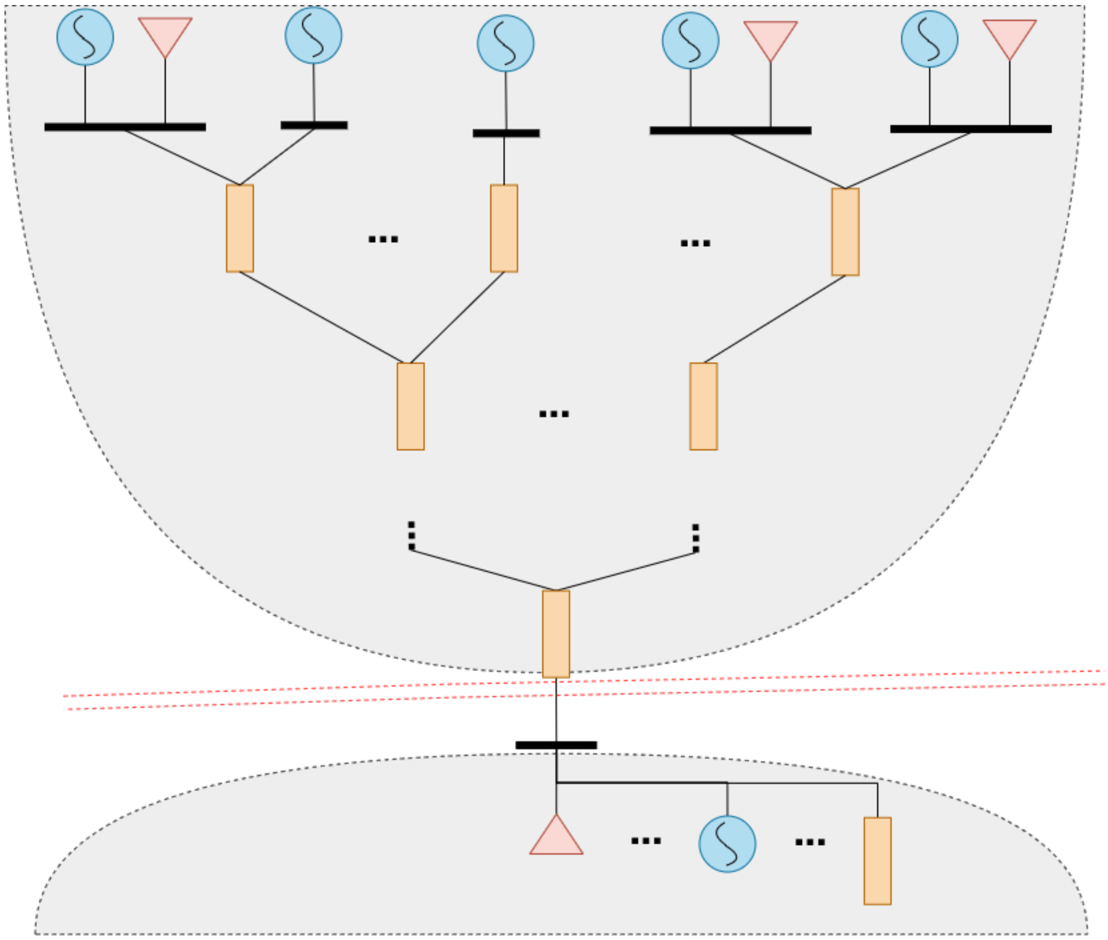



*Figure 3.6. Illustration of boundary composition in a real power system*

### 3.1.3 "Probabilistic", "standard-robust", or "soft-robust"?

Referring to the obligation defined in SQSS, the priority of probabilistic analysis should be put on examining the network performance on the periods of high boundary transfer other than winter peak. In this respect, Figure 3.7 depicts the distributions of boundary capability and probabilistic[18] boundary transfer profiles (which can be acceptable or not).

- The **boundary capability** refers to the dynamic one which can only be calculated via analytical methods, as explained in the last section.
- The **acceptable boundary transfer profile** denotes the boundary transfer of a dispatch profile in a snapshot without network constraint violation, such as "Dispatch.1", "Dispatch.3" and "Dispatch.4" in Figure 3.4 and Figure 3.5 respectively.
- The **unacceptable boundary transfer profile** denotes the boundary transfer of a dispatch profile in a snapshot with at least one of the network constraints violated, such as "Dispatch.2" and "Dispatch.5" in Figure 3.3 and Figure 3.5.

[18] In this context, the "probabilistic boundary transfer profiles" is referred to as a cluster of system dispatch profiles, which are derived from economic dispatch simulation without considering network constraints.

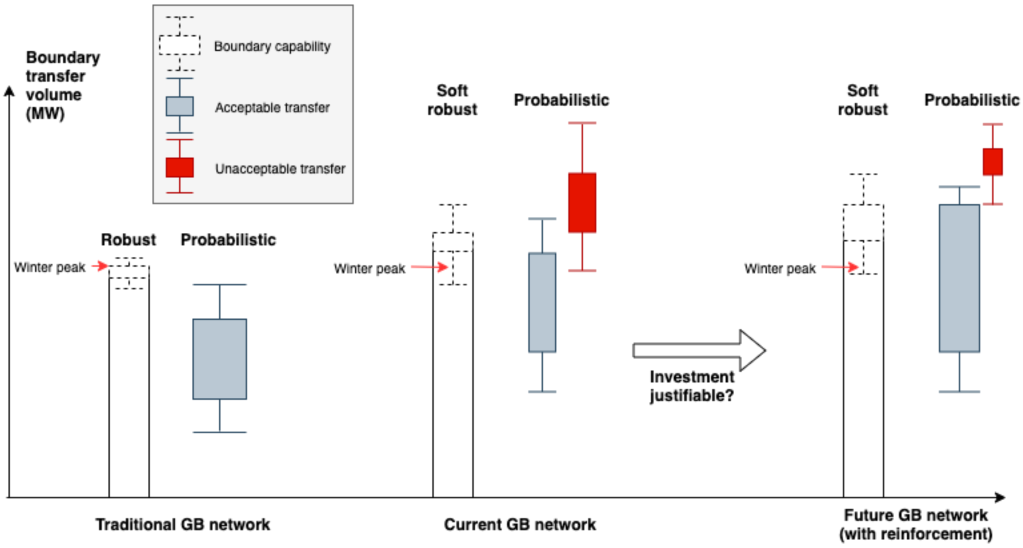



*Figure 3.7. Illustration of boundary capability and transfer distributions in different GB network scenarios*

The distribution is plotted in the box plot format, which indicates the maximum/minimum value at the end of whisker and the 0.75 and 0.25 quantiles at top and bottom edges of the box[19].

In order to demonstrate the impact of renewable energy integration, we have designed three scenarios regarding network configurations in Figure 3.7. However, it needs to be clarified that the profiles shown in Figure 3.7 are hypothetical and for illustration only:

1. **Traditional GB network**: The system has no or very limited renewable penetration and therefore the boundary transfer is determined by dispatching only conventional generators to meet demand. The uncertainty which results from the variation of boundary capability is originated from the distribution of demand profiles and the possible outage of network components. For example, if C1 in Figure 3.2 is broken down, then the boundary transfer capability is solely determined by the loading level of C2, which does not exceed 600 MW compared with the potential maximum capability of 1100 MW.
2. **Current GB network**: The network system has a relatively higher renewable penetration level. In this case, the distribution range of boundary capability and boundary transfer profiles are both widened, because the variable output of RES could also lead to a higher level of uncertainty, as demonstrated in Figure 3.5.
3. **Future GB network**: There are asset-based reinforcements in addition to the current GB network.

As seen in Figure 3.7, in the traditional GB network, the values of boundary capability are narrowly varied because the main contribution of uncertainty are unexpected outages of system components, such as a transmission line being unavailable due to unplanned maintenance, etc. However, it is still worth mentioning that the boundary capability should not be a static number and it is largely dependent on the system conditions in network analysis (e.g., generator output level, contingency, etc.). In this network, the transfer

[19] It should be noted that boundary transfer volume is usually bi-directional, and only the profiles of one direction (e.g. from North to South) is plotted in Figure 3.7.

capability is tested at the winter peak snapshot based on the procedure defined in SQSS, which refers to the most stressful period of a year, and therefore it is prudent to conclude that this single value of boundary transfer capability is robust to be used for constraining power flow in the network.

The second scenario reflects the numerical distribution of boundary capability and transfer profiles in the current GB network. It can be noticed in Figure 3.7 that the distribution ranges of both capability and transfer profiles are widened compared to that of the traditional network. Most importantly, there are unacceptable boundary transfer profiles when network-based corrective actions are not sufficient to address constraints violations. In this case, reinforcing the network to eliminate all constraint violations might not be economical[20] in the CBA. This process balances the robustness requirement of the network relevant to the economic value created by adding reinforcement, which can be called “soft robust”. The principle of soft robust is to relax the standard notion of robustness, which was required to be absolutely robust under any designated conditions, so that the decision can be made according to different risk acceptance in terms of the assets performance across the uncertainty set [24]. However, it needs to be emphasised that the network should still maintain the capability to satisfy the winter peak, which fits the standard notion of technical robustness by guaranteeing the security of supply.

The last scenario in Figure 3.7 shows the technical benefits of reinforcement, which would hypothetically increase the boundary capability region and consequently reduces the number of unacceptable transfer profiles. However, the current CBA methodology has only used the constraint costs reduction of reinforcement as the only index to quantitatively measure the benefits of reinforcement. The winter peak test defined in SQSS is the only method to determine the technical performance of the network, which has only one indicator: secure or insecure. Therefore, we believe it is worth proposing analysis of more indices to evaluate network performance from different perspectives, such as the quantity of constrained power transfer, the duration of constraint violation and vulnerable network components performance, etc. The method to calculate these indices are further elaborated from 3.1.5.2 to 3.1.8.

If the designated purpose of probabilistic analysis is beyond the technical aspects (i.e., identifying the network performance in different scenarios), but ultimately to derive this boundary transfer capability for NOA’s CBA, then the current methodology may be good representation to the average network performance. The current methodology uses probabilistic approach to identify the “average” performance of the network by offsetting the “energy at risk” volume with “opportunities lost” volume, as explained in 2.2.2. However, we would like to suggest a potentially better approach by implementing redispatch and curtailment functions, which would allow a full system simulation with network constraints in NOA’s CBA, so that the potential inaccuracy of network modelling resulted by the boundary constraint can be avoided. More details on generator redispatch and renewable curtailment will be given in 3.2.

[20]As explained in sections 4.7-4.10 in SQSS [9], the statements suggest investment in transmission capacity if economically justified to secure for thermal, voltage and stability for conditions reasonably to be foreseen.

### 3.1.4 System operation modelling

Before introducing any technique on improving sampling or performance evaluation, we would like to firstly discuss how to generate generation dispatch profiles. As explained in 2.2.2, the system dispatch profiles are currently generated with unit commitment. However, we recommend **using economic dispatch to replace unit commitment**. The reason of replacing UC with less constrained economic dispatch (ED) is that the focus of this analysis is to identify acceptable/unacceptable boundary transfer profiles based on network constraints (e.g., thermal, voltage and stability), while these constraints usually don't have any intertemporal feature. It is also likely that the less constrained ED will generate more diversity in the boundary transfer flows, which can further stress-test the boundary definition. Therefore, using ED can accelerate the simulation substantially. More importantly, parallel computation can be used for the simulation without intertemporal constraints. Thus, the computation efficiency can be further improved by applying parallel computation, when it is generating unconstrained boundary transfers and using POUYA to label the transfers.

### 3.1.5 Boundary capability sampling

As explained in 3.1.3, using one number to define the boundary capability is rather ambiguous, as the transfer capability depends on the specific system conditions. The common methods or probabilistic power flow simulation can be generally classified into two types, namely, analytical methods and sampling methods (normally coupled with Monte Carlo simulation). Analytical methods usually use convolution techniques [25] and require different levels of simplifications, which may lead to an unclear performance quality [26]. Therefore, sampling techniques with Monte Carlo simulation is more widely accepted. With regard to sampling techniques, except for simple random sampling of Monte Carlo simulation, there are various variants that can improve the efficiency of sampling and consequently reduce the computational time, for example, importance sampling (IS) [21] and stratified sampling (e.g., Latin hypercube [22]).

NGESO's current methodology of probabilistic analysis is to use sampling methods to generate a large number of profiles and then determine a value between the overlapping region of acceptable and unacceptable boundary transfers as probabilistic capability, as shown in Figure 3.8. It is probabilistic because it tries to balance, within the overlapping region, the benefit of capturing as high as possible acceptable flows against the risk of unacceptable flows. However, it may be convenient to explore further approaches to determining probabilistic capability setpoints. Here we explore the benefits of defining "**marginal**" and "**robust**" capabilities respectively as ways to evaluate a boundary's capability. The marginal capability setpoint refers to the maximum acceptable transfer volume in the simulation, while the robust setpoint refers to the maximum acceptable transfer volume without any unacceptable dispatch profiles, as depicted in Figure 3.8. The calculation of these two points would indicate the potential range for setting boundary transfer capability, which allows further analysis to be carried out to select the most appropriate value for the capability depending on the criteria set by NGESO, such as the threshold of values for indices explained in 3.1.6.

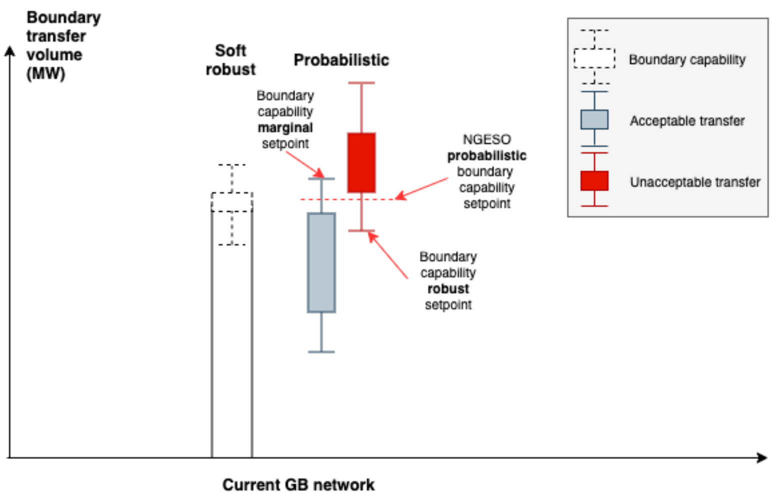



*Figure 3.8. Illustration of boundary capability potential setpoints*

#### *3.1.5.1 Profiles clustering technique in NGESO probabilistic boundary capability calculation*

In the evaluation of boundary capability setpoint with probabilistic method, the first step is to generate weekly demand and renewable generation profiles from the corresponding PDFs. Then, these profiles are input into UC model to generate unconstrained network flows. The number of scenarios in the current methodology used by NGESO is ten, as mentioned in 2.2.2.1. However, on the one hand, there is no mechanism in place to demonstrate whether ten scenarios are sufficient to cover the variability and uncertainty of boundary transfer profiles across the examined period (e.g. a year or a season). On the other hand, there is usually an upper limit of scenarios that can be run due to the availability of computational resources and time constraints of publishing ETYS. Therefore, it is necessary to indicate how to select the representative demand and renewable generation profiles, so that the "breakpoint" of acceptable and unacceptable transfer profiles (explained in 2.2.2.4) can be accurately captured.

In order to improve the current approach, the **K-means clustering method** can be used to select representative profiles from a pre-generated database. The procedure is explained below:

1. **Define the time horizon of individual profile samples, which can e.g. be hourly, daily or weekly**. Currently, the time horizon of profile is weekly in POUYA.
2. **Generate the candidate database for representative profiles selection**. The number of profiles in the database needs to be sufficiently large (e.g., 10,000+).
3. **Determine the feature for K-means clustering and calculate the value of the feature at each snapshot ($t$). Depending on the computational efficiency of the UC/ED and available computation resources, the feature could be the "net" demand profiles at each node ($n$) of the network with or without the dispatch profiles of conventional generators and renewable energy curtailment. Two options of the feature are:**
    a. **Net demand before ED/UC:** If it is deemed to be too computationally intensive to perform ED/UC for all profiles in the candidate database, then the net demand at each node would be calculated based on the load and solar and wind generation profiles as:

$$NL(t,n) = Load(t,n) - Wind(t,n) - Solar(t,n) \qquad (3.2)$$

b. **Net demand after ED/UC:** If it is feasible to perform ED/UC for all profiles within the timeframe set by NGESO, then the net demand at each node based on the dispatch profiles can be calculated as (3.3), which considers the output of conventional generators ($Gen(t,n)$) and wind and solar curtailments ($\mu_{wind/solar}(t,n)$) in addition to (3.2):

$$NL(t,n) = Load(t,n) - (Wind(t,n) - \mu_{wind}(t,n)) - (Solar(t,n) - \mu_{solar}(t,n)) - Gen(t,n) \tag{3.3}$$

4. **Decide the number of scenarios to be run in the UC/ED and apply K-means clustering to select the representative profiles**. For instance, if ten scenarios need to be run in the UC and the simulation time horizon is one week, the number of representative profiles is about $365 \div 7 \times 10 \approx 521$. The procedure to carry out K-means clustering algorithm is explained as follows:
   a. The initial centre of clusters is randomly selected from the database before any iteration. The profile of the cluster $i$ centre is denoted as $C_i$;
   b. Each profile $m$ in the database is assigned to its "closest" cluster $i$. The selection principle is based on the time-series value (e.g., net load) of the cluster centre profile and the selected database profile ($X_m$);

$$\min_{\forall i \in I} ||C_i - X_m||^2 \tag{3.4}$$

   c. The centre of cluster $i$ is updated by calculating the average profile of all the database profiles assigned to this cluster ($x_l$), while $N_{L^i}$ represents the number of samples assigned to cluster $i$;

$$C_i = \frac{1}{N_{L^i}} \sum\nolimits_{l \in L^i} X_l \tag{3.5}$$

   d. The steps *b* and *c* are repeated until the sum of "distances" between cluster centre and the samples assigned to this cluster have converged. The sum of distances is calculated as:

$$J = \sum\nolimits_{i \in I} \sum\nolimits_{l \in L^i} ||C_i - X_l||^2 \tag{3.6}$$

   The convergence of K-means algorithm is determined by the following rule, where $\varepsilon$ is a suitably small value (e.g., 0.1%).

$$\frac{|J^{(r)} - J^{(r-1)}|}{|J^{(r)}|} \leq \varepsilon \tag{3.7}$$

   e. Finally, since each cluster usually does not represent the same number of samples in the database, as $N_{L^i}$ used in (3.5) would not be kept equal across all clusters, it may be convenient to calculate the weight of each profile and use the weight to scale up/down the boundary transfer frequency shown in Figure 2.5. The weight of each representative profiles ($w_i$) can then be calculated with the number of samples assigned to one cluster ($N_{L^i}$) and the total number of samples in the database ($N$):

$$w_i = \frac{N_{L^i}}{N} \times 100\% \tag{3.8}$$

#### 3.1.5.2 Stratified sampling for marginal and robust setpoints calculation

The calculation of marginal and robust setpoints require the dispatch profiles with extreme transfer volumes to be generated. In this case, the K-means method explained is inapplicable, since the snapshots with extreme large transfer volumes may not be selected by an algorithm that naturally looks at identifying "average" conditions. The deterministic method explained in 2.2.1 uses a uniform scaling approach to artificially generate the dispatch profiles so that they can induce a higher boundary flow. The principle of this method is similar to stratified sampling. However, the dispatch profiles generated in this way lose the temporal and spatial correlation between renewable generation and demand in different areas of the system, and may consequently lead to an unrealistic system dispatch profile.

The following methodology is then proposed to generate system dispatch profiles with high boundary transfer volumes, while preserving the spatial and temporal correlations between wind and solar outputs and demand. The steps of the proposed methodology are outlined below:

1. **Database generation**: Use the PDFs of wind, solar and demand to generate a large number (e.g., 1 million) of snapshots. This procedure is consistent with the current scenario preparation work done by the SC team for probabilistic analysis.
2. **System operation modelling**: Use economic dispatch to generate system dispatch profiles of all the snapshots. No boundary or network constraint is imposed at this stage.
3. **Boundary transfer profiles generation:** Calculate the transfer volumes of all boundaries in each snapshot, and then sort snapshots by transfer segments. For example, if the transfer profile across the boundary B6 varies from -2130 to 4512 MW and the analysis segment is 100 MW, then we will put the snapshots with a transfer volume in the range of $[-2150, -2050]$ into the - 2100 MW segment.
4. **Samples selection:** Starting with the maximum positive/negative transfer segment, randomly select an appropriate number of snapshots (e.g., 1,000 snapshots[21]) from all the snapshots allocated to this segment.
5. **Network simulation and classification:** Use POUYA to classify the dispatch profiles of all samples as either acceptable or unacceptable, depending on whether there is any violation of network constraints. Calculate the percentages of acceptable and unacceptable profiles in the samples at this segment.
6. Repeat Steps 4 and 5 for all transfer volume segments at the selected boundary.
7. **Marginal setpoint searching**: For selection of marginal boundary capability in positive flow profiles, start from the maximum positive segment and examine the percentage

[21] We recommend the number of snapshots to be set to no less than 1000, so that when we apply a certain confidence margin (e.g., 1%) to determine the setpoint there would be at least 10 snapshots with acceptable/unacceptable profiles. In fact, for example, there would only be one acceptable/unacceptable snapshot required if the total number of snapshots is 100, which might be triggered by outliners. See also the last paragraph of 3.1.5.2.

of acceptable profiles at each segment. Select the first segment with a percentage of acceptable profiles being larger than 0% as the marginal capability setpoint.

8. **Robust setpoint searching**: The initial segment would be 0 MW and examine the percentage of unacceptable profiles at each segment. Find the first segment with a percentage of unacceptable profiles being larger than 0% and set the robust capability setpoint as the segment before this one.
9. Repeat Steps 7 and 8 for selecting negative boundary capability.

The criteria of determining marginal and robust setpoints in Steps 8 and 9 can be flexible. For example, in the determination of the marginal capability setpoint, instead of selecting a segment where an acceptable profile is presented, we could increase the requirement by setting the criterion that the acceptable profiles percentage should be at least 1%. This would increase the confidence in selecting values of setpoints by removing outliers.

The marginal and robust setpoints can be used as the upper and lower limits of selecting potential values for boundary transfer capability. Then, the reliability indices of each potential boundary setpoint can be calculated, which would inform the decision on determine the appropriate value to be applied in NOA's CBA. The calculation of reliability indices is introduced in the following section 3.1.6.

### 3.1.6 Reliability indices for robustness evaluation of capability setpoints

In power system reliability assessment, there are various indices, such as loss of load probability (LOLP) and expected energy not supplied (EENS), which are used to assess the system performance as a whole. For boundary analysis it may be convenient to introduce similar indices to assess the performance at the boundary level and within the boundary (e.g., at the individual component level), as shown in Table 3.1. These indices may be used to indicate **how the network handles the system dispatch profiles generated by economic dispatch**, which shows the network performance under the standard notion of robustness[22]. Then, these indices can **help to inform the level of robustness when setting the boundary transfer constraint to a given value**. This would also consequently **improve the confidence of applying these single value constraints to resemble the network constraints in a simplified way for cost-benefit analysis in NOA, as the indices quantify the risks of using static boundary constraints instead of network constraints in simulating system operation**.

*Table 3.1. Reliability metrics for boundary transfer capability assessment*

| Index | Unit | Analysis level |
|---|---|---|
| **Boundary congestion probability (BCP)** | % per year/season | Boundary |
| **Boundary congested energy (BCE)** | MWh per year/season | Boundary |

[22] The standard notion of robustness in this case would be that a network can handle a given system dispatch profile without any network constraint violation, which is like the technical requirement to "handle" the winter peak defined in SQSS.

| | | |
|---|---|---|
| **Component over-loading frequency (COLF)** | hours per year/season | Sub-boundary (network component) |
| **Component over-loading probability (COLP)** | % per year/season | Sub-boundary (network component) |

First of all, we introduce two indices that provide direct indication of the boundary adequacy by mimicking the meaning of LOLP and EENS.

The first one, called **boundary congestion probability (BCP)**, represents the percentage of periods with unacceptable transfer in a year. More specifically, let $b$ represent the selected boundary number, and $TC_{-}(t,b,s)$ and $TC_{+}(t,b,s)$ the bi-directional transfer capability setpoints[23] of the selected boundary $b$ in the portfolio $s$ at the given time $t$ of a year. These setpoints can be derived from different approaches, such as the deterministic method explained in 2.2.1, the probabilistic method elaborated in 2.2.2, and the stratified sampling method in 3.1.5.2. The values of these setpoints are kept same for all snapshots in each season following the current NOA methodology, as mentioned in 2.2, but this portfolio of seasonal setpoints can be adapted to a monthly one or even more dynamic values (i.e., depending on the demand and renewable output levels) to reflect the evolving system conditions. The transfer capability is used to constrain the active power flow ($P(t,b,s)$) across the boundary:

$$TC_{-}(t,b,s) \leq P(t,b,s) \leq TC_{+}(t,b,s) \tag{3.9}$$

Each portfolio $s$ stores the combination of capability setpoints of all boundaries in a year-round system dispatch simulation (i.e., obtained via a boundary flow-constrained UC or ED). If $N_U(b,s)$ and $N_A(b,s)$ refer to the number of snapshots with unacceptable and acceptable transfers, respectively, then the BCP index can be defined as:

$$BCP(b,s) = \frac{N_U(b,s)}{N_A(b,s) + N_U(b,s)} \times 100\% \tag{3.10}$$

The second index is called **boundary congested energy (BCE)**, which is used to determine the amount of energy that cannot be transferred through a specific boundary due to network constraints; this is modelled as boundary transfer limit, as mentioned above. The calculation of BCE is shown in the following equation, which involves the boundary transfer volume in unconstrained ED/UC simulation ( $P(t,b,0)$ ), the boundary transfer in boundary-flow constrained ED/UC simulation ($P(t,b,s)$), and simulation time resolution (Δ).

$$BCE(b,s) = \sum_{t=1}^{T} |P(t,b,0) - P(t,b,s)| \cdot \Delta \tag{3.11}$$

[23] All indices introduced in this section can be calculated based on unconstrained market dispatch profiles, and the value of these indices in this case may be used to indicate the upper limit of the indices, as the boundary flow is "maximised" without considering network constraints. In this case, the boundary flow constraint (3.9) is deactivated, which indicates $TC_{-}(t,b,s) = -\infty$ and $TC_{+}(t,b,s) = \infty$.

At the sub-boundary level, it may be sensible to carry out the assessment of the loading level of critical components. In this respect, there are two indices (COLF and COLP) introduced here that give the frequency and probability of the component operating above a certain loading level over a year, respectively. In this case, the number of over-loaded operational snapshots ($NOL(\alpha, c, b, s)$) is calculated with respect to the loading level ($LL(t, c, b, s)$) of the component $c$ at time step $t$, the corresponding component rating ($CR(c)$), and a pre-defined overloading parameter ($\alpha$) and then counting the occurrence number of overloading in the year-round simulation, as depicted in (3.12). Then, the value of COLF and COLP can be calculated as illustrated below.

$$NOL(\alpha, c, b, s) = \sum_{t=1}^{T} [LL(t, c, b, s) \geq (CR(c) \cdot \alpha)] \tag{3.12}$$

$$COLF(\alpha, c, b, s) = NOL(\alpha, c, b, s) \cdot \Delta \tag{3.13}$$

$$COLP(\alpha, c, b, s) = \frac{NOL(\alpha, c, b, s)}{N_A(b, s) + N_U(b, s)} \tag{3.14}$$

Table 3.2 describes some hypothetical values[24] of boundary congestion probability and components overloading frequency. The values presented here are calculated with simulation results of one boundary capability setting, while multiple potential settings of boundary capability should be examined in order to select the most appropriate one for NOA's CBA.

*Table 3.2. BCP and COLP of a boundary and top three overloading components in the boundary with a given transfer capability setting*

| Target | Boundary congestion probability (% per season) | Component overloading probability (% per season) | | |
|---|---|---|---|---|
| | | 130% | 150% | 200% |
| **Boundary X** | 26% | \ | \ | \ |
| **Component x1** | \ | 20% | 10% | 3% |
| **Component x2** | \ | 13% | 8% | 1% |
| **Component x3** | \ | 7% | 4.5% | 0.5% |

### 3.1.7 Monte Carlo simulation convergence

The reliability indices introduced above are calculated on an annual basis. However, the simulation result of one year cannot accurately indicate their values, as dispatch profiles of a single year may fail to cover all the system operating conditions normally encountered, especially for a planning exercise that include RES profiles. Therefore, it is necessary to use Monte Carlo simulation to generate the distribution of the indices, so that their mean value

[24] These values of indices shown in Table 3.2 are only for illustration purpose and do not represent the simulation results generated in NOA.

can be derived. Hence, the question becomes how scenarios should be simulated to ensure MC simulation convergence in these studies.

The classic criterion for sufficient number of samples in MC simulation is the ratio of the standard deviation of the sample mean of a selected index over the sample mean of the same index [27]. The calculation steps are displayed as the follows:

Step 1: Calculate the mean value ($E_i(X)$) and the standard deviation ($\sigma_i(X)$) of the index across all samples. $X_i(n)$ can be either the boundary transfer capability or the reliability indices, such as BCF, BCE, COLF and COLP.

$$E_i(X) = \frac{1}{N} \cdot \sum_{n=1}^{N} X_i(n) \tag{3.15}$$

$$\sigma_i(X) = \sqrt{\frac{1}{N-1} \cdot \left[ \sum_{n=1}^{N} X_i(n)^2 - N \cdot E_i(X)^2 \right]} \tag{3.16}$$

Step 2: Determine the standard deviation of the sample mean of the index.

$$\sigma_i[E(X)] = \frac{\sigma_i(X)}{\sqrt{N}} \tag{3.17}$$

Step 3: Set up the stopping criterion for the MC simulation. This maximum allowed error is usually set to 5% [28].

$$\frac{\sigma_i[E(X)]}{E(X)} \leq \varepsilon \tag{3.18}$$

A simple example is presented here to explain how the convergence rule is deployed in NOA for the assessment of proposed reliability (introduced in 3.1.8). Taking boundary congested energy (BCE) as the selected index $X$ in (3.15):

1. Select the portfolio of seasonal capability setpoints and assign the setpoint to each boundary, for example in B5, the capability is set to $\pm$5000 MW during summer, -4000 MW and 3000 MW during winter, etc.
2. Determine the initial number of scenarios to be run, such as 50 scenarios, while each scenario corresponds to a combination of demand and renewable generation profiles of a year.
3. Perform two separate simulations of economic dispatch with and without boundary-flow constraints in the same scenario so that the BCE in each scenario can be calculated by comparing two simulation results.
4. Assuming that the values of BCE in B5 are ranging from 100 to 400 GWh, with a mean value of 250 GWh and a standard deviation of 100 GWh, following the calculation given in (3.15) and (3.16). Then the standard deviation of the sample mean is around 14 GWh based on (3.17).
5. Finally, the error can be calculated as $14/250 = 5.6\%$ and being larger than the maximum allowed error (5%). Therefore, additional scenarios should be run until the

error is smaller than 5%, and then the mean value of BCE in B5 can be selected as the representative value in this converged Monte Carlo simulation.

Computation time may also be a critical factor to be considered other than hard convergence requirement[25]. As a suitable trade-off, the stopping criterion could be either the convergence having been reached following the calculation in (3.18) or the maximum number of scenarios having been simulated - whichever is satisfied first in the computation process.

### 3.1.8 Risk metrics for reliability indices

Once the convergence criterion mentioned above has been applied, a large number of scenarios are expected to be simulated, and the probability distribution of reliability indices in the results can be determined accordingly. It may then be valuable to also include some risk measurements, which can further enhance the network performance analysis. The risk metrics adopted here are value at risk (VaR) and conditional value at risk (CVaR) metrics [29].

As explained in 3.1.3, there is a lot of uncertainties in the system which can result in different dispatch profiles. Therefore, the simulation result of one scenario may not accurately indicate the network performance in the future. VaR and CVaR could help to quantify the network performance in the worst circumstances. For example, let us take the probability distribution of BCE index calculated in (3.11) and depicted in Figure 3.9. It needs to be emphasised that the data plotted here is for illustration purpose and doesn't indicate actual performance of GB network. If only one scenario is simulated, and the value of BCE is 100 GWh in this case, this value might just fall around the median value of the BCE distribution, while the network performance in the worst scenarios would not be represented. By using VaR with a 95% $\alpha$, we can see in Figure 3.9 that the value at risk of BCE is 200 GWh. This can be interpreted as saying that "there is 5% of chance that the BCE would exceed 200 GWh in this year." Furthermore, if we wanted to understand how the network performs in the 5% worst scenarios, the conditional value at risk could be calculated which reflects the average value of BCE in those worst scenarios. For instance, the CVaR for BCE is 220 GWh in Figure 3.9, which means the average value of BCE in the worst 5% scenarios is equal to 220 GWh.

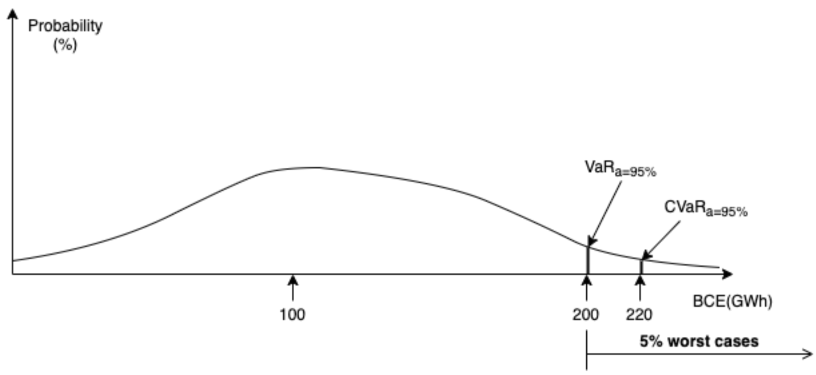



*Figure 3.9. Illustration of risk metrics of boundary congested energy index*

[25] For example, the Australian Energy Market Operator (AEMO) uses 1000 scenarios for each reference year for their adequacy studies [53].

In summary, this risk can be crucial for network planning, as network owners are not only interested in average performance of network assets (measured as mean value of metrics), but also the extreme circumstances (measured as VaR and CVaR).

## 3.2 Redispatch and curtailment

In ETYS, the constrained probabilistic power flow (CPPF) analysis is performed, as we have explained in 3.1.1. In this CPPF analysis, post-fault corrective actions are carried out in snapshots with a network constraint violation. However, post-fault corrective actions only include the network-based remedial actions (e.g., post-fault ratings, QB and FACTs) and procured commercial solutions. Therefore, the power flow profiles of a large number of snapshots may still be unacceptable, as these corrective actions could be insufficient to resolve network constraint violations. After the discussion with the experts in SC team, we understand that NGESO cannot rely on unconfirmed market solution, such as redispatch of generators and renewable curtailment, in long-term planning to assess boundary capability, because the availability and relevant service costs of these units are unknown. However, the numerical value of boundary capability could actually be better derived by introducing the options of redispatching conventional generators and curtailing renewable generation output.

In fact, redispatch and renewable curtailment have the potential to bring the network to operate on a secure operating envelope from an unacceptable (exceeding the predetermined boundary limit) dispatch point, with an intrinsic potential to expand, by means of corrective actions, the secure boundary transfer limit in first place.

Below, a system operation snapshot is designed to show some numerical results of redispatch and renewable curtailment functionalities. The five bus system introduced in Figure 3.2 is applied here and its configuration in this case study is slightly modified that among four generators, only G4 is the renewable plant as seen in Figure 3.10 and Figure 3.11. “Snapshot(E)” is designed with high output of G4 and high demand at D5, so that we can show a boundary transfer profile being close to the hypothetically maximum boundary transfer capability, which is the sum of capacity of network components directly connected to D5. Again, it is important to highlight that NGESO has applied a much more sophisticated process to determine boundary transfer capability in NOA as explained in section 2.2, while this “sum of ratings” approach applied here is to simplify the case study and allows reader to understand the pros and cons of using boundary constrained economic dispatch to determine system operational cost.

“Dispatch.6” shows the simulation result of economic dispatch and C2 is overloaded which results a violation of network constraints, as shown in the left subfigure of Figure 3.10. However, if redispatch is allowed, then the output level of G3 can be reduced by 50 MW while G2’s output increases 50 MW, which is named as “Dispatch.7” in the right subfigure of Figure 3.10. On the other hand, instead of redispatching G3, the overloading issue of C2 could also be resolved by curtailing the output level of renewable plant G4. This new dispatch profile is marked as “Dispatch.8” in the right subfigure of Figure 3.11. By doing redispatch and curtailment, an acceptable dispatch profile with 1000 MW boundary transfer can be generated, which is close to its dynamic boundary transfer capability 1100 MW at this snapshot.

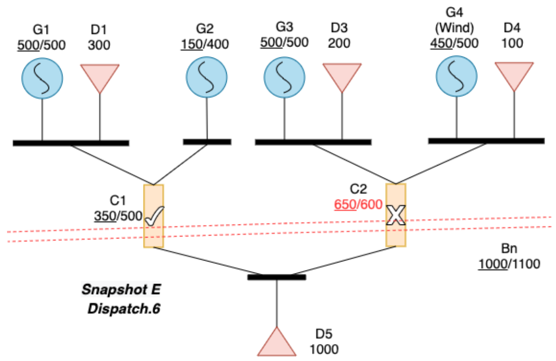



*Figure 3.10. Comparison of dispatch results of Snapshot E: Dispatch.6 (original) and Dispatch.7 (conventional generator redispatched).*

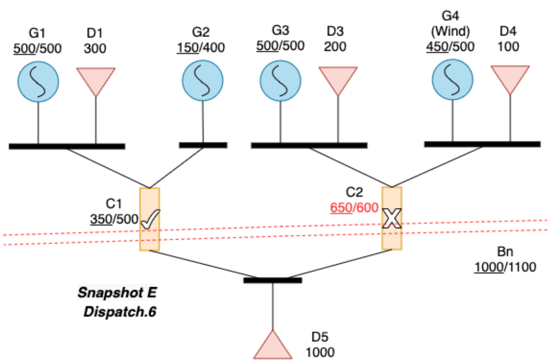



*Figure 3.11. Comparison of dispatch results of Snapshot E: Dispatch.6 (original) and Dispatch.8 (renewable output curtailed).*

This transition from "unacceptable" to "acceptable" dispatch profiles by using redispatch and curtailment is depicted in Figure 3.12. We have highlighted in Figure 3.12 that the marginal capability setpoint can be higher when it is derived from redispatch and curtailment profiles.

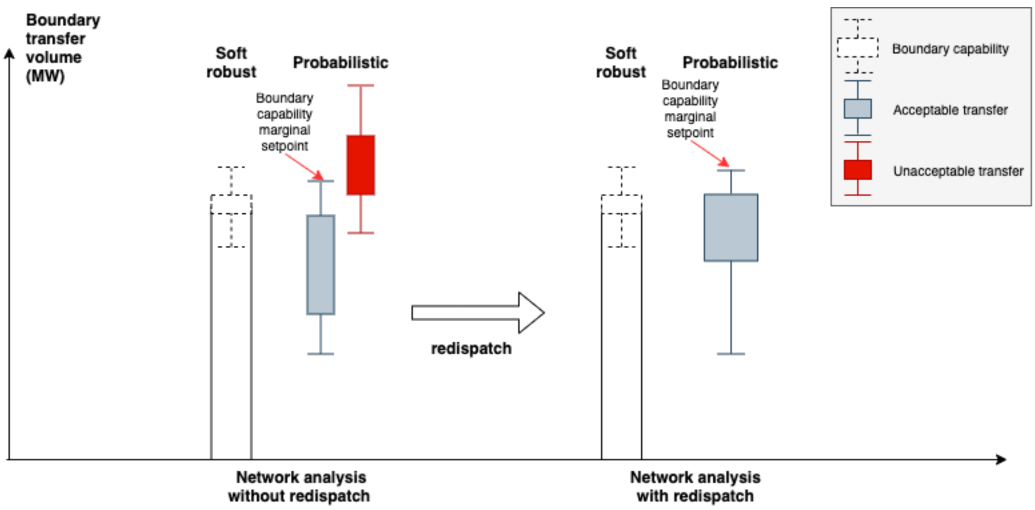



*Figure 3.12. The distribution of acceptable and unacceptable transfer profiles before and after applying redispatch*

Although both redispatch and curtailment have the capability of converting an unacceptable profile into an acceptable one, as seen in "Dispatch.7" and "Dispatch.8", it may be unclear which one of them should be used *a priori*. Therefore, a mathematical formulation of redispatch and curtailment model is explained below. We think that integrating this model into NOA's CBA can substantially improve the accuracy and consistency of system operating cost assessment. The integrated framework of economic dispatch and OPF for assessing constraint costs is shown in Figure 3.13.

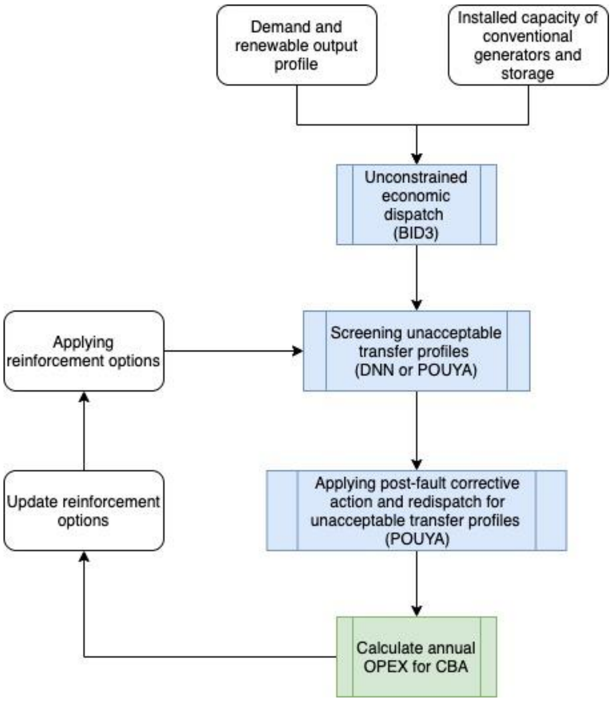



*Figure 3.13. Integrated framework of economic dispatch and OPF for constraint costs assessment*

The current methodology of NOA still uses static boundary transfer capability for each season, which is firstly assessed in SQSS winter peak condition and then scaled down to fit into other seasons. The economic dispatch in NOA's CBA can be treated as an optimisation which has implicitly considered the redispatch function in accommodating the boundary transfer constraints. In this integrated framework shown in Figure 3.13, POUYA and/or BID3 would need to gain the capability of performing redispatch, so that the constraint costs of each snapshots could be independently and accurately evaluated, instead of applying a predefined boundary capability to limit flow across boundaries.

Modelling of redispatch may be performed via a simple DC power flow approximation and linear programming (LP) based corrective actions. Redispatched generation profiles could be for example generated by following these steps [19]:

Step 1: Perform economic dispatch without network constraints to retrieve market-based power flows.

Step 2: Run DC power flow on the unconstrained dispatch profiles or use machine learning model (e.g., deep neural network (DNN) – see further below) to identify unacceptable transfer profiles.

Step 3: Add DC power flow network constraints and remedial action options to an economic dispatch program. In this optimisation program, the objective function is set to minimise the deviation of the redispatch operating points ($P^r(g,t)$) from the original dispatch points ($P^o(g,t)$) by adding a penalty factor ($\rho(g)$), also considering a load curtailment penalty ($\delta$).

$$objective = \min \sum_{t=1}^{T} \left\{ \sum_{g=1}^{G} [P^o(g,t) - P^r(g,t)] \cdot \rho(g) + \left[ \sum_{g=1}^{G} P^o(g,t) - \sum_{g=1}^{G} P^r(g,t) \right] \cdot \delta \right\} \tag{3.19}$$

By using a penalty factor, this application also gives us the flexibility of adding redispatch cost of different generators to the boundary capability modelling, which is not fully captured in NOA's CBA. This would also allow a more flexible modelling of commercial solutions (e.g., de-loading, intertrip of generators, etc.), potentially also accounting for availability fee and utilisation fee in a more accurate way.

## 3.3 Commercial solutions integration

On the one hand, it needs to be acknowledged that there are certain differences between redispatch and commercial solutions on several aspects, such as procurement process, which are procured through balancing mechanism (BM) and Pathfinder projects respectively. On the other hand, there are also some similarities of their purposes, which is to adjust the power output of generators to address the violation of network constraints in system operation. Therefore, the integration of redispatch into NOA's CBA may enable a better assessment of commercial solutions, so that its economic benefits on constraint costs reduction can be derived in a manner that is consistent with the evaluation of the network-based options proposed by TOs. In fact, the current evaluation process of commercial solutions is planned to run through Pathfinder projects, which run separately from NOA. The benefit of the conceptual[26] commercial solutions would be firstly evaluated in the ETYS/NOA annual cycle. This evaluation process of commercial solutions exhibits a few drawbacks, such as:

- Lack of a clear definition of the criteria to select which part of the network that requires the support of commercial solutions most urgently.
- Lack of consistent backgrounds (i.e., demand and renewable generation profiles in next 20 years) and system operating configurations (i.e., using BID3 or system historical service price) to evaluate constraint costs reduction by commercial solutions in comparison with network-based options proposed by TOs.

Eventually, commercial solutions should be treated as an alternative to network-based assets, given their potential (flexibility) benefits from having more flexible contract periods and faster deploy times relative to large assets such as transmission lines.

As a further point, keeping the boundary concept in BID3 may have hindered the effort of accurately modelling the technical performance of commercial solutions in NOA's CBA, which is usually adjusted at component level while benefits are assessed at boundary level instead of whole system level. That's why the recommendation made in 3.2 is to integrate the

[26] "Conceptual" here refers to solutions which are not analysed for a specific limiting issue, available assets or certain market provider.

network model into NOA's CBA, so that commercial solutions performance in operation can be derived in a consistent way instead of relying on historical results.

A potential framework to integrate commercial solutions into the current NOA's CBA could be based on a two-phase adjustment.

In the first phase, the procedure of evaluating economic benefits of commercial solutions explained as the following:

1. **Generate unconstrained market flow**: In addition to the boundary-constrained economic dispatch simulated with BID3, use BID3 to run an economic dispatch without boundary flow constraint.
2. **Identify congested boundary:** With both constrained and unconstrained dispatch profiles, calculate the BCE index defined in 3.1.6 (the aggregated value of BCE over the planning horizon (e.g. 5-10 years) should be calculated). Derive and rank the values of aggregated BCE for different boundaries, to determine the boundary which has a largest congestion issue.
3. **Determine technical requirements**: By comparing the boundary flow between constrained and unconstrained profiles at each snapshot, plot the frequency and magnitude of congestion as a PDF. By selecting the mean value of the PDF and frequency of activation of specific commercial solutions, derive the capacity requirement and the number of annual utilisation times.
4. **Request for information to stakeholders**: Send the technical requirements evaluated above to stakeholders and request the proposal of commercial solutions with a similar feature, such as storages, batteries, etc.
5. **Final evaluation**: After receiving the cost (i.e., availability and utilisation fees) of commercial solutions sent by stakeholders, rerun BID3 with a reinforced boundary constraint considering commercial solutions. After deriving the system operating costs in the simulations with/without commercial solutions, determine the constraint cost reduction brought by this commercial solution and compare with options of TOs on a consistent basis.

In the second phase, we want to enable an analysis for commercial solutions at network component level. This analysis would rely on the simulation results generated in CBA after integrating DC OPF and redispatch function into the current CBA methodology, as explained in Figure 3.13. The implementation instruction of redispatch with DC OPF at component level is elaborated in 3.2. Then, instead of calculating the BCE at step 2 above, we can calculate the generator output deviations from its optimal position and the component overloading level (in economic dispatch) to give the indication of the most frequently overloaded components. Moreover, the sum of output deviation in the planning horizon can be calculated and ranked to determine which generators are most frequently redispatched to provide active or reactive power support[27], which gives potential opportunities for introducing commercial solutions at these locations of the network. The request for information and final evaluation shall be the same as the procedure explained in the first phase.

[27] The inclusion of commercial solution for voltage control or reactive power support would require the capability of running AC OPF. NGESO is currently developing POUYA's capability of running AC power flow in another research project, which would not be discussed here.

## 3.4 Machine learning applications in ETYS and NOA

### 3.4.1 Literature review of ML applications in power system

Machine learning and artificial intelligence have grown in interest over the last few years owing to the their potential operational applications [30]–[34]. This is because ML and AI can usually give a result with a much shorter computational time in comparison with traditional optimisation approaches, which may also have nonconvex features and require substantial computational resources besides feasibility issues [35], [36].

For example, Refs. [31], [33], [34] have used machine learning techniques to predict different outages and contingencies under N-1 and N-2 criteria. There are also many publications which have applied ML to classify the feasible and infeasible dispatch profiles with the help of physics-informed techniques to reduce the prediction errors [35], [37]–[39]. Moreover, power flows in lines and generators dispatch points in AC OPF problems can also be predicted by using ML, as demonstrated in [30] and [40].

However, most if not all ML power system applications have focused on short-term operation, while the long-term expansion planning problem is rarely addressed.

This may be caused by the lack of database of potential solutions in planning problems, which is often required for training the ML model. This lack of data profiles has actually also affected research on short-term operation, leading to considering generation of such databases as a research topic *per se* [38].

In the contest of this work, we propose the following two ideas to explore potential applications of ML in support of the ETYS and NOA processes:

- **Use ML model to classify system dispatch profiles as acceptable or unacceptable** depending on whether there is a violation of network constraints, as already been mentioned in Section 3.2. By using ML model instead of running power flow analysis with POUYA, the computational time can be substantially reduced. Although there may be minor error on the classification with ML model, as seen in [39], [41], it is expected that this will be less critical in long-term planning relative to short-term operations, as failing to identify few unacceptable snapshots will only have limited impact on the total constraint costs.
- **Build a ML model to automatically scan the information of options submitted by TOs and explore the potential optimal combinations of options**. Traditionally, the scanning process is part of the Challenge and Review process, which needs to identify potentially "abnormal" data of options submitted by TOs. For instance, Network Development (ND) teams need to check whether the boundary transfer capability of an option has a significant difference relative to the value of the same option submitted in last NOA. Currently, this work is done manually. However, if the application is solely used for cross-comparison of the information of same options submitted in two adjacent NOA, it seems less necessary to use ML model, as data extraction and cross-comparison can be done with a simple program. The main ML application could in fact be to project the boundary capability of combination of options that have not been examined through simulation. The ND teams could then use this projected boundary capabilities to decide whether it is necessary to run the

technical analysis of some potentially promising combinations, which have not been recommended previously.

In the following subsections, we will elaborate on how to potentially implement these two ML models.

### 3.4.2 Neural network for security assessment

A possible implementation approach for the first ML model could be found in [39], [41], using a deep neural network (DNN) structure. An example is depicted in Figure 3.14, which demonstrates how secure and insecure dispatch profiles may be split under different network topologies. For instance, only one numerical constraint is needed to split the secure and insecure dispatch profiles when the outputs of two generators are concentrated to component C1, as shown in Figure 3.14. However, if the generators are connected to network components individually, as seen in the right side of Figure 3.14, then two numerical constraints would be presented to split the secure and insecure dispatch profiles.

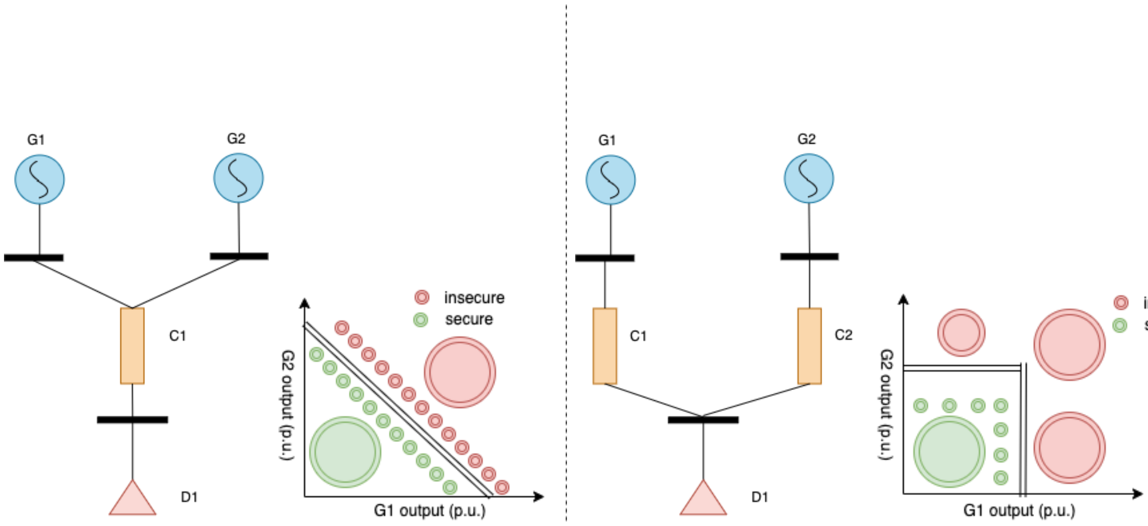



*Figure 3.14. secure and insecure operating regions under different network topologies*

In practice, there are many more components and generators in the network, which would require a cluster of constraints to differentiate the secure and insecure dispatch profiles. That is why we would like to propose to use deep neural networks to derive these constraints and give classification result of network security assessment in a relatively quick way.

In this DNN model, the input features would be the output level of generators across the system, while the output would be a classification label, to determine whether this dispatch profile is acceptable or unacceptable (or say secure or insecure). The model developing procedure is elaborated below:

1. **Training dataset preparation**: The DNN model requires a large number of training samples[28] (e.g., 10,000 [35]) to derive the parameters of the neural network. In this case, a large number of dispatch profiles have already been generated in order to

[28] A training sample indicates a snapshot of generation dispatch profiles and the verification result of network constraints (through simulation in POUYA or Power Factory), which can be acceptable or unacceptable.

calculate reliability indices and risk metrics explained in 3.1.6 and 3.1.8. These profiles, which would have been classified by Power Factory, could then be used for DNN training purposes.

2. **Common network topology**: One thing to emphasise is that the network topology and contingency settings need to be same for the training dataset and the profile classification in NOA's CBA. That means a DNN model needs to be trained separately for every network topology in the future years with each reinforcement options.
3. **Future use**: As explained above, the DNN model can only be used in the same network topology. If there is no change to the base network topology in the NOA of last two years, then the DNN model for base network classification could be repeatedly used.

In summary, instead of using Power Factory to classify each dispatch profiles, a DNN tool could be a promising alternative to accelerate the processing time of the integrated approach of DC OPF and redispatch shown in Figure 3.13.

Further to security assessment, there is a potential application of ML for options verification and recommendation. This will be elaborated in the following subsection.

### 3.4.3 Neural network model for "challenge and review" of reinforcement options

As mentioned above, this model is developed for two purposes:

- Verify the information submitted by TOs;
- Explore potentially valuable combinations of options which are not included in the current candidate list of NOA.

The recommend configuration of this ML model would be deep neural network: a typical DNN structure is depicted in Figure 3.15. The reason for using a deep neural network instead of a linear regression model is the possibility to exploit the feature of hidden layers to simulate the XOR or XNOR logics. These two logics are required in NOA, as there are reinforcement options which cannot exist simultaneously (mutually exclusive) and options which must happen together. The relationship between options have been elaborated in section 2.3 of the first report of this project [7].

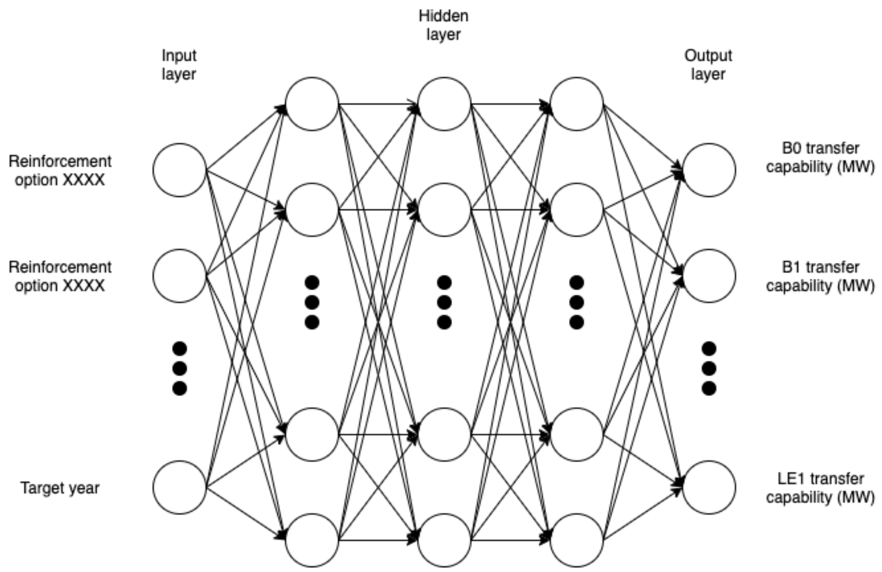



*Figure 3.15. DNN structure for "challenge and review" of reinforcement options*

As shown in Figure 3.15, the input features of the DNN would be the commitment state of each reinforcement option in the network and the selected year for boundary capability assessment. The output feature would be the boundary capability.

A neural network model can generally be considered as an aggregated linear regression model with the following equation:

$$w \times X + b = Y \tag{3.20}$$

In this application, the physical meaning of these parameters and variables are explained below:

- $b$ can be treated as the boundary transfer capability without any reinforcement.
- $X$ is the commitment state of each option and the selected year
- $w$ mostly corresponds to the boundary capability contribution of individual options, while the input unit corresponding to the selected year represents the boundary capability contribution of approved reinforcement options.
- $Y$ is the transfer capability of boundary.

A multi-task learning approach could be adopted [42], which means that the output layer would have multiple activation units corresponding to each boundary in the GB network. The reason of using multitask learning is that this would allow the boundary capability to be derived from a similar DNN configuration, also saving time to train individual DNNs for each boundary separately. With regards to the activation function, a rectified linear unit (ReLU) function could be used for the hidden layers, while applying the identity function to output layer. The reason for using identity function is that we want the model to output the boundary capability, which is a MW value.

Before inputting the training dataset into DNN model, the information of options (i.e., reinforcement options list and corresponding boundary transfer capability) stored in the database used in the NOA CBA needs to be restructured to fit the training purpose. The input and output of training dataset should be restructured as shown in Table 3.3 and Table 3.4 respectively. As mentioned in Figure 2.2, SC team only evaluates the boundary capability in network models of Year-1/3/5/7/10 and assumes the boundary in unexamined year has the same transfer capability as the previous year. For example, only Year-1 and Year 3 networks are examined, and boundary capability in Year-2 is kept the same as Year-1, while Year-4 is kept the same as Year-3. However, we need to replicate the boundary transfer capability data and use them explicitly on a yearly basis for training purposes, so that the DNN would not somehow wrongly infer a linear increase of boundary capability between Year 1 and 3.

*Table 3.3. Database structure of DNN model input features*

| **Profile No.** | **Reinforcement options commitment state** | | | | | | **Year** |
|---|---|---|---|---|---|---|---|
| | FBRE | LBRE | BLN2 | E4DC | … | TURC | |
| **1** | 0 | 0 | 0 | 0 | … | 0 | 2019 |
| **2** | 1 | 0 | 0 | 0 | … | 0 | 2023 |
| | | | | **…** | | | |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| **XXXX** | 0 | 0 | 0 | 1 | … | 1 | 2028 |

*Table 3.4. Database structure of DNN model output*

| **Case No.** | **Boundary** | | | | | |
|---|---|---|---|---|---|---|
| | B0 | B1 | B2E | B2F | … | LE1 |
| **1** | 1401 | 3099 | 3557 | 3557 | … | 7600 |
| **2** | 1500 | 3099 | 3557 | 3557 | … | 7600 |
| **…** | | | | | | |

The procedure to apply this model in Challenge and Review process would be:

1. Use verified options from last NOA to train a DNN model, named as DNN-1.
2. Apply DNN-1 to screen and verify the information submitted by TOs. The verification criterion would be that the difference of boundary capability of a same option or combination of options in two NOAs does not exceed a specified threshold $\varepsilon$ (e.g., 5%). A small variation can be understandable due to the scenario update.
3. Use verified options submitted to this year's NOA to train a new DNN, called DNN-2.
4. Apply DNN-2 to simulate the projected boundary capability of options combinations that would not have been explored in the current NOA and decide if this combination features certain interest to be further simulated in POUYA in order to explore its technical performance.

It needs to be emphasised that the effectiveness of this DNN model for boundary capability projection is subject to the availability and complexity of the training dataset, which allows the DNN to properly "understand" the boundary capability contribution from reinforcement options.

## 3.5 Concluding remarks

In this section, we have discussed how to improve the methodology of ETYS and NOA in terms of technical modelling in capturing network performance and opportunities in a system with increasing penetration of renewable energy, distributed energy resources, and more non-network solutions that are available. Ten recommendations made in this section are summarised in Table 3.5 with their importance, benefits and complexity of implementation explained.

The potential improvement proposed can, amongst others, also be used to *integrate* the evaluation of different types of reinforcement options (e.g. network-based and commercial solutions) in the same framework, so that the constraint costs reduction contributed by reinforcement can be calculated in a more accurate and consistent way. Furthermore, the work introduced aims to create a better understanding of the short-term uncertainty faced by transmission network from the system operational perspective. How long-term uncertainties can be better addressed via flexible investment measures in network planning is discussed in the following section.

*Table 3.5. Summary of technical modelling recommendations*

| | | |
|---|---|---|
| Recommendation 1 | Action: | **Use economic dispatch to replace unit commitment in POUYA's system operation modelling** |
| | Importance highlight: | Improving the computational efficiency of POUYA would allow more snapshots to be examined in its Monte Carlo simulation within the timeframe of NOA preparation, which would lead to a better security assessment and boundary capability estimation. |
| | Benefits on decision making: | • Reduce the computation time of POUYA and allow parallel computation;<br>• The generation profiles simulated by economic dispatch may be more diversified, which allows further stress-test on network security. |
| | Implementation complexity: | Relatively quick. Deactivate intertemporal constraints of generators and reducing the optimisation timescale of UC from one week to single snapshot. |
| Recommendation 2 | Action: | **Use K-means clustering method to evaluate setpoint for boundary capability with probabilistic analysis** |
| | Importance highlight: | The clustering technique would ensure the snapshots applied in security assessment are more representative in terms of power flow across the network. |
| | Benefits on decision making: | The boundary capability derived from the security assessment of representative snapshots would more accurately reflect the benefits of reinforcement options and enhance the credibility of NOA's CBA. |
| | Implementation complexity: | Implementation is underway based on the discussion with SC team. |
| Recommendation 3 | Action: | **Use stratified sampling to evaluate marginal and robust setpoints for boundary capability** |
| | Importance highlight: | The marginal and robust setpoints indicate the upper and lower limits of boundary capability respectively. More candidates of setpoints within this range can be tested in order to select the most appropriate one for NOA's CBA. |
| | Benefits on decision making: | By defining the potential range of the setpoint, multi-criteria analysis can be applied to select the most appropriate value for boundary capability of various reinforcement options and better informs NOA's CBA. |
| | Implementation complexity: | Requiring extra time to implement stratified sampling. System modelling and security assessment are kept same. |
| Recommendation 4 | Action: | **Introduce reliability indices for robustness evaluation of boundary capability setpoints** |
| | Importance highlight: | Current methodologies of NOA and ETYS lack the method to quantitatively describe the performance of boundary other than mapping energy transfers. Indices can be applied to quantify the performance of boundary and critical components at sub-boundary level. |

| | | |
|---|---|---|
| | **Benefits on decision making:** | • Identify vulnerable boundaries and overloaded network components within the boundary;<br>• Improve the confidence of selecting a specific value for seasonal boundary transfer capability. |
| | **Implementation complexity:** | Result analysis with data mining technique is required to pick up vulnerable components and subsequently calculate the corresponding reliability indices. |
| **Recommendation 5** | **Action:** | **Set up convergence criterion in POUYA's Monte Carlo simulation** |
| | **Importance highlight:** | Criterion needs to be set up to determine how many scenarios are sufficient so that the boundary capability and reliability indices are derived from a converged simulation result. |
| | **Benefits on decision making:** | Provide a clear criterion on the number of scenarios to be simulated instead of a static number, which is 10 in the existing probabilistic analysis. |
| | **Implementation complexity:** | No modelling work is required. Only extra simulation tasks need to be performed in order to satisfy the convergence criterion. |
| **Recommendation 6** | **Action:** | **Introduce risk metrics (value at risk and conditional value at risk) for reliability indices** |
| | **Importance highlight:** | Risk metrics can be used to enhance the evaluation of network performance, which provides an illustration of the probability distribution of reliability indices. |
| | **Benefits on decision making:** | Understand the network performance in the worst circumstance, which may also be used to determine the network reinforcement requirement rather than based on the network "average" performance. |
| | **Implementation complexity:** | No extra modelling work is required. Once the convergence criterion is set up, a large number of scenarios are expected to be simulated, which allows the probability distribution of indices to be mapped and risk metrics to be derived. |
| **Recommendation 7** | **Action:** | **Implement redispatch and curtailment functions in POUYA and BID3** |
| | **Importance highlight:** | Currently, redispatch and renewable curtailment are implicitly modelled through the static boundary-transfer constraint in BID3, while unacceptable boundary transfer profiles classified by POUYA cannot be altered (through redispatch) to indicate system operation under network congestion conditions. The modelling of redispatch and curtailment would allow the simulation to mimic the system operation in practice and consequently improve the boundary transfer capability evaluation. |
| | **Benefits on decision making:** | • POUYA's result would be all acceptable ones in terms of network security assessment through redispatch, which can be used to indicate the boundary transfer limits in various circumstances.<br>• BID3 can discard the boundary-transfer constraints and allow a more accurate estimation of the technical benefits of reinforcement options in NOA's CBA. |
| | **Implementation complexity:** | Requiring the linearisation of network constraints and the modelling of optimal power flow in POUYA and BID3, which can be time-consuming. |

| | | |
|---|---|---|
| Recommendation 8 | **Action:** | **Streamline the development of commercial solutions** |
| | **Importance highlight:** | NOA Pathfinder projects are independently proceeded, which may lack consistent scenarios and system operation modelling comparing with NOA's CBA. |
| | **Benefits on decision making:** | By creating a consistent evaluation framework for commercial solutions and network-based reinforcement, a better combination of short to medium-term options (i.e., commercial solutions) and long-term options (i.e., network-based reinforcement) can be explored for network development scheme. |
| | **Implementation complexity:** | The adjustment is more focused on the project execution process rather than technical modelling. |
| Recommendation 9 | **Action:** | **Neural network model for network security assessment** |
| | **Importance highlight:** | Network security assessment is a very time-consuming task due to its non-linearity of security constraints. Neural network model provides a way to quickly classify the dispatch profiles as acceptable or unacceptable by learning from the simulation results of POUYA. |
| | **Benefits on decision making:** | By reducing the time spent on network security assessment, more reinforcement options can be analysed which enhances the credibility of NOA's CBA. |
| | **Implementation complexity:** | Extra work is required to set up input data preparation by selecting and organising the simulation results of POUYA during boundary capability evaluation process and then train the neural network. |
| Recommendation 10 | **Action:** | **Neural network model for "Challenge and Review" of reinforcement options** |
| | **Importance highlight:** | The "Challenge and Review" process is currently carried out by experts in NGESO. This process is highly labour-intensive and may not be able to perform a systematic examination of all the options submitted by TOs within the limited time given for NOA preparation. A model which can automatically perform this task can significantly enhance "Challenge and Review" process and improve work efficiency. |
| | **Benefits on decision making:** | • Systematically identify the discrepancy of the boundary capability of different options submitted by TOs;<br>• Explore potential combination of reinforcement options which was not included in TOs original submission. |
| | **Implementation complexity:** | Extra work is required to set up input data preparation based on the information submitted by TOs and then train the neural network. |

# 4 Investment Flexibility

This section discusses how to capture more flexibility from the reinforcement options. Three main aspects are covered: an introduction on elements affecting investment flexibility, theory on investment flexibility, and current practices of National Grid and potential improvements to capture more flexibility.

## 4.1 Introduction

Let's start by providing a clear definition for *investment flexibility*. The literature has addressed this topic in multiple instances [43], [44] referring to concepts like investment flexibility and compromise solutions in a variety of ways, but without a clear and unified definition. Based on these elements we will use the concept of *flexible investment options* to refer to investments options (single or multiple assets) whose technical, locational, operational and/or procurement characteristics allow them to act as compromise solutions capable to adapt and provide value in a wide variety of scenarios, thus intrinsically hedging against planning uncertainty; these scenarios can describe changes to endogenous system characteristics (e.g. demand growth, renewable energy variability, etc) and/or to exogenous system characteristics (e.g. technological development, market conditions, etc).

The assessment of the flexibility associated to a given investment options must be conducted by means of a suitable stochastic methodology [43], [45], [46], where decisions are made *here-and-now* assuming uncertainty regarding the unfolding of the future (e.g. start the procurement of permits to deploy a transmission line) and other decisions are made in the future when more information is available; these decisions are known as *wait-and-see* decisions (e.g. start construction, decisions on transfers through a high voltage direct current (HVDC) link, etc.). The more *wait-and-see* decisions are available for an investment option, the more flexible the option is. In some cases, the benefits associated to the flexibility of an option can be compensated by high investment and/or operation costs, which can render one particular investment strategy more or less attractive depending on the pool of options against which it is simultaneously being compared. Without a suitable stochastic methodology it is not possible to effectively discriminate the best investment plan from a flexibility point of view.

Before we delve into the specific aspects of the methodology to select flexible transmission options let's step back for a moment. National Grid ESO's main task is to provide recommendations on a set of reinforcement options proposed by the Transmission Owners. However, this objective is getting increasingly entwined with new challenges and options in the operation of power systems, represented in this case, for example, by the objectives of the pathfinder projects, which look to provide novel solutions for the management of secure transfers through the boundaries of the system, as discussed in the previous sections. This reality is putting pressure on the methodological aspects to assess the technical characteristics of the reinforcement options, potentially novel approaches to deal with the factors that affect the secure transfer of power, and the cost-benefit analysis that takes all these options and has to produce a decision based on a pair formed by one metric and one indicator, as it was discussed in [7]; examples of this are stochastic decisions, which rely on the Manhattan metric and costs as the indicator, and least worst regret decisions (LWR), which use the Chebyshev metric and regrets as the indicator.

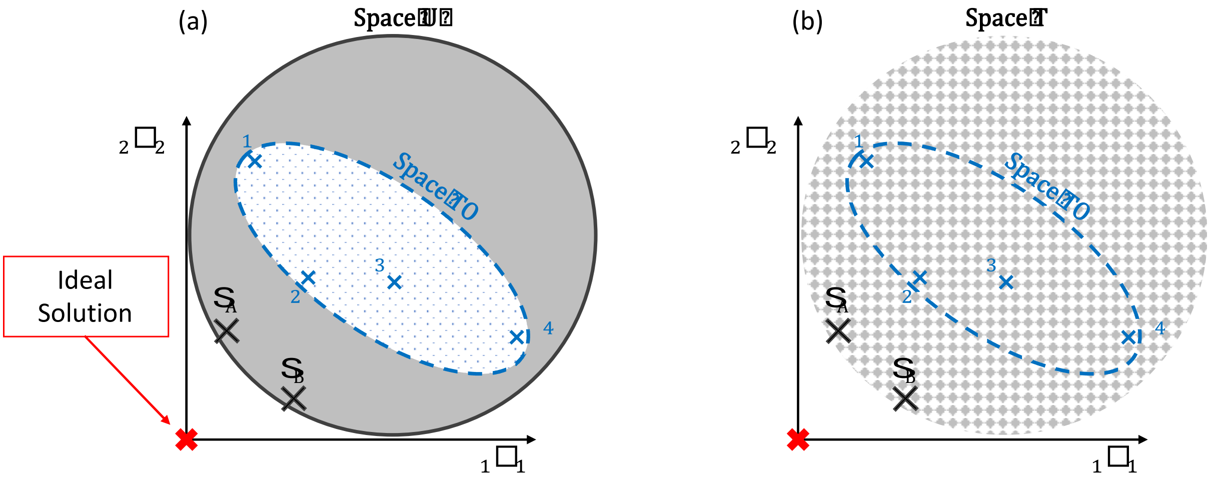



*Figure 4.1. Interaction of the solution space associated with options proposed by transmission owners (Space TO), (a) the global set of solutions (Space U) and (b) the global set of transmission solutions (Space T)*

Figure 4.1 presents the different spaces of search that National Grid ESO is currently facing. The set of options presented by the TOs is labelled *Space TO* and is depicted as the area bounded by the dashed line that encloses all the strategies presented by the TOs. *Space TO* is not a continuous set, it is composed by a limited number of strategies, considering that each reinforcement presented by the TOs has well-defined characteristics (e.g., the capacity of a proposed transmission line reinforcement is fixed). The universe of potential solutions, labelled *Space U,* is much larger than *Space TO.* It can be approximated as a continuous set considering all the different combination of solutions (and possible sizes), like transmission, storage, demand response, intertrips, etc. If only transmission options are considered, but all potential combinations of transmission links and sizes, which we call *Space T,* it would still be much larger than *Space TO,* and although still disjoint, it would be also much denser. *Space T* would offer strategies like $S_A$ and $S_B$, which can be missed by the TOs because they can only search a finite amount of options and, more importantly, they are blind to the options being considered by other TOs and therefore by networked effects (impacts and benefits) that only a system-level view can capture.

The increasing number of options available to provide solutions for the reliable operation of power systems is pushing National Grid ESO to step into the realm of decisions linked to what can be described as a *system architect approach* (equivalent to exploring the search *Space U* in Figure 4.1.

In the coming sections the focus is put on addressing the search of solutions within *Space TO;* however, it is relevant to highlight that current state-of-the-art models could efficiently search a much larger portion of *Space U*, conducting a CBA analysis with optimality assurance and risk aversion control through risk constrained stochastic approaches using DC power flow [43], [47]. For example, one of the implementations based on [43] – for an investment horizon of 20 years sampled every 5 years and the operation represented by typical weeks within each year, with pool of investment options including transmission, pumped-storage and battery energy storage systems – yielding a combination of over $3\text{x}10^{12}$ investment strategies in a given year, currently takes around 1-2 days to find the optimal solution depending on various modelling considerations and available computational resources (in that case ca. 100 parallel CPUs). This type of approach could be of interest for extensions of the ETYS, which would allow narrowing down the critical links and, for instance, needed storage solutions for the subsequent analyses conducted by the TOs and the pathfinder project teams. The same models can be used to narrow down the interesting areas of *Space T,* if co-optimising for other technologies is not in scope. Also, by using only the set of reinforcements presented by the TOs, the *Space TO* can be explored using the same models to find the optimal strategy using the information available on the impact on boundary capability for different combinations of reinforcements, either under deterministic or stochastic conditions.

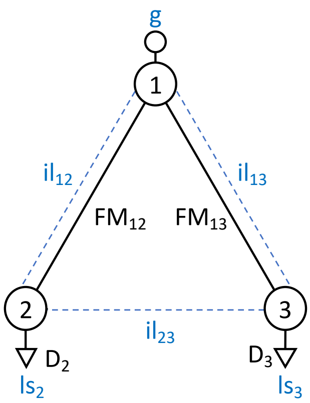
For the sake of clarity, in the coming sections we will call this approach based on suitable stochastic methods to search the space the *integrated approach*; on the other hand, we will refer to NGESO CBA methodology as the *sequential approach*. Sequential approaches correspond to methods that contain a series of steps that aim to find an optimal solution by reducing the search space through heuristics, which may or may not contain probabilistic considerations.

## 4.2 Introductory example

To allow for a simpler way to examine all the elements involved in capturing investment flexibility, in this section we introduce a small example that will provide context and highlight the relevant factors affecting flexible investment decisions.

### 4.2.1 Single snapshot case

Let's consider the 3-bus system presented in Figure 4.2, which consists of one generator connected to bus 1 and two loads, one connected to bus 2 and the other to bus 3. The scenarios are given by the values of the load at bus 2 (2 per unit [pu] in scenario 1, 1pu in scenario 2) and bus 3 (1pu in scenario 1, 2pu in scenario 2). Initially, line 1-2 and line 1-3 have a transfer capacity of 1.5pu, and there is no line between nodes 2 and 3. The generator can produce energy at a cost of $1 (per unit of output per unit of time). Value of lost load is $30. The investment options are 3: reconductoring existing lines to increase transfer capacity in 0.5pu at a cost of $4 and to build line 1-3, at a cost of $6, resulting in a transfer capacity of 0.5pu between bus 2 and 3. For the sake of simplicity we ignore Kirchhoff's voltage law; while this approximation has substantial effects on the physical results, however it helps to readily understand the principles that we are trying to depict through this example.




| **Parameters:** | **Value:** |
|---|---|
| $FM_{12}$: maximum flow line 12 | [1.5pu] |
| $FM_{13}$: maximum flow line 13 | [1.5pu] |
| $D_2$: demand bus 2 | [SC1: 2pu SC2: 1pu] |
| $D_3$: demand bus 3 | [SC1: 1pu SC2: 2pu] |
| **Variables:** | **Associated information:** |
| g: generation bus 1 | [unconstrained, $1 pu output pu time] |
| $ls_2$: load shedding bus 2 | [unconstrained, $30 pu lost pu time] |
| $ls_3$: load shedding bus 3 | [unconstrained, $30 pu lost pu time] |
| $il_{12}$: reconductor line 12, binary | [$FM_{12}$+0.5pu, $4] |
| $il_{13}$: reconductor line 13, binary | [$FM_{13}$+0.5pu, $4] |
| $il_{23}$: build line 13, binary | [$FM_{23}$=0.5pu, $6] |

*Figure 4.2. 3-bus system*

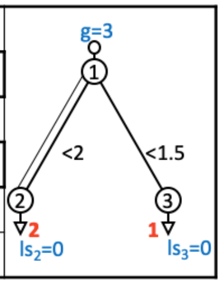
Let's start by solving the deterministic cases. As the network is completely symmetrical, the solutions are also symmetrical, as shown in Figure 4.3. The objective function (*OF*) of the problem, shown in (4.1), considers the investment and operation costs:

$$OF = \overbrace{[4 \cdot (il_{12} + il_{13}) + 6 \cdot il_{23}]}^{\text{Investment cost}} + \overbrace{[1 \cdot g + 30 \cdot (ls_2 + ls_3)]}^{\text{Operation cost}} \tag{4.1}$$

In scenario 1 it is beneficial to proceed with the reconductoring of line 1-2, hence increasing the capacity of that link to cover all the demand in node 2 and avoid any load shedding. Similarly, in scenario 2 the optimal deterministic decision is to reinforce line 1-3 to cover the demand on bus 3. Investing in line 2-3, which is more expensive than reconductoring any of the lines, naturally yields a worse result. Not investing in any line produces load shedding in both scenarios, , and investing in the reconductoring of the wrong line produces the highest cost (investment and load shedding).

**Scenario 1**

| Inv | OF value | Non-zero variables |
|---|---|---|
| - | 0 + 17.5 = 17.5 | g=2.5, $ls_2$=0.5 |
| $il_{12}$ | 4 + 3 = 7 | $il_{12}$=1, g=3 |
| $il_{13}$ | 4 + 17.5 = 21.5 | $il_{13}$=1, g=2.5, $ls_2$=0.5 |
| $il_{23}$ | 6 + 3 = 9 | $il_{23}$=1, g=3 |




**Scenario 2**

| Inv | OF value | Non-zero variables |
|---|---|---|
| - | 0 + 17.5 = 17.5 | g=2.5, $ls_3$=0.5 |
| $il_{12}$ | 4 + 17.5 = 21.5 | $il_{12}$=1, g=2.5, $ls_3$=0.5 |
| $il_{13}$ | 4 + 3 = 7 | $il_{13}$=1, g=3 |
| $il_{23}$ | 6 + 3 = 9 | $il_{23}$=1, g=3 |

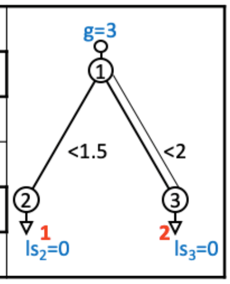



*Figure 4.3. Deterministic results*

It is important to highlight that the combination of investment decisions in this particular example will always yield substantially higher costs with no additional benefits, so they are not analysed. This simplification can only be done because of the size and simplicity of the example; formally, 7 different investment combinations should be analysed[29] on top of not investing in new assets.

[29] Considering the effect of Kirchhoff's voltage law in this example would completely change the dynamic of the decisions, because in order to unlock transfer capacity in one link, additional transfer capacity would need to be available in the other links.

The "stochastic" version of this problem, from formal mathematical programming approaches, solves the same scenarios simultaneously, looking to making investment decisions that can find "compromise results" across the multiple possible futures [43], [44]. The stochastic problem is modelled as a two-stage problem, where the investment decisions are the same as before, but the operation is modelled separately for each scenario (variable superscript denotes scenario in the objective function (4.2), where the subscript $S$ stands for "stochastic"). We assume equal probabilities for both scenarios.

$$OF_S = \overbrace{[4 \cdot (il_{12} + il_{13}) + 6 \cdot il_{23}]}^{\text{Investment cost}} + 0.5 \overbrace{[1 \cdot g^1 + 30 \cdot (ls_2^1 + ls_3^1)]}^{\text{Operation cost scenario 1}} \\ + 0.5 \overbrace{[1 \cdot g^2 + 30 \cdot (ls_2^2 + ls_3^2)]}^{\text{Operation cost scenario 2}} \tag{4.2}$$

When solving this problem, the solution is now to build line 2-3, which allows covering both loads in both scenarios, as shown in Figure 4.4. This is by definition and as from practical evidence a "compromise" solution, which, as it can be seen, may also be completely different from what was suggested by the solution of each individual deterministic scenario. This compromise solution also intuitively corresponds to the concept of "flexibility" as it allows navigating across uncertain scenarios simultaneously.

| | | Non-zero Variables | | |
|---|---|---|---|---|
| Inv | OF value | Inv | Scenario 1 | Scenario 2 |
| - | $0 + 0.5 \cdot 17.5 + 0.5 \cdot 17.5 = 17.5$ | - | $g^1$=2.5, $ls_2^1$=0.5 | $g^2$=2.5, $ls_3^2$=0.5 |
| $il_{12}$ | $4 + 0.5 \cdot 3 + 0.5 \cdot 17.5 = 14.25$ | $il_{12}$=1 | $g^1$=3 | $g^2$=2.5, $ls_3^2$=0.5 |
| $il_{13}$ | $4 + 0.5 \cdot 17.5 + 0.5 \cdot 3 = 14.25$ | $il_{13}$=1 | $g^1$=2.5, $ls_2^1$=0.5 | $g^2$=3 |
| $il_{23}$ | $6 + 0.5 \cdot 3 + 0.5 \cdot 3 = 9$ | $il_{23}$=1 | $g^1$=3 | $g^2$=3 |

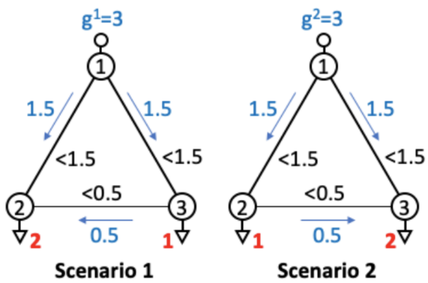



*Figure 4.4. Stochastic Results*

This example shows the value of considering all potential scenarios in a single problem and assessing potential *compromise* solution, which emerges from a *stochastic* version of the original (scenario-based, deterministic) problem formulation. A few interesting points can be highlighted further based on this example.

Firstly, the integer nature of this problem does not allow for an "average" solution based on the independent solutions of the deterministic cases[30]. Also, even if such a solution were to be feasible, it would not necessarily produce a solution close to the optimal compromise solution obtained by a formal stochastic approach [48], [49].

Second, the integer nature of the investment decisions in the transmission expansion problem[31] generates, in principle, the possibility to recreate the stochastic solution by ideally

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[30] It should be noted that the solutions identified under the "probabilistic" setting discussed in our previous report [7] belong to this category.

[31] At least in the version emerging from the NOA context, where all decision variables are integer and referring to investment in specific assets at a given year. Mathematically, this corresponds to an integer programming problem and can be solved with various techniques, for example dynamic programming approaches. A more

listing *all* the deterministic solutions for the different investment options. Such a comprehensive analysis of all options could then be carried out by running an *exhaustive search* of all ex-post combinations of deterministic solutions, to work out the best compromise option. In our simple example, this can be checked for the case of the stochastic option by inspecting the deterministic results in the tables of Figure 4.3 and comparing them with the stochastic results in Figure 4.4. It is possible to see that the stochastic operation in each scenario is the same as the deterministic operation for the corresponding scenario. Since the investment option is the same in both deterministic scenarios, and the sum of probabilities equals 1, the results will match. However, this, again, is only true in the case of integer investment decisions, because it is possible to list all potential solutions. Also, although possible in this example, listing all conceivable investment options can be infeasible in most real cases due to the combinatorial explosion of number of possible integer decisions, in particular if the investment options are more complex: this is for example the case when the investment decisions can be made not only now but in the future too and also when a given investment decision can be retracted or delayed.

The key takeaway of this simple example is that it highlights how critical is the role of compromise solutions in the presence of uncertainty; this, in turn, reinforces the relevance of the way information is used to arrive at a decision, which will be discussed in the following sections. Also, the advantage of having the possibility to list all independent solutions associated to the integer nature of the decisions in the TEP is limited to the practical capacity to effectively cover all options. Any attempt to proceed by listing a subset of options without a clear understanding of what is being left out of the analysis can lead to substantial loss of efficiency associated to the decision that will be made. This aspect is also covered in the following sections.

### 4.2.2 Multiperiod extension

Let us now extend the example of the previous section to a multiperiod version. The aim is to compare the fundamental elements of the NGESO's CBA methodology to highlight its strengths and weaknesses. Both the system structure and the investment options will be the same as before; the changes only impact the profiles of demand in both scenarios, which in this case are represented with the numbers presented in Figure 4.5.

| **Period** | **1** | | **2** | | **3** | |
|---|---|---|---|---|---|---|
| **Demand (pu)** | D2 | D3 | D2 | D3 | D2 | D3 |
| **Scenario 1** | 1.5 | 1.5 | 2 | 1 | 2.5 | 1.5 |
| **Scenario 2** | 1 | 1.5 | 1 | 2 | 1.5 | 2.5 |

*Figure 4.5. Demand profiles for the multiperiod example*

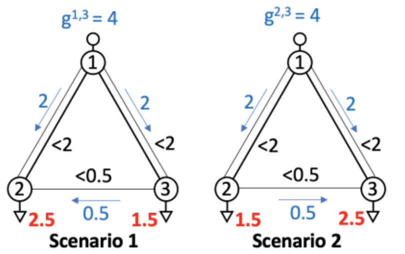
An additional assumption is made on the reinforcements: their earliest in-service date (EISD) for all reinforcements is in period 2. A yearly discount rate is considered (to reflect the fact

general version of the problem would envisage continuous decision variables too (e.g., the size of investment), which would make it impossible to exhaustively search the solution space and calling for more sophisticated approaches to solve the corresponding mixed-integer programming problem.

that it may be desirable to delay projects that do not create immediate benefit as much as possible) and we assume each period represents the operation of one year.

Let's proceed following NOA CBA methodology (see [7] for further details), that is, let's find the optimal path of reinforcement for each scenario. There is no need to do calculations, since period 1 does not need any reinforcement (also, no reinforcement may be implemented due to EISD), period 2 has already been studied, and period 3 requires all reinforcements in both scenarios, as shown in Figure 4.6a.

**a) Optimal operation of the system in period 3**




**b) Optimal deployment (deterministic)**

| | Scenario 1 | Scenario 2 |
|---|---|---|
| $il_{12}$ | Period 2 | Period 3 |
| $il_{13}$ | Period 3 | Period 2 |
| $il_{23}$ | Period 3 | Period 3 |

*Figure 4.6. Operation of the system in period 3 and deterministic optimal deployment*

Considering the time value of money, the optimal way to deploy the reinforcements for Scenario 1 is to have reinforcement 1-2 ready in period 2 and then all reinforcements in place in period 3. For Scenario 2 the optimal deployment path includes reinforcement 1-3 in period 2, and all reinforcements in period 3. Following the current CBA methodology, the next step would require determining what reinforcements enter the LWR stage, that is, those that are critical (optimal entry date equals EISD) only in some scenarios. This is presented in Figure 4.6b; reinforcements 1-2 and 1-3 are critical in only one scenario each, hence the LWR strategies would correspond to the permutation of reinforcement 1-2 and reinforcement 1-3, while fixing reinforcement 2-3 in the period that the deterministic assessment determined for each scenario, which in both scenarios is period 3.

We do not present here the specific results for the permutation exercise, but it is possible to see from the outcomes presented in Figure 4.6 that proceeding reinforcement 2-3 now would make it available for period 2, yielding optimality. Then, reinforcements 1-2 and 1-3 can be proceeded in Period 2 for them to be available in Period 3. Hence, the overall optimal LWR strategy is to proceed reinforcement 2-3 and hold reinforcements 1-2 and 1-3.

The difference in the results stem from the step in which the set of options that enter the LWR process is reduced by selecting the reinforcements that are critical in only some of the deterministic scenarios. As a matter of fact, reducing the set of reinforcements in any way may always result in preventing the best possible assessment of a specific combination of reinforcements that could act as a compromise solution, which is exactly what we seek as investment flexibility.

## 4.3 Seeking investment flexibility

Flexibility in an investment problem is affected by aspects that can be gathered under two main categories, both being closely connected with the way the problem is modelled. These categories are *information accessibility* and *information use*. To understand them, it may be convenient to provide some examples.

From the perspective of increased **accessibility to information**, the decision maker can consider larger sets of investment options (technical characteristics, costs, etc.), more detailed description of each investment options or, among other things, a larger set of information about the characteristic of future scenarios to model the operation as detailed as possible. A larger set of investment options will provide flexibility by simply giving more solution alternatives and potential paths; more information about each investment options will create flexibility by enabling actions within a project that before were not described; a more ample data set to describe operation in each scenario will potentially allow capturing more value from each investment option. Each of these options will unlock flexibility, but this naturally will come at the cost of dealing with a larger problem.

On the other hand, there is the **information use** aspect. Considering that the information sets are fixed for a given problem, the way in which the decision maker structures the decision process will impact how the investment options will allow hedging against the future. Considering independent deterministic scenarios to drive decisions will produce fundamentally different solutions compared to strategies that combine the view of the future across scenarios to make decisions. Also, the latter approach is not unique; there is always a possibility to make the decision less often or consider different degrees of uncertainty as deeper into the future a given decision is. Clearly, the more often a decision can be made, or the more complex the structure of uncertainty and the decision-making problem are, the heavier a problem will result – to be traded off with gain in flexibility.

These two information related aspects interact in different ways depending on the selected **methodology** (e.g., deterministic vs stochastic, risk awareness, etc.). The methodologies are structured as algorithms that make decisions based on different decision indicators (e.g., costs, regrets) and metrics (Manhattan, Euclidean, Chebyshev, etc.); each *methodology* will *use* the *accessible* information in different ways.

In general, the main idea behind the concept of investment flexibility is to find solutions whose characteristics can produce/capture value in a broad range of scenarios, hence hedging more effectively against an uncertain future. Although both information categories are relevant, the impact of the accessibility aspect is more natural to understand than the usage aspect; in the following sections we mainly focus on explaining the methodological aspects of improved information usage in the transmission expansion problem.

From a deterministic point of view, it is relatively straightforward to understand the process of finding a set of candidate investments whose impact in relieving system constraints is such that the cost savings will balance out the associated investment costs. If this process is repeated for each independent scenario, the decision maker can use the information to select a unique investment set that will guarantee a certain behaviour across scenarios given a certain rule. This approach can be improved by finding *compromise* solutions that will hedge better against the different uncertain scenarios under consideration; below we set forth to present a brief example to depict this concept and its implications on the optimality of decisions.

The example in section 4.2 shows how certain reinforcements can act as compromise solutions. While these reinforcements can be overlooked due to their relatively higher costs or their low NPV performance in a deterministic context, they exhibit the capacity to capture value in multiple scenarios, which is exactly what a flexible investment option is. On the other hand, some of these options may simply not be present at all in the decision set coming from the deterministic solutions pool.

Figure 4.7 presents the fundamental aspects that interact and impact the capacity to capture flexibility when making investment decisions.

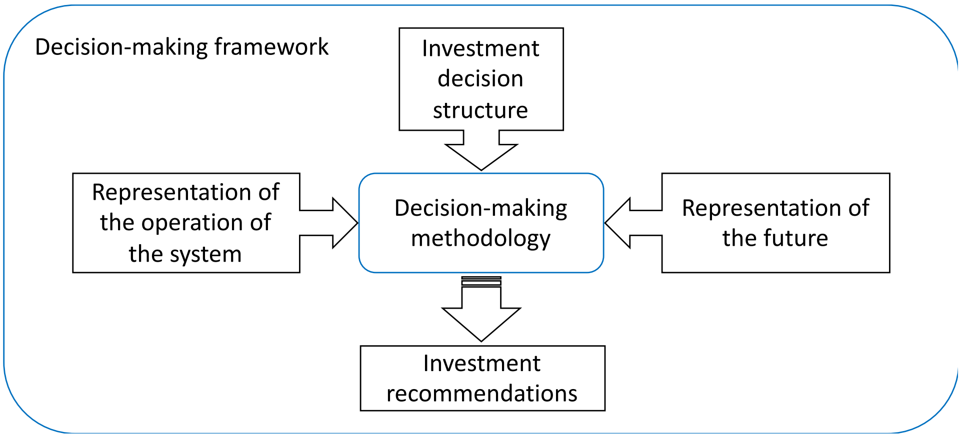



*Figure 4.7. Factors influencing investment flexibility*

**Representation of the system operation** refers to the level of details in the operation of the system that are being captured to drive the evaluation of the investment alternatives. This aspect of the process is captured to a great extent in the analysis run by the TOs in the evaluation of the boundary capability for each combination of reinforcements (see Sections 2 and 3 of this report for details of different aspects). Some elements are captured by the information used to represent the system within the decision-making framework, for instance, the refinement of the sampling of demand and renewable energy availability. This section of the report will not touch on this particular subject because the principle is simple: higher precision in the representation of the operation will help harnessing more value when adding different investment options.

**Decision making methodology** corresponds to the set of metrics, indicators, risk measures, algorithms and processes used to incorporate all the information about the system behaviour, representation of the future and decisions structure to determine what investments to proceed. A large part of the discussion about methodological aspects was presented on the first report [7]; algorithmic aspects about current practices and potential improvements in that regard are covered in this report.

**Investment decisions structure** includes all the decision stages associated to the process of deploying a new asset and the set that results from combining all the reinforcement options and their associated decisions. Basically, it allows departing from the idea of modelling a single decision of the type build/not build towards a real options-like approach that considers project deferrals, resizing, etc [45]. This approach naturally provides more flexibility to the decision-making process because it allows modifying the nature of the project dynamically as uncertainty unfolds. It, however, imposes challenges from the point of view of information accessibility and modelling.

**Representation of the future** refers to how the future and uncertainties are represented/considered in order to identify the optimal development path for the system. The central task in this regard corresponds to identifying the relevant uncertain variables in the long-term and build a representation of the future; to keep all the relevant correlations within the system adequately represented the usual approach corresponds to define a finite set of scenarios to describe the possible futures. The uncertainty set will then interact with the methodological considerations and the decisions structure, yielding different stages of decisions (e.g. decision tree for stochastic optimisation) depending on the assumption about how uncertainty can unfold as time passes.

This section addresses two of the topics that influence the amount of flexibility that each investment option can provide in an evolving environment characterised by high uncertainties. First, we discuss the concepts associated to the structure of investment decision in transmission and then we focus on discussing aspects associated with the representation of the future.

### 4.3.1 Investment decisions structure

In general, the decision process behind the deployment of new assets in transmission focuses on incorporating lots of detail on the operation representation and some information associated with future scenarios. This already represents a substantial challenge, so many simplifications are done when it comes to how projects are implemented and managed, and how risk is incorporated. As described in [50] the decision-making process can be modelled under one of the following approaches:

- **Deterministic approach**
  The discounted cash flows are used to determine what to do with an investment option considering a binary decision on the execution of the project. The project will continue to exist even if it is reporting negative cashflow in the future and the risks are incorporated in the discount rates used to value future income and expenditures.

- **Scenario approach**
  The uncertain variables that can have a substantial effect on the behaviour of the system are used to create structured accounts of possible futures of operation of the system/market, also known as scenarios. These scenarios are then explored through different approaches to assess the value of the different investment options and drive decisions considering their performance across possible futures. The approaches include sensitivity analysis, probabilistic assessment, application of risk measures, and decisions analyses which can consider decision trees and more elaborate metrics and indicators to join the information of multiple scenarios and produce a single decision on each candidate that maximises expected benefits.

- **Real option approach**
  Real Options theory was developed in the context of financial option pricing and was specifically tailored to deal with uncertainty when evaluating investment options; its purpose is to assess the viability of engineering projects like transmission assets. This approach can be very useful in the context of power system development as it enables to identify possible flexible investment strategies to cope with uncertainties. Its value resides in the development of adaptive paths of investment decisions that minimise the exposure to risk, by exploiting the fact that decision-makers will incorporate new information as uncertainty unfolds and will take actions accordingly.

However, Real Options theory was created in the context of financial theory and the underlying assumptions to work with analytical solutions are often not fully or at all applicable when dealing with engineering problems. The application of this theory in the context of transmission investment should then aim to "mimic" the optionality concept through mathematical programming techniques that can be applied to engineering problems; this should be done in order to develop flexibility in the decisions for each investment project so that its development can be "optimally" (flexibly) adjusted as uncertainty unfolds. From the perspective of centralised transmission planning this approach can represent an information access/management challenge, because the planner needs to have access to all the options and associated costs faced by the transmission owners.

The real options faced by an engineering project are defer, time to build, alter operating scale, abandon, switch, growth, and multiple interacting options. Below is a brief summary of each RO as presented in [50].

- Defer: This is the most common RO found in the literature. They concern the alternative to delay investment decisions with the objective of gathering additional information to better assess the projects.
- Time to build: This is the alternative to build a project in stages; each stage involving a small investment and the reassessment of the project. This provides an option to abandon the project before the whole capital needed to build it has been compromised.
- Alter operating scale: This is the alternative to expand the project in favourable scenarios and reduce or abandon it in negative scenarios. These RO usually involve supplementary investments in additional capacity, or the sale of franchises and infrastructure.
- Abandon: This is the option to abandon a project and sell its infrastructure if the project is resulting in significant losses.
- Switch: This is the alternative to change the technology or size of the project.
- Growth: Growth options involve the alternative to invest in an R&D or pilot project meant to secure resources or provide information about the project's environment. These assets can facilitate investment decisions in additional interrelated projects. In other words, the growth option is the option to begin investments with a small project that can grow into one or more larger projects.
- Multiple interacting options: This is the alternative of analysing several RO in combination instead of assessing each RO independently. In practice, projects might possess several available RO that affect each other. In other words, in real life applications, the combined value of the RO might defer from the sum of each option assessed in isolation. Accordingly, assessing RO and their interactions is deemed convenient for most projects in real life applications.

It is relevant to highlight that the theory usually used to conduct real options valuation of financial assets cannot be directly applied to the assessment of options in transmission project [45], [50]; in this context, the real options aspect corresponds to the design flexibility that is considered and represented within the decision framework. The issue lies in the effective identification of real options in an engineering project at every point in time; the set of options can be effectively not countable which renders the theory not applicable.

When the set of decisions associated to each reinforcement option has been defined, then the real set of decisions that the decision maker faces corresponds to the combination of all decisions for all project in each time step when a decision can be made. This set is very relevant, because it corresponds to the foundation of the different decision spaces presented in Figure 4.1. Reducing the decision space in any way can reduce the capacity of the underlying methodology to find the most flexible investment path.

### 4.3.2 Representation of the future

The discussion on how much information and how to use information is paramount to understand investment flexibility. Both aspects enter in direct conflict with the time and resources necessary to account for them, so it is essential to identify what information is really useful to make a decision and how to use it to reduce costs and risks.

In the previous section we presented a way to achieve more flexibility in the investment problem by expanding the number of decisions associated to each of the reinforcements under consideration. Here we present elements associated to how to model the decision process under uncertainty in order to capture flexibility in the form of compromise solutions.

The theory of decision making under uncertainty [48] divides the set of decisions into two groups. There is a number of decisions taken before uncertainty unfolds (also known as here-and-now decisions), which are called first-stage decisions; there are also decisions that have to be taken after uncertainty unfolds which correspond to the second-stage decisions (or wait-and-see decisions). These different variables are clearly represented in the example of Section 4.2, with investment decisions being the first stage decisions, and the operation of the system (generator outputs, line flows, load shedding) correspond to second-stage decisions (one independent set of decisions for each scenario). The stages represent states of uncertainty, they have nothing to do with the periods that are being considered within the problem. For instance, first-stage decisions can cover many different periods (for instance years) that are all included in the second stage, as presented in Figure 4.8.

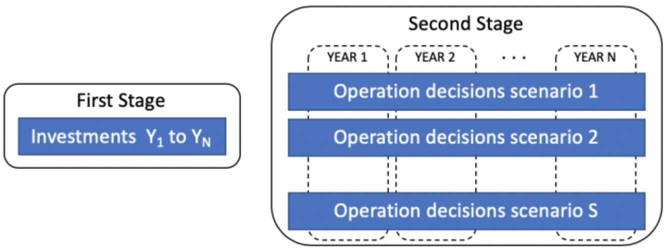



*Figure 4.8. Two-stage investment problem.*

The two-stage approach can be adequate to represent decisions facing uncertainty, but it can be insufficient to capture all the investment flexibilities that exist in a real problem like the TEP with the consideration of real options, where the future can unfold in different paths not only in the beginning of the problem, but also at different points in the future. In this sense, the CBA methodology considers the single-year proceed/delay decisions for the subset of reinforcements that are permuted as the here-and-now decisions. All other decisions coming from the deterministic assessment are wait and see decisions that are made assuming that the uncertainty has already unfolded.

It is relevant to highlight that the two-stage approach supports making decisions for multiple years, which is something that the NOA CBA methodology could readily incorporate to make the decisions more flexible. Considering more scenarios within the two-stage approach would also help in identifying compromise solutions that can adapt to a broader range of scenarios. However, the two-stage approach is incapable of incorporating the reality that these decisions will be updated as the future evolves.

In order to increase the flexibility of an investment option, the model has to incorporate the reality that decisions will be updated as the future unfolds; this is achieved by incorporating several decision stages, each of them assuming certainty of the path followed up to the point where decisions are updated and also modelling the future ahead at that point. The two-stage model can therefore be extended to a so-called *multistage* decision process; such an approach will allow explicit implementation of further levels of decision (e.g. real options) as uncertainty unfolds to capture flexibility of different projects (e.g. stop one project and implement another option which can compromise the uncertainty seen at that point). Figure 4.9 shows a graphical representation of the chain of stages and investment decisions, where the stages of uncertainty coincide with each year under analysis.

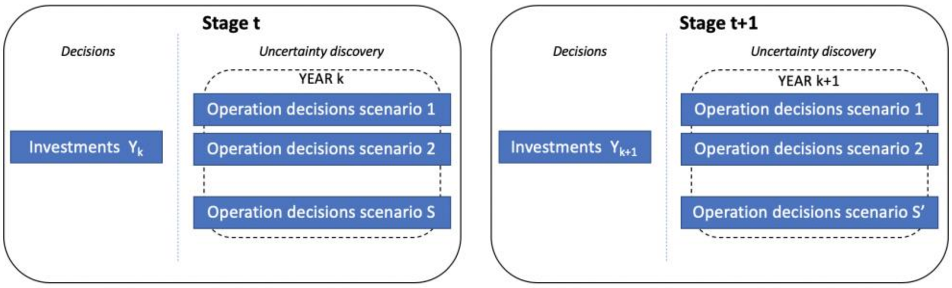



*Figure 4.9. Multistage approach*

A multistage representation leads naturally to a more complex problem representation, given the fact that the decisions made in stage t+1 will depend on the scenario realisation in stage t. This structure may seem to isolate the decisions of each stage, but, in reality, they are all strictly interrelated. Modelling flexibility in the future can have a substantial impact on the decisions that are being made today, because of the potential to modify them as uncertainty unfolds.

This difference in the modelling approach (two-stage vs multistage) is paramount to achieve an efficient development of the system. It could be argued that the investment flexibility provided by the multistage approach could be achieved by the two-stage approach by repeating the investment exercise as often as possible (rolling horizon). However, this is incorrect in the sense that, although the rolling horizon is effective in correcting the investment strategy as uncertainty unfolds, the two-stage approach might be blind to future compromise solutions that could be found if the future is modelled as it would reveal itself sequentially in multiple stages; in turn, this will affect the decisions made in each rolling period[32]. As a matter of fact, the multistage approach can also be use in the context of a rolling horizon exercise, as shown in Figure 4.10.

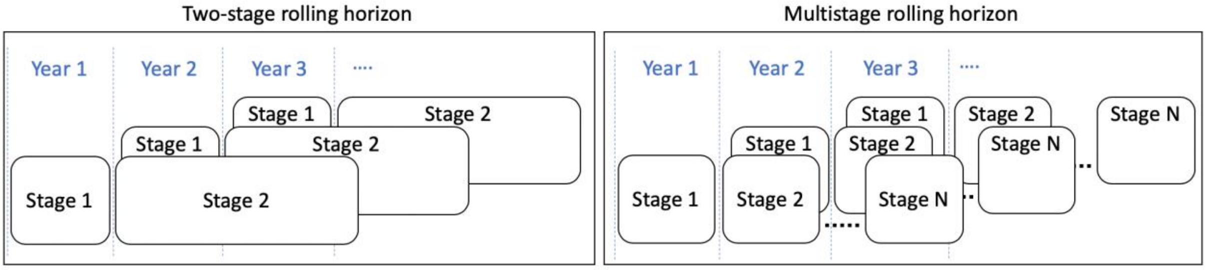



*Figure 4.10. Conceptual application of rolling horizon in two-stage and multistage decision approaches*

A multistage representation generally creates challenges from the point of view of the size of the problem. This can render infeasible any approach relying on exhaustive analysis of investment combinations.

Among the options to make decisions in the context of a multi-stage setup (to capture more flexibility), the two natural options to consider correspond to the multistage stochastic decision approach and the multistage LWR approach, as presented in Figure 4.11.

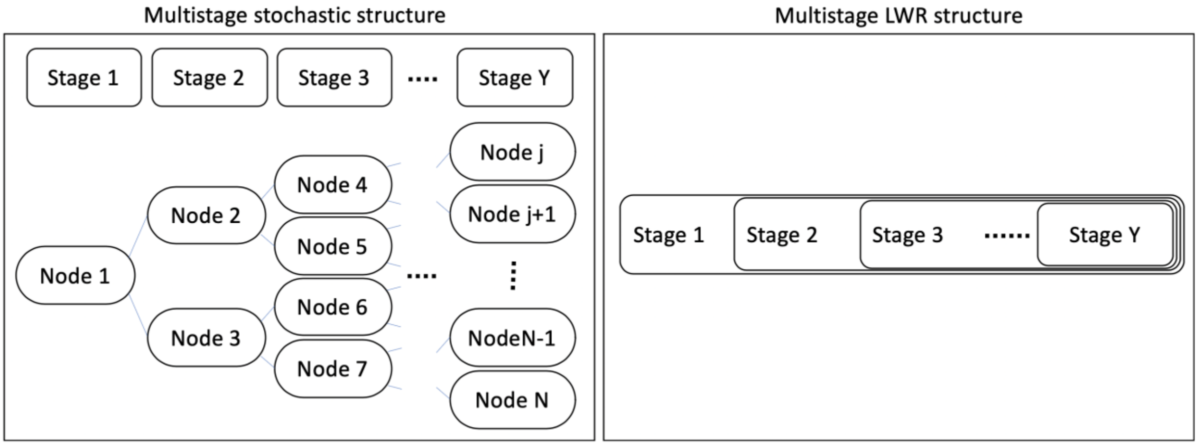



*Figure 4.11. Structure of multistage decision approaches*

The multistage stochastic approach has been widely used in the context of power system expansion and the solution methods are well-known. Since in every stage a minimisation problem is solved, it is possible to find solution strategies that scale well for large problems, through decomposition approaches [48]; also, adequate risk measures can be included in the formulation with the aim to search for solutions that keep the downside risk limited to fit the risk aversion requirements [29].

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[32] The concept could also be expressed as follows. Even if the decisions were adjusted ("corrected") systematically through the rolling horizon, modelling with a two-stage approach would only capture a reduced amount of investment flexibility simply because after the first stage everything else would become wait-and-see decisions associated to each scenario. That is, the loss of flexibility comes from assuming that the future is set after stage 1. Of course, this is not strictly a problem of the two-stage approach, but rather a more general implication of how the future is modelled.

The corresponding multistage problem using the LWR approach is a rather complex problem [46]. As seen in Figure 4.11, the resulting multistage problem yields a *nested* structure, which stems from the subsequent min-max problems that have to be solved in each stage. There are solution strategies that have been proposed for this problem, typically based on dynamic programming. However, the issue lies with the classic shortcoming of dynamic programming, the so-called curse of dimensionality, which in this case is activated by the number of reinforcements that are being considered and also the different decisions that can be made for each reinforcement.

Each modelling approach has advantages and disadvantages, both from a computational and theoretical (characteristics of the decisions, [7]) perspective. However, if the methodology is structured as a multistage decision problem this will allow accessing as much investment flexibility as possible.

## 4.4 Current practices and recommendations

### 4.4.1 Current practices

In the first report [7] the CBA stage of the NOA process was described in detail, and we briefly summarise it here for convenience.

The principles behind the most important steps of the CBA methodology in regard to investment flexibility are reflected in the example presented in Section 4.2.2 of this report. The CBA consists of a series of phases that aim to determine first the optimal deployment path for each of the scenarios under analysis and then the LWR decisions for a subset of reinforcements. The reinforcements that enter the LWR stage correspond to those that fit the criterion of being critical in some scenarios; a reinforcement is said to be critical in a given scenario if it appears active at its earliest in service date (EISD) in that scenario, which in turn means that it has to be proceeded today to make that happen.

Then, if a reinforcement is critical in only some scenarios and not all of them, it enters the single-year LWR process to determine what of the reinforcements that comply with the abovementioned criterion have to be proceeded this year. This way, the single-year LWR mirrors a two-stage decision process where the first stage corresponds to making the decisions of what reinforcements to proceed, and the seconds stage operates the system with the selected reinforcements under each scenario conditions (that are not supposed to change in the future).

In the context of the CBA the first-stage decisions of the LWR only consider a subset of reinforcements and the subsequent operation of the system under different scenario conditions is run considering that all other reinforcements have been fixed to start operation according to their optimal deterministic deployment. The decisions made in the LWR problem correspond only to proceed or hold (not proceed) a reinforcement. However, as pointed out in the first report [7], the CBA also produces other recommendations that are solely defined based on the results of the deterministic assessment for each of the scenarios (e.g. if a reinforcement is not being built yet and it is not selected in any of the scenarios, the decision is *do not start*).

This analysis is run on a yearly basis; it includes all reinforcements under development plus all the new reinforcements options that the transmission owners have presented to be considered in the current process. From this pool of reinforcement options, only a few of them reach the LWR stage.

All these elements place the CBA methodology in the realm of two-stage decision processes applied on a yearly basis in the form of a rolling horizon problem (Figure 4.10). The two-stage approach combined with the reduced set of reinforcements that enter the LWR has the advantage of keeping the decision search space limited while enabling to make proceed/hold decisions on the subset of reinforcements based on worst regret minimisation. However, as it has been presented in previous sections, the two-stage decision structure assumes that there is only one point in time in which decisions can be made to address a future represented by a set of scenarios; when uncertainty unfolds, it is assumed to strictly follow one of the scenarios up until the end of the analysis horizon. Assuming this particular behaviour has the effect of limiting the decisions made today to reinforcements that are optimal (according to the metric being used) only if the future unfolds in this particular way. Also, it neglects the flexibility associated with decisions that can be made in the future to correct the development path, as more information of the future is revealed; this impacts the capacity to proceed reinforcements that can act as compromise solutions in the future. Also, the reduced set of reinforcements that enter the decision-making process under uncertainty limits the combinations of options that can be explored to reduce cost and risk.

### 4.4.2 Recommendations

In this section we set out to describe recommendations for potential improvements to the CBA of the NOA process. It is important to recognise that potential improvements to the CBA methodology will impact other stages of the process (like the studies conducted by the system capability team that have been discussed in this report in Sections 2 and 3); also, they might affect or require investments in infrastructure in order to keep other factors constant, like for example, the number of people involved or the time required to accomplish the tasks. Our recommendations are primarily focused on improving the methodological aspects.

*Short/mid-term recommendations (to be potentially operational for NOA 2021/2022)*

<u>Determination of optimal deterministic expansion</u>

Assuming the current methodology remains as it is, the process to determine the optimal set of reinforcements for each scenario (see phases I to III, first report [7]) could be automatized as much as possible, both with the objective to reduce the possibility to lose optimal solutions and with the objective to release valuable human resources for tasks that are harder to or cannot be automated. The quickest solution is to aim at increasing computational resources to the point where a *brute force (exhaustive search)* strategy is feasible*:* keeping the current structure within BID3, calculate the optimal costs of operation for all years and all possible combinations of reinforcements that have an associated impact on boundary capability[33].

[33] NGESO already has in place the infrastructure and procedures to simultaneously determine the costs of operation for different selections of years, scenarios and reinforcements. Although solving all current possible

This process would result in a map between years, active reinforcements, and associated annual operation costs. With this map the determination of the optimal path of deployment for each scenario can be conducted with the current steps that NGESO uses (COMP sheet) or by means of other suitable algorithm (see Appendix B for some examples) that can guarantee optimality. The increase in computational resources should not represent an excessive expense compared to the benefits of freeing human resources currently being used to conduct the heuristic assessment over 10 weeks.

Capturing more investment flexibility

The current *sequential* methodology reduces the set of options that enters the two-stage LWR analysis, the only point where compromise solutions can be found in the current set-up. This reduction should be avoided as much as possible to decrease the chance of missing the optimal solution. The current nature of the LWR approach in the NOA CBA prevents the consideration of more than 12-15 reinforcements simultaneously.

With this in mind and considering that substantial changes are not possible in the short run, the best strategy could probably be to reconsider the strategy to identify the reinforcements that can provide flexibility across scenarios. Several exploration strategies can be applied to identify this subset of reinforcements, all of which would involve conducting multiple LWR experiments with smaller sets of reinforcements to find those options that create the most value.

Operational details

The current CBA methodology bases its assessment on the calculation of the costs of operation for each year in full. When heavy intertemporal constraints are not present in the model (e.g. large-scale storage), there is no strict need to model each specific year in full, but rather it can be more efficient to identify typical weeks within the year that can, without much loss of precision, summarise the relevant operation aspects of an entire year.

This approach would have great impact on the computational burden associated to this problem, by reducing the current computational times and as a steppingstone that will enable the future use of integrated approaches that can greatly enhance the quality of the solutions, which generally rely on shorter operation periods to determine operational costs (if the system conditions allow that).

The reduction of the size of the operational problem can solve the current need to use 3-hour or 6-hours steps to model operation; 12 typical weeks represented with hourly steps produce a lighter problem than 52 weeks modelled with 3-hour steps. The right balance between operational details and computational burden needs to be further assessed to determine the best balance.

The task of selecting the right periods that effectively represent the operation of the system can be conducted by means of similar tools to those presented in Section 3.1.5.1 of this report.

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combinations (4 scenarios, 10 to 20 years, and 8000+ reinforcement combinations) is a computationally expensive task, it is feasible to do so with the right amount of computational infrastructure. It is estimated that 100-150 CPUs would complete this task within 4 weeks, without substantial intervention from human resources.

Frequency of analysis (full NOA process)

This is a critical aspect of the process that requires a review (see Appendix C for further information on the approach taken by AEMO in Australia, for example). The benefit of reducing the frequency of the NOA process is straightforward: there would be more time to analyse information, refine options, possibly develops a sounder investment methodology with automatic algorithms. This time could indeed be used to contemplate more network and non-network options, to check network capabilities, to run more simulations, to include further aspects for consideration in the assessment of boundary capability (e.g., inertia and frequency stability and security ), among many other aspects of the process that would benefit from an extended assessment period. All these studies will yield a better decision on what reinforcements to pursue and what reinforcements to discard; also, it would provide more time to transmission owners to better assess their options. The main disadvantage of a less frequent assessment is the potential delay in making decisions associated to starting or stopping reinforcements. Further assessment is necessary to quantify the trade-off between delaying decisions and having a better understanding of the set of options available to expand transmission. The intuition[34] here is that the negative effects associated with reducing the frequency from making decisions every year to doing so every, say, second year could be (largely) compensated by the benefits of allowing more time to refine the analysis and present more flexible options, as previously discussed.

### *Mid-term improvements*

Determination of optimal deterministic expansion

If the steps to determine the reinforcements that enter the LWR assessment remain as they are, the deterministic solutions will still be necessary. However, if the set of candidate reinforcements grows too large, the current sequential approach or the brute force approach can become infeasible. To solve this issue an *integrated* optimisation algorithm could be used, based on a selected decomposition approach or formal algorithm if necessary[35], to search efficiently for the optimal deployment of reinforcements to minimise the costs of operation under each deterministic scenario. This would yield savings on time as well as on computational and human resources; however, it would require the implementation of a search algorithm (see Appendix B). It is possible that such an algorithm can be implemented as a layer that will make use of the current BID3 infrastructure. The underlying algorithm could be based on classical dynamic programming approaches, as well as on nested Benders decomposition and/or Dantzig-Wolfe decomposition – this would depend on the size and complexity of the specific problem that needs to be solved, which would have to be analysed in detail as part of a future project.

[34] We would need to run specific studies to formally assess this, which is however outside the timeline and scope of the current work.

[35] If the number of options grows too large, solving the problem by brute force might be infeasible even for a deterministic case. Currently, the brute force approach would need to solve four scenarios, for 20 years, with some 8000 reinforcement combinations, which would worsen if the number of reinforcement combinations grows.

Capturing more investment flexibility

According to the elements presented in this report, in order to capture more flexibility from the investment options, there is the option of increasing the details of the decision set for each reinforcement (real options modelling) and also enhance the representation of the decision space by implementing a multi-stage decision problem.

a. *Real options modelling*:

Increasing the set of decisions associated to each reinforcement option will naturally create more flexibility in the decisions. However, this can only capture flexibility if NGESO can access credible information associated to costs of making other real options decisions. The current model with *five* different decisions (proceed, delay, hold, stop, do not start; see definition in [7]) seems to provide good trade-off between information requirements, complexity and precision. Further options should be coming from a more systematic analysis of the deterministic scenario decision space and relevant combinations.

b. *Multi-stage decision model*:

Transforming the model from a two-stage to a multi-stage approach presents several challenges. In general, the sheer size of the underlying problem will increase, which in the case of the CBA analysis already poses a great challenge under the current conditions.

The associated comprehensive cost map described earlier in this section can be used not only to find the optimal deterministic path but also in the context of a multi-stage decision model. In this context a bespoke algorithm (see Appendix B for examples) could be implemented to search the option space under a desired metric, using the map to evaluate each feasible combination of decisions to derive the optimal solution. The time needed to run such a search algorithm would have to be determined with further assessments, and it would be added on top of the time required to create the comprehensive map of operational costs.

- The additional time associated with the search of the stochastic (plus risk metric) approach can be in the order of hours depending on the size of the associated stochastic tree (see Figure 4.11).
- The multistage LWR would pose higher challenges due to the nested nature of the model (whose possible solution resides in the realm of dynamic programming), resulting in a search algorithm that might take weeks to find a solution for a few decision stages. A precise evaluation of the additional times involved, and the structure of the specific algorithms, would require further studies.

### *Mid- to long-term improvements*

Extensions of the planning methodology to systematically include more options and other technologies

It is expected that, as the number of non-network options increase, the *sequential* assessment will naturally become infeasible due to the expanding and/or denser search region (see Figure 4.1, passing from analysing Space TO to Space T or Space U).

In the long run, an *integrated* approach with enhanced representation of operation details (see for example Appendix B) could be a much better (if not the only) approach to search for the optimal reinforcement path without relying on assumptions to reduce the search space. A *reliable* integrated multistage approach would be most readily implemented with a stochastic program, in case with risk constraints (e.g., CVaR), which would extend the current LWR approach while maintaining the risk-controlled philosophy[36]. This would also include solutions that are in principle outside the deterministic search space, thus truly unlocking the possibility of exploring both operational and investment flexibility in a stochastic programming/real options set-up.

Our advice is therefore for NGESO to start exploring the application of integrated stochastic programming approaches. In order to incorporate the degree of risk aversion associated to the LWR approach a suitable risk aversion metric can be used to control the risk position. This would help coping with the growing set of reinforcement options and novel investment options, while providing the capacity to capture compromise solutions through an enhanced representation of the future.

[36] A multi-stage LWR approach might be difficult to implement and/or impractical.

# 5 General feedback and roadmap for recommendations

## 5.1 Feedback and recommendations

Considering the review of SC team's workflow in the preparation of ETYS and boundary capability evaluation for NOA, we would like to provide the following feedback to the current methodology:

- The uncertainty brought by increasing penetration of renewable energy might require network planners to redefine their planning methodology, so that it can account for the impact of this uncertainty in the evaluation of network's technical performance, and consequently accommodate these changes in the cost-benefit analysis which decides the worthiness of a network investment. NGESO has already been actively developing a probabilistic analysis to enhance the existing deterministic one which only derives boundary capability in winter peak snapshot. We have made recommendations which can enhance the current methodology from several perspectives, such as using different sampling techniques to derive boundary capability setpoints, proposing reliability indices and risk metrics to monitoring network performance, and using machine learning techniques to perform network security assessment and predict boundary capability contribution from reinforcement options.
- Although the computational time of NOA's CBA could be substantially reduced by using *static*[37] boundaries to represent network constraints in system operational modelling, with more and more variable power flows it may introduce more inaccuracy in measuring constraint cost reduction contributed by reinforcement options. Therefore, it may be beneficial to integrate the network technical modelling into the CBA's economic dispatch analysis; this would consequently enable a more precise calculation of network constraint costs in NOA's CBA.
- Commercial solutions can be a great complement to network-based options for network reinforcement, as these solutions feature significant technical and economic flexibility. Taking grid-scale battery as an example, it might be able to provide different ancillary services (e.g., frequency response, balancing mechanism) besides reducing network congestions. Commercial solutions have a more flexible service contract length (e.g., 5-10 years), which could be shorter than the lifetime of network-based options (e.g., 30-40 years from transmission lines). This feature represents a valuable factor in investment flexibility. NG has also been developing commercial solutions which are included in the reinforcement options list published in NOA. However, the methodology of commercial solutions evaluation, which is explained in 2.3, could be further improved by integrating it into the NOA framework to evaluate the constraint costs under a unified framework.

Regarding the current methodology of NOA's CBA, it was analysed in detail in the first report [7], focusing on discussing the core elements of the decision-making process. In this report

[37] "Static" means using a single value to represent the upper limit of power flow across a boundary in a season or a year.

we delved deeper in the aspects related to the identification of investment options that would provide more flexibility across scenarios:

- The structure of decisions associated with each reinforcement option seems to provide sufficient flexibility to initiate, hold or stop a project. However, this structure of decisions is used in the context of a two-stage decision process where many of the decisions are fixed based on the deterministic assessment of the scenarios. This is reducing the space of investment strategies that can be selected by the LWR to a point where possibly very little flexibility can be captured.
- Seeking more flexibility is a process that in general has very high computational requirements because many combinations of options have to be assessed under different operation conditions; in this context, in the short-term, we recommend to focus in automatising the deterministic assessment of each scenario as much as possible, reduce computational burden by finding the right periods of operation of the system that capture the system behaviour for each year and each scenario, and improving the selection of the reinforcements that enter the LWR in order to be able to capture more flexibility
- In the long run the CBA assessment should aim to evolve into a multistage *integrated* model that can evaluate network and non-network solutions without the need to first assess the operation of the system for all combinations of investment options in all scenarios. These integrated models are currently available for risk-constrained stochastic approaches; however, no efficient solutions exist, to our knowledge, in the realm of multistage LWR. Not evolving into an integrated approach in the long run might render the current methodology inadequate to fully assess flexible investment options and incorporate more complex representations of future decisions; this, in turn, might generate larger regrets than those that the current methodology is capable to prevent.

## 5.2 Roadmaps for recommendations

Two technical roadmaps are shown in Figure 5.1 and Figure 5.2, which streamlines the development of the recommendations we have proposed in sections 3 and 4 for ETYS and NOA, respectively. The implementation of these technical changes is arranged in a sequential way with different timeframes (e.g., short term, medium term and long term). These two roadmaps consider the feasibility and urgency of each task after discussing with the SC and ECON team, who will be in charge of the corresponding developments (subject to the approval of the stakeholders of ETYS and NOA).

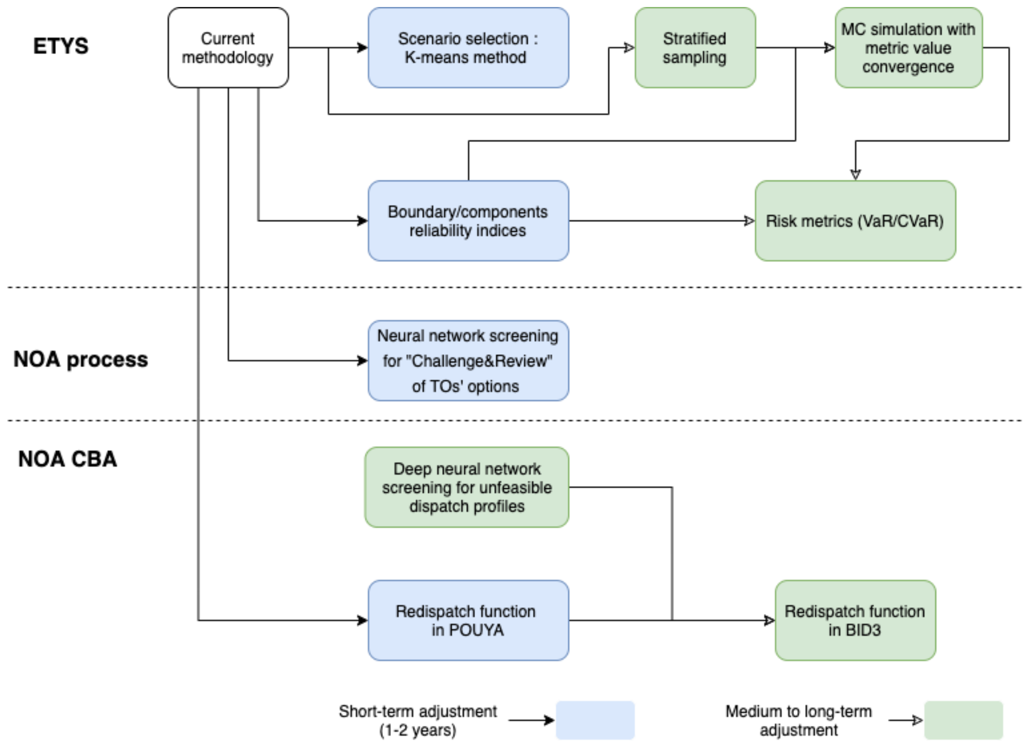


*Figure 5.1. Technical roadmap of the recommendations suggested for the improvement of ETYS and NOA processes*

Figure 5.1 depicts the roadmap for potential technical modelling improvements, which is aimed at better capturing the operational assessment of future GB power systems.

In terms of short-term developments, which we think could be applied relatively quick to the methodology of ETYS in the next couple of years:

- The K-means method could be used to select the demand and renewable generation profiles in the probabilistic boundary transfer analysis.
- Other than identifying a single number to reflect the boundary transfer capability in a season, specific reliability indices could be introduced to reflect the network performance at boundary and components level; for example, we discussed indices such as "boundary congested energy", "boundary congestion probability", "component overloading probability" and "component overloading frequency". By calculating these indices, the confidence of applying *one* specific boundary capability figure in NOA's CBA could be further boosted.
- Two neural network models could be adopted to strengthen some aspects of the current methodology. The first one could be used to quickly classify the network operating states (secure/insecure) in any given dispatch profile, which could reduce the computational time of NOA's CBA, as depicted in Figure 3.8. The second neural network model could be adopted to replace manual scanning in the "Challenge and Review" process of reinforcement options submitted by TOs, which could substantially improve work efficiency of SC team in this process and explore more complete combinations of reinforcement options.

After working on the potential short-term developments, more extensive work could be done to enhance the boundary transfer capability assessment. In this case, we suggest the following:

- To use stratified sampling to firstly identify multiple potential values of boundary transfer capability, rather than use the single value calculated by following SQSS or the current probabilistic method presented in Section 2.2.2.
- By applying different bi-directional transfer constraints with the potential values derived above, Monte Carlo simulation could be performed with an appropriate number of scenarios until the value of all indices have converged.
- The probability distribution of each index value in MC simulation results could be retrieved and the corresponding risk metric calculated, such as value at risk (VaR) and conditional value at risk (CVaR), which would indicate the network performance in the worst scenarios. By deriving these two risk metrics, the network owner would not only better understand the average performance of the network, but also its performance in stressful scenarios, which is an important factor to be considered in network planning.
- The last potential enhancement refers to integrating the technical modelling of network into NOA's economic dispatch instead of using static boundary constraints to mimic network components performance at an aggregated level. By integrating redispatch and post-fault corrective actions into NOA's economic dispatch process, the accuracy of constraint costs estimation could be improved and a fairer comparison in the LWR analysis enabled (details on this are in the first report of this project [7]).

Figure 5.2 presents the summary of assessments and changes that are proposed in the context of the NOA process and the NOA CBA for capturing investment flexibility.

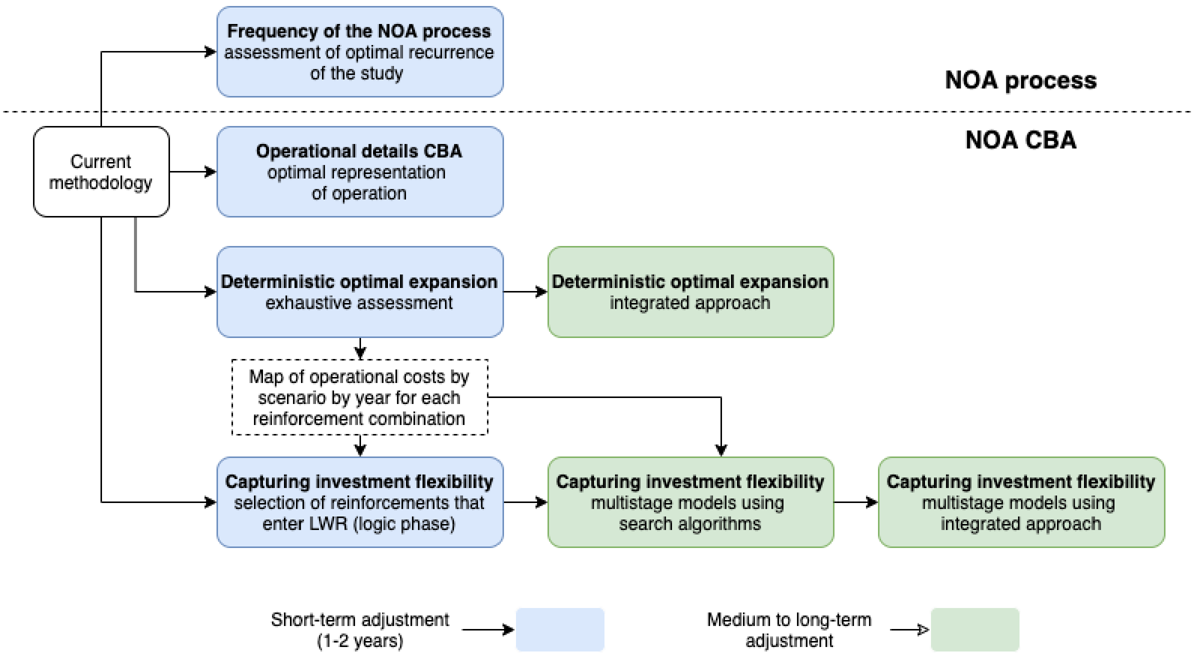


*Figure 5.2. Roadmap of recommendations for the NOA process and the NOA CBA*

- Assessing the optimal frequency of the NOA process is a task that needs to be conducted in the short term due to the impact this would have in the implementation of other recommendations. Presumably implementing changes in this regard can take much longer, but understanding the real trade-offs between running the process every year versus making it less recurrent might have substantial impact on the need of implementation of other recommendations and eventually on the overall quality of the recommendations.

- Determining the right degree of details in the representation of the operation could reduce substantially the computational burden associated to the path determination in the CBA analysis. This can be achieved by comparing the current optimal investment strategy with those obtained while progressively reducing the number of operational periods represented for each year (the selection of representative operation periods can be conducted by appropriate clustering methods). Since all other recommendations for the NOA CBA are strictly connected to the representation of operation, any gains in this regard can improve the overall performance of the methodology.
- Under the current methodology, the determination of the optimal paths of deployment is conducted through a heuristic methodology, heavily reliant on human intervention. In the short term this process should be automatised as much as possible, through an exhaustive search of the optimal path or, in the mid-long run, through algorithms capable of doing an integrated assessment of investment and operation to determine the optimal deterministic path for each scenario.
- Finally, in order to capture more flexibility for investment options, the short-term strategy should be focused on identifying compromise solutions among the global set of reinforcements that is being considered. This will require exploration of options that the current methodology is not finding due to the approach used to select the reinforcements that are subject to the single-year LWR decisions; this will involve the assessment of new heuristic approaches to select that set. In the mid-long term, the efforts should be put in making the timing of the decisions more flexible as much as possible and advancing towards a multistage decision model. To do this systematically the long-term aim should be to build an integrated multistage model (most likely based on risk-constrained stochastic cost minimisation) that can decide what areas of the space of options are interesting to search by progressively studying the operation of the system under different combinations of network and non-network options.

# 6 Acknowledgement

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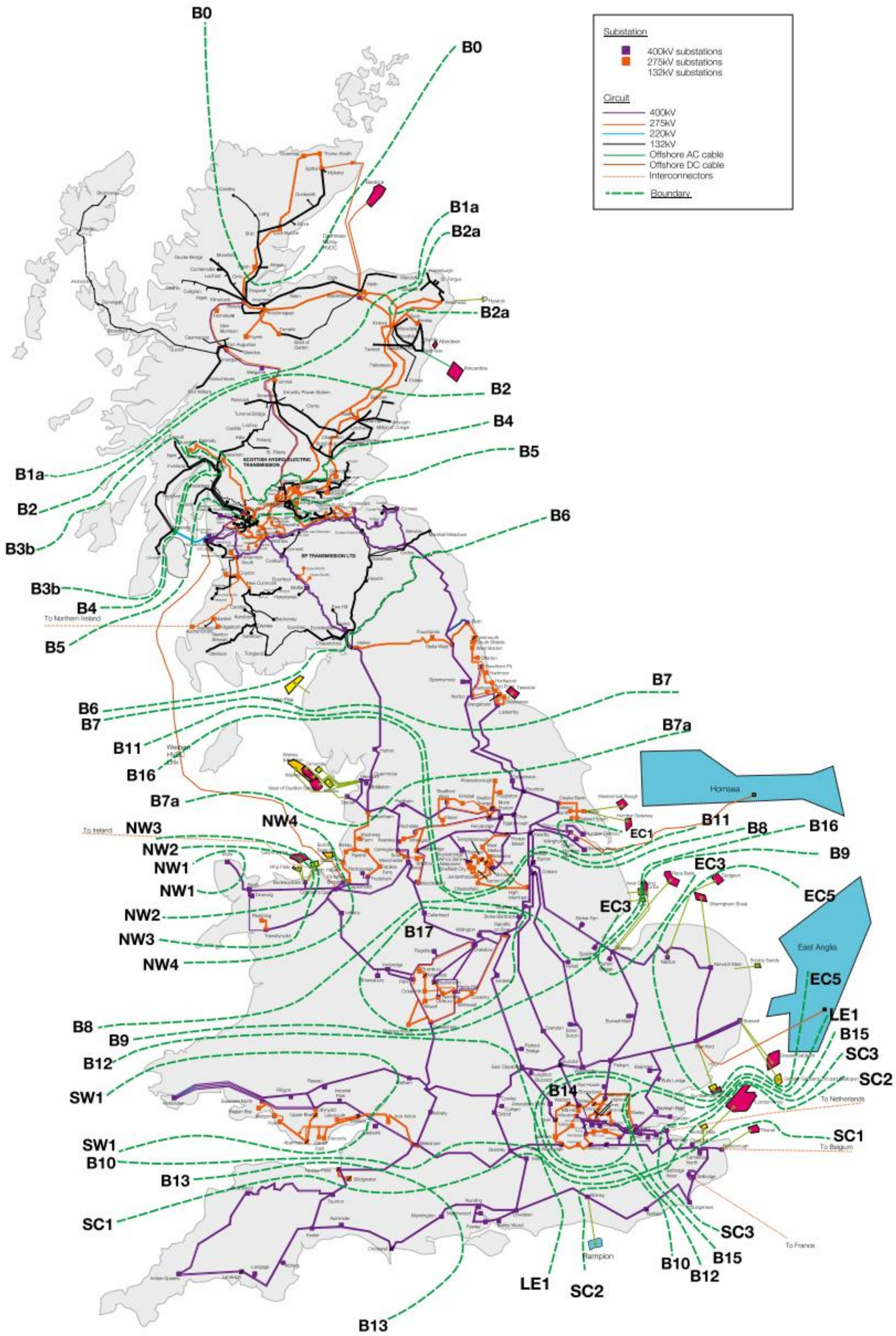
# 8 Appendices

## 8.1 Appendix A: GB system boundary map [2]



## 8.2 Appendix B: Algorithms to find optimal development paths

### 8.2.1 Optimal investment paths under pre-defined assessment of operational costs

The availability of an existing assessment linking all scenarios, years, and reinforcement combinations to corresponding system operation costs (referred to as *map of operation costs*) can reduce substantially the complexity of the approach to search for the optimal path of development, either in a deterministic or stochastic context. Such a map may actually be built in the context of the current NOA methodology thanks to the integer nature of the decisions involved in the transmission expansion problem (all feasible solutions can be listed[38]).

If the operation costs associated with the reinforcement combinations that need to be studied can be mapped (in advance), all the burden associated to the determination of optimal operation can be decoupled from the investment problem. Then the efforts can be focused on building an adequate model to select the optimal reinforcements, and in turn developing a suitable search strategy.

**Reinforcement selection optimisation problem**

If the map is available, it is feasible to create a single integer optimisation problem that can incorporate all the information contained in the map to make the decision about what reinforcements to deploy and when to do it. This approach can work both for the deterministic assessment for each independent scenario, which we present below, or it can be extended to its stochastic version based on cost minimisation (including a suitable risk measure like CVaR).

In order to clarify better how this optimisation problem would be implemented, we present the following example for a deterministic case considering the map of operation costs presented in Table 8.1. In the case of the assessment of the optimal path of deployment for scenario 1 (deterministic), the only relevant variable is to know if a given reinforcement is active or not, which will be represented by symbol $i_{r,y}^{s}$ whose value will be equal to 1 if reinforcement *r* is active in scenario *s* and year *y,* and 0 if not. Annualised investment costs are represented by $IC_{r,y}^{s}$. All costs are referenced to the same year using a discount rate.

*Table 8.1. Map of operation costs*

| | Year 1 | | Year 2 | |
|---|---|---|---|---|
| **Reinforcement** | **Scenario 1** | **Scenario 2** | **Scenario 1** | **Scenario 2** |
| - | $\boldsymbol{OC_{0,1}^{1}}$ | $OC_{0,1}^{2}$ | $\boldsymbol{OC_{0,2}^{1}}$ | $OC_{0,2}^{2}$ |
| R1 | $\boldsymbol{OC_{1,1}^{1}}$ | $OC_{1,1}^{2}$ | $\boldsymbol{OC_{1,2}^{1}}$ | $OC_{1,2}^{2}$ |
| R2 | $\boldsymbol{OC_{2,1}^{1}}$ | $OC_{2,1}^{2}$ | $\boldsymbol{OC_{2,2}^{1}}$ | $OC_{2,2}^{2}$ |
| R1+R2 | $\boldsymbol{OC_{1+2,1}^{1}}$ | $OC_{1+2,1}^{2}$ | $\boldsymbol{OC_{1+2,2}^{1}}$ | $OC_{1+2,2}^{2}$ |

[38] If any of the investment decision was continuous (e.g., to define the optimal transfer capacity of a particular reinforcement), it would be impossible to build an exact map, simply because in that case the investment options would not be enumerable. One could circumvent that issue by discretizing the continuous variable, but the resulting map would not be totally precise, and its size would potentiality grow considerably depending on the number of discrete steps for each continuous variable. In the case of the options provided by the TOs, the decision variables are binary, so the combinations can be enumerated. Also, the limited number of boundary capabilities studies that can realistically be run reduces the combinations of reinforcements that have to be included. In fact, the combinatorial nature of the exercise could eventually render the overall task intractable as more reinforcements are considered.

The resulting optimisation problem is presented below. The expression for the investment (*INV)* is straightforward, considering the annualised investment costs and investment variables.

$$INV: IC_{1,1}^{1} \cdot i_{1,1}^{1} + IC_{2,1}^{1} \cdot i_{2,1}^{1} + IC_{1,2}^{1} \cdot i_{1,2}^{1} + IC_{2,2}^{1} \cdot i_{2,2}^{1}$$

The operation costs are represented by expressions $OP_1$ and $OP_2$ for years 1 and 2, respectively. Auxiliary variables $rc_{p,y}^{s}$ are used to represent when a combination (or portfolio) $p$ of active reinforcements unlocks lower associated operation costs; these variables are also binary, taking value 1 if the reinforcements in the set are all active, and 0 if at least one of the reinforcements activation variables is also 0. This yields the following expressions:

$$OP_1: \; OC_{0,1}^{1} \cdot rc_{0,1}^{1} + OC_{1,1}^{1} \cdot rc_{1,1}^{1} + OC_{2,1}^{1} \cdot rc_{2,1}^{1} + OC_{1+2,1}^{1} \cdot rc_{1+2,1}^{1}$$

$$OP_2: \; OC_{0,2}^{1} \cdot rc_{0,2}^{1} + OC_{1,2}^{1} \cdot rc_{1,2}^{1} + OC_{2,2}^{1} \cdot rc_{2,2}^{1} + OC_{1+2,2}^{1} \cdot rc_{1+2,2}^{1}$$

This results in the following objective function:

$$\min_{\vec{i},\vec{rc}} INV + OP_1 + OP_2$$

The relationship between variables representing investment in reinforcement decisions and the variables representing the activation of sets of reinforcements unlocking of corresponding operation costs are represented by the following expressions (set of reinforcements can take value 1, which unlocks its associated operational cost, if and only if all the corresponding reinforcements activation variables are also 1).:

$$i_{1,1}^{1} \geq rc_{1,1}^{1}$$

$$i_{2,1}^{1} \geq rc_{2,1}^{1}$$

$$i_{1,1}^{1} + i_{2,1}^{1} \geq 2 \cdot rc_{1+2,1}^{1}$$

$$i_{1,1}^{1} \geq rc_{1,2}^{1}$$

$$i_{2,1}^{1} \geq rc_{2,2}^{1}$$

$$i_{1,1}^{1} + i_{2,1}^{1} \geq 2 \cdot rc_{1+2,2}^{1}$$

Of course, if no reinforcement is built, the corresponding operation costs for the system without reinforcements have to be activated in the objective function, which is represented by means of variable *rc* with subindex $p = 0$. This condition can be guaranteed by ensuring that for each year only one variable $rc_{rs,y}^{s}$ has to be equal to 1:

$$rc_{0,1}^{1} + rc_{1,1}^{1} + rc_{2,1}^{1} + rc_{1+2,1}^{1} = 1$$

$$rc_{0,2}^{1} + rc_{1,2}^{1} + rc_{2,2}^{1} + rc_{1+2,2}^{1} = 1$$

If an investment is active in year 1, it has to be active in year 2:

$$i_{1,2}^{1} \geq i_{1,1}^{1}$$

$$i_{2,2}^{1} \geq i_{2,1}^{1}$$

$$i_{1+2,2}^{1} \geq i_{1+2,1}^{1}$$

All variables $rc_{rs,y}^{s}$ and $i_{r,y}^{s}$ are binary.

This formulation can be extended to incorporate further constraints to reflect *rules of deployment* as in the current NOA methodology (mutual exclusivity, must happen together, must follow, avoid operational clashes during construction; for more information on these rules see [7]) and other considerations that need to be included to obtain a feasible deployment path.

**Solution approaches**

The problem presented before can be solved in various ways. Here we present two options, through a suitable mixed integer optimisation solver or using dynamic programming.

Probably the most effective approach is searching for the solution using a mixed integer optimisation solver; these solvers implement searching algorithms that progressively cover combinations of integer variables, selecting what potential solutions are worth exploring based on the information extracted from the combinations that have been visited already (branch and bound algorithm). The problem can be formulated in-house or by a third party and run using free or off-the-shelf proprietary solvers. If the resulting problem is too large, this could be addressed through a suitable decomposition approach too.

The dynamic programming approach is based on determining, for each year y, the combination of possible investment transitions between year y and y+1 (in this case it is said that the *state of the system* is determined by the reinforcements that are available at the end of year y). Based on the operation costs presented in Table 8.1, the total cost for each possible state of the system in each year are listed in Table 8.2.

*Table 8.2. Total costs of operation for each state of the system in both years for Scenario 1*

| | Scenario 1 | |
|---|---|---|
| **Reinforcement** | **Total Cost Year 1** | **Total Cost Year 2** |
| - | $OC_{0,2}^{1}$ | $OC_{0,2}^{1}$ |
| R1 | $IC_{1,2}^{1} + OC_{1,2}^{1}$ | $IC_{1,2}^{1} + OC_{1,2}^{1}$ |
| R2 | $IC_{2,2}^{1} + OC_{2,2}^{1}$ | $IC_{2,2}^{1} + OC_{2,2}^{1}$ |
| R1+R2 | $IC_{1,2}^{1} + IC_{2,2}^{1} + OC_{1+2,2}^{1}$ | $IC_{1,2}^{1} + IC_{2,2}^{1} + OC_{1+2,2}^{1}$ |

By assessing all the feasible transitions between subsequent years (e.g., if year one is in state R1, the possible feasible states for year 2 are R1 and R1+R2, because when a reinforcement is in place it cannot be removed), it is possible to build a transition list like the one presented and to proceed in a backward way. The feasible states are presented in Table 8.3.

*Table 8.3. Feasible states between year 1 and year 2*

| Scenario 1 | |
|---|---|
| **State Year 1** | **Feasible State Year 2** |
| - | - / R1 / R2 / R1+R2 |
| R1 | R1 / R1+R2 |
| R2 | R2 / R1+R2 |
| R1+R2 | R1+R2 |

For each state in year 1, the algorithm would determine the minimum total cost of operation in year 2 among the feasible states. This value would then be added to the cost of the corresponding state of year 1.

The output of the previous step is a list of states in year 1 with the corresponding total costs for years 1 and 2 if a given state is selected in year 1. Proceeding similarly as before, the minimum total cost is selected from the new list, defining the optimal decision for year 1 and by extension from the previous step, also the optimal decision for year 2.

This procedure can be extended for multiple years. Also, it can address multiple scenarios through its stochastic dynamic programming version. The drawback of this approach is that it becomes very heavy if the number of transitions between states is too large, which in this case is directly related to the number of reinforcements being considered (this is known as *the curse of dimensionality*).

### 8.2.2 Integrated approach

Fully integrated approach refers to those algorithms that do not rely on the existence of an exhaustive map for the costs of operation under different investment combinations and different system conditions. These algorithms can find a solution for the expansion problem by systematically searching the best balance between operation and investment costs. This is done by splitting the full problem into smaller problems that iteratively interact to narrow down the solution space until they find the optimal investment set.

Although there are many different integrated algorithms available, only one fully integrated approach is presented here, the Dantzig-Wolfe decomposition with column generation algorithm. This is because this approach is one of the most flexible to incorporate different types of operational constraints in different forms. The purpose here is to shed some light on the main steps contained in these approaches and the information that is required to effectively run them.

**Dantzig Wolfe decomposition with column generation algorithm**

Without delving into mathematics behind the decomposition [51], the result of applying this approach is a set of smaller problems (called *"slave" problems*) that can represent the operation of the system in different years and under different scenarios (if the original problem models multiple scenarios), as presented in Figure 8.1. Each slave problem will contain all the constraints to characterise the operation of the system in the period of time it represents; the objective function of the slave problem contains all the terms to evaluate the costs of operation and also a set of terms ("duals" that are obtained from the master problem, whose structure is described below) that is updated in each iteration, containing information about the global cost reduction associated to activating different investment options.

The *"master" problem* receives the information produced by the slave problems in each iteration – this information is referred to as "column"; each column contains the operation cost and the associated investments selected in each slave problem (also known as "pricing subproblems"). The master problem, usually referred to as the restricted master problem, then selects one of the columns found in previous iterations for each slave problem looking to minimise the overall investment costs and the associated operation costs. For instance, each year's operation can be represented by a number of slave problems covering each a given timeframe (usually 1 week).

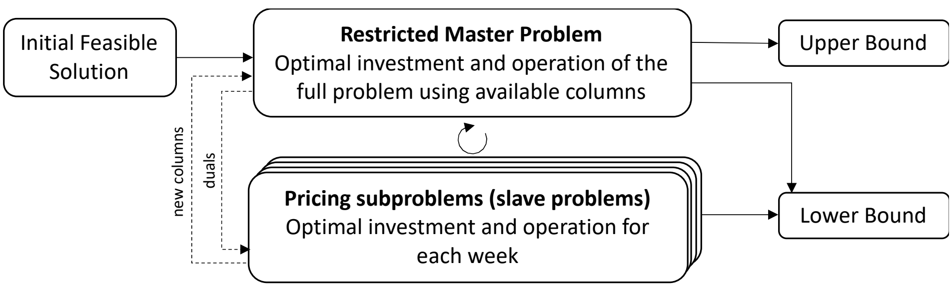



*Figure 8.1. Structure of Dantzig Wolfe decomposition with column generation*

Each iteration consists of running a series of steps which are described below:

1. The restricted master problem is run.
2. The investment sensitivities (also called "duals") are passed to the slave problems.
3. All slave problems are run.
4. The new columns generated in each slave problem are returned to the master problem.
5. The lower and upper bounds for the target value are calculated using the results from the master and slave problems.
6. If the difference between the lower and upper bounds is within a tolerance, the algorithm stops and the solution is obtained.
7. If the difference is outside the accepted tolerance, go to step 1.

There are considerations regarding the *integrality* of the solutions[39] and the nature of the master problem that are not described here, but the general procedure does not change substantially.

The relevance of this kind of approach is that the algorithms progressively inspects only the combinations of investments that produce more value, which of course reduces the need to solve all possible operation conditions associated to all possible investment combinations. In turn, this allows for a higher number of investment options to be considered, because the algorithm will concentrate only in those combinations whose associated investment costs are balanced out by the reductions in operation costs. Also, this particular algorithm allows for the slave problems to be mixed integer linear problems, which can represent a substantial advantage if the operational conditions of the problem can benefit from using integer variables.

[39] The decomposition algorithm requires that the integer variables of the master problem are *relaxed* (made continuous) in order to obtain the *dual* values for the investment constraints. When the algorithm converges, the restricted master problem might thus yield investment solutions that are not integer; this issue is solved with further steps that are not specified in this document.

## 8.3 Appendix C: AEMO's LWR approach

The Australian Energy Market Operator (AEMO) has recently updated their methodology[40] to assess the reinforcement requirements of the Australian eastern system's interconnection capacity (this refers to the transmission capacity between Australian states). This process is known as the Integrated System Plan (ISP) [52], which differs substantially from the NOA process. This is mainly because it includes many elements associated with the FES process (definition of scenarios), so that the overall exercise is closer to a *system architect approach* rather than a pure transmission expansion model. However, the ISP has at least two features that are relevant for the discussion in this section. First, in order to determine what investment projects to recommend, a LWR methodology is applied, whose main steps are described below. Second, the formal outcomes of the ISP are presented every two years, with an interim report (called draft report) between final reports; this approach also can provide a reference for the discussion about the frequency at which is optimal to run the analysis in order to balance out the benefits and the costs associated with carrying out this process as frequently as possible.

The ISP considers five different scenarios which are defined in a similar fashion to the scenarios of the FES (considering degree of decentralisation and decarbonisation). Also, they describe several sensitivities on top of each scenario, generally connected to large changes in the system topology or composition that can substantially affect the behaviour of the system.

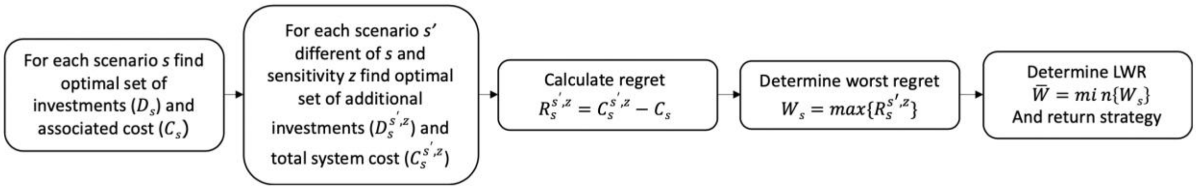



*Figure 8.2. Steps for determination of LWR strategy in the transmission expansion stage of the ISP*

The methodology, summarised in Figure 8.2, starts by calculating the optimal set of reinforcements for each deterministic scenario; this strategy will be referred to as "original strategy". Then, assuming the original strategy is fixed, the underlying conditions of the scenario are changed, one by one, to those described in the sensitivities and the other scenarios (which we refer to as "alternative conditions"). Each of these new problems is optimised considering the remaining reinforcement options that were not chosen in the original strategy; this yields a new total cost of investment and operation for each of the alternative conditions. In turn, this allows building a set of regrets associated with pursuing the original development strategy. The next two steps are fairly standard: first, determine the maximum regret associated to each original strategy and then minimising the maximum regret to decide the strategy that should be deployed to minimise the worst regret.

There are fundamental differences but also similitudes between AEMO's approach to transmission expansion recommendation and the NOA CBA's methodology. The methodologies are similar in the sense that both of them are *not* multistage decision models;

[40] The current description of AEMO's methodology is based only on the interpretation of the methodological description made available to the general public.

they select an original strategy for each deterministic scenario and then they assume that at some point one particular scenario will unfold and the future will be completely determined by the characteristics of that scenario. This limits the capacity of both models to find compromise solutions.

As for the differences, the set of options for reinforcements that AEMO considers is smaller (33 candidates over 5 boundaries) than the set considered by National Grid ESO (145 candidate projects over 56 boundaries, which later on is reduced to less than 15 when the LWR phase is run). Mostly important from a methodological perspective, the assessment of regrets is substantially different: the NOA process considers the possible strategies as all the combinations of decisions about proceeding or holding the current year the reinforcements that enter the LWR, whereas AEMO considers the strategies as those resulting from reinforcing the network to adapt each original strategy to operate under a different scenario. To summarise, the NOA CBA LWR methodology modifies only decision associated to the first year, while AEMO's LWR methodology can modify decision at any point in the horizon.

The frequency of revisions of investment recommendations in AEMO's methodology is 2 years. It can be conjectured that such frequency is deemed enough to amend investment decisions and propose new options, and also to provide sufficient time between official recommendations to assess the status of the system, the view of the future and to run appropriate technical studies on the different investment options.

# 9 Disclaimer